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GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

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Battery electric vehicles:

Open-source modeling of time series data and their application in power systems models

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- Motivation
  - Battery-electric vehicles (BEV): a major strategy to decarbonize transportation, using renewable electricity
  - Two relevant effects of growing BEV fleets on power sector:
    - Growing electricity demand → vRES capacity also needs to increase
    - Potential provision of temporal flexibity → BEV may contribute to vRES integration
    - Trade-off between these two effects
  - Numerical analyses require detailed time series of BEV charging availability and energy demand
    - These are now availble thanks to emobpy

- Research question
  - Quantitatively explore the trade off between increasing vRES, EV power demand and the provision of flexibility at different levels
  - Sensitivity of results to varying assumptions on vehicle charging and V2G
  - Indicators of interest:
    - System costs
    - Dispatch effects
    - EV charging patterns

emobpy

- Open-source code tool in Python for e-mobility time-series
- Python Package Index https://pypi.org/project/emobpy/
- Preprint in arXiv https://arxiv.org/abs/2005.02765 (v2)
- Zenodo https://doi.org/10.5281/zenodo.3931663
- For this project:
  - We created 50 BEV profiles
  - Each profile consisted of 4 types of time-series
    - **Vehicle mobilty**: Mobility data from Mobility in Germany (MiD2017)
    - **Driving electricity consumption**: Four models (Model 3, Kona, Zoe, ID.3)
    - **Grid availability**: Four types of charging station with power rating in kW (home: 3.75, public: 22, work: 11, fast: 75)
    - **Grid electricity demand**: Two charging strategies (Immediate and Night@home)
      Two system optimized G2V and V2G

4 emobpy: time-series types (Example of a single vehicle)

(1) + (2) + (3)

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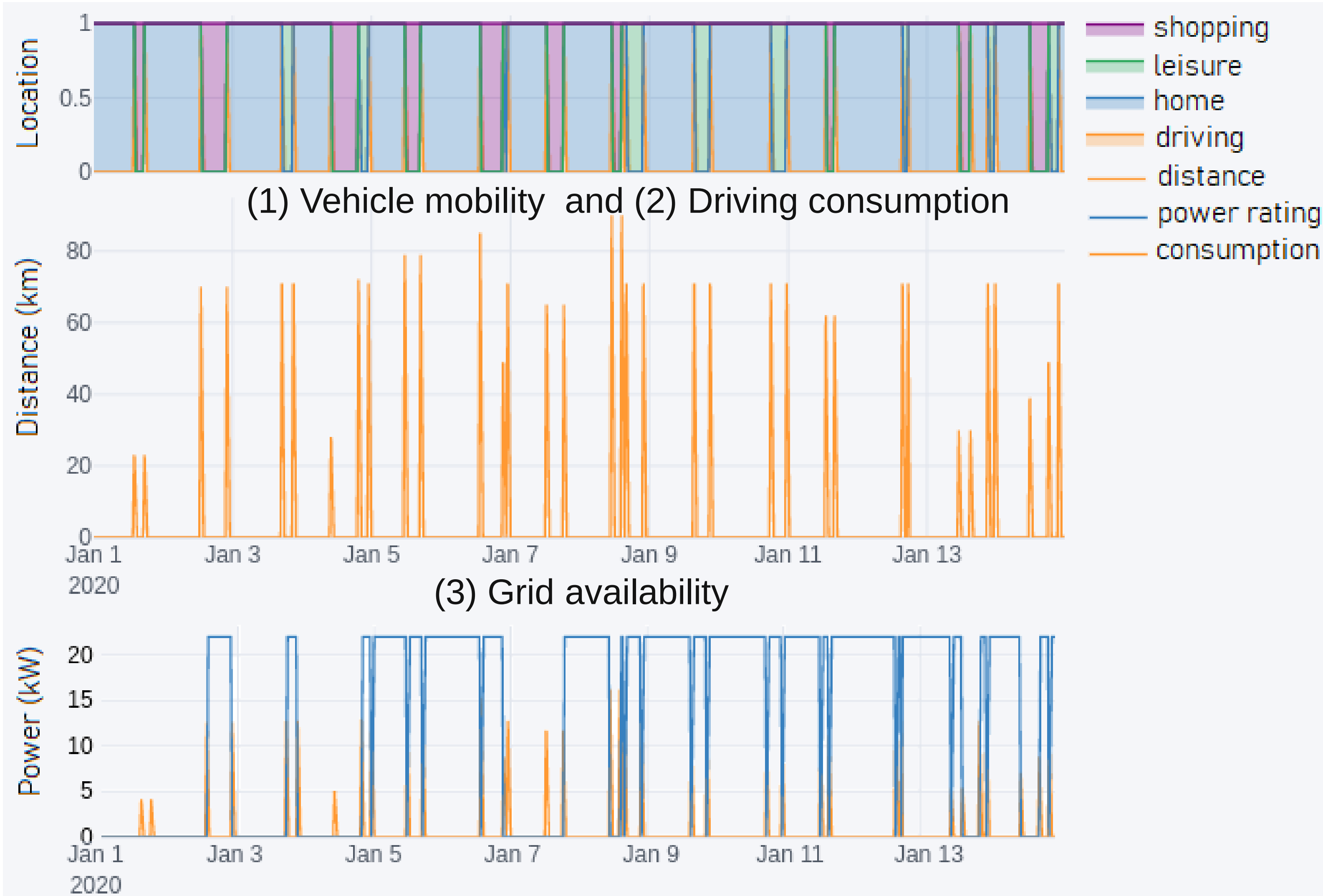
(4)
Grid demand

System Optimized Approach



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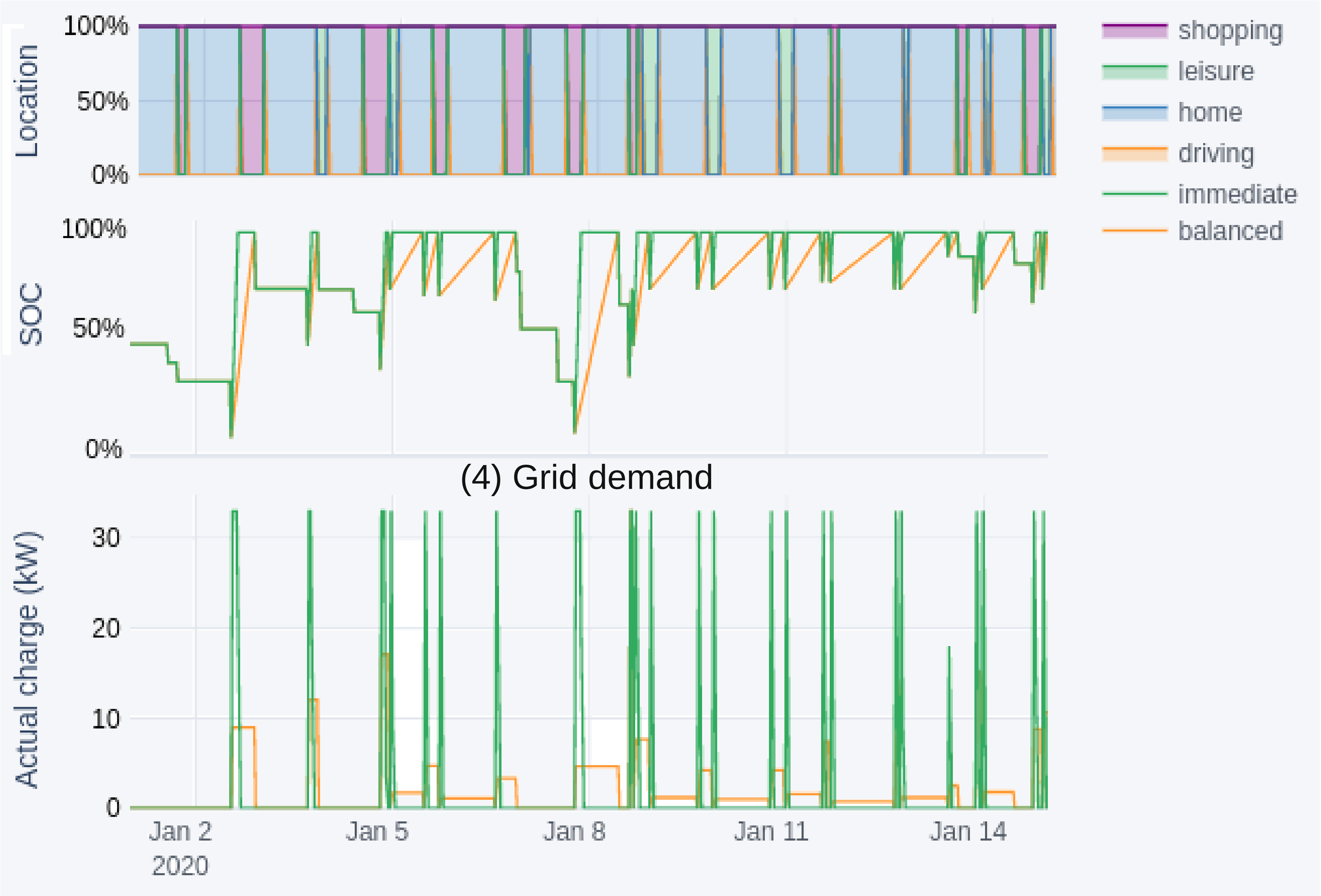
emobpy: time-series types



Methods

- DIETERpy
  - Is a python framework that runs DIETER by using GAMS API
  - Open-source code tool
  - Python package index https://pypi.org/project/dieterpy
  - Preprint available on https://arxiv.org/abs/2010.00883 (v2)
  - In this project:
    - Run several scenarios by setting the following configuration:
      - Brownfield - 2030
      - Investment and dispatch model

        + Endogenous BEV module -> Model decides the EV charge

        + Exogenous BEV module (Immediate and Night@home)
      - 0 , 1M, 3M, 5M, 7M, 10M, 20M, 40M BEVs
      - G2V and V2G
      - 65% and 100% Minimum RES constraint

Results outline

Emobpy

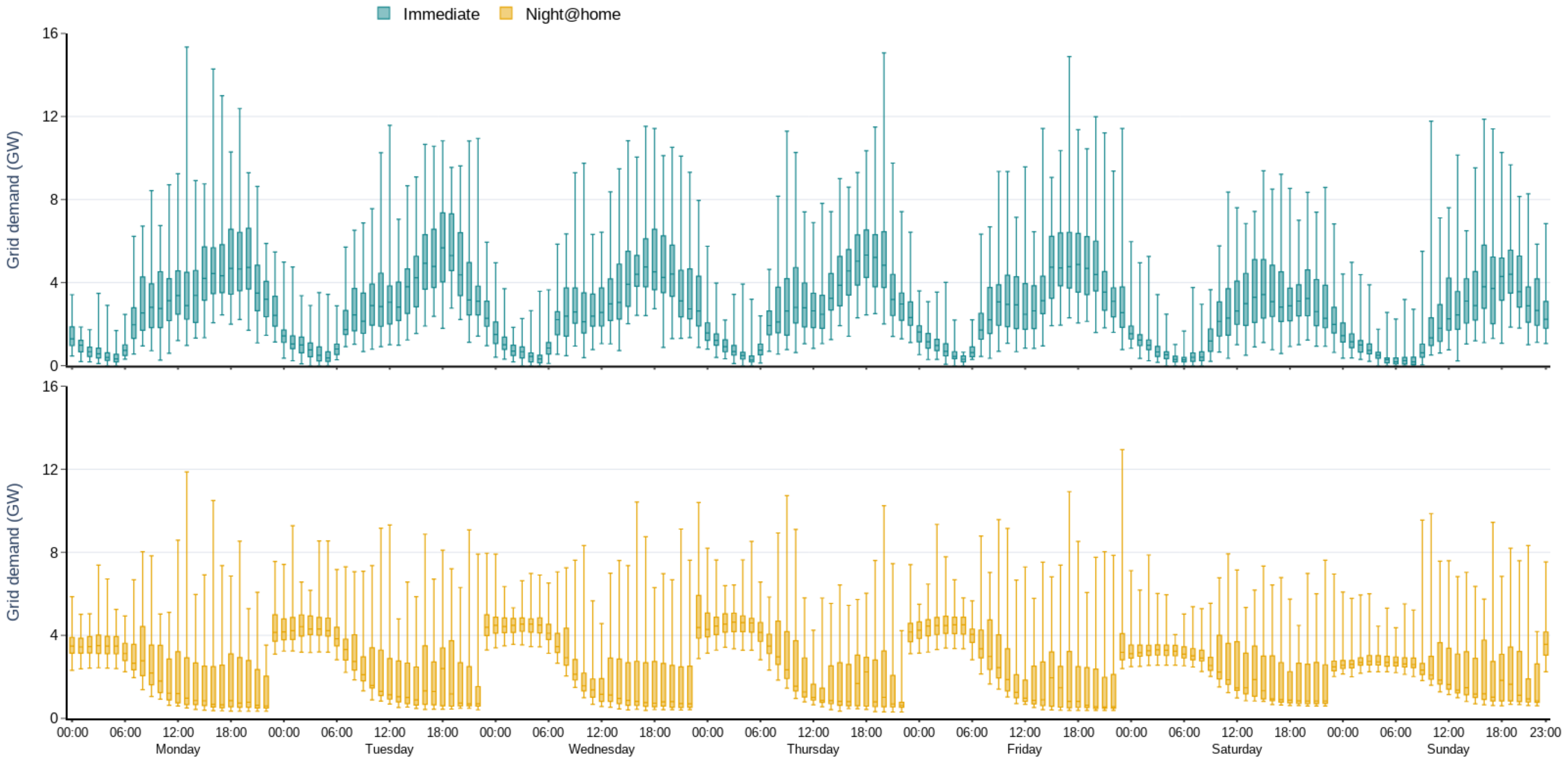
- Grid demand

DIETERpy

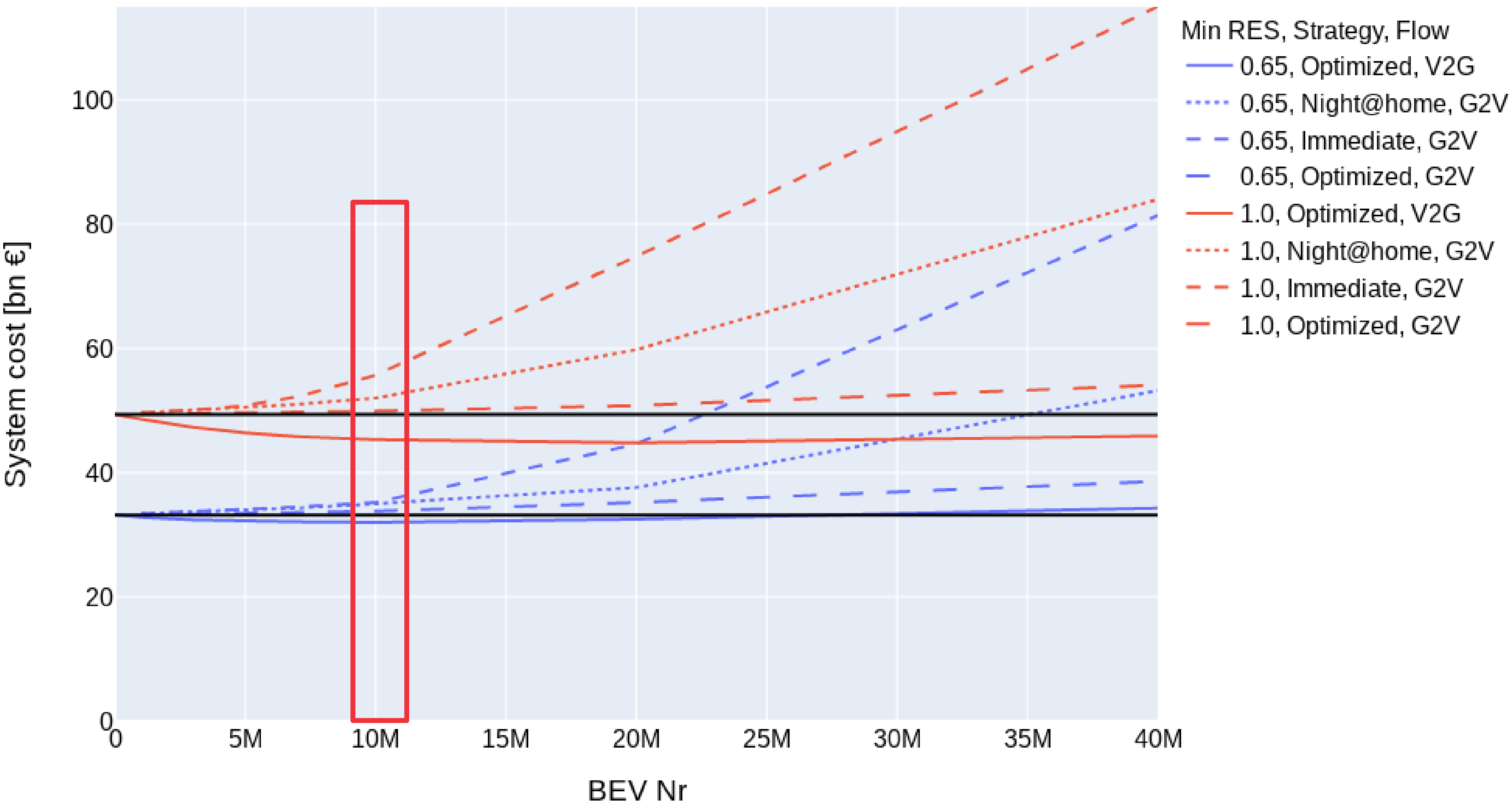
- Total system costs
- Residual load duration curve (RLDC)
- Hourly charging pattern of BEV

emobpy: Results

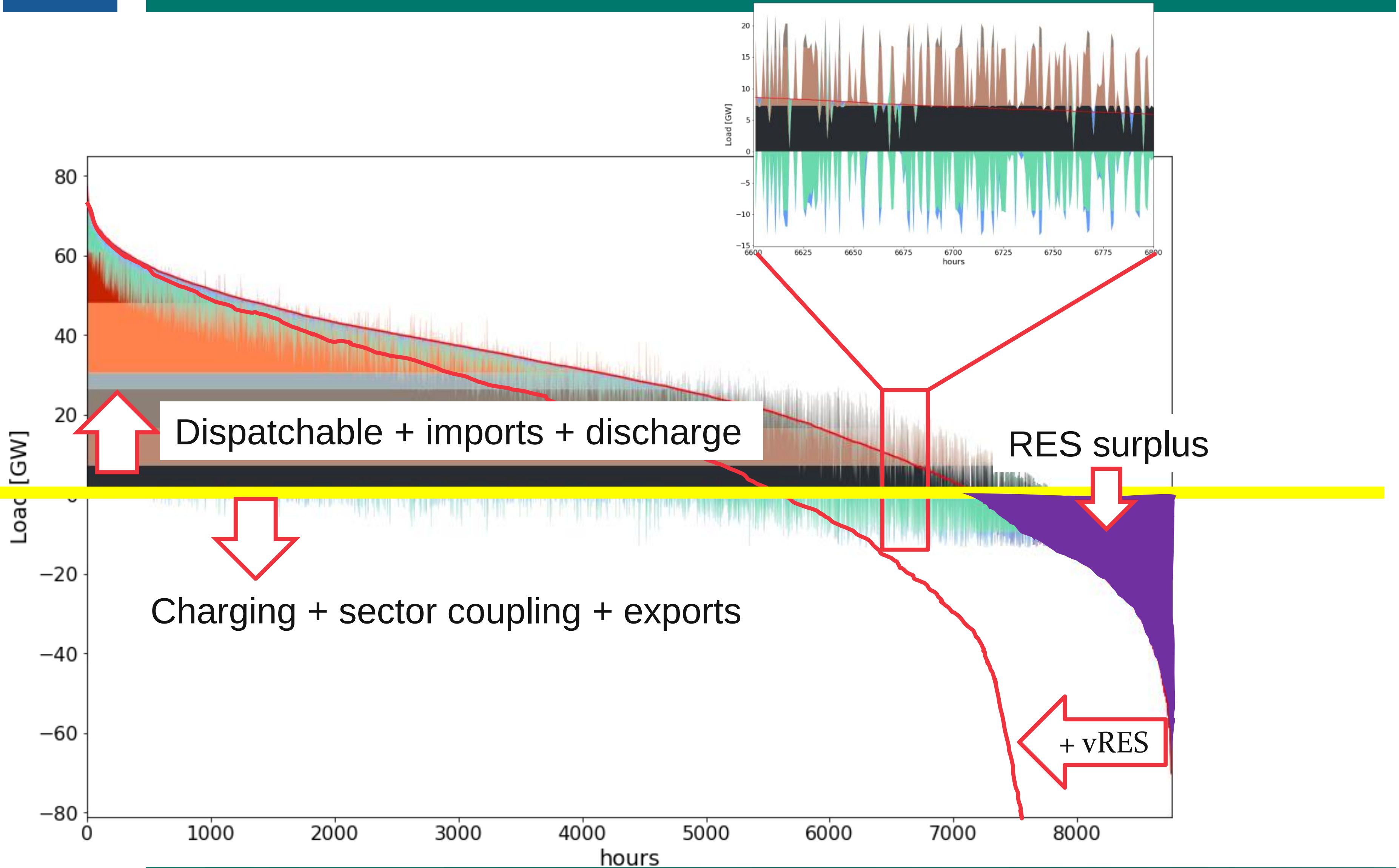
Grid electricity demand time series:
- Two charging strategies: **Immediate** and **Night@home**
- Represent 10M electric vehicles (from 50 time series)



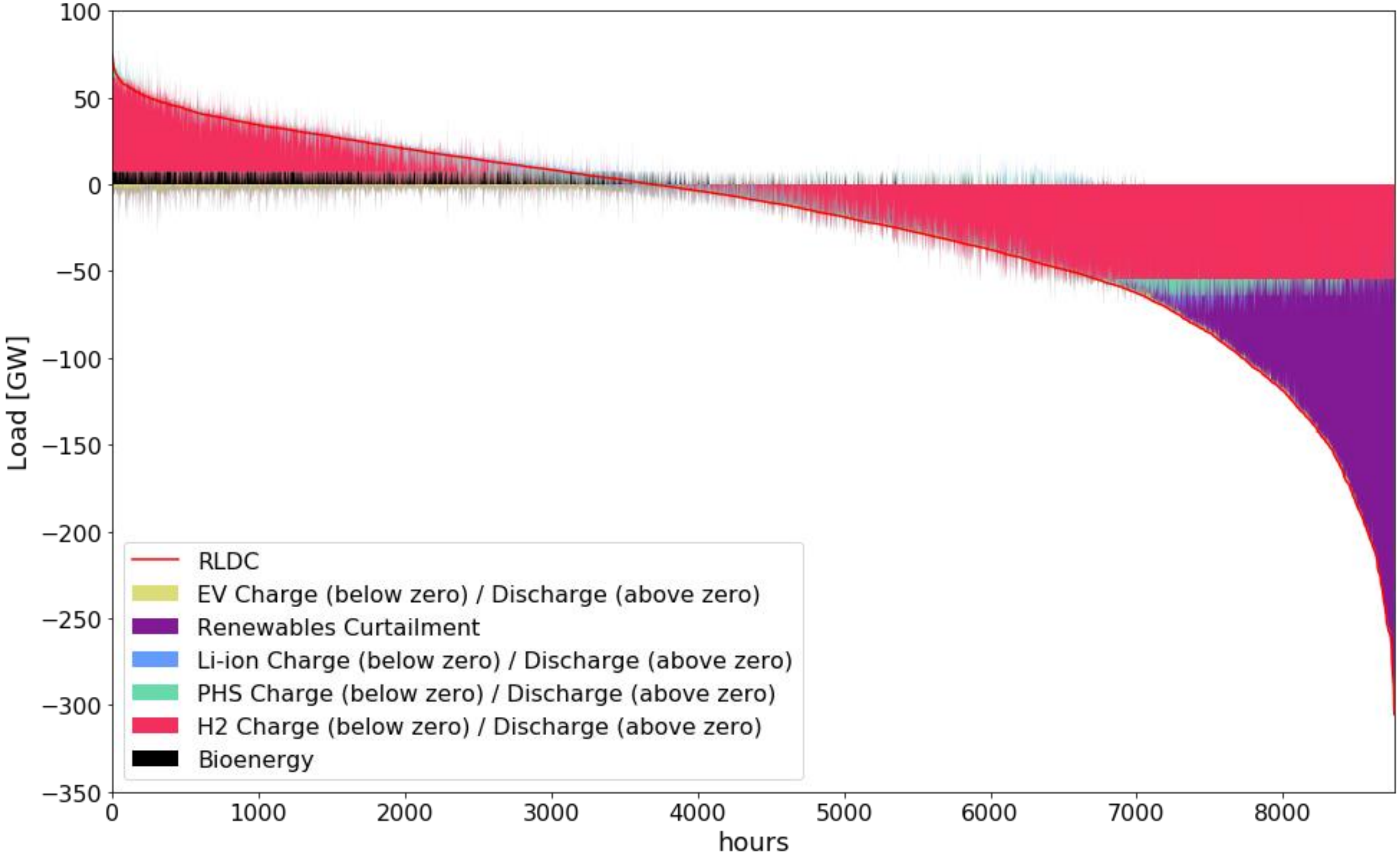
9 Total system costs: Minimum RES share – BEV quantity – Charging strategy

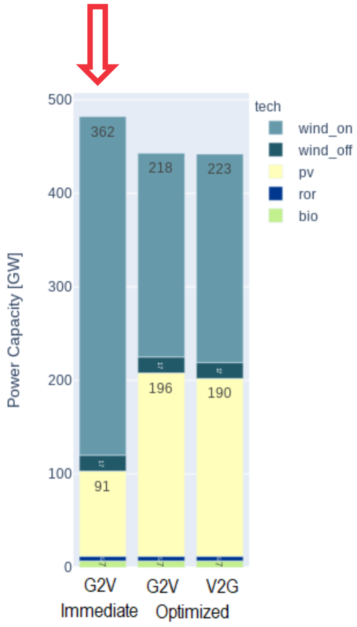


RLDC: Interpretation example



RLDC: 10M BEV – 100% minimum RES – G2V - **Immediate** charging strategy





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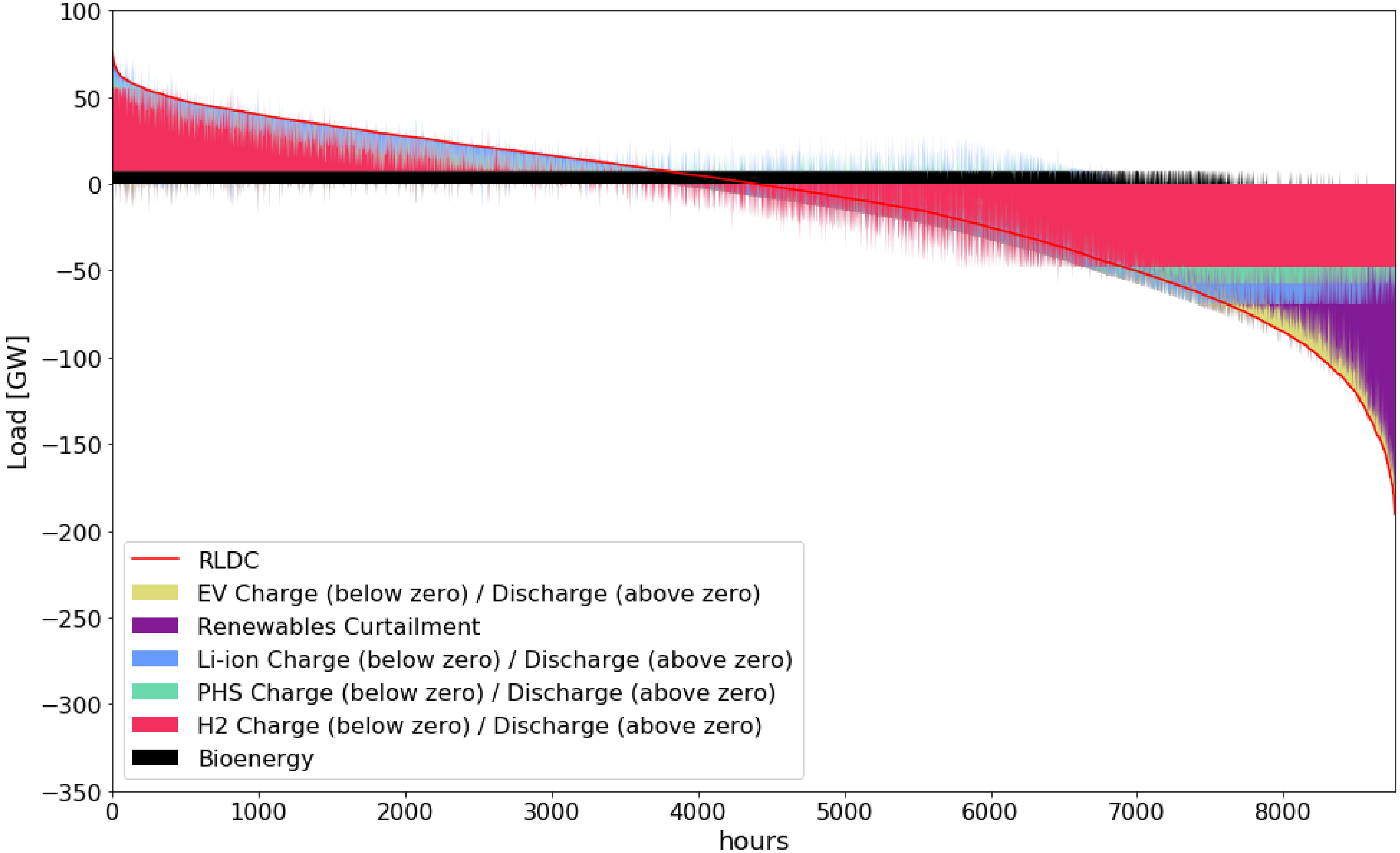
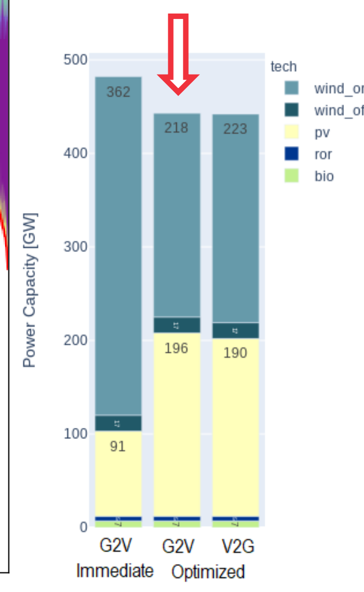
RLDC: 10M BEV – 100% minimum RES – G2V – System optimized





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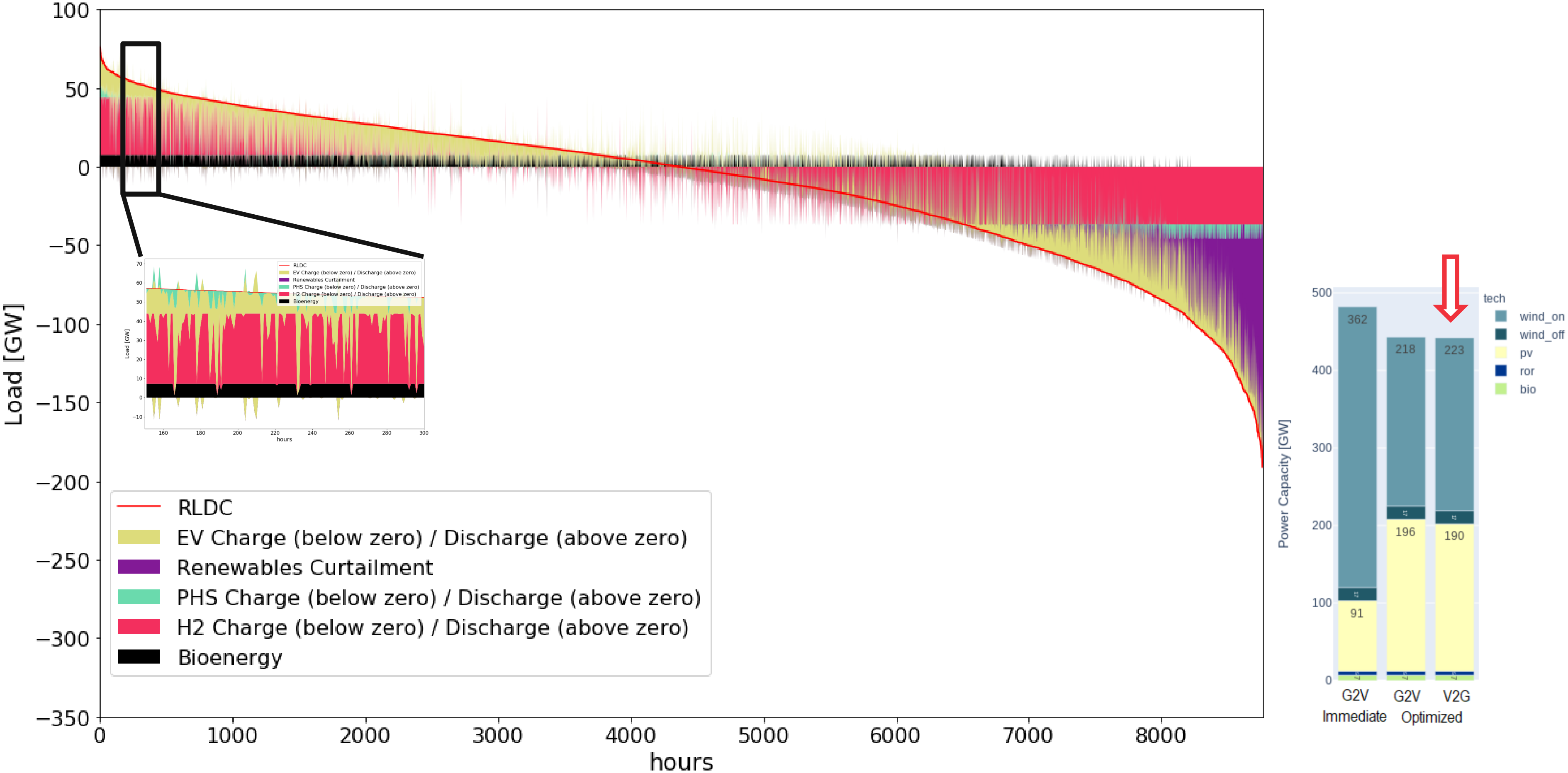
13 RLDC: 10M BEV – 100% minimum RES – V2G – System optimized



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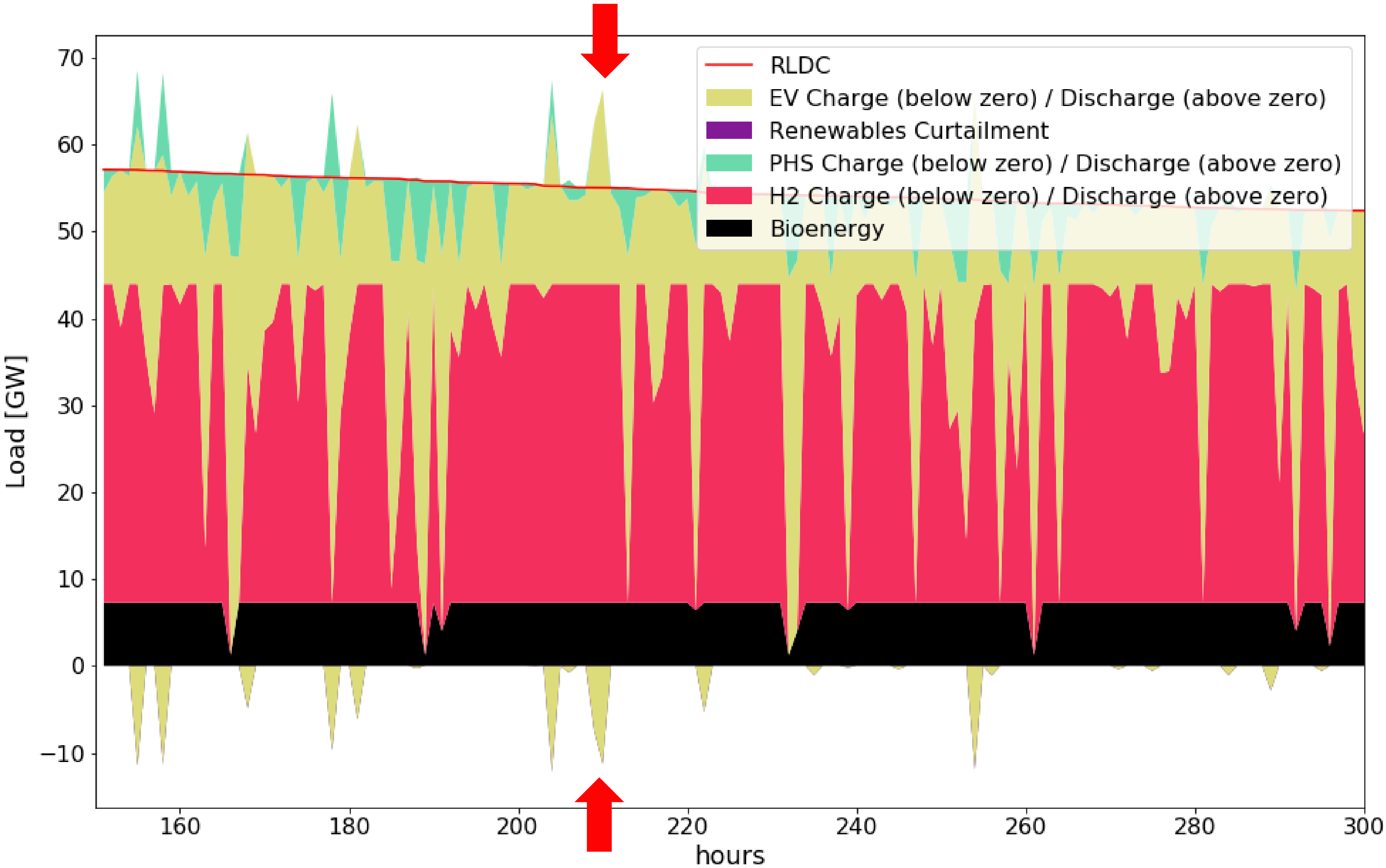
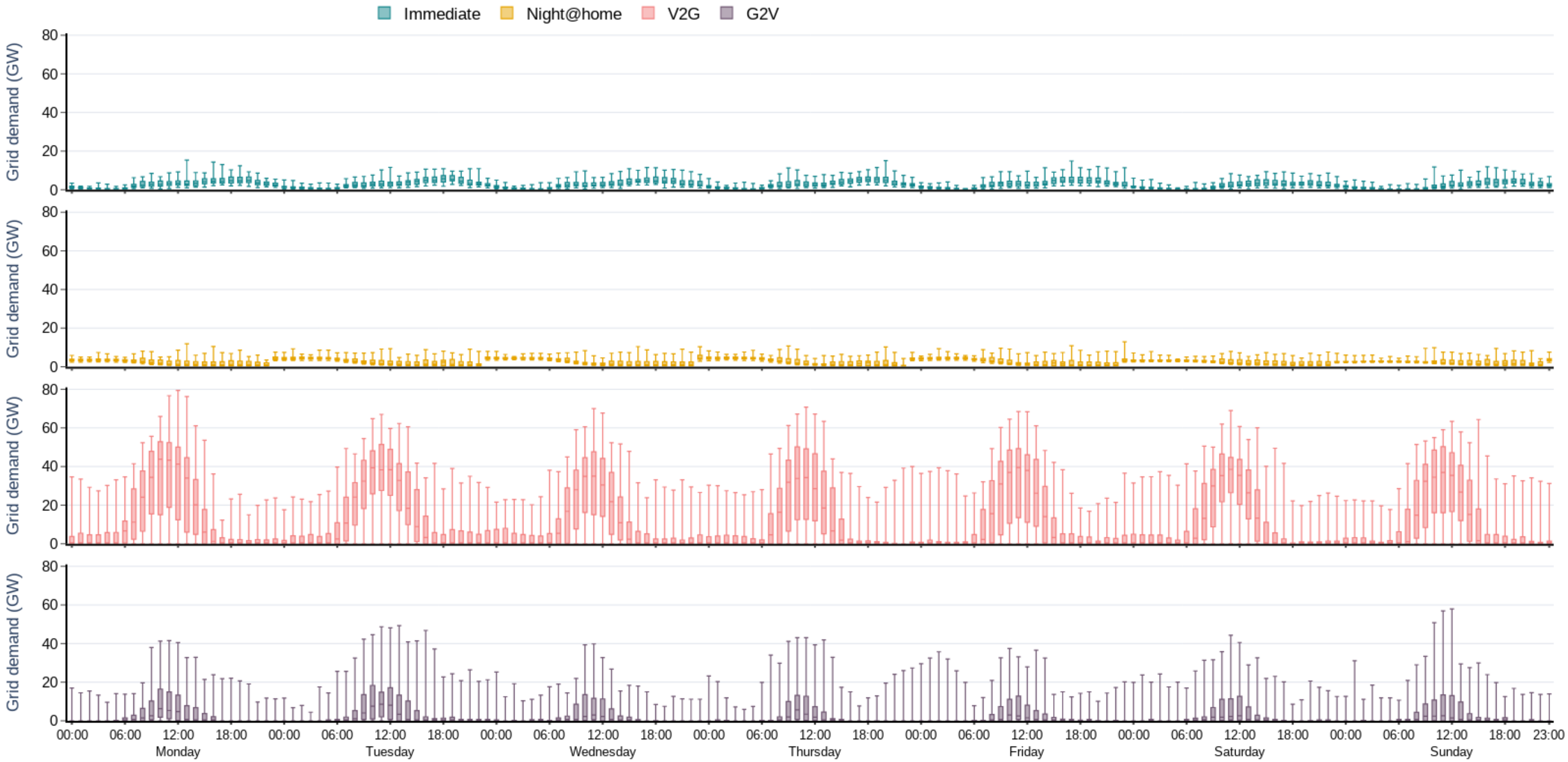
RLDC: 10M BEV – 100% minimum RES – V2G – System optimized (zoom in)



Hourly charging pattern of BEV

Comparison: 10M EV, two chargin strategies and system optimized charging



Conclusions

- 100% RES scenarios costs are greater than 65% scenarios (+ 36%)
- V2G shows significant benefits by reducing the system costs, this effect increases when renewables are higher, while the maximum benefit is reached in the range of 7 – 10 M BEV
- System optimized approach for charging (discharging) of BEV is largely desirable, either G2V or V2G
- V2G provides sort-term storage, partially long-therm storage and makes an efficient use of vRES
- Larger BEV fleets (+40M), the flexibility decreases, taking over demand
- BEV charging is coupled with solar generation, large load poses several challenges

https://gitlab.com/diw-evu/emobpy/emobpy

Vielen Dank für Ihre Aufmerksamkeit.

https://gitlab.com/diw-evu/dieter_public/dieterpy

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