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Applying Simple Data-Driven Control Algorithms In Low-Voltage Grids With Flexibility Provided By Electric Vehicles For Grid-Oriented Control

Yuzhuo Fu, Maik Plenz, Detlef Schulz

Helmut Schmidt University / University of the Federal Armed Forces Hamburg

Electrical Power Systems

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Zentrum für Digitalisierungs- und Technologieforschung der Bundeswehr

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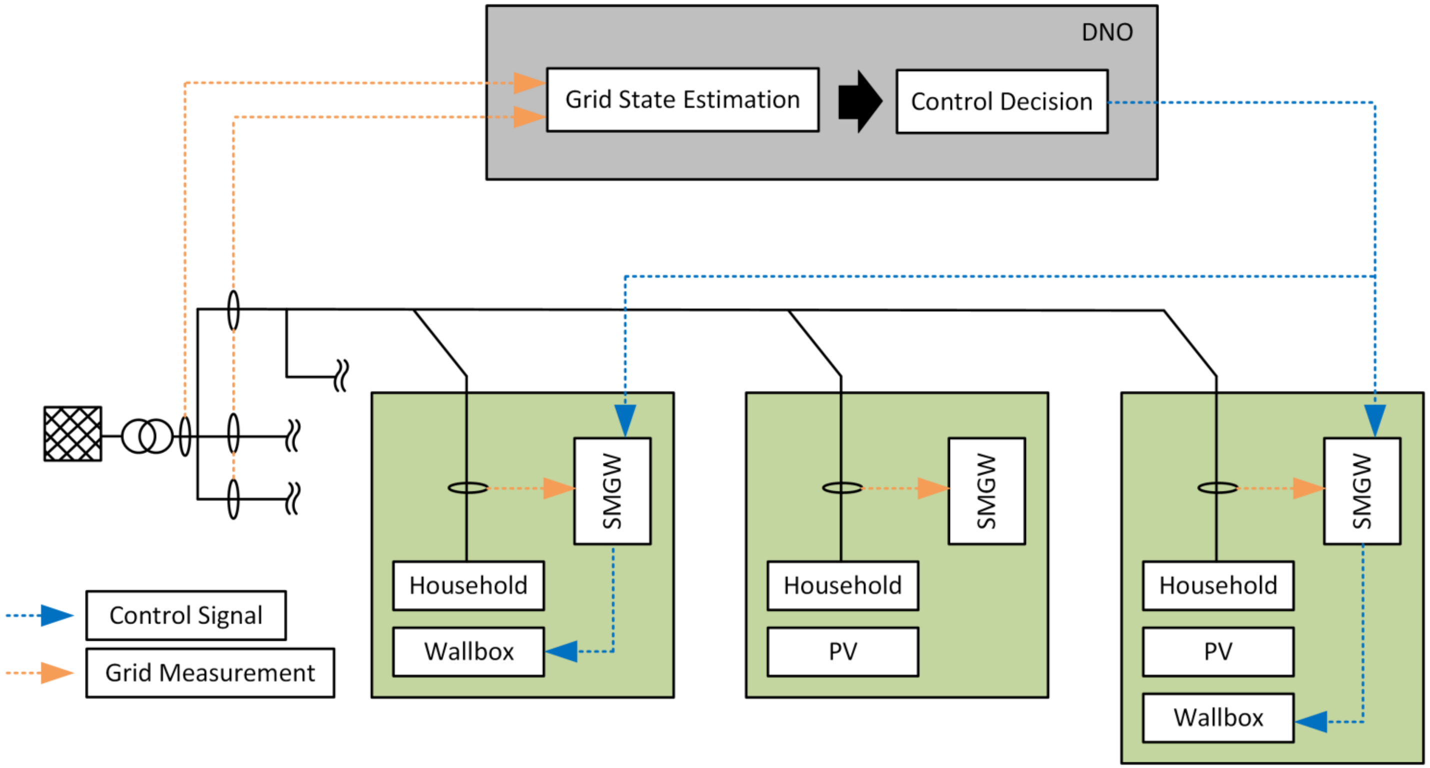
Agenda

Development: The number of electric vehicles (EVs) is increasing rapidly

Potential Issue: Charging processes of EVs can lead to grid congestion

Available Solution: Distribution system operators (DSOs) are allowed to reduce EV charging power if critical grid states are identified



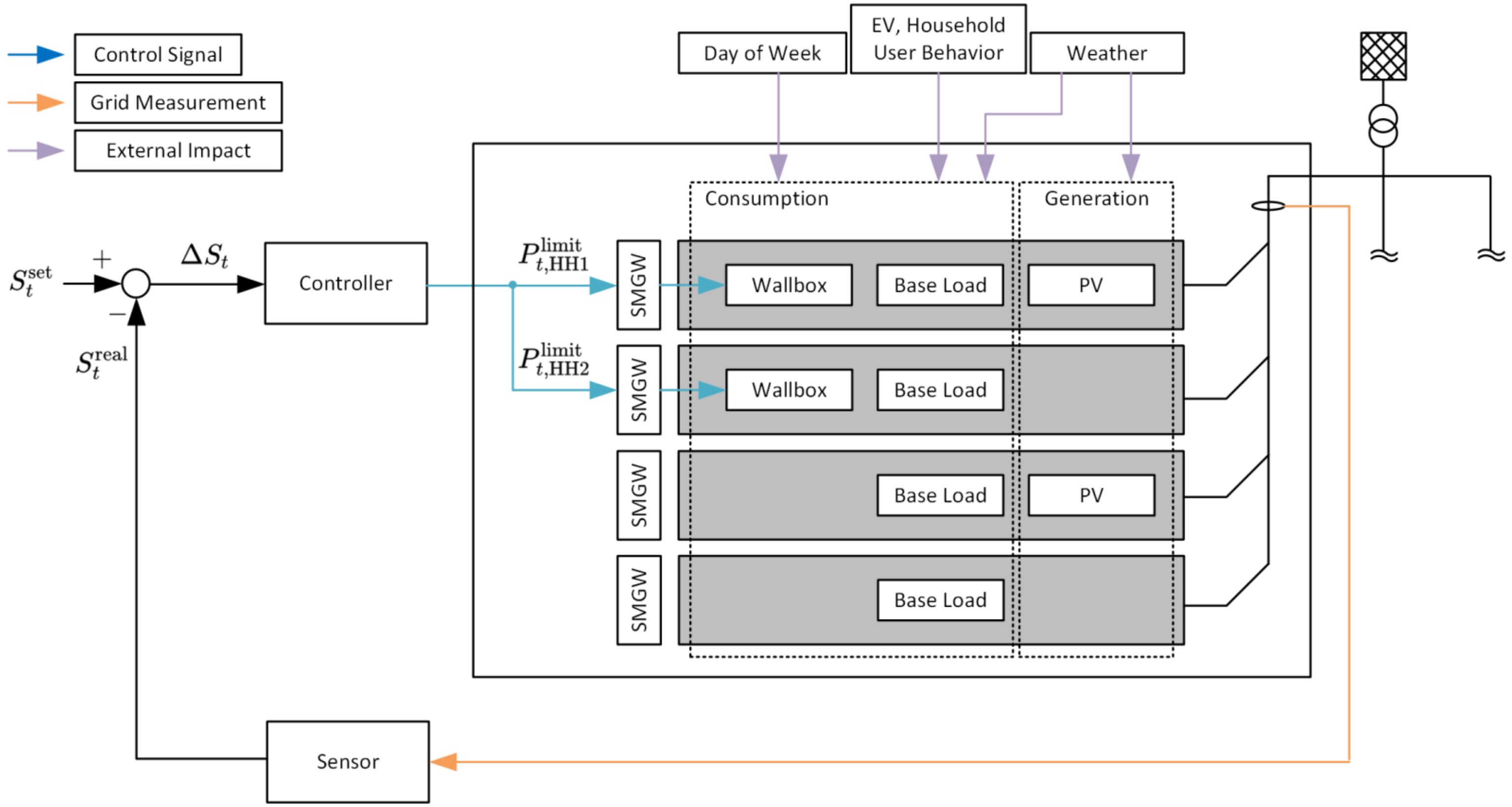
1. Real-time measurement data is limited
2. Grid models in low-voltage (LV) grids are not exact

Requirements for the grid-oriented control in LV grids in this paper:

Data Availability	No access to smart meters, rather grid states measured at transformer-level
Model Accuracy	No grid model is needed for decision-making in the control process
System Complexity	Control algorithm contains few parameters and uses only online data

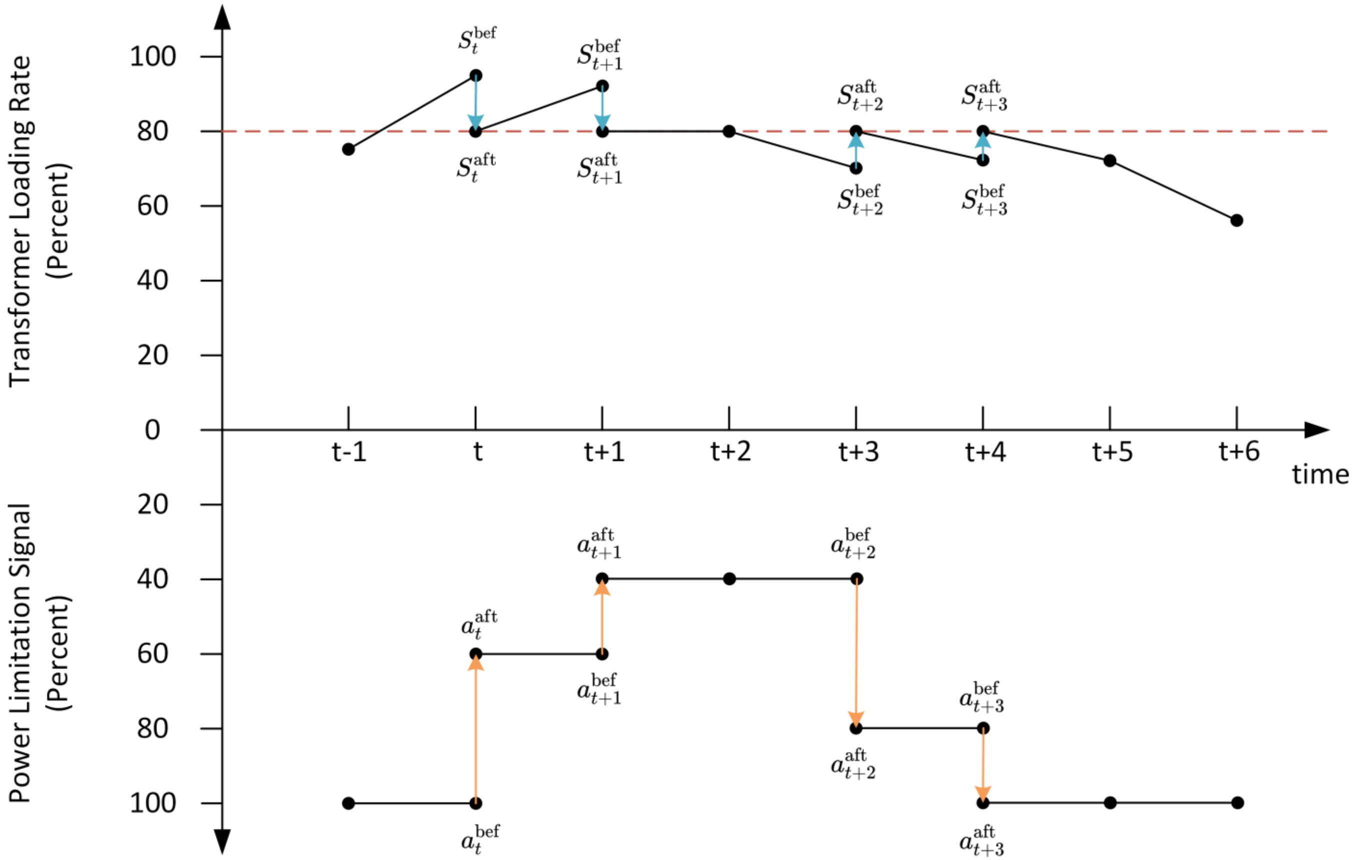
Research question of this work:

What is the performance of a simple data-driven control method based on online algorithms using limited real-time measurement data in the grid-oriented control?



The objective of the controller is to find the solution of this optimization problem:

$$a_t^* = arg \min_{a_t} |S_t^{set} - S_t^{real}| \quad with \quad P_{t,HH\,i}^{limit} = a_t * P_{HH\,i}^{install} \quad \forall i \in W$$



The most important relationship that needs to be estimated is:

$$S_t^{aft} - S_t^{bef} = f(a_t^{aft} - a_t^{bef})$$

Basic idea of the control algorithm:

Model-Free Adaptive Control (MFAC): build a dynamic linearization model using input and output from controlled plant without knowledge about system models and system states

Step 1: estimate the pseudo partial derivative

$$\hat{\phi}_t = \hat{\phi}_{t-1} + \frac{\eta \Delta a_{t-1}}{\mu + \Delta a_{t-1}{}^2}\left(\Delta S_{t-1} - \hat{\phi}_{t-1}\Delta a_{t-1}\right)$$

Step 2: calculate needed control decision

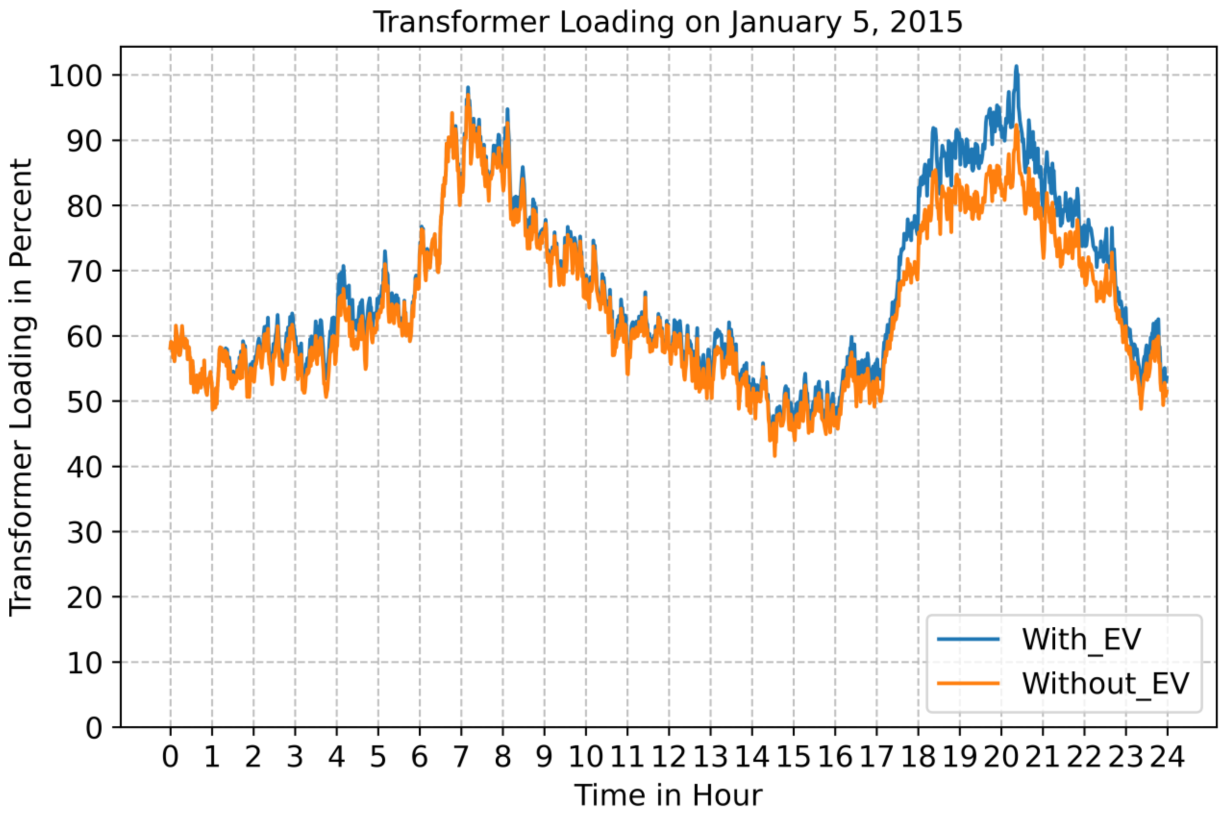
$$a_t^{\mathrm{aft}} = a_t^{\mathrm{bef}} + \frac{\rho \hat{\phi}_t}{\lambda + \hat{\phi}_t{}^2}\left(S_t^{\mathrm{set}} - S_t^{\mathrm{bef}}\right)$$

Reference LV grid model from SimBench

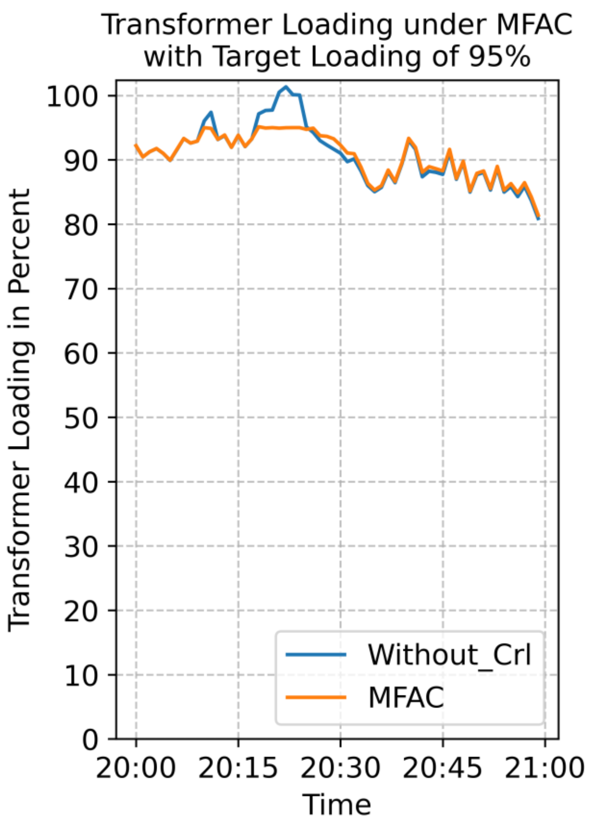
- One MV/LV transformer
- 7 LV feeder lines
- Radial structure
- Germany

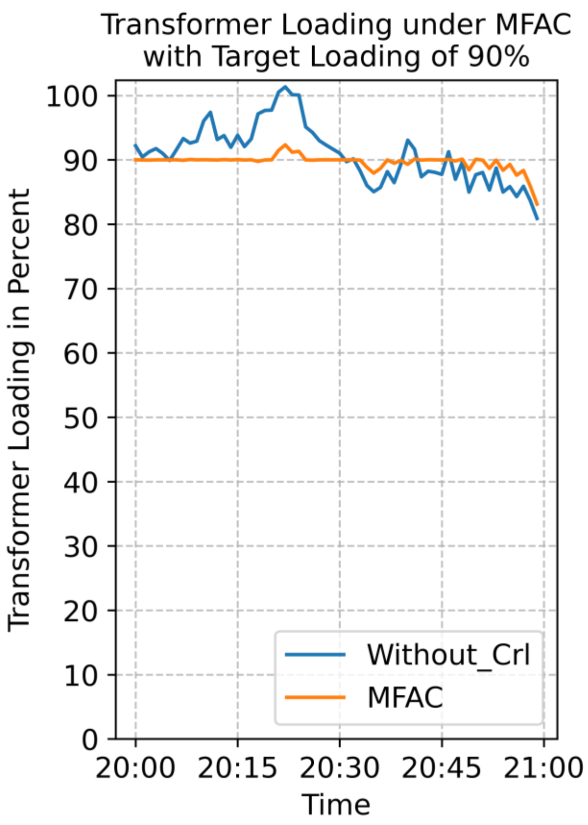
Load profiles of households from Pecan Street

- 350 Households
- 54 private EV charging points
- 10 PV panels
- Texas USA

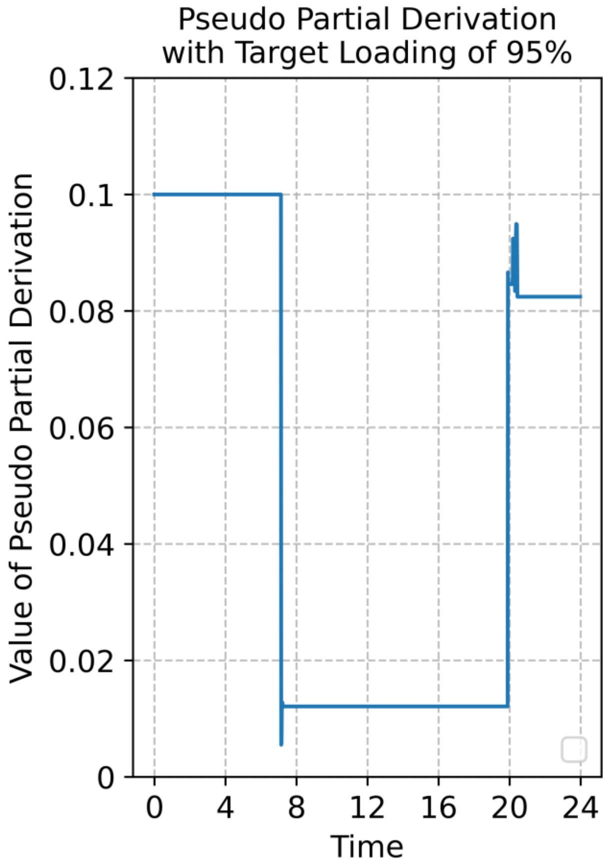


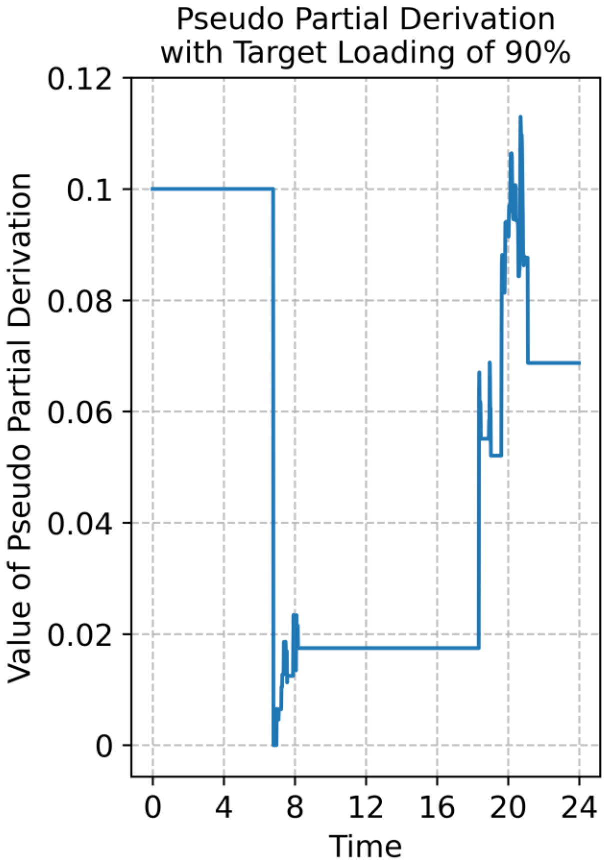
1. Two peak loads are observed at about 7:30 and 20:30
2. Maximum loading rate of transformer has reached 100%





Target transformer loading	Number of time steps with overloads	Mean transformer loading during overloads
95%	1	95.14%
90%	12	90.57%





Parameter	Value
η	1.0
μ	$1 * 10^{-6}$
ρ	1.0
λ	$1 * 10^{-6}$
$\hat{\phi}_0$	0.1

Answer to the research question:

- MFAC control algorithm can successfully relive the overloads of transformer without knowledge about real-time states of EVs and exact grid models
- Pseudo partial derivative with only one parameter that needs to be estimated can extract and follow the frequent change of system dynamic in LV grids
- Mean control error regarding transformer loading during the overload period is less than 1%

Future work:

- Other forms of MFAC algorithm can be tested
- Find out the impact of hyperparameters on control performance

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Thanks for your attention!

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yuzhuo.fu@hsu.hamburg