Estimating Parking Search Times for Transport Modelling in Europe: A Hierarchical Bayes Approach with Cross-Regional Data Integration

Ariane Kehlbacher*[1], Gregor Rybczak[2], Felix Rauch[3], and Jens Hellekes[3]

[1]Research Associate, German Aerospace Center (DLR), Institute of Transport Research, Berlin, Germany
[2]Research Associate, TU Berlin, Chair of Transport Systems Planning and Transport Telematics, Berlin, Germany
[3]Research Associate, German Aerospace Center (DLR), Remote Sensing Technology Institute, Wessling, Germany

Short summary

Transport simulation frameworks often exclude parking because data are scarce. This study show how to predict parking search times as inputs for transport simulation frameworks for Europe, where only few observations are available, by using a prior distribution constructed from a large data set on parking search times in North America. An accelerated failure time model is estimated using Hierarchical Bayes methods so that information between parameters for different regions and data sources is shared. We make probabilistic predictions for search times in Zurich and Berlin. Our results show that an appropriate model needs to capture both the likelihood of finding parking as well as search time. Our results highlight the usefulness of drawing on different data sources for parameter estimation, and the importance of generalising from sample to population when simulating a range of plausible parking search times at a given location.
Keywords: parking search time, time-to-event data, prediction, Europe, data integration, partial pooling

1 Introduction

Parking policies in the form of pricing or restrictions are important for managing travel demand (Shoup, 2021). Nevertheless, they are often overlooked, under-accounted or simply excluded from transport simulation frameworks (Thomas, 2024). A review by Young et al. (1991) found that the majority of early transport models did not account for time spent searching for parking; only Nour et al. (1981), Gur & Beimborn (1984) and Axhausen et al. (1988) incorporated in their models. Axhausen et al. (1994) presented an aggregated search time model to investigate the effectiveness of a parking guidance information system. Belloche (2015a) reference this work and find that an association between the occupancy ratio and time spent searching for on-street parking given survey data for Lyon, France. However, occupancy data are difficult to obtain on a large scale for different locations. Cao et al. (2019) utilised a macroscopic assignment model. However, the required input from MATSim limiting transferability of its outputs to new locations.
Various agent-based models have been proposed. These include the works of Benenson et al. (2008), Dieussaert et al. (2009), Vuurstaek et al. (2018), Bischoff & Nagel (2017), Waraich (2016). However, only Tchervenkov (2022) presented average parking search times in comparison to empirical values, using the approach by Bischoff & Nagel (2017) to integrate parking search into an iterative MATSim loop.
Thus, attempts to model parking in transport simulation frameworks are currently hampered by a lack of data on parking search times. For Europe, only few studies that provide values in the form of point estimates without any indication of variability and skew. This makes it difficult for practitioners to come up with robust conclusions about which assumptions they could plausibly make for parking search time at a given European location.

We develop an approach for predicting parking search times based on small number of observation from Europe and a large data set from North America. We outline a formal way of combining observations from these different regions and data sources such that predictions can be made for existing and new locations in Europe. An accelerated failure time model (AFT) is estimated using

Hierarchical Bayes to partially pool information from different data sources and locations whilst accounting for uncertainty. We illustrate our model by simulating parking search times for a location “seen” by the model (Zurich) and an “unseen” location (Berlin).

All code will be published at the time of paper presentation.

2 Data

Parking search times

Data for Europe are obtained from reported values in seven studies. Multiple observations are available for Zurich, Switzerland. Tchervenkov (2022) measured parking search times for 11,461 car trips conducted by 1,151 participants using GPS data. Their overall estimate is 2.9 minutes, with results also detailed for Zurich’s 12 districts. Montini et al. (2012) use GPS data from over 32,000 person-days. They also report estimates for both the city overall and per district. Cao et al. (2019) employed a survey-based approach, randomly administering questionnaires to assess parking search times. They include 89 observations and express results in terms of percentage of drivers who found a parking spot within specified time intervals. Maurer et al. (2023) tracked drivers in central Zurich, combining GPS tracking with a survey. Their survey encompasses 871 observations. For Lyon, Belloche (2015b) analysed parking search times of 923 trips across Zurich districts. For Turnhout, Belgium, van der Waerden et al. (2015) utilised GPS data from 97 car trips compute average parking search time. Finally, average parking search time for the Netherlands was calculated at 36 seconds by van Ommeren et al. (2012). Because its log is negative it had to be excluded from our analysis (see model below). For North America, data were collected by Geotab Inc. (2020). The data set contains average parking search times at 4,750 polygons spanning across Canada, the United States (US) and Mexico. These rectangular polygons vary in size and are restricted to cities with populations exceeding 100,000 inhabitants. For better comparability with European cities only polygons located in Canada and the US are used, and three observations are omitted to also avoid negative values of logged search times. Because of missing data on motorisation rates, 11 cities in Connecticut cities are excluded from the final data set, resulting a total of 4,635 polygons.

Predictors

Different predictors were tested as described in 3. The final model includes two types of predictors. First, motorisation rates (number of cars registered per 1000 inhabitants) for North America were computed with 2022 data on vehicle registrations in the US (CEIC, 2022) and Canada (Statistics Canada, 2022a) and 2019 census data for the US (census.gov, 2019) and 2022 census data for Canada (Statistics Canada, 2022b), respectively. Motorisation rates for European locations were obtained from publicly available figures. We hypothesised that higher car ownership may be associated with more competition for parking, leading to longer search times.
The second type of predictor is street intersection density (SID). Sallis et al. (2016) define it as “the number of pedestrian-accessible street intersections divided by the area”. Since this study focus on parking, we create two types of SID to capture differences in infrastructure supporting active and motorised traffic. We hypothesised that higher SIDs and therefore a more connected street network, allowing drivers to navigate more easily to find available parking. For the calculation of SID for the various study areas, polygons delineating these areas were either acquired or digitised. For each polygon, Open Street Map (OSM) linestrings intersecting the polygons were downloaded with the OSMnx tool (Boeing, 2017). Tab. 1 displays the classification into active and motorised OSM objects; other key/value pairs are excluded. Afterwards, all intersections between OSM objects within the same class were identified and normalised by the area of the respective polygon. The SID extraction process largely followed the instructions provided by Uhjaval (2024), which were adapted into a Python script for automation. Fig. 1 provides an overview of the SID calculation process using a subset of Zurich.
Fig. 2 illustrates the distribution of SID values grouped by study areas. North American polygons exhibit significantly higher SID values for OSM objects classified as motorised compared to European SIDs, while the difference in active SID values is smaller but still evident. The density of data points in the figure also reflects the disparity in sample sizes between the North American and European studies. Notably, the outlier for European active SID values corresponds to the Grange

Table 1: OSM keys and values of objects used for the SID calculation.

Class	Key	Value
active	highway	living street, pedestrian, track, footway, bridleway, steps, corridor, path, cycleway, crossing
motorised	highway	motorway, trunk, primary, secondary, tertiary, unclassified, residential, motorway link, trunk link, primary link, secondary link, tertiary link, service, road, busway

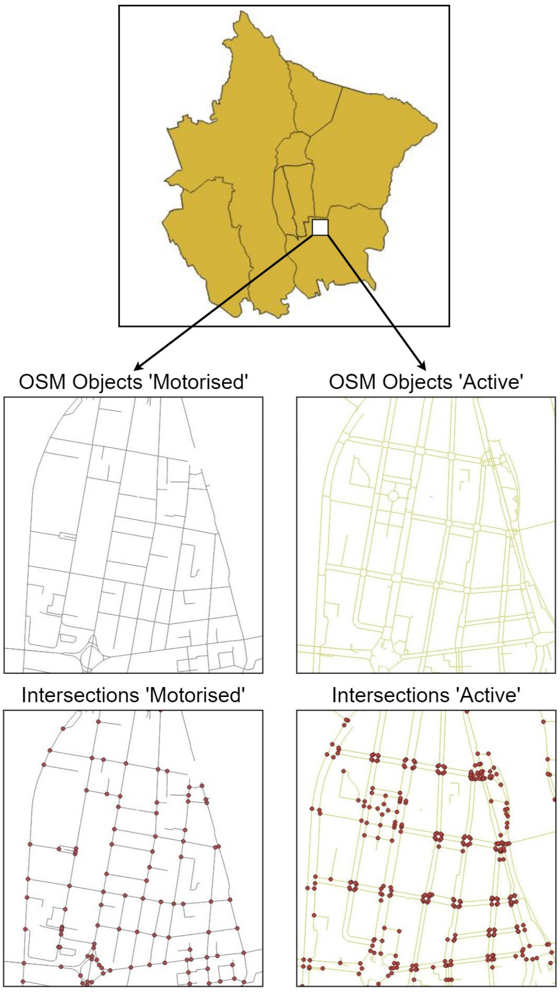

Figure 1: Flowchart for the extraction of OSM objects in Zurich.

Blanche district in Lyon. Summary statistics of all variables included in the model are reported in Table 2.

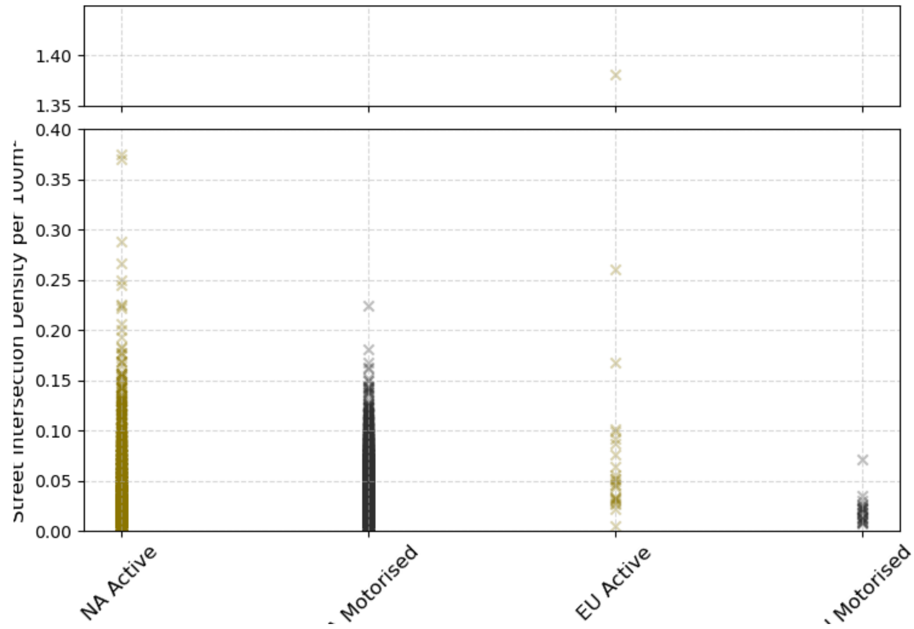

Figure 2: SID values of all study areas in North America (NA) and Europe (EU), grouped by infrastructure supporting active and motorised traffic.

Table 2: Summary statistics of all variables included in the model.

Data source	Variable	Mean	5 %	95 %	Min	Max
North America	avg. parking search time (min)	4.81	2.29	8.07	1.09	11.55
1 data set	motorisation rate per 1000 inhbts.	598	193	736	120	875
(n=4635)	SID active per 100 m^2	0.018	0.000	0.080	0.000	0.375
	SID motorised per 100 m^2	0.036	0.004	0.087	0.000	0.224
Europe	avg. parking search time (min)	3.57	1.40	8.98	1.18	11.10
6 studies	motorisation rate per 1000 inhbts.	587	470	800	415	800
(n=26)	SID active per 100 m^2	0.115	0.023	0.242	0.005	1.381
	SID motorised per 100 m^2	0.019	0.008	0.034	0.007	0.071

3 Model specification and estimation

Parking search times are time-to-event data, which can be analysed using hazard scale or accelerated failure time (AFT) models. We chose the latter because it model the (logged) time until an event occurs directly. We assume that logged search time, $\ln(t)$, follows a Weibull distribution such that

$$\ln(t_n) \sim \text{Weibull}\left(\alpha_n, \sigma_n\right) \tag{1}$$

$$\sigma_n = \frac{\mu_n}{\Gamma\left(1 + \frac{1}{\alpha_n}\right)} \tag{2}$$

where n indicates an observation, and α and σ are shape and scale parameters, respectively. The shape parameter captures the likelihood of finding parking as time progresses and therefore the distribution's skew and tails. The scale parameter captures the typical time it takes to find parking with higher values indicating longer search times, and vice versa.

Data include observation for Europe as reported in six studies and a large data set for North America (see Sec. 2). Parking search times in Europe and North America are related, they have the same data generating process. But they also differ, namely in terms of data sources (6 European studies, 1 North American data set) countries (3 in Europe, 2 in North America) and cities (3 in Europe, 306 in North America). To account for these differences we estimate our model using a hierarchical Bayes (Gelman, 2006; Gelman et al., 2013) approach. Shape and scale parameters of the Weibull distribution are themselves specified as models:

$$\ln(\alpha_n) = a + a_{g[n]} + x_n^a A \tag{3}$$
$$\ln(\mu_n) = b + b_{g[n]} + x_n^b B \tag{4}$$

where a and b are overall intercepts of shape α and mean μ, respectively. Parameters a_g, b_g capture deviations of groups from the overall mean, where each group $g = 1, ..., G$ is a combination of country, city and data source and $G = 325$. Predictors x_n^a and x_n^b are mean-centred and scaled motorisation rates and SIDs. Prior distributions are:

$$\begin{aligned}
a &\sim \mathsf{Student\text{-}t}(3, 0.5, 2.5)\\
b &\sim \mathsf{Student\text{-}t}(3, 0, 2.5)\\
a_g &\sim \mathsf{N}(0, \tau_a)\\
b_g &\sim \mathsf{N}(0, \tau_b)\\
\tau_a &\sim \mathsf{Student\text{-}t}^{+}(4, 0, 2)\\
\tau_b &\sim \mathsf{Student\text{-}t}^{+}(4, 0, 2)\\
A &\sim \mathsf{Student\text{-}t}(3, 0, 2.5)\\
B &\sim \mathsf{Student\text{-}t}(3, 0, 2.5)
\end{aligned} \tag{5}$$

Thus, shape and scale parameter vary by group at lower levels of the hierarchy and common parameters are estimated at the higher level in the form of standard deviations τ_a and τ_b. Estimates for each group-specific intercept a_g and b_g are partially informed by data for the specific group and by data available for all other groups. This process is referred to as partial pooling, where the degree of pooling is determined by the data. It leads to more stable and generalisable estimates (Gelman et al., 2013), which is important for making predictions for particular in new locations.
The joint posterior density combines the likelihood in (1) to (4) with prior distributions in (5). Estimation is performed in Stan using Hamiltonian Markov chain Monte Carlo sampling (Stan Development Team, 2024) and the R package brms version 2.21 (Bürkner, 2017). Four independent Markov chains, with 2,500 warmup iterations and 5,000 sampling iterations each are estimated. Convergence is checked via the split potential scale reduction factor (Rhat) (Vehtari et al., 2021). The reliability of estimates is further verified by checking that bulk and tail effective sample sizes (ESS) are sufficiently large.
To evaluate model fit we conduct posterior predictive checks, and out-of-sample predictive accuracy of the model is evaluated using Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics (Vehtari et al., 2017). The latter is important for checking if predictions can be generalised to the population.

4 Model results

Various predictors were tested including some based on OSM data (e.g. counts of various tags related to shopping and leisure activities per area, proportions of land use types). However, the sampler did not converge, if these predictors were included in the model, suggesting non-identifiability of their parameters in the likelihood. Thus, OSM land use and groups of OSM tags are unsuitable. They lack systematic variation with parking search times. Instead, models including motorisation rate and/or SIDs as predictors converged. Various combinations were compared based on their predictive performance using PSIS-LOO. The best model includes motorisation rate, motorised SID and active SID in the sub-model for the scale parameter, and motorisation rate and active SID in the sub-model for the shape parameter. This highlights the heterogeneity of parking search times in terms of both scale and shape.
We present the results for the best model. Scale reduction factors of all parameter are 1, indicating convergence of the sample, and bulk and tail ESS are sufficiently large (see Tab. 3). Fig. 3 shows ten data sets simulated from the posterior predictive distribution which closely match with the observed data. This indicates that our model fits the sample well. To verify that the model parameters can be generalised to the population, we investigate the out-of-sample predictive accuracy of our model, the results of which are depicted in Fig. 4. All observations have k-Pareto values below 0.7, which indicates that removing any observation would have little effect on the joint posterior distribution (and therefore on our predictions) so that inferences about the population can be made.

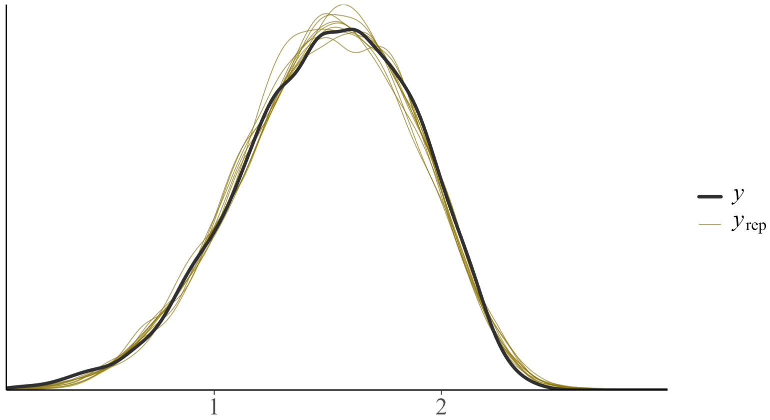

Figure 3: Kernel density estimate of the observed data set $y = \ln(t_n)$ (dark line), with density estimates for 10 simulated data sets y_{rep} drawn from the posterior predictive distribution (yellow lines).

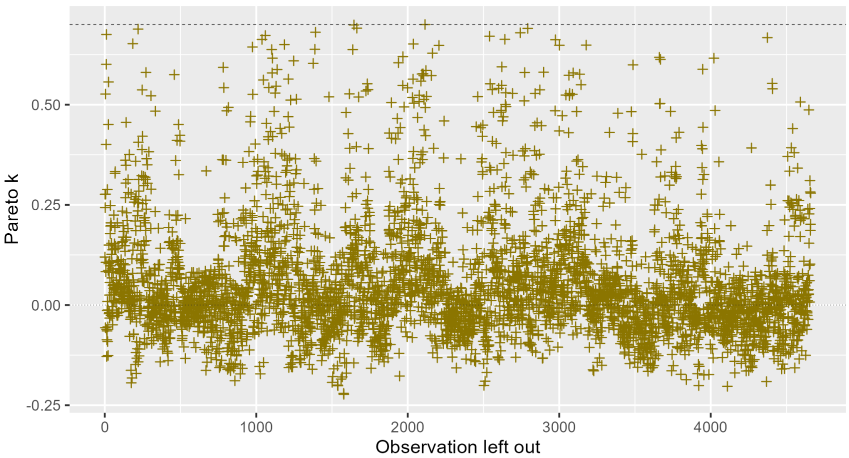

Figure 4: Pareto-k-values from PSIS-LOO.

Posterior estimates are reported in Tab. 3. First, the magnitudes of the estimated standard deviations of the varying intercepts, τ_a and τ_b, suggest that there is evidence of substantial variation in parking search time across data sources and locations. It is higher and more uncertain when it comes to the likelihood of finding parking over time (the shape), than in terms of much time is spent to find it (the scale). Second, the posterior mean the overall intercept of the shape, a is greater than one (exp(0.177)=1.19). This says that at average motorisation rate and SIDs levels, the likelihood of finding parking increases as time progresses, which is expected. The likelihood of finding parking also is higher in areas with higher SIDs for active traffic, but it decrease as time progresses in areas with higher motorisation rates. The posterior mean of the scale parameter, b, is expected log parking search time if motorisation rate and SIDs are at the mean. It shows that overall expected parking search time ranges between 4.3 and 4.5 minutes; and it is longer in areas with higher SID of active traffic shorter in areas with higher SID of motorised traffic. The association between motorisation rate and scale is uncertain and possibly zero.

Table 3: Posterior means, lower and upper 95 % credible intervals (CI), Rhat diagnostic, and bulk and tail effective sample sizes (ESS) of the ACF model parameters. Motorisation rate is scaled by 100; SIDs per 100 m^2 and motorisation rates are mean-centered.

Parameter		Mean	l-95% CI	u-95% CI	Rhat	Bulk ESS	Tail ESS
a	intercept of shape α	0.177	0.021	0.138	1.00	3297	5448
A_1	motorisation rate	-0.122	-0.160	-0.084	1.00	3182	5288
A_2	SID active	2.269	1.520	2.998	1.00	10186	8000
τ_a	std. deviation of a_g	0.177	0.138	0.221	1.00	2773	4899
b	intercept of mean μ	0.391	0.374	0.409	1.00	1752	3028
B_1	motorisation rate	-0.043	0.006	-0.056	1.00	2613	4435
B_2	SID motorised	-0.551	-0.771	-0.334	1.00	10245	7154
B_3	SID active	0.707	0.086	0.540	1.00	10040	7326
τ_b	std. deviation of b_g	0.102	0.089	0.116	1.00	2356	4423

These results can be interpreted as follows. The likelihood of finding parking in the first place is lower in areas with higher motorisation rates compared to areas with lower motorisation rates. The likelihood of finding parking in the first place is higher in areas with better infrastructure supporting active traffic compared to areas with worse infrastructure, but it takes longer to find parking in these areas. Parking search times tend to be shorter in areas with better infrastructure for motorised traffic than in areas with worse infrastructure supporting motorised traffic. Finally, our results highlight that accounting for the likelihood of finding parking as captured by skewness and tail behaviour of the data distribution is also important when modelling the time to find parking.

5 Probabilistic predictions for locations in Europe

Hierarchical Bayes models assume infinite exchangeability between group-specific parameters, where our groups are combinations of data sources, countries and cities. The implied conditional independence allows making predictions for locations unseen by the model, alongside those that the model has already seen. The posterior predictive density of parking search time, $\tilde{t}$, given motorisation rate and SID active and SID motorised, $\tilde{x}^a$ and $\tilde{x}^b$, and given existing data t, x^a and x^b is

$$p(\tilde{t} \mid \tilde{x}^a, \tilde{x}^b, t, x^a, x^b) = \int p(\tilde{t} \mid \theta, \tilde{x}^a, \tilde{x}^b, g \in E)\ p(\theta \mid t, x^a, x^b)\ d\theta \tag{6}$$

where $\theta = \{a, b, A, B, \tau_a, \tau_b\}$ and E is the set parameters relating to Europe. Because of partial pooling, the predictive density in (6) is informed by both the global average parking search time and European-specific search times and their associations with motorisation rates and SIDs. It reflects the uncertainty in the model parameters and also the variability of the data by marginalising the density of $\tilde{t}$, given parameter estimates θ, over the posterior distribution of the parameters given the observations of t, x^a and x^b included in data.
Fig. 5 shows the posterior predictive density of parking search time in Zurich, where $x^a = \tilde{x}^a$ and $x^b = \tilde{x}^b$ refer to the motorisation rate and SIDs of Zurich. Values reported by studies of Zurich are indicated by coloured dashed lines. They mostly lie within the mass of the predictive density, which is expected. However, based on our model, longer average parking search times of 5 to 7 minutes, than those observed in the data are also quite probable, whereas search times of less than 2 minutes seem less likely. This demonstrates the effect of partial pooling. Zurich-specific information was balanced by the model with the information from all data sources. As a result, Zurich-specific estimates are regularised by "shrinking" them toward the global average, and the model suggests low probability of observing very short search times based on the little data available for Zurich. Thus, practitioners who need to pick a value for Zurich may confidently choose a value between 3 to 4 minutes. An assumption of longer search time can also be reasonable made, but very short parking search times are unlikely given all available evidence. This highlights the importance of generalising from sample (or observation) to population when picking values for model parameters for transport simulation frameworks.

Figure 5: Posterior predictive distribution of average parking search time in Zurich, Switzerland. Dashed lines indicate values reported in the four studies included in the analysis.

Figure 6: Posterior predictive distribution of average parking search time in Zurich, Switzerland and Berlin, Germany.

Next, we predict parking search time for Berlin, which is not included in the data. Values for motorisation rate, SID active and SID motorised in Berlin, $\tilde{x}^a$ and $\tilde{x}^b$ are required. The motorisation rate for Berlin is 319.4 cars per 1000 inhabitants, SID active is 0.019 and SID motorised is 0.011. Transformations are applied. Also, values for the Berlin-specific intercepts a_{g^*} and b_{g^*} are drawn from posterior densities $\mathsf{N}(0, \tau_a)$ and $\mathsf{N}(0, \tau_b)$, respectively. Fig. 6 depicts the posterior predictive density of average parking search time in Berlin (in grey) alongside that of Zurich (in yellow). Its mean is 5.7 minutes and its mode is 9.8 minutes. A practitioner may confidently choose values between 4 and 7 minutes depending on the context of the scenario. The prediction for Berlin is higher than that for Zurich. This is informed by global average search time, European-specific search times and the estimated associations between the rate and scale of the Weibull distribution and motorisation rate and SIDs.

6 Conclusion

We present a method for simulating average parking search times at different locations in Europe. In doing so, we test and rule out predictors based on OSM land use and OSM tags, and we identify useful predictors to be active and motorised SIDs and motorisation rate, data for which are readily available and calculable (code provided on Github).
Our approach has several advantages. The ACF model is based on theory account for the time-to-event nature of parking search times. The models finds that both length of time and likelihood of finding parking over time have are important. The probabilistic approach provides practitioners with a range of plausible values, which makes it more flexible than having to choose one value

based on a point estimate. It also makes transparent the uncertainty of the predicted search time, which can be communicated and taken into account by practitioners when making assumptions for their simulation frameworks. Another advantage is that, if new data points or data sets become available, the herein estimated joint posterior density can be easily updated to improve the accuracy of model predictions. This also means the spatial refinement of the model as new data (for example at district level) can become available.
There are limitations to our approach. First, it assumes that all drivers can only search and find parking within the spatial unit. Second, the model does not account for variability of search time over the course of a day. Third, predictors capturing specifically demand-side influences on parking, are missing. However, this is important for practitioners considering the effects of demand-side parking policy interventions on mode choice. We leave this for future research.

Acknowledgements

We gratefully acknowledge Maria Lopez Diaz for preparing OSM data, for sourcing data and computing motorisation rates for the polygons in North America.

References

Axhausen, K. W., Beyerle, A., & Schumacher, H. (1988). Choosing the type of parking: A stated preference approach. In *20th Annual UTSG Conference.*

Axhausen, K. W., Polak, J., Boltze, M., & Puzicha, J. (1994). Effectiveness of the parking guidance information system in Frankfurt am Main. *Traffic engineering & control*, *35*(5), 304–309.

Belloche, S. (2015a). On-street parking search time modelling and validation with survey-based data. *Transportation Research Procedia*, *6*, 313-324. Retrieved from `https://www.sciencedirect.com/science/article/pii/S2352146515000526` (4th International Symposium of Transport Simulation (ISTS'14) Selected Proceedings, Ajaccio, France, 1-4 June 2014) doi: https://doi.org/10.1016/j.trpro.2015.03.024

Belloche, S. (2015b). On-street parking search time modelling and validation with survey-based data. *Transportation Research Procedia*, *6*, 313–324. doi: 10.1016/j.trpro.2015.03.024

Benenson, I., Martens, K., & Birfir, S. (2008). Parkagent: An agent-based model of parking in the city. *Computers, Environment and Urban Systems*, *32*(6), 431–439.

Bischoff, J., & Nagel, K. (2017). Integrating explicit parking search into a transport simulation. *Procedia Computer Science*, *109*, 881–886. Retrieved from `http://www.sciencedirect.com/science/article/pii/S1877050917310906` doi: 10.1016/j.procs.2017.05.414

Boeing, G. (2017). Osmnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, *65*, 126-139. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0198971516303970` doi: https://doi.org/10.1016/j.compenvurbsys.2017.05.004

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. doi: 10.18637/jss.v080.i01

Cao, J., Menendez, M., & Waraich, R. (2019). Impacts of the urban parking system on cruising traffic and policy development: The case of Zurich downtown area, Switzerland. *Transportation*, *46*, 883–908.

CEIC. (2022). *Car registrations in the US.* Retrieved from `https://www.ceicdata.com/en/united-states/motor-vehicle-registration/motor-vehicle-registration-total` (accessed 06/2024)

census.gov. (2019). *Census data api.* Retrieved from `https://api.census.gov/data/2019/acs/acs5/groups/B01003.html` (accessed 06/2024)

Dieussaert, K., Aerts, K., Steenberghen, T., Maerivoet, S., & Spitaels, K. (2009). Sustapark: An agent-based model for simulating parking search. In *Agile international conference on geographic information science, hannover* (pp. 1–11).

Gelman, A. (2006). Multilevel (hierarchical) modeling: What it can and cannot do. *Technometrics*, *48*(3), 432–435.

Gelman, A., Carlin, J., Stern, H., Dunson, D., Vehtari, A., & Rubin, D. (2013). *Bayesian data analysis* (3rd ed.). Chapman & Hall/CRC.

Geotab Inc. (2020). *Parking Statistics in North America.* Retrieved 19.12.2024, from https://www.openml.org/search?type=data&sort=runs&id=43564&status=active

Gur, Y. J., & Beimborn, E. A. (1984). Analysis of parking in urban centers: Equilibrium assignment approach. *Transportation Research Record*(957).

Maurer, L., Roca, F., Treffinger, N., Henke, L., Hofmann, V., & Leonhartsberger, O. (2023). Tracking parking search and occupancy in Zurich.

Montini, L., Horni, A., Rieser-Schüssler, N., & Axhausen, K. W. (2012). Searching for parking in GPS data. In *13th International Conference on Travel Behaviour Research (IATBR 2012).*

Nour, E., El Reedy, T., & Hk, I. (1981). A combined parking and traffic assignment model.

Sallis, J. F., Cerin, E., Conway, T. L., Adams, M. A., Frank, L. D., Pratt, M., ... Owen, N. (2016). Physical activity in relation to urban environments in 14 cities worldwide: a cross-sectional study. *The Lancet*, *387*(10034), 2207-2217. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140673615012842 doi: https://doi.org/10.1016/S0140-6736(15)01284-2

Shoup, D. (2021). *High cost of free parking.* Routledge.

Stan Development Team. (2024). *RStan: the R interface to Stan.* Retrieved from https://mc-stan.org/ (R package version 2.32.6)

Statistics Canada. (2022a). *Car registrations in canada.* Retrieved from https://www150.statcan.gc.ca/t1/tbl1/en/dtl!downloadDbLoadingData-nonTraduit.action?pid=2010002402&latestN=5&csvLocale=en&selectedMembers=%5B%5B1%5D%2C%5B%5D%2C%5B1%5D%2C%5B1%5D%5D&checkedLevels=1D1%2C1D2 (accessed 06/2024)

Statistics Canada. (2022b). *Census data canada.* Retrieved from https://www.statcan.gc.ca/en/developers/csv/user-guide (accessed 06/2024)

Tchervenkov, C. (2022). *Empirical and simulation studies on parking in Switzerland* (Doctoral Thesis, ETH Zurich, Zurich). doi: 10.3929/ethz-b-000593365

Thomas, A. (2024). *Exploration of traffic area segmentation on aerial imagery to address the parking data requirements of travel demand models.* Retrieved from https://www.mos.ed.tum.de/fileadmin/w00ccp/tb/theses/2024/Thomas_2024_webVersion.pdf

Uhjaval, G. (2024). *QGIS tutorials.* https://github.com/spatialthoughts/qgis-tutorials. Retrieved from https://github.com/spatialthoughts/qgis-tutorials

van Ommeren, J. N., Wentink, D., & Rietveld, P. (2012). Empirical evidence on cruising for parking. *Transportation Research Part A: Policy and Practice*, *46*(1), 123-130. Retrieved from https://www.sciencedirect.com/science/article/pii/S0965856411001443 doi: https://doi.org/10.1016/j.tra.2011.09.011

van der Waerden, P., Timmermans, H., & Van Hove, L. (2015). GPS data and car drivers' parking search behavior in the city of Turnhout, Belgium. *Geoinformatics for intelligent transportation*, 247–256.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and computing*, *27*, 1413–1432.

Vehtari, A., Gelman, A., Simpson, D., Carpenter, B., & Bürkner, P.-C. (2021, June). Rank-normalization, folding, and localization: An improved r^ for assessing convergence of mcmc (with discussion). *Bayesian Analysis*, *16*(2). Retrieved from `http://dx.doi.org/10.1214/20-BA1221` doi: 10.1214/20-ba1221

Vuurstaek, J., Knapen, L., Kochan, B., Bellemans, T., & Janssens, D. (2018). First steps towards a state-of-the-art parking simulator. *Procedia Computer Science*, *130*, 779-784. Retrieved from `https://www.sciencedirect.com/science/article/pii/S1877050918304976` (The 9th International Conference on Ambient Systems, Networks and Technologies (ANT 2018) / The 8th International Conference on Sustainable Energy Information Technology (SEIT-2018) / Affiliated Workshops) doi: https://doi.org/10.1016/j.procs.2018.04.135

Waraich, R. A. (2016). Parking. In A. Horni, K. Nagel, & K. W. Axhausen (Eds.), *The Multi-Agent Transport Simulation MATSim* (chap. 13).

Young, W., Thompson, R. G., & Taylor, M. A. (1991). A review of urban car parking models. *Transport reviews*, *11*(1), 63–84.