

Behaviour-driven electric vehicle charging decisions and its implications on demand response flexibility for the integration of renewable energies in Germany

4NEMO summerschool, IFO institute Munich

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2019/07/31



EVer Energie und Verkehr



KOPERNIKUS
ENavi >>> PROJEKTE
Die Zukunft unserer Energie



Knowledge for Tomorrow

Agenda

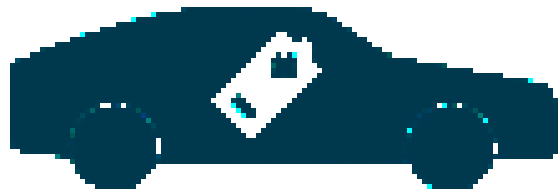
Introduction

Models and model coupling

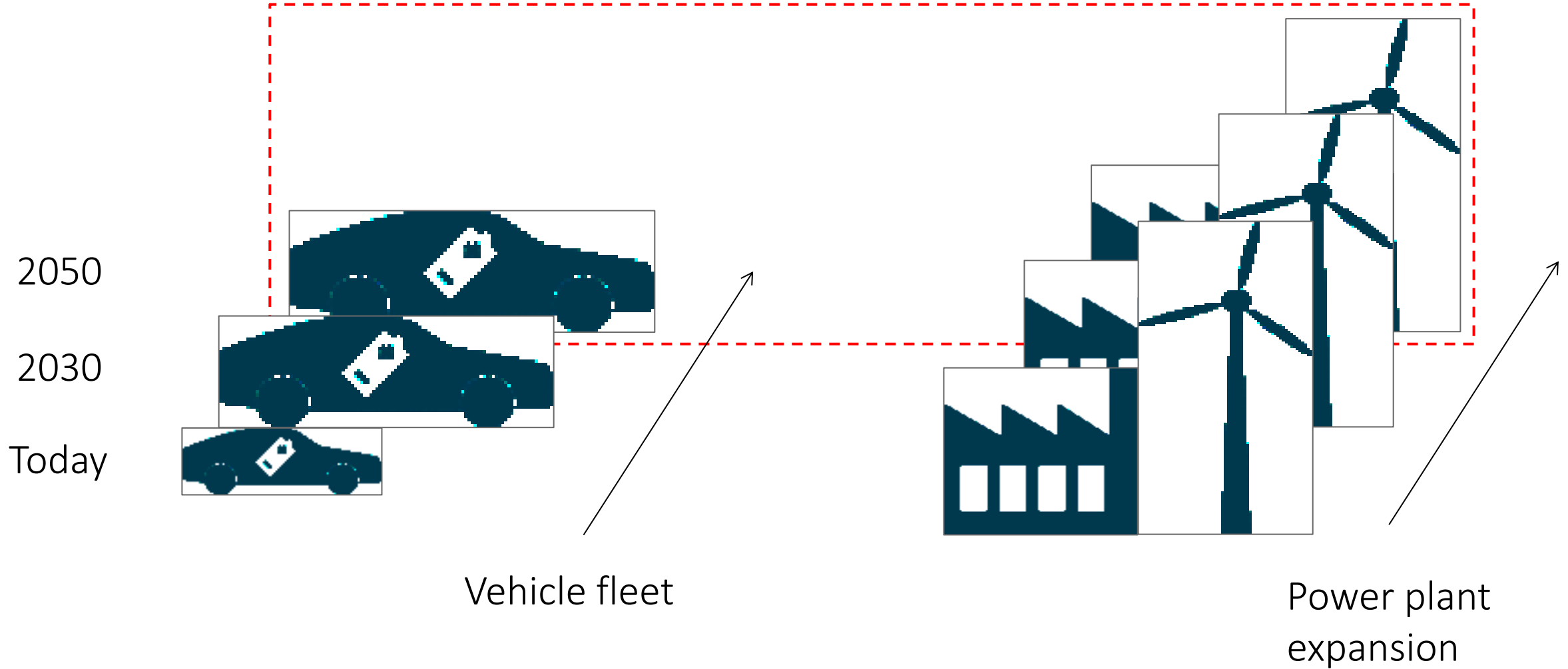
Preliminary results



Introduction

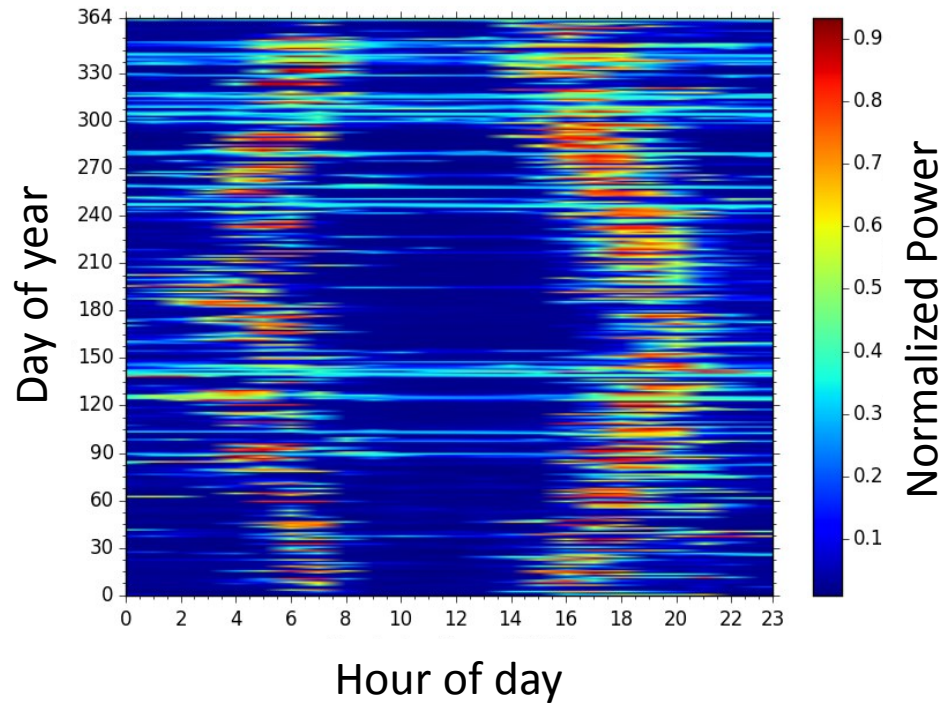


Introduction

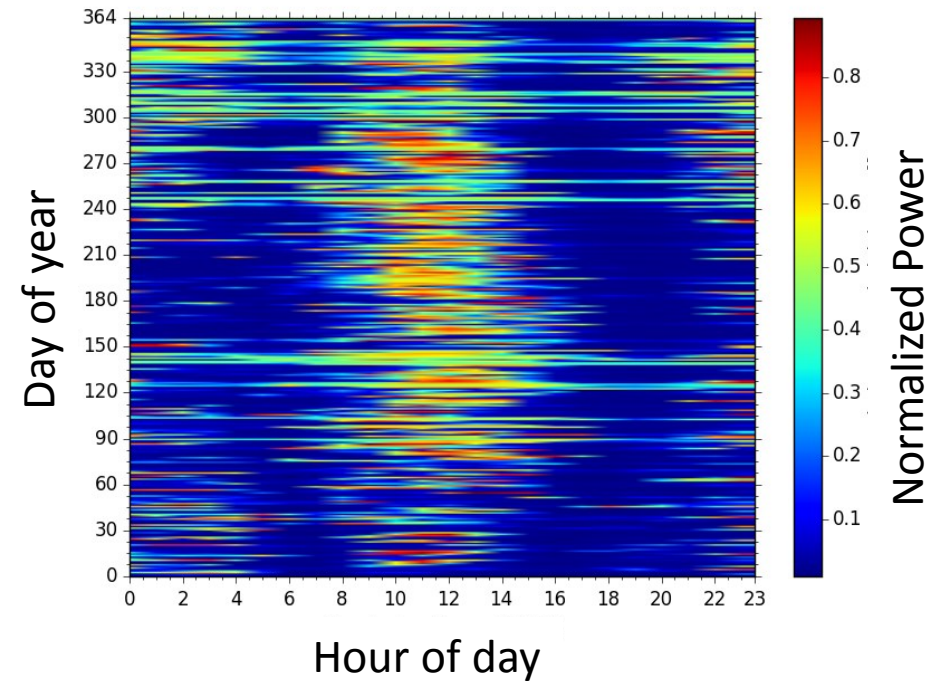


Introduction – What flexibility demand does the German energy system have (over time)?

Lithium ion battery discharge
High residual load



Lithium ion battery charge
Low residual load

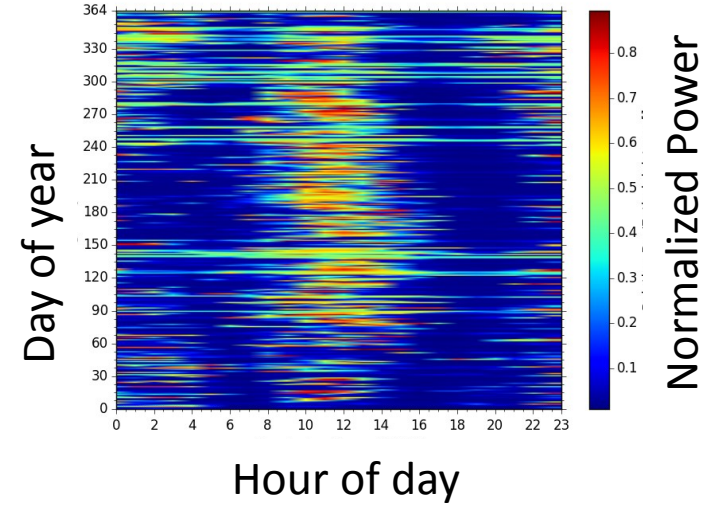
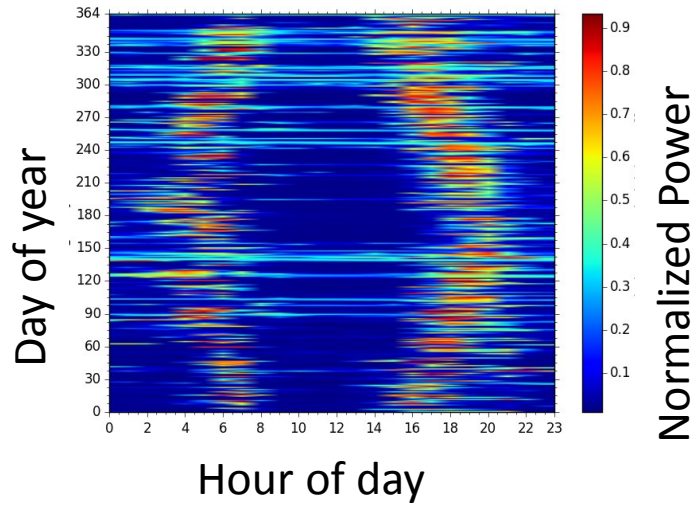


Cebulla et al. (2017)

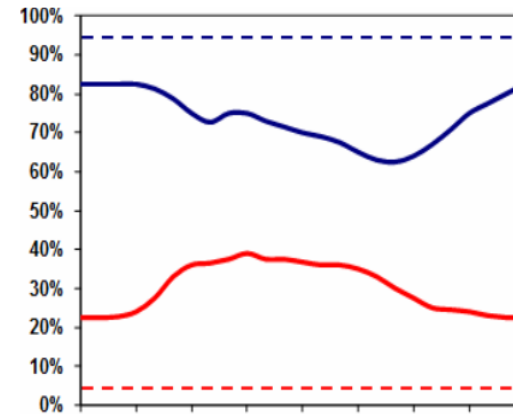
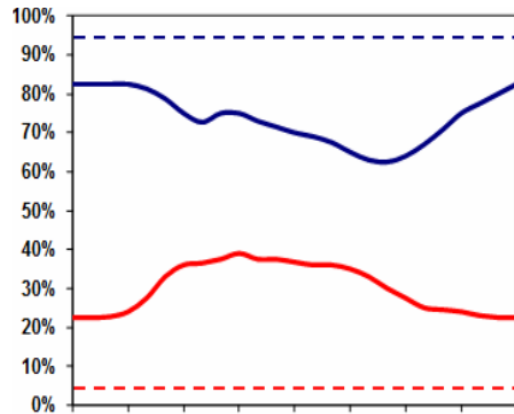


Introduction – Electric vehicle fleet as balancing option for the power system's short-term flexibility demand

Cebulla et al. (2017)



Luca de Tena (2014)



Motivation – findings from literature (power sector)

- - 9.2% reduction in grid capacities (Luca de Tena & Pregger, 2018)
- - 0.9% - +2.69% in total capacity expansion in time horizon 2020-2050 (Taljegard et al. 2019)
- - 9.28 % - +10.31% new interconnectors in time horizon 2020-2050 (Taljegard et al. 2019)

Technology capacity

- - 6 TWh system losses (Luca de Tena & Pregger, 2018)
- - 1.6-1.8 TWh system losses (Gnann et al., 2018)
- - 19.05 % reduced wind power curtailment in 2030 (Taljegard et al. 2019), total curtailed wind power in base: 2%

Curtailment

Reduced peak power

- - 4.5 GW (Luca de Tena & Pregger, 2018)
- -2.2-+0.76 GW (Gnann et al., 2018)
- -3-9 GW (21-59 %) reduced investments in peaking capacity in time horizon 2020-2050 (Taljegard et al. 2019),

System costs

- 850 bn. € system cost savings (Luca de Tena & Pregger, 2018)
- 0-12 % increased system cost from operation in 2030 (Taljegard et al. 2019)
- 5-12 % increased system cost from investment modeling (Taljegard et al. 2019)



Research Questions

1. What structural effects do behaviour-driven charge decisions for future electric vehicle fleets in future cost-optimal power systems with high shares of photovoltaic and wind power plants?
2. How do hourly power prices affect charge decisions? How do these changes affect load shifting potential of future electric vehicle fleets?



Agenda

Introduction and motivation

Models and model Coupling

Preliminary results



Model description - CURRENT

$$U_{i,n} = \beta_LOC_i + \beta_PRICE * p_i + \varepsilon_{i,n}$$

U: Utility

i: activity

n: electric vehicle

Beta_LOC: preference for location

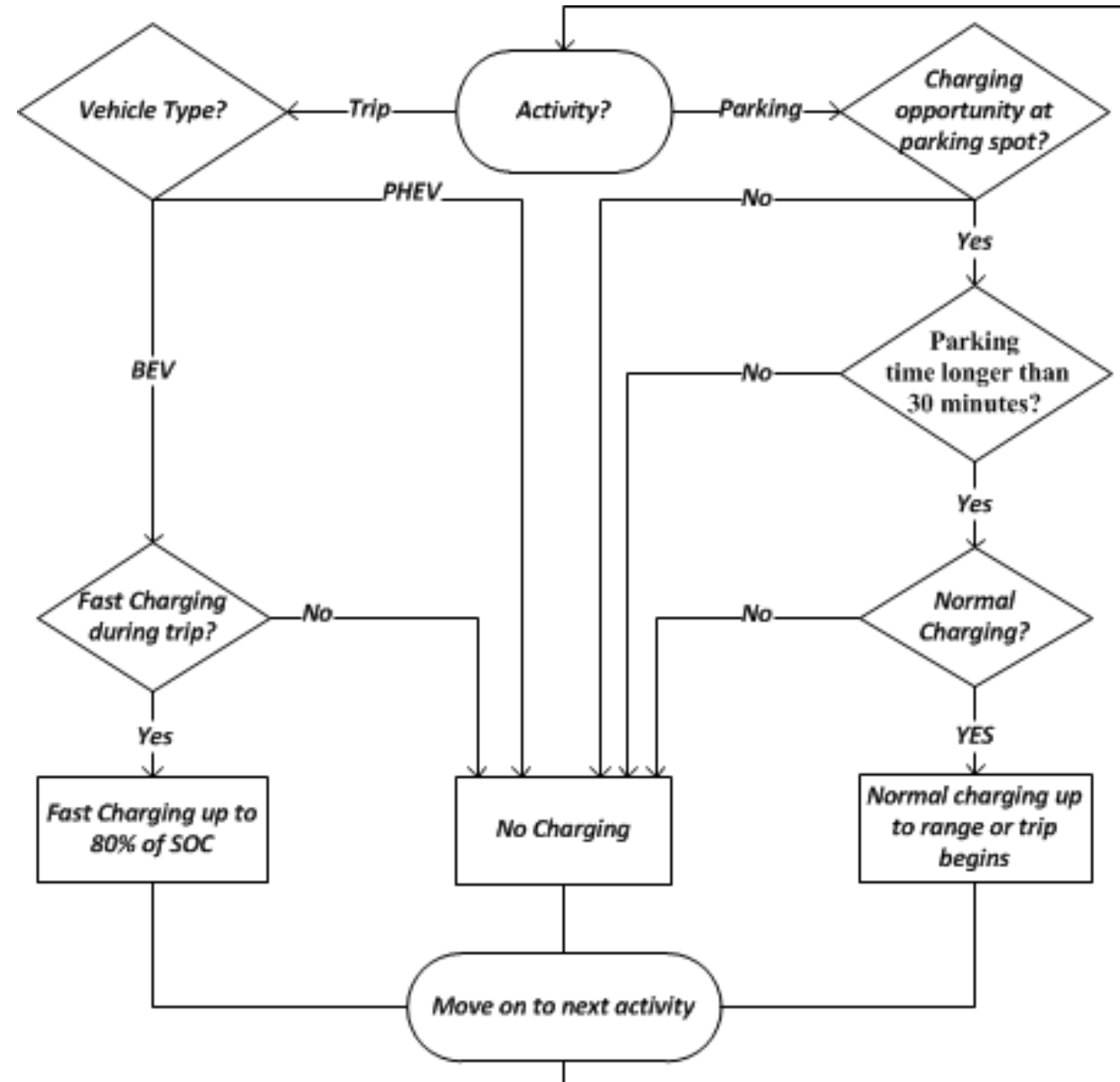
Beta_PRICE: preference for price

p_i: price

Epsilon: stochastic term

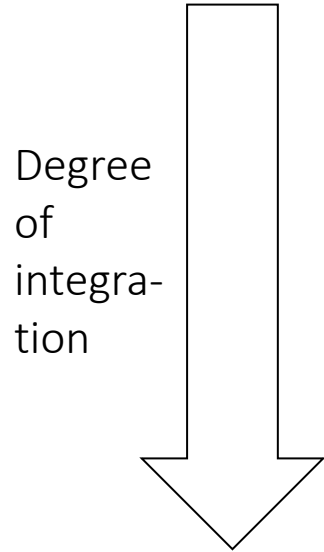
$$U_{nonchoice,n|i} = SOC_{nonchoice,n|i} + \varepsilon_{nonchoice,n}$$

$$P_{i,n} = \frac{e^{V_{i,n}}}{\sum_{j=1}^J e^{V_{j,n}} + \gamma_{i,n} * (e^{V_{nonchoice,n|i}} + \alpha)}$$



Steck et al. (2019)

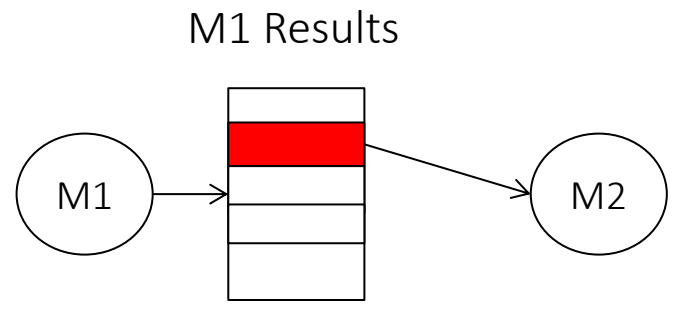
Systematics of model coupling



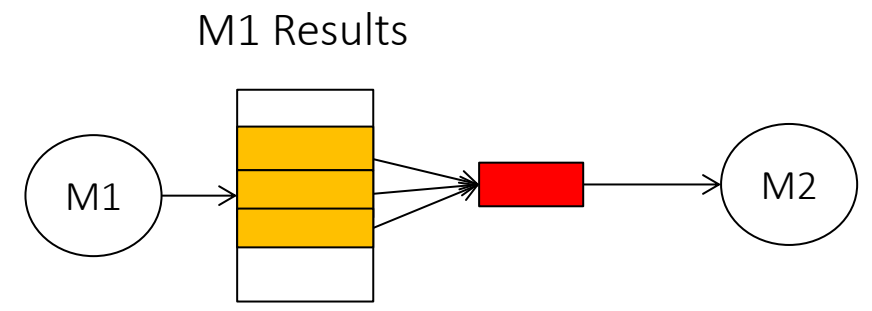
Exemplary Aim	Degree of integration	Data harmonization	Scope harmonization	Methodological harmonization
Comparison	Harmonization	Central assumptions	Optional	No
Model chain	Model linking	For relevant dimensions	Optional	No
Feedback effects	Model coupling	Yes	Yes	No
Model refinement	Model integration	Selection	Yes	Yes



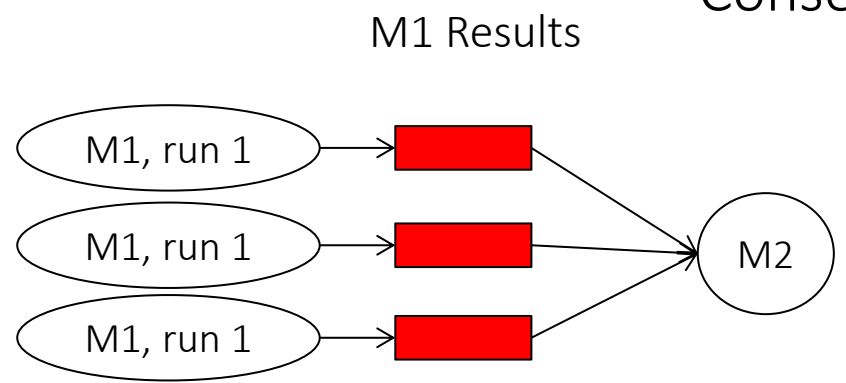
Methods of model coupling without a strict harmonization of scope



Selection

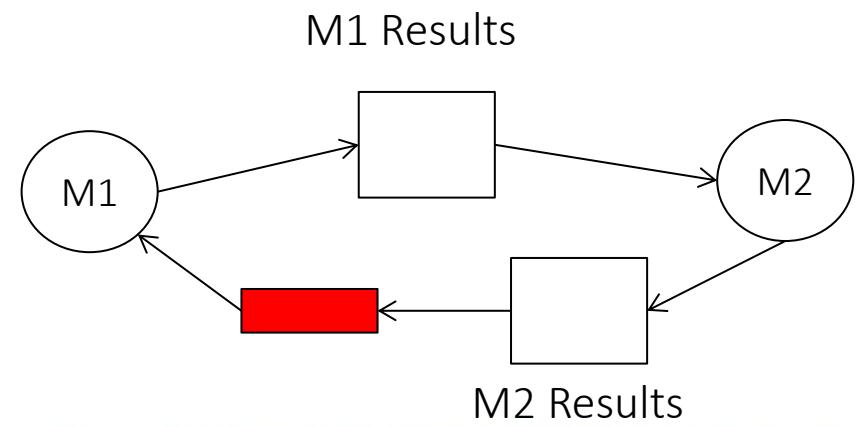


Aggregation

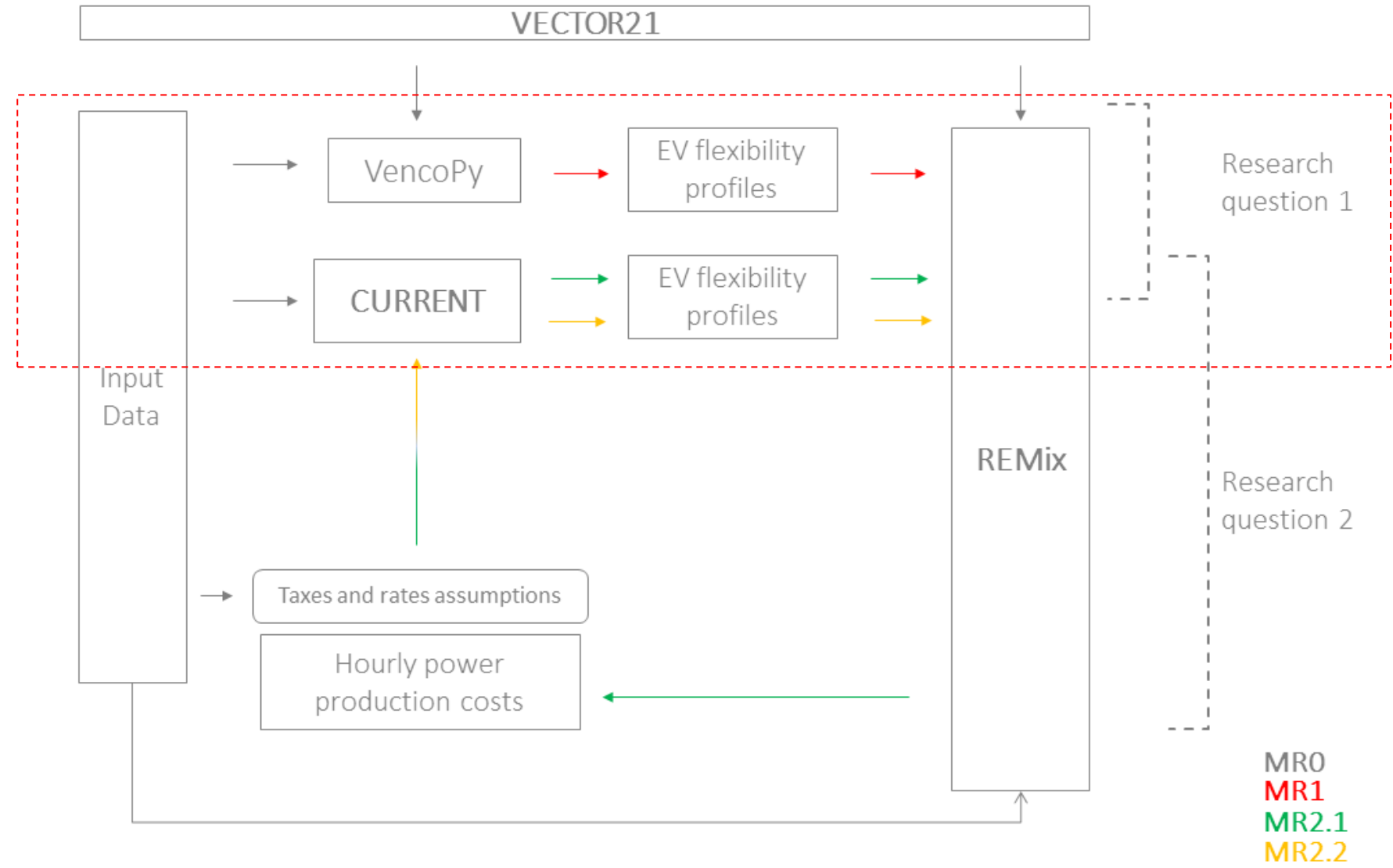


Consecutive runs

Data processing



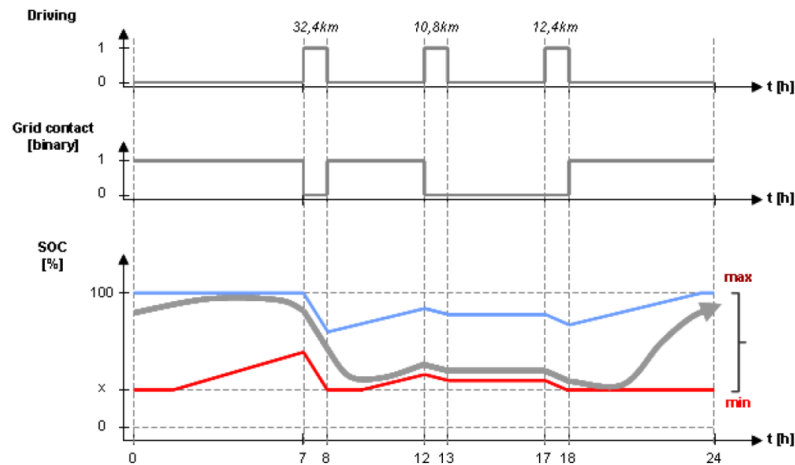
Methodological framework and depiction of model runs



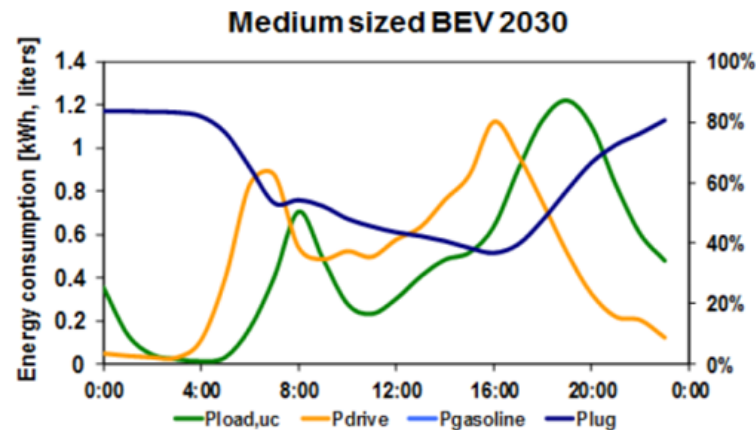
Input – load shifting profiles

Car owners' view

Power system view



Source: DLR/IFHT/ISE, 2012



- Data: Mobility demand survey of 25k German households, 60k persons and 35k cars for one day each
- Aggregated to ~18k hourly drive profiles as well as hourly boolean connection profiles
- Resulting profiles for each technology:
 1. SOC max
 2. SOC min
 3. Electric demand
 4. Charge availability
 5. Uncontrolled charging

Input – load shifting profiles

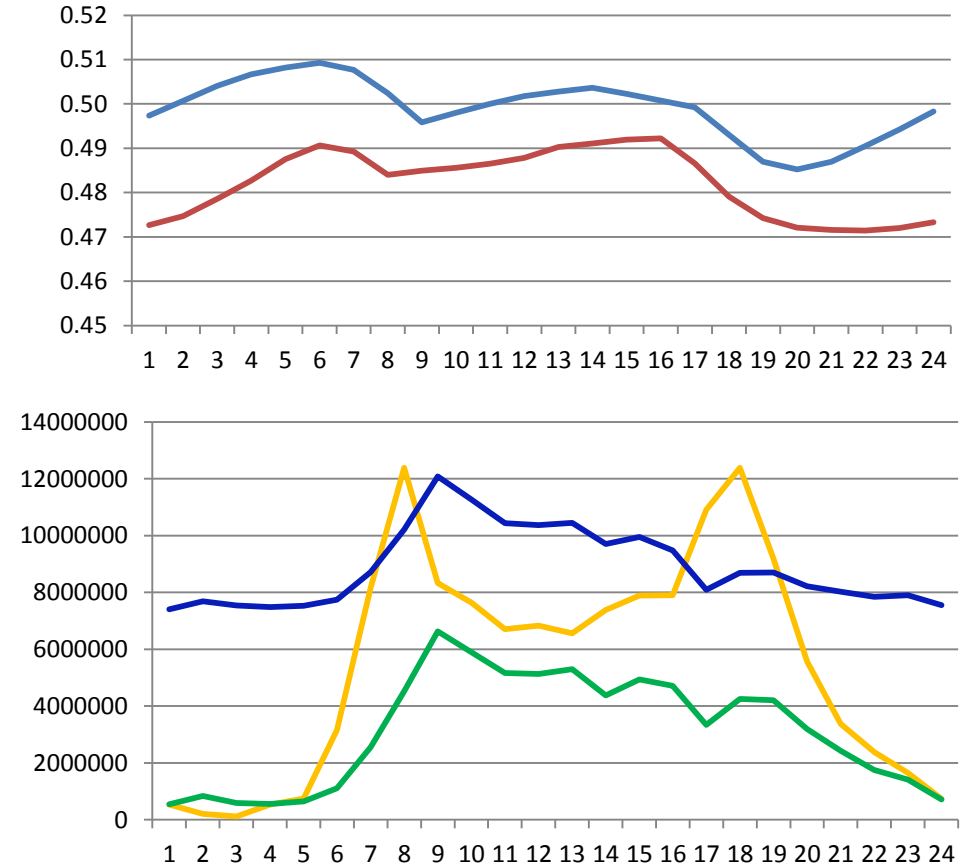
Power system view

$$U_{i,n} = \beta_LOC_i + \beta_PRICE * p_i + \varepsilon_{i,n}$$

$$U_{nonchoice,n|i} = SoC_{nonchoice,n|i} + \varepsilon_{nonchoice,n}$$

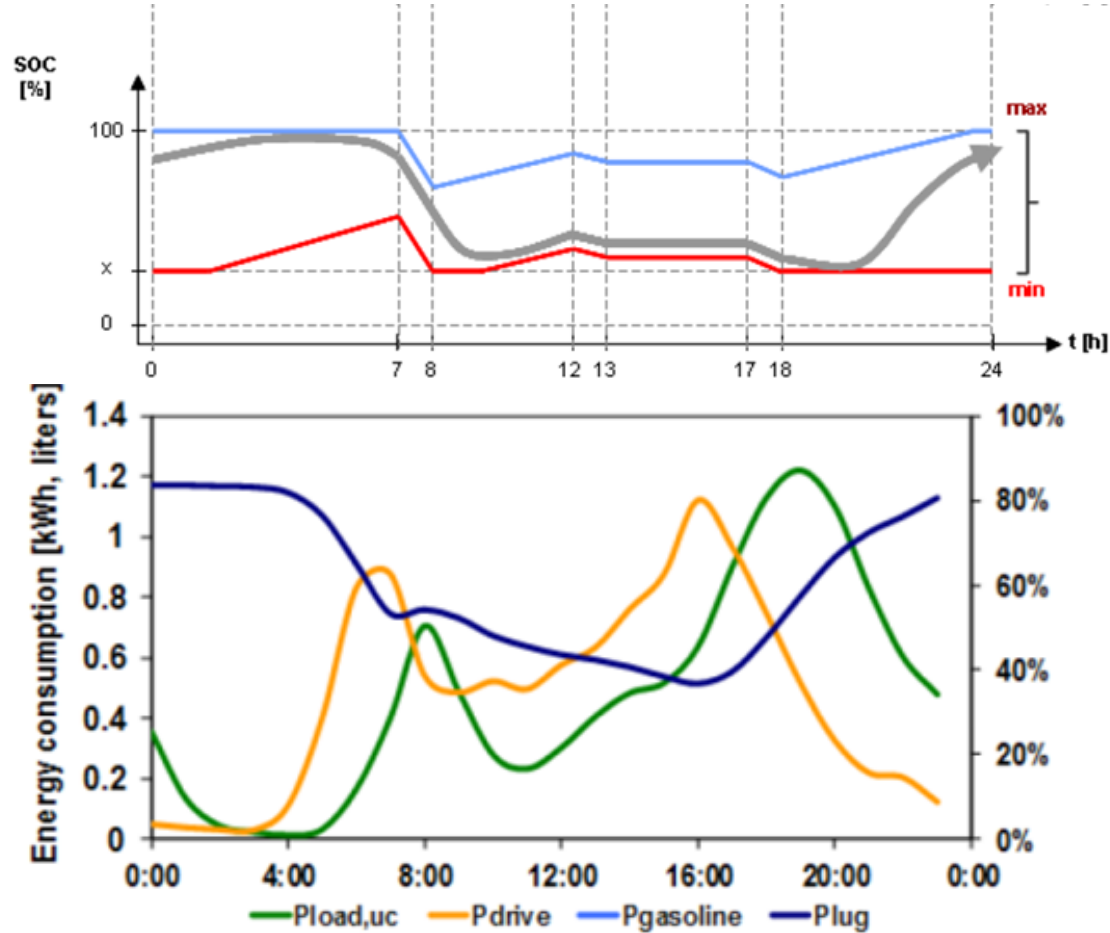
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Car owners' view

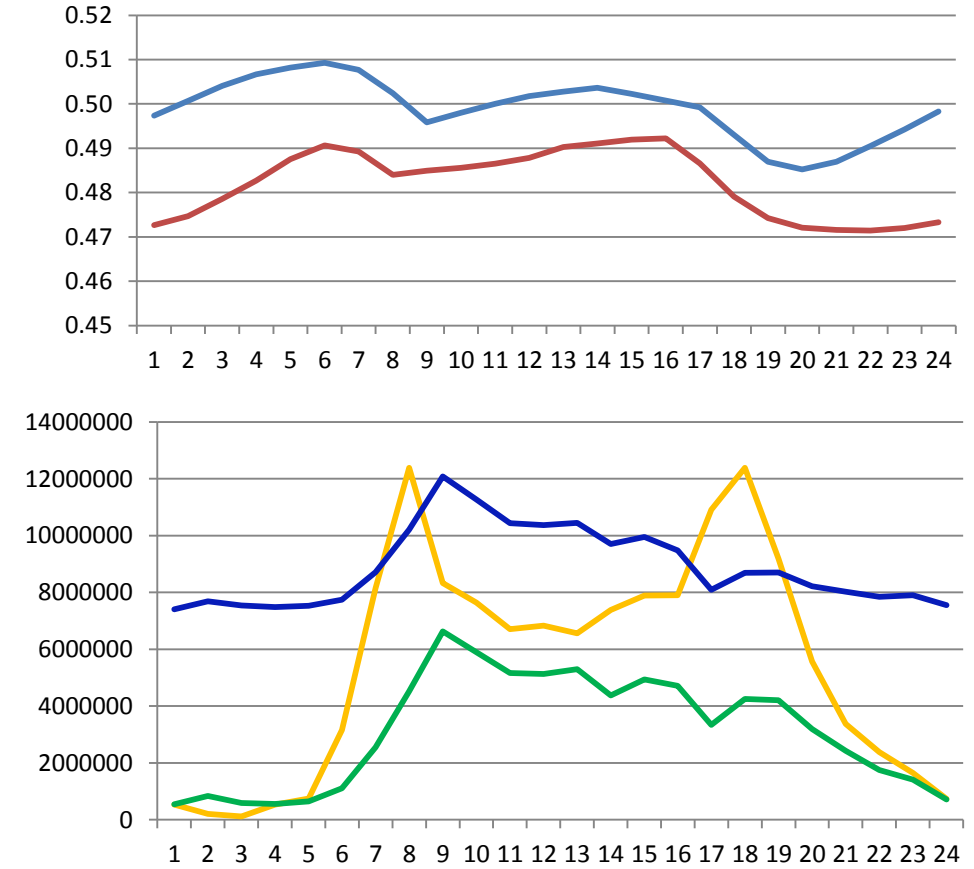


Input – load shifting profiles

Power system view

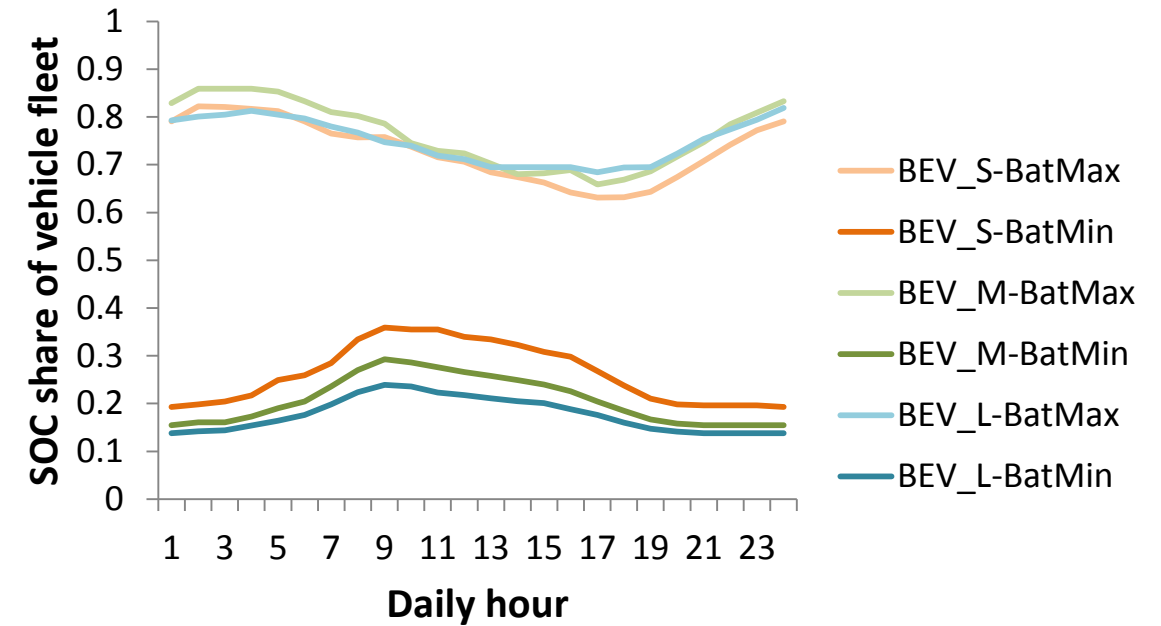


Car owners' view



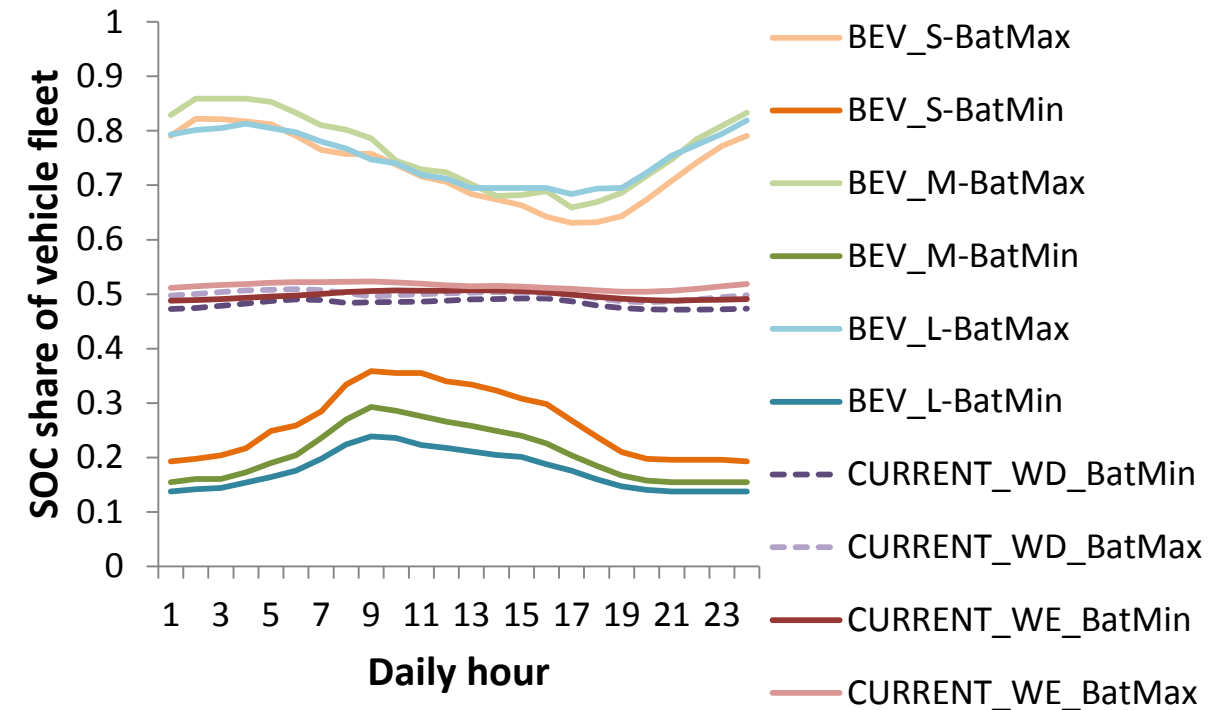
Input – load shifting from EV fleet

Model run (MR)	Demand for electric driving in TWh/a	Hourly load shifting potential in Germany in GWh		
		Average	Max	Min
MR0	0	0	0	0
MR1	100	749	935	592
MR2.1				
MR2.2				
Taljegard et al. (2019)	110 (S2), 210 (S6)	1300 (S2), 2300 (S6)		



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Agenda

Introduction and motivation

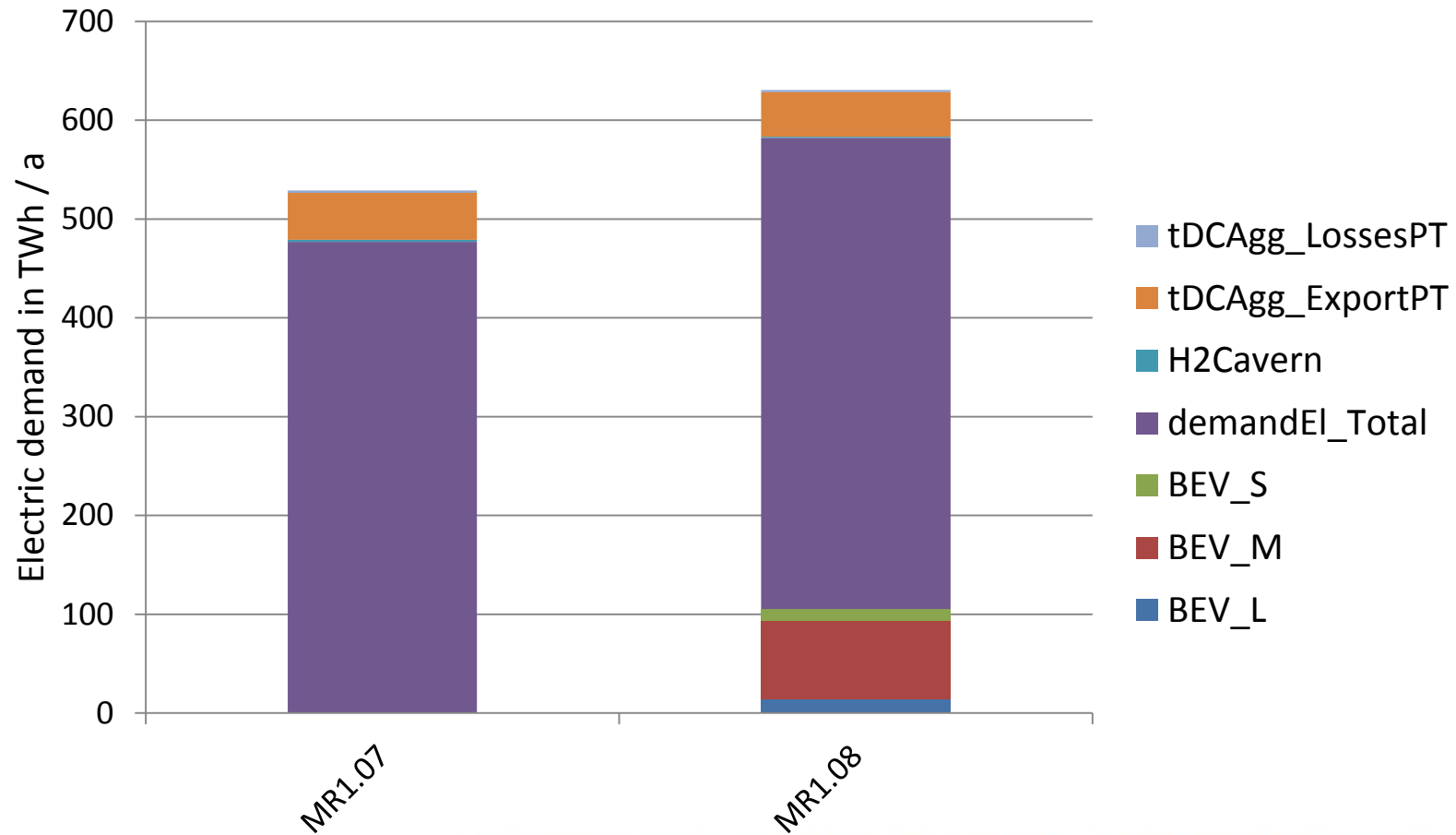
Model Coupling

Preliminary results



Preliminary results – MR0 vs. MR1

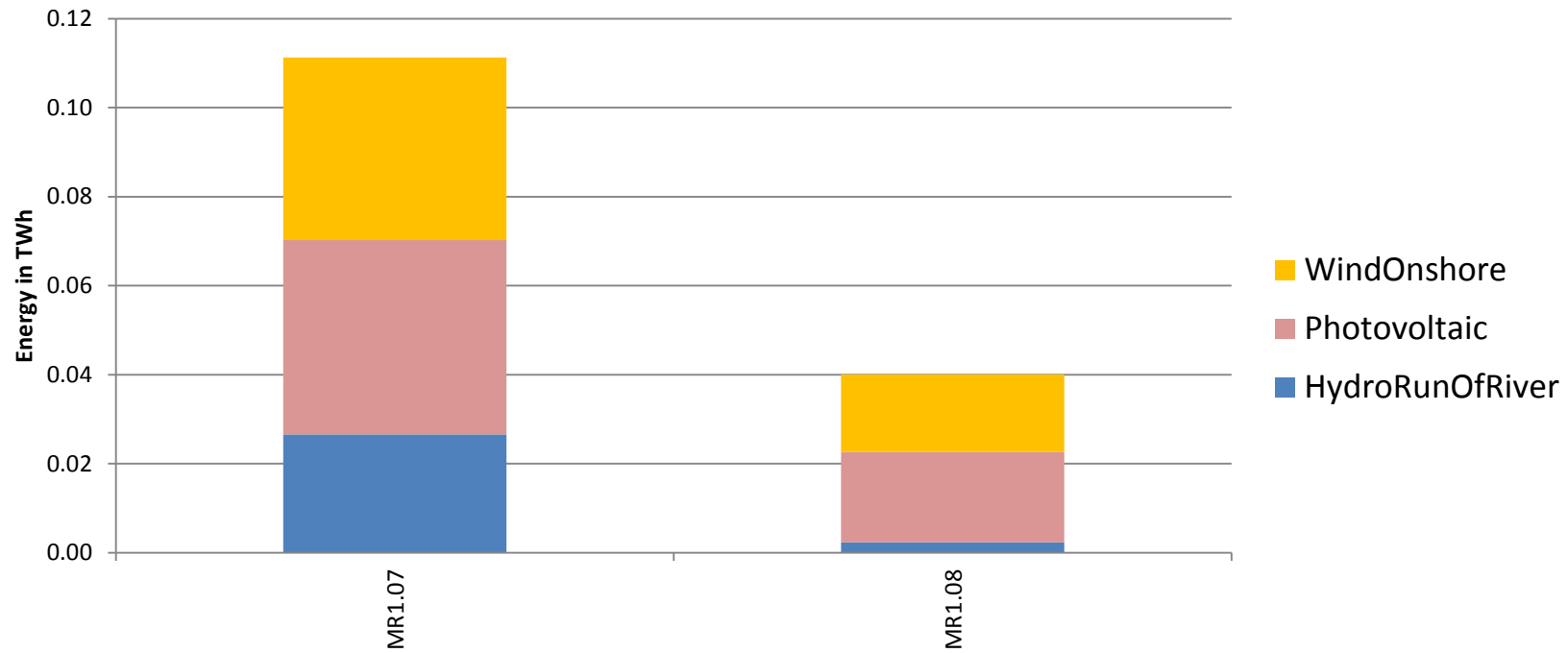
Power demand



Preliminary results – MR0 vs. MR1

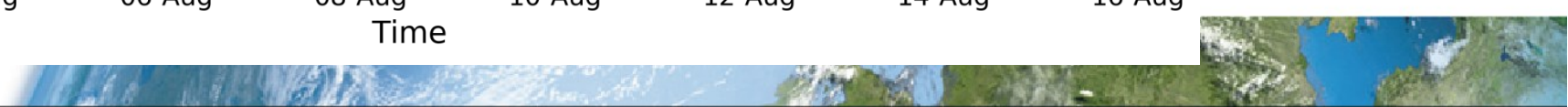
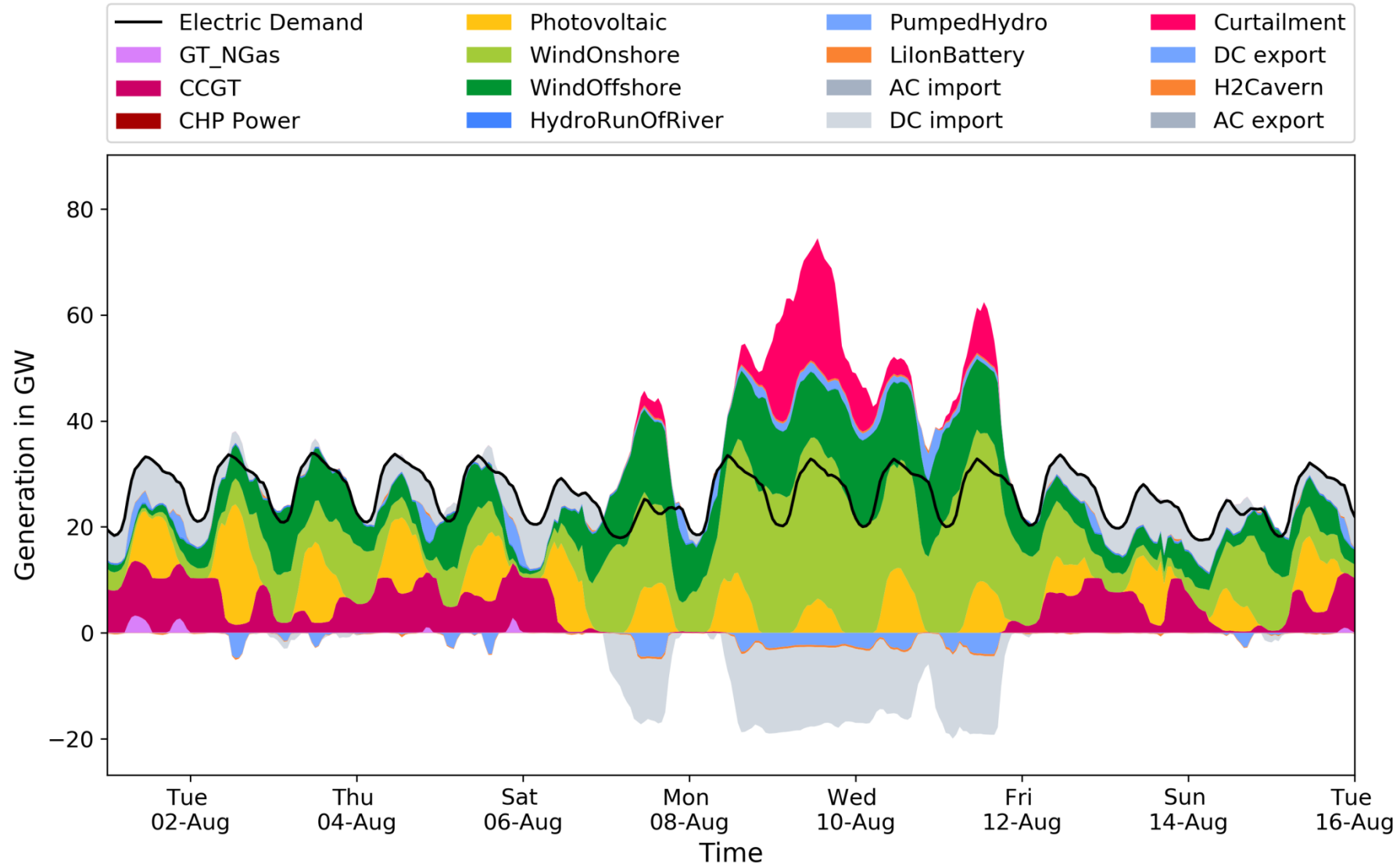
Curtailment

Power curtailment in Germany



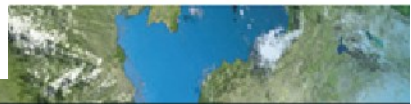
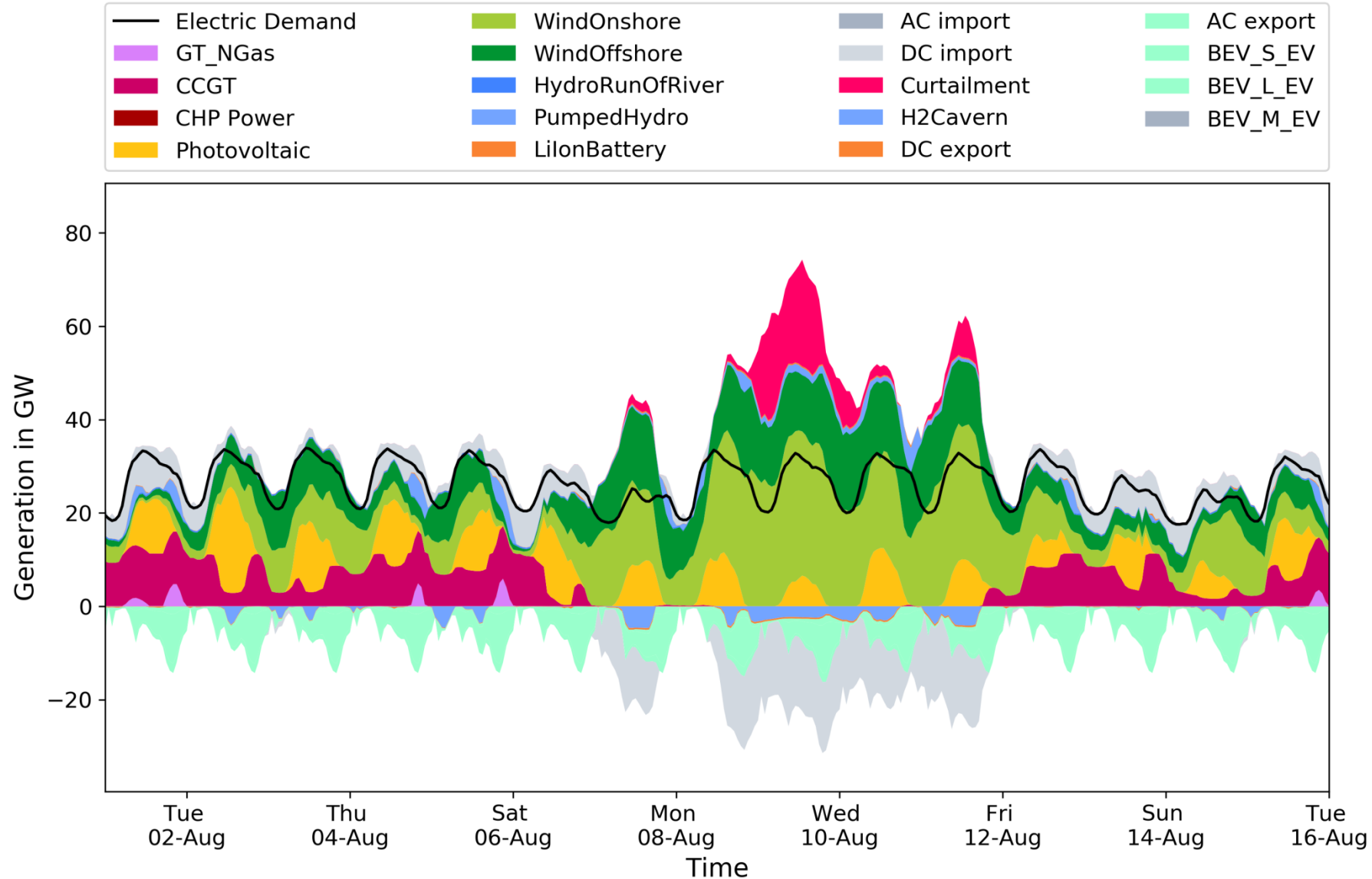
Preliminary results – MR0 vs. MR1

Dispatch



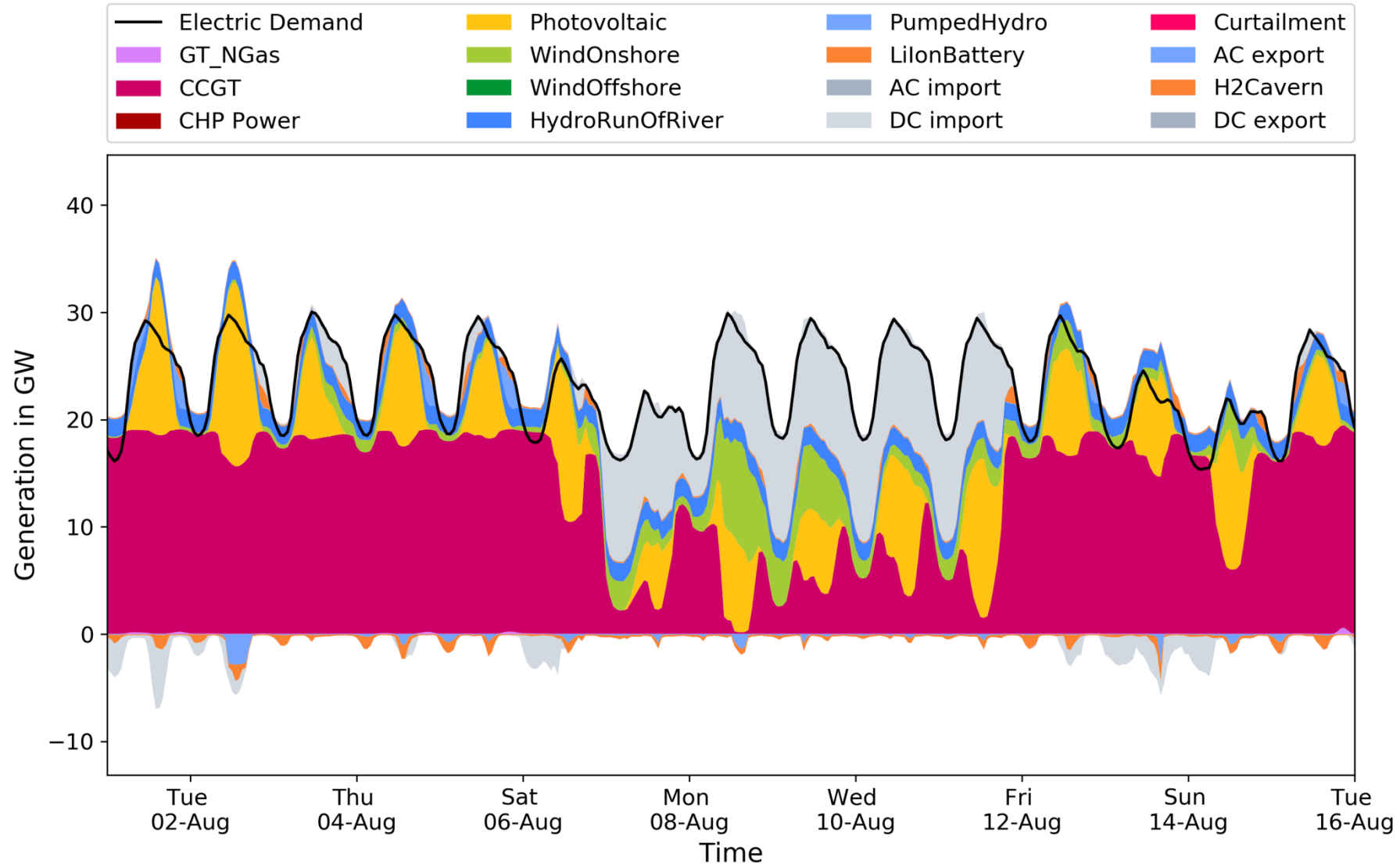
Preliminary results – MR0 vs. MR1

Dispatch



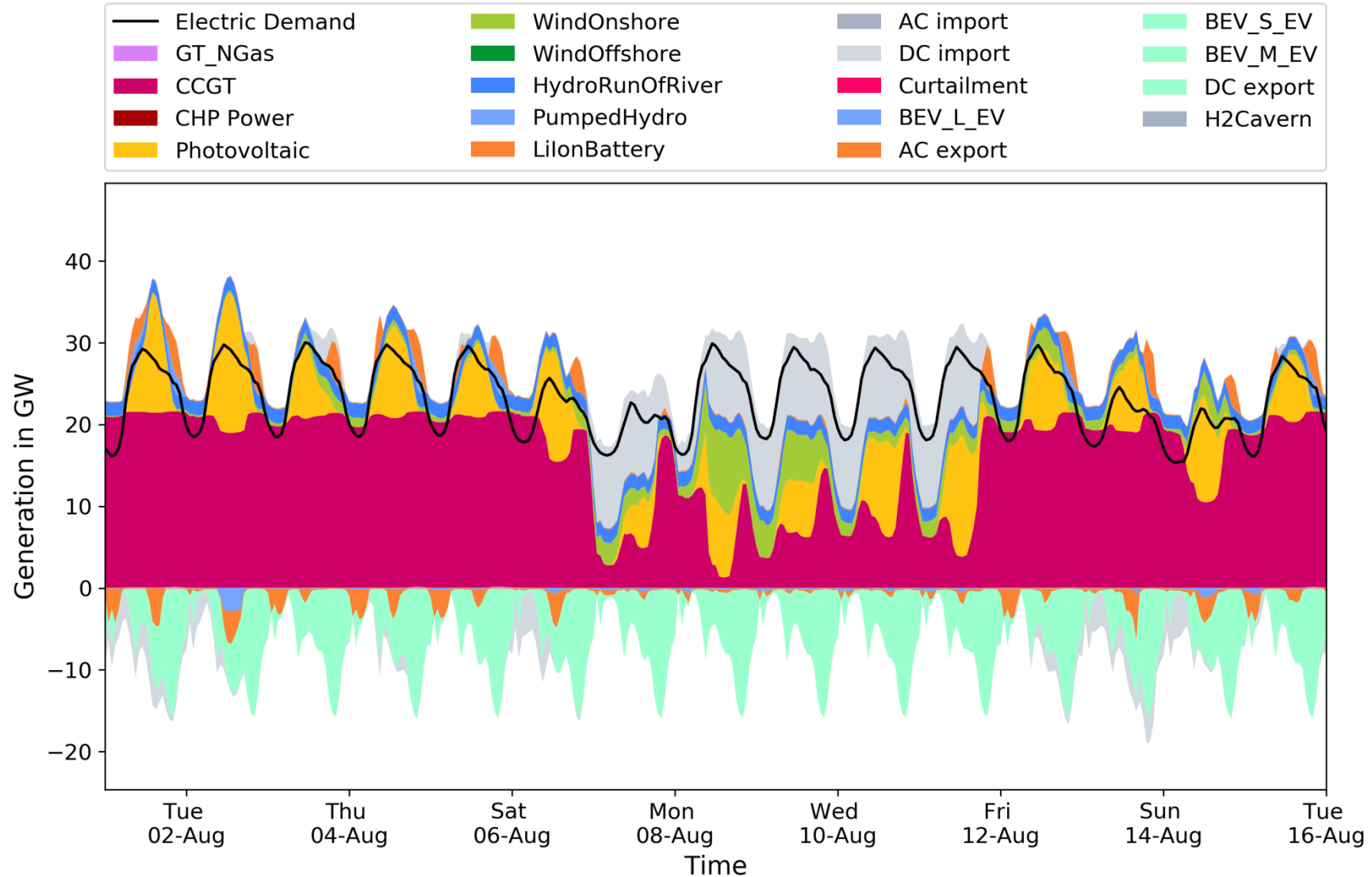
Preliminary results – MR0 vs. MR1

Dispatch



Preliminary results – MR0 vs. MR1

Dispatch



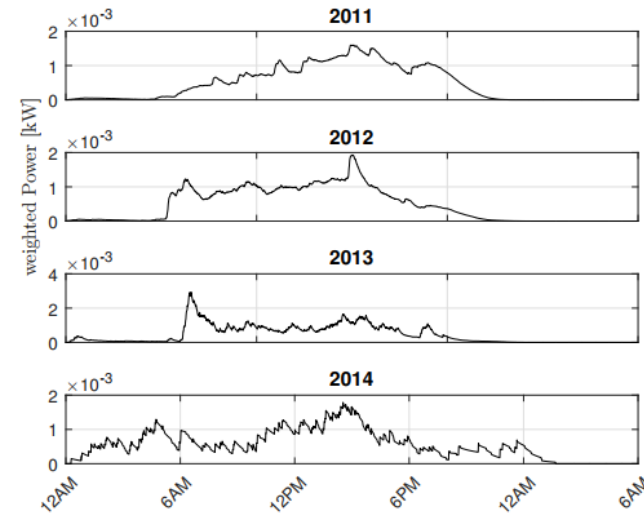
Further work and weaknesses of the analysis

Next steps

- REMix-Model Run 2 with CURRENT-Output
- Setting up feedback loop for power prices
- Result depiction
- Sensitivity analyses for different weather and load years (currently 2011)

Further improvements

- Validation of charging decisions modelling
- Change in charging behaviour
- Assumptions on taxes and rates



Schaeuble et al. (2017)



Background Literature

Cebulla, F., Naegler, T. & Pohl, M. (2017). Electrical energy storage in highly renewable European energy systems: Capacity requirements, spatial distribution, and storage dispatch. *Journal of Energy Storage* 14, 211-223. doi: <https://doi.org/10.1016/j.est.2017.10.004>

Gerhardt et al. (2018) Entwicklung des Strassenverkehrs.. Fraunhofer IEE. Online:

Gils et al. (2017).

Gnann, T., Klingler, A.-L. & Kühnbach, M. (2018). Load shift potential of plug-in electric vehicles with different amounts of charging infrastructure. In: *Journal of Power Sources* 390 (2018), 20-29, Elsevier. DOI: <https://doi.org/10.1016/j.jpowsour.2018.04.029>

Kugler et al. (2017). Powertrain Scenarios for Cars in European Markets to the Year 2040. In: TAE conference proceedings - 11th International Colloquium Fuels. 11th International Colloquium Fuels – Conventional and Future Energy for Automobiles, 27.-29.06.2017, Stuttgart, Deutschland. Online: https://elib.dlr.de/114744/1/20170331_Powertrain_Scen_Schmid_etal_TAE_final.pdf [accessed 2019-07-28]

Luca de Tena, D. (2014). Large Scale Renewable Power Integration with Electric Vehicles. Long term analysis for Germany with a renewable based power supply. Dissertation at University of Stuttgart.

Luca de Tena, D. & Pregger, T. (2018). Impact of electric vehicles on a future renewable energy-based power system in Europe with a focus on Germany. *Int J Energy Res.* 42, 2670–2685. doi: 10.1002/er.4056

MinFuture (2019). Müller, D.B. et al. MinFuture project website. Online: <https://minfuture.eu/index.html> [accessed 2019-07-27].

Schaeuble, J., Kaschub, T., Ensslen, A., Jochem, P. & Fichtner, W. (2017). Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany. Preprint submitted to Elsevier.

Sach, T. (2016). Flexibility Tracker. Indicators for Power System Flexibility. Presentation at Strommarktgruppentreffen, 05.08.2016. Online: https://www.strommarkttreffen.org/2016-08-05-Sach-Flexibility-Tracker_Indicators-for-Power-System-Flexibility.pdf [accessed 2019/04/04].

Steck, F., Anderson, J.E., Kuhnimhof, T. & Hoyer-Klick, C. (2019). Comprehensive transportation and energy analysis: A price sensitive, time-specific microsimulation of electric vehicles. Transportation Research Board 98th Annual Meeting. Washington, D.C.

Taljegard, M., Göransson, L., Odenberger, M. & Johnsson, F. (2019). Impacts of electric vehicles on the electricity generation portfolio – A Scandinavian-German case study. In: *Applied Energy* 235. Elsevier. DOI: <https://doi.org/10.1016/j.apenergy.2018.10.133>

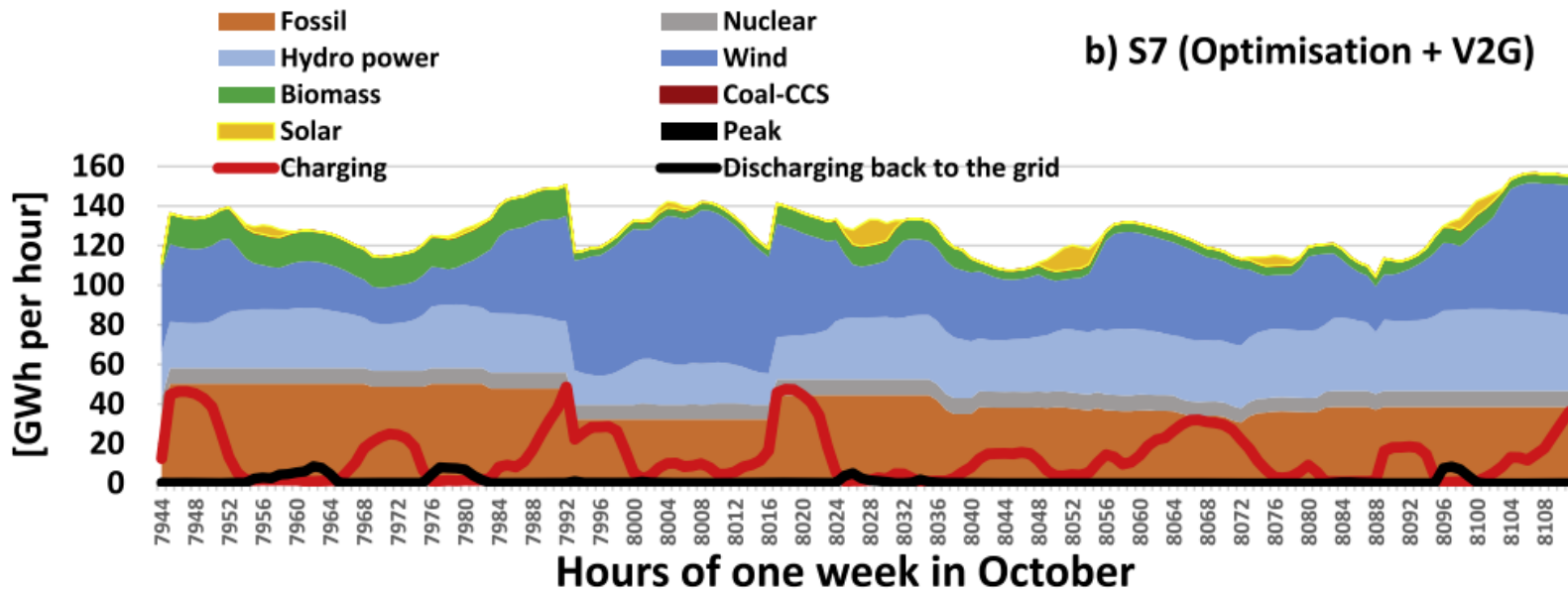
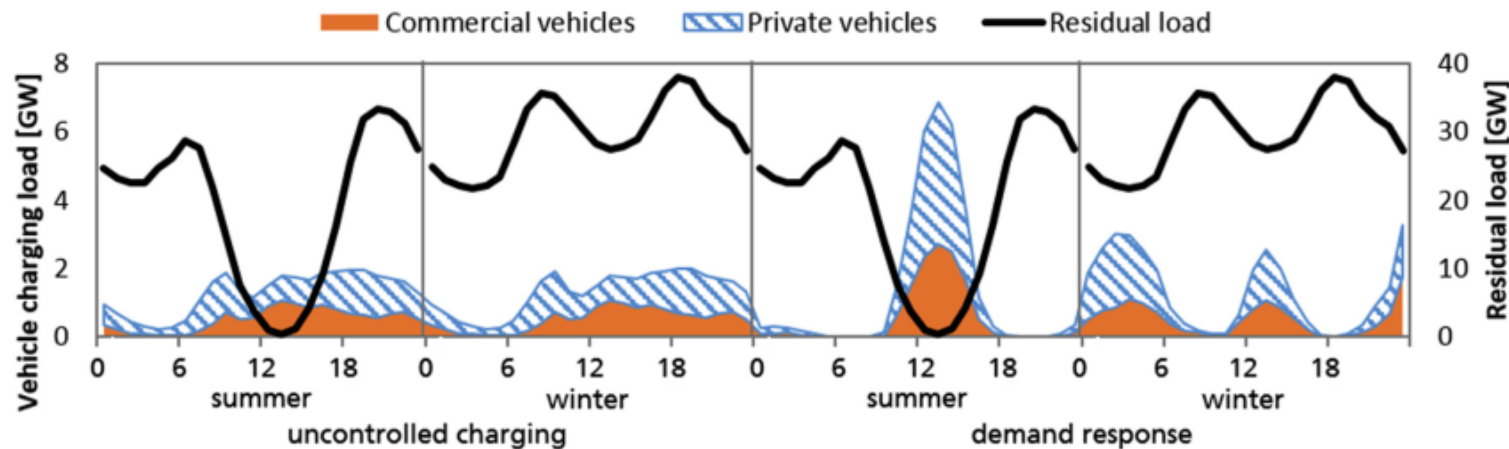


Back-up slides

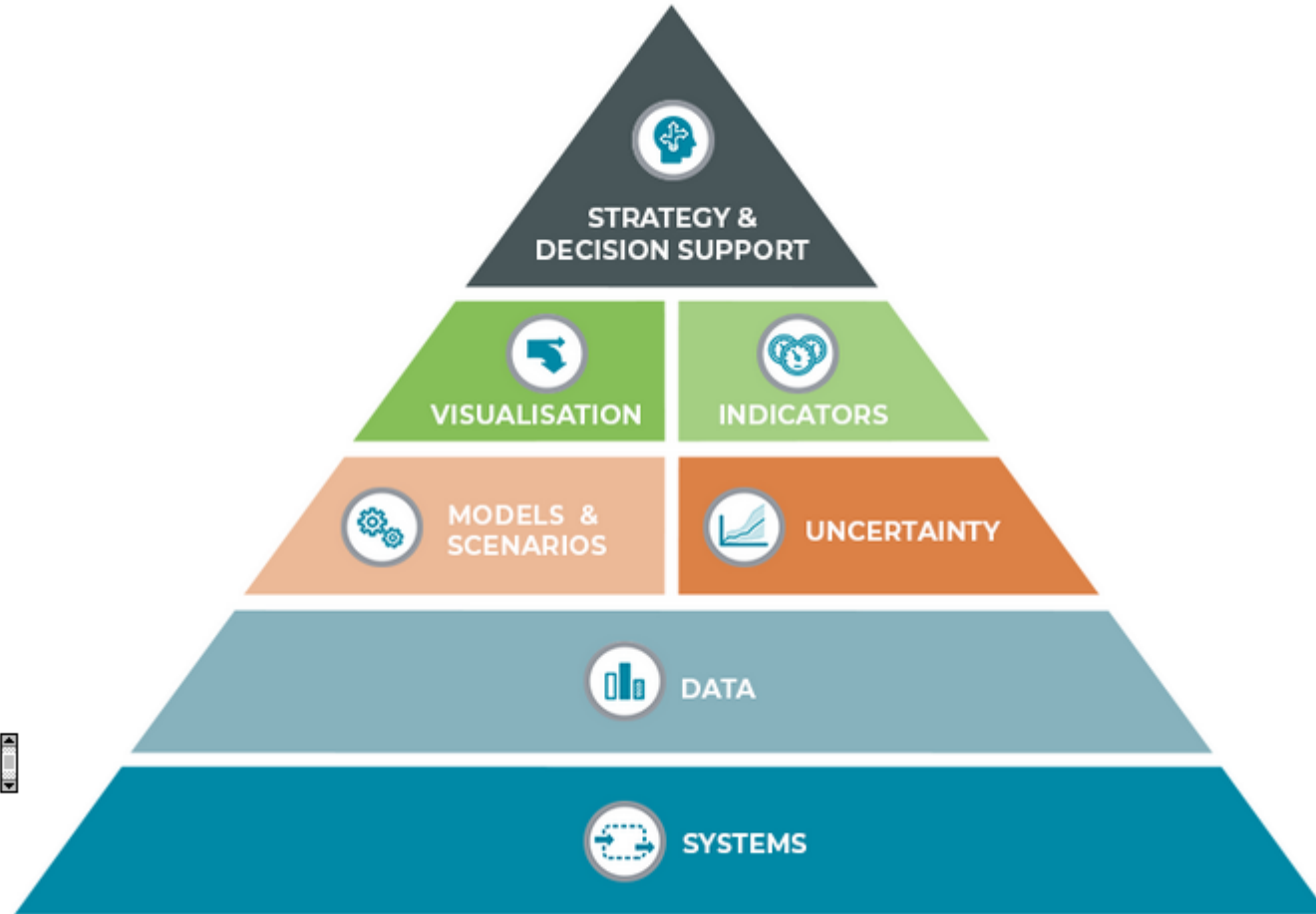


Motivation – findings from literature (power sector)

Other



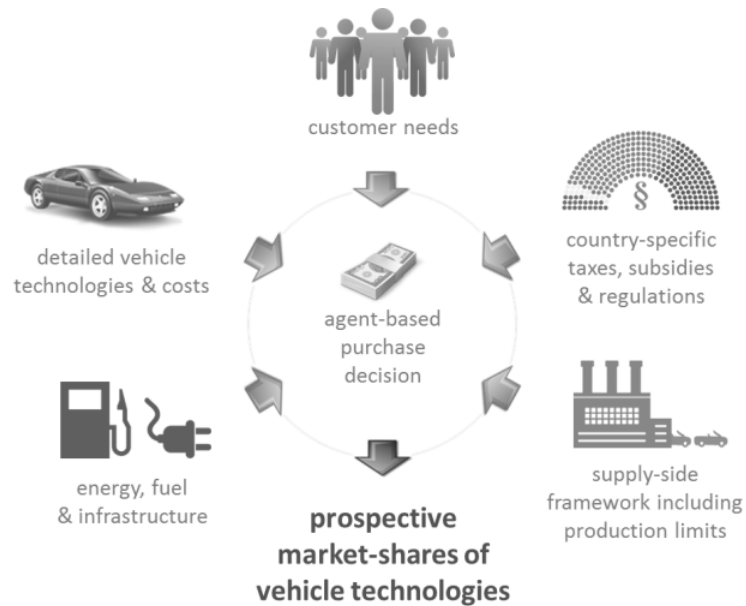
Introduction



MinFuture (2019)



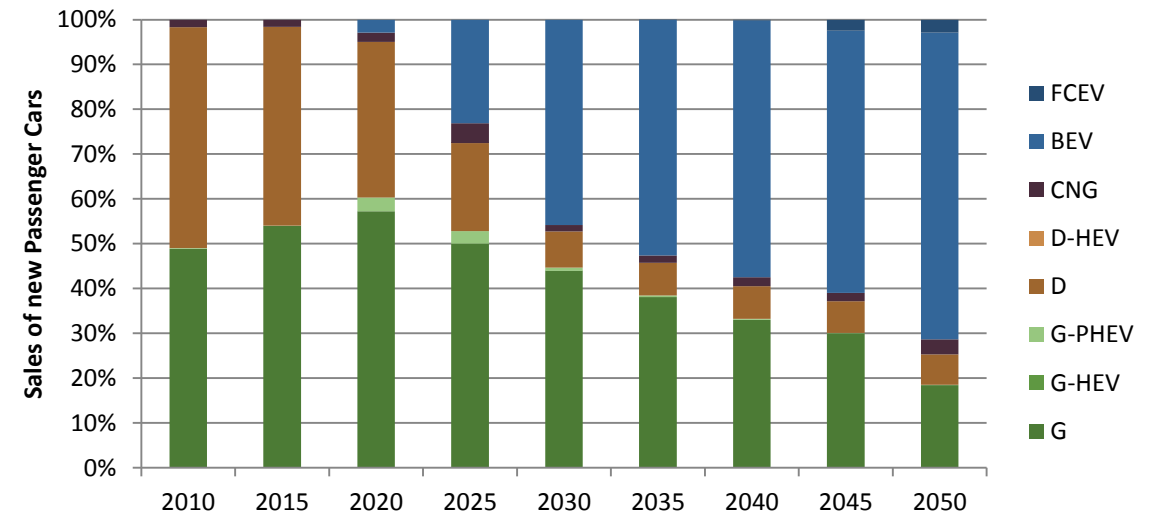
Model 1 – VECTOR21



Relevant cost of ownership

$$RCO = I \cdot (1 + r)^n + \sum_{t=1}^n (A(t) \cdot (1 + r)^{n-t}) - R$$

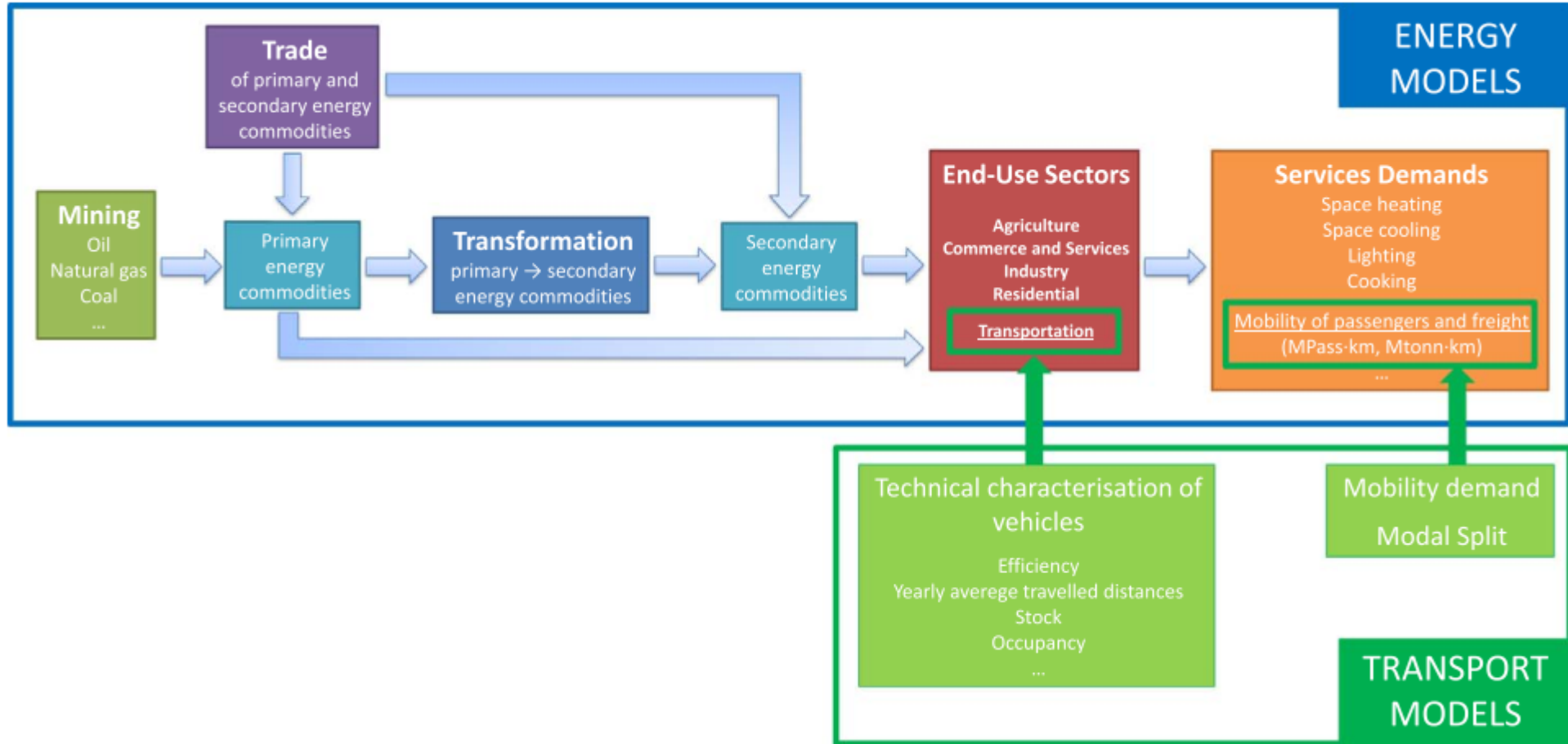
No of agents	92,135
Infrastructure availability	100% from 2040 onwards
CO2 emission cap in 2050	5 kg/100km



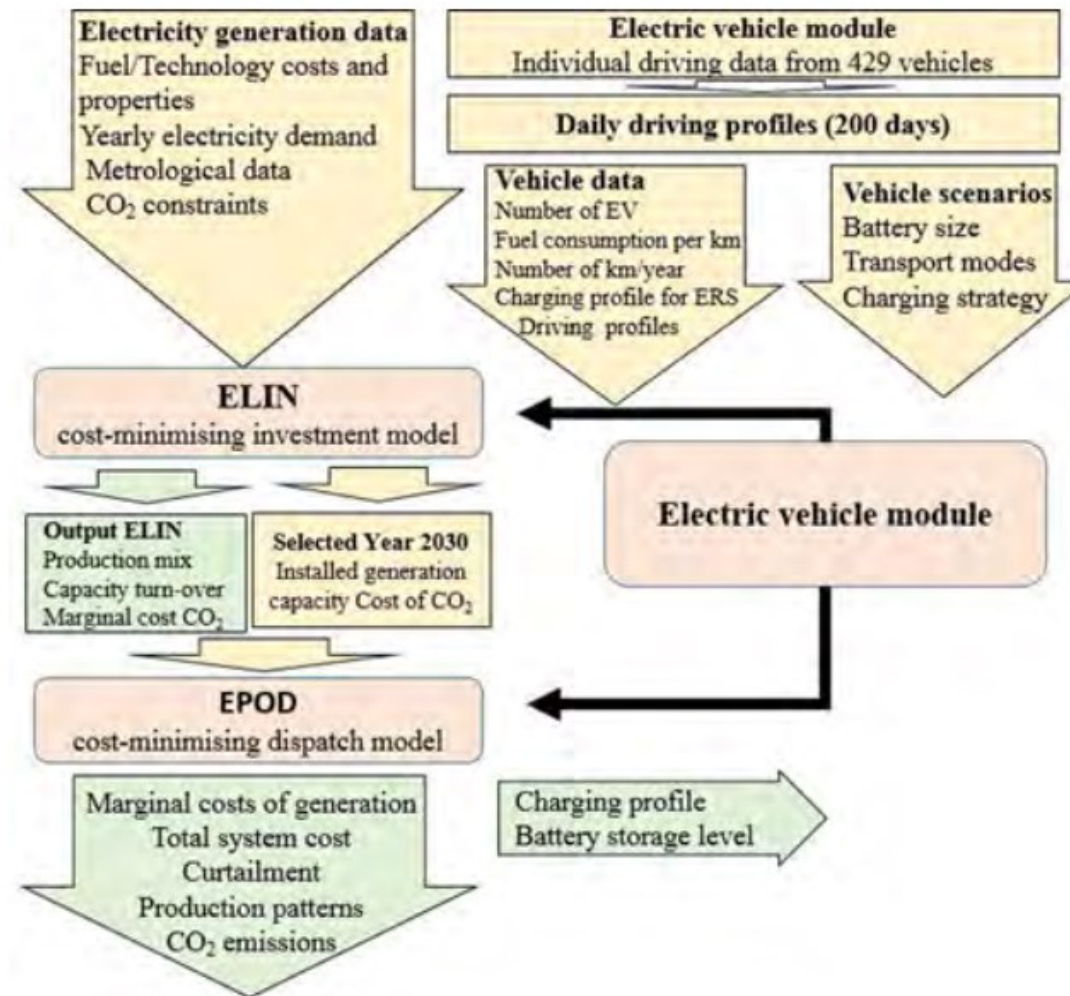
Kugler et al. (2017)



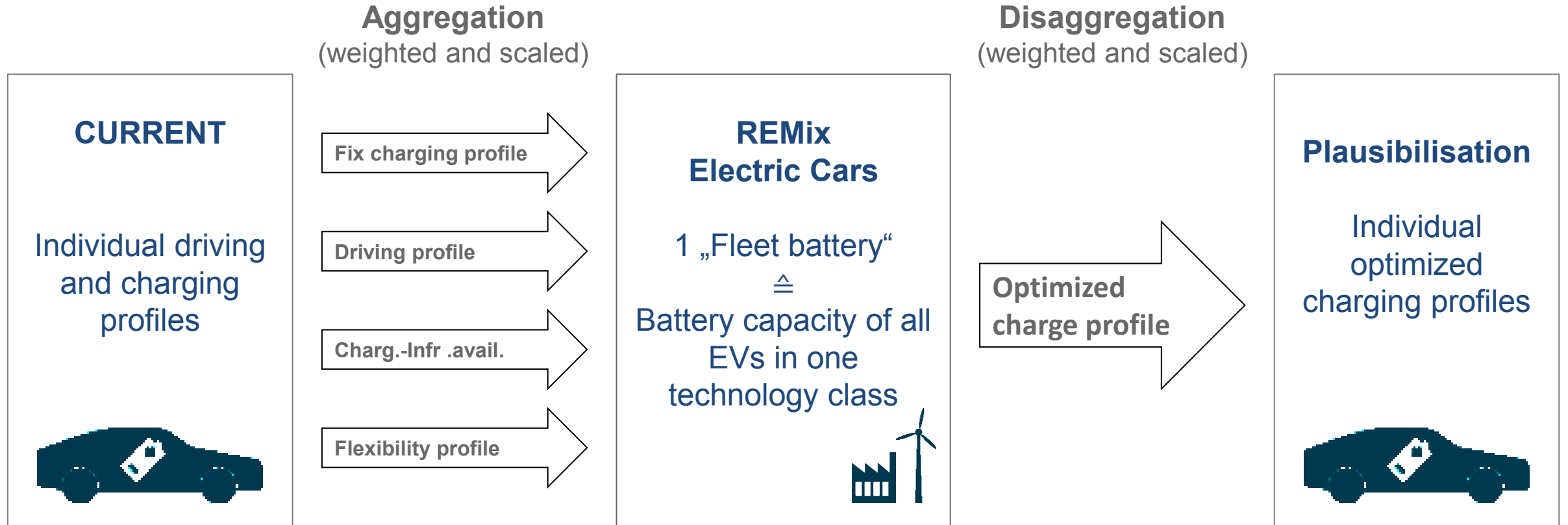
Model coupling – Gerboni et al. (2017)



Model coupling – Taljegard et al. (2019)



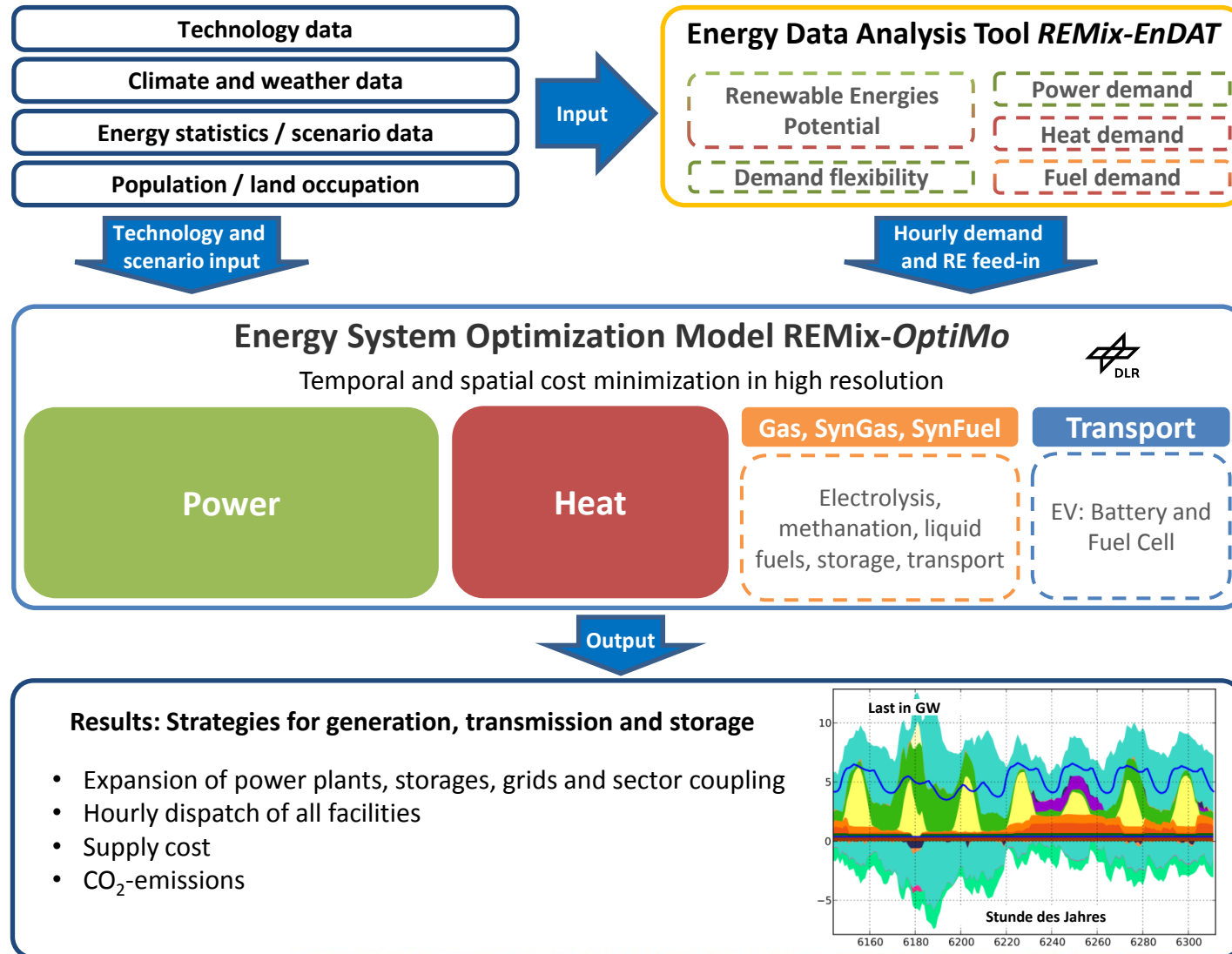
Method – User-behaviour implications for power systems



Unidirectional model communication



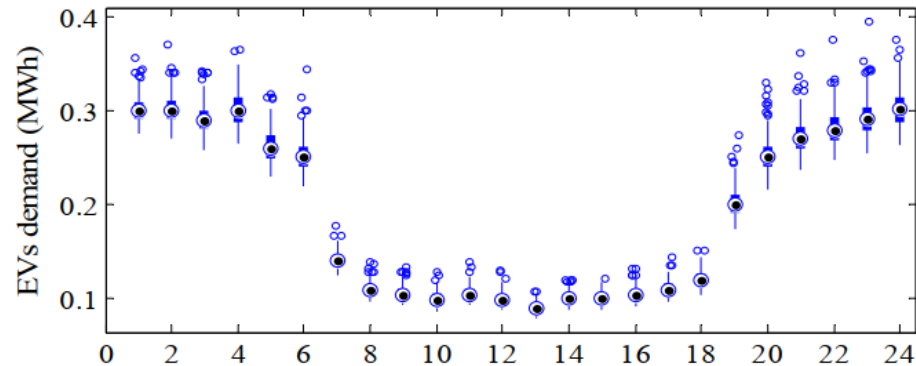
Model description - REMix



Based on Gils et al..
(2017)

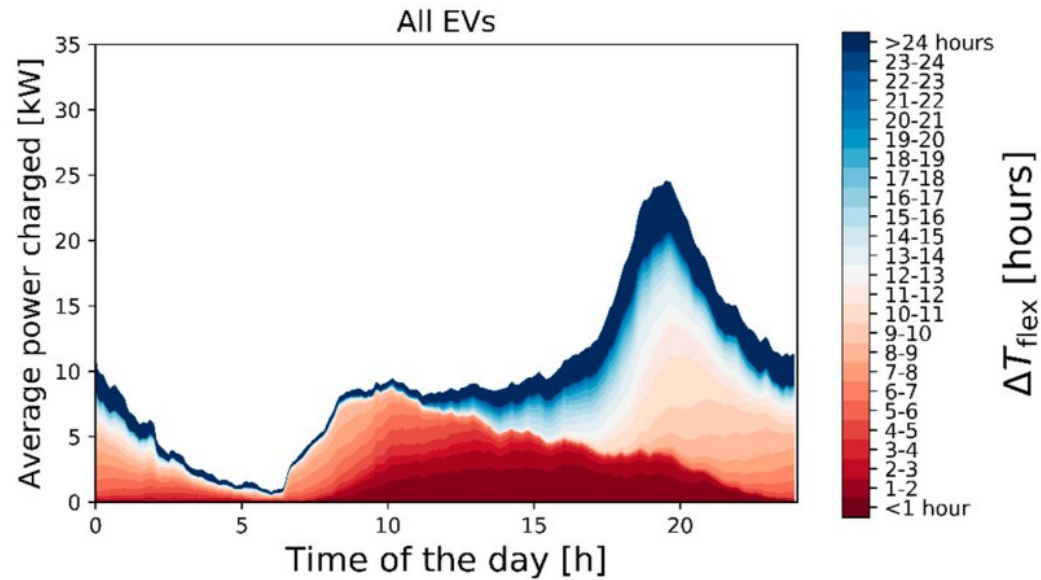
Data and daily charging behaviour

Rashidzadeh-Kermani et al. (2018)



- Analysis of an electricity aggregator
- ARIMA-simulation varying stochastic parameters ~200 scenarios
- Nordpool market data, 100 Evs, 16 kWh battery size

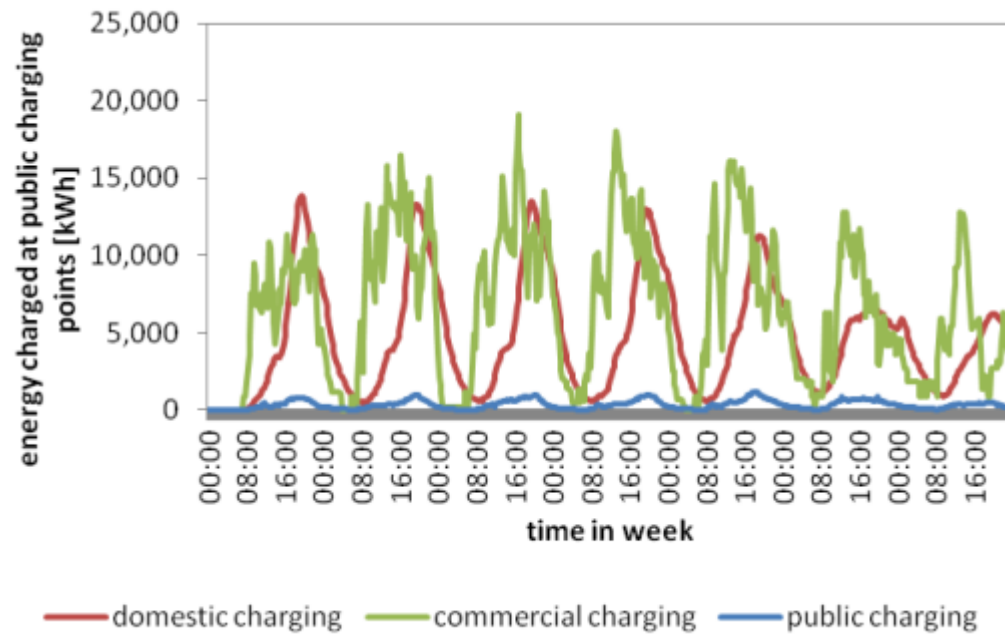
Gerritsma et al. (2019)



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Data and daily charging behaviour – different effects (Gerhardt et al. (2018))

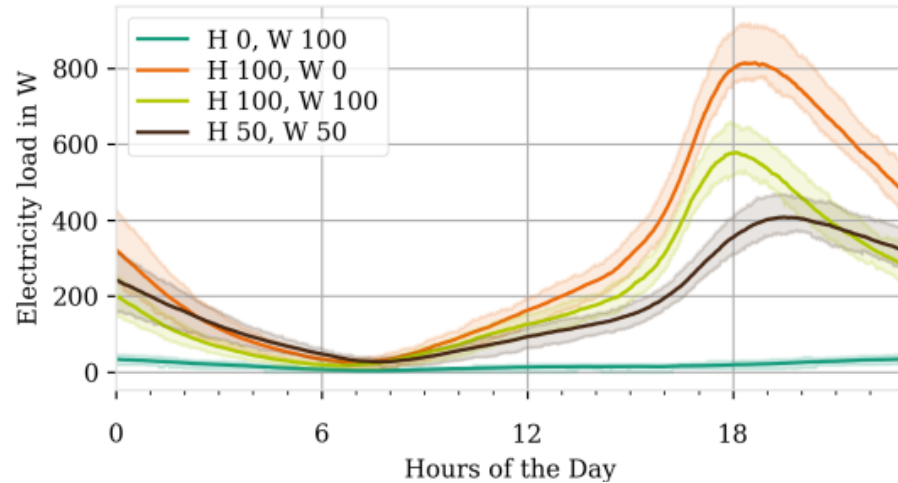


- Infrastructure availability



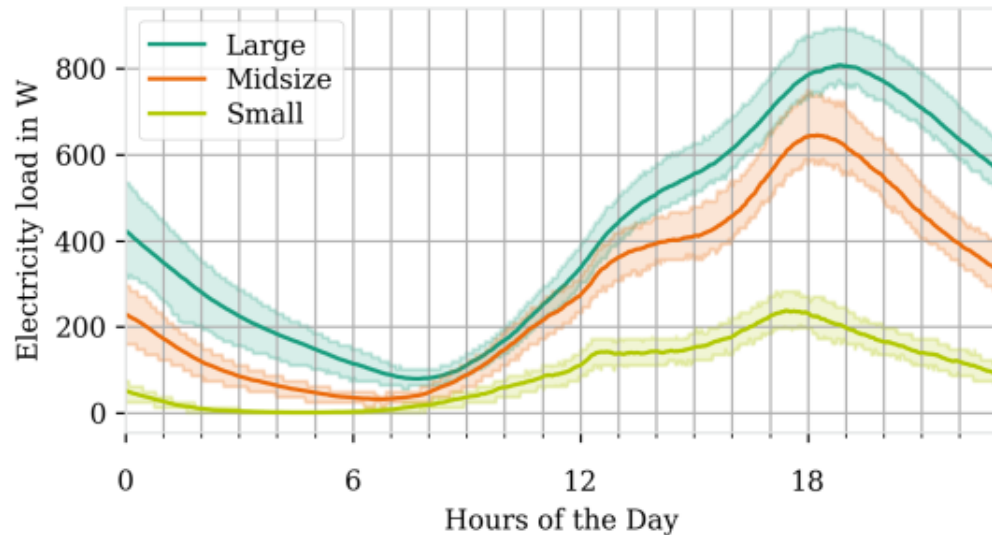
Data and daily charging behaviour – different effects (Fischer et al. (2018))

Charge location (thresholds)

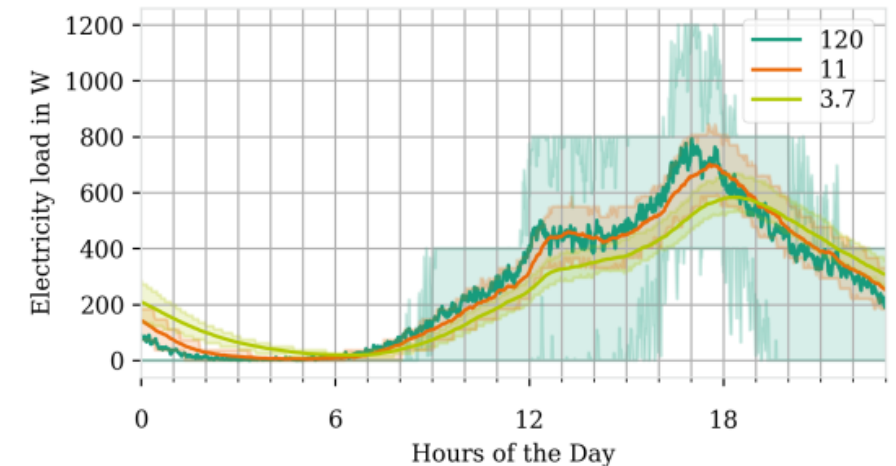


- Statistical simulation of EV load profiles using synPro
- Based on MiD data

Vehicle size

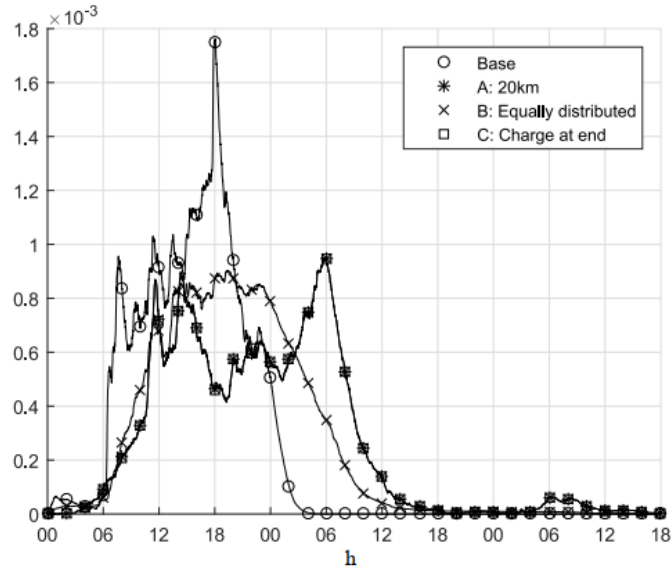


Charge power



Data and daily charging behaviour – different effects (Fischer et al. (2018))

Charge location (thresholds)



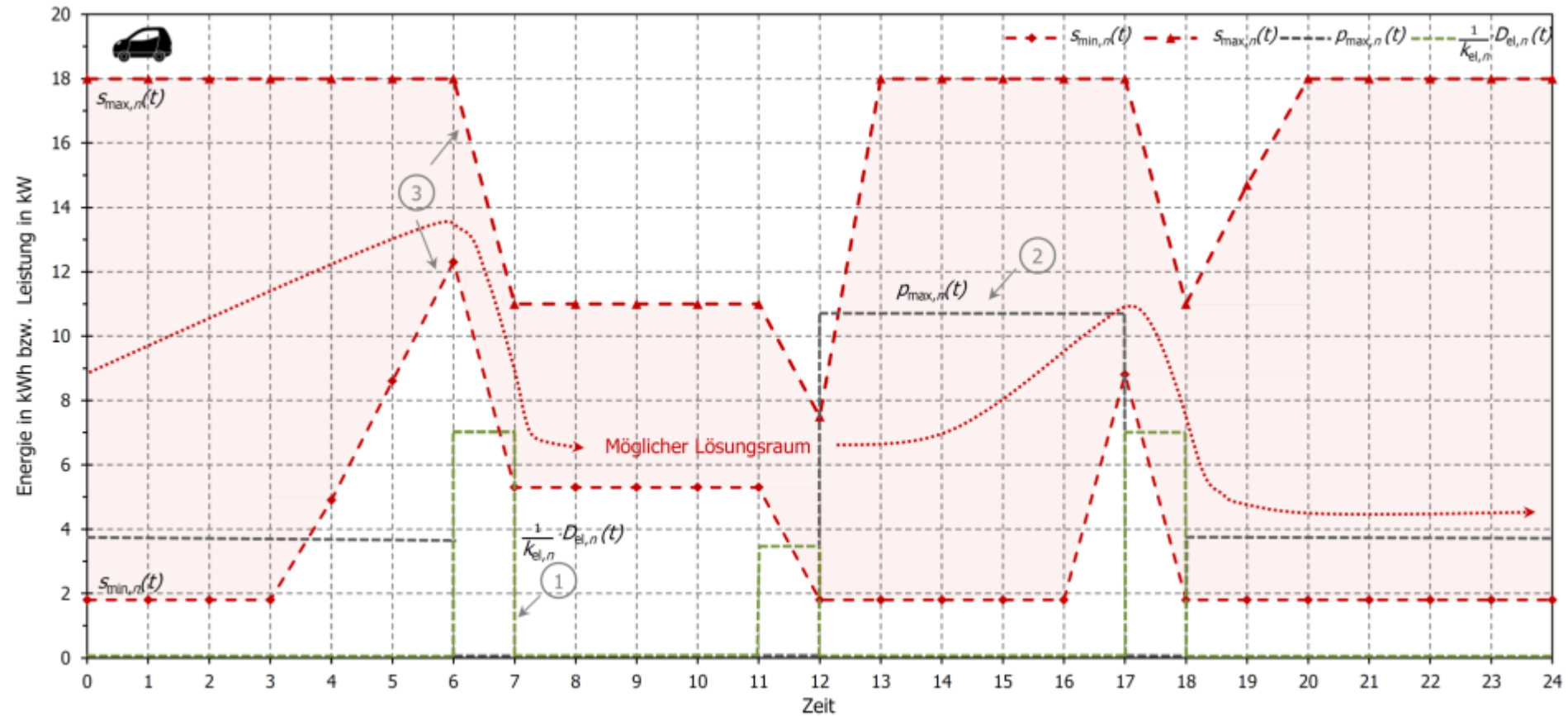
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Vehicle size

Charge power



Assumed power system flexibility – Gerhardt et al. (2018)



Gerhardt et al. (2018)

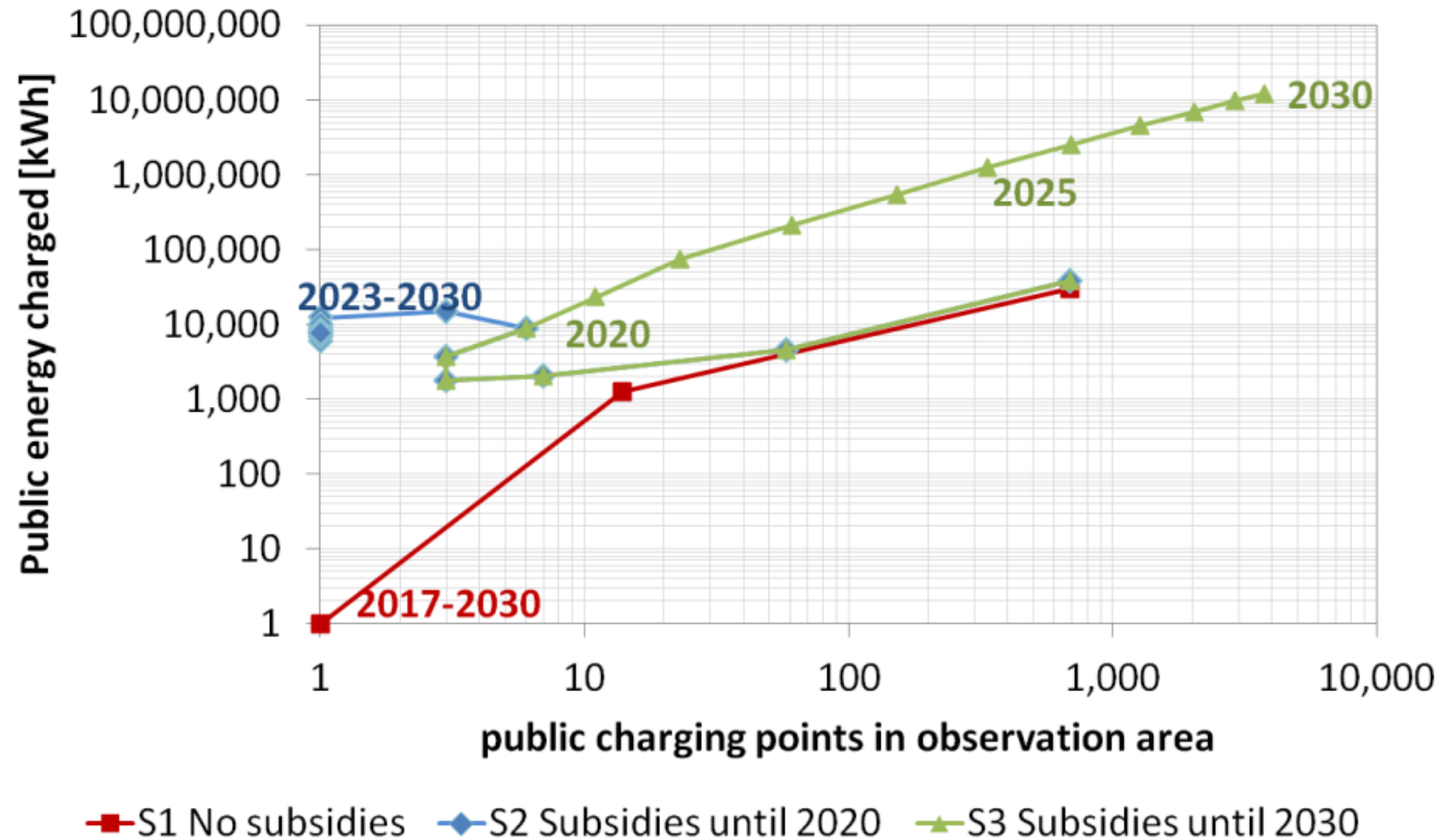
Infrastructure availability for controlled charging

	2030		2050	
	Tagsüber laden	Nachts laden	Tagsüber laden	Nachts laden
Kein Netzanschluss	62,5%	25,0%	50,0%	25,0%
3,7 kW	24,7%	67,3%	29,5%	64,5%
11,3 kW	3,1%	1,9%	5,0%	2,5%
22,2 kW	3,1%	1,9%	5,0%	2,5%
43,5 kW	6,3%	3,8%	10,0%	5,0%
132 kW	0,3%	0,1%	0,5%	0,5%

Gerhardt et al. (2018)



Infrastructure availability for controlled charging



Gnann et al. (2018)

Model coupling of VECTOR21, REMix and CURRENT

Dimension	VECTOR21	REMix	CURRENT	Harmonization method
Spatial horizon	Germany	Germany plus neighbouring countries	Germany	CR
Spatial resolution	ZIP codes	Germany in 2 nodes, others in 1 each	1 node	A (V-R), S (C-R)
Temporal horizon	2010-2050	1 year in 2040	10 days in 2040	S (V-R/C), DP (C-R)
Temporal resolution	Annual	Hourly	Activity / hourly	Harmonization
Technological resolution	3 drivetrain technologies, 3 car sizes	Transport: 3 technologies, Power: 9 technologies	1 technology	S (V-R/C), CR (C-R)



Input data – Mobilität in Deutschland

