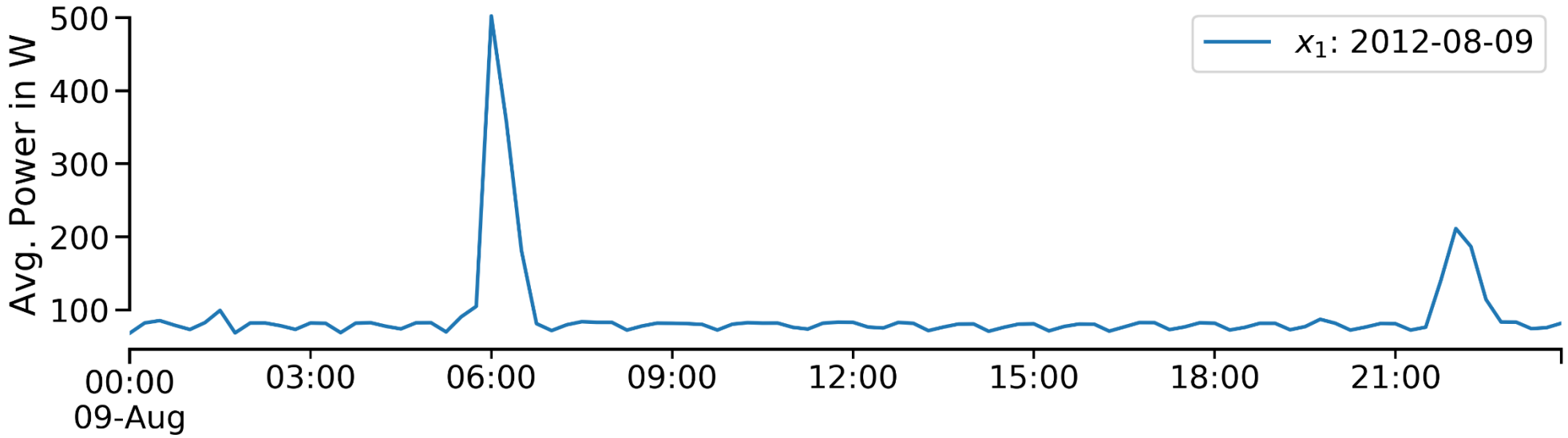
DAI-Labor
TU Berlin

Permutation-Based Residential Short-term Load Forecasting in the Context of Energy Management Optimization Objectives

Marcus Voß, Technische Universität Berlin (DAI-Labor)

A household-level electric load profile in 15-minute resolution



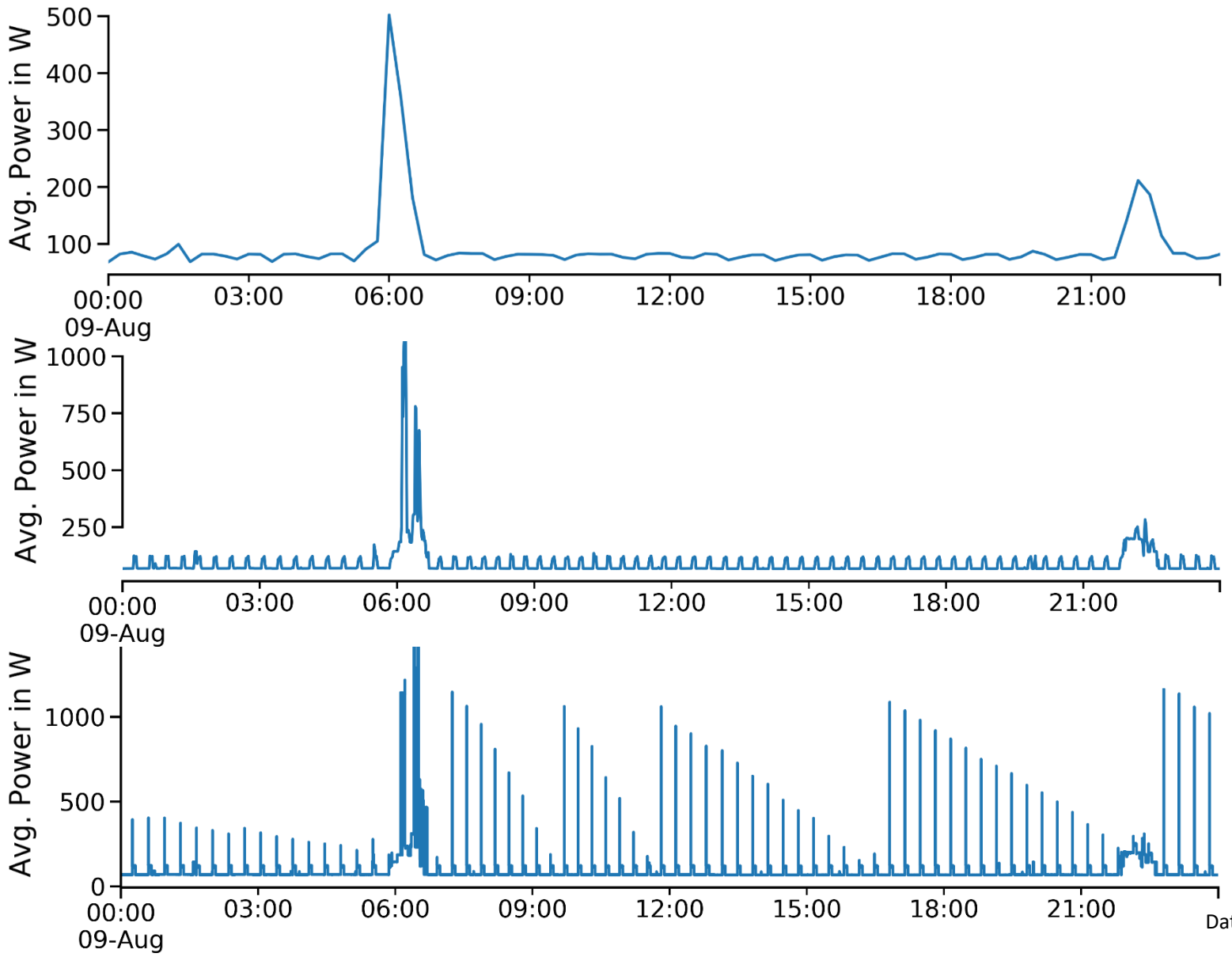
Data: [ECO2014]

A household-level electric load profile in higher resolutions

15-minute resolution

1-minute resolution

1-second resolution



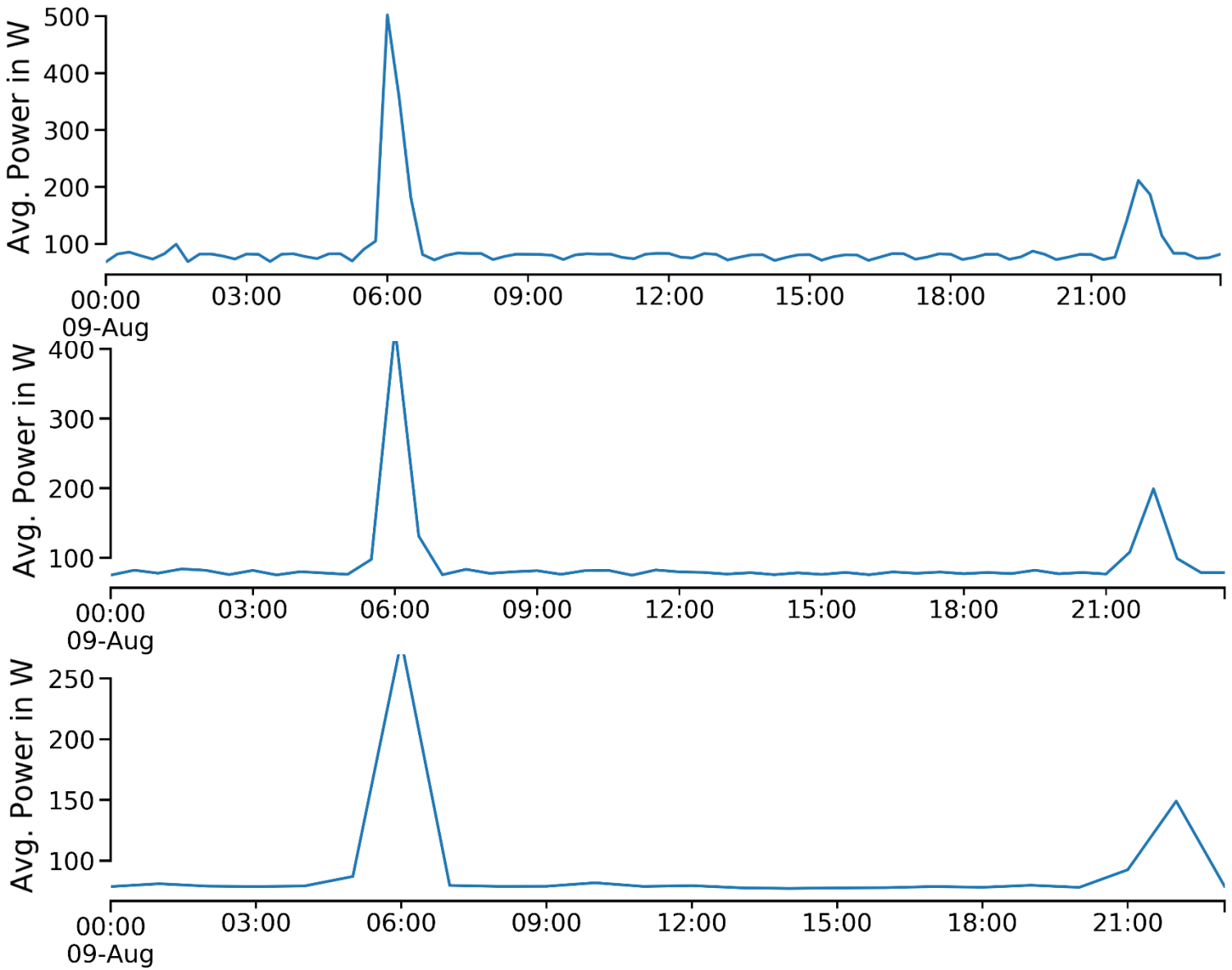
Data : [ECO2014]

A household-level electric load profile in lower resolutions

15-minute resolution

30-minute resolution

60-minute resolution



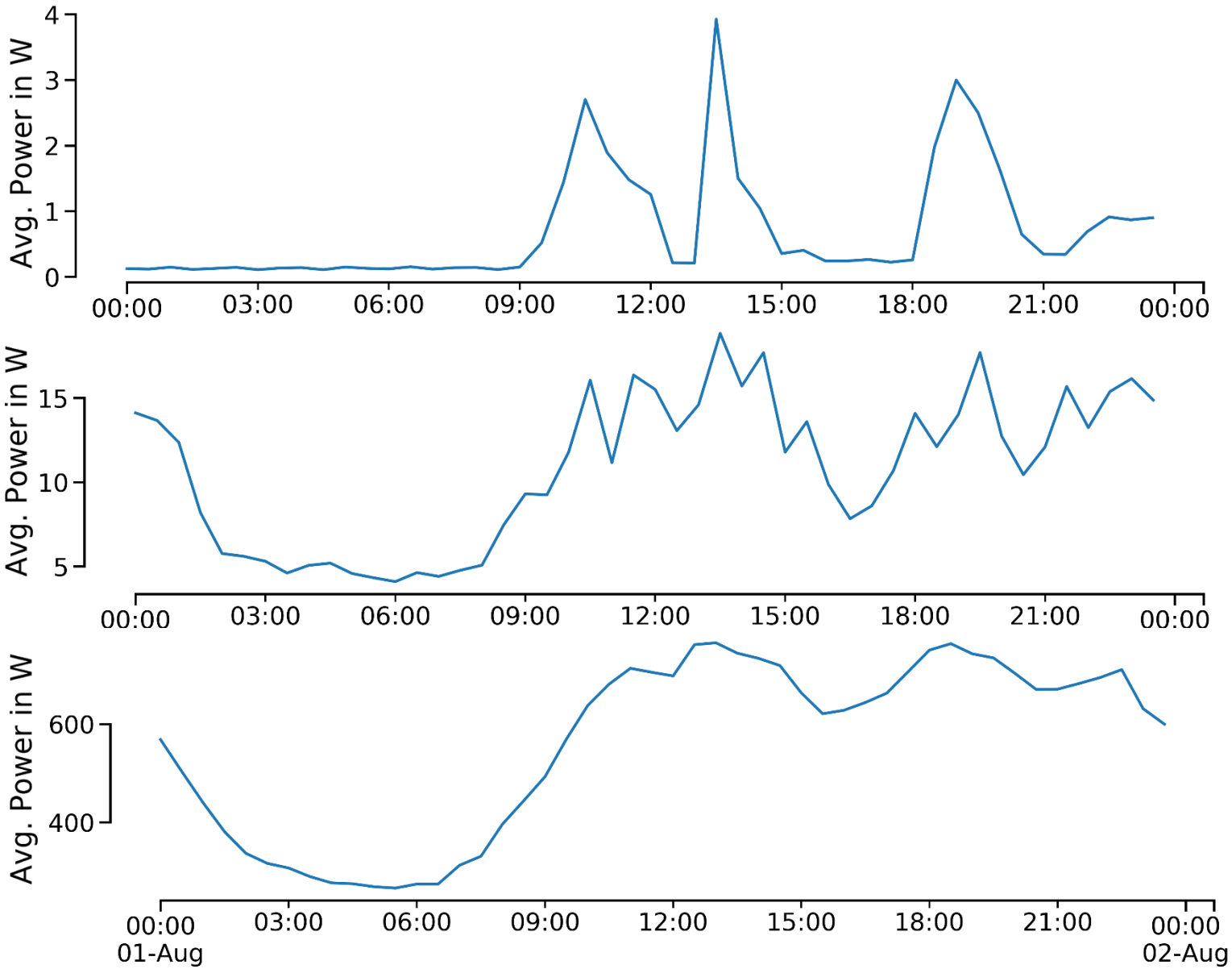
Data : [ECO2014]

A household-level electric load profile in higher aggregations

1 household

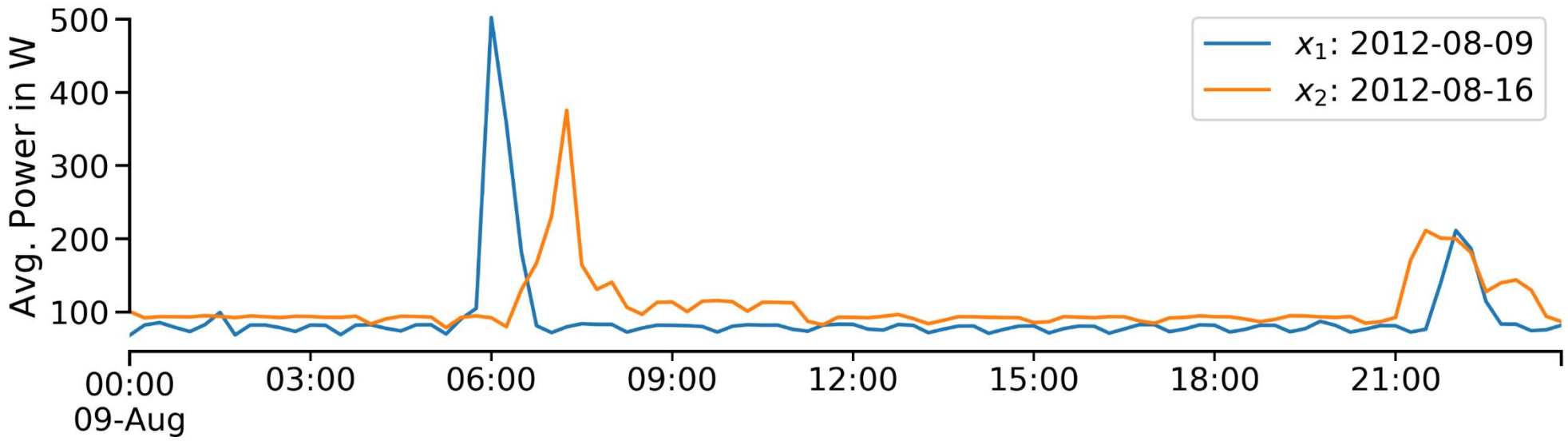
20 households

1000 households



Data: [CER2012]

When are two load profiles similar?



Euclidean distance:

$$d(\boldsymbol{f},\boldsymbol{x}) = \|\boldsymbol{f} - \boldsymbol{x}\|_2 = \sqrt{\sum_{i=1}^{n} (f_i - x_i)^2}$$

Forecast Error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (f_i - x_i)^2}{n}}$$

$d(\boldsymbol{x_1}, \boldsymbol{x_2})$: 668,7 W

Data: [ECO2014]

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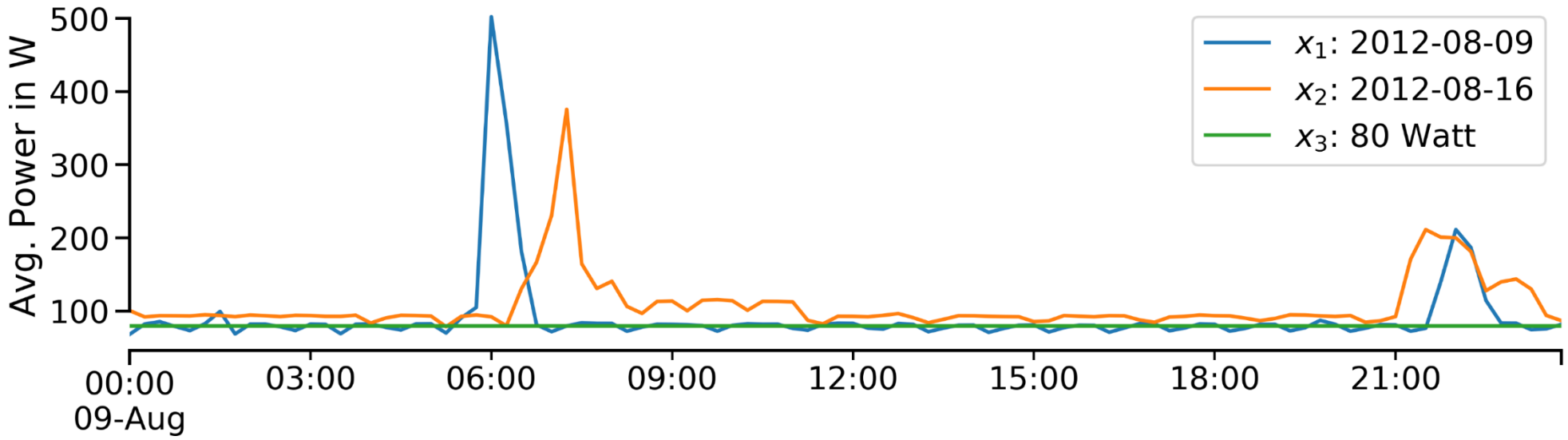

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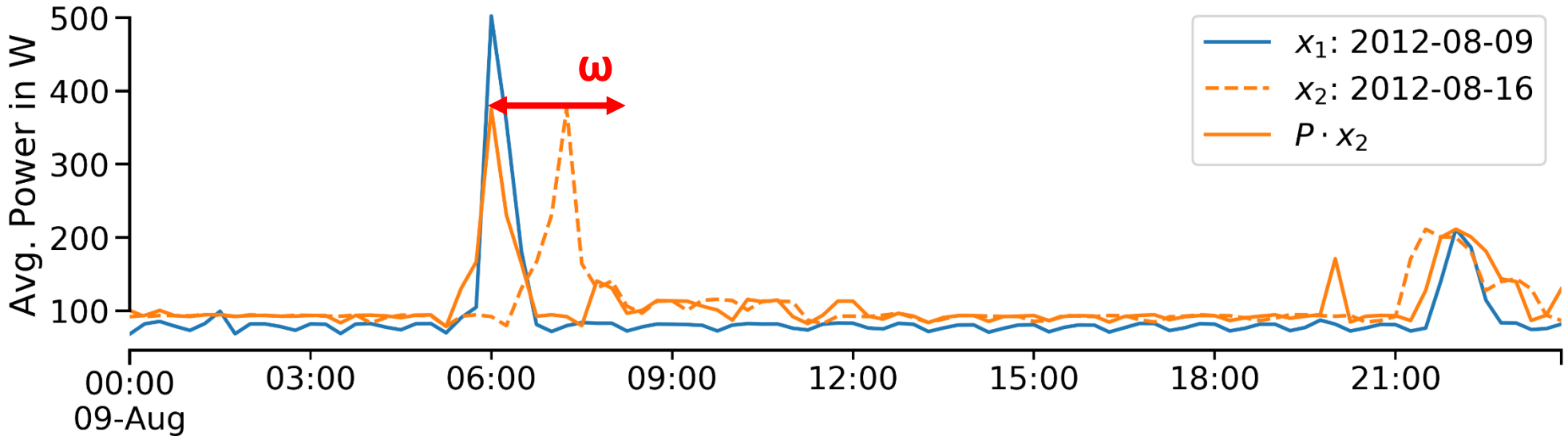
$d(\boldsymbol{x_1}, \boldsymbol{x_2})$: 668,7 W

$d(\boldsymbol{x_2}, \boldsymbol{x_3})$: 549,6 W

Data: [ECO2014]

When are two load profiles similar?



LPI−Distance (based on Adjusted Error of [Haben2014]):

$$LPI(\boldsymbol{f},\boldsymbol{x};\omega) = \min_{P \in \mathcal{L}_n^{\omega}} \|P\boldsymbol{f} - \boldsymbol{x}\|_2$$

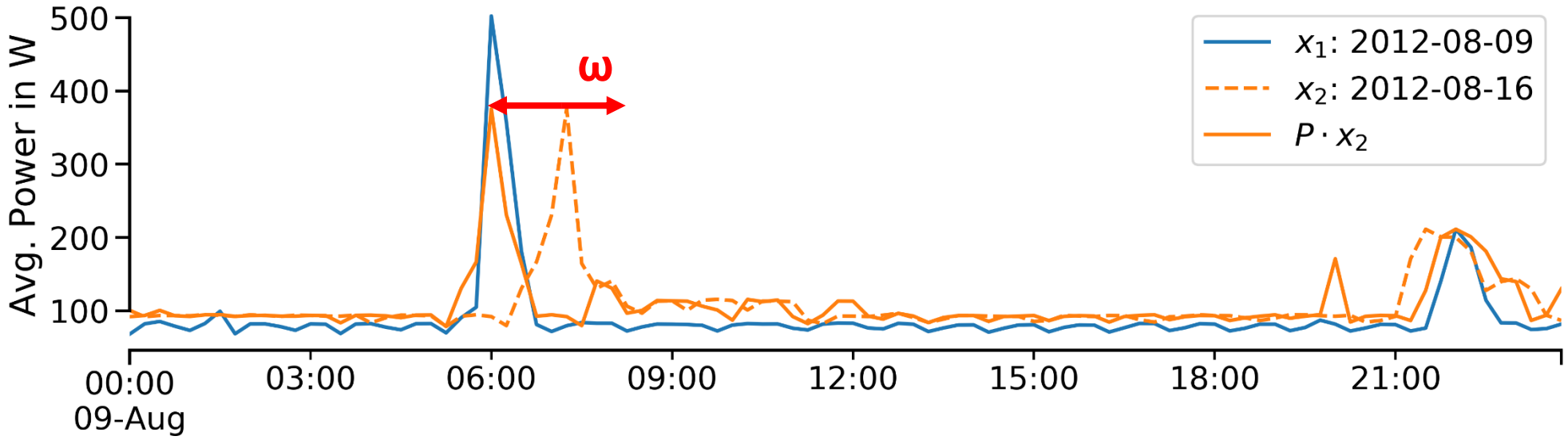
Forecast Error

$$\mathcal{E}_{\omega} = \frac{1}{\sqrt{n}} LPI(\boldsymbol{y},\boldsymbol{x};\omega)$$

ω	Bandwidth parameter.
$\mathcal{L}_n^{\omega}$	Set of by ω restricted permutation matrices of size n.
P	p-norm minimizing permutation matrix.

Data: [ECO2014]

When are two load profiles similar?



d(x_1, x_2): 668,7 W

d(x_2, x_3): 549,6 W

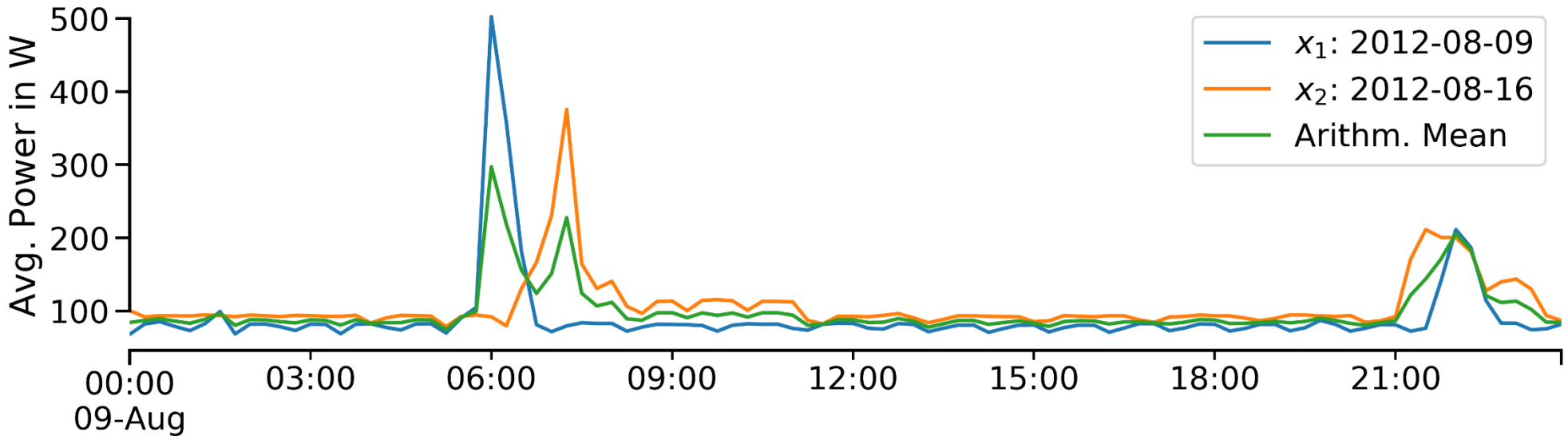
$LPI(x_1, x_2; \omega=5)$: 308,3 W

$LPI(x_2, x_3; \omega=5)$: 549,6 W

Data: [ECO2014]

What is a good average of household load profiles?

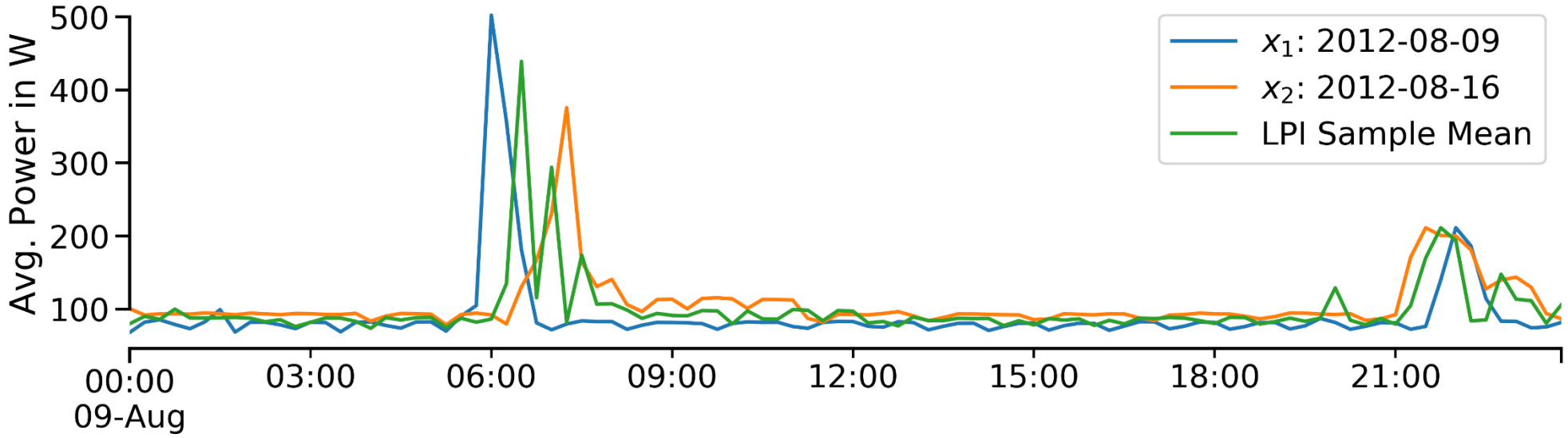
- The sample mean $\bar{x}$ of a set of n profiles is a profile with minimal distance to each of the profiles.
- The arithmetic mean minimizes the Euclidean distance.



Data: [ECO2014]

What is a good average of household load profiles?

The LPI mean is the a sample mean under the Local Permutation Invariant (LPI) distance.

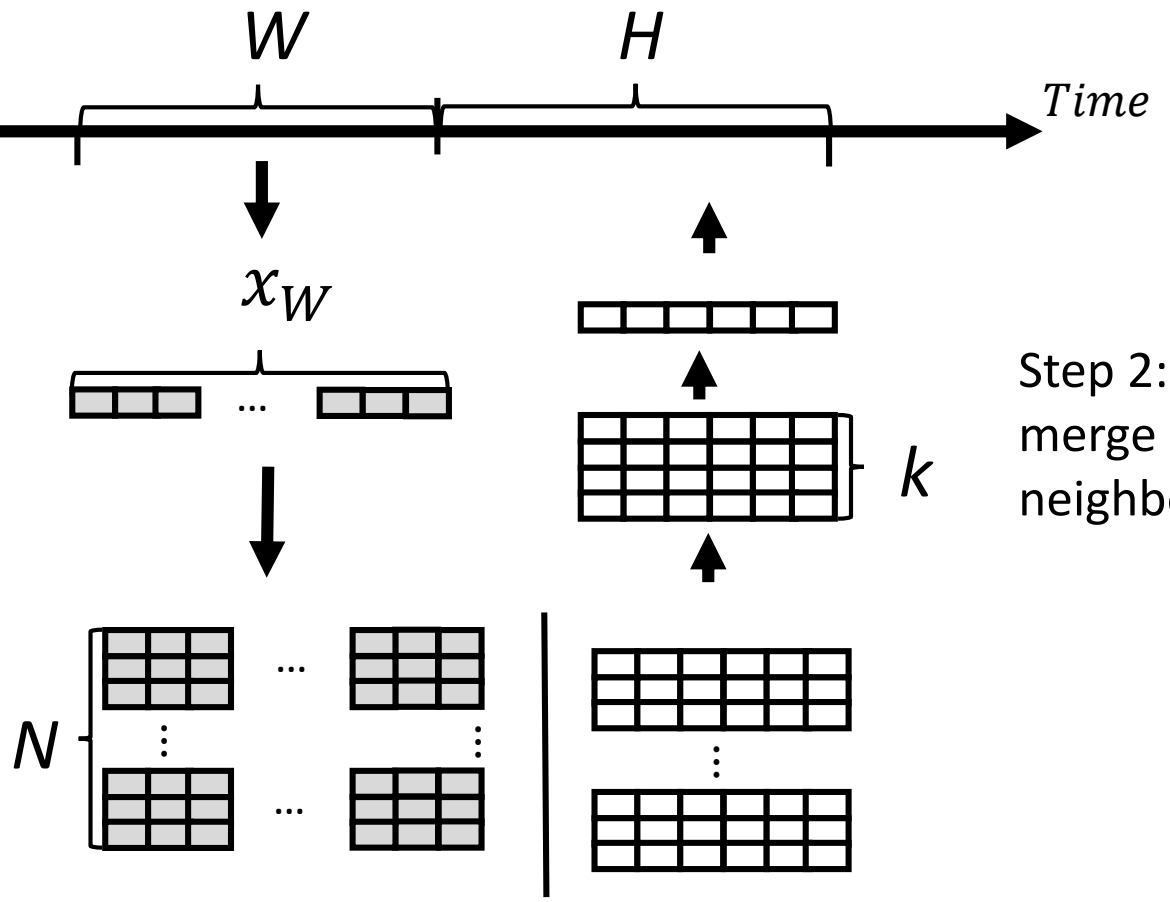


[Voss2019] Marcus Voß, Brijnesh Jain, and Sahin Albayrak (2019). Subgradient Methods for Averaging Household Load Profiles under Local Permutations. In: 13th IEEE PowerTech 2019

Data: [ECO2014]

Adjusted kNN – Load forecasting for lowly-aggregated load

Step 1: Search k-nearest neighbors under LPI distance (using ω_1)

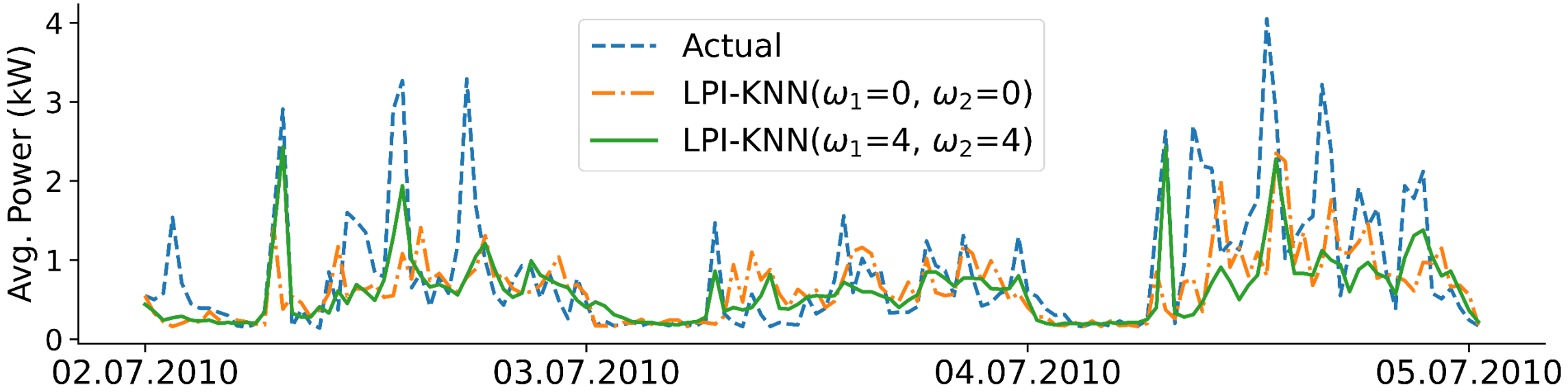


Step 2: Use LPI sample mean to merge successors of k nearest neighbors (using ω_2)

[Voss2018] Marcus Voß, Asmaa Haja, Sahin Albayrak (2018). Adjusted Feature-Aware k-Nearest Neighbors: Utilizing Local Permutation-Based Error for Short-Term Residential Building Load Forecasting. In: IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm).

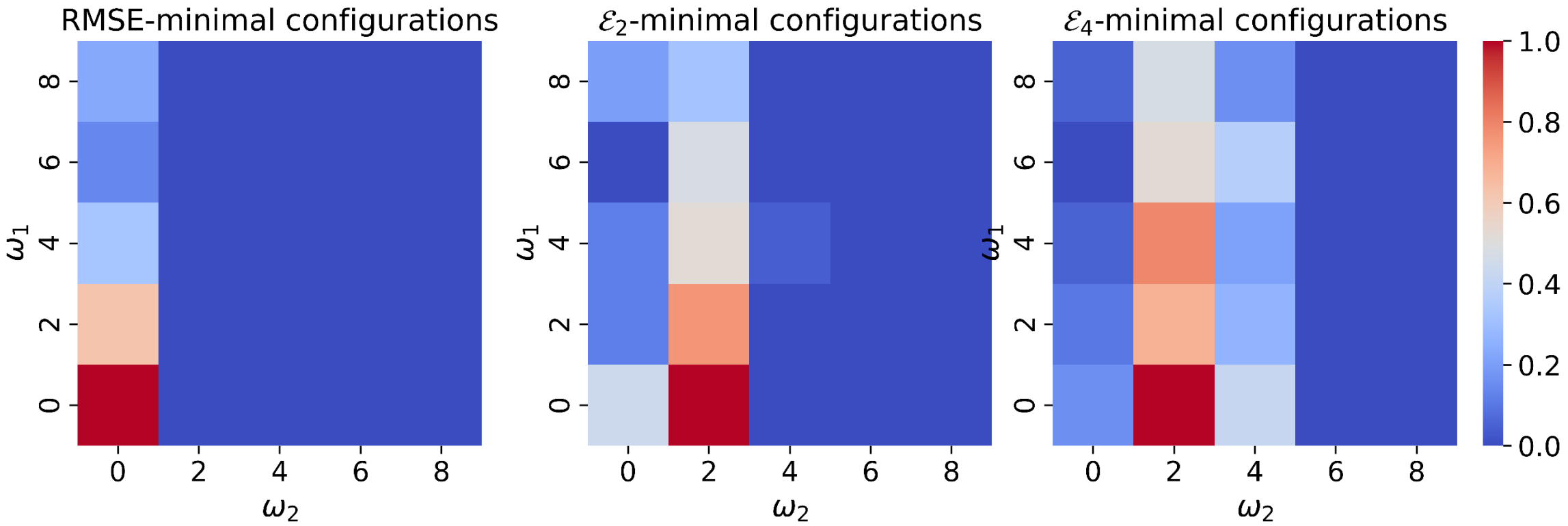
Comparison of forecasts by RMSE-minimizing KNN and ε_5 minimizing LPI-KNN

Example traces of a household from the CER dataset [CER2012].



Comparison of configurations of RMSE-minimizing KNN and $\mathcal{E}_5$ minimizing LPI-KNN

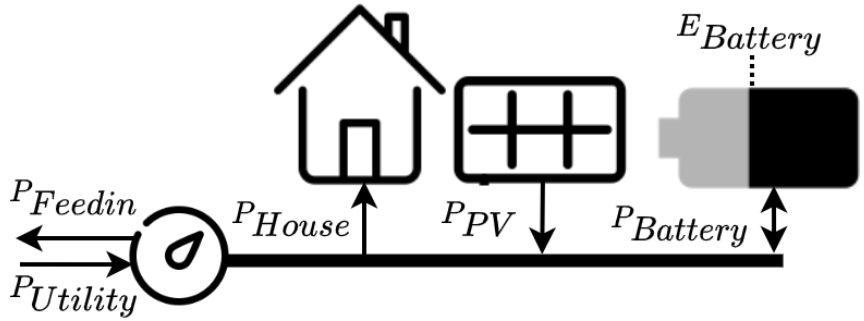
Distribution of the best configurations for the 100 households of the CER dataset [CER2012].



How to establish ground truth in load forecasting?

Objective 1 Minimize Cost: O_{Cost}: $\min \sum_{t=1}^{H} c_{Utility}(t) \cdot P_{Utility}(t) \cdot \tau - p_{Feedin}(t) \cdot P_{Feedin}(t) \cdot \tau$

Objective 2 Max. Autarky: $O_{Autarky}$: $\min \sum_{t=1}^{H} P_{Utility}(t)$



Objective 3 Min. Peak O_{Peak}: $\min \sum_{t=1}^{H} \varepsilon$

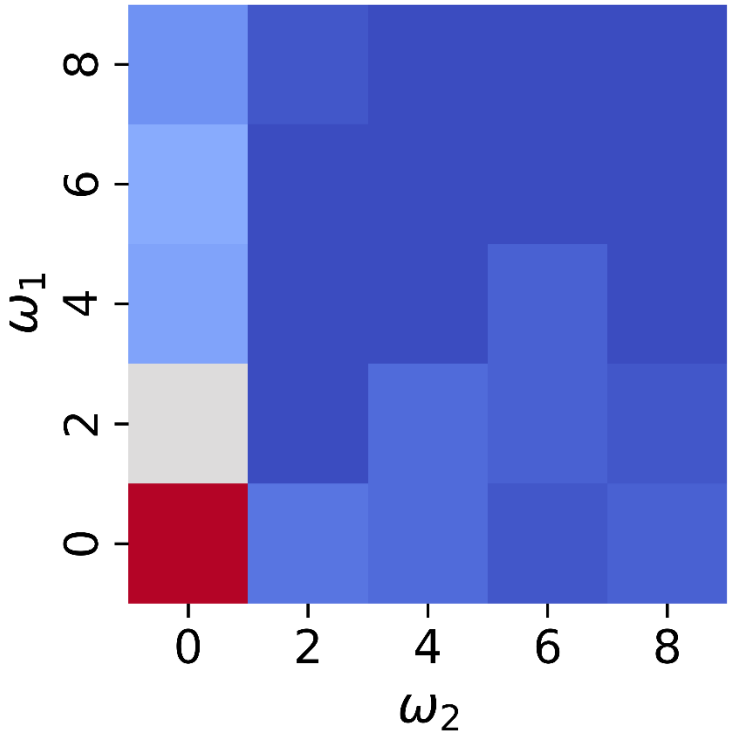
$s.t. \quad \varepsilon \geq P_{Utility}(t) - P_{Bill}$

ε is the amout that the peak demand within the horizon H is expected to exceed the highest peak of the current billing period P_{Bill}.

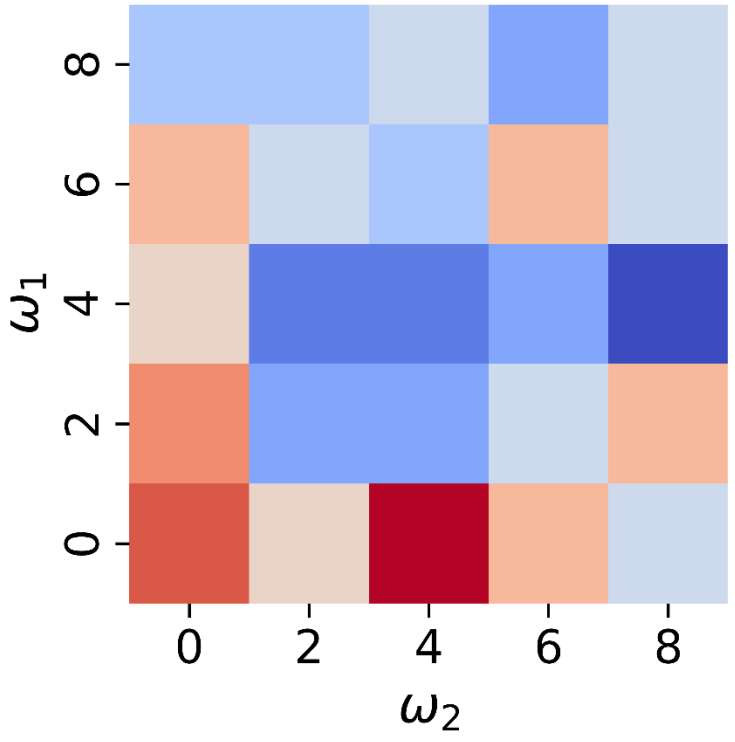
Comparison of configurations of respective objective-minimizing KNN

Distribution of the best configurations for the 100 households of the CER dataset [CER2012].

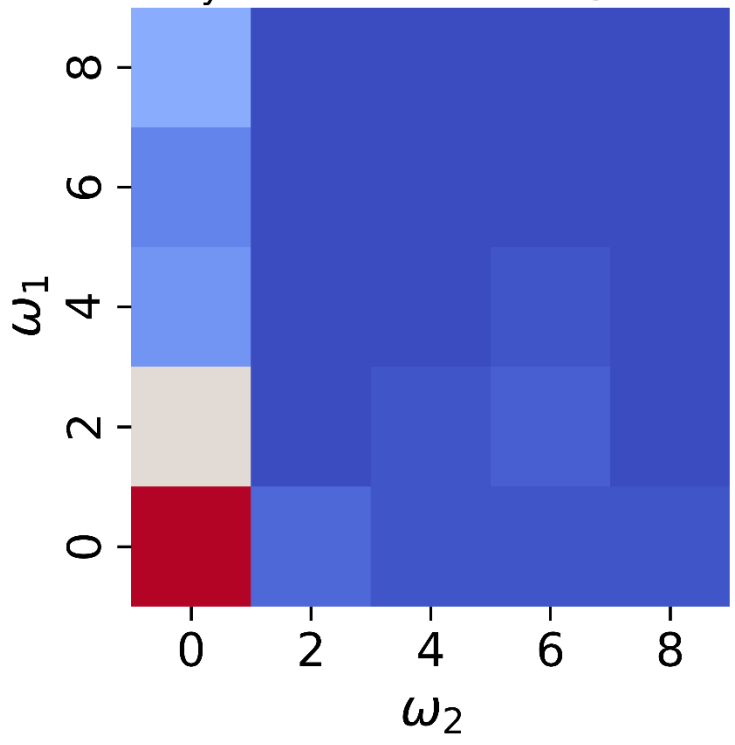
O_{Cost}-minimal configurations



O_{Peak}-minimal configurations



O_{Autarky}-minimal configurations

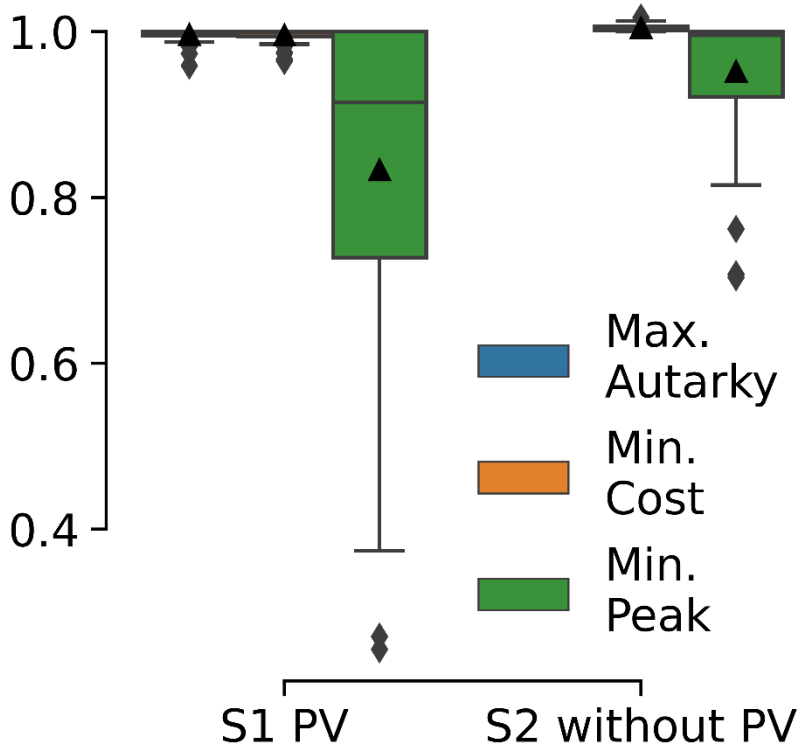


Conclusion

- Low aggregated load profiles at high resolutions and low aggregations are intermittent and have few structure to be exploited by data mining.
- The LPI distance and adjusted error measure can be alternatives to the standard Euclidean distance and RMSE for comparing low-voltage load profiles.
- We showed how this can be done by establishing a *ground truth*, by considering the forecast error in the context of the energy management optimization goal (here: minimum cost, minimum long-term peak load, maximum autarky).
- Peak reduction by average of 22.5% using optimal configuration over RMSE-minimizing forecasting model.

Current Work/Future Work:

- Analyze the choice of distances for clustering and other data analytics tasks on smart meter data.
- Compare the LPI distance (adjusted error) more thoroughly to DTW.
- Standard LAP scales in $O(n^3)$ and the choice of the implementation makes a big different. Currently, I develop a heuristic with good accuracy on minute resolution.



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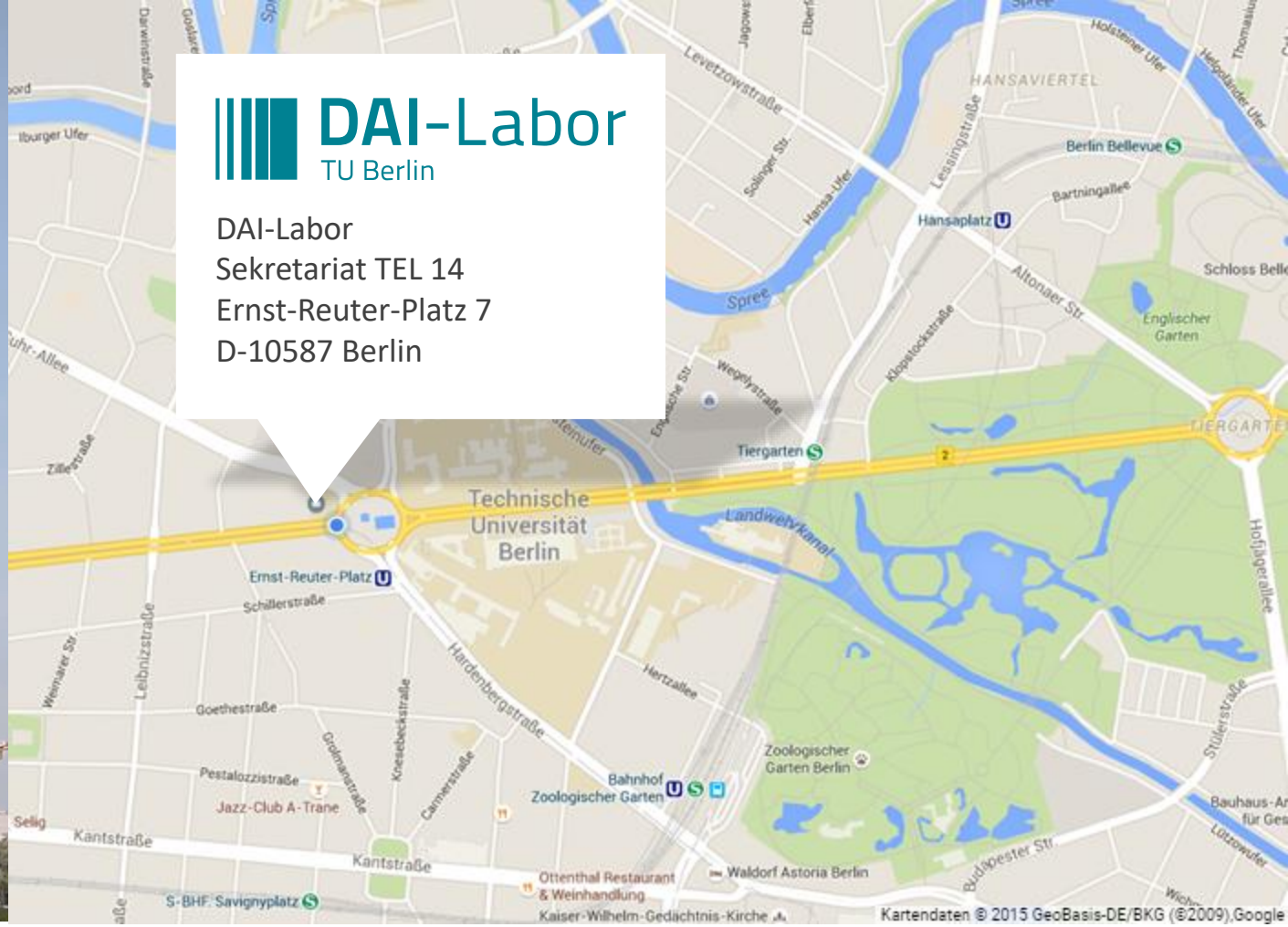

Get In Touch

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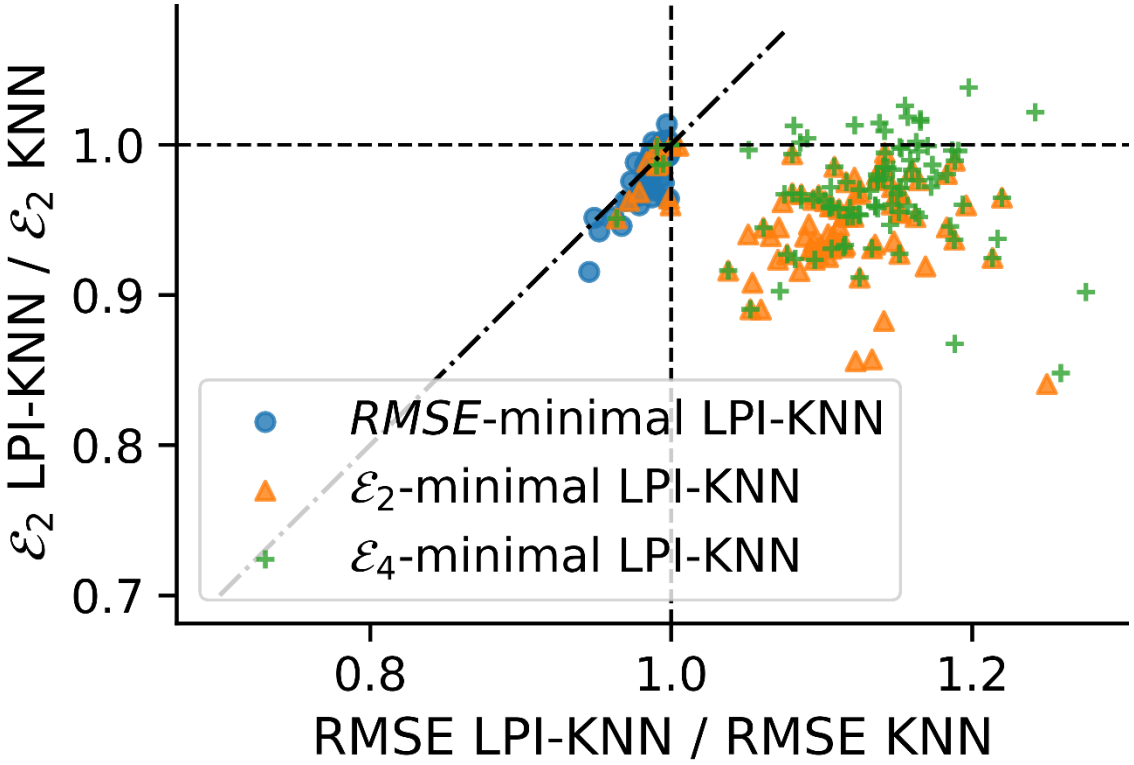
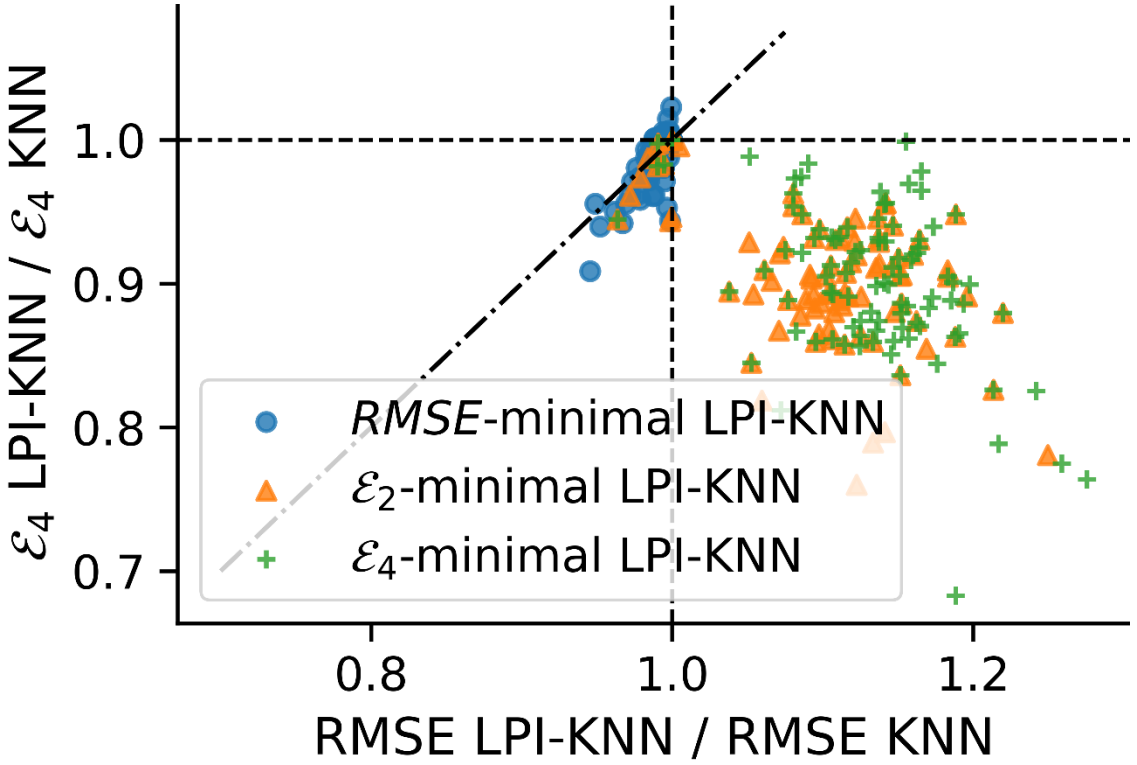
Comparison of forecasts by RMSE-minimizing KNN and $\mathcal{E}_5$ minimizing LPI-KNN

Results for 100 households of the CER dataset [CER2012].





Comparison of forecasts by respective objective-minimizing KNN

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