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The demand-side mitigation gap in German passenger transport

Marlin Arnz^{1,2*}

Abstract

Deep transport decarbonisation requires not only technological measures, but also large-scale changes towards sustainable mobility behaviour. Researchers and decision-makers need suitable tools for corresponding strategy development on a macroscopic scale. Aiming at broad accessibility to such methods, this paper presents an open source passenger transport model for policy analysis in German medium- to long-distance transport. It discusses model design and data, limitations, alternative approaches, and its base year results and concludes, that macroscopic transport modelling is very suitable for policy analysis on national scales. Alternative approaches promise more insight on smaller scales. As an exemplary case study, the model is applied to ambitious technology projections for the year 2035, showing the ambition gap towards reaching the 1.5 degree-target of the Paris Agreements. Results indicate that 66 million tCO_{2eq} per year must be mitigated through further technological substitution or demand-side mitigation strategies.

Keywords: Transport modelling, Mobility behaviour, Emissions reduction, Discrete choice, Transport decarbonisation, Network accessibility

1 Introduction

Fast transport sector decarbonisation is deemed difficult yet crucial for climate change mitigation in alignment with the Paris Agreements [24]. Since time until reaching an average global temperature increase of 1.5 degree Celsius is limited, unleashing full transport mitigation potential requires not only technological measures, like fuel switches and new propulsion technologies, but also large-scale behavioural changes towards sustainable mobility [64]. These different mitigation strategies are often referred to as avoid, shift, improve: Avoiding the need for traffic, shifting traffic to more environmentally friendly modes, and improving vehicle technologies [40]. Avoid and shift measures are especially effective and low-cost in the long term [24] and promise high increases of

well-being as co-benefits to (GHG) emissions reduction [25].

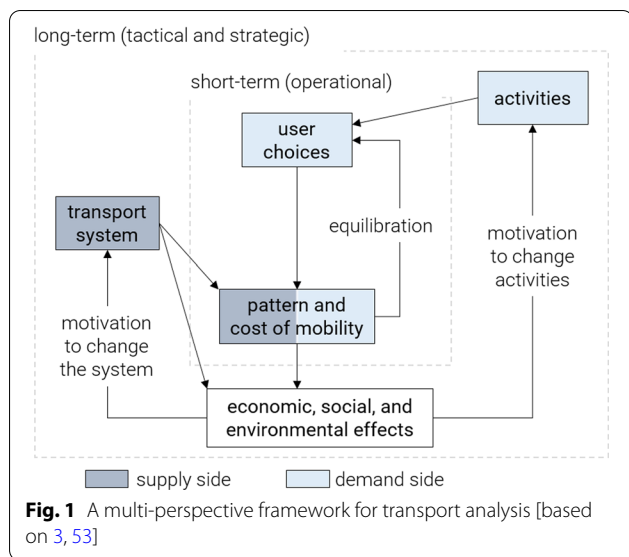
Yet, quantitative analysis of the role of sufficiency in swift transport mitigation is comparably rare: Only one third of the measures analysed in national transport mitigation studies address the demand side, which makes policy strategy comparison uncertain [35]. The same picture occurs for measures included into national climate action plans in nationally determined contributions [34], which highlights policy relevance of this research field. On a global scale, some integrated assessment studies advanced methods for the depiction of demand-side action [see reviews from 30, 76]. On local scales, Creutzig [22] finds that transport modelling yields the most realistic representation of behaviour. Transport modellers increasingly use their tools for long-term scenarios towards emissions mitigation and sustainability [10]. However, large-scale models are usually proprietary, making it difficult for new ideas to enter the field [50].

This paper presents *quetzal_germany*, an open source, macroscopic passenger transport model for Germany. It

*Correspondence: maa@wip.tu-berlin.de

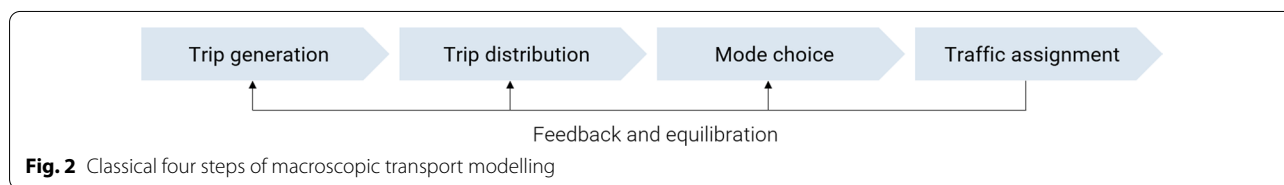
¹ Workgroup for Infrastructure Policy, Technical University Berlin, Berlin, Germany

Full list of author information is available at the end of the article



to observe; and estimating them in circumstances that do not yet exist. The first purpose describes the work of classic transport economists, while the second is particularly interesting for comprehensive emissions mitigation scenarios.

Transport analysis applications must meet a number of requirements: On the demand side they need (1) a probabilistic distribution of travel demand over space and time, (2) variation of demand depending on perceived travel cost or its benefit, and (3) differences among travellers in perception of cost or benefit and its variation over time. Supply-side requirements comprise (4) different classes of vehicles or modes in the network (private and public), (5) flow-dependent link cost, and (6) options for traffic management [3]. Accurate depiction of the transport sector in an energy system context further requires (7) choice of not making a trip (physically), (8) vehicle ownership and drive train technologies, (9) private vehicle use patterns, and (10) infrastructure investment deci-



explores the suitability of macroscopic transport modelling for nation-wide analysis of demand-side mitigation pathways. In the following, Sect. 2 gives a brief overview of transport system analysis, corresponding methodological requirements, national transport modelling in practice, and starting points for open source approaches. Section 3 presents *quetzal_germany's* structure and method. Its base year results are discussed in Sect. 4, followed by a critical review of its capabilities and normative assumptions. Section 5 gives an exemplary outlook into the year 2035 to quantify the ambition gap towards reaching the 1.5 degree-target of the Paris Agreements. Section 6 concludes.

2 Background on transport system analysis

2.1 Classification and requirements of models

Transport system analysis is naturally complex because it involves a large number of heterogeneous decision-makers with difficult to predict behaviour on the demand side, as well as different temporal layers at the supply side and the built environment. Figure 1 outlines short-term interactions between supply and demand side, as well as long-term impacts of external effects on decision making, land use, and transport supply. Allsop [3] defines two main purposes of transport analysis: estimating features and use of existing transport systems that are difficult

sions [4, 28, 52, 63, 67, 76].

While techno-economic energy models usually fail to represent behavioural aspects of above [46], transport modelling has been a central tool for simulation of mobility behaviour since the late 1950s [17]. There are two major approaches: activity-based (micro-) and aggregated (macro-) modelling. Micro-modelling is the younger field of research and utilises agent-based modelling techniques with rich sets of dependent variables and usually involves high spatial and temporal resolutions [8, 69]. Macro-modelling, on the other hand, follows the classical four steps of transport modelling (Fig. 2) and simulates travel between aggregated demand zones for aggregated demand segments (e.g. trip purposes or population groups) at the desired level of detail.

Transport models with national scope are particularly interesting for the analysis of large-scale policies within the transport sector and beyond. Even though publications concerning design of large-scale transport models are rare in scientific literature, they shed light on many non-trivial considerations. The Danish [59], Italian [12], Norwegian [56], Swedish [13], UK [27], and Dutch [42] national transport models have aggregated designs with inter-connected demand and supply modules. All of them are Logit models, based on discrete choice theory.

The four latter models have separate modules for short- and long-distance travel to ensure high levels of detail and high computational performance. This differentiation further helps to accurately depict the impact of few, but long trips on the overall traffic system [60]. Similarly, the German national DEMO model divides passenger travel into distances at a threshold of 100 km, which allows simulation of mobility choices at a resolution of 6,561 zones [73].

2.2 Open source modelling

Availability of models and corresponding data is crucial in order to support—and often enable—quantitative analysis of sufficiency measures in transport. Open source modelling and open data is desirable as it promotes barrier-free co-development of new perspectives and approaches of complex problem solving. It helps reducing parallel efforts in maintaining large code bases and data sets, allowing researchers to collaborate efficiently on shared problems [54]. Additionally, closed source modelling often lacks options to integrate into other simulation or optimisation tools, which is deemed important for thorough decarbonisation pathway analysis [46].

Still, there are no open source transport models on national scales to the author's knowledge. In many countries, an underlying reason can be lack of required data sources (that are openly licensed). For many practitioners however, required open source software has high entry barriers, such as a poor overview of appropriate solutions, steep learning curves, and lack of an established community. Until today, proprietary software largely dominates transport modelling [50]. While there are many frameworks for micro-modelling approaches, the only open source software for macroscopic transport modelling is Quetzal [20]. It implements methods of the classical four-step model and beyond, allows full demand-supply interaction, spatially explicit network representation, full flexibility in demand group segmentation, and is highly modular due to its implementation in Python.

3 Introduction of quetzal_germany

quetzal_germany is an aggregated transport model (see Fig. 2) for medium- and long-distance passenger travel within the area of Germany. It is divided into 2225 zones, simulating traffic in between them. They are defined by clustering 4605 municipality unions to similar zone sizes. If computational power is limited, the zoning system can easily be reduced to 401 NUTS3-level zones. Inner-zonal traffic is computed from other data sources, making local and urban mobility an exogenous element (see

Sect. 3.3). The model is developed in Python under use of the Quetzal open source transport modelling suite [20]. It is openly available on github (see section “Availability of data and materials”).

Trip generation and distribution (steps one and two in Fig. 2) are currently covered by an exogenous (OD) matrix from the Federal Transport Infrastructure Plan 2030 (VP2030) [61]. Transport demand of the whole population, linearly interpolated between 2010 and 2030 to the base year 2017, is divided into twelve demand segments, corresponding to the national mobility survey (MiD2017): commuting, business, education, grocery shopping or medical executions, leisure, and accompanying trips; each trip purpose further divided into car availability in the household. Mode choice is designed as a Multinomial Logit model for each of these segments with land and air transport alternatives. Logit models and random utility maximisation are by far the most common and best understood applications in discrete choice analysis [11, 19, 53]. Section 3.2 describes the choice model specification and its variables in detail.

The network model for Germany with measurable (LoS) attributes is described in Sect. 3.1. Both road and public transport use the Dijkstra algorithm to find shortest paths in terms of travel time. Demand-supply equilibrium is implemented as iterative convergence between the equilibrium road traffic assignment, using the Frank-Wolfe algorithm [33], and the Logit modelling step. In a subsequent step, quetzal_germany calculates emissions from transport activities as described in Sect. 3.4.

3.1 Network model and level-of-service attributes

quetzal_germany includes a highly detailed network model based on OpenStreetMap data for (MIT) and GTFS feeds for (PT). The latter is aggregated to the most relevant services for inter-zonal travel, using agglomerative clustering and filtering methods, in order to increase computational performance for the German-wide model. As a blueprint for regional studies however, the whole network graph can be selected. There are seven different network layers for corresponding transport modes:

- 1 Long-distance rail transport: ICE, IC and EC rail services
- 2 Short/medium-distance rail transport: Local and regional rail services
- 3 Local public transport: Bus, ferry, tram and underground services
- 4 Coach transport: Connections based on FlixBus' network coverage
- 5 Air transport: Connections between 22 major airports

- 6 Road: Motorways, A and B roads, as well as interconnecting links
- 7 Non-motorised transport: Straight-line connections between zone centroids with distances up to 40 km

All relevant PT interconnections are realised through footpaths between stops of different layers. Network access/egress links connect each layer to sources and sinks of transport demand in the population centroid of each zone. As measures of LoS, every network link is equipped with two attributes: travel time (Eq. (1)) and monetary travel cost (Eq. (5); Table 2).

$$TT = T^{iv} + T^{wait} + T^{ae} + T^{walk} \tag{1}$$

In-vehicle time T^{iv} results from the network graphs. Road network average speeds are calculated from OpenStreet-Map speed limits and conversion factors from [48]. PT link duration stems from real GTFS schedule data. Waiting time T^{wait} applies as zero for car transport and as the average waiting time at PT stops based on vehicle headways of the respective route. Entering an airplane costs 45 minutes including security checks, luggage handling, boarding, and longer walking distances within airports. Delay times of any kind are currently neglected. Walking time T^{walk} accrues for PT intermodal transfers (at 5 km/h) or cycling connections between centroids (at 17km/h). T^{ae} is the average access/egress time and represents a measure of accessibility. It is constant five minutes for MIT, depicting access, starting, and parking, while PT accessibility depends on the corresponding zone’s and network’s characteristics. Expression (2) calculates PT $T_{z,j}^{ae}$ for mode j and zone z , inspired by a two-step floating catchment technique presented in [49]:

$$T_{z,j}^{ae} = \sum_{m \in M} \eta_{m,u_z} \cdot \overline{d_{m,n}} \cdot \alpha_m \quad \forall n \in N_{z,j} \tag{2}$$

The mean of weighted distance $d_{m,n}$ over all PT stops (i.e. nodes) n in $N_{z,j}$ is again, weighted by share η_{m,u_z} of PT access/egress mode m in $M = \{\text{walk, bicycle, car}\}$. Values for η_{m,u_z} depend on the zone’s urbanisation degree u_z and can be found together with speed variable α_m in Table 1.

$$d_{m,n} = \sum_{c \in Z} \frac{\sum_{n' \in N_{z,j}} s_{n'} \cdot D_{n',c}}{\sum_{n'' \in N_{z,j}} s_{n''}} w_{m,n}^p \tag{3}$$

Distance measure $d_{m,n}$ is based on the geodesic distance $D_{n,c}$ from node n to population cell c (at a resolution of 100×100 m). $d_{m,n}$ is weighted by the number of PT vehicles that depart from this stop between 6 a.m. and 6 p.m. during the week s_n and by the population weight measure $w_{m,n}^p$

$$w_{m,n}^p = \frac{\sum_c D_{n,c} \cdot P_c \cdot \left(\frac{D_{n,c}}{d_{\max,m}}\right)}{\sum_c P_c \cdot \left(\frac{D_{n,c}}{d_{\max,m}}\right)} \quad \forall c \in D_{n,c} \leq d_{\max,m} \tag{4}$$

Each access/egress mode has a catchment area defined by $d_{\max,m}$, wherein the cell population P_c is counted and linearly weighted by its distance to node n . This double weighting makes population counts close to a node more relevant than distant ones, or, from the perspective of PT users, closer nodes more attractive. It also reduces the impact of distance thresholds choice for access/egress modes. As a result, $\overline{d_{m,n}}$ yields realistic average distances relative to population density and service frequency of stops. Access/egress mode parameters can be varied in scenario settings as an approximation to inner-zonal mobility choices.

$$TC = \frac{D \cdot c_d + T^{iv} \cdot c_t + c_{\text{fix}}}{f} \tag{5}$$

Travel cost TC is composed of distance-specific cost c_d in EUR/km, in-vehicle time specific cost c_t in EUR/h, fix cost c_{fix} in EUR per trip, and a split factor f , used for car occupancy rates or average shares of PT subscriptions in the population. Sunk costs, like car ownership cost or PT subscriptions, are not included. Empirical evidence frequently shows, that individuals usually do not account them in daily mode choice [e.g. 5]. Table 2 summarises all cost function parameters for the base year except for local PT. Pricing schemes are very diverse within Germany so that the following assumptions apply: Unimodal bus trips cost 7 EUR. They reduce to 5 EUR, if origin or destination is a city, because cities are centers of price zoning systems and there is a higher share of subscriptions in the population. If bus transport occurs on the first or last leg of a multimodal trip, half these cost accrue, respectively.

Travellers decide upon their route and mode based on a set of shortest paths between their origin and destination. The Dijkstra algorithm computes shortest paths for car and bicycle transport, and for every PT mode

Table 1 Values for access/egress link parametrisation

Variable	Walk	Bicycle	Car
η			
$u_z = 1$	0.948	0.017	0.035
$u_z = 2$	0.899	0.034	0.067
$u_z = 3$	0.883	0.026	0.091
α in km/h	5	17	30
d_{\max} in km	0.4	10	30

η values are derived from the calibration data set

Table 2 Monetary cost function components by mode of transport in 2017

Mode	C_d	C_t	C_{fix}	f	Min	Max
Rail short	0.233	0	1.47	2	5	50
	Linear regression of DB price list 2nd class; subscription shares from calibration data set					
Rail long	0.053	7.33	15.56	1	19	139
	Linear regression with 56 OD-specific prices from DB website in Jan. 2021; 30% savings tariff					
Coach	0.057	0	0	1	5	60
	Average coach prices in Germany					
Airplane	0	0	OD-specific	1	50	-
	Economy prices from Sept. 2020 where available; 50 EUR elsewhere					
MIT	0.114	0	0	1.5	-	-
	Average fuel cost for 2017's new car models with mileage of 15,000 km/a; average car occupancy in Germany					
Non-motorised	0	0	0	1	-	-

combination available. The main leg's transport mode represents the path's main mode, which is the decision variable in the mode choice model.

3.2 Mode choice model specification and calibration

Scope, explanatory power, and policy analysis suitability of the demand-side model depend on the attributes included and how they apply for different demand groups. Witte et al. [75] show that travel time and price are the most frequently used LoS attributes across multiple disciplines, while others, such as car availability or income, have a higher significance. All national transport models shown in Sect. 2 use time and price as mode choice variables, and so does *quetzal_germany*. Moreover, PT mode accessibility and frequency is included through T^{ae} in TT , while demand segmentation includes car availability. Other individual or social attributes are neglected due to limited data availability.

For distance-dependent cost factors, many transport studies find non-linear marginal utilities, i.e. decreasing cost sensitivity over time [26]. Modellers commonly encounter this issue by so-called "cost-damping" mechanisms like the Box-Cox transformation [16] to generate realistic elasticities of demand [58]. It is also common practice to aggregate time and price into a generalised cost term GC , using exogenous value of time (retrieved by mode, purpose and distance from [7]), in order to decrease model complexity [53]. Given the available mode choice variables, four different utility formulations V for alternative j , with (ASCs) and marginal utility parameters β , were tested:

- 1 Box-Cox transformation of GC with $\hat{\tau}$ fitted to the calibration data: $V_j = ASC_j + \beta \frac{GC_j^{\hat{\tau}} - 1}{\hat{\tau}}$

- 2 log-power transformation of GC : $V_j = ASC_j + \beta \cdot \log(GC_j)^3$
- 3 log-power spline of GC from [57] with knot points corresponding to a mean GC at distances of 20km and 60km: $V_j = ASC_j + \mathcal{F}(\beta, GC_j)$
- 4 log-power spline of TT with knot points at 1h and 3h plus linear perception of TC : $V_j = ASC_j + \mathcal{F}(\beta_t, TT_j) + \beta_c \cdot TC_j$

The German mobility survey *MiD2017* is a revealed preference, repeated, and cross-sectional survey with the same zonal resolution as *quetzal_germany*. Out of 417,094 inner-German trips with observed origin, destination, mode, and purpose, 134,637 inter-zonal trips serve as calibration data set. Prices are calculated using the same assumptions as described in Sect. 3.1, because *MiD2017* does not report them. OD distance comes from the network model's shortest paths, because 17% of stated distances don't fit the survey's routed distances. Travel times from the shortest paths are mapped to the observations so that the mode combination and route with a travel time closest to the stated time applies. The choice set is defined as $M = \{\text{rail, road PT, air, MIT, non-motorised}\}$. Corresponding modes of the network model are aggregated because responds in *MiD2017* do not differentiate among short-distance and long-distance rail or road PT accurately.

All of above's models can be estimated with this data set using Maximum Likelihood Estimation in the *Biogeme* software [14]. Due to the aggregation of the choice set, a hierarchical model always collapses into a Multinomial Logit model. In terms of final log-Likelihood, the Box-Cox

transformation performs worst, followed with similar log-Likelihoods by the log-power transformation and the GC-log-power spline. The log-power spline of TT with linear perception of TC performs best with a difference in final log-Likelihood of 65 (which is reasonable). The linear-in-the-parameters model does not produce significant results at all. These results imply, that the difference in perception of time and price cannot be captured by exogenous values of time sufficiently. Hence, the mode choice model is specified as

$$V_j^i = ASC_j^i + \mathcal{F}(\beta_t^i, TT_j) + \beta_c^i \cdot TC_j \quad (6)$$

for demand segment i with a log-power spline function as proposed in [57]:

$$\mathcal{F}(\beta, x) = \beta \sum_{q=1}^Q \lambda_q(x) \left[\theta_q \ln(x)^{Q-q+1} + \alpha_q(\beta) \right] \quad (7)$$

$$\theta_q = \frac{Q}{Q-q+1} \prod_{r=2}^q \ln(c_{r-1}) \quad \forall q = 2, \dots, Q$$

$$\alpha_q(\beta) = \alpha_{q-1}(\beta) + \frac{(q-1)! \beta}{Q-1} \ln(c_{q-1})^{Q-q+2} \prod_{r=1}^{q-2} \ln(c_r)$$

where λ_q is a binary parameter such that $\lambda_q(x) = 1 \Leftrightarrow x \in [c_{q-1}, c_q]$ and zero elsewhere. The spline has a number of $Q = 3$ knot points c_q with $c_0 = 0$ and $c_Q = \infty$, defining the cost intervals at which different log-power expressions operate. The Rich spline function conforms with random utility theory for $\beta < 0$ (see [57] for proof). Iterative adjustment of knot points c_1 and c_2 yields approximated optimal knot points for each segment’s model.

All β values were found significant on a 1% confidence interval (see section “Availability of data and materials”). Estimation results show that travel price has no impact on mode decisions for business trips, whereas price sensitivity for commuting trips is double the average. Moreover, commuting and business trips have a larger time sensitivity on longer distances (higher knot points), while education and shopping trips become less sensitive earlier.

3.3 Inner-zonal travel

Aggregated transport models cannot depict inner-zonal travel by design. `quetzal_germany`’s zoning system explains 86.7% of total traffic endogenously, while local mobility is approached as follows: Inner-zonal trip volumes come from VP2030, segmented by the same demand segments as above. MiD2017 data yields trip distances as means by segment, mode, and the zone’s urbanisation degree, which are relevant for (pkm) calculation. Travel time and prices are calculated with the same formulas and assumptions as

for inter-zonal travel in order to allow subsequent transport system evaluations.

3.4 Emissions calculation

GHG emissions are a relevant indicator for transport system sustainability. Direct and indirect driving emissions (well-to-wheel) can be calculated in a post-processing step, whereas a full life-cycle analysis goes beyond the scope of transport modelling. Calculation methods differ between private and public transport: MIT emissions directly depend on transport demand (formula 8); PT emissions depend on transport supply, which reacts to transport demand only with delay.

$$Em_{MIT} = \sum_i pkm_i o_i \cdot \sum_d \gamma_d em_d \quad (8)$$

Total MIT emissions are the product of vehicle kilometres—as demand segment i -specific pkm times occupation rates o from MiD2017—and distance-specific emission factors. The latter is the weighted mean over drive-train technologies d . In 2017, diesel cars have the largest share ($\gamma_{diesel} =$) 0.66 with real driving emissions of 173.6 gCO_{2eq}/km; gasoline cars have a share of 0.33 and $em_{gasoline} = 187.6$ gCO_{2eq}/km; the rest is dominated by natural gas, which has emissions of 104 gCO_{2eq}/km (data from TREMOD based on HBEFA; see [2]).

Classic PT modes (i.e. no shared or pooled systems) are scheduled services corresponding to prior demand analysis or political decisions. Small mode share changes might lead to increased vehicle loads under constant emissions, whereas large-scale changes require adaptation in the supply system. Most transport models do not consider vehicle loads endogenously and assume proportional increase of capacities [37]. So does `quetzal_germany`, as it is designed for long-term scenarios. Hence, it calculates GHG emissions using 2017 pkm-specific values from TREMOD (well-to-wheel; see [2]). This method diverts from official numbers in rail transport, where supply-chain emissions of electrified rail transport are omitted to prevent double counting.

4 Base year results and discussion

4.1 Validation of inter-zonal mode shares

All the described modelling ambitions aim at a realistic depiction of German passenger transport in the base year 2017. But there is no data set available for validation of absolute inter-zonal model results except VP2030, which is already used as input data. Hence, `quetzal_germany`’s mode shares can be validated with relative figures from MiD2017 by demand segments or all together (see Fig. 3. In this context, mode shares always refer to the trip’s main mode. Summed over all demand segments,

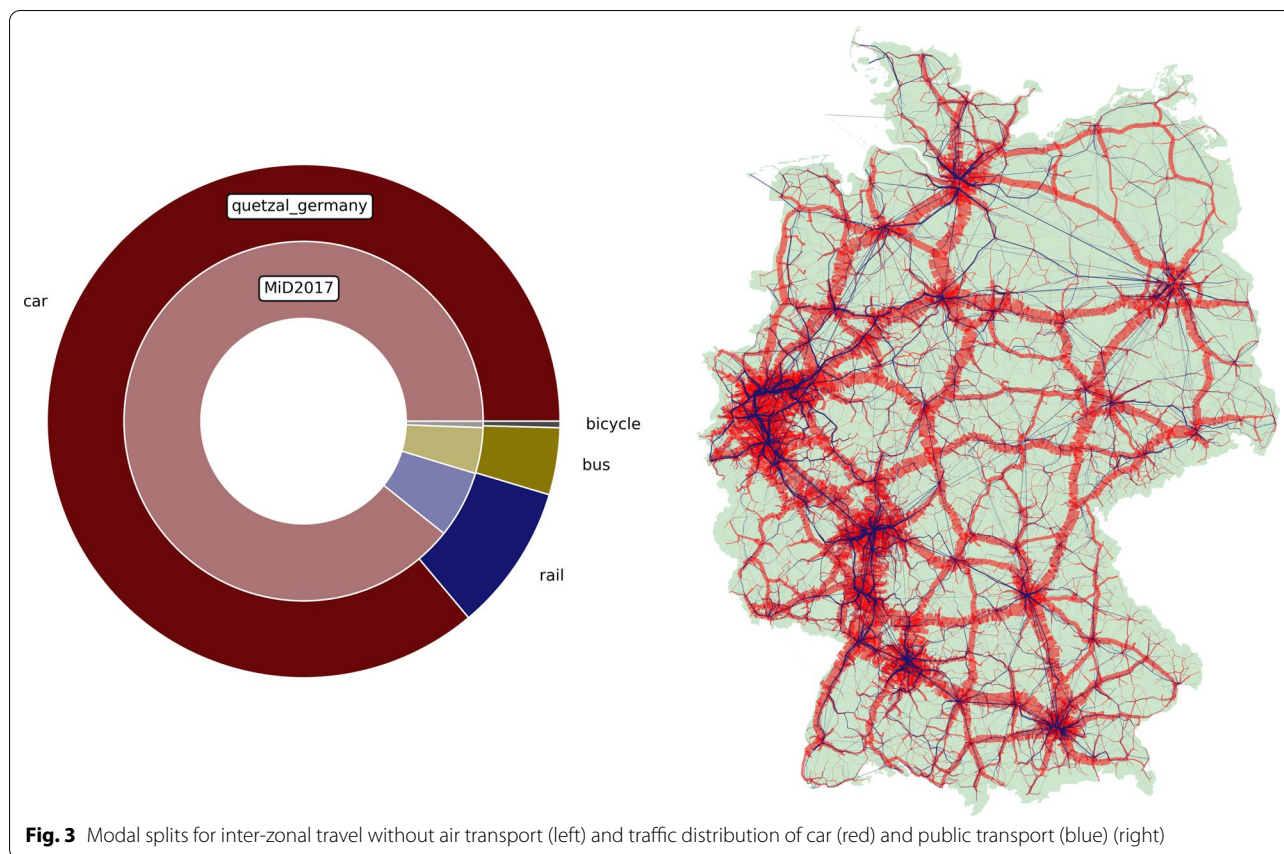


Fig. 3 Modal splits for inter-zonal travel without air transport (left) and traffic distribution of car (red) and public transport (blue) (right)

quetzal_germany’s modal splits vary only slightly from MiD2017 data (see Table 3).

In quetzal_germany’s results, air travel is underestimated even though it accounts only for a very small share of inner-German traffic. In the education segment, rail transport takes over a big share from road PT; in all other segments a small share of MIT. These inaccuracies largely stem from unrealistic depiction of pricing systems in rail transport. In quetzal_germany, prices mostly rely on linear regression and crude assumptions (see Table 2), while real pricing mechanisms are fairly complex. Again, a major barrier is the lack of open data for PT and air prices. Another reason for higher rail shares lies in the network connection: Travellers can choose freely any major rail stop within origin or destination zone, respectively, all having the same accessibility. The result is lower average trip cost. Non-motorised travel, on the other hand, is slightly underestimated, because trips are assumed to happen between zone’s geometric centroids. In reality however, people who are located close to the destination zone’s border set out for most of these trips.

Except these inaccuracies, the mode choice model performs well. Since there is no measured data for the entire German medium- to long-distance passenger transport

system, above figures cannot validate quetzal_germany’s results with certainty. Still, they suggest a realistic representation of the 2017 transport system.

4.2 Total traffic and emissions

quetzal_germany accounts for inter-zonal traffic through endogenous simulation (86.7% of total pkm), as well as inner-zonal traffic through exogenous calculations (see Sect. 3.3). This allows subsequent computation of indicators for policy effects, such as total pkm and GHG emissions.

A relevant indicator for validity of results is the yearly mileage of an average private vehicle: quetzal_germany yields 15,618 km, which comes close to the official 14,290 km [2]. Table 4 compares pkm results to figures from ViZ. Total pkm of MIT might be overestimated in quetzal_germany for three reasons: travellers are assumed to start and end their journey at the zone’s geometric centroid, which might not represent residential structures in reality; inadequate representation of air travel (see above); and inner-zonal travel is overestimated. This mainly explains higher total pkm, too. Rail pkm divide between long- and short-distance services. quetzal_germany yields 13 and 76 bn. pkm respectively, while the German

Table 3 Modal shares by main mode, segmented by trip purpose in percent

Main mode	Commuting	Education	Buy/execute	Business	Leisure	Accompany	All
MIT	84.6	43.9	91.8	90.2	86.5	96.8	86.1
	<i>88.0</i>	<i>40.4</i>	<i>94.2</i>	<i>91.5</i>	<i>90.1</i>	<i>98.2</i>	<i>89.2</i>
Rail	11.8	26.8	5.3	7.5	9.0	2.3	9.3
	<i>8.2</i>	<i>21.4</i>	<i>3.1</i>	<i>6.4</i>	<i>5.8</i>	<i>1.0</i>	<i>6.0</i>
Road PT	3.5	28.4	2.4	2.0	3.8	0.8	4.2
	<i>3.5</i>	<i>36.9</i>	<i>2.1</i>	<i>1.6</i>	<i>3.2</i>	<i>0.6</i>	<i>4.1</i>
Air	0.00	0.00	0.00	0.10	0.02	0.00	0.02
	<i>0.00</i>	<i>0.00</i>	<i>0.01</i>	<i>0.26</i>	<i>0.05</i>	<i>0.00</i>	<i>0.03</i>
Non-motor.	0.1	0.9	0.5	0.2	0.7	0.1	0.4
	<i>0.3</i>	<i>1.3</i>	<i>0.5</i>	<i>0.2</i>	<i>0.9</i>	<i>0.1</i>	<i>0.6</i>
Segment share	26.6	4.3	25.7	5.7	31.4	6.3	100.0

Validation data in italic font

The upper value represents quetzal_germany's results, the lower is the survey average from MiD2017

national transport emissions model calculates 40 and 55 bn. pkm, respectively ([2]; figures are more reliable than those of ViZ). Besides aforementioned pricing inaccuracies in long-distance rail transport, the difference in pkm is explained by inaccurate network distances: quetzal_germany uses air-distances between stations, while real distances depend on the rail network's curvature.

Table 5 shows, that MIT's emissions are overestimated to roughly the same extend as its pkm. While air transport results are not adequately modelled in quetzal_germany, road PT is. The difference of rail transport emissions is caused by different accounting methods, as described in Sect. 3.4.

4.3 Evaluation of transport system analysis requirements

Requirements for transport system analysis, as collected in Sect. 2, make a tool more or less suitable for its purpose. On the demand-side, a major limitation to endogenous explanatory power of quetzal_germany is the outplacement of choices related to physical mobility and trip destination. Currently, this is covered by results from the German national modelling study, which also covers inner-zonal travel volumes. Hence, variation of demand on trip cost is limited to mode choice between zones. Here, quetzal_germany differentiates between travellers by trip purpose and car availability, which allows more detailed policy analysis and evaluation of traffic flows on specific routes or means of transport. However, trip cost is limited to travel time and monetary cost. These are, in a macroscopic setting, the most significant influence levers, while other LoS attributes like service frequency and reliability translate easily into time or willingness-to-pay. Still, further research should look into utility formulations with more LoS or individual attributes.

The supply-side, i.e. the network model, has great spatial detail and covers all modes of transport spatially explicit. The reduction of temporal complexity by using a PT headway model instead of minutely resolved itineraries increases computational performance and allows analysis of comprehensive PT-supply policies, which do not have to be specified in regional detail. It makes the implementation of a time-of-day choice redundant, which is a common element of demand models and their reaction to traffic. However, reduced temporal complexity also diminishes the impact of traffic situations on transport demand (i.e. supply-demand equilibration): Road link capacities, which are usually critical during rush hours, are rescaled and applied to yearly aggregates. Further research should investigate time-expanded demand modelling or appropriate computation of aggregate road capacities based on OpenStreetMap data.

Depiction of passenger transport in an energy system context requires more features than quetzal_germany—and transport modelling in general—offers. Vehicle ownership, drive train technologies, and infrastructure investment are exogenous assumptions, that require thorough consideration. quetzal_germany depicts individual every-day mobility choices, which are influenced by above's factors. A feature not represented are individual car driving styles. Agent-based modelling approaches can depict corresponding energy demand of MIT more advanced, even though its applicability and data availability on national scales are uncertain.

What is more, the open source model quetzal_germany serves as a blueprint for other regions, where administrative borders, population density, and PT schedules are openly available (applies for all EU countries). The demand model further requires a mobility survey, which is available in sufficient detail in most high-income

Table 4 Total traffic (billion pkm) by mode for ViZ and quetzal_germany results (the upper value shows modelled results, the lower value shows data generated from VP2030 and MiD2017)

		MIT	Rail	Road PT	Air	NM	All
quetzal_germany	Inter-zonal	985.3	75.8	37.1	1.5	0.0	1100
	Inner-zonal	92.6	13.2	34.3	0.0	28.6	169
ViZ	Total	950.4	95.7	81.4	10.4	55.3	1195

Column NM comprises non-motorised trips

Table 5 Driving emissions (million tCO_{2eq}) by mode from quetzal_germany results (the upper value shows modelled results, the lower value shows data from VP2030 and MiD2017) and values retrieved from [15]

		MIT	Rail	Road PT	Air	All
quetzal_germany	Inter-zonal	116.5	3.8	2.7	0.3	119.2
	Inner-zonal	10.9	0.7	2.5	0.0	18.3
BMU	Total	98.2	1.0	NaN	1.9	NaN

countries. At least in Europe, demand model structure adaption is not required because of the implemented cost damping mechanism and similar mobility behaviour across countries [32]. Due to its open design and full documentation, quetzal_germany may contribute towards opening up macroscopic transport modelling and the investigation of demand-side mitigation strategies in passenger transport across Germany and beyond.

4.4 Discussion of alternative methods

In general, micro-simulation is an attractive alternative approach, because it can better capture population heterogeneity and other externalities of transport than GHG emissions. Moreover, it would endogenise quetzal_germany’s workaround for inner-zonal travel. However, data requirements and computing times of these models tend to be enormous, which drastically reduces their applicability to large scales [71].

Yet, both approaches rest upon the same method: Discrete choice modelling. It is based on random utility theory, which draws from micro-economic utility maximisation and rational choice, adding a probabilistic error component. Random utility theory is the most elaborate theoretical basis for analysis of discrete choice problems [53]. It shows great flexibility with a simple mathematical formulation at low computational complexity. Yet, it has normative assumptions and limitations, which modellers must reflect on.

In high-income countries, it is obvious and well-researched, that mobility behaviour often deviates from rational choice. An extensive review of reviews by [41] supports that argument, finding strong correlations between non-rational factors and low-carbon mode adoption in urban contexts. Empirical evidence shows,

that the Theory of Planned Behaviour [1] or the Norm Activation Model [62] perform well in describing patterns of more sustainable mode choice [39]. Moreover, behavioural economics exhibit concepts, which can enhance our understanding of mobility decisions and corresponding sustainability-directed policies [6, 51]. Witte et al. [75] argue that Kaufmann’s mobility concept [43] is the most promising framework for bridging economic, social, cultural, and political aspects in mobility research and build upon their own multi-disciplinary framework. Finally, Creutzig [23] argues, that the liberal world view connected to utility maximisation theory is ill-suited to cope with global challenges we face today.

Logit modelling, however, has advanced in recent decades. Mixed Logit models are state-of-the-art [21, 66], acknowledging taste variations within aggregated demand groups and allowing for the inclusion of individual and social attributes. Another advancement are latent choice models, capable of including individual attitudes of mobility choices. Bahamonde-Birke et al. [9] extend this further by differentiating between perceptions and attitudes in order to “represent the decision making process and the way in which the different variables take part in it as accurately as possible”. However, Vij and Walker [68] show, that most latent choice models have the same explanatory power as the corresponding multinomial logit model formulation. And still, they are based on rational choice theory.

In practice, demand model formulations crucially depend on data availability (surveys and socio-economic details), while the price for data gathering strongly increases with the size of the model region and its heterogeneity. Hence, large model regions often come with rather simple Logit model specifications. This can well

Table 6 Yearly user cost increase between 2017 and 2035, following assumptions from [2, 61]

	Price development [% p.a.]
MIT, combustion engines	0.5
MIT parking cost	2.0
Road PT	1.0
Rail	0.5
Air	0.5

be sufficient, when the level of detail in simulated decarbonisation strategy measures fits. As an example: While at small model regions, individual perceptions within a neighborhood might contribute great insight for policy advise, national-level policies, like fuel taxation, do not require more advanced model attributes than monetary cost. Within the limitations of data availability, *quetzal_germany* can depict a broad set of transport policies through price mechanisms and transport supply system changes (travel time and network accessibility), segmented by useful demand groups.

5 German passenger transport towards the Paris Agreements

Germany can contribute to limiting global temperature increase to 1.5 degree Celsius by becoming climate neutral by 2035 across all sectors [see 65]. With current policy and technology pathways, transport emissions would not be lower than 154 million tCO_{2eq} in 2030 [38]. This projection clearly fails the climate neutrality goal, even though projections become more optimistic over time due to the implementation of new policies and faster technology deployment than expected. In *quetzal_germany*'s base year 2017, passenger transport had a share of 65 % of the transport sector's GHG emissions [15]. This section's outlook shows the GHG emissions gap that would appear in 2035 without demand-side strategies for passenger transport, i.e. no behavioural change in transport demand except its linear increase proportional to population growth.

5.1 Supply-side development

In general and across all modes, transport supply remains constant relative to transport demand: Capacities get expanded proportional to traffic volume increase so that congestion remains at 2017 levels. Future pricing follows assumptions from VP2030 in order to be consistent with trip generation and distribution, which is consistent with [2] (see Table 6). According to the authors, these projections exhibit a clear political intention to make transport

more environmentally friendly. Only aviation ticket prices increase due to higher cost of synthetic fuels [see 18].

5.2 Technological development

Private vehicle technology development is heavily discussed in German society, industry, science, and politics. Will Germany continue to be diesel-driven or switch to EVs? Common techno-economic approaches to this question [such as 36] neglect socio-technical aspects like co-evolution, niche-regime interactions, and behavioural change [see 47]. In a thorough robustness and uncertainty analysis, Wanitschke [70] shows that battery EVs are likely to claim a significant share of vehicle sales in the medium term. However, production capacities will cap their market penetration at least until 2030. After dialogues with automobile manufacturers, Windt and Arnold [72] calculate a maximum stock of 14.8 million EVs in 2030 (including plug-in hybrid EVs; corresponding to 32% of 2017's private vehicle stock). Drees et al. [29] project 15.1 million EVs in their progressive scenario, which is in line with production capacities and assumptions of this outlook. Future EV charging cost are highly controversial, yet crucial for its competitiveness [70]. For sake of simplicity, all EVs are assumed to be operated at cost of battery-driven vehicles with today's home charging price of 0.3 EUR/kWh. The remaining vehicles are assumed to have the same drive train shares and operating cost as in 2017, while efficiencies of combustion engines continue to increase with 1.5% p.a. as a mean across fuel types [61]. Car ownership rates are assumed to stay at 2017 levels, as influencing variables (i.e. socio-economic household variables and PT coverage) do not change.

A deep-decarbonisation scenario as ambitious as this, requires fossil-free electricity generation by 2035, which yields zero driving emissions for all electric drive trains. The German rail operator "Deutsche Bahn" already announced climate neutrality in 2038, even earlier in passenger transport. Hence, rail transport is assumed emissions free, here. The same assumption applies to road PT, though mainly driven by the European Union's clean vehicle directive. Air transport technology displays the least robust pathways and faces high technological barriers towards full decarbonisation. Hence, 50% of its fuels are assumed to be climate neutral (i.e. biofuels or synthetic fuels), while technologies remain unchanged.

5.3 Emissions in 2035

Above's assumptions yield modal shares very similar to those of 2017. Higher vehicle efficiencies of private cars decrease driving cost per kilometre, which produces a mode shift of 0.5% towards MIT on medium to long distances, taking equally from rail and road PT. Total traffic

increases to 1,407 billion pkm (7% more than in 2017). Through technological development, passenger transport emissions decrease to 65.5 mio. tCO_{2eq}, which is a reduction of 45% compared to 2017, but still far from climate neutrality.

Several national research projects have investigated pathways for (passenger) transport decarbonisation in the past: *Transport and Environment* analyses three explorative bottom-up scenarios until 2040, of which the reference scenario yields 45% emissions reduction compared to 2010, mainly through improve strategies [31, 74]. With similar assumptions and within the same time horizon, the *GreenLate* scenario in the *RESCUE* study achieves a 46% emissions reduction [55]. The technology pathway report of the *Ariadne* study concludes that a technology shift alone does not contribute enough to short-term (2030) decarbonisation goals and further demand-side mitigation measures are needed [45].

Full decarbonisation of the German energy system by 2035 is challenging [see 44] and this exemplary scenario already includes progressive technological assumptions. There are natural barriers towards technology deployment, which are usually considered in energy system modelling [e.g. 55]. Avoid and shift strategies would support decarbonisation without challenging technological boundary conditions such as renewable fuel imports, electricity generation capacities, production chain ramp-up, or resource availability.

6 Conclusion and outlook

Unleashing full transport decarbonisation potential is crucial for reaching the 1.5 degree-target of the Paris Agreements. This paper's outlook for Germany's passenger transport emissions shows that even in an ambitious technology scenario, there remains a large emissions gap. It can be bridged by further technological ambition, i.e. improve strategies, within uncertain boundary conditions. Avoid and shift strategies, on the other hand, do not violate these boundary conditions, but affect society's well-being. How much they can contribute, and which effect they would have, remains open.

quetzal_germany, as presented here, can be used to analyse strategies to fill this knowledge gap. It realistically depicts mode choice behaviour on medium- to long-distance travel in Germany and exhibits useful levers for national policy analysis. Future development ambition should direct towards endogenous depiction of trip generation and distribution to make it standalone and aid as an open source blueprint for other countries or regions. The discussion of quetzal_germany's properties shows: Macroscopic transport modelling is a suitable tool for large-scale transport demand-side analysis and should

be used to support deep decarbonisation scenarios in techno-economic modelling.

Abbreviations

ASC: Alternative-specific constant; EV: Electric vehicle; GHG: Greenhouse gas; LoS: Level-of-service; MiD2017: "Mobility in Germany 2017"; MIT: Motorised individual transport; OD: Origin destination; pkm: Passenger kilometre; PT: Public transport; VoT: Value of time; ViZ: "Transport in figures"; VP2030: "Forecast of transport interconnectivity 2030".

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Availability of data and materials

The open source transport model quetzal_germany can be found in form of Jupyter Notebooks on github: https://github.com/marlinarnz/quetzal_germany; Archived version: <https://zenodo.org/badge/latestdoi/340406296>; License: MIT; Input data availability: The input data set supporting this repository is available on Zenodo: <https://doi.org/10.5281/zenodo.5659679>. The traffic assignment step and a new calibration of the mode choice model require access to data from the Federal Ministry of Transport.

Author details

¹Workgroup for Infrastructure Policy, Technical University Berlin, Berlin, Germany. ²Graduate School Energie System Wende, Reiner Lemoine Institut, Berlin, Germany.

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