Electric Vehicle Day-Ahead Load Forecasting Utilizing Adjusted Error and Average Concepts

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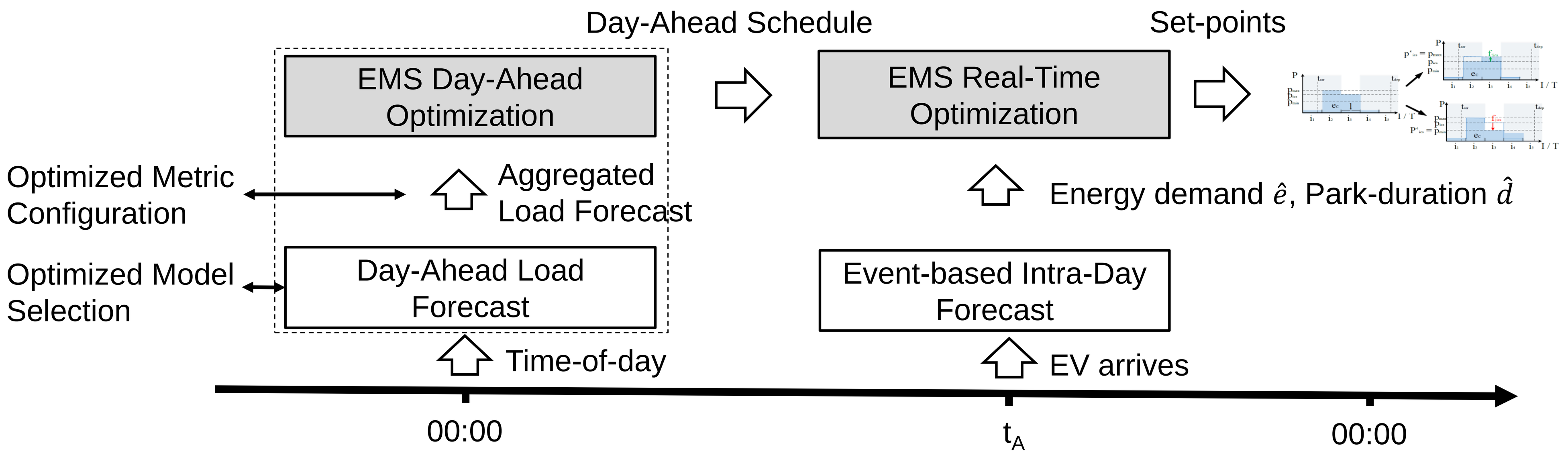
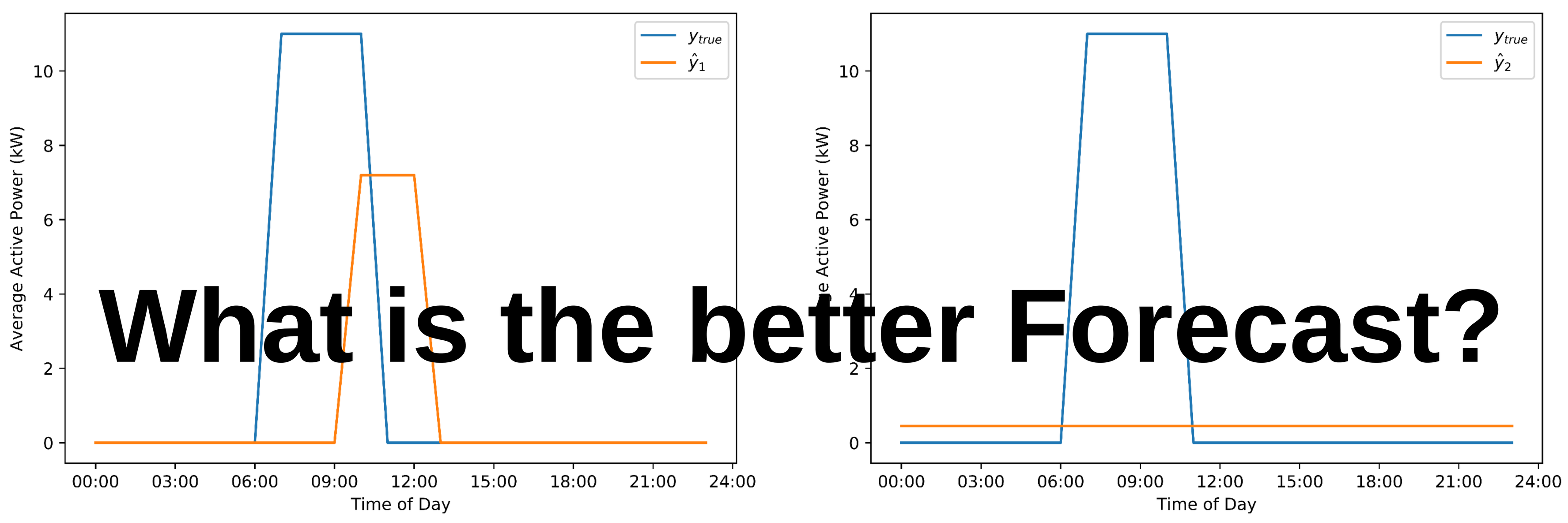
M2G EV Controlled Charging Overview

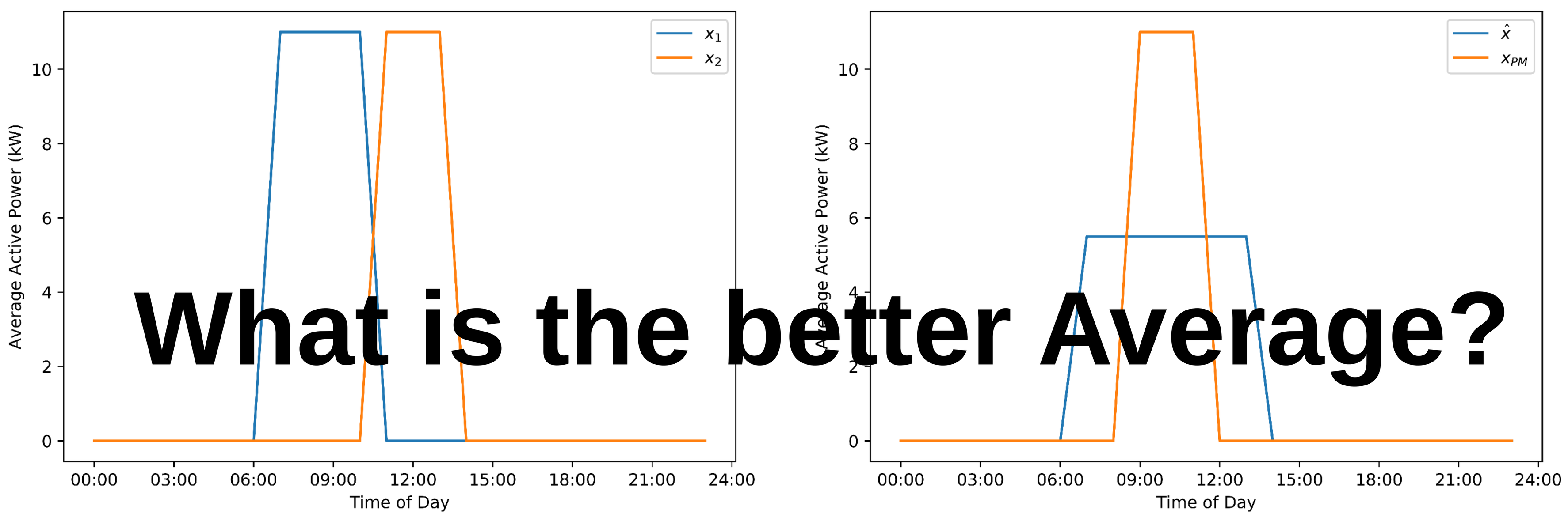
- *Day-ahead forecasts of aggregated load* are useful input to a Day-Ahead optimization to produce an initial optimal schedule
- *Intra-day forecasts of individual charging stations* are needed to determine optimal set-points for providing flexibility



Motivation



Forecasts $\hat{y}_1$ and $\hat{y}_2$ have identical Mean Absolute Error. $\hat{y}_1$ has arguably more value to optimization in energy management systems (EMS), depending on the specific use *case* (e.g. control of storage, load management, marketing energy, ….)



When averaging x_1 and x_2 using the traditional mean $\hat{x}$ the peak gets flattened out, while the *adjusted average* x_{PM} keeps the peak at the same height. In specific use cases a peak-preserving average may be more useful in forecast models.

Adjustable Metric and Average

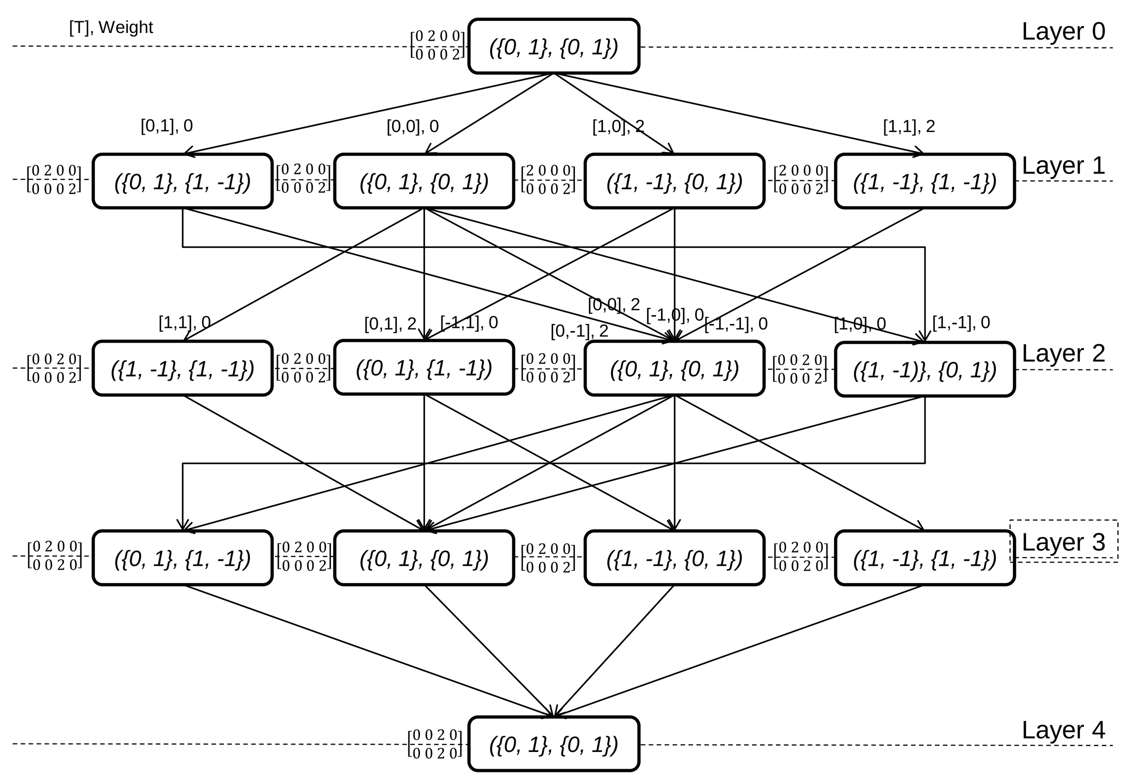
Extending the work of (Haben 2014) and (Charlton 2013), we propose to develop forecast models based on:

an adjusted error $E_p^\omega = \min_{\pi \in \mathcal{P}} \|\pi\hat{y} - y\|_p$ **+** *an adjusted average* $\sum_{i=1}^{N} \left(E_p^\omega(x_i, \hat{y})\right)^p$

ω: configures the amount dislocation of time steps that are allowed
p: configures if outliers should be punished heavier
π: optimal by ω restricted permutation matrix

We implemented the following forecast algorithms capable of minimizing the *adjusted error* and utilizing the *adjusted average:*

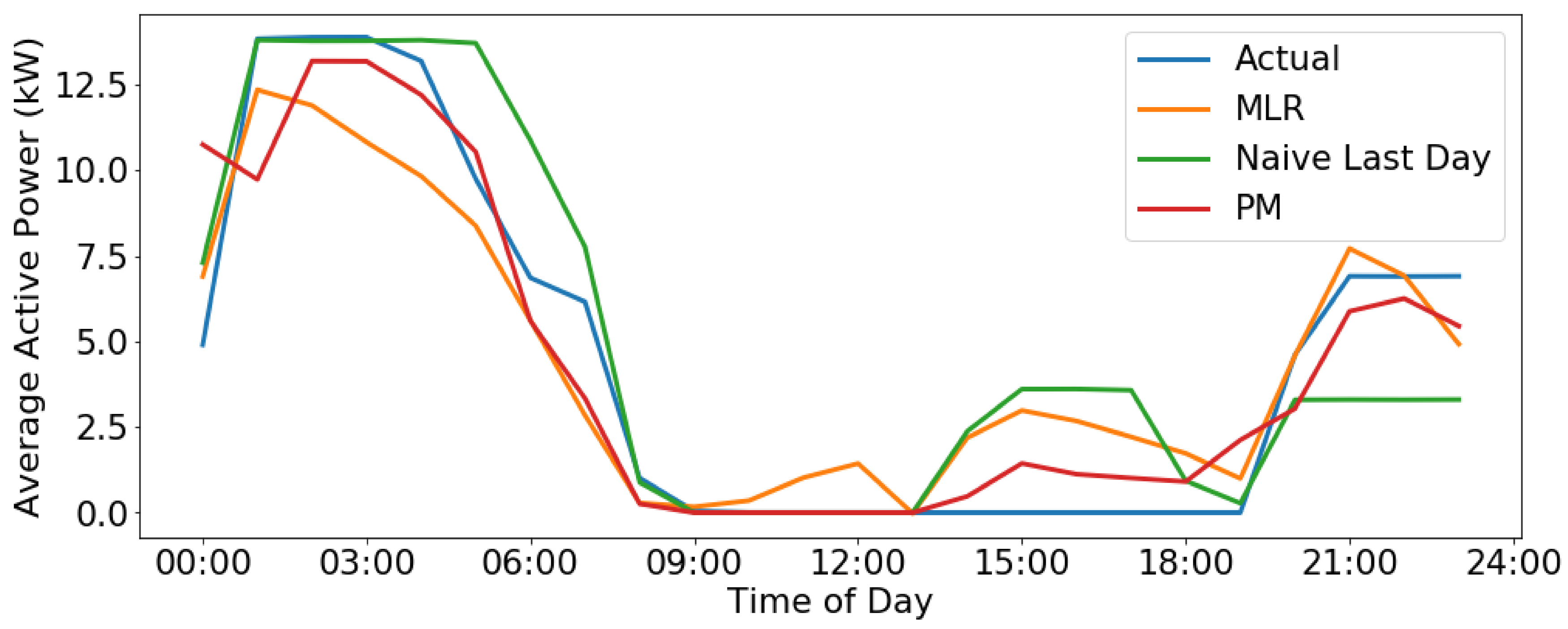
- *Adjusted Average Forecaster (AAF)* based on (Haben 2014)
- *Permutation Merge Forecaster (PM)* based on (Charlton 2013)
- *Adjusted K-nearest Neighbors (AKNN)*



The problem of calculating the *adjusted error* and *the adjusted average* can be solved by finding the shortest path in a directed acyclic graph (Charlton 2013). We propose a more efficient algorithm utilizing the layered structure of the graph.

Forecaster Evaluation

	Ridge	Naive	AAF	PM	AKNN
$E_{p=1}^{\omega=0}$ (MAE)	1.78	1.83	1.93	1.80	**1.73**
$E_{p=2}^{\omega=0}$ (*RMSE*)	**2.42**	3.18	2.88	2.72	2.51
$E_{p=2}^{\omega=1}$	11.52	14.68	13.08	12.51	**11.43**
$E_{p=2}^{\omega=3}$	11.48	14.73	13.14	12.47	**11.41**
$E_{p=4}^{\omega=1}$	**7.11**	9.58	8.55	7.98	7.13



- AKNN and Permutation Merge can most robustly minimize the adjustable error, while Ridge works best to minimize RMSE
- Future work will investigate the optimization of the forecast configuration based on a specific use case and implement more machine learning models capable of minimizing the adjusted error

(Haben 2014) Stephen Haben, Jonathan Ward, Danica Vukadinovic Greetham, Colin Singleton, and Peter Grindrod. A new error measure for forecasts of household-level, high resolution electrical energy consumption. International Journal of Forecasting, 30(2):246–256, 2014.
(Charlton 2013) Nathaniel Charlton, Danica Vukadinovic Greetham, and Colin Singleton. On minimum cost local permutation problems and their application to smart meter data. University of Reading