Journal of Transport Geography 88 (2020) 102862

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

The end of travel time matrices: Individual travel times in integrated land use/transport models

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ARTICLE INFO

Keywords:
Integrated land use/transport models
Microsimulation
Agent-based models
Travel time matrices

ABSTRACT

To reduce inaccuracies due to insufficient spatial resolution of models, it has been suggested to use smaller raster cells instead of larger zones. Increasing the number of zones, however, increases the size of a matrix to store travel times, called skim tables in transport modeling. Those become difficult to create, to store and to read, while most of the origin-destination pairs are calculated and stored but never used. At the same time, such approaches do not solve inaccuracies due to lack of temporal resolution. This paper analyzes the use of personalized travel times at the finest spatial resolution possible (at x/y coordinates) and a detailed temporal resolution for synthetic agents. The approach is tested in the context of an existing integrated land use/transport model (ILUT) where travel times affect, among others, household relocation decisions. In this paper, person-level individual travel times are compared to traditional skim-based travel times to identify the extent of errors caused by spatial and temporal aggregation and how they affect relocation decisions in the model. It was shown that skim-based travel times fail to capture the spatial and temporal variations of travel times available at a microscopic scale of an agent-based ILUT model. Skims may provide acceptable averages for car travel times if a dense network and small zones are used. Transit travel times, however, suffer from temporal and spatial aggregation of skims. When analyzing travel-time-dependent relocation decisions in the land use model, transit captive households tend to react more sensitively to the transit level of service when individual travel times are used. The findings add to the existing literature a quantification of spatial biases in ILUT models and present a novel approach to overcome them. The presented methodology eliminates the impact of the chosen zone system on model results, and thereby, avoids biases caused by the modifiable spatial unit problem.

1. Introduction

In 2000, Spiekermann and Wegener (2000) published an article with the title “Freedom from the tyranny of zones”. The idea was to use small raster cells instead of zones to reduce spatial biases in spatial models. For matrix-based travel time skims, however, raster cells proved to be impractical. The matrix grows by a factor of n^2, where n is the number of zones. In systems with many zones, the matrix becomes difficult to create, to store and to read, while most of the origin-destination pairs are calculated and stored but never used. In addition, every travel time matrix is created for one point of time during the day, which may not represent well travel times for another time of the day. Finally, a separate matrix has to be created for each transport mode considered in the model.

This paper proposes a new method to process travel times that allows for the finest spatial resolution possible (i.e. x/y coordinates) and a detailed temporal resolution in an integrated land use/transport (ILUT) model. Updated travel times are provided by a transport simulation. Future year travel times are simulated, too, as ILUT models typically run for multiple decades into the future. Results suggest that ILUT models and similar applications (e.g. mode choice models (Javanmardi et al., 2015)) would benefit from this microscopic representation of travel times.

In traditional ILUT models, the transport model provides zone-to-zone travel times in the form of skim matrices. Those affect accessibilities, and thereby, household relocation decisions. While the accuracy of skims could be improved by providing multiple skims for different time slices, there is commonly only one travel time for each zone-to-zone-relation, which is aggregated in time (e.g. one travel time value for the peak hour) and space (e.g. one centroid per zone) (Slavin et al.,

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https://doi.org/10.1016/j.jtrangeo.2020.102862
Received 17 October 2019; Received in revised form 11 September 2020; Accepted 15 September 2020
Available online 22 September 2020

2015). In reality, however, a worker who commutes at 5:00 am experiences a different level of congestion and different mode options than a commuter traveling at 8:00 am. The impact of travel options on accessibility becomes even more complex for households with multiple workers. The temporal aggregation ignores that travel times may vary during the day, which is of interest when trips are not made during peak hours. Especially for transit travel times, the time of day plays an important role due to service hours and frequencies.

In this paper, a new microscopic ILUT model is used to compare person-individual travel times against traditional skim-based travel times for the feedback from a transport to a land use model. The individual travel times use x/y coordinates and represent traffic conditions at specific times of day. The skim-based approach uses peak-hour travel times and centroid connectors. The goal of this paper is to identify the benefits of dynamic, individual travel time queries in comparisons to more traditional skim-based travel times.

2. Literature review

Disaggregated microscopic models help capturing heterogeneities in travel behavior and household relocation (Wegener and Spiekermann, 2009; Davidson et al., 2007). High spatial resolutions support the representation of environmental issues (Kuehnel et al., 2020; Spiekermann and Wegener, 2008). On the other hand, Wegener and Spiekermann (2009) point out that many disaggregate transport models are too slow to be executed multiple times in ILUT models. Wegener concludes that 'the more micro the better' may be misleading.' The computing time of full-scale microsimulation models can exceed days or weeks. Adding too much complexity to simulation model is one of the sins Lee also describes in his "Requiem for Large-Scale Models" (Lee, 1973). One should pay attention to not increase complexity of models too much and keep models – as Einstein is said to have said – as simple as possible but no simpler.

Nevertheless, there is a continued interest in increasing the spatial and temporal resolution in models (Miller et al., 1999). Policies that test local impacts (e.g. as transit-oriented development) or time-specific impacts (e.g. dynamic tolling) require more detailed representations of space and time. To strive for the right level of detail remains a challenge for many transport and land use modelers (Donnelly et al., 2010).

There have been previous attempts to evaluate the variability of travel times and incorporate less aggregated transport indicators in models. In a recent study, Blanchard and Waddell (2017) developed a methodology to measure transit accessibility at fine spatial and temporal scales based on a weighted network graph derived from a transit schedule. Nicolai and Nagel (2014) introduced a tool to compute high-resolution accessibilities based on simulated travel times. Based on a transit schedule, Farber et al. (2014) analyzed transit accessibilities to find temporal dynamics throughout the day. Javanmardi et al. (2015) developed a mode choice model that queried personalized travel time and costs online with an API.

The level of zonal aggregation affects simulation outcomes. This is also known as the modifiable areal unit problem (MAUP) described by Openshaw (1977), which states that results of spatial analyses are influenced by the chosen zone size (scale effect) and the criteria used to form spatial units (aggregation effect) (Viegas et al., 2009). While the aggregation effect is reported to be hardly solvable (Fotheringham and Wong, 1991), Openshaw (1984) proposes four ways of dealing with the scale effect: ignore it, use individual data, use an 'appropriate' scale or use spatial units that the results produce a predicted outcome. According to Stępniak and Jacobs-Crisioni (2017), methods to reduce the MAUP have been proposed for location-allocation problems. However, the problem has not yet been resolved in spatial interaction models (such as in ILUT models). They present an approach that uses interaction-weighted travel times based on population density to reduce errors in aggregated zone-to-zone travel times. The impact of MAUP on spatial interaction models, which was also analyzed by Putman and Chung (1989) and Zhang et al. (2018) does not exist if individual (=non-aggregated) data are used (Fotheringham, 1989). The study presented here aims to overcome the MAUP by using individual data in form of individual travel times.

Typically, there is a tradeoff to make between few large zones with coarse resolution and many intra-zonal trips and many small zones with a finer granularity but much higher computing times. Choosing the right zone size has been described as being more art than technique (Viegas et al., 2009; Hargrove and Hoffman, 2004), and changing the zone system requires to recalculate and recalibrate skims (Mollov and Moeckel, 2017). In general, the MAUP can be reduced by reducing the size of zones. For large study areas, a fine grid of zones is not feasible. Therefore, zone system algorithms have been developed to generate smaller zones where urban density is high (Mollov and Moeckel, 2017) and to use larger zones in less dense areas. Spatial bias is additionally introduced by the chosen network density and selection of zone connectors/centroids. Chang et al. (2002) report that more detailed networks show lower errors than less detailed networks, although the impact becomes smaller in larger zones. In addition, previous studies confirmed that smaller zone sizes improve the model fit (Lovelace et al., 2014). Another study identified that the level of detail should be high for travel time queries to nearby zones and can be lower for more distant zones (Hagen-Zanker and Jin, 2012).

While the problem of spatial biases is well known, 'the effects of spatial biases on LUTI models remain largely unexplored and underestimated' (Thomas et al., 2015). In a review of existing ILUT studies, Badoe and Miller (2000) identified several studies that "have worked with zonal-aggregate variables for gross spatial units […] thus clouding the effects […]". The MAUP affects the true representation of travel times (Homer and Murray, 2002). Rosenbaum and Koenig (1997) report that zone-based land use models may be limited in their ability to assess policies that aim at influencing development at small spatial scales, such as areas near a transit stop. Jones (2016) presented sensitivity analyses for spatial biases in ILUT models caused by the *spatial resolution* (i.e. size, number and shape of areal units/zones) and the *spatial extent* (i.e. size and boundaries of the study area) of the model input. Results indicate that both resolution and extent significantly impact model outputs.

Microscopic ILUT models have been developed for more than two decades. However, previous applications do not account for microscopic travel time representations. The MOEBIUS project is a microscopic ILUT model that has been applied to Luxembourg (Gerber et al., 2018). The model consists of components for synthetic population, residential mobility and land-use. Similar to the modeling suite presented in the present paper, the agent-based transport simulation MATSim (Horni et al., 2016) is used for assigning traffic. MOEBIUS operates on fine 20 m grid cells to allocate residential population by using a multiscale, bid-rent approach in the base and the final year. Agent-based travel plans can be derived from microscopic locations for traffic assignment. However, as to the authors' understanding, the integration seems to be based on a file-based approach and only goes from the land-use to the transport model, as the transport results are "used in appraisal, but not feedback, of residential location decisions". In other words, updated travel times are not accounted for in simulated land-use choices.

A similar approach was taken by the SustainCity project, which applied an ILUT model in multiple European cities (Bierlaire et al., 2015). Here, the microscopic land use model UrbanSim (Waddell, 2002) was coupled with MATSim, and alternatively with the dynamic transport model METROPOLIS (de Palma et al., 1997). UrbanSim operates on different levels of scale from zones to grids to individual parcels. In the SustainCity handbook (Bierlaire et al., 2015), the authors acknowledge and discuss problems of spatial aggregation and delineation aspects that lead to statistical artifacts. They argue that the effect of MAUP on discrete choice models has not been studied extensively and that there currently is no methodological consensus on a solution to the problems that arise because of the MAUP and study area delineation. Delineation and scale of the study area are subject to the choices of the modelers, which often are not justified well. The ILUT model of the SustainCity project microscopically links transport and land use. However, while microscopic accessibilities were computed, the authors report the issue that, similar to the MOEBIUS approach, the integration is file-based and that it is "impossible for simulated 'persons' making choices in UrbanSim to query the MATSim model directly"(de Palma et al., 2015).

In a preceding study, the land use model SILO was already coupled with MATSim (Ziemke et al., 2016). MATSim replaced an aggregated transport model to produce zone-to-zone skim matrices for the land use model, and it was proposed to implement a query architecture that allows agents in the land use model to query individual travel times from the transport model instead of updating a skim matrix. This functionality has been implemented in the meantime and is applied for the research of the present paper. Individual travel times are expected to reduce the bias introduced by temporal and spatial aggregation while increasing computation times.

3. The FABILUT modeling suite

The FABILUT (flexible, agent-based integrated land use/transport) modeling suite consists of the land use model SILO (Moeckel, 2016) and the transport simulation model MATSim (Horni et al., 2016). For travel demand generation, MITO (Microscopic Transportation Orchestrator; Moeckel et al., 2020) is used in this study. All three models are open source and written in Java, which allows for a tight integration. For studies with no travel demand model available, the FABILUT modeling suite can also be run with SILO and MATSim only, which e.g. allows to simulate the commute segment of traffic (Ziemke et al., 2016).

On a year-by-year basis, SILO models demographic events (e.g. birth, marriage, death, etc.), household relocation and real-estate updates, such as construction of new dwellings, renovation, price updates, etc. SILO belongs to the class of land use models that incrementally update an existing synthetic population. MATSim is used to simulate traffic. In MATSim, each person is resolved as an agent and has one or more plans. A plan is a chain of activities at different locations which are connected by trips. MATSim is based on a co-evolutionary algorithm which iterates over the three steps *traffic simulation*, *scoring* of plans, and *replanning*, which eventually leads to a stochastic user equilibrium (Horni et al., 2016). MATSim's efficient queue-based model makes it suitable to simulate large metropolitan regions. A common approach to reduce computing times is using sampled scenarios where only a sample of the full population of agents is simulated in the transport supply system whose properties are scaled-down correspondingly (Ziemke et al., 2019; Llorca and Moeckel, 2019).

In the current setup, MITO is used to model travel demand. MITO is a microscopic transport demand model that creates home-based tours and non-home-based trips. MATSim is used to simulate the tours/trips created by MITO, i.e. sub-segments of full day plans. As replanning strategy, only route choice is enabled, such that the application of MATSim in this particular setup resembles that of a pure dynamic traffic assignment tool. Based on the MATSim transport simulation, spatially and temporally highly resolved travel times can be queried by SILO. Currently, travel times are used for relocation and job search decisions in SILO.

Traditionally, the transport model provides skim matrices with zone-to-zone travel times for a given time of day (sometimes distinguishing peak and off-peak travel times). Such skim matrices aggregate spatially (zone-to-zone) and temporally (at peak hours) and are only valid for a certain transport mode definition. In this research, we explore the use of individual travel times. We call these travel times individual because.

1. they reflect travel times from a micro location to a micro location in x/y coordinates. The size of zones becomes irrelevant, as all locations are stored in x/y coordinates
2. they reflect travel times for a specific time of day. Someone traveling to work at 5:00 AM in the morning will see different travel times than someone traveling to work at 9:00 AM. Also, the availability of travel modes will differ by time of day.

We implemented both skim-based travel times and individual travel times. This allows us to test both approaches and explore the differences between querying skim-based versus individual travel times.

3.1. Household relocation

The representation of travel times is particularly relevant for the household relocation module of SILO. A household will evaluate a sample of 20 randomly drawn vacant dwellings inside a region (i.e. a set of zones) which has been chosen in a prior step. For evaluation, a multinomial logit choice model is used in which the probability of choosing a dwelling depends on the utility of the dwelling in comparison of the utilities of all other dwelling alternatives:

$$p(d) = \frac{e^{\beta \times u_d}}{\sum_i e^{\beta \times u_i}} \tag{1}$$

where u_d is the utility of option d and u_i are utilities of all choice alternatives. The utility of a dwelling accounts for the size, quality and price of the dwelling and accessibility of the zone where the dwelling is located. For households with workers, the expected commute times from this new dwelling for each worker are included in the evaluation to ensure that a household attempts to find a location within an acceptable commute time for all workers in this household. A Cobb-Douglas function is used for the utility calculation with the commuting times being one of the factors.

Both travel time to work by auto and by transit are considered in the evaluation. The utility component for commuting times for dwelling d is defined as

$$u_{commute,d} = \prod_j e^{-\lambda * tt_{d,j}} \tag{2}$$

where $tt_{i,j}$ is the commute time from dwelling d to work place j. An exponentially decreasing function represents the probability of commuting for the given amount of time. $tt_{i,j}$ is defined as a composite travel time consisting of car and transit travel times, depending on the ratio of cars and workers in the household:

$$tt_{i,j} = \tau \times tt_{i,j,car} + (1 - \tau) \times tt_{i,j,transit} \tag{3}$$

where $\tau = \frac{cars}{workers}$ is the ratio of cars to workers (capped at 0 and 1) and $tt_{i,j,car}$ and $tt_{i,j,transit}$ are car and transit travel times from dwelling i to workplace j. This definition will make households with cars less sensitive to transit travel time while households without cars are considered to be transit captives that rely on transit travel times.

3.2. Query architecture for individual travel times

The implemented query architecture allows agents to query for *expected* individual travel times from and to micro-locations in the form of x/y coordinates at a specific time of day. Whenever SILO requires travel times, MATSim's trip router is queried. Transit is not explicitly simulated but only routed based on the schedule using the recent implementation of the efficient raptor transit router (Rieser et al., 2018). The router also includes access and egress times as well as transfer times for public transport queries. For car travel time queries, it is assumed that the car is parked very close to origin and destination, resulting into access and egress times that can be neglected.

Travel times are not computed preemptively as it is done for skim matrices. Instead, the query architecture returns individual travel times as they are needed.

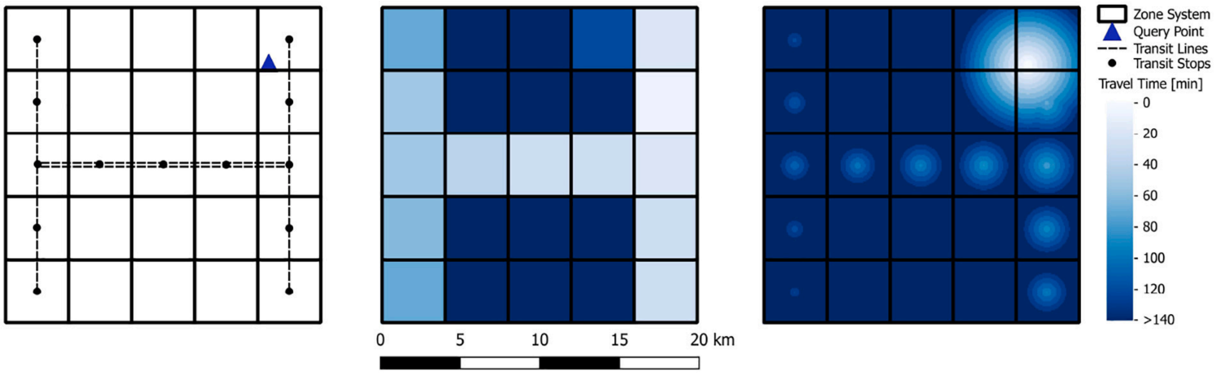

Fig. 1. A comparison of obtained travel times for a hypothetical scenario. Zone system and transit lines (left), skim zonal travel times to a fixed destination (middle) and the respective individual travel times (right).

4. Study area

The zone system for the Munich study area, for which a skim matrix was generated, was developed with a quad-tree based automated zone system generator that iteratively creates smaller raster cells in densely populated areas and larger raster cells in rural areas, while respecting administrative boundaries (Mollov and Moeckel, 2017). This leads to zones with similar population sizes but different areas. While most zones are square-shaped, zones at municipality borders follow the municipal delineation. Undesirably small raster cells may occur near municipality boundaries where raster cells might get split. A post-processor merges those “zone snippets” with neighboring raster cells within the same municipality. Nesting the generated zones within municipalities simplifies and improves the disaggregation of socio-economic data, which were available at the municipality level only. In this setup, large zones usually have a low population and transport network density. It is therefore expected that the accuracy of skim travel times decrease in larger zones with low population densities. The real-world scenario allows to have an actual insight on aggregation issues faced during a usual simulation. As stressed by Thomas et al. (2018), the delineation of the study area can have an important impact on ILUT model results that may lead to additional spatial bias. They argue that the study area should be associated to its functional area and include the nearby competing cities to cover major commute flows. In line with their suggestion, the Munich study area includes all municipalities from where 25% or more of the working population commutes to one of the five core cities in the region, including Munich, Augsburg, Landshut, Ingolstadt and Rosenheim. This 25% threshold was chosen to include all major commute flows while also keeping the study area size computationally feasible.

The synthetic population for this study area (Moreno and Moeckel, 2018) includes household and job locations and was created using iterative proportional updating (Konduri et al., 2016). The population consists of approximately 4.5 million people in 2.2 million households and dwellings.

5. Skim matrices for comparison

The skims are calculated for auto and transit travel times by routing between weighted zone centroids of each zone at a defined and fixed peak hour (once for the morning and once for the afternoon peak). For 4,924 zones, each skim matrix has $4{,}924^2 = 24{,}245{,}776$ travel time values, of which many entries are never used. Zone centroids are obtained by geographically averaging the micro-coordinates of dwellings, weighted by their residents' household size. This is in line with Stępniak and Jacobs-Crisioni (2017) who report that population-weighted centroids are to be preferred to reduce uncertainty due to spatial aggregation. For intrazonal travel times, we consider Z as the set of zones that include the n closest neighbors in terms of travel times. The intrazonal travel time $tt_{i,i}$ of zone i is defined as a given share λ of the average travel time to these closest neighbors:

$$tt_{i,i} = \lambda * \frac{\sum_{j \in Z} t_{i,j}}{n} \tag{4}$$

where $t_{i,j}$ is the travel time from zone i to j and λ is a configurable parameter. By trial-and-error, reasonable (i.e. not biased by systematic under- or overestimation) estimates are obtained by setting n to 5 and λ to 0.66. In other words, the intrazonal travel time is set to two thirds of the average travel time to the next five zones. For individual travel times, all queries ask for explicit origin and destination x/y coordinates, i.e. no intrazonal travel times need to be calculated.

For transit travel times skims, all stops in a 1000 m radius around the weighted centroid of the origin are routed to all stops in the same radius around the centroid of the destination zone. In cases where no stops are found within the 1000 m radius, the (single) closest stop to the centroid at any distance is selected. The most optimistic route is then selected and access/egress times by walk are added between the stops of the selected route and the centroids of zones. In a last step, the resulting zone-to-zone travel time by transit is compared to the direct walk travel time. The shorter option is saved in the skim matrix.

6. Results

6.1. Hypothetical scenario

To showcase the problem of spatial aggregation in the case of transit, the implemented model was applied to a simplistic hypothetical study area. Fig. 1 shows a coarse grid scenario which consists of 5 × 5 square zones with a side-length of 5000 m each (i.e. the area of the study area is 25 km × 25 km). Two U-shaped transit lines connect the corners with the center of the study area. A fixed destination point was picked at the top right corner (blue triangle). Next, the individual and skim travel times to this point were queried in a 100 × 100 meters resolution. In the case of individual travel times, one can clearly see isochrones around the fixed point that show increasing travel times as distance increases. Here, the router would just return a direct walk trip in the transit case. It is important to see that the isochrones span over the zonal boundaries. In the zone in the second row in the last column, the isochrones have an uneven extension, which is due to the transit stop that is located at the center of the zone and that connects to the upper zone. Every other zone that is connected with the transit system has their own isochrones around stops that stick out from the zones that are not connected. Here, one can see that the size of the isochrones gets smaller as the number of stops to the target zone increases. The isochrones in the top left transit zones are slightly larger than their counterparts in the bottom right which is due to the fact that the zones in the bottom right are not directly connected and passengers need to transfer to the other line, which adds waiting time.

In the skim case, every zone consists of one value only. While the overall pattern is similar, one can clearly see the issues that arise due to aggregation. The first issue is that the top right zone does not show the lowest travel time, which is due to the fact that the intrazonal travel time takes an average to all nearest neighbors including the zone to the left that is inaccessible by public transport. Secondly, travel times abruptly change when a zone border is crossed. This refers to the partitioning bias of the MAUP. While parts of the fourth zone in the second row have some reasonable travel times in the individual case, it is considered completely unaccessible by the skim case. A third issue is that the skim travel time cannot capture the decreasing isochrone area in more distant zones, as it computes the zonal value for the zone centroid which is the geographical center in this example. Finally, the skim travel times seem to be biased towards shorter travel times in general. This is due to the fact that the destination, too, is represented by a zonal centroid that is close to the transit stop in the upper right corner. This omits the egress travel time to the actual location.

6.2. Comparison of travel time provision methods in the real-world application

For further analysis, the travel times queried by agents throughout the first simulation year of the ILUT model for both the skim and the individual case are compared. A sample of 200,000 queries during housing search of the first simulation year was recorded. To allow for a fair comparison, both the skim and the individual travel time queries were obtained from the same relaxed MATSim simulation of each scenario. Fig. 2 shows a visualization of dwelling evaluations in the study area. It can be seen that the density of queries correlates with the population and employment density which is highest in the five larger cities of the study area.

Four different setups are compared to determine the influence of the car network density and the choice of the representative time for creation of the peak-hour skim on travel times. Two networks with different network densities were analyzed with two peak-hour alternatives. The dense network consists of *504,109* links, while the coarse network has *142,703* links. Based on traffic count data, the morning peak hour is set to be 8 AM and the afternoon peak hour to 5 PM, which are used to create travel time skims for the skim case. For the Munich case, the afternoon peak hour is more congested than the morning peak hour. Table 1 shows the root mean squared errors (RMSE) and correlation coefficient (r) between the individually queried travel times and the respective skim query for the four setups. Travel times, and in consequence *RMSE*, is given in minutes.

Both setups using the afternoon peak hour for the skim computations show higher RMSE values than their morning peak counterparts. This is expected as the queries from SILO use job start times as their query time, and the majority of workers starts their job in the morning hours.

When comparing network density, the dense network setups exhibit more congruent results for both peak-hour alternatives. This can be understood as another variant of the MAUP. The accuracy of routing decreases with less realistic networks. At the same time, there will be fewer route alternatives for congested route segments. This increases the impact of congestion and leads to higher fluctuations. Additionally, the coarser network is less connected, which leads to high under- and overestimation of travel times depending on the actual queried coordinate or centroid. The results are in line with previous findings that concluded that increased network density will always lead to lower errors, regardless of zone size (Khatib et al., 2001; Chang et al., 2002).

Fig. 3 shows scatter plots for the four scenarios. The setup that uses the morning peak and the dense network shows the best match between skim and individual travel times. For both plots where the morning peak was used for the skims, there are point clouds to right of the diagonal that represent travel times that are underestimated by the skim, presumably from households in which the workers start work at untypical times (e.g. afternoon or evening, where congestion is actually higher).

In the setup where afternoon peaks are used as representative times for the skims, they clearly overestimate travel times. Here, skims were built on congested afternoon conditions, while most commuters for whom travel times are requested do these trips in the morning. It appears that in this particular case where only commutes are considered, inaccuracies due to the use of a time-invariant skim matrix can be remedied by an appropriate choice of the representative time. It is clear, however, that this is not possible in more general cases where different demand segments of travel (that do not take place at the same time of day) need to be taken into account.

Fig. 4 depicts the comparison of the transit case. Results are neither affected by car network density (because transit is routed on a separate, congestion-free network based on a planned schedule) nor the peak hour used for the skim because travel times are almost identical in the afternoon and morning peaks. It can be seen that the spread between individual and skim travel times is much larger than for auto travel times. The RMSE for the transit comparison is 66.45 min, the correlation coefficient is 0.84. The RMSE is rather high, because skim-based and individual travel times tend to be more different, especially in the range of longer travel times. This is plausible as those queries are usually between more rural zones, which also tend to be larger zones. There, transit accessibility is low and the correct actual distance to the next stop is more decisive. In the skim case, the transit travel times are the same for the whole zone, which can be very inaccurate for large, rural zones. The correlation coefficient is relatively high as most of the queries are from households which live in one of the major cities in the study area, where zones are small. Overall, there seems to be no systematic bias to under- or overestimate transit travel times, the mean percentage error is −4%, while the mean absolute percentage error is 23%. The error for transit travel times is higher than for auto travel times as the car network is much more connected than the transit network, which makes it less crucial to query from/to specific points (i.e. stops) in the network.

In the following sections, only the morning peak and the dense network will be considered to analyze auto travel times. This is the setting where skim-based and individual travel times are most similar. By choosing this setup, we allow the skim-based approach the best possible performance in comparison to individual travel times. One should keep in mind, however, that skims will perform worse in many applications other than presented below.

6.2.1. Spatial influence

To analyze the effect of the spatial aggregation for the skim, the comparison is repeated with the time of day of the query fixed in the individual case as well, i.e. the individual travel times are queried for the same time of day that was used to compute the peak hour skim in the skim case. As such only the finer spatial resolution in the individual case remains as a difference to the skim case. For car travel times, the RMSE reduces to 1.89 min (compared to 3.14 min without isolation of the spatial influence), which suggests that for the dense network the spatial aggregation is not too inaccurate. Additionally, the outliers in which the skim travel times underestimate travel times are reduced, which supports the hypothesis that those are emerging from queries at untypical times. In the transit case, however, the RMSE hardly drops, to 59.26 min. This suggests that the spatial aggregation is impacting the difference between individual and skim travel times much stronger than in the car case. Again, this can be explained by the importance of the actual microlocation in relation to stop locations.

The MAUP can be evaluated when comparing the travel time differences against the zone sizes of origin or destination. Fig. 5 shows the zones in the study area, classified by their area. The same classification is applied to analyze the distribution of differences between skim and

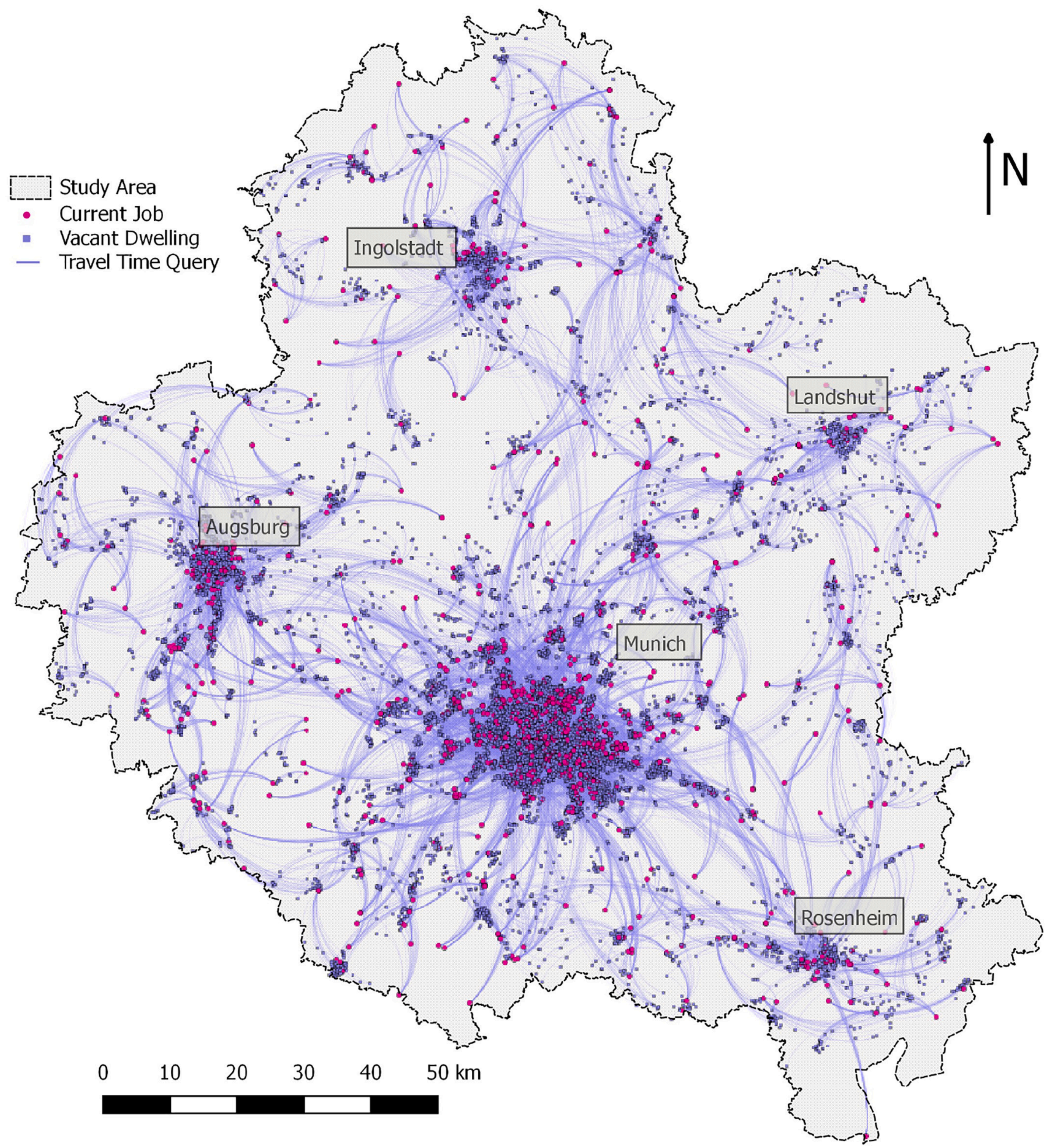

Fig. 2. Visualization of dwelling searches simulated by SILO (sample of 25,000 searches shown). Red dots indicate job locations of workers of the household looking for a new dwelling. Purple dots represent vacant dwellings that were evaluated by these households. The lines show which dwellings were assessed in terms of commuting times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

individual travel times in relation to the size of the origin zone of the query (i.e. the dwelling zone) in Fig. 6. It can be seen that the differences do not change much when zone size increases for the car travel time comparison. In fact, the RMSE in those classes stays around 3 min. For transit, however, the differences are not only larger in general, but their spread also increases significantly when the zone size increases. The RMSE values increase from 50 min for origin zones that are smaller than 3.9 km^2 and increase to 93 min for zones that are larger than 32.6 km^2. This is because larger zones in this model have lower population densities, and therefore, lower transit network densities. Lower network densities increase the variation of travel times for exact coordinates inside the zone. The high RMSE values can be explained by the large amount of outliers in which individual transit queries would return a direct walk trip. For example, for a night time queries or remote

Table 1
Root mean square errors (in minutes) and correlation coefficients between individual and skim-based travel times for different setups. Travel times, and thus RMSE, are given in minutes.

		Both queries use	
		Dense network	Coarse network
Skim matrix comes from	.Morning peak	RMSE = 3.139 r = 0.929	RMSE = 8.339 r = 0.709
	Afternoon peak	RMSE = 7.094 r = 0.817	RMSE = 26.731 r = 0.487

locations, no transit connection is available and the model provides the travel time by walking instead. As the whole study area covers an area of almost 15,000 km^2, walk trips can easily become very long.

6.2.2. *Temporal influence*

The impact of temporal aggregation of skim travel times is analyzed by comparing skim and individual travel time by fixing the zone connectors in the case of individual travel times, but still using job starting times for travel time queries in the individual case. The RMSE in the comparison of car travel times is 2.88 min, which confirms that for car travel times, the impact of temporal aggregation is higher than the impact of spatial aggregation. In contrast to the comparison with fixed query times, we find that fixing the spatial component (i.e. zone

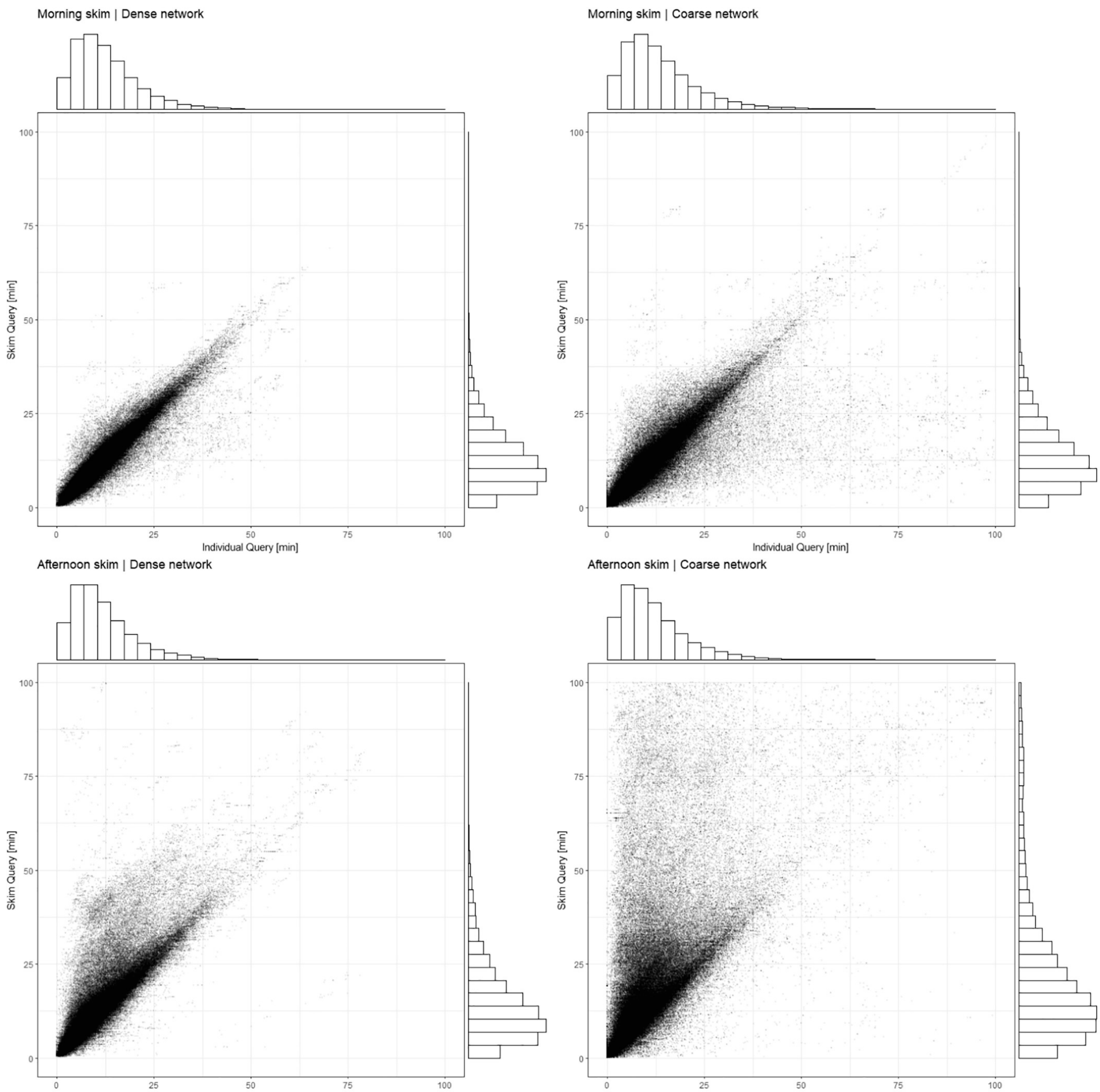

Fig. 3. Comparison between individual and skim-based travel times for four different setups: morning peak - dense network (top left), morning peak - coarse network (top right), afternoon peak - dense network (bottom left) and afternoon peak - coarse network (bottom right).

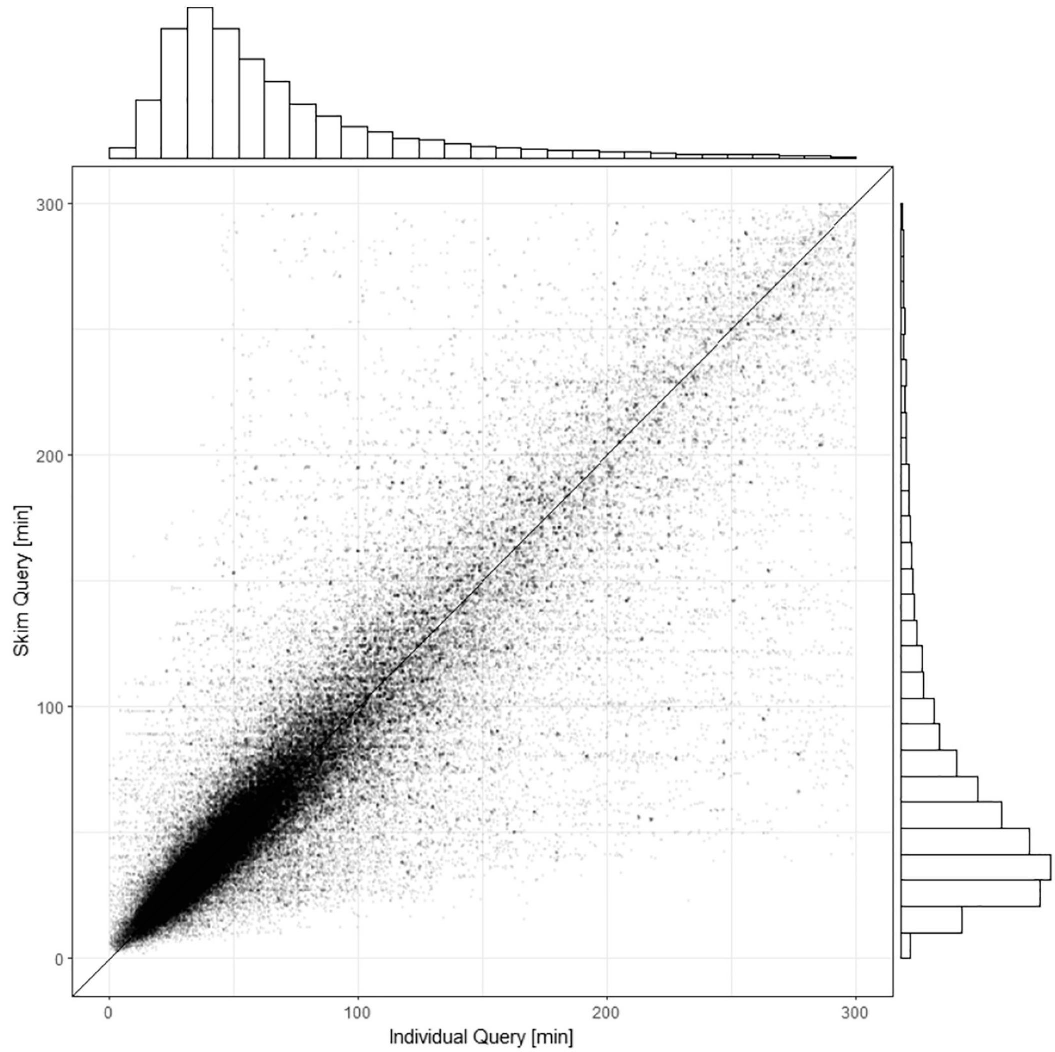

Fig. 4. Query result comparison between individual and skim based travel times for transit modes.

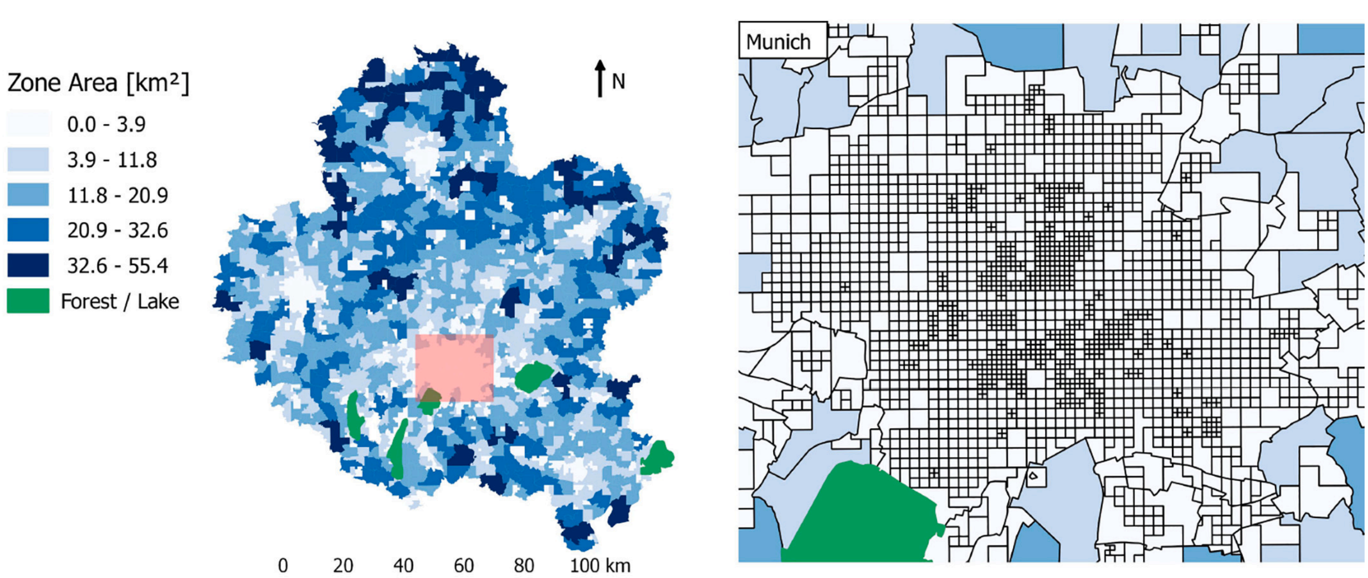

Fig. 5. Zone system and respective zone sizes of the study area (left) and in Munich (right).

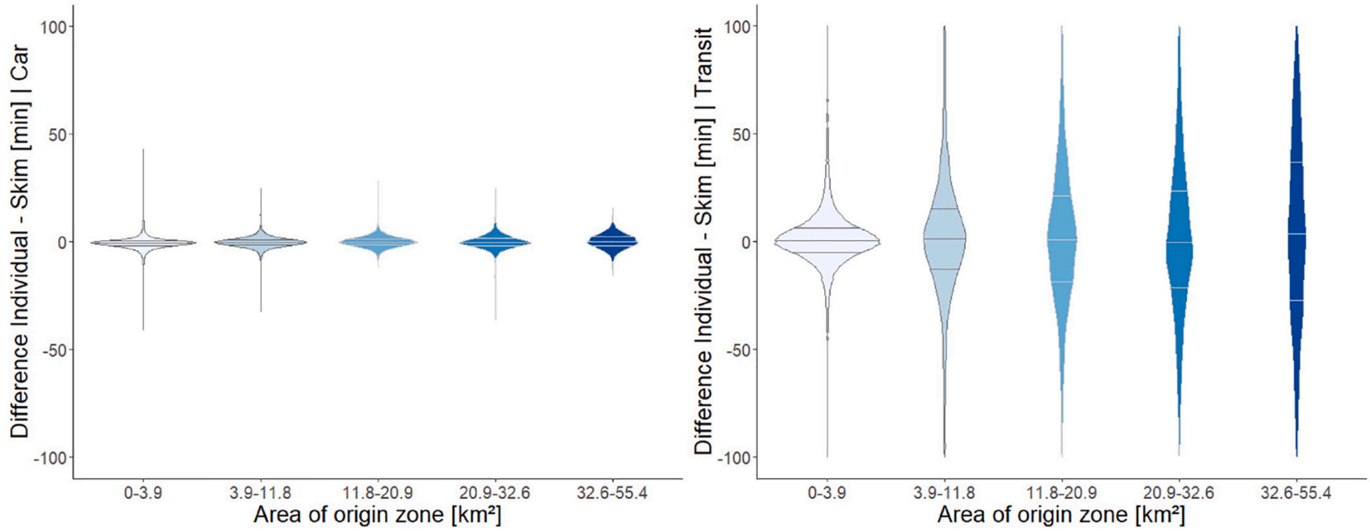

Fig. 6. Violin plots of the difference in travel times between individual and skim travel times by zone area for car (left) and transit (right). The colors correspond to zone sizes shown in Fig. 5.

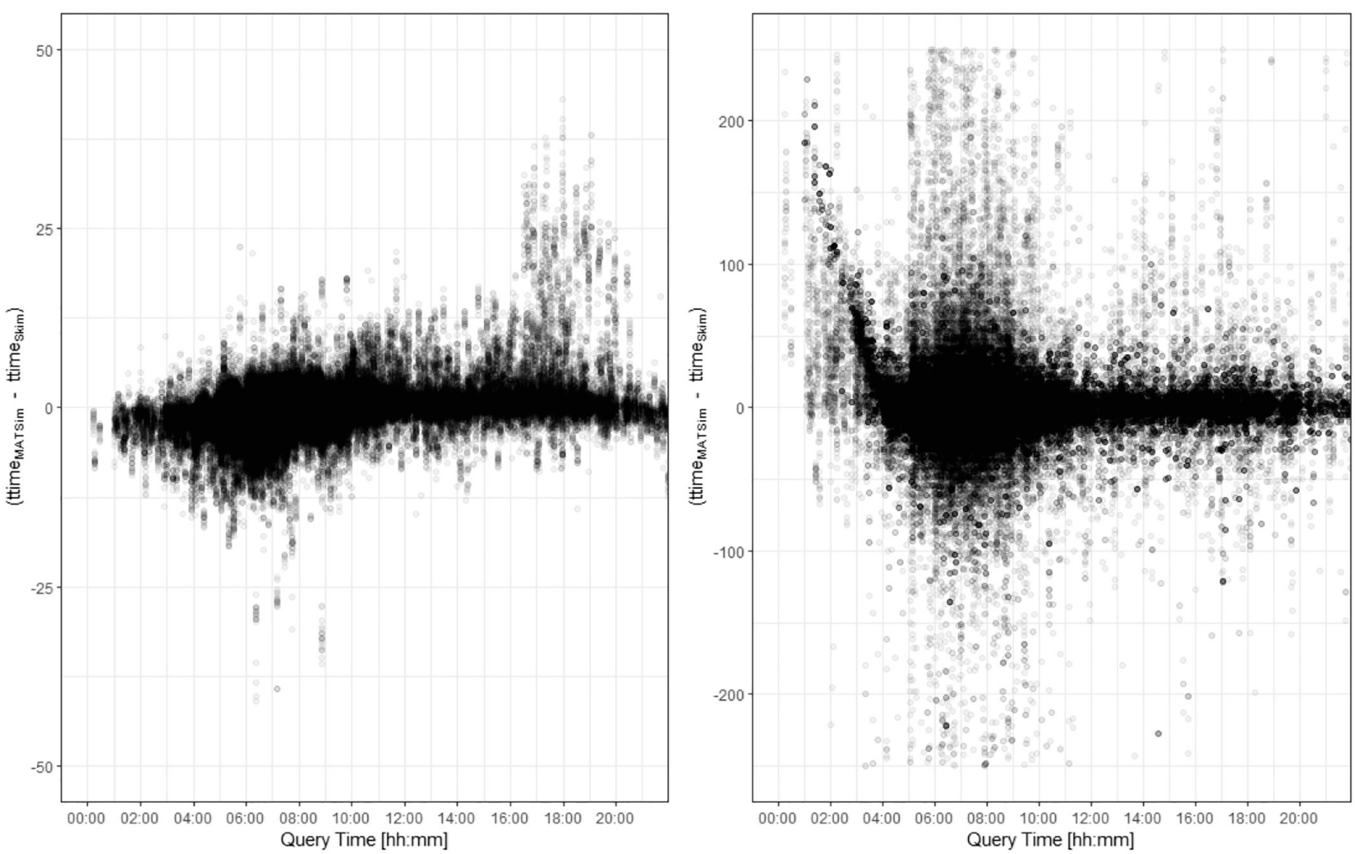

Fig. 7. Difference between individual and skim travel times by time of day for car (left) and transit (right). Note different scales.

connectors) reveals the outliers in which the skim underestimates travel times. This confirms that these outliers are an artifact of temporal aggregation which is inaccurate for untypical job start times. This is confirmed by looking at the deviations of travel time throughout the day (see Fig. 7). The RMSE for queries from 6 am to 10 am is 2.44 min. In the afternoon from 3 pm to 7 pm the RMSE increases to 6.55 min, with most of the queries underestimated by the skim. In Munich, the congestion in the afternoon peak hour is typically higher than in the morning peak hour. This is not captured when the skim is computed for the morning peak hour. Additionally, there are people with anticyclical behavior that start their job in the afternoon and who have to travel in the opposite direction of the main congestion and whose travel time is thus underestimated in the skim case.

Contrary to car travel times, the transit travel times seem to be less distorted by temporal aggregation than by spatial aggregation. The RMSE drops to 25.01 min when querying from fixed zone connectors which is less than half of the error of the spatial impacts comparison. This can be explained by the fact that transit travel times are routed based on scheduled times on a separate network without congestion. As service is similar in terms of frequencies for most of the day, the time of day does not have a strong effect on transit travel time queries. The RMSE is 59.52 min from 6 am to 10 am and hardly changes to 57.40 min in the afternoon from 3 pm to 7 pm. The seemingly larger variations in the morning hours in Fig. 7 can be explained by the fact that the number of queries is much higher than in the afternoon hours, leading to a higher spread.

However, the RMSE is still high and large differences can be seen during night and off-service hours. Fig. 7 shows an almost diagonal line in the early morning hours until 4 am during which the skim underestimates travel times. As most of the transit services do not operate in those hours, the transit router will return a large direct walking trip, making transit very unattractive. The underestimation of travel times reduces towards the start of the transit operation around 4 am as people might as well wait for the start of the service. It can be expected that the error increases when the schedule varies more throughout the day.

6.3. Impacts on household relocation

It is expected that the aggregations in skims lead to inconsistent behavior in microscopic relocation decisions. Transit captive households without cars that only evaluate transit travel times will select more randomly when choosing from dwellings within the same zone in the skim case as the zone-to-zone transit travel times will be the same. In the query analysis it was shown that the spatial impact is high for transit skims. Compared to individual travel times, households should on average move closer to transit stops because the exact microlocation in relation to stop positions is important. To test this, all household moves of the first simulation year of the Munich scenario were recorded for the skim and the individual travel time representation. In both scenarios the households that decided to look for a new dwelling were randomly chosen with a probability of 1%. This is to prevent that the current housing satisfaction, which is also based on current travel times, would lead to different households that decide to move. After the simulation, the distances of the new dwelling locations to the nearest stop according to the transit schedule were calculated. When looking at all relocations (28,430 cases), the average distance to the closest transit stop after moving is 1085.45 m in the skim scenario and 1085.19 m in the individual travel time scenario. The average distances are the same when looking at all relocations which includes the majority of households which are not "'transit captives"'. However, when looking at the relocations of households that have no cars and at least one worker who has to commute (2886 cases), the average distance to the closest stop drops to 605.57 m for the skim scenario and to 569.51 m in the individual travel times scenario. One can see that those households correctly show a higher sensitivity to transit accessibility in both scenarios. In the individual travel time scenario households seem to be slightly more sensitive (about 6%) to transit stop distance than in the skim scenario, which is a small effect but confirms the hypothesis of a more random selection of dwellings in the skim case. It is important to note that the nearest stop distance is not necessarily the stop which is served by the actually taken transit line for getting to work.

7. Discussion

The presented results suggest that the temporal and spatial aggregation of travel times can have a large impact on their accuracy and that individual travel times help to overcome this issue in ILUT models. While aggregation is less of a problem for car travel times if a dense network is used, it becomes even more important in the case of transit travel times which proved to be very inaccurate. A disadvantage of the individual query is the extended computation time. Still, a model run of the FABILUT modeling suite with individual travel times run multiple decades into the future can be finished in less than two days for the Munich case. On the other hand, skim-based approaches that aim to improve accuracies (e.g. using multiple distinct time-of-day-specific matrices or a very high spatial resolution) also increase computing times, and lead to memory requirements that can become unwieldy. In the presented setup, the creation of a car skim for one time-of-day period takes about 4 to 7 min, depending on network density. For transit, the skim creation takes about 1 min for one time-of-day period. In contrast, individually routing the members of roughly 200,000 moving households for up to 20 potential dwellings takes about 40 min per year.

Besides using individual travel times, there are basically three common methods to improve the accuracy of skim-based travel times:

- Use smaller zones. While this reduces the MAUP, the number of entries in the skim grows as n^2, where n is the number of zones. The Munich study area has a total area of approximately 15,000 km^2 in 4924 zones with an average zone size of 2.94 km^2. If finer zones with, e.g., an average area of 1 km^2 were used, the number of zones would almost triple, while the skim matrix would grow by a factor of 9. In Java, the resulting two-dimensional array would take up around 1.7 GB of RAM just to store values for one mode for one time of day. In addition, the calculation time for the skim matrix would increase (by $\sim n$, since skims can be retrieved from Dijkstra trees).
- Use more skim matrices for more detailed time slices. This helps to reduce the effects of temporal aggregation, but linearly increases the consumption of computation time and memory. One could, for example, use four matrices to describe morning and afternoon peaks, off-peak and night time. However, especially for low-frequent transit services which can run in 30+ minutes intervals, the exact time of departure can make a difference.
- Use more zone connectors per zone. This would result in a more smoothed value per O-D pair that might be more valid on average. However, the actual spread of travel times over space and time is still not captured. The impact of zone connector placement is reported to have a small impact when small zones are used (Chang et al., 2002). Stępniak and Jacobs-Crisioni (2017) report small increases in accuracy for the price of higher computational complexity. It should be noted that the population concentration is not a stable attribute in ILUT models and the respective changes are key results of the simulation. This means that zone connectors should take into account not only the base year distribution of population and employment but also future distributions.

The spatial resolution impacts spatial biases. In the presented zone system, zones are smaller where population density is high. As it was shown that larger zone sizes are correlated with higher errors, the chosen detailed zone system ensures that the majority of agents that live in dense areas experience smaller aggregation errors than the smaller number of agents that live in remote areas. In very dense areas of the core cities, the smallest zones are only 100 by 100 m in area. If a zone system with the same number of zones with an even surface with the above-mentioned average zone size of 2.94 km^2 was used, the errors would be more similar for all agents. However, this would reduce the error of a few extreme cases at the costs of the majority of agents in dense areas whose error would increase.

Next to the spatial resolution, the spatial extent has an impact on the spatial biases Jones, 2016). The chosen threshold of 25% of commute flows could have been set lower or higher and would lead to the inclusion of more or fewer municipalities on the fringe of the study area. Given the rather rural nature of the regions near the fringe of the study area, the impact of the threshold on this analysis is small. The variety of errors throughout different zone sizes has been captured in this study. On the other hand, a larger spatial extent would potentially include a few *longer* commute trips. In an analysis that is not presented here, the trip distance did not have a major impact on the aggregation errors for commute trips by car. For transit travel times, distance did have an impact on the error for the few cases where aggregate skims provide a transit connection while individual travel times show that walking is faster than waiting for transit (e.g., for a trip at 3 AM in the morning). For these rare cases, the error increases with distance.

The impact of individual travel times on relocation were small but clearly visible and confirm the increased accuracy of individual travel times. A reason for the relatively small impact is that household relocation does not react very sensitively to changes in transit travel times. The model assumes the same commute probability distribution for car as for transit, even though travel times by car tend to be shorter. Another limitation of the current approach is that workers only evaluate their trip going to work and do not consider the travel time for the return trip.

8. Outlook

This research shows the relevance of individual travel times for ILUT models. We were able to show that it makes a difference when we introduce the spatial and temporal detail of individual travel times compared to aggregate skim matrices. This finding suggests that it will also make a substantial difference when we replace skim matrices with individual travel times in travel demand modeling. Most destination choice and mode choice models in operation use skim matrices to calculate the utilities of different destinations and various modes. Sometimes, peak hour skims and off-peak hour skims are distinguished. One could imagine, however, that replacing skims with individual travel times may have an equally substantial impact as shown in this paper for land use/transport model integration. For example, the transit schedule differs by time of day, which is likely to affect the tripmaker's mode choice depending on their departure time. Similarly, congestion changes over the course of a day, which may entice them to choose different destinations for trips in the morning than in the afternoon. Last but not least, many travel demand models suffer from a coarse zone system. In a skim-based world, every trip to a larger zone takes the same travel time, no matter whether the final destination is close to the zone centroid or at the outskirts of the zone. Individual travel times allow to overcome this spatial and temporal aggregation. In addition, the definition of the zone system, zone connectors and skim time slices does not influence the accuracy of travel times anymore, removing potential sources of bias and error. Travel times become independent of zone definitions and do not change when the zone system is adjusted. While biases introduced by an inappropriate spatial resolution are avoided, the presented approach does not overcome spatial biases introduced by inappropriate spatial extents of the study area.

The implemented query approach can be extended to additionally include person attributes (e.g. age, gender, disability status, value of travel time, access/egress mode) or vehicle attributes (e.g. fuel type, noise and pollutant emission rates). Furthermore, policy-relevant network attributes can be implemented (e.g. environmental zones, time-dependent tolls etc). In addition, high-occupancy vehicle and/or express lanes that require personal information and would otherwise lead to additional matrices are easier to model. The microscopic travel times can further be used to calculate microscopic accessibilities, as described by Ziemke et al. (2017). This would further reduce the impact of the zone system.

Another important benefit of this method is that intrazonal travel times are eliminated. It is inherently difficult to calculate intrazonal travel times (Okrah et al., 2016; Moeckel and Donnelly, 2009), because the origin and destination are represented with the same zonal centroid. The method proposed here uses true x/y coordinates, and thereby, eliminates the need to define intrazonal travel times.

Declaration of Competing Interest

None.

Acknowledgments

This work was supported by the Deutsche Forschungsgemeinschaft (DFG) under project 5051013. It was completed with the support of the Technische Universitt München Institute for Advanced Study, funded by the German Excellence Initiative and the European Union Seventh Framework Programme [grant number 291763].

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