E-carsharing: would shared e-cars foster or impede the integration of variable renewables?

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Motivation

In Germany:

- Overall number of passenger cars (2023): 48.8 million (+4% in 5 years).
- Passenger car density (2022): 58 cars per 100 inhabitants (in 2011: 51.7).
- The average vehicle occupancy of car drivers' trips is 1.5 person.
- 43% of car trips are shorter than 5km; 63% $\leq$ 10km, 82% $\leq$ 20km.

$\Rightarrow$ Room for reducing the car fleet size under same car mobility choices.

Motivation

- ◇ Net-zero cannot be reached without decarbonizing the transport sector
  - Passenger road transport: $\sim$ 13.5% of total emissions in Germany.
- ◇ Electrification of road transport is one key strategy
- ◇ But passenger car fleet electrification might create new problems from the resource extraction perspective.

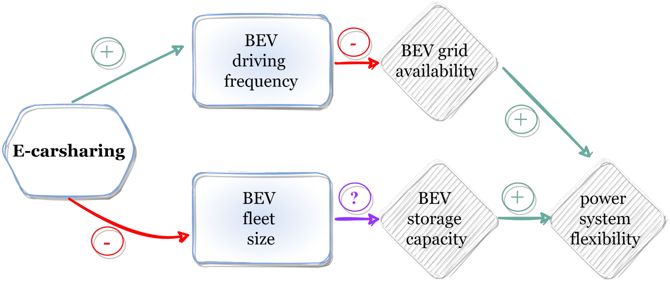
⇒ Electric carsharing
  - could alleviate the pressure put on resource extraction for manufacturing batteries
  - while ensuring the electrification of the fleet more rapidly
  - and bringing along many co-benefits (noise, congestion, parking space...)

Research question

What are the impacts of electric carsharing on the German power system, assuming constant car mobility needs and renewable integration targets, in 2030 ?

Definition

Flexibility "describes the degree to which a power system can adjust the electricity demand or generation in reaction to both anticipated and unanticipated variability [1]"



Literature

◇ Impacts of electric cars on power system flexibility

- Increase peak loads if no controlled charging available. Depends on driving profiles, urbanization level and plug-in behaviours [6].
- Increase flexibility with controlled charging which supports renewable integration [9].

◇ Impacts of carsharing

- Decreases local air pollution [3], increase parking space in central areas [4], reduces impacts on mineral resource scarcity and marine and freshwater ecotoxicity [10], [5].
- Decreases private car ownership [7], [8].

⇝ This work bridges these two literature strands and specifically scrutinizes electric carsharing's impacts on the power system when scaled up at systemic levels.

- Brinkel et al. (2022) [2] show that e-carsharing might help mitigating grid congestion but take a very different approach.

Outline

1. Methodological framework
2. Results
3. Conclusion

Overview

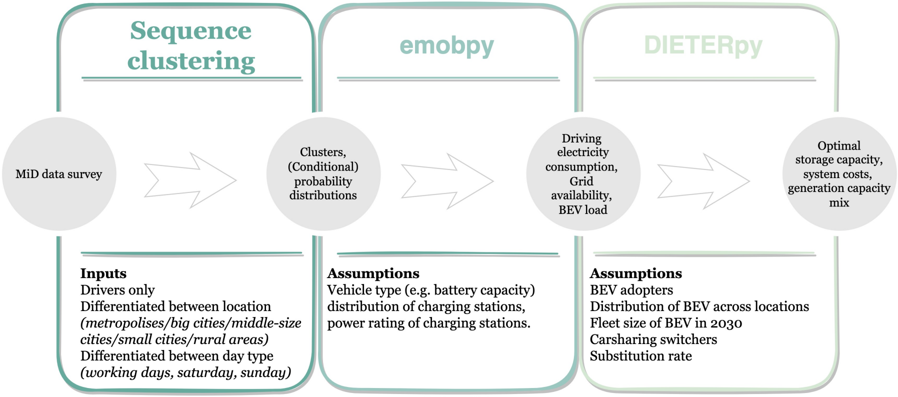


Figure: Modeling electric carsharing: workflow

Sequence analysis of travel diaries

- Mobility in Germany (MiD) representative survey, version B1 (2017)
  - Travel diaries at the individual level.
  - People surveyed only one day.
- Consider car trips undertaken as a driver
  - $\sim$ 357k car trips; $\sim$ 90k households; $\sim$ 120k individuals.
- Rearrange diaries into a sequence format Sequence format Sequence features
  - $\sim$ 120k sequences in total.
  - 5-minutes time step $\rightsquigarrow$ a full day has 288 steps.
  - States describe trip destination and not location during dwell-times.
  - Possible states: idle, work/school, errands, leisure, home.

Clustering sequences

- Apply hierarchical clustering on sequence subdatasets depending on urbanization level and type of day. Clustering algorithm

⇒ Average trip duration and distance along total travelled distance seem to be the determining criteria to cluster sequences. Cluster 1 Cluster 2 Cluster 3 Cluster 4 Cluster 5 Cluster 6

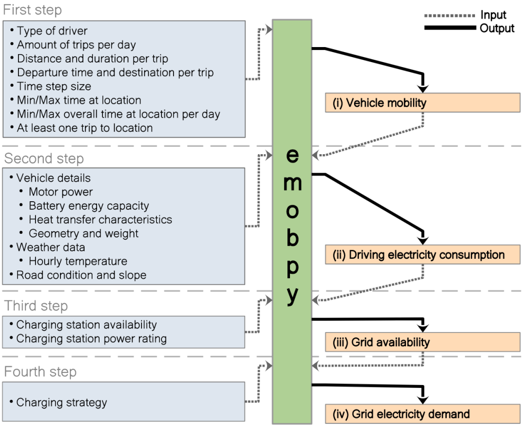
Table: Statistics for sequences of metropolises/weekdays (n=11,904)

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Number of sequences (units)	107	363	790	2,984	3,188	3,662
Cluster share (%)	1.0	3.3	7.1	26.9	28.7	33.0
Number of trips	2.3	3.5	3.9	3.6	2.8	2.1
Average trip duration (in min)	343.7	126.6	57.9	34.2	24.5	14.1
Total dwell-time (in hours)	15.1	19.3	21.2	22.3	23	23.5
Total distance (in km)	410.3	239.3	112.6	49.7	25.2	10.6
Average trip distance (in km)	249.2	116.1	43.8	18.5	11.1	5.5
Average vehicle occupancy	1.8	1.7	1.5	1.4	1.3	1.4

Time series generation

emobpy

Probability distributions | Grid availability assumptions



Source: Gaete-Morales et al. (2021)

Power system modelling

DIETERpy

- Objective function: minimize total investment and dispatch costs
- Constraints:
  - Energy balance and other feasibility constraints (e.g. storage level)
  - Policy
    - RES integration: $\geq 80\%$ of power demand
- Technologies:
  - Generation: 6 conventional and 5 renewable
  - Storage: 3 technologies (li-ion battery, generic long-duration storage, pumped-hydro storage).
- Perfect expansion of the transmission grid.
- Calibration for Germany only (no interconnection) in 2030.
- Sector coupling: electric vehicles, inflexible heat pump demand; hydrogen demand in some scenario.

Scenario definition

- Reference: all EV profiles are considered privately-owned BEVs
- Shared-only: all EV profiles are taken from the cluster of smallest overall travelled distance, across all cities (i.e. rural areas are not considered).
- Shared + other BEVs: all clusters of BEV adopters are modeled but only the cluster of smallest overall travelled distance switches to carsharing.

Table: Scenario assumptions

	Shared-only scenarios				Shared + other BEVs scenarios			
	Reference	Uncontrolled	Smart charging	Bidirectional	Reference	Uncontrolled	Smart charging	Bidirectional
Overall number of cars (in million)	5	1	1	1	10,7	6,8	6,8	6,8
Substituted cars (in million)	-	4	4	4	-	3,9	3,9	3,9
Overall battery capacity (in GWh)	225	100	100	100	521	404	404	404
Substituted battery capacity (in GWh)	-	125	125	125	-	116	116	116
Number of profiles	60	12	12	12	60	38	38	38
Number of cars per profile (in 1,000 units)	83	83	83	83	178	179	179	179

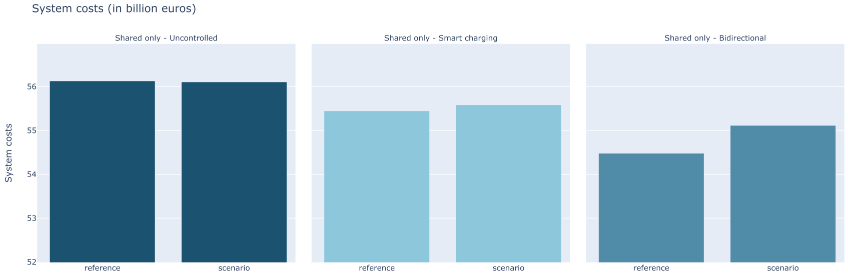
Car distribution

Outline

System costs

Impact of the charging strategy

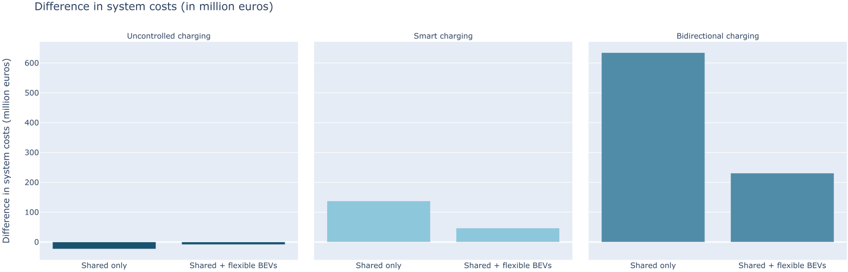
- Cost increase of ∼ 138 million euros per year in the shared-only smart charging scenario i.e. ∼ 34.5 euros per substituted car.
- Cost increase higher in the bidirectional charging scenario ∼ 635 million euros i.e. ∼ 159 euros per substituted car. Figures



System costs

Impact of the BEV fleet composition

- Cost increase dampened when there are additional vehicles considered in the model which are not shared.
- Cost increase decreases by ∼ 67% (Smart Charging) and ∼ 64% (Bidirectional).



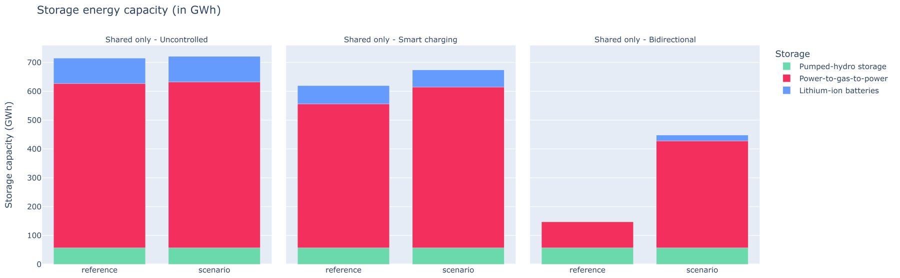
Absolute system costs

Optimal investment

Storage capacity

- Cost increase driven by investment in higher long-duration storage: +58 GWh for Smart Charging scenario and +281 GWh for the Bidirectional Charging scenario.
  Generation mix

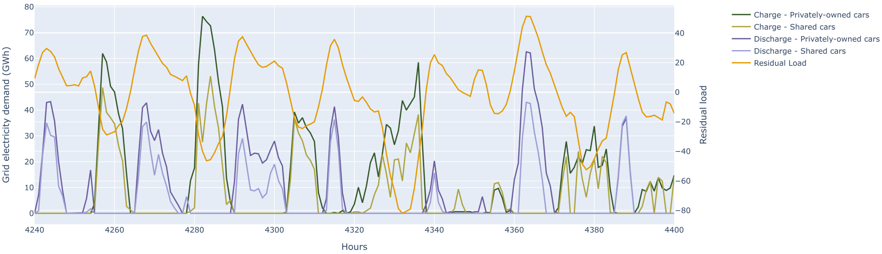
- For Bidirectional scenario: cost increase also driven by additional li-ion battery storage capacity (+ 20 GWh).



Optimal charging (and discharging) BEV load

- Shared-BEVs charging load is still flexible enough to make use of periods with high availability of renewables but to a lesser extent than privately-owned BEVs. Charging load Winter
- Discharging (Bidirectional scenario) also happens with shared BEVs but to a lesser extent. Discharging load Winter

Figure: Optimal charging and discharging load and residual load



Outline

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Conclusion

- The switch to electric carsharing entails increased power system costs.
- The increase in costs is higher in case the BEV fleet is operated in an optimized V2G mode in the reference.
- The cost effect is dampened if there are other, non-switching (flexible) cars, or other flexible sector coupling.
- The cost increase per substituted car remains moderate and shoud be put in perspective with the co-benefits brought by carsharing overall.

Thank you for your attention!

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Data for (electric) carsharing

- Main sources for vehicle-based mobility data: travel diaries (survey) or GPS-based traffic data (tracking).
- Existing data for carsharing are rare and potentially biased
  - Specific to given
    - geographical settings (level of urbanization, population density, city shape, interaction with existing transport infrastructure)
    - operational carsharing features (station-based vs. free-floating; fleet size; type of vehicles (electric or not); pricing schemes...)
    - car users (early adopters)
  - With little possibility to correct for these biases
    - No additional data on car ownership of users
    - No additional data on car mobility behaviours outside carsharing use
  - And hence little scalability to a prospective national framework

→ Synthetic mobility time series might be more robust for modelling purposes.

Car mobility behaviours

- Car mobility behaviours are influenced by
  - Location
    - e.g. city-dwellers travel smaller distances on average that people living in rural areas, but trips do not last less.
  - Type of day
    - e.g. trips during the week days (Monday to Friday) are more shorter and more regular than on weekends.
  - Mobility needs
    - e.g. people have different habits and belong to different socio-economic classes (students, young parents, old people...).
- These features are likely to influence the probability to switch to carsharing
  - Easier to find carsharing options in cities than in rural areas
  - More likely to be willing to give up one's car if only using a car for short trips and/or not so often.

⇒ Identify groups, controlling for the location and the day types, in order to better represent car mobility patterns and better identify groups likely to switch to carsharing.

Sequence analysis of travel diaries

Illustrative example: travel diaries and travel sequences

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Table: Example of car travel diaries as displayed in the MiD dataset.

HP_ID	H_ID	P_ID	W_ID	Start time	End time	Trip purpose
11	1	1	1	08:00	08:17	Work
11	1	1	2	17:00	17:32	Home
12	1	2	1	09:03	09:15	Work
12	1	2	2	16:15	16:27	Leisure
12	1	2	3	17:30	17:48	Home
21	2	1	1	07:56	08:12	School
21	2	1	2	08:13	08:28	Work
21	2	1	3	12:14	12:36	Errands
21	2	1	4	17:03	17:20	Home
22	2	3	1	07:45	07:52	Work
22	2	3	2	17:02	17:19	Home

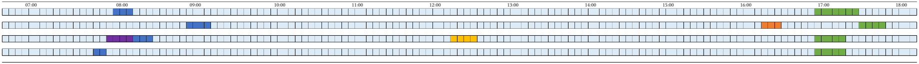

Table: Illustration of travel diaries converted to a sequence format

Sequence analysis

◇ Sequences translate into a simple numerical format...
  - $\cdots$ 0000011110000000000044400000220000 $\cdots$

◇ ...several paramount mobility behaviour features
  - number of trips per day
  - trip purpose ordering
  - trip duration for each trip
  - departure and arrival times for each trip

⇒ Powerful way of condensing multidimensional information in a unidimensional object

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Clustering sequences

- ◇ Compute pairwise distance between each pair of sequences (idle vs. moving)
  - Optimal matching uses "edit distance". Possible editing operations: insertion, deletion, substitution
  - Associates a cost to each operation + matrix of substitution costs between each possible state
  - Pairwise distance = overall cost of editing one sequence into another

  ⇒ Dissimilarity matrix summarizes the pairwise distance between any two sequences.

- ◇ Unsupervised classification algorithm on the dissimilarity matrix
  - Hierarchical Cluster Analysis (HCA): agglomerative algorithm.
  - Ward linkage: minimize the variance within clusters, maximize the variance between clusters.

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Sequence index plot

Cluster 1

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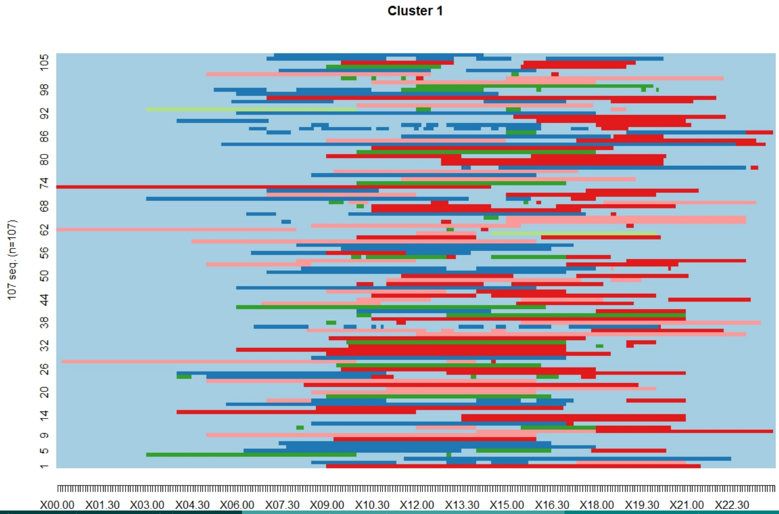

Sequence index plot

Cluster 2

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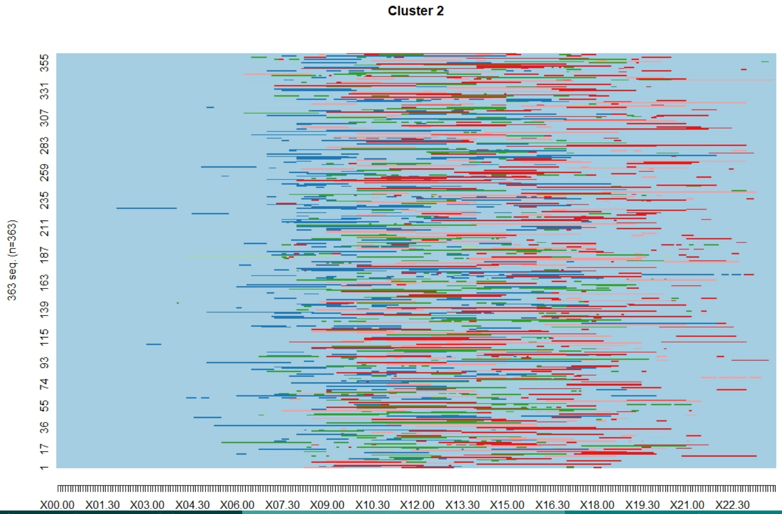

Sequence index plot

Cluster 3

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Sequence index plot

Cluster 4

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Sequence index plot

Cluster 5

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Sequence index plot

Cluster 6

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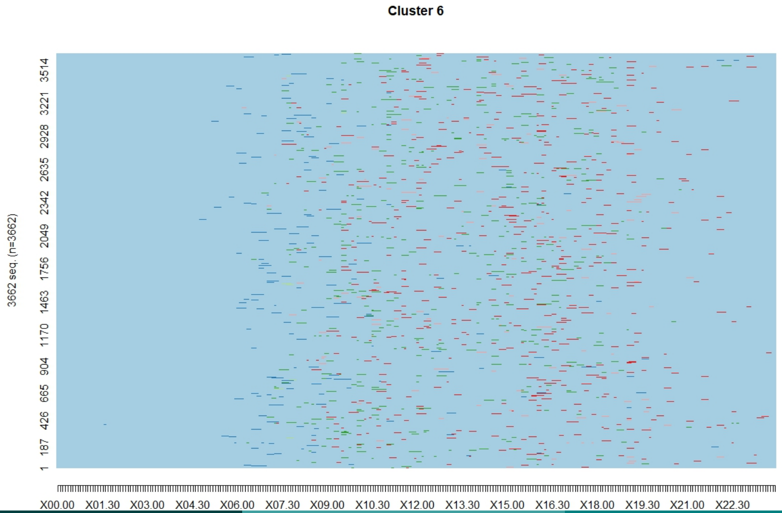

Empirical probability distributions

- Generate empirical probability distributions to characterize mobility behaviors.
- We assume a given substitution rate between private-owned cars and shared cars in order to derive the distribution of number of trips per day for shared cars.

		Weekday (Mo-Fri)		Saturday		Sunday	
		Conditionality	Level	Conditionality	Level	Conditionality	Level
Privately-owned cars	Number of trips	no	cluster x location	no	location	no	location
	Destination departure time	number of trips trip rank		number of trips trip rank		number of trips trip rank	
	Joint distance/duration	number of trips destination		number of trips destination		number of trips destination	
Shared electric cars	Number of trips	no	cluster x location	no	location	no	location
	Destination departure time	no		no		no	
	Joint distance/duration	destination		destination		destination	

Table: Conditionality criteria and levels for empirical probability distributions

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Time series generation

Assumptions

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- Vehicle type: Volkswagen ID.3
- Weather year: 2016

Table: emobpy assumptions for generating grid availability time series

	destination	Charging station availability	Power rating 0 kW	3.7 kW	11 kW	22 kW	75kW	150 kW	Battery capacity (kWh)
Privately-owned cars	home	0.9	0.1	0.6	0	0.3	0	0	45
	work	0.9	0.1	0	0.3	0.5	0.1	0	
	errands	0.8	0.2	0	0.2	0.5	0.1	0	
	leisure	0.8	0.2	0	0.2	0.5	0.1	0	
	driving	0.01	0.99	0	0	0	0.005	0.005	
Shared cars	home	1	0	0	0	0	1	0	100
	work	1	0	0	0	0	1	0	
	errands	1	0	0	0	0	1	0	
	leisure	1	0	0	0	0	1	0	
	driving	0.01	0.99	0	0	0	0.005	0.005	

Distribution of cars across locations

◇ Only driving profiles with medium to short trips switch to electric cars by 2030.

◇ 15 million BEVs in 2030

◇ Distribution of BEVs across locations: same as in the MiD survey.

Table: Distribution of cars across location types

	Metropolises	Big cities	Middle-size cities	Small cities	Rural areas	Total
Cars (%)	11	12	22	27	29	100
Cars (million units)	1.62	1.73	3.30	4.05	4.29	15

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System costs

Table: System costs for different scenarios

	Shared-only scenarios			Shared-only + flex. BEV scenarios		
	Uncontrolled	Smart Charging	Bidirectional	Uncontrolled	Smart Charging	Bidirectional
Overall system costs (in billion euros)	56,1	55,6	55,1	59,1	57,2	56,4
Additional system costs (in million euros)	-23,2	137,6	635,6	-8,4	46,8	230,8
Additional system costs per substituted car (in euros)	-5,8	34,4	158,9	-2,1	11,7	57,7

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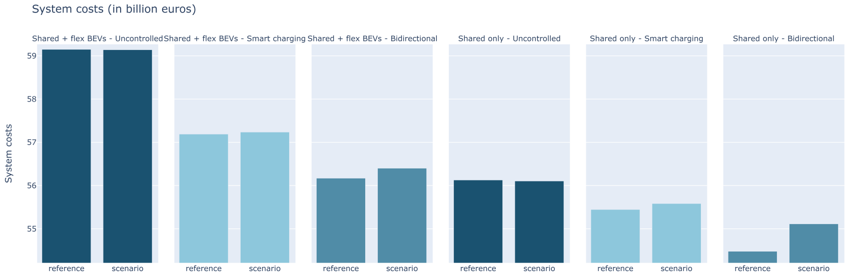
System costs

Effect of the BEV fleet composition



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Generation capacity mix

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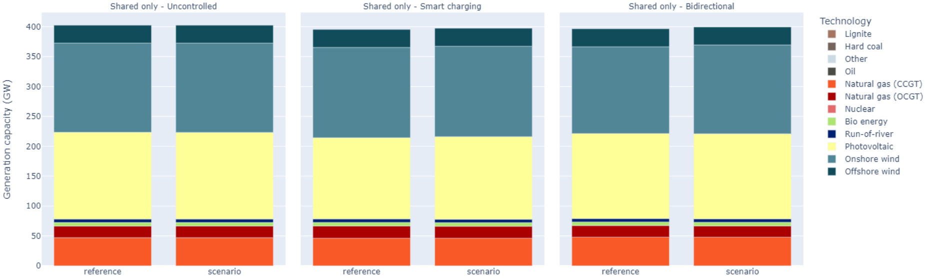
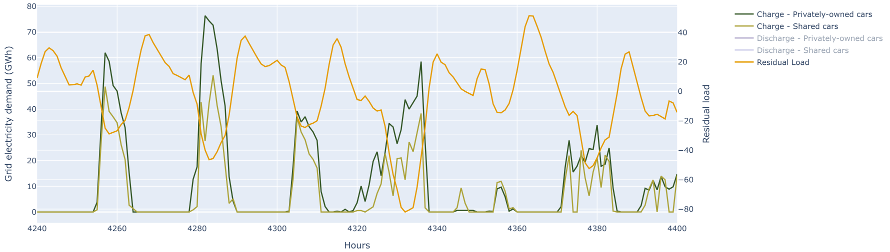


Optimal BEV charging load



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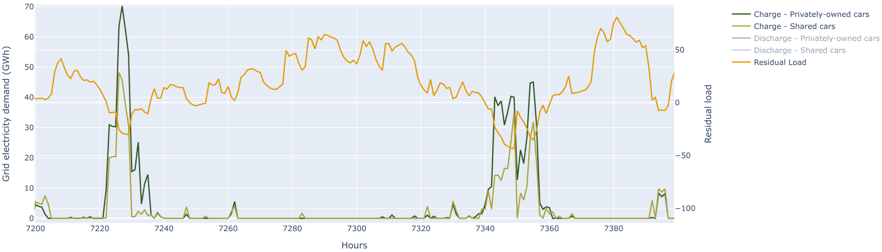
Optimal BEV charging load in winter



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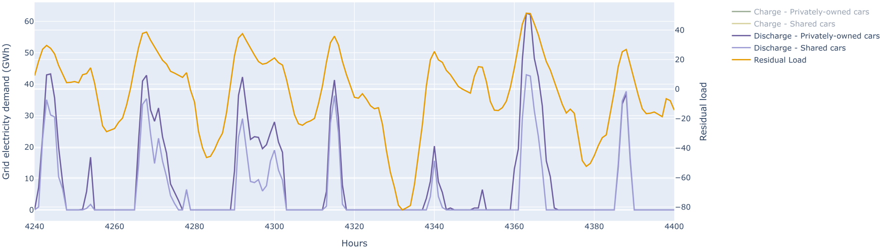
Optimal BEV discharging load



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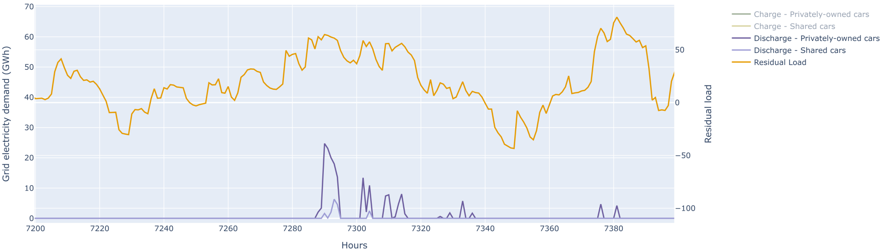
Optimal BEV discharging load in winter



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