Stochastic Model Predictive Control for Smart Grid Applications

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PHD Thesis Defence
Freiburg, 13.03.2023
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Control of Residential PV Battery Systems under Uncertainties

Introduction

Fade-out of fossil-based electricity generation

Less controllable renewable sources

→ Use decentralized flexibilities

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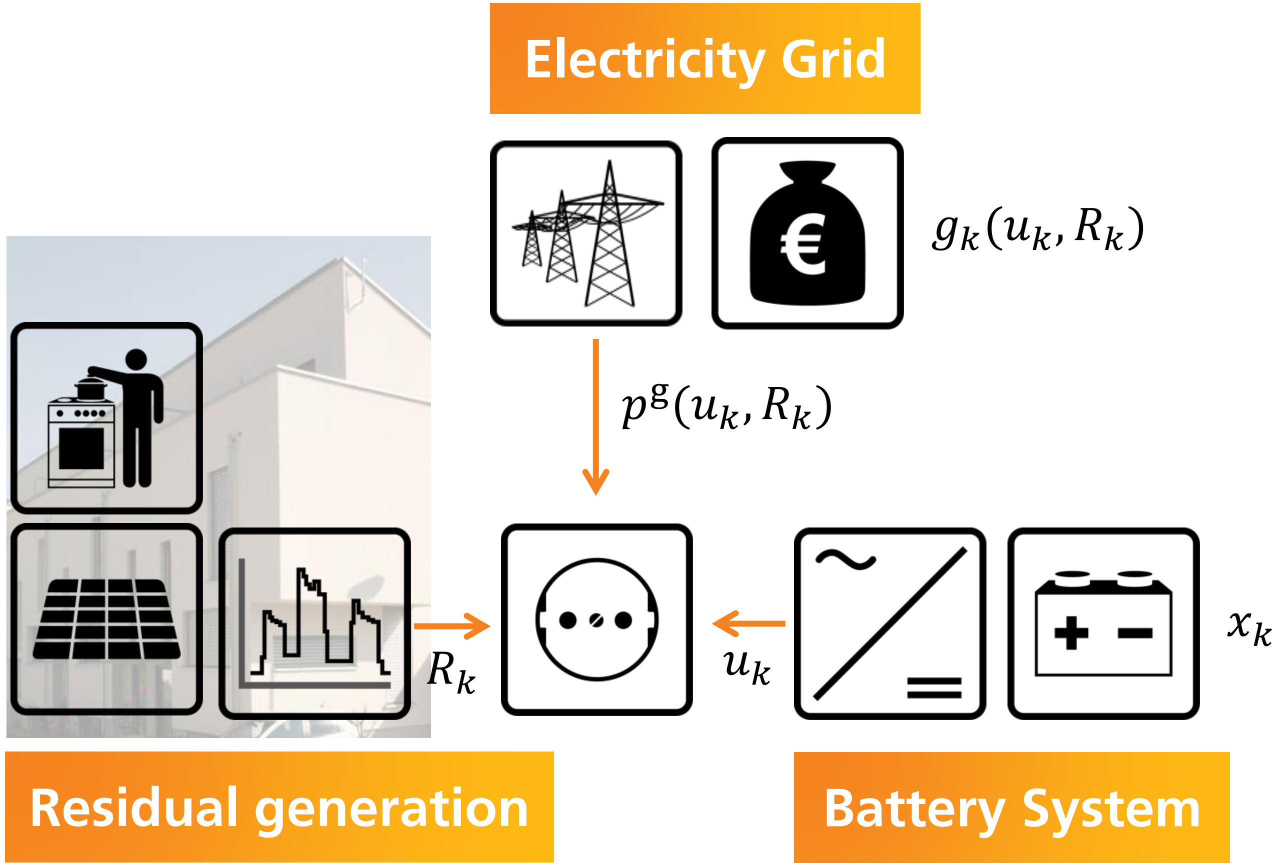


Control of Residential PV Battery Systems under Uncertainties
Introduction

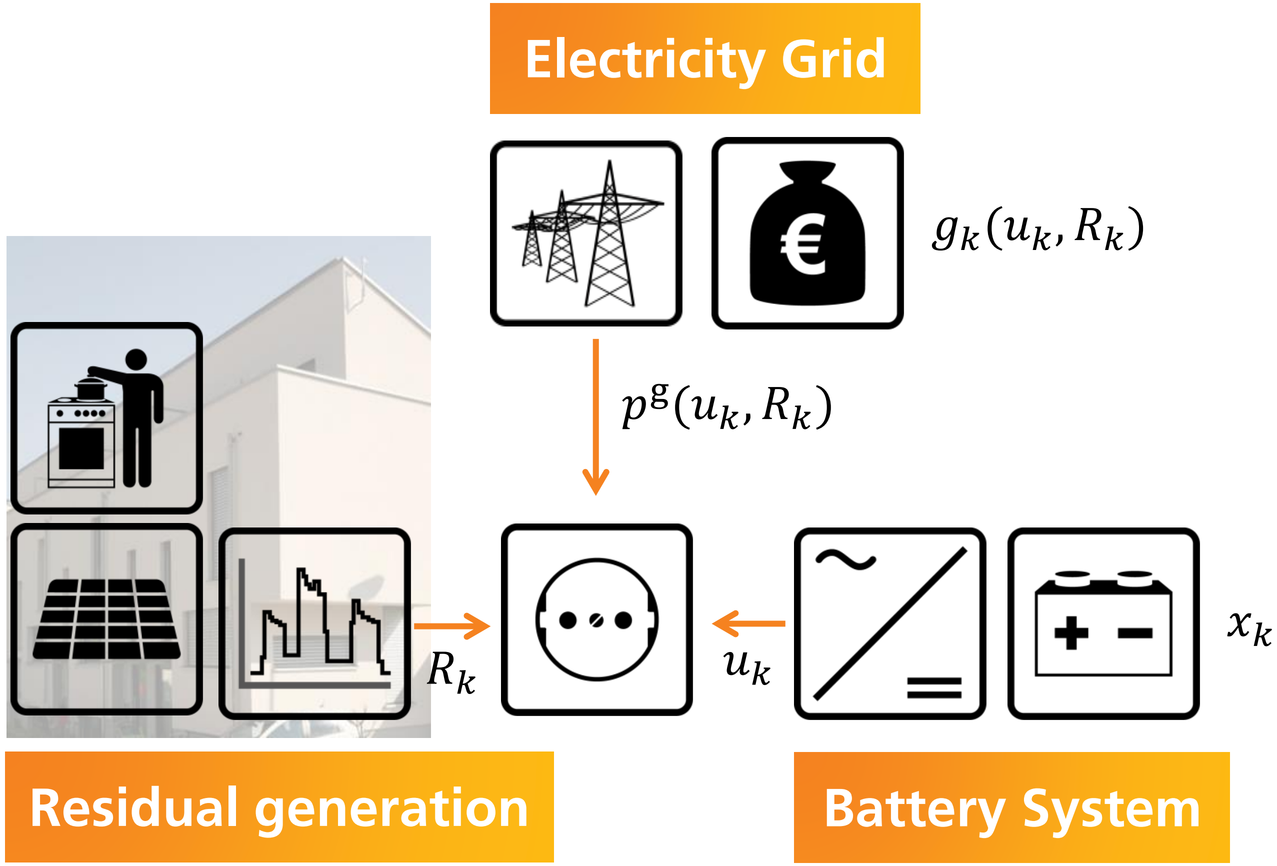
Fade-out of fossil-based electricity generation

Less controllable renewable sources

→ Use decentralized flexibilities

Control storage optimally while …

- mitigating uncertainties in forecasts
- navigating a complex economic environment
- considering efficiencies of the system



Thesis Goal and Contributions

Introduction

Development of a Stochastic Control Algorithm Applied to Smart Grid System

Stochastic Control

- Groß, A., Wittwer, C., and Diehl, M. Stochastic model predictive control of photovoltaic battery systems using a probabilistic forecast model. European Journal of Control 56 (Nov. 2020), 254–264

Stochastic modeling

- Groß, A., Wittwer, C., Lenders, A., Zech, T., and Diehl, M. Using Probabilistic Forecasts in Stochastic Optimization. In The 16th International Conference on Probabilistic Methods Applied to Power Systems (2020)
- Groß, A., Lenders, A., Schwenker, F., Braun, D. A., and Fischer, D. Comparison of short-term electrical load forecasting methods for different building types. Energy Informatics 4, 3 (Sept. 2021), 13

System modeling

- Groß, A., Wille-Haussmann, B., Wittwer, C., Achzet, B., and Diehl, M. Stochastic Nonlinear Model Predictive Control for a Switched Photovoltaic Battery System. IEEE Transactions on Control Systems Technology (2022)

Applications

- Groß, A., Schumann, J., Marchand, S., Mittelsdorf, M., Kohrs, R., and Diehl, M. Electric Vehicle Charge Management taking into account Grid State and Forecast Uncertainties of Photovoltaic Generation. In EVS33 (Sept. 2020)

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Notation Deterministic MPC

Stochastic Control

Deterministic Optimal Control Problem (OCP)

$$
\begin{aligned}
\min_{\mathbf{x},\,\mathbf{u}} \quad & J(\mathbf{x}, \mathbf{u}|\mathbf{R}) = \sum_{k=0}^{N-1} g_k(x_k, u_k, R_k) + g_N(x_N) \\
\text{s.t.} \quad & x_k \in \mathbb{X} && \forall k = 0, \dots, N, \\
& u_k \in \mathbb{U}(x_k) && \forall k = 0, \dots, N-1, \\
& x_{k+1} = f^x(x_k, u_k, R_k) && \forall k = 0, \dots, N-1, \\
& x_0 = x^{\text{init}}
\end{aligned}
$$

Where

x_k: State of charge (SoC) of battery system

u_k: Control input i.e., battery power

$R_k = p^{\text{pv}} - p^{\text{load}}$:Residual generation

$g_k(x_k, u_k, R_k)$: stage costs (supply price, feed-in tariff)

$g_N(x_N)$: terminal costs (final battery SoC)

$f^x(x_k, u_k, R_k)$: state transition (charging / discharging / losses)

Multi-stage Stochastic MPC

Stochastic Control

Define new state variable residual generation

$$R_{k+1} = f^R(R_k, \bar{\mathbf{R}}, \varepsilon_k) \quad \varepsilon_k \sim \mathcal{F}_k$$

Multi-stage OCP – residual generation model

Stochastic Modeling

Define new state variable residual generation

$$R_{k+1} = f^R(R_k, \bar{\mathbf{R}}, \varepsilon_k) \quad \varepsilon_k \sim \mathcal{F}_k$$

Markov-Chain instead of deterministic forecast

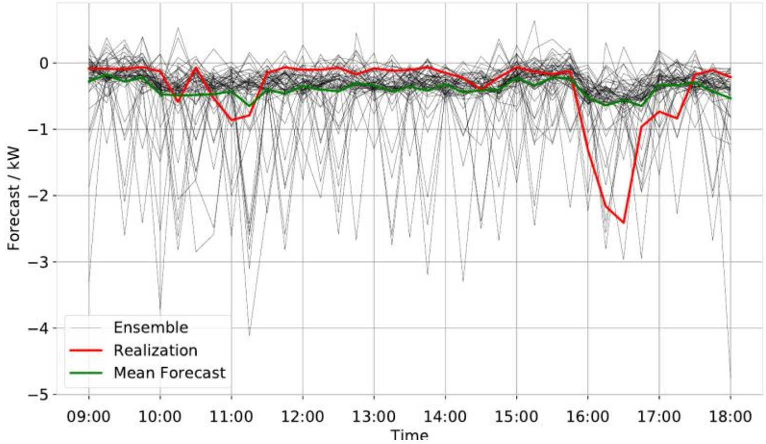
$$R_{k+1} = f^R(R_k, \bar{\mathbf{R}}, \varepsilon_k) = \bar{R}_{k+1} + \tau(R_k - \bar{R}_k) + \varepsilon_k$$

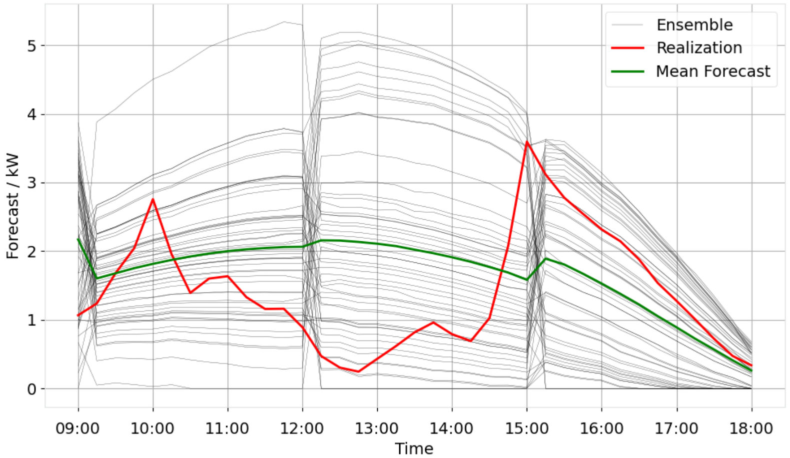
Forecast next step | Persistence term | uncertainty

Use Probabilistic Forecasts to Determine Short-term Model

Stochastic Modeling

Probabilistic Forecasts





Parameters can also be obtained from past data (fc + meas)

Maximum Likelihood estimation

e.g., Gaussian with width

$$\hat{\sigma} = \sqrt{\frac{1}{N-1}\sum_{k=0}^{N-2}\frac{1}{M}\sum_{m=0}^{M-1}(\bar{R}^m_{k+1} - \rho_{k+1}(\bar{R}^m_k, \hat{\mathbf{R}}))^2}$$

Markov-chain model parameters

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Multi-stage Stochastic MPC

Stochastic Control

Define new state variable residual generation

$$R_{k+1} = f^R(R_k, \bar{\mathbf{R}}, \varepsilon_k) \quad \varepsilon_k \sim \mathcal{F}_k$$

Summarize

$$y_k = (x_k, R_k)^{\mathrm{T}} \in \mathbb{Y} := \mathbb{X} \times \mathbb{R}$$

With combined state transition

$$y_{k+1} = F(y_k, u_k, \varepsilon_k) := \begin{pmatrix} f^x(x_k, u_k, R_k) \\ f^R(R_k, \bar{\mathbf{R}}, \varepsilon_k) \end{pmatrix}$$

Multi-stage Stochastic MPC

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Define policies $\mu(y)$ in set of policies

$$\mathbb{M} := \{\mu : \mu(y) \in \mathbb{U} \wedge F(y, \mu(y), \varepsilon) \in \mathbb{Y} \quad \forall y \in \mathbb{Y}, \forall \varepsilon\}$$

Iteratively yielding state trajectories

$$y_{k+1}(\mu, \hat{y}, \varepsilon) := F(y_k(\mu, \hat{y}, \varepsilon), \mu_k(y(\mu, \hat{y}, \varepsilon)), \varepsilon_k)$$

Multi-stage Stochastic MPC

Stochastic Control

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Arriving at the stochastic multi-stage OCP for the optimal policies

$$\min_{\mu \in \mathbb{M}^N} \mathbb{E}_{\varepsilon \sim \mathcal{F}} \left[\sum_{k=0}^{N-1} g_k(\mu_k(y_k(\mu, \hat{y}, \varepsilon)), y_k(\mu, \hat{y}, \varepsilon)) + g_N(y_N(\mu, \hat{y}, \varepsilon)) \right]$$

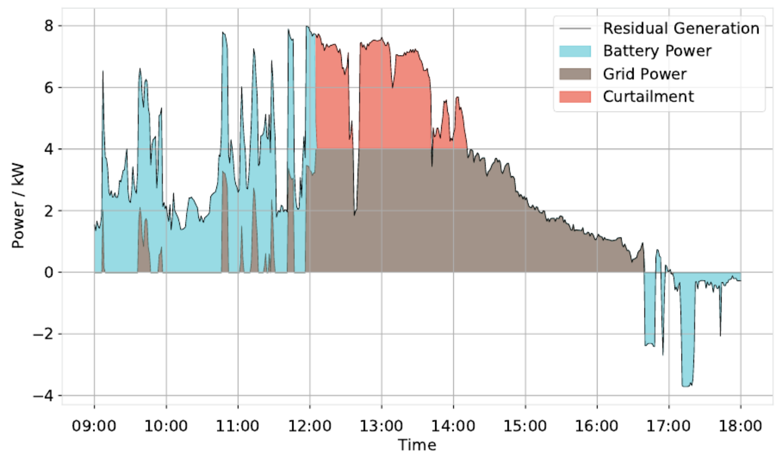
Sample Case: PV Battery System with curtailment limit

System Modeling

Standard control: Charge battery with excess PV

Maximizes self-sufficiency

Feed-in is limited to 50% of nominal power → curtailment

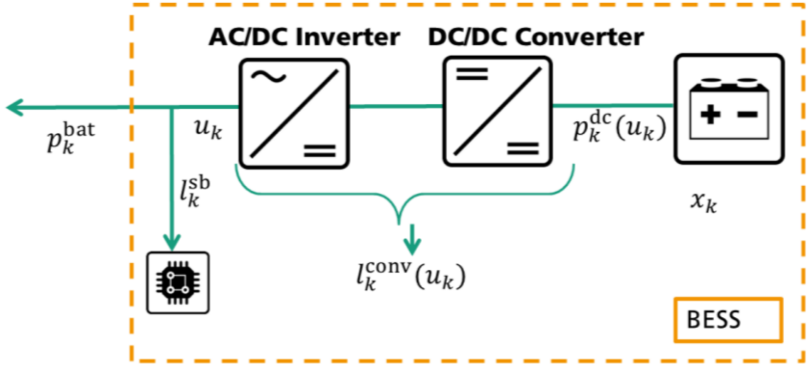


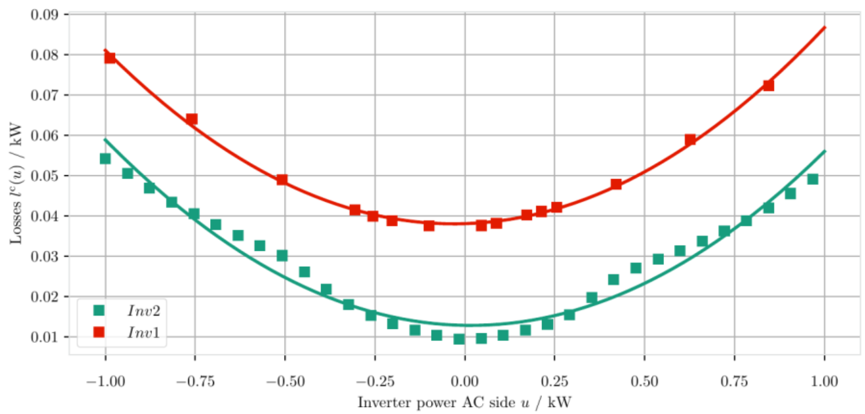
Inverter modeling

Losses due to conversion: non-linear

Standby losses reduced

when converter is switched off





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Sample Case Optimal Policies

System Modeling

Policy evaluation maps measurement to control

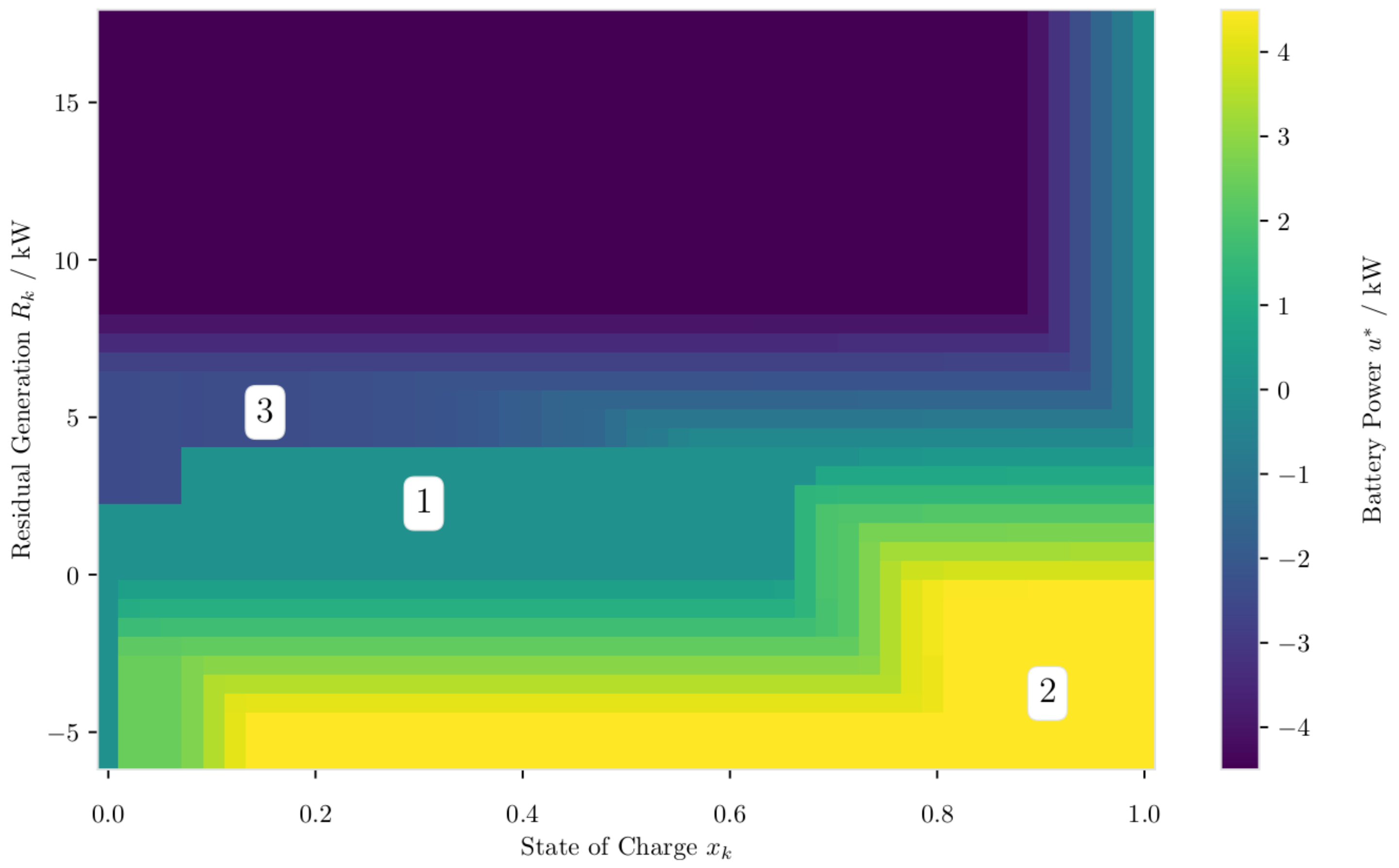
Legend

Yellow: Discharging

Dark Blue: Charging

Exemplary rules for a sunny morning

Charge Battery before curtailment (3)
Do not Charge at low powers (1)
Supply Load from battery (2)



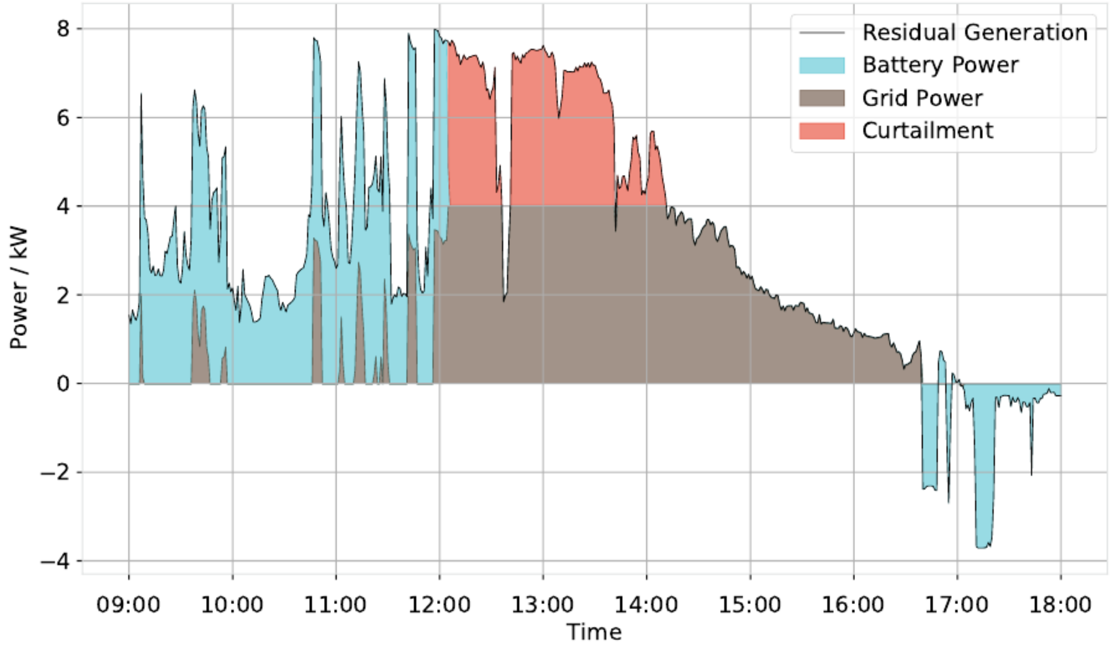
- Policy with 8 kWp PV, 4 kW feed-in limit, 9 kWh battery

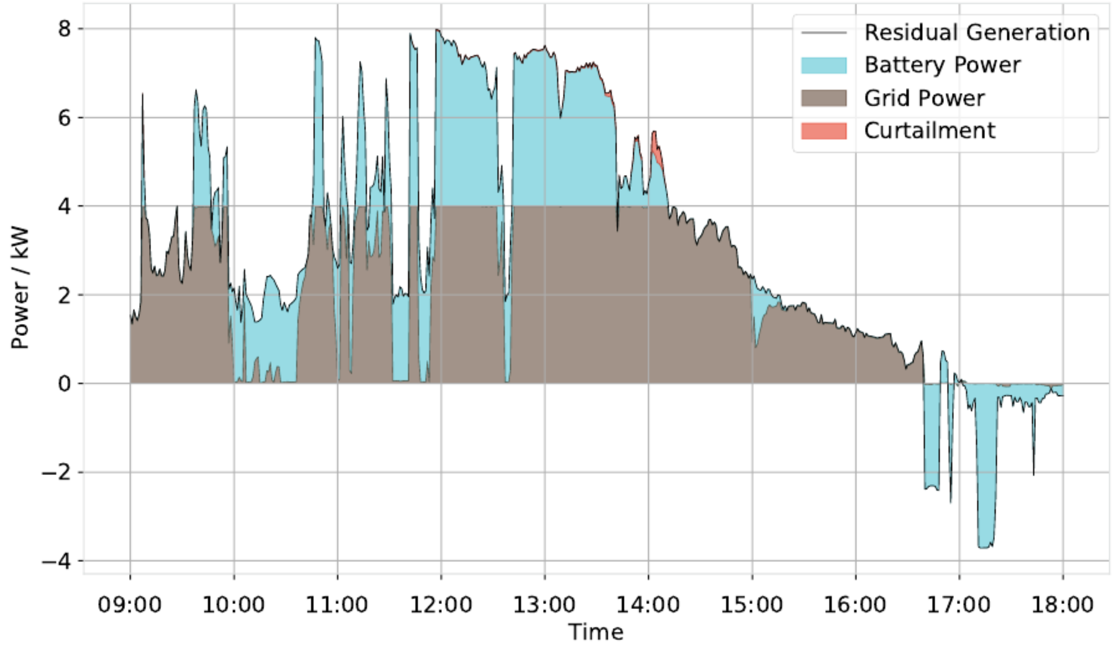
Sample Case: Operation on one day

System Modeling

Curtailment can be reduced

More PV-energy can be integrated into the grid without grid reinforcements





Simulation Setup & Parameter Tuning

Perform a simulation on 4 load / PV combinations

1 kWh battery, 1 kWp PV installation per 1 MWh yearly load

Calculating costs of yearly operation using method X

→ Defining exploited potential

$$\Pi^{\exp}(X) = \frac{C^{\text{el}}(\text{Standard}) - C^{\text{el}}(\text{X})}{C^{\text{el}}(\text{Standard}) - C^{\text{el}}(\text{Ideal})}$$

	Site 1	Site 2	Site 3	Site 4
Energy [kWh]	2225	4662	5700	6507
Night Fraction [%]	40.6	47.6	42.5	55.6
Specific PV Yield [kWh / kWp]	1108	1102	1184	1183
Energy above 50% [kWh / kWp]	107	121	160	165

Compared methods

- Deterministic MPC
- Two-stage Stochastic MPC
- Multi-Stage Stochastic MPC (SDP)
- Heuristic

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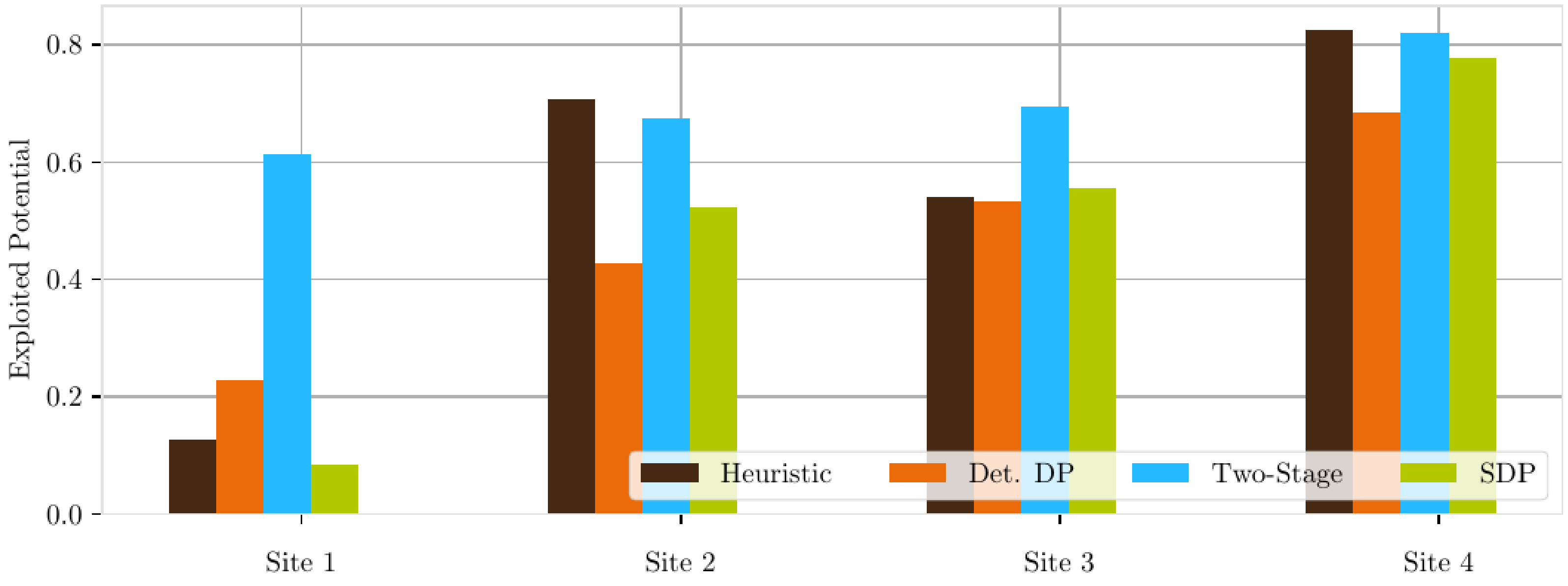
Results of yearlong simulations for 4 households

SDP (green) performs better than deterministic MPC

Simple heuristic better in many cases

Two-stage stochastic MPC performs best in 3/4 cases

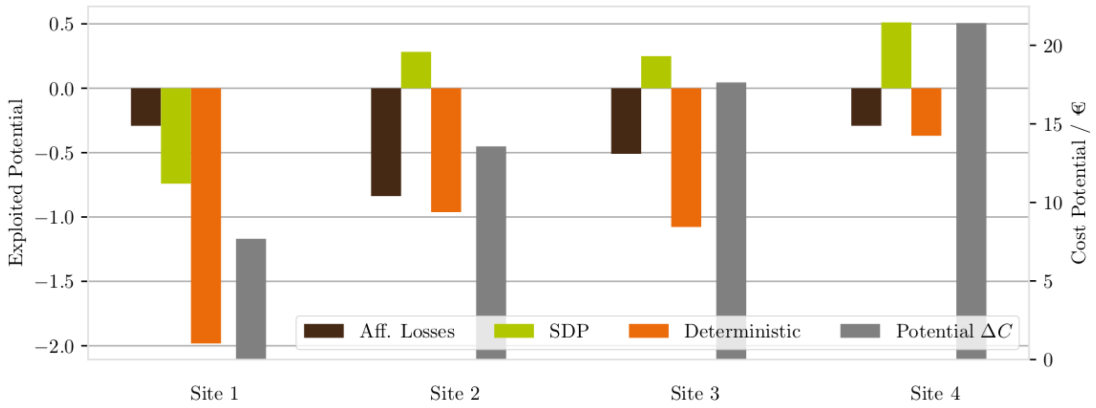


Results from two other application cases

Case 2: Switchable Inverter

No feed-in limit, pure self-sufficiency

Focus on operation at high inverter efficiency

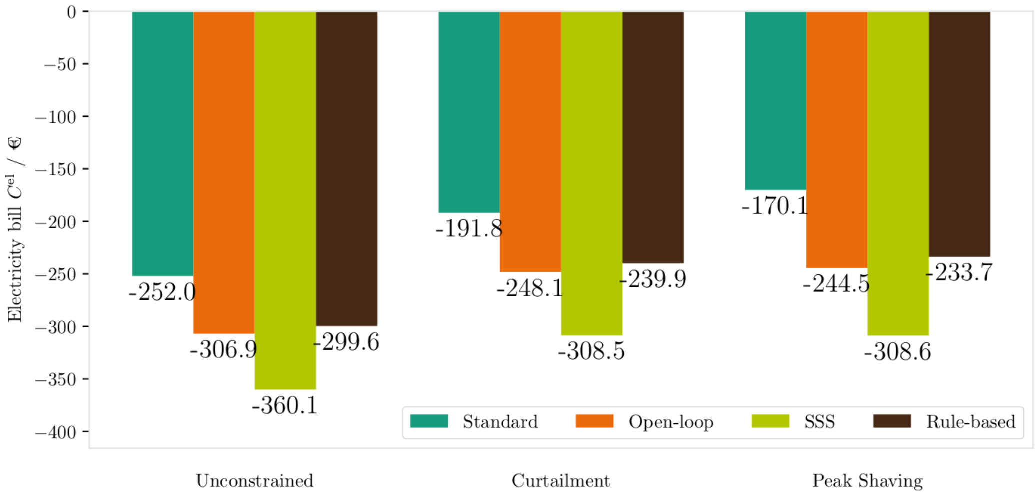


Considering switching and nonlinear losses increases self-sufficiency and reduces costs.

Case 3: Electric Vehicle Charging

Reach high PV-coverage of charging process

Affected by charge limits, PV power, user requests



SDP shows best results

Summary of Contributions

Forecasts and Stochastic Modeling

Stochastic Markov-chain model for residual generation

Maximum likelihood parameter estimation in data

System Modeling for Optimization

Nonlinear losses of power converters

On-Off switches with downtime

Integration in SDP algorithm

Simulation Studies

Studied three application cases: PV-Battery with and without feed-in limit, residential charging of electric vehicles

Lower cost and more renewable energy harvested with stochastic modeling

Software Integration in Real-life Systems

Implemented SDP algorithm in C++ with interfaces to shell, python, and Java

Field tests for PV-battery system (with Varta Storage) and EV-charging (with other team at ISE) showing proof of concept

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- Thank you for your attention