



# The Announcement Effect: The Dependency of Demand Response on Timely Information and the Impact on Efficient System Operation



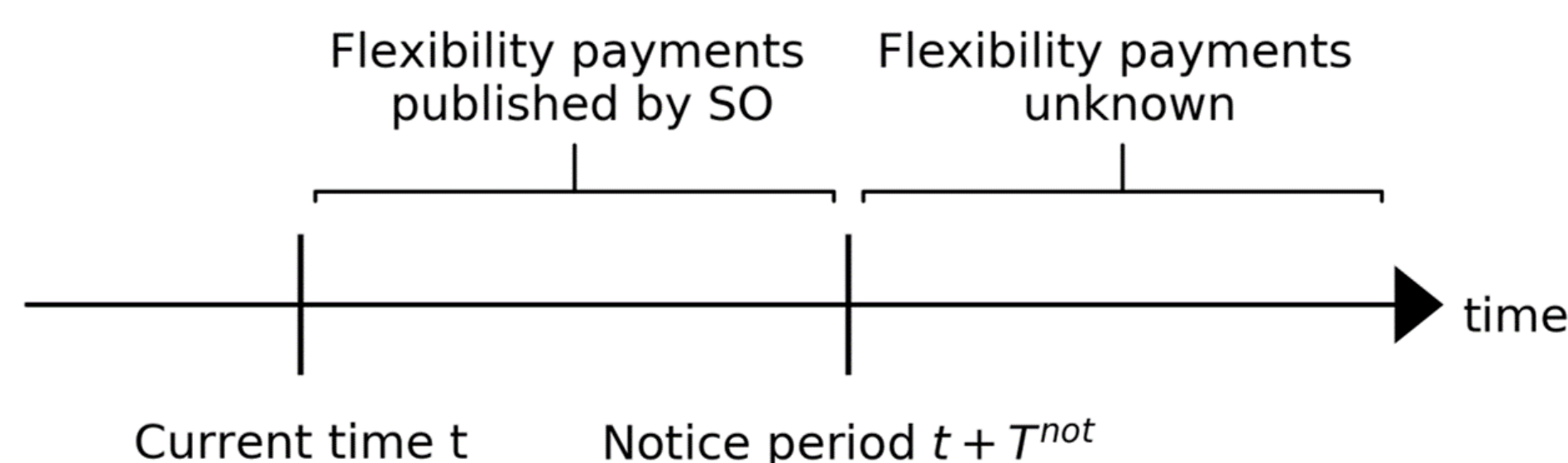
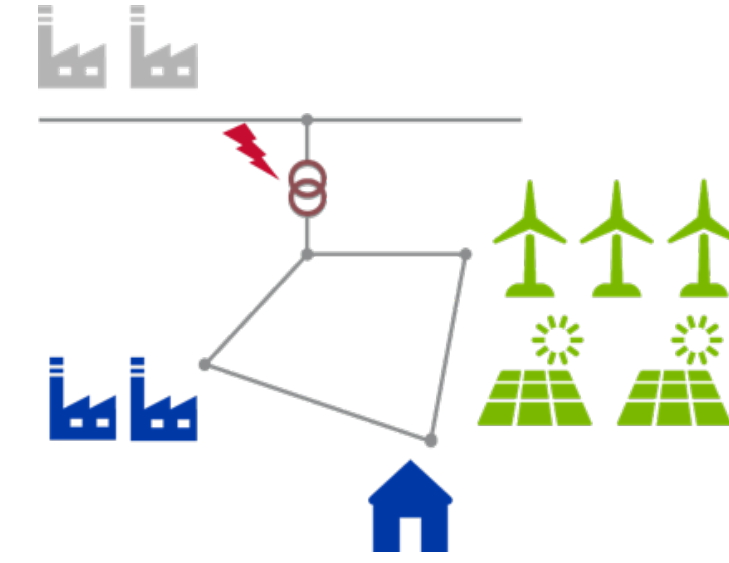
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## Introduction

- Power systems with significant renewable energies often experience system imbalances or congestion.
- System operators (SO) can leverage **Critical Peak Pricing (CPP)**:
- SOs reduce (or increase) retail rates on CP days to incentivize load increase (or reduction) and inform customers in advance.



- In this project, we analyse the application of temporary net price changes for general system operation objectives.
- It is unknown** how much response can be achieved and how net price changes should be efficiently determined.

## Objectives

- We analyze **time- and state-dependent flexibility potentials** of relevant flexible load types.
- We present **guidance for the design of CPP programs**, in particular with regard to net price changes and the notification period for future price changes.

## Methodology

### Approach

- Formulate the SO's optimization problem
- Identify relevant flexible load types
- Formulate the stochastic cost optimization problem of flexible load operators
- Solve and identify optimal policy functions for dispatch
- Analyse dispatch behaviour of relevant load types under different scenarios and parametrization of loads
- Use reinforcement learning to optimize net price changes

## Perspective of the System Operator

### Description

- The SO **minimizes aggregated system operation cost** of incentive payments and curtailment compensations by choosing net price changes  $\Delta p$ .

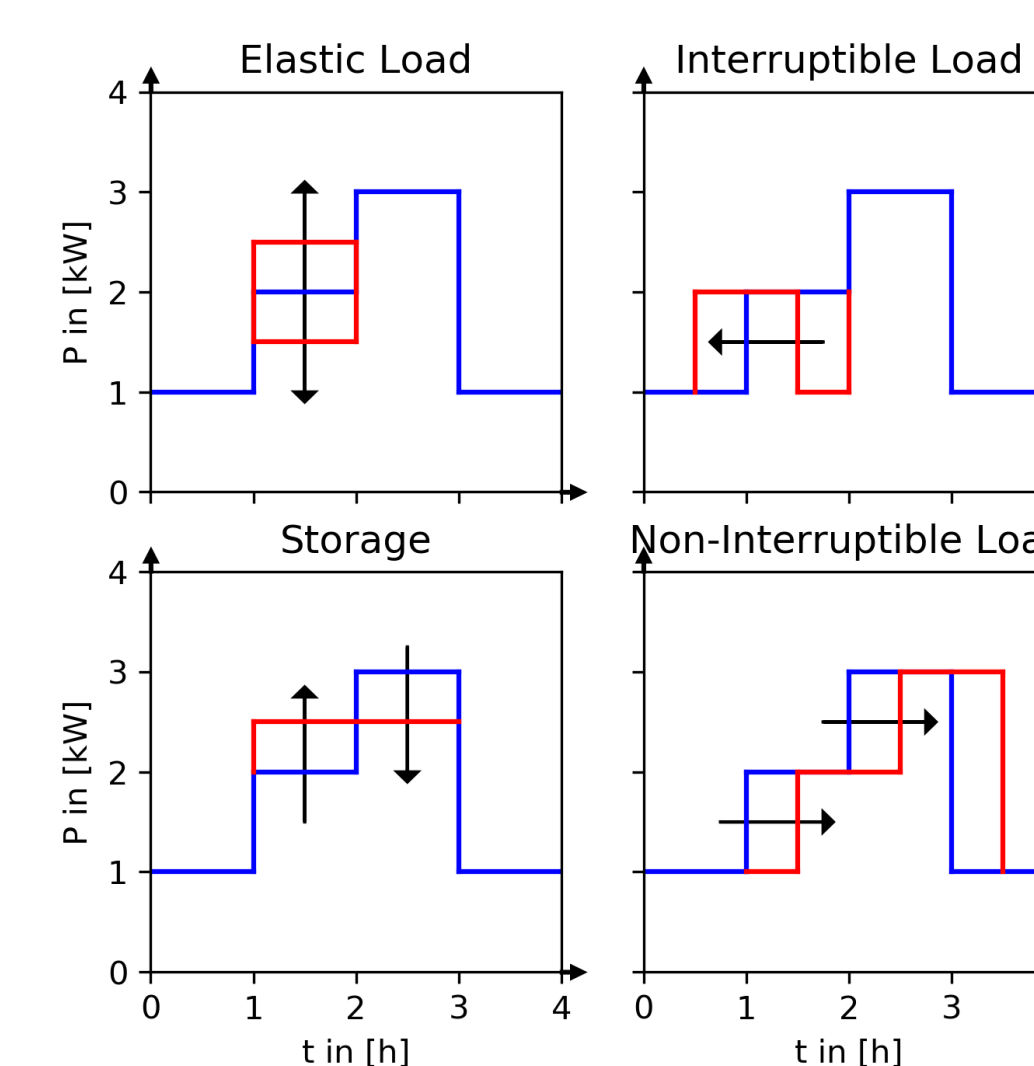
$$\min_{\Delta p} C^{SO}(\Delta p) = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^T \{L_t^{tot} \Delta p_t + \Delta L_t^+ Curt^L + \Delta G_t^+ Curt^G\}$$

$$s.t. DR_t^{tot}(\Delta p_t, \mathbf{x}_t)$$

- $DR_t^{tot}(\Delta p_t, \mathbf{x}_t)$  describes the total demand response of the aggregated system load which is **unknown to the SO**.
- The choice of net price changes is therefore an **optimal control problem under uncertainty**. We model it as a Partially Observable Markov Decision Process (POMDP).
- Data used for case study.** We use congestion data from SH Netz AG for the year 2017 and label congestion events for hours with more than 50 wind generators curtailed.

## Relevant Flexible Load Types

- We select four relevant flexible load types (Barth et al. 2018).
- Consumers minimize electricity costs under price uncertainty.
- We develop a unified optimal control framework** and find optimal policy functions.
- $\mathbf{x}_t$  describes the state of loads (e.g. SOC of a battery) and  $\mathbf{u}_\tau$  their control (e.g. charging):



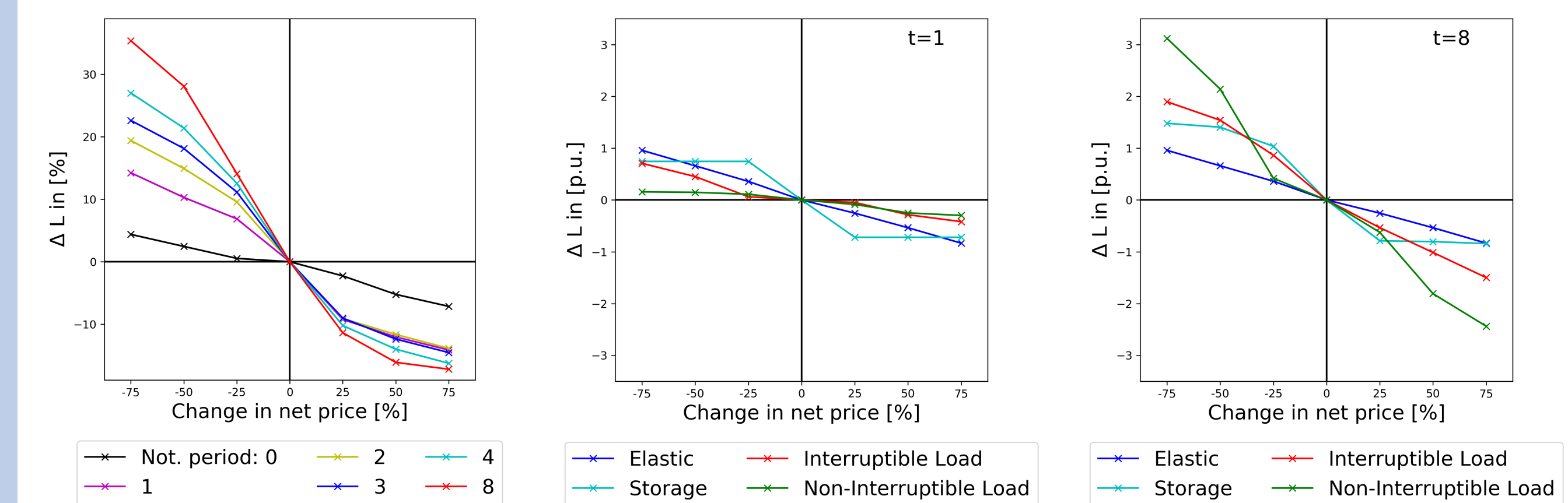
$$\min_{\mathbf{u}_\tau} \mathbb{E}\{C_t(\mathbf{u}_\tau, \mathbf{x}_t, K_t)\} = \min_{\mathbf{u}_\tau} \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E}\left\{\sum_{\tau=t}^{T-1} c_\tau(\mathbf{x}_\tau, \mathbf{u}_\tau)\right\}$$

$$= \min_{\mathbf{u}_\tau} \lim_{T \rightarrow \infty} \frac{1}{T} \left\{ \sum_{\tau=t}^{T-1} (\rho_\tau + \mathbb{E} \Delta p_\tau) [L_\tau(\rho_\tau) + \Delta L_\tau(\mathbf{x}_\tau) \cdot \mathbf{u}_\tau] + \mathbf{b}_\tau \cdot (\Delta L_\tau(\mathbf{x}_\tau) \circ \mathbf{u}_\tau) \right\}$$

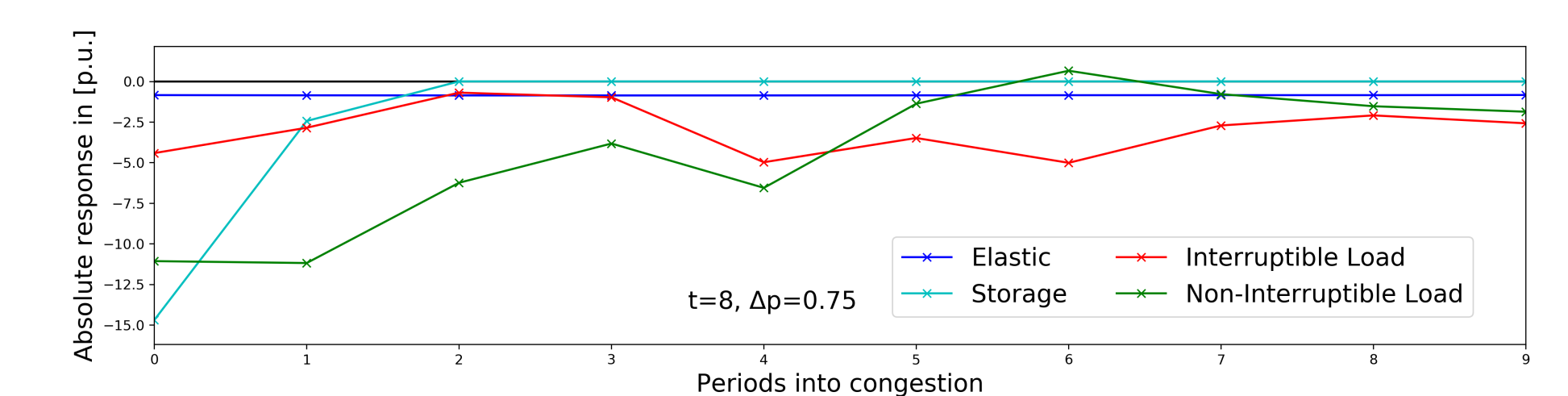
- $\Delta L_\tau$  is the load profile and  $\mathbf{b}_\tau$  the cost of exercising the flexibility. Type-specific technical constraints apply.
- Data used for case study.** We randomly generate a synthetic flexible load portfolio.

## Results

- In general, longer notification periods and higher flexibility payments can increase load elasticity.**
- The aggregated DR supply function **depends on the portfolio of flexibility types** in the system and their parametrization.
- The following DR functions are based on a synthetic flexible load portfolio of six storages, nine interruptible and four non-interruptible loads, and thirteen elastic loads based on German residential and commercial standard load profiles (BDEW 2017).



- The available flexibility potential is **not constant over time**. The following diagram shows responses in the first ten periods into a congestion period.



- Storage is not able to provide flexibility in long congestion periods. Interruptible and shiftable loads can only provide flexibility when their constraints allow for it.

## Outlook

- We will use actual load data to calibrate a load portfolio and run a realistic scenario.
- We will implement different reinforcement learning algorithms with changing parametrization to find the most efficient CPP scheme for the system operator.
- We will evaluate results using social welfare analysis.