1 Transport model quetzal_germany

quetzal_germany simulates transport demand as individual decisions of trip frequency, trip destination, and mode of transport. This demand is routed on spatially explicit transport networks, yielding passenger kilometres (pkm). The model is developed in Python under use of the Quetzal open source transport modelling suite (Chasserieau and Goix, 2019) and is openly available on github (Arnz, 2023).

It follows the method of aggregated transport modelling, having 2,225 zones, defined by clustering 4,605 municipality unions to similar zone sizes. Aggregated transport models simulate traffic between zones, whereas inner-zonal traffic, accounting for 13 % of total traffic, is computed exogenously based on the German National Travel Survey (infas et al., 2017).

1.1 Network model and level-of-service attributes

quetzal_germany incorporates a highly intricate network model that utilises OpenStreetMap data for the road network and GTFS feeds for public transportation (PT) in Germany. It consists of seven distinct network layers, each corresponding to different modes of transportation:

1. Long-distance rail transport: Includes ICE, IC, and EC rail services.
2. Short/medium-distance rail transport: Encompasses local and regional rail services.
3. Local public transport: Comprises bus, ferry, tram, and underground services.
4. Coach transport: Represents connections based on the network coverage of FlixBus.
5. Air transport: Includes connections between 22 major German airports.
6. Road: Consists of motorways, A and B roads, as well as interconnecting links.
7. Non-motorised transport: Involves straight-line connections between zone centroids, with distances of up to 40 km.

Footpaths are established between PT stops to facilitate seamless connections between different layers. Furthermore, network access/egress links connect each layer to the sources and sinks of transport demand located at the population centroid of each zone. Two attributes, travel time (eq. (1)) and monetary travel cost (eq. (2)), are assigned to every network link as indicators of the level of service.

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

$$TC = \frac{D \cdot c_{\mathrm{d}} + T^{\mathrm{iv}} \cdot c_{\mathrm{t}} + c_{\mathrm{fix}}}{f} \tag{2}$$

In-vehicle time T^{iv} is the result of link speed and length in the network graph. Additionally for PT, there is waiting and walking time, T^{wait} and T^{walk}, respectively, that applies at PT stops during transfer. Access/egress-time T^{ae} depends on the number of parking lots in the origin and destination zone for car transport and on the PT stop density of the corresponding PT mode, respectively. Travel cost TC is composed of distance-specific cost c_{d}, variable in-vehicle time specific cost c_{t}, fix cost c_{fix}, and a split factor f, used for car occupancy rates or average shares of PT subscriptions in the population. Further details can be found in Arnz, 2022.

1.2 Transport demand model

Classical aggregated transport models simulate demand in three mobility choices: trip frequency, trip destination, and mode of transport. The following paragraphs briefly describe all of these models, while further information can be found in Arnz, 2022 and Blinded, 2023. The German National Travel Survey (infas et al., 2017) serves as calibration dataset for all forthcoming models. Their calibration parameters are given in Greek letters.

The first step in the mobility demand choice tree is the number and destination of trips. Compulsory trips (i.e. commuting, education, and business trips) are computed using a doubly constrained distribution with the logsum of mode choice utility building the deterrence matrix. Trips for other purposes (utilities, leisure, and accompany) utilise multinomial logit models to depict trip generation and destination choice, respectively. The generation model's utility function looks as follows:

$$
\begin{aligned}
V_j^i = & ASC_j + log\left(\text{pop}_z\right) * \alpha_j^i + \text{hh\_size}_z * \beta_j^i \\
& + \text{hh\_income}_z * \gamma_j^i + \text{is\_working}_z * \delta_j^i \\
& + \text{is\_learning}_z * \epsilon_j^i + \text{is\_caring}_z * \zeta_j^i \\
& + \text{acc}_z * \eta_j^i
\end{aligned} \tag{3}
$$

For all zones z and for each demand segment i: with and without car availability for each non-compulsory trip purpose. Choice alternatives $j \in 0, 1, ..., 5$ describe the number of trips per day with alternative-specific constants ASC being fixed to zero for $j! = 0$. Zone population *pop*, average household size hh_size, household income hh_income, and the population share of a certain occupation (is_working, is_learning, is_caring; not for buy/execute trips) influence the decision. Moreover, the trip frequency depends on the accessibility acc (calculated as the average cost of mobility to other zones), linking the generation of trips to the transport system design. Building upon the trip frequency for non-compulsory trips, a binary logit model formulates the choice between executing a trip within or beyond the origin zone's boundaries:

$$
\begin{aligned}
V_{inner}^i = log\left(\text{pop\_dens}_z\right) * \alpha^i + log\left(1 + \sum_{a_n \in A^i} a_{n,z}\right) * \beta^i \\
V_{inter}^i = ASC + \text{acc}_z * \gamma^i
\end{aligned} \tag{4}
$$

with

$$
\begin{aligned}
A^i \in A = \{ & \text{childcare, school, higher education, medical,} \\
& \text{daily leisure, occasional leisure, shop, special shop} \}
\end{aligned}
$$

Inter-zonal choice utility depends on the zone's accessibility and an ASC, while inner-zonal utility consists of the zone's population density pop_dens and the number of attractions a_n of the attraction categories A^i that are relevant to this demand segment. Corresponding points of interest data for these categories are sourced from OpenStreetMap in 2022.

Another multinomial logit model applies for the choice between inter-zonal trip destinations. Its utility function concerns the same demand segments and zones, while choice alternatives d comprise the full set of model zones:

$$
\begin{aligned}
V_d^i = & log\left(\text{pop\_dens}_d\right) * \alpha^i \\
& + log\left(1 + \sum_{a_n \in A^i} a_{n,z} * exp\left(\beta_n^i\right)\right) * \gamma^i \\
& + D_{z,d} * \delta^i + D_{z,d}^2 * \epsilon^i + CC_{z,d} * \zeta^i
\end{aligned} \tag{5}
$$

with $\beta_0 = 0$. The distance $D_{z,d}$ between origin and destination and the squared distance $D_{z,d}^2$ are significant choice variables. Here too, cost of mobility CC influence the distance distribution of trips. It entails the composite cost of the nested logit mode choice model, depending on the route's level-of-service attributes described above. The choice tree contains all modes of the network model, as listed in subsection 1.1, with one nest for rail transport and another nest for use of private car and car sharing. The mode choice model is specified as

$$
V_j^i = \text{ASC}_j^i + \mathcal{F}\left(\beta_t^i, TT_j\right) + \beta_c^i \cdot TC_j \tag{6}
$$

for each demand segment i with a log-power spline function as proposed in Rich (2020):

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

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

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

2 Energy system model EuSys/AnyMOD.jl

For the analysis of renewable energy systems, we employ a linear optimisation model that determines the expansion and operation of technologies to meet final energy demand. The model's objective is to minimise the total system cost, which includes annualised expansion cost, operation cost of technologies, and costs associated with energy imports from external sources. The expansion and operation aspects in the model encompass two components: technologies for energy generation, conversion, or storage, and grid infrastructure for energy exchange between different regions.

To handle high shares of fluctuating renewables and sector integration, the model utilises a graph-based formulation specifically designed for this purpose, allowing for varying temporal and spatial resolutions within a single model (Göke, 2021b). This feature enables the application of high resolutions where the system is sensitive to small imbalances of supply and demand, such as in the power sector, while modelling more inert parts, like gas or hydrogen transmission, at a coarser resolution. This approach reduces computational complexity and captures the inherent flexibility in the energy system. Göke, 2021a elaborates this approach in greater detail and Göke et al., 2023 present a case study including mathematical formulations.

The potential of battery-electric vehicles (BEVs) in future energy systems remains uncertain and relies on technological and regulatory advancements. On one hand, we anticipate charging flexibility within certain limits and adaptability to supply, although this does not currently align with regulations in all European countries and does not necessitate additional infrastructure (Strobel et al., 2022). On the other hand, we do not assume that BEVs can supply electricity back to the grid, which is also known as bidirectional charging or vehicle-to-grid, as it requires the use of bidirectional chargers (Hannan et al., 2022). It is important to note that BEV technologies are not restricted to passenger cars but are also applicable to all forms of road transport.

The model implements flexible charging based on a driving and charging pattern. First, an hourly profile restricts the charging of BEVs to reflect the capacity of vehicles currently connected to the grid. A second hourly profile provides the actual driving patterns that determine when electricity is being consumed. To supply this electricity, the vehicle batteries must be charged sufficiently while they are plugged in. As such, BEVs are effectively modelled like storage systems with a predefined discharging pattern and a temporal profile restricting vehicle charging. The assumed maximum charging capacity amounts to 10 kW and the battery capacity to 50 kWh for private vehicles. BEVs for public passenger and heavy road transport have maximum charging rates of 150 kW (ENTSO-E and ENTSO-G, 2022). Applying a safety margin, all charging profiles are reduced by 75%.

The AnyMOD.jl framework is applied to the region of Europe, covering all countries of the European Union, along with the United Kingdom, Switzerland, and the Balkans. The model's time frame encompasses a single year. It takes a brownfield approach, utilising the available transmission infrastructure and hydro power plants without any expansion. The model encompasses a comprehensive set of 22 distinct energy carriers, which can be stored and converted among each other using 120 different technologies. These technologies cover various sectors such as heating, transportation, industry, and the production of synthetic fuels. The full documentation of the case study model can be accessed in Göke et al., 2023. Figure 1 depicts available transport technologies and their energy carriers. Vertices in the graph either represent energy carriers, depicted as coloured squares, or technologies, depicted as grey circles. Entering edges of technologies refer to input carriers; outgoing edges refer to outputs. Green squares are the mobility demand of each mode. Air transport is exogenously defined as a static demand for liquid fuels, depending on scenario assumptions on domestic and international aviation. Efficiencies, cost, and reference case load factors for transport technologies come from Robinius et al., 2020.

3 Model coupling process and assumptions

The coupling process of the two models is one-directional: Passenger travel demand feeds into the energy system model by mode of transport and region within Germany. We refrain from iterative hard-linking by implementing an interchange of energy prices for two reasons: First, transport demand is relatively inelastic to fuel price changes (not so for public transport fares), which makes an iterative coupling disproportional to its computational cost. Second, the definition of prices differ between both models. The energy system model calculates marginal prices, while the transport model uses consumer prices including taxes and supply revenues. Making assumptions about the latter factors is as good as assuming consumer prices in total.

In general, we assume a yearly inflation rate of 1.5 % applying to all fuel prices and public transport fares. The average charging cost for electric vehicles amount to 0.4 EUR/kWh, based on 2022 prices. The double applies for trips that use public charging, approximated as half of all shopping and execution trips. Plug-in hybrid electric vehicles are assumed to have an electric driving range of 80 km, which is fully utilised

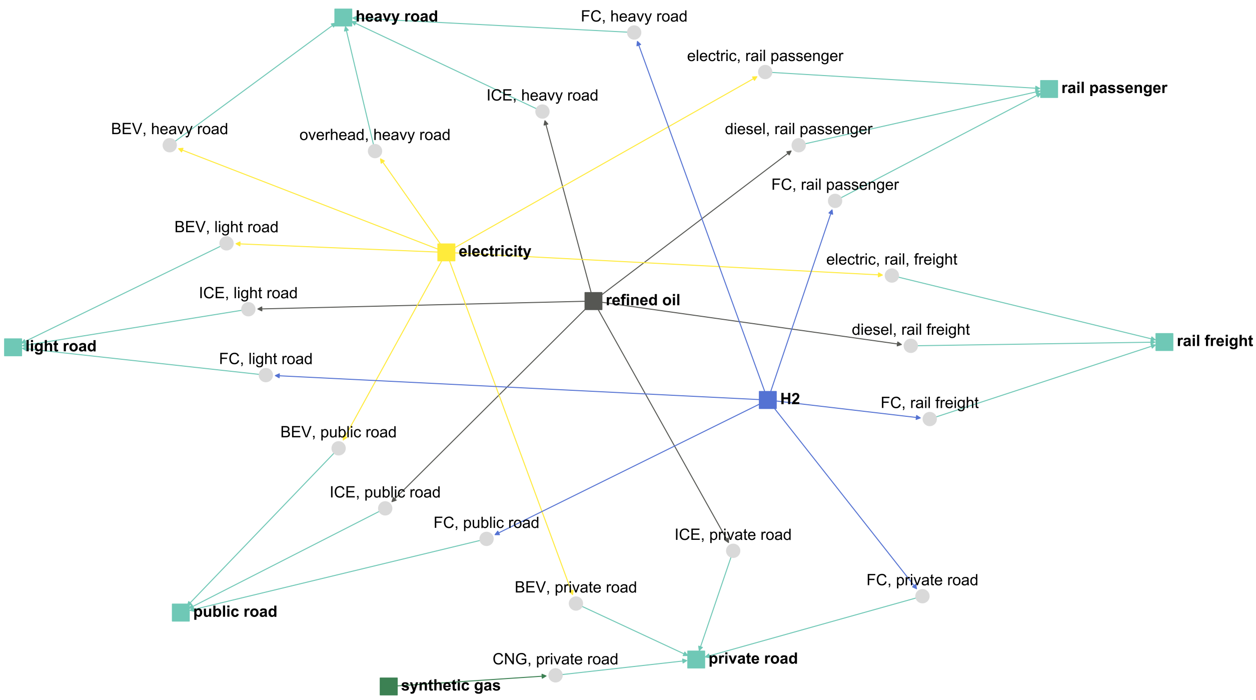


Figure 1: Sub-graph of transport technologies and corresponding energy carriers.

before switching to synthetic fuels because these are more expensive (i.e. the same as inflation-adjusted petrol prices in 2022).

Extending the transport demand scenarios to other countries would require other national transport models, which are very resource-intensive and inaccessible (Arnz, 2020). Assuming the same macroscopic transport demand changes as in Germany for other countries is problematic because the socio-cultural and infrastructural conditions vary widely. Our approach to corresponding scenarios relies on fine-granular drivers of change (see sec. 4) that most probably differ from country to country. Hence, we focus our study to the region of Germany. Still, comprehensive passenger transport demand-side mitigation scenarios have never been studies for a region as large and populated.

However, the energy system model optimises the full European energy system, as described in sec. 2. We fix other countries to a reference case in order to coarsen the energy system analysis to Germany, too. Specifically, we run the optimisation problem for the reference+Improve scenario for all of Europe, yielding the cost-optimal energy system. Non-German capacities are then fixed to this solution for all other scenario runs. This allows us to study impacts of German passenger transport demand only on German energy capacities. Other countries cannot trade more energy with Germany, as in the reference+Improve case. Fixing Europe to the reference+Mix scenario would generate large generation capacities for synthetic fuels in southern Europe, which is then available in all other scenarios, omitting the impacts of transport demand changes.

International air travel is not affected by our scenarios, as we can only model inner-German transport. We do not make assumptions about medium- and long-distance flight reductions because they are not covered by our qualitative-quantitative research design and would outweigh other levers of change. Air travel is expected to account for more than half of German passenger transport's energy demand in the future (Gnann et al., 2022). On the technological side of air transport, we do not assume large changes, except slight efficiency gains and adoption of 100 % synthetic fuels.

Public transport vehicles, on the contrary, are assumed to be fully electrified in all scenarios by 2040. The German rail operator already announced full climate neutrality by 2038 and the European Union's clean vehicles directive is a strong driver for electrified drivetrains in public road transport.

Finally, the assumptions for vehicle occupancy are as follows. No changes apply for air transport. Car occupancy rates differ by scenario, as defined in its quantification process (sec. 4): 1.5 applies for the reference and Shift scenarios, 1.8237 for the Avoid and Avoid+Shift scenarios. For public transport, the relative increase in road and rail use per pkm is calculated, and this increase is multiplied by the corresponding average occupancies found in the energy system model's input data set (Robinius et al., 2020). We ensure no overcrowding of transport carriers by setting a cap of 70 % occupancy, under which all scenarios stay below. The Shift scenarios introduce on-demand ride pooling services, which account for 90 % of road PT traffic. Zech et al., 2022 suggest high ride pooling system efficiencies with average loads of 6 persons in 8-person

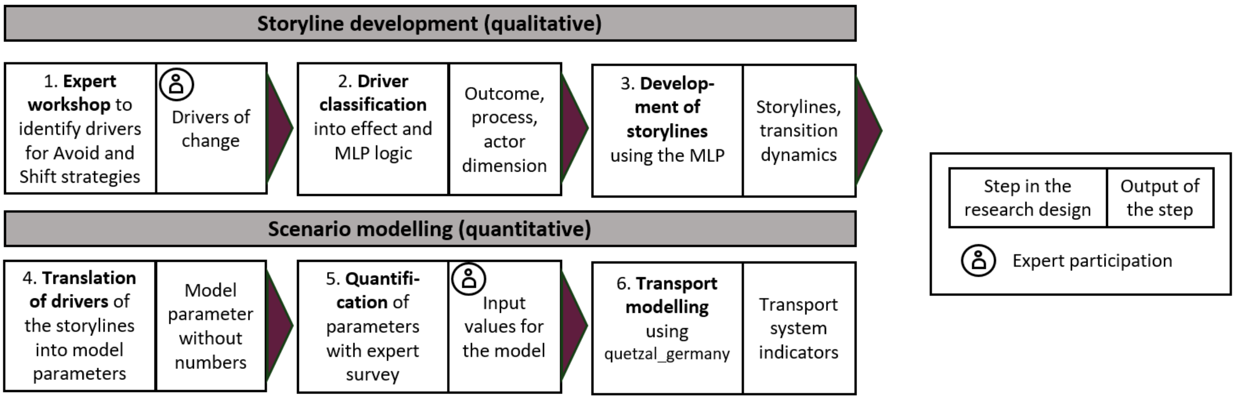


Figure 2: Research design divided into a qualitative and quantitative phase. Steps 1 and 5 involve mobility and sufficiency experts. Source: Blinded, 2023.

vehicles. However, due to the spatial and temporal periphery of these services, the average occupancy is set to 3, which is still a progressive assumption.

4 Transport demand scenarios description

The qualitative-quantitative transport demand scenarios are a crucial element for the novelty and extent of this study because they allow analysis beyond techno-economic assumptions and shed light into socio-cultural processes. Figure 2 demonstrates the steps of scenario creation. The following paragraphs briefly describe the process, while the fully detailed description can be found in (Blinded, 2023).

In the first phase, we collect drivers of change towards sufficiency for the German passenger transport system by consulting 15 transport and sufficiency experts from various disciplines. The guided brainstorming process results in 133 sufficiency drivers, encompassing infrastructure, social, individual, and systemic factors. These drivers are categorised as policy interventions, individual mindset changes, corporate actions, and consumption changes. To construct the storylines, we classify the drivers as traffic avoidance, mode shift, or both, with the help of expert knowledge. Three storylines are created: one with traffic avoidance drivers only, one with mode shift drivers only, and one incorporating all drivers of change. We employ the Multi-Level Perspective framework to analyse transition dynamics, considering the interactions between niches, regimes, and landscapes. The storylines provide insights into the outcomes, processes, and actors involved in achieving sufficiency in German passenger transport. A summary of the storylines can be found in table 1, while their written form is available in Blinded, 2023.

The translation of storylines into modelling scenarios involves quantifying model parameters. Out of the 133 sufficiency drivers, 64 are identified as model-affecting drivers, and each of them corresponds to one or more distinct model parameters. To enhance transparency and reproducibility, a survey method is used to inform the quantification process. The survey is distributed among participants of the sufficiency driver workshop and additional experts in transport sector transitions. The survey consists of 59 questions related to different action fields, and the responses from 12 participants are used to generate average values for the model parameters. These quantitative values define three modelling scenarios based on the sufficiency storylines, along with a reference scenario that serves as a comparison. Some parameters require implementation of specific levers into the model logic, which is – together with all other drivers, their specifications, corresponding survey question, and responses – accessible in the supplemental material.

5 Car stock modelling and assumptions

We construct a simplified car stock model in order to depict the private vehicle stock development towards the target year. Noteworthy, this model is not designed for accuracy, neither does it include elaborate methods. It is a simple collection of mathematical formulations that provides two things: a rough estimate about the total cost of car sales, and an impression about the required sales rates per technology in each scenario. All assumptions and data are included in the supplemental material. Here is a brief summary.

We differentiate in three different drivetrain technologies: BEVs, plug-in hybrid electric vehicles (PHEVs), and internal combustion engine vehicles (ICEVs). Fuel-cell electric vehicles are not part of our vehicle stock because they are not expected to play a role by the year 2040 in the reference case of any major national scenario (e.g. Luderer et al., 2021; Gnann et al., 2022). The vehicle fleet's drivetrain composition of our

Table 1: Summary of sufficiency storyline outcomes. Source: Blinded, 2023.

	Avoid	Shift	Avoid+Shift
outcome dimension	High availability of goods, services, amenities, and social activities in local environment; digitisation in work relations and distant social contacts	Minimum car dependency; efficient, attractive, interconnected PT; safe and comfortable cycling infrastructure; increased public health	Main aspects in addition to Avoid and Shift: New core principles of integrated transport and spatial planning; private cars as anti-status symbol
transition dynamics	Several digitalisation niche developments with large momentum reduce the need for traffic; local and shared economies (niches) build up momentum, while landscape developments put the economic growth imperative under large pressure; the welfare state regime stabilises	Strong niches advance diverse mobility offers, helping public and non-motorised transport regimes stabilise and grow (enabled by a large number of landscape developments)	In conjunction with Avoid and Shift dynamics: Radical landscape changes exert large pressure on the automobile regime, which becomes subaltern; further landscape pressures and formerly small niches lead to regime breakdown of materialism
driver classification	moderate policy intervention (56 %) and large cultural shifts from equal shares of mindset and consumption changes, as well as corporate action	largely driven by policy intervention (73 %) and corporate action (17 %) with minor mindset shifts (7 %)	60 % policy interventions, 21 % individual mindset changes, 14 % corporate action, 5 % consumption changes

Mix scenarios corresponds to the "Mix" scenario in the German national *Ariadne* project in the year 2040 (Luderer et al., 2021) because it employs the highly detailed *Vector21* car stock model and its assumptions are broadly accepted in the community.

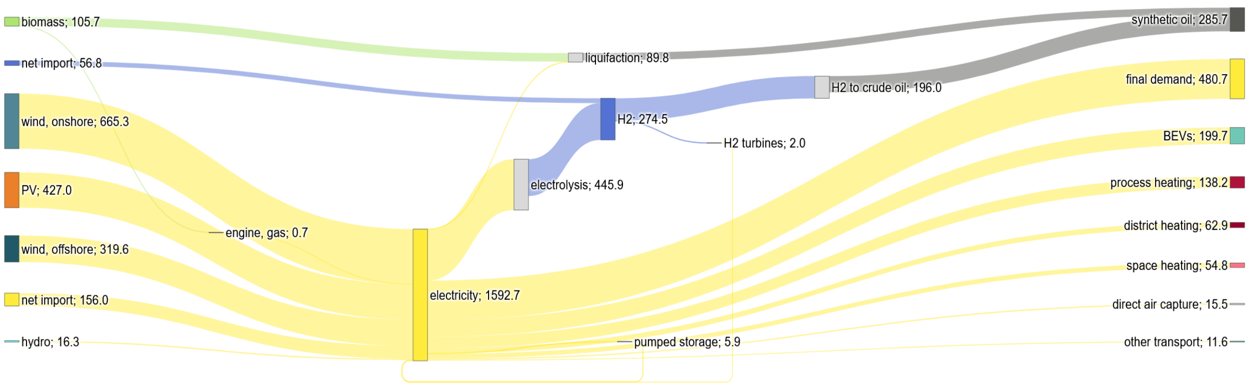
Our cost data stems from E3-Modelling, 2020, linearly interpolated between five-year steps, as can be seen in the supplemental material. The source diversifies into three vehicle size groups (small, medium, and large), which we adopt. The reference and Shift scenarios retain the same size distribution as of 2020 in Germany (KBA, 2021), while the Avoid and Avoid+Shift scenarios shift 50 and 100 % of large vehicles to small vehicles, respectively. The shift occurs linearly towards 2040.

BEV adoption is not linear, but a progressive exponential function that is tuned to yield the final year's BEV proportion of the corresponding scenario's total vehicle stock. The latter comes from the transport demand scenarios (sec. 4) and we assume a linear decrease in car ownership. The adoption function is capped to the scenario's maximum car sales per year, which is the final year's total car stock divided by the lifetime of a vehicle (15 years, in line with input data of the energy system model). PHEVs are linearly adopted towards the final stock and ICEVs make up the rest.

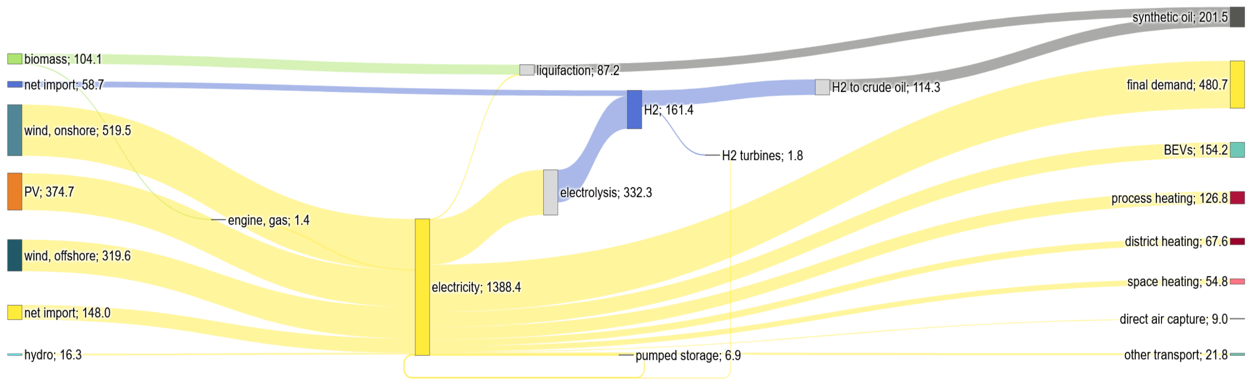
We do not account for BEV production capacities because they stay uncertain and the global BEV distribution is up to future market dynamics. All Mix scenarios stay within bounds of foreseeable BEV availability in Germany by 2030 (Windt and Arnhold, 2020). In the Improve case, only the Avoid+Shift scenario stays under the threshold of 9.6 mio. BEVs in 2030, which the authors of the study find reasonable after confidential dialogues with car manufacturers. The reference+Improve scenario accounts for 15.9 mio. BEVs, exceeding this threshold by two thirds.

6 Energy system results analysis

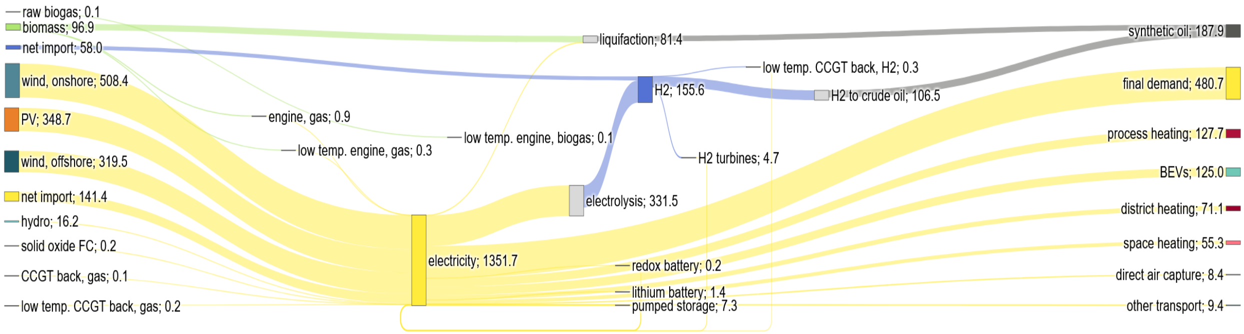
Even though we summarise the most important results of the energy system model in the article, it is difficult to sketch a full picture of the resulting energy system configurations. Sankey diagrams allow for a more intuitive understanding of these configurations by depicting energy inputs, outputs, flows, intermediate steps, efficiencies, and technologies. Figures 3 and 4 describe energy flows in the Mix and Improve scenarios, correspondingly.



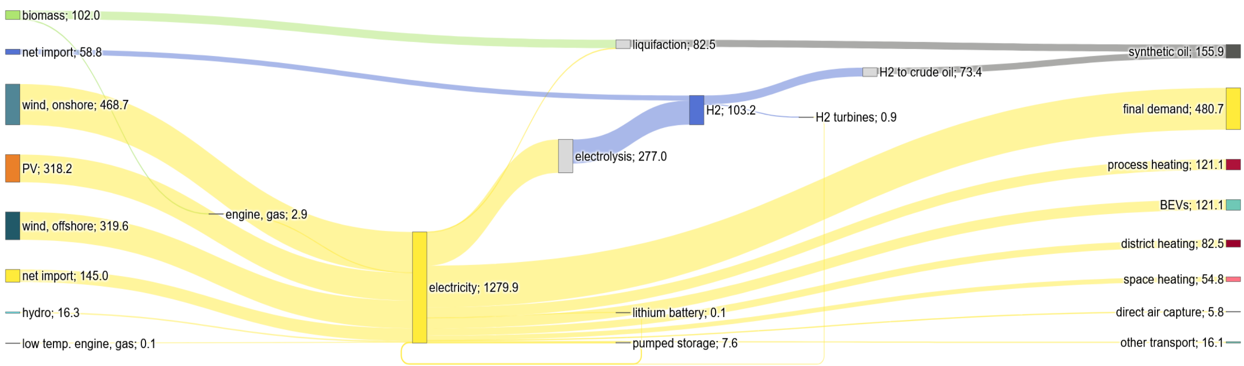
(a) reference+Mix



(b) Shift+Mix

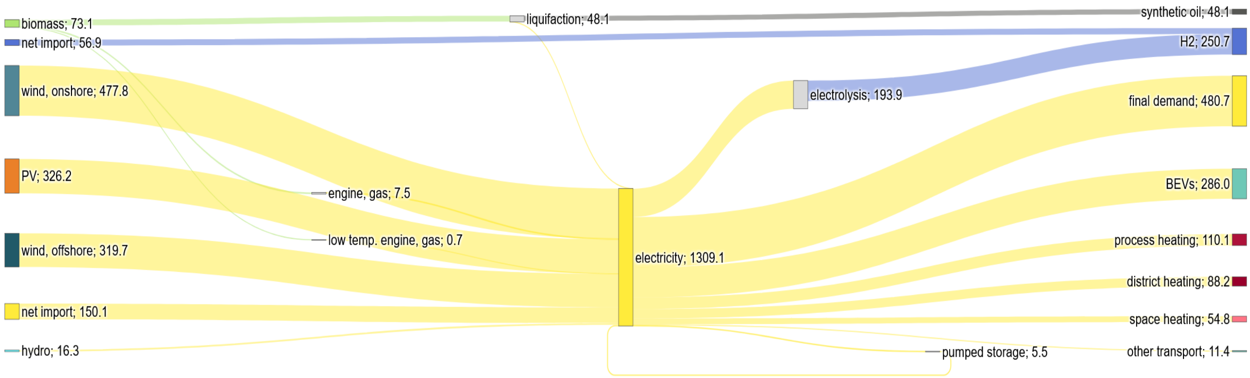


(c) Avoid+Mix

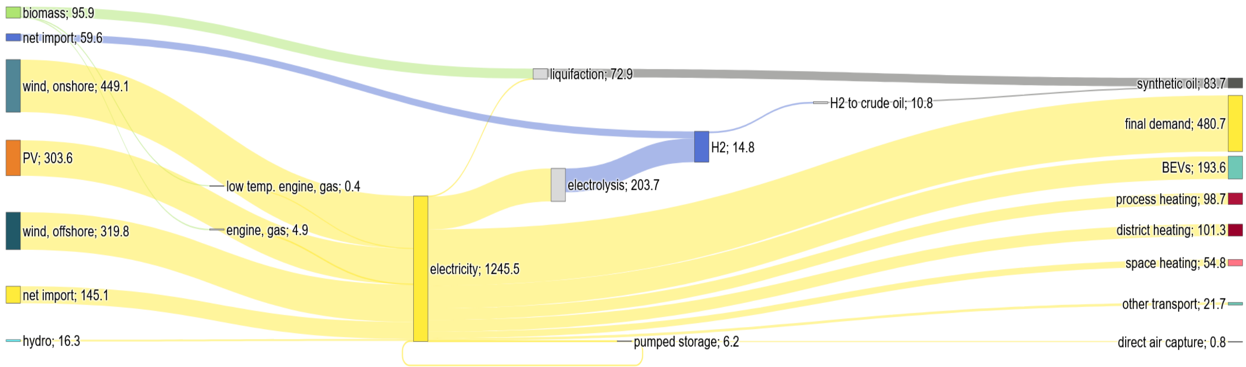


(d) Avoid+Shift+Mix

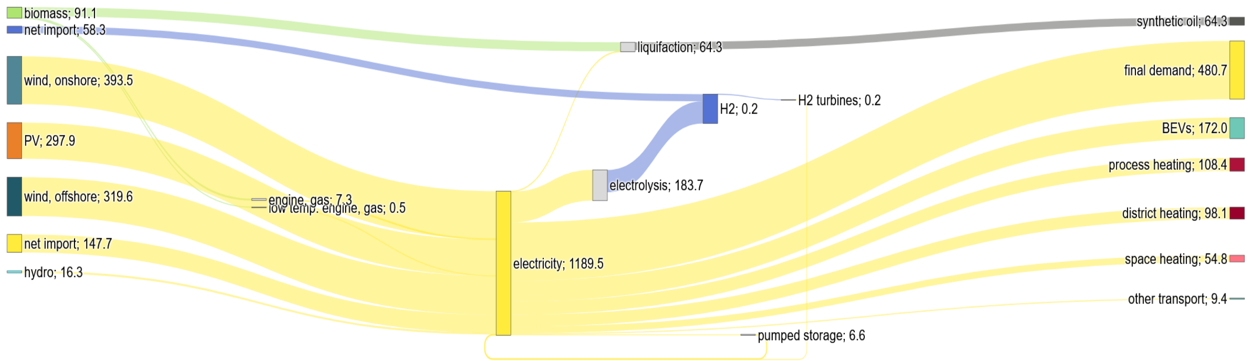
Figure 3: Mix scenarios have a vehicle stock drivetrain composition of 56 % BEVs, 14 % PHEVs, and 30 % ICEVs.



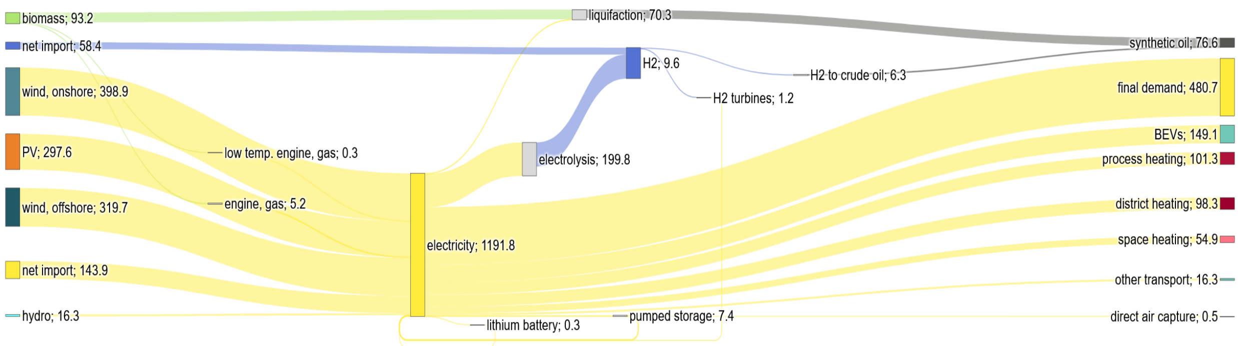
(a) reference+Improve



(b) Shift+Improve



(c) Avoid+Improve



(d) Avoid+Shift+Improve

Figure 4: Improve scenarios have a 100 % BEV share.

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