

Eichenberg, Jannis; Hobbie, Hannes; Schug, Tizian

Working Paper

Designing Incentive Mechanisms for Grid-Serving Demand-Side Behavior in Transmission Grids: Exploring Market Equilibria through Bi-Level Programming

Suggested Citation: Eichenberg, Jannis; Hobbie, Hannes; Schug, Tizian (2024) : Designing Incentive Mechanisms for Grid-Serving Demand-Side Behavior in Transmission Grids: Exploring Market Equilibria through Bi-Level Programming, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/302046>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Designing Incentive Mechanisms for Grid-Serving Demand-Side Behavior in Transmission Grids: Exploring Market Equilibria through Bi-Level Programming

Jannis Eichenberg^a, Hannes Hobbie^a, Tizian Schug^b

^aTUD Dresden University of Technology, Chair of Energy Economics, Münchner Platz 3, 01069 Dresden, Germany

^bHamburg University of Technology, Institute for Operations Research and Information Systems, Am Schwarzenberg-Campus 4, 21073 Hamburg, Germany

Abstract

Increasing renewable electricity generation and the electrification of industry, mobility, and heating through sector coupling pose significant challenges to grid operators in maintaining secure and reliable system operations. Demand-side sector coupling applications increase electricity demands and stress electricity grids, but they also offer transmission system operators increased flexibility for congestion management. Due to the complexity of directly controlling decentralized demand-side technologies, incentive mechanisms present a promising solution for harnessing demand-side flexibility.

This study investigates various incentive schemes to promote grid-supportive demand-side behavior by developing a bi-level programming framework. The framework models the decision-making processes of key stakeholders, including a TSO, an aggregator, and a market clearing agent, considering model-endogenous wholesale market equilibrium formation and congestion management optimization. The economic efficiency of different design options for grid congestion management is evaluated using an extended IEEE test system applied to a case study of the German electricity transmission system.

The findings highlight the critical importance of time-dynamic premium design concepts due to the variability of renewable generation. While incentive-based market interventions increase electricity market costs and thereby shifting consumer rents to producers, the reduced transmission system operation cost leads to overall gains in total system welfare.

Keywords: OR in energy, Flexibility premium, Bi-level optimisation, Congestion management, Transmission grid

1. Introduction

1.1. Motivation and background

The urgent need to mitigate climate change has driven the transition towards decarbonizing electricity systems in numerous countries worldwide. Central to this transition is the gradual replacement of large-scale fossil fuel generation with small-scale renewable plants, such as rooftop solar photovoltaics and wind turbines, especially when hydropower and bioenergy are limited resources. However, the variable and intermittent nature of electricity generation from solar and wind technologies, combined with potential regional disparities between generation and demand locations, presents significant challenges for operators and market stakeholders in the energy supply chain.

For instance, the German regulator experienced a 1.75-fold increase in congestion management requirements and a nearly threefold rise in congestion management costs due to rapid

fuel price increases over the past five years (see [Bundesnetzagentur \(2024\)](#)). Efficiently integrating renewable sources into electricity systems and addressing the resulting grid congestion from their fluctuating characteristics is therefore crucial for the stable and secure operation of future electricity grids.

In parallel with decarbonizing electricity generation, numerous heating, mobility, and industrial applications are being electrified to reduce greenhouse gas emissions in these sectors. The degree of this electrification varies across countries, depending on their progress in decarbonizing their energy supplies. This shift towards electric-powered applications increases electricity demand beyond conventional levels. Although the operation of these applications adds stress to electricity grids, their demand is typically price-elastic, providing valuable flexibility to system operators. This flexibility supports the integration of renewable energy into the grid, enhancing overall system resilience and efficiency when system operators have access to the applications. Although direct access by grid operators to end-user load applications would significantly improve system operation, it poses challenges due to the associated information and communication requirements and the high legal implications involved.

Email addresses: jannis.eichenberg@tu-dresden.de (Jannis Eichenberg), hannes.hobbie@tu-dresden.de (Hannes Hobbie), tizian.schug@tuhh.de (Tizian Schug)

Instead grid operators could access flexibility load applications indirectly in two main ways. Firstly, regional flexibility markets might become an important alternative for providing operators with sufficient flexible demand-side capacity necessary for congestion management through competitive bidding processes. For a detailed conceptual understanding and technical implications of such market-based provisions, it is referred to [Jin et al. \(2020\)](#) or [Rebenaque et al. \(2023\)](#). Despite the need for more consensus on the exact organization of regional flexibility markets, the concept of aggregators is prominent in the literature in this context (see [Burger et al. \(2017\)](#) or [Kerscher & Arboleya \(2022\)](#)). Aggregators leverage smart-grid applications to have direct, real-time access to the energy loads of end-users — ranging from single households and apartment buildings to small-scale businesses and industrial enterprises. They manage the bundled energy procurement and marketing of flexibility sources, enabling end-users, who generally lack access to wholesale markets, to participate in energy trading. However, designing and operating market platforms for flexibility trading introduces additional complexities for regulators and to system operations, in particular due to its locational characteristic required for handling regional grid constraint.

Alternatively, the flexibility inherent in end-user and industrial applications can be made available to grid operators through incentive-based mechanisms. These mechanisms offer aggregators additional monetary gains for dispatching their customers' load applications in ways that benefit the grid, thereby reducing energy procurement costs and end-user electricity bills. The specific value of such incentives is determined by regulatory measures rather than competitive processes. While this approach simplifies the delivery of flexibility, it may reduce the economic efficiency of flexibility supply due to the lack of competition among suppliers.

1.2. Literature review on incentive-based mechanisms

Given the accelerated decarbonization efforts observed in many countries and advantages that incentive-based mechanisms provide, the literature on incentive-based flexibility provision systems for managing grid congestion has significantly expanded in the recent past.

[Ghaemi et al. \(2023\)](#) use a bi-level program to examine how electrolyzer flexibility can contribute to congestion management in distribution grids. Their case study indicates that congestion pricing effectively encourages investments in electrolyzers while reducing total distribution grid operation and reinforcement costs. [Meyer et al. \(2022\)](#) study three different charging strategies for electric vehicles concerning their implications for the operation of distribution grids. Their findings indicate that charging strategies optimized against time-variable grid charges outperform other strategies in terms of grid load management. Similarly, [Stute & Klobasa \(2024\)](#) investigate various electricity price and grid charging models, focusing on residential consumer electricity procurement

and grid reinforcement costs. The results of their study emphasize the importance of considering both temporal and local variations in price components for effective congestion management. [Godron et al. \(2023\)](#) further emphasize the need to update time-varying price components frequently to prevent inefficiencies resulting from incentivizing undesired grid load behavior when the dynamic side payments are offered throughout larger time windows.

When additional side payments are granted to the owners of flexible load applications at the stage of market clearing, such as dynamic end-user price components, incentivized changes in load behavior can affect the wholesale market clearing results. If flexible demands reach a significant quantity, shifting large amounts of electricity demand can alter wholesale clearing prices, thereby increasing purchase costs. [Avau et al. \(2021\)](#) focus on this aspect of incentive mechanisms and investigate the resulting outcomes regarding grid operation cost, reinforcement requirement, and market outcomes. Their findings indicate that outweighing increases in market cost from market interventions with potential reductions in grid operation costs is essential for designing efficient incentive mechanisms.

Summarizing the findings, incentive-based instruments for grid-serving demand-side behavior constitute a valuable means of supporting grid operators in managing congestion in future distribution grids. However, potential market distortions must be thoroughly considered in the design of such mechanisms to prevent undesired inefficiencies at a system level, particularly if large amounts of flexible load applications are incentivized, which is especially the case in large transmission systems. This requirement highlights the need to incorporate model-endogenous market clearing in the model-based representation of optimizing electricity system models for grid management studies that investigate possible incentive design solutions, as opposed to relying on exogenous market information like in the sources discussed.

1.3. Research contribution

Considering the transition toward renewable-based electricity systems with a growing number of electrified load applications, novel solutions for congestion management must be developed. Incentive-based mechanisms emerge as promising alternatives to market-based ways due to their reduced complexity and the pressing need to decarbonize energy supplies in many countries. Previous research has primarily focused on incentive mechanisms for congestion management in distribution systems. This work proposes a game-theoretic bi-level framework specifically developed to explore regulatory design options for grid-serving incentive mechanisms supporting the operation of transmission grids in a stylized case study. The framework includes model-endogenous congestion management optimization, wholesale market clearing, and aggregator decision-making, adding to existing works in the research landscape. Specifically, this research examines:

- (i) The effects of incentive-based mechanisms on congestion management in electricity transmission systems,
- (ii) The economic efficiency of different design options for mechanisms that incentivize grid-serving load behavior,
- (iii) The interdependencies between incentives for grid management and wholesale market outcomes, and
- (iv) The implications for the future design of congestion management practices in the German transmission system.

The remainder of this paper is organized as follows: Section 2 introduces an electricity market modeling framework used to evaluate various incentive-based congestion management strategies. Section 3 presents a case study based on an IEEE test system, adapted to reflect the future German generation infrastructure, and outlines different premium-based incentives for mitigating grid congestion. In Section 4, market outcomes are assessed to derive implications regarding the efficiency of the different incentive instruments, initially at a system level, and subsequently, the impact on different market stakeholders is discussed. Finally, Section 5 offers insights into the efficient design of future congestion management regulations relevant to German policymakers and, more broadly, renewable-dominated electricity supply systems.

2. Methodology

Modeling electricity systems can be approached in numerous ways, taking into account the various regulation alternatives and market clearing principles used across wholesale electricity markets. This modeling framework presents a stylized setting aligned with German market principles.

2.1. Modelling framework

First, a zonal market clearing and redispatch problem are formulated and sequentially solved (section 2.2). This model simulates market clearing and congestion management based on the current market design in Germany, providing insights into how alternative, incentive-based market designs can impact market outcomes. In this model, a central market clearing agent aims to minimize costs by controlling not only the generation dispatch, but also the dispatch of flexible demands. The result is an optimal solution that is equivalent to what would happen if individual aggregators minimized their own procurement costs. With the future electricity system expected to feature significant amounts of flexible demand-side technologies due to sector coupling, section 2.3 details the modeling of these flexible demand-side applications used in the mentioned model and explains how flexibility is used to minimize corresponding procurement costs.

Given the objective of this work to explore incentive mechanisms for grid-serving demand behavior, the modeling

framework is extended to include the decision-making processes for designing efficient grid load incentives. Generally, incentive mechanisms can be implemented at different energy trading stages: before, during, or after day-ahead market clearing. This work assumes incentives are provided to market stakeholders before the market clearing stage, close to current policies, e.g., dynamic electricity tariff components. To enable incentivized flexible dispatching, which diverges from a purely market-optimized approach, an aggregator is introduced as a new actor. The aggregator can be conceptualized as a collective of competitors operating in a purely rational manner, which allows for its implementation as a single actor. It can respond to given incentives while adhering to flexibility constraints introduced in section 2.3. This extended framework (section 2.4) enhances the market clearing and redispatch problem by integrating regulatory decisions and is described using a game-theoretic Stackelberg framework formulated as a bi-level program.

Capital letters denote model-endogenous decisions in all mathematical expressions, while parametric inputs are represented differently. Superscripts identify the actor controlling specific variables or further specify model entities. Greek letters are used for dual variables.

2.2. Model I - Sequential linear optimization

Zonal market clearing problem

The following model represents a market clearing agent (mca) responsible for determining the least-cost generation dispatch to satisfy all demands. For enhanced comprehension, the model's equations and inequalities have been simplified to their essentials, following standard textbook formulations:

$$\min C^d = \sum_{p,t} G_{p,t}^{mca} \cdot oc_p \quad (i.1)$$

s.t.

$$\sum_n d_{n,t} + \sum_{n'} H_{n',t}^{mca} - \sum_p G_{p,t}^{mca} = 0 \quad : \Pi_t^{mc} \quad \forall t \quad (i.2)$$

$$0 \leq G_{p,t}^{mca} \leq c_{p,t}^G \quad \forall p, t \quad (i.3)$$

$$0 \leq H_{n',t}^{mca} \leq c_{n'}^H \quad \forall n', t \quad (i.4)$$

$$dem_{n',t}^H - \epsilon \leq \sum_{i \leq t} H_{n',i}^{mca} \leq dem_{n',t}^H + \epsilon \quad \forall n', t \quad (i.5)$$

The objective function (i.1) determines the cost-minimizing dispatch, $G_{p,t}^{mca}$, over all time steps $t \in T$ and power generating units $p \in P$, considering their corresponding generation costs oc_p . The energy balance (i.2) ensures that, for all $t \in T$, the inflexible demand $d_{n,t}$ plus the flexible demand $H_{n',t}^{mca}$ is met across all nodes $n \in N$ and the nodes associated with flexible demands $n' \in N' \subset N$. Constraint (i.3) limits the generated

Nomenclature

Sets

$l \in L$	Power lines
$n \in N$	Grid nodes
$n' \in N'$	Nodes with heat pumps ($N' \subset N$)
$p \in P$	Plants
$reg \in REG$	Regions
$t \in T$	Time steps

Scalars

ϵ	Flexibility constraint
$\hat{\epsilon}$	Incentive enhancement factor
m	Some large positive constant

Parameters

$c_{p,t}^G$	Available generation capacity
$c_{n'}^H$	Heat pump limit
c_l^{th}	Thermal line capacity
$d_{n,t}$	Fix electricity demand
$dem_{n',t}^H$	Heat pump energy demand

$g_{p,t}^{mca,*}$	Power generation (market equilibrium)
$h_{n',t}^{mca,*}$	Heat pump dispatch (market equilibrium)
oc_p	Operational cost
$ptdf_{l,n}$	Power transfer distribution factors
$slp_{n',t}^H$	Standard load profile
$u_{n',t}$	Noise

Primal variables

C^{agg}	Total aggregator costs
C^{cm}	Total congestion management cost
C^d	Total dispatch cost
C^{flex}	Total flexibility cost
C^{rd}	Total redispatch cost
$DEM_{n',t}^{H^{mca}}$	Heat pump endogenous demand (market clearing agent)
$F_{reg,t}^{P^{iso}}$	Flexibility premium
$G_{p,t}^{mca}$	Power generation

$G_{p,t}^{iso,+}, G_{p,t}^{iso,-}$	Pos./neg. redispatch
$H_{n',t}^{agg}$	Heat pump dispatch (aggregator)
$H_{n',t}^{mca}$	Heat pump dispatch (market clearing agent)
$H_{n',t}^{iso,+}, H_{n',t}^{iso,-}$	Heat pump in-/decrease
$LF_{l,t}$	Line flow
$NI_{n,t}$	Nodal injection

Dual variables

$\bar{o}_{p,t}, \underline{o}_{p,t}$	Power generation constraints
Π_t^{mc}	market clearing price
$\bar{\eta}_{n',t}, \underline{\eta}_{n',t}$	Heat pump limit constraints
$\bar{\theta}_{n',t}, \underline{\theta}_{n',t}$	Heat pump flexibility constraints

Binary variables

$B_{n',t}^{\bar{\eta}}, B_{n',t}^{\underline{\eta}}$	Disjunctive heat pump limit constraints
--	---

electricity of each power plant in each time step to its available capacity $c_{p,t}^G$. Equations (i.4) and (i.5) describe the modeling of the characteristics of flexible demands (see section 2.3). The (zonal) market clearing price in each time step, Π_t^{mc} , is derived from the dual variable of the energy balance (i.2).

It should be noted that grid restrictions are not yet taken into account at this stage of computing the market equilibrium according to market principles. Consequently, the resulting power plant dispatch might lead to grid congestion when realizing power grid injection, resolved in subsequent congestion management optimization.

Congestion management problem

The equilibrium power plant dispatch and activation of flexible load applications serve as inputs for the congestion management optimization. The following system of equations and inequalities represents the optimization problem of a transmission system operator (tso), who adjusts the market clearing dispatch considering load flow constraints in a cost-minimizing manner subsequently to the market clearing, commonly referred to as redispatch:

$$\min C^{rd} = \sum_{p,t} (G_{p,t}^{iso,+} - G_{p,t}^{iso,-}) \cdot oc_p \quad (i.6)$$

s.t.

$$\sum_{p(n)} (g_{p,t}^{mca,*} + G_{p,t}^{iso,+} - G_{p,t}^{iso,-})$$

$$\begin{aligned} & - h_{n',t}^{mca,*} - H_{n',t}^{iso,+} + H_{n',t}^{iso,-} \\ & - d_{n,t} - NI_{n,t} = 0 \quad \forall n, t \quad (i.7) \end{aligned}$$

$$\sum_n NI_{n,t} = 0 \quad \forall t \quad (i.8)$$

$$LF_{l,t} = \sum_n (NI_{n,t} \cdot ptdf_{l,n}) \quad \forall l, t \quad (i.9)$$

$$- c_l^{th} \leq LF_{l,t} \leq c_l^{th} \quad \forall l, t \quad (i.10)$$

$$0 \leq G_{p,t}^{iso,+} \leq c_{p,t}^G - g_{p,t}^{mca,*} \quad \forall p, t \quad (i.11)$$

$$0 \leq G_{p,t}^{iso,-} \leq g_{p,t}^{mca,*} \quad \forall p, t \quad (i.12)$$

$$0 \leq h_{n',t}^{mca,*} + H_{n',t}^{iso,+} - H_{n',t}^{iso,-} \leq c_{n'}^H \quad \forall n', t \quad (i.13)$$

$$\begin{aligned} & dem_{n',t}^H - \epsilon \leq \sum_{\hat{t} \leq t} (h_{n',\hat{t}}^{mca,*} + H_{n',\hat{t}}^{iso,+} - H_{n',\hat{t}}^{iso,-}) \\ & \leq dem_{n',t}^H + \epsilon \quad \forall n', t \quad (i.14) \end{aligned}$$

Power flow constraints are imposed by incorporating a transmission topology network and adding power flows resulting from power injection at each node using a DC load flow approximation. The nodal injection $NI_{n,t}$ is computed by subtracting the demands from the market clearing dispatch $g_{p,t}^{mca,*}$ assigned to each node n and in each time step t (i.7). Generation dispatch can be adjusted through simultaneous positive redispatch ($G_{p,t}^{iso,+}$) and negative redispatch ($G_{p,t}^{iso,-}$) of generation quantities or by temporal load shifting ($H_{n',t}^{iso,+}, H_{n',t}^{iso,-}$). Constraint (i.8) ensures a balanced system-wide energy balance.

Power transfer distribution factors (PTDF) are used to compute line flows $LF_{l,t}$ on each line l and in each time step t , resulting from the nodal injections (i.9). Line flows are constrained by line-specific thermal transfer capacities (i.10).

Constraints (i.11), (i.12), (i.13), and (i.14) restrict the use of redispatch and load shifting capacities according to their market dispatch. For a detailed description of the modelling of load shifting (i.14) it is referred to section 2.3. The objective function (i.6) aims to minimize only redispatch costs based on the incremental fuel cost of the power generating units considered, without explicit cost components for load-shifting. However, these are indirectly included via inter-temporal redispatch considerations. For enhanced comprehension, the following example is provided.

Example 2.1. Any load shift from time step t_i to t_j necessitates a corresponding generation redispatch to maintain the system-wide energy balance (i.8). Specifically, if the TSO reduces the load in t_i ($H_{n',t_i}^{tso,-} > 0$), a simultaneous negative redispatch ($G_{p,t_i}^{tso,-} > 0$) is required to preserve power equality. Conversely, if the TSO increases the load at t_j ($H_{n',t_j}^{tso,+} > 0$), a positive redispatch ($G_{p,t_j}^{tso,+} > 0$) is necessary to meet the additional load in t_j . Thus, load shifting indirectly contributes to the objective function value through the incremental fuel cost of conventional generators associated with the inter-temporal redispatch. The TSO evaluates the economic implications of both conventional redispatch and load shifting, selecting the most economically advantageous alternative.

2.3. Modeling of demand side flexibility

This study explores incentive mechanisms for providing flexibility in load applications connected to lower-voltage grids (eqs. i.4-i.5), which are then made available to transmission system operators (eqs. i.13-i.14). These applications are grouped into a technological aggregate and managed by aggregators as a bundle. The following sections detail the modeling of demand-side flexibility used in this research. Flexible load applications cannot be dispatched entirely flexibly. For example, interruptions in operating heat supply technologies, such as heat pumps, may result in comfort losses. The model-based representation of load applications considers operational constraints to account for these limitations, utilizing a flexibility corridor derived from the application's standard load profile. While heat pumps are the primary example of a flexible load application, the methodology introduced here can be easily applied to other flexible demand-side technologies.

Definition of standard load profiles

The grid model distinguishes between various heat pump pools across different nodes. The subset $N' \subset N$ represents all nodes where demand can be partially flexibilized. The standard load profile for a heat pump, $slp_{n',t}^H$, is based on Hartmann

et al. (2003) and is used to calculate the power consumption of heat pumps aggregated as a pool per node. Each aggregated pool consists of an exogenous demand component and a flexible share, the latter of which is determined by model-endogenous optimization. The exogenous components are calculated by summing the aggregated standard load profile over all time steps \hat{t} until each time step t at each node:

$$dem_{n',t}^H := \sum_{\hat{t} \leq t} slp_{n',\hat{t}}^H \quad \forall n', t. \quad (1)$$

Figure 1 illustrates the operational characteristics of the heat pump pool at an exemplary transmission grid node. The red line displays the aggregated standard load profile, while the dashed black line represents the total electricity consumption (1).

Introduction of flexibility constraints

The following introduces constraints that describe the flexible components of the heat pump demand tied to the standard load profile. The dispatch of each pool of heat pumps, $H_{n',t}^{mca}$, is constrained by its electrical power capacity $c_{n'}^H \in \mathbb{R}^+$ at each node and in each time step:

$$0 \leq H_{n',t}^{mca} \leq c_{n'}^H \quad \forall n', t \quad (2)$$

To allow for flexible dispatch within a defined range, a corridor based on the summation of the standard load profile (1) is introduced. Within these boundaries, the heat pump can be dispatched flexibly

$$dem_{n',t}^H - \epsilon \leq \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca} \leq dem_{n',t}^H + \epsilon \quad \forall n', t \quad (3)$$

where the scalar $\epsilon \in \mathbb{R}^+$ denotes the boundaries of the corridor. In simple terms, these boundaries determine the maximal duration of operation interruption that is considered feasible for avoiding any reduction in the utility resulting from applying the technical application, e.g., comfort losses.

Figure 2 displays the model-endogenous dispatch of the aggregated heat pump pool after solving the market clearing problem, to illustrate how the market's driving forces affect the dispatch of flexible applications. The blue area surrounding the total electricity consumption (black dashed line) describes the flexibility corridor. The dashed blue line represents the model-endogenous market clearing price (dual value of energy balance). The dashed red line refers to the flexible dispatch of the heat pump pool constrained by the flexibility corridor. Note that $DEM_{n',t}^{H^{mca}} := \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca}$ in Figure 2 for improved readability.

The following three observations explain how the flexibility inherent to the heat pump pool can minimize the aggregator's electricity purchase costs:

1. Prices are at a local maximum \rightarrow electricity consumption is at the lower bound.

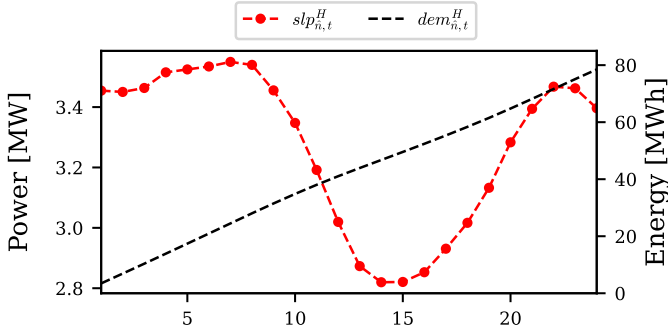


Figure 1: Standard load profile and total electricity consumption for aggregated pool of heat pumps located at node \hat{n} (24 hours extraction).

2. Prices are low \rightarrow electricity consumption increases toward the upper bound.
3. Prices rise to a local maximum \rightarrow electricity consumption decreases again.

The model-endogenous optimization of the heat pump dispatch yields a deviation of the dispatch profile from the standard load profile. The wholesale electricity price formation drives this deviation which minimizes the aggregator's electricity purchase costs to supply his customers with electricity.

This study, however, explores the potential for utilizing the flexibility of the aggregated pool in a grid-serving capacity, potentially diverging from the cost-minimal dispatch. This deviation may be initiated through a direct control signal as seen in *Model I* (section 2.2) or by an offered incentive, reducing the purchasing costs in otherwise more expensive hours (*Model II*, section 2.4). In both cases, the aforementioned flexibility constraints must still be observed.

2.4. Model II - Bi-level modeling framework

The following model extends the sequential market clearing and congestion management problem, see section 2.2, by incorporating model-endogenous aggregator optimization and incentive design. The modeling framework includes three players whose decision levels feature a nested structure. At the upper-level, the TSO optimizes all grid congestion resulting from the market clearing dispatch. The lower-level players comprise the market clearing agent and the aggregator. This bi-level framework allows for studying different incentive mechanism design options, considering the aggregator's reactions and their implications for grid operation. Figure 3 illustrates the decision levels and players involved.

2.4.1. Upper-level problem

The upper-level represents the decision-making process of a regulated TSO responsible for grid operation. To resolve grid congestion, the TSO has two options:

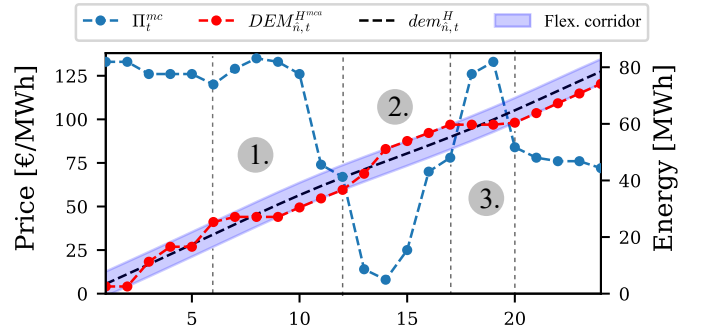


Figure 2: Flexibility corridor utilization vs. market clearing price at node \hat{n} (24 hours extraction).

1. Adjust the market clearing dispatch of conventional generators through simultaneous redispatch. This action only impacts the supply side and does not alter the dispatch of heat pumps. The cost associated with conventional redispatch, C^{rd} , is similar to that in *Model I* (see eq. (i.6)):

$$C^{rd} := \sum_{p,t} (G_{p,t}^{tso,+} - G_{p,t}^{tso,-}) \cdot oc_p \quad (\text{ii.1})$$

2. Pay a premium to the aggregator to incentivize load-shifting in a manner that serves the grid. The cost for this flexibility provision, C^{flex} , depends on the incentivized load-shifting quantities and the corresponding premium:

$$C^{flex} := \sum_{n',t} H_{n',t}^{agg} \cdot FP_{reg(n'),t}^{tso} \quad (\text{ii.2})$$

The premium paid can be considered a time- and region-varying price component that reduces the aggregator's wholesale cost

$$FP_{reg,t}^{tso} \geq 0 \quad (\text{ii.3})$$

and which is defined over all regions $reg \in REG$ and time steps $t \in T$, with each node mapped to a specific region

$$reg : N \rightarrow REG; \quad n \mapsto reg(n). \quad (\text{ii.4})$$

The objective function of the upper-level problem (ii.5) minimizes the total congestion management costs resulting from conventional redispatch and flexibility provision:

$$\min C^{cm} := C^{rd} + C^{flex} \quad (\text{ii.5})$$

s.t.

$$\sum_{p(n)} (G_{p,t}^{mca} + G_{p,t}^{tso,+} - G_{p,t}^{tso,-}) - H_{n'(n),t}^{agg} \quad (\text{ii.6})$$

$$-d_{n,t} - NI_{n,t} = 0 \quad \forall n, t \quad (\text{ii.6})$$

$$\sum_n NI_{n,t} = 0 \quad \forall t \quad (\text{ii.7})$$

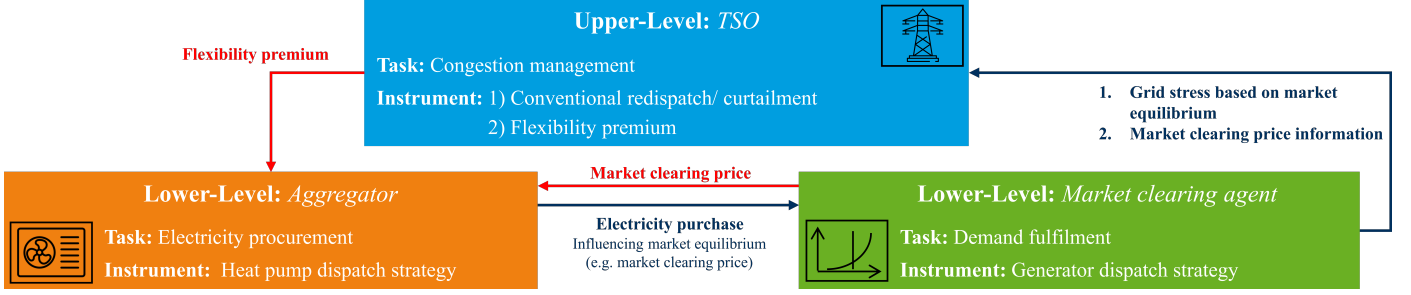


Figure 3: Bi-level modeling framework for incentive-based congestion management via flexibility premiums: Financial incentives intersect with market clearing prices (red).

$$LF_{l,t} = \sum_n (NI_{n,t} \cdot ptdf_{l,n}) \quad \forall l, t \quad (\text{ii.8})$$

$$-c_l^{th} \leq LF_{l,t} \leq c_l^{th} \quad \forall l, t \quad (\text{ii.9})$$

$$0 \leq G_{p,t}^{tso,+} \leq c_{p,t}^G - G_{p,t}^{mca} \quad \forall p, t \quad (\text{ii.10})$$

$$0 \leq G_{p,t}^{tso,-} \leq G_{p,t}^{mca} \quad \forall p, t \quad (\text{ii.11})$$

Constraints (ii.7), (ii.8), (ii.9), (ii.10), and (ii.11) remain unchanged compared to the congestion management problem formulated in *Model I* (see section 2.2). The main difference in this model version is that generation and heat pump dispatch are no longer parameters but variables controlled by the associated lower-level players. Since the grid-serving operation of the heat pumps is now incentivized by the TSO during the market clearing stage, the load-shifting variables in the nodal energy balance (ii.6) are no longer controlled by the TSO. Therefore, this model version has no positive and negative adjustment variables for the heat pump redispatch.

2.4.2. Lower-level problems

Aggregator

The following system of equations and inequalities represents the decision process of the aggregator who minimizes his energy procurement costs, whereby dual variables are presented at the right hand side of the constraints in greek letters:

$$\min C^{agg} = \sum_{n',t} H_{n',t}^{agg} \cdot (\Pi_t^{mc} - FP_{reg(n'),t}^{tso}) \quad (\text{ii.12})$$

s.t.

$$0 \leq H_{n',t}^{agg} \leq c_{n'}^H \quad : \eta_{n',t}, \bar{\eta}_{n',t} \quad \forall n', t \quad (\text{ii.13})$$

$$dem_{n',t}^H - \epsilon \leq \sum_{i \leq t} H_{n',i}^{mca} \leq dem_{n',t}^H + \epsilon \quad : \theta_{n',t}, \bar{\theta}_{n',t} \quad \forall n', t \quad (\text{ii.14})$$

The aggregator's objective function includes the wholesale market procurement cost based on the time-varying market clearing price Π_t^{mc} and flexibility provision revenues based on the flexibility premium $FP_{reg(n'),t}^{tso}$ (ii.12). These revenues reduce

the total procurement cost, whilst incentivizing a grid-serving dispatch of flexible load applications, assuming rational behavior that leads to a cost-minimizing purchase strategy. However, the dispatch of the aggregated pool of heat pumps is still subject to the flexibility constraints outlined in section 2.3, specifically eqs. (ii.13)-(ii.14).

Market clearing agent

During market clearing, the operator aims to dispatch generators cost-minimizing to meet all inflexible electricity demands and align with the aggregator's procurement strategy. The following system of equations and inequalities represents the optimization problem of the clearing agent:

$$\min C^d = \sum_{p,t} G_{p,t}^{mca} \cdot oc_p \quad (\text{ii.15})$$

s.t.

$$0 \leq G_{p,t}^{mca} \leq c_{p,t}^G \quad : \varrho_{p,t}, \bar{\varrho}_{p,t} \quad \forall p, t \quad (\text{ii.16})$$

$$\sum_n d_{n,t} + \sum_{n'} H_{n',t}^{agg} - \sum_p G_{p,t}^{mca} = 0 \quad : \Pi_t^{mc} \quad \forall t \quad (\text{ii.17})$$

The generation dispatch is constrained by the available generation capacity (ii.16). The total generation must satisfy all demands in the power balance (ii.17). Since the operation of heat pumps across the nodes, $\sum_{n'} H_{n',t}^{agg}$, is now a decision variable in the aggregator's optimization problem, affected by the incentives provided by the TSO, the flexible demand levels may differ from those observed in *Model I* (see section 2.2). Depending on the TSO's incentivization strategy to handle grid congestion, wholesale market outcomes may be altered, influencing market prices Π_t^{mc} .

2.5. Reformulation of bi-level problem into MILP

The bi-level problem cannot be solved with ordinary MIP solvers due to its nested structure and several non-linearities in its current form. For these reasons, the following illustrates how the bi-level program is reformulated into a mixed-integer linear program that can be solved with greater ease.

2.5.1. Reformulation procedure

The reformulation breaks down into two essential steps:

1. *MPEC formulation:* First, both lower-level problems are reformulated using their corresponding Karush-Kuhn-Tucker (KKT) conditions, rendering two mixed complementary problems (MCP). By incorporating the MCPs into the upper-level constraints, a mathematical problem with equilibrium constraints (MPEC) is obtained. Due to the convexity of the two lower-level objectives and the linearity of their corresponding constraints, their constraint qualifications hold. Consequently, the KKTs are necessary and sufficient, ensuring optimality of the lower-level problems. For a detailed description, it is referred to [Gabriel et al. \(2013, Chapter 2.8\)](#).
2. *MILP formulation:* Then, the complementary slackness conditions (associated with the MCPs) are linearized using a big-M approach, and the strong duality theorem is applied to express the remaining bilinear terms through a linear combination. See [Gabriel et al. \(2013, Chapter 6.4\)](#) for comprehensive understanding.

The bi-level problem proposed here is ill-posed due to the non-unique solution set of the aggregator's optimization problem (see [Appendix A](#) for illustration). Thus, solving the reformulated single-level problem yields optimal lower-level solutions concerning the upper-level objective function, commonly referred to as *optimistic approach* (see, e.g., [Zemkoho \(2016\)](#) for a detailed description). This may alter the comparability of the results computed in different model runs regarding the incentive mechanism design options investigated in the case study conducted here (see section 3). Regularization techniques are applied to mitigate such optimistic bias artifacts, outlined in [Appendix A](#).

2.5.2. MPEC formulation

The lower-level problems expressed as MCPs are obtained by taking the first-order conditions of their corresponding Lagrangian functions together with their associated complementary slackness conditions, as follows.

Aggregator

The Lagrangian function of the aggregator's optimization problem has the following form:

$$\begin{aligned} \mathcal{L}^{agg} = & C^{agg} + \sum_{n',t} \left(-H_{n',t}^{agg} \cdot \underline{\eta}_{n',t} - \left(c_{n',t}^H - H_{n',t}^{agg} \right) \cdot \bar{\eta}_{n',t} \right) \\ & - \epsilon \cdot \left(\bar{\theta}_{n',t} + \theta_{n',t} \right) + \left(dem_{n',t}^H - \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{agg} \right) \cdot \left(\theta_{n',t} - \bar{\theta}_{n',t} \right) \end{aligned} \quad (\text{ii.18})$$

- a) with first-order condition, $\forall n', t$

$$\frac{\partial \mathcal{L}^{agg}}{\partial H_{n',t}^{agg}} = \Pi_t^{mc} - F P_{reg,t}^{lso} - \underline{\eta}_{n',t} + \bar{\eta}_{n',t} + \sum_{\hat{t} \geq t} \left(\bar{\theta}_{n',\hat{t}} - \theta_{n',\hat{t}} \right) = 0 \quad (\text{ii.19})$$

- b) and complementary slackness conditions

$$0 \leq H_{n',t}^{agg} \quad \perp \quad \underline{\eta}_{n',t} \geq 0 \quad \forall n', t \quad (\text{ii.20})$$

$$0 \leq c_{n',t}^H - H_{n',t}^{agg} \quad \perp \quad \bar{\eta}_{n',t} \geq 0 \quad \forall n', t \quad (\text{ii.21})$$

$$0 \leq -dem_{n',t}^H + \epsilon + \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca} \quad \perp \quad \theta_{n',t} \geq 0 \quad \forall n', t \quad (\text{ii.22})$$

$$0 \leq dem_{n',t}^H + \epsilon - \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca} \quad \perp \quad \bar{\theta}_{n',t} \geq 0 \quad \forall n', t \quad (\text{ii.23})$$

Market clearing agent

The Lagrangian function of the market clearing agent's optimization problem is as follows:

$$\begin{aligned} \mathcal{L}^{mca} = & C^d + \sum_{p,t} \left(-G_{p,t}^{mca} \cdot \underline{q}_{p,t} - \left(c_{p,t}^G - G_{p,t}^{mca} \right) \cdot \bar{o}_{p,t} \right) \\ & + \sum_t \left(\sum_n d_{n,t} + \sum_{n'} H_{n',t}^{mca} - \sum_p G_{p,t}^{mca} \right) \cdot \Pi_t^{mc} \end{aligned} \quad (\text{ii.24})$$

- a) with first-order condition, $\forall p, t$

$$\frac{\partial \mathcal{L}^{mca}}{\partial G_{p,t}^{mca}} = oc_p - \Pi_t^{mc} - \underline{q}_{p,t} + \bar{o}_{p,t} = 0 \quad (\text{ii.25})$$

- b) and complementary slackness conditions

$$0 \leq G_{p,t}^{mca} \quad \perp \quad \underline{q}_{p,t} \geq 0 \quad \forall p, t \quad (\text{ii.26})$$

$$0 \leq c_{p,t}^G - G_{p,t}^{mca} \quad \perp \quad \bar{o}_{p,t} \geq 0 \quad \forall p, t \quad (\text{ii.27})$$

$$0 = \sum_n d_{n,t} + \sum_{n'} H_{n',t}^{mca} - \sum_p G_{p,t}^{mca} \quad \perp \quad \Pi_t^{mc} \geq 0 \quad \forall t \quad (\text{ii.28})$$

Combining the upper-level constraints (section 2.4.1) with the lower-level problems, after substituting them with their corresponding MCPs (ii.19)-(ii.23) and (ii.25)-(ii.28), results in a single-level MPEC.

2.5.3. MILP formulation

The MPEC can be reformulated as a MILP by linearizing all non-linearities to provide better solvability. These include all complementary slackness conditions and the product of the flexibility premium with the day-ahead dispatch of heat pumps in the objective function of the aggregator (see (ii.2), resp.

(ii.5)).

The complementarity conditions are reformulated using a big-M approach, as illustrated by the example of the complementary slackness condition formulated in equation (ii.20):

$$H_{n',t}^{agg} \leq m \cdot B_{n',t}^\eta \quad \forall n', t \quad (\text{ii.20a})$$

$$\eta_{n',t} \leq m \cdot (1 - B_{n',t}^\eta) \quad \forall n', t \quad (\text{ii.20b})$$

where $B_{n',t}^\eta \in \{0, 1\}$ represents a newly introduced auxiliary variable and $m \in \mathbb{R}^+$ is a sufficiently large constant. For the linearization of the remaining complementarity constraints, (ii.21)-(ii.23) and (ii.26)-(ii.28), it is referred to [Appendix C](#).

Recalling the bilinear term (ii.2) included in equation (ii.5), Lemma 2.1 is used to express it exactly as a linear combination.

Lemma 2.1. *Given an optimal solution of the lower-level problems of the bi-level problem formulated in section 2.4, the following equality holds:*

$$\begin{aligned} \sum_{n',t} H_{n',t}^{agg,*} \cdot FP_{reg(n'),t}^{tso} &= \sum_{p,t} (G_{p,t}^{mca,*} \cdot oc_p + c_p^G \cdot \bar{o}_{p,t}^*) - \sum_{n,t} d_{n,t} \cdot \Pi_t^{mc,*} \\ &- \sum_{n',t} (-c_{n'}^H \cdot \bar{\eta}_{n',t}^* + (dem_{n',t}^H - \epsilon) \cdot \theta_{n',t}^* + (-dem_{n',t}^H - \epsilon) \cdot \bar{\theta}_{n',t}^*) \end{aligned} \quad (\text{ii.2a})$$

where "*" denotes optimality for the decision problems.

Proof. The left-hand side of equation (ii.2a) represents the bilinear term of interest and is also present in the objective function of the aggregator's decision problem in the lower-level (ii.12). As previously mentioned, the constraint qualifications hold for both lower-level problems. Consequently, the strong duality theorem applies, allowing the primal objectives to be equated with their respective Lagrangians at the optimum.¹ [Appendix B](#) demonstrates the derivation of the optimal values for the dual problems (right-hand side of (ii.29) and (ii.32)).

For the aggregator, the following holds:

$$\begin{aligned} \sum_{n',t} H_{n',t}^{agg,*} \cdot (\Pi_t^{mc} - FP_{reg(n'),t}^{tso}) &= \\ \sum_{n',t} (-c_{n'}^H \cdot \bar{\eta}_{n',t}^* + (dem_{n',t}^H - \epsilon) \cdot \theta_{n',t}^* + (-dem_{n',t}^H - \epsilon) \cdot \bar{\theta}_{n',t}^*), \end{aligned} \quad (\text{ii.29})$$

¹ $H_{n',t}^{agg,*}$, $\bar{\eta}_{n',t}^*$, $\theta_{n',t}^*$, $\bar{\theta}_{n',t}^*$ denote optimality for the aggregator's decision problem. $FP_{reg(n'),t}^{tso}$ and Π_t^{mc} are controlled by the TSO and the day-ahead market clearing agent, respectively, and can be treated as parameters in the aggregator's problem. Similarly, $\Pi_t^{mca,*}$, $G_{p,t}^{mca,*}$, and $\bar{o}_{p,t}^*$ denote optimality for the market clearing agent's decision problem, allowing $H_{n',t}^{agg}$ to be treated as a parametric input.

which can be reformulated to

$$\begin{aligned} \sum_{n',t} H_{n',t}^{agg,*} \cdot FP_{reg(n'),t}^{tso} &= \sum_{n',t} H_{n',t}^{agg,*} \cdot \Pi_t^{mc} \\ &- \sum_{n',t} (-c_{n'}^H \cdot \bar{\eta}_{n',t}^* + (dem_{n',t}^H - \epsilon) \cdot \theta_{n',t}^* + (-dem_{n',t}^H - \epsilon) \cdot \bar{\theta}_{n',t}^*). \end{aligned} \quad (\text{ii.30})$$

The right-hand side of equation (ii.30) now exhibits a second bilinear term:

$$\sum_{n',t} H_{n',t}^{agg,*} \cdot \Pi_t^{mc}. \quad (\text{ii.31})$$

The theorem of strong duality is applied again to linearize this non-linearity. Since (ii.31) is part of the Lagrangian (ii.24) representing the market clearing, the market clearing agent's decision problem is utilized:

$$\sum_{p,t} G_{p,t}^{mca,*} \cdot oc_p = \sum_{p,t} -c_{p,t}^G \cdot \bar{o}_{p,t}^* + \sum_{n,t} (d_{n,t} + H_{n',t}^{mca}) \cdot \Pi_t^{mc,*}, \quad (\text{ii.32})$$

which can be reformulated to

$$\sum_{n,t} H_{n',t}^{mca} \cdot \Pi_t^{mc,*} = \sum_{p,t} (G_{p,t}^{mca,*} \cdot oc_p + c_{p,t}^G \cdot \bar{o}_{p,t}^*) - \sum_{n,t} d_{n,t} \cdot \Pi_t^{mc,*}. \quad (\text{ii.33})$$

Finally, Lemma 2.1 can be obtained by substituting equation (ii.33) into equation (ii.30). \square

Since the application of Lemma 2.1 results in a mathematically exact linear reformulation of the bilinear term in the TSO's objective function (ii.5), the MPEC can be expressed as a MILP, enhancing solvability.

3. Case Study

The developed model is applied to an extended IEEE test system within a market scenario framework to represent various incentive design alternatives. The following section describes the techno-economic key parameters of the system configuration and each grid management concept investigated.

3.1. System configuration

The transmission topology consists of a 118-bus high-voltage grid with high renewable penetration. The test system, adapted from [Barrios et al. \(2015\)](#), was adjusted to match Germany's generation capacity projected in the TYNDP 2022 *distributed energy scenario*. However, it was scaled down based on the ratio between the demand levels in the test system and the scenario report to align with the capacity of the transmission system. Figure 4 provides a graphical

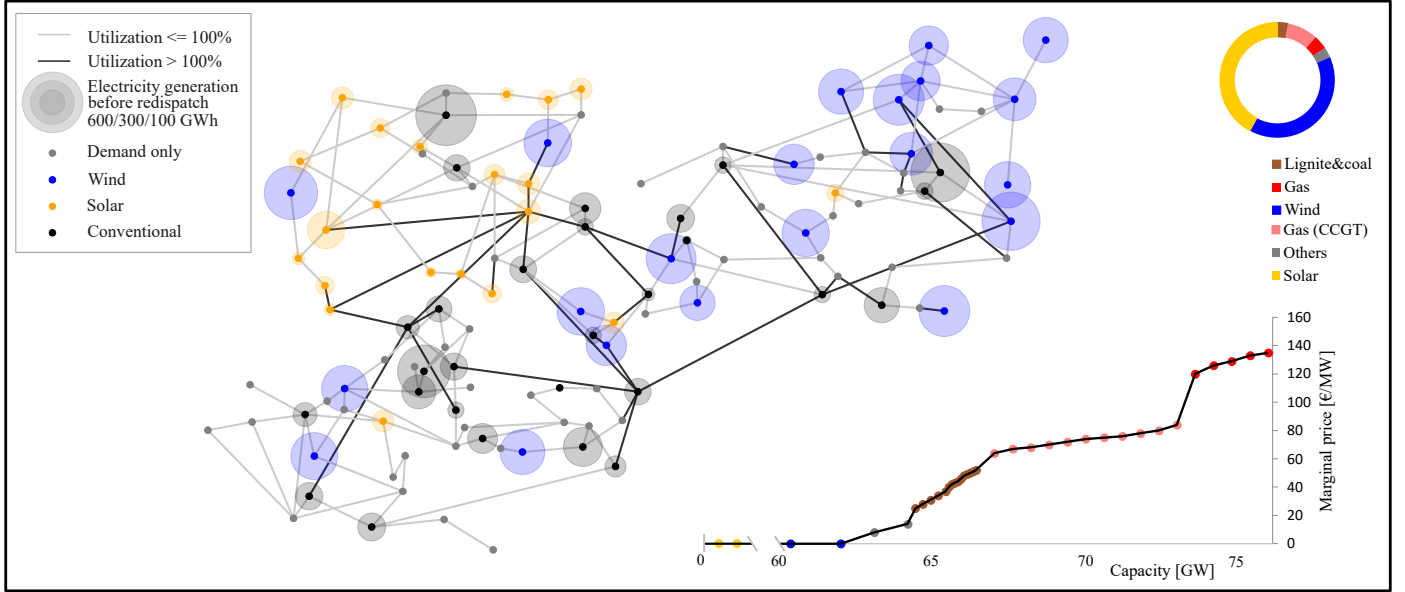


Figure 4: Techno-economic system configuration

representation of the test system including the grid topology and the generation structure, and table 1 lists all key parameters.

The system also assumes significant electrification of the residential heating sector, with heat pumps being the primary heat source. These heat pumps are allocated across grid nodes according to nodal electricity demands. The operation of the heat pumps accounts for 2.9% of the total electricity demand, with a total electrical capacity of 8.74 MW.² The heat pump dispatch is parameterized to allow interruption for up to 1 hour under full load (see the flexibility corridor ϵ introduced in section 2.3).

The model’s temporal horizon spans 28 days, with an hourly resolution. To simplify the solving procedure, the model employs a rolling planning approach with additional foresight to handle inter-temporal constraints such as load-shifting (local time-coupling). Rolling planning has been widely used in previous studies to solve congestion management problems similar to the model developed in this work that does not have global time-coupling constraints³. *Model I*, being a linear program (LP), is solved using CPLEX, while *Model II* utilizes ODH-CPLEX. Both models are implemented in the General Algebraic Modelling Language (GAMS).

3.2. Control instruments and premium concepts

Instruments incentivizing load-shifting can be designed with varying spatial and temporal granularity degrees. Given the

²This value aligns with projections for Germany in 2030 energy scenario studies, such as EntsoG & Entso-e (2022) or Sensfuß et al. (2021), which assumes a 5% demand share.

³For a detailed discussion on different solving procedures for congestion management problems see Hobbie et al. (2022)

Category	Specification/ Parameter	Value	Unit
Grid	$\text{card}(N)$	118	[1]
	$\text{card}(N')$	114	[1]
	$\text{card}(L)$	317	[1]
Generation	Capacity	76050	[MW]
	Share RES cap.	82	[%]
	Share conv. cap.	18	[%]
Demand	$\varnothing_{n,t} \text{dem}_{n,t}$	158.0	[MW]
	$\varnothing_{n',t} H_{n',t}^{mca,agg}$	4.6	[MW]
	Share flexible load	2.9	[%]
	$c_n^H \quad (\forall n' \in N')$	8.74	[MW]
	$\epsilon = \frac{c_{n^*}^H}{2} \quad (n^* \in N')$	4.37	[MW]

Table 1: Key technological system configuration parameter

complexity associated with each design in real-world market applications, this study examines various design concepts and compares their implications to benchmark cases. While instruments with high spatial and temporal resolution may be too complex to implement, reducing granularity increases their practicality from an operational perspective. Table 2 summarizes the key features of the grid management concepts distinguished in this work.

The first set of concepts assumes that aggregators do not face any incentives for grid-serving load behavior, which is correlated with *Model I*. This set helps interpret general market interactions resulting from grid management practices and enables comparing them with design alternatives including incentive instruments. Concept UC considers that aggregators do not respond to wholesale market prices and the flexibility of

Concept	Model	Flex. utilization	CM-Instruments	Premium characteristics		
				Spatial	Temporal	Estimation
UC	I	-	RD	-	-	-
PO	I	Market	RD	-	-	-
PO.DC	I	Market + CM	RD + direct control	-	-	-
PO.P- a)	II	Market + CM	RD + premium (a)	Nodal	Time-varying	Endogenous
PO.P- b)	II	Market + CM	RD + premium (b)	Regional	Time-varying	Endogenous
PO.P- c)	II	Market + CM	RD + premium (c)	Nodal	Time-static	Exogenous

Table 2: Overview on grid management concepts' key characteristics

heat pumps is not utilized by TSOs for grid optimization. This market framework can be modeled through sequential market clearing and redispatch optimization (*Model I*), with heat pump operation set as fixed parameters. This framework yields the highest market costs, due to the economically inefficient dispatch of the heat pump. Since heat pump operation is not optimized during market clearing and congestion management, it is referred to as *uncontrolled*.

Relaxing heat pump operation constraints during market clearing reduces electricity procurement costs resulting from the more efficient dispatch associated with the flexibility. A second concept considers heat pump operation as flexible within the boundaries outlined in section 2.3 during the market clearing stage, assuming profit-maximizing aggregator behavior. However, grid operators cannot access heat pump flexibility to optimize grid operation, resulting in high congestion management costs and serving as an upper bound against which all incentive instruments can be benchmarked. This scenario is referred to as *price-optimized (PO)*. Additionally, concept **PO.DC** assumes a flexible operation of heat pumps during the congestion management stage, controlled by TSOs. This concept is expected to yield the lowest congestion management costs, serving as a lower bound to benchmark incentive instruments, but involves very high information and communication requirements and legal implications. Since heat pump operation is considered *price-optimized* and TSOs are assumed to have *direct control*, this concept is referred to as **PO.DC**.

A second set of grid management concepts is explored, where aggregators receive a side payment known to them prior to the market clearing stage. This payment incentivizes grid-serving load behavior and reduces wholesale energy procurement costs. Due to the endogenous optimization by aggregators in response to these incentives, *Model II*, as described previously, is employed for their study. Three grid management concepts that incentivize aggregator load application are investigated, denoted as **a)**, **b)**, and **c)**.

In concept **PO.P- a)**, aggregators are offered a time- and location-varying premium, i.e. each region corresponds to a single node (cf. (ii.3) and (ii.4)). This premium, a model-endogenous result of transmission system optimization,

balances expected conventional redispatch and load-shifting costs. Alternatively, concept **PO.P- b)** merges adjacent transmission grid nodes into four regions, each receiving the same premium to simplify legal requirements like non-discriminatory grid and market access. These regions are defined based on hierarchical clustering of nodal prices, resulting in regions with similar grid load characteristics. See figure D.10 in the annex for a graphical representation of the four grid regions.

Due to the time-varying characteristics, the previously described grid management concepts require regular premium updates. This complexity may hinder their practical application in real-world market practices. Therefore, concept **PO.P- c)** assumes a time-static premium design. This premium is determined using a simple yet pragmatic heuristic based on the differences between nodal and zonal prices. A clustering algorithm identifies critical time windows during a day that consistently exhibit significantly higher nodal prices than zonal prices. During these windows, increased load would further stress the electricity grids beyond the levels induced by market clearing. The premium is calculated to cover the additional costs aggregators would incur when shifting their loads to adjacent time steps next to these critical time windows, whereby the time windows are kept constant over the model's planning horizon.^{4,5}

4. Results

The presented grid management concepts are investigated using the previously introduced modeling frameworks within the IEEE test system. The following focuses on market outcomes, starting with wholesale market and congestion management costs, and then discusses their implications regarding distributional effects.

4.1. Market outcomes

4.1.1. Congestion management and market costs at a system level

Incentivizing grid-serving load dispatch impacts both power plant dispatch and associated expenses, expressed as market

⁴The premium considers a cap of 30 €/MWh to avoid excessive flexibility management expenses during single time steps.

⁵Though this concept relies on model-endogenous market clearing at a nodal and zonal clearing auction, it can be easily applied to historical market results.

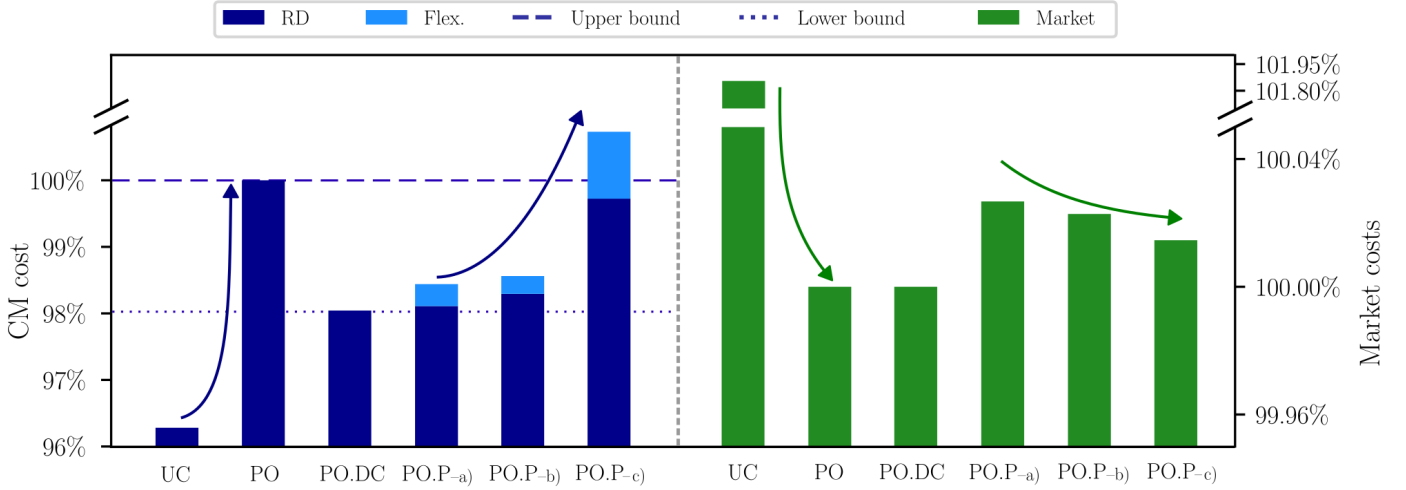


Figure 5: Congestion management and market costs (rel.)

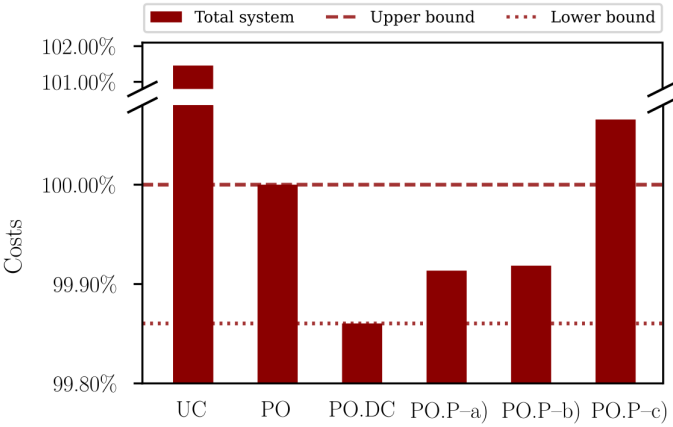


Figure 6: Total system costs (rel.)

Table 3: Cost overview (abs.)

	RD [€M]	Flex. [€M]	Market [€M]	System [€M]
UC	15.652	-	215.471	231.123
PO	16.257	-	211.547	227.804
PO.DC	15.918	-	211.547	227.485
PO.P-a)	15.949	0.054	211.604	227.607
PO.P-b)	15.979	0.043	211.595	227.618
PO.P-c)	16.212	0.163	211.578	227.953

clearing costs and congestion management costs. Figure 5 summarizes the market outcomes observed in each investigated grid management concept. Note that market and congestion management costs are displayed on two different axes for better readability of the observed volumes. Due to the small flexible share of total demand, results are given in relative terms. The absolute values are listed in table 3.

In concept **UC**, aggregators do not respond to market signals, leading to economically inefficient dispatch of heat pumps with respect to wholesale market outcomes. This concept results in the highest total market costs. However, due to the lower simultaneity⁶ of heat pump operation, load peaks are avoided, resulting in the lowest grid congestion and associated congestion management costs.

The flexible dispatch of heat pumps within the boundaries

⁶Simultaneity refers to the number of load applications operating at full load in a given time step in this context.

defined in section 2.3 assumed in concept **PO** reduces market costs by 1.82%. Despite only 2.9% of the load being flexible and constrained by technical limitations, this decrease is significant. However, the price response assumed in this concept increases the simultaneity of heat pump dispatch, causing load peaks and grid congestion, thereby raising congestion management requirements and costs. Incentivizing aggregators to dispatch their loads in a grid-serving manner should decrease congestion management costs below the level observed in concept **PO**, serving as an upper benchmark for incentive instruments. In concept **PO.DC**, relaxing heat pump operation constraints during congestion management optimization reduces associated costs by 1.96%, making it the most economically efficient alternative from a grid operation cost perspective and thus presenting a lower bound to compare results with.

When aggregators are offered a premium to incentivize load-shifting before the market-clearing stage, market expenses and load-shifting revenues influence the aggregator's

cost-optimal electricity procurement strategy. The time- and location-varying premium assumed in concept **PO.P- a)** most efficiently resolves grid congestion, yielding the lowest congestion management costs among all alternatives in which incentive strategies are investigated. However, incentivizing load-shifting strongly intervenes in the resulting wholesale market equilibrium, increasing wholesale market costs beyond those observed in a purely price-optimized market dispatch. Concept **PO.P- b)** results in slightly higher congestion management costs due to less efficient locational management of flexibility quantities. Consequently, the reduced level of market intervention in favour of congestion management is resulting in a slight decline in market costs. In summary, it is an efficient practice-oriented simplification of **PO.P- a)**, given its proximity to **PO.P- a)** itself and to the lower bound. Lastly, concept **PO.P- c)** exhibits the least efficient management of load-shifting quantities for resolving grid congestion. Here, aggregators receive premiums even during time-steps when load-shifting has little or no value for grid operation, significantly decreasing economic grid management efficiency.

4.1.2. Total costs at a system level

Summarizing the results on the wholesale market and congestion management costs reveals an intricate opposing relationship: the more efficiently grid congestion is handled by incentivizing grid-serving load behavior, the more market equilibria are affected, leading to increased power plant dispatch costs. From a regulatory perspective, any policy must be evaluated in terms of its overall system effect. Combining wholesale market and congestion management costs for each grid management concept, figure 6 displays the total system cost for supplying the total electricity demand in the IEEE test system. While direct control of load applications via a TSO yields the lowest system costs, concepts **PO.P- a)** and **PO.P- b)** still exhibit more economically efficient power supply compared to not utilizing flexibility during congestion management (concept **PO**), with only marginally cost increases in concept **PO.P- b)**. However, a time-static premium, as assumed in concept **PO.P- c)**, cannot be recommended based on the resulting system costs.

4.1.3. Incentive structure and premium volumes at a grid node level

The IEEE test system used in this study assumes high levels of renewable energy penetration, aligning with Germany's 2030 energy transition goals. It is thus crucial to consider not only the costs of congestion management and market operation but also the role of load-shifting as a congestion management strategy and its effects on renewable integration to interpret market outcomes under different grid management concepts. Figure 7 illustrates the statistical relationships between load-shifting activities and renewable generation across various

hours within the modelling horizon displayed as daily values.⁷ The results highlight an exciting dependency: Aggregators

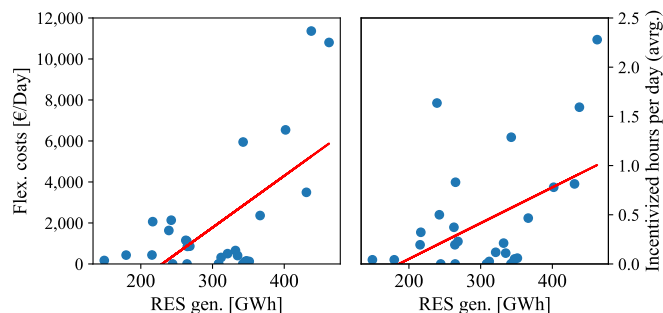


Figure 7: Statistical relationship between load-shifting activity and renewable generation

are more strongly incentivized to dispatch their flexible loads grid-supportively on days with higher renewable generation. This observation holds also for the grid management concepts **PO.P- b)** and **PO.P- c)** (see figure D.11 and D.12 in the annex). Generally, renewable curtailment incurs very high congestion management costs due to the significant difference between the marginal costs of renewable generators and conventional power plants for corresponding upward redispatch. This relationship makes load-shifting particularly economically efficient in systems dominated by renewables, especially during hours with high renewable curtailment volumes. In fact, renewable curtailment decreased from 264.6 GWh in concept **PO** to 259.4 GWh in **PO.P- a)** and 259.8 GWh in **PO.P- b)**. In summary, load shifting can be regarded as a dominant congestion management alternative, particularly in the context of reducing curtailment. However, given the relatively low flexible shares, it cannot be considered a complete substitute.

Renewable generation is a fluctuating electricity source due to its weather dependency, which causes variability in wind velocity and solar radiation over time and across regions. This variability necessitates congestion management strategies with precise temporal and locational effects. Figure 8 shows the magnitude of successful flexibility premium offers accepted by aggregators across transmission grid nodes and time steps for the three grid management concepts that rely on incentivizing load-shifting considered in this work.

The premium offers observed in concept **PO.P- a)** highlight the significance of location- and time-varying premium designs (top plot of figure 8). The structure of premium payments is highly heterogeneous across nodes and over the modeling horizon, with no systematic patterns evident upon visual inspection. Aggregating nodes into regions results in less

⁷The Pearson correlation coefficient of the relationship between RES generation and flexibility costs is 0.65, while the coefficient of the relationship between RES generation and incentivized hours per day is 0.48. These coefficients indicate a strong, respectively moderate, positive linear relationship between the variables.

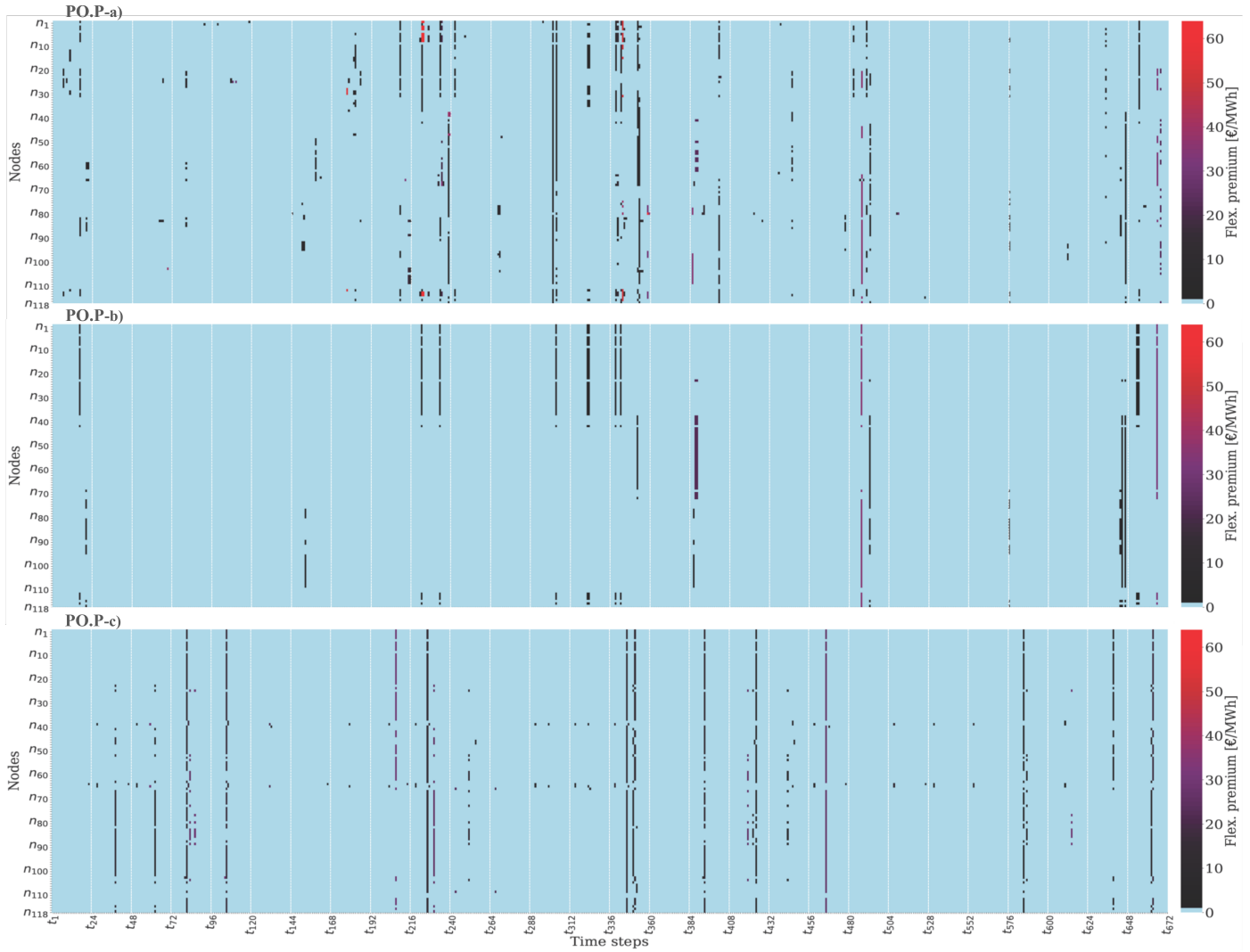


Figure 8: Successful premium offers across time steps and nodes. Each square represents the acceptance decision of a premium offering in each time step (left to right) for each node (top to bottom). The color indicates the offered premium amount. For consistency, the scale for premium offers in **PO.P- c)** goes beyond its cap at 30 €/MWh.

frequent premium payments (center plot). This approach, which causes incentivization costs at numerous grid nodes (merged into regions), leads to undesirable responses that increase overall flexibility management costs and reduce efficiency. Consequently, load-shifting is utilized less frequently as a congestion management strategy. Lastly, the results of concept **PO.P- c)** show a repeating pattern due to time-static premium payments. Note that a 30 €/MWh price cap was applied to avoid excessive payment volumes. When aggregators reject capped offers due to higher opportunity costs for load shifting, the structure of payments displayed in the bottom plot in figure 8 exhibits some interruptions.

4.2. Distributional effects

Incentivizing load applications before the market clearing stage means intervening in wholesale market equilibria. Figure 9 shows the resulting distributional effects, i.e., consumer

and producer rents, as an absolute difference compared to the rents in grid management concept **PO**. Consumer rents are displayed both with and without consideration of effects on resulting grid operation costs.⁸

Since concept **PO.DC** assumes direct control of flexible load applications by the TSO, market outcomes are the same as in concept **PO**. Consequently, rents for producers and consumers are identical. However, utilizing flexible loads for congestion management reduces grid operation costs, leading to a net increase in consumer rents. According to market principles, electricity supply and demand determine wholesale prices and equilibrium quantities. The extent of incentivized load-shifting can alter wholesale price formation, resulting in a price effect. In concept **PO.P- a)**, incentivized load-shifting for grid management purposes increases prices during certain hours of

⁸In liberalized electricity supply systems, such as in Germany, grid operation costs are typically reallocated to final electricity-consuming customers.

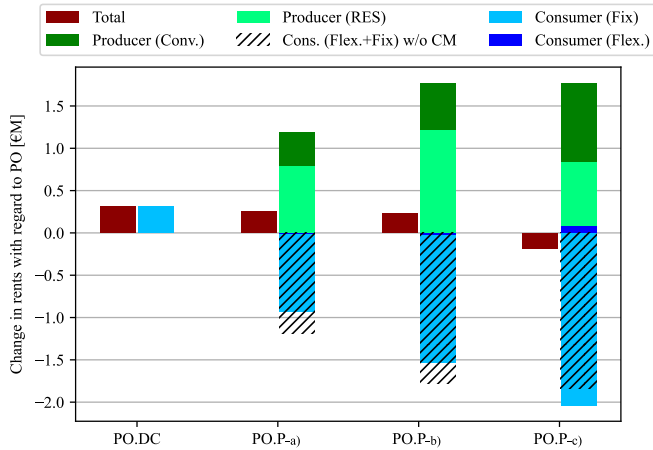


Figure 9: Absolute difference of producer and consumer rents to concept **PO**. The hatched areas display the difference when congestion management costs are not allocated to consumers

the modeling horizon. Although the aggregator is compensated via *regional* premium payments, higher *zonal* wholesale prices negatively impact the rents of all other consumers (including flexible demands at nodes that are not incentivized), resulting in a net negative effect on total consumer rent. However, decreases in grid operation costs slightly counterbalance these losses. Since concept **PO.P- b)** incentivizes load applications across entire grid regions rather than single nodes, the price effect is more pronounced, leading to greater losses in consumer rents. The incentivization structure in concept **PO.P- c)** results in very inefficient market outcomes. Consumers face higher market prices and increased grid operation costs.

The price effect observed in the concepts using incentivization as a congestion management strategy also affects producer rents. Concept **PO.P- a)** shows an increase in producer rents, which is even more significant in concept **PO.P- b)**. Intriguingly, conventional producers profit more in concept **PO.P- c)** than renewable producers.

Calculating the difference between producer and consumer rents indicates the total welfare effect of the different congestion management concepts examined in this study. Direct control of load applications by TSOs results in the highest net positive welfare effect, though it requires stringent legal measures and additional costs for communication and information infrastructures, which are not accounted for in the calculations. Incentivizing load applications through premiums, which provide aggregators with additional revenue streams, also yields net positive welfare effects. Interestingly, these effects are similar for concepts **PO.P- a)** and **PO.P- b)**, where rents shift from consumers to producers. In contrast, concept **PO.P- c)** results in net negative welfare effects due to the inefficient use of flexible load applications. The increase in consumer rents yields a net positive welfare effect in concept **PO.DC**.

5. Conclusions

Integrating large amounts of renewable generation into electricity systems requires novel congestion management solutions. With the gradual phase-out of large thermal-based generators to decarbonize the German energy supply, incentive-based load-shifting emerges as a promising measure alongside traditional redispatch practices. This study investigates three distinct incentive-based congestion management strategies, which vary in the temporal and regional granularity of premium design, and compares their effects on market outcomes.

More general findings from this work highlight the significant economic value of load-shifting in renewable-dominated electricity systems. Renewable curtailment is an inefficient method for resolving grid congestion from an environmental perspective and considering economic implications, as it requires redispatching generators with the greatest marginal cost differences. Therefore, designing incentive instruments for load-shifting should focus on avoiding renewable curtailment and encouraging the dispatch of load applications during these hours, especially when market signals alone are insufficient to attract such behavior.

Comparing the different grid management concepts studied in this work reveals a central relationship between market and grid efficiency. Efficiently managing grid congestion through incentivizing grid-serving dispatch of flexible load applications, such as temporal and locational varying premium payments, results in higher market costs. This result is due to the price effect associated with increased demand when incentivized flexible demand quantities reach a certain magnitude. In simple terms, while local grid congestion is mitigated through demand shifting, the resulting price increases raise electricity costs for all consumers due to zonal market clearing and associated wholesale prices accounting for the entire market zone. Alongside associated losses in consumer rents, producers will profit, particularly when the zonal market clearing is combined with a uniform pricing auction, as in Germany, from these price increases. Regulators, thus, should consider distributional effects when designing efficient demand-side incentive instruments for grid operation purposes and thoroughly outweigh who will bear the additional burden connected with such a congestion management strategy.

The findings of this study further highlight the critical importance of time-specific premium design when developing incentives for grid-serving load application behavior. The inherent variability of renewable generation, such as wind and solar power, necessitates this focus on timing. While aggregating nodes into regions with a uniform premium across nodes for flexible electricity demand increases consumer rent losses, the total welfare effects are similar to those of time- and location-specific premium designs examined in this research, suggesting that regional incentive designs offer a viable alternative to nodal ones. However, reducing the temporal granularity of premium designs leads to undesirable incentives,

as it overlooks short-term fluctuations in renewable generation and grid congestion. Therefore, incentive instruments should be seamlessly integrated into daily market practices, allowing for regular updates to premium offers to accommodate the variability in generation within systems with high renewable penetration.

The bi-level modeling framework developed in this work effectively reproduces stakeholder behavior with their specific objectives by nesting optimization problems. This structure is well-suited for studying various premium design concepts. However, the results are limited to a test system configuration due to the numerical complexity of the applied optimization problems. Given the time constraints imposed by market clearing processes and their interaction with congestion management practices, this framework is not viable for determining efficient premiums in real-world applications. Future research should focus on optimization techniques that can handle larger-scale modeling without reducing the technical granularity of system representation while still accounting for the diverse objectives of the stakeholders involved.

Acknowledgments

The authors would like to acknowledge Professor Kathrin Fischer for her valuable support in this work, particularly her contributions to the proofreading process. Furthermore, the authors would like to thank Professor Dominik Möst and all members of the BMWK project *EffiziEntEE* for their insightful input and helpful discussions during the research and development phase.

Founding

This work was supported by the BMWK project *Effiziente Einbindung hoher Anteile Erneuerbarer Energien in technisch-wirtschaftlich integrierte Energiesysteme - EffiziEntEE* (fund number 03EI1050B).

Appendix A. Regularization techniques to mitigate optimistic bias artifacts for the ill-posed Model II

Well-posed optimization problems distinguish from ill-posed problems i. a. by the existence of a unique solution. However, the lower-level problem of the used bi-level framework - in particular the aggregator - is generally not uniquely solvable in terms of what we call *temporal indifference*. Temporal indifference may occur in two situations:

1. If several time steps are close together and equally expensive (in terms of market clearing prices), or
2. each time an incentive is set in the model.

In the first situation, the solution set for each node is not necessarily unique, since the temporal choice of the dispatch decision does not affect the aggregator's purchasing costs (as long as feasibility is provided). The second situation implies the first one not in terms of market clearing prices, but purchasing costs: The aggregators' opportunity costs for grid-serving load shifts are determined by price gaps between the time steps during which load-shifting occurs. As the smallest possible successful incentive, a premium must reduce this price gap to zero to pay out exactly those opportunity costs. However, the aggregators' objective remains unchanged, regardless of whether it responds to the incentive or not.

In conclusion, the bi-level problem is ill-posed. Thus, the upper-level only draws those solutions from the (not unique) lower-level solution set that enable cost-optimized congestion management. This is known as the *optimistic approach* and may lead to bias artifacts, disturbing the comparability of incentive effects regarding different incentive designs. In the following, it is described which premium designs may be affected by the optimistic approach and which regularization techniques are developed to mitigate corresponding bias artifacts:

Since **PO.P-a** is characterized by a premium where temporal and spatial resolution correspond to the model resolution, a non-optimistic formulation of the model could take control of temporal indifference, by setting an (additional) $\hat{\epsilon}$ -small incentive to the same nodes and time steps, the optimistic approach would draw. If $\hat{\epsilon} \rightarrow 0$, the upper-level objective function is not affected and both approaches, optimistic and non-optimistic yield equivalent solutions. This implies that there is no requirement for the application of regularization techniques.

Suppose a premium is set for a whole region, because of situation 2, the upper-level in **PO.P-b** may draw solutions where only nodes useful for congestion management are reacting to the incentive, while others do not take part in the congestion management measure. These nodes are subject to the incentive, but neither generate flexibility costs nor do they exert an overriding influence on load flows. In conclusion, the optimistic character transforms the regional design into a nodal one. This

necessitates an actual implementation of a regional additional $\hat{\epsilon}$ -small incentive:

1. Since variable costs of all power plants and thus all market clearing prices in the case study are integers, defining Π^{mc} as an integer variable does not impact model results:

$$\Pi_t^{mc} \in \mathbb{Z} \quad (\forall t \in T). \quad (\text{A.1})$$

2. Because of 1., all price gaps and thus all incentives in our optimistic approach will be integers. Thus, defining premiums as integer variable does not impact model results, too:

$$FP_{reg(n'),t}^{tso} \in \mathbb{Z} \quad (\forall n' \in N', t \in T). \quad (\text{A.2})$$

3. Expanding the objective function of the aggregator about $\hat{\epsilon} = 1.01$ results in the modified objective,

$$\min C^{agg} = \sum_{n',t} H_{n',t}^{agg} \cdot (\Pi_t^{mc} - FP_{reg(n'),t}^{tso} \cdot \hat{\epsilon}). \quad (\text{A.ii.12a})$$

Thus the first-order condition modifies to

$$\begin{aligned} \Pi_t^{mc} - FP_{reg(n'),t}^{tso} \cdot \hat{\epsilon} - \underline{\eta}_{n',t} + \bar{\eta}_{n',t} + \sum_{\hat{t} \geq t} (\bar{\theta}_{n',\hat{t}} - \underline{\theta}_{n',\hat{t}}) \\ = 0, \quad \forall n', t. \end{aligned} \quad (\text{A.ii.19a})$$

Since 1., 2. and $\hat{\epsilon}$ imply that an incentive overwhelms opportunity costs, we denote $\hat{\epsilon}$ as *incentive enhancement factor*. Consequently, the aforementioned concerns are addressed by enforcing a unique incentive-response mechanism, whereby each node within an incentivized region will react to.

4. Dividing the right-hand side of equation (ii.2a) by $\hat{\epsilon}$ adjusts the flexibility costs to the original model version while maintaining the unique characteristic of the regional incentive.

Since **PO.P**-c) disables $\hat{\epsilon}$ -small premiums during time steps $t_n^c \in T_n^{incC}$ not element of an incentive window T_n^{inc} , the argument formulated in **PO.P**-a) does not hold again. To mitigate the resulting bias, normal distributed noise is added to the aggregator's objective, so the first-order condition modifies to

$$\begin{aligned} \Pi_t^{mc} + u_{n',t} - FP_{reg(n'),t}^{tso} \cdot \hat{\epsilon} - \underline{\eta}_{n',t} + \bar{\eta}_{n',t} + \sum_{\hat{t} \geq t} (\bar{\theta}_{n',\hat{t}} - \underline{\theta}_{n',\hat{t}}) \\ = 0 \quad \forall n', t, \end{aligned} \quad (\text{A.ii.19b})$$

where $u_{n',t} \sim \mathcal{U}(-0.1, 0.1)$. Consequently, in all time steps t_n^c , a unique random solution is enforced, eliminating any optimistic bias. Similar regularization techniques are discussed in [Zemkoho \(2016\)](#).

Appendix B. Estimating optimal values of dual problems

For optimal values λ^*, μ^* of the corresponding dual problem of the optimization problem

$$\min_x f(x) \quad s.t. \quad g(x) \leq 0, \quad h(x) = 0, \quad (\text{B.1})$$

estimating the optimal value of the dual, means to minimize its Lagrangian with respect to x :

$$\begin{aligned} \mathcal{L}_{x,\lambda^*,\mu^*} &= \min_x \mathcal{L}_{x,\lambda^*,\mu^*} \\ \iff \mathcal{L}_{x,\lambda^*,\mu^*} \quad s.t. \quad \frac{\partial \mathcal{L}_{x,\lambda^*,\mu^*}}{\partial x} &= 0. \end{aligned} \quad (\text{B.2})$$

In the following, we want to apply the relationships mentioned to the lower-level problems.

Aggregator

Regarding the Lagrangian (ii.18) and its derivative (ii.19) of the aggregator, $\frac{\partial \mathcal{L}^{agg}}{\partial H_{n',t}^{agg}} = 0$ is equivalent to

$$\Pi_t^{mc} - FP_{reg(n'),t}^{tso} - \underline{\eta}_{n',t} + \bar{\eta}_{n',t} + \sum_{\hat{t} \geq t} (\bar{\theta}_{n',\hat{t}} - \underline{\theta}_{n',\hat{t}}) = 0 \quad \forall n', t. \quad (\text{B.3})$$

With the equivalency in (B.2) we receive the optimal value of the dual problem denoted by $\mathcal{L}^{agg,*}$ as

$$\begin{aligned} \mathcal{L}^{agg,*} &= \sum_{n',t} \left(-c_{n'}^H \cdot \bar{\eta}_{n',t}^* + (dem_{n',t}^H - \epsilon) \cdot \underline{\theta}_{n',t}^* \right. \\ &\quad \left. + (-dem_{n',t}^H - \epsilon) \cdot \bar{\theta}_{n',t}^* \right). \end{aligned} \quad (\text{B.4})$$

Day-ahead market clearing operator

Regarding the Lagrangian (ii.24) and its derivative (ii.25) of the day-ahead market clearing operator, $\frac{\partial \mathcal{L}^{mca}}{\partial G_{p,t}^{mca}} = 0$ is equivalent to

$$oc_p - \underline{q}_{p,t} + \bar{q}_{p,t} - \Pi_t^{mc} = 0 \quad \forall p, t. \quad (\text{B.5})$$

With the equivalency in (B.2) we receive the optimal value of the dual problem denoted by $\mathcal{L}^{mca,*}$ as

$$\mathcal{L}^{mca,*} = \sum_{p,t} -c_p^G \cdot \bar{q}_{p,t} + \sum_{n,t} (d_{n,t} + H_{n'(n),t}^{mca}) \cdot \Pi_t^{mc,*} \quad (\text{B.6})$$

Appendix C. Linearization: complementary slackness conditions

The introduction of binary variables $B \in \{0, 1\}$ allows a mixed integer reformulation of the remaining equations (ii.21) - (ii.23) and (ii.26) - (ii.28):

Aggregator

$$c_{n',t}^H - H_{n',t}^{agg} \leq m \cdot B_{n',t}^{\bar{\eta}} \quad \forall n',t \quad (\text{C.ii.21a})$$

$$\bar{\eta}_{n',t} \leq m \cdot \left(1 - B_{n',t}^{\bar{\eta}}\right) \quad \forall n',t, \quad (\text{C.ii.21b})$$

$$-dem_{n',t}^H + \epsilon + \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca} \leq m \cdot B_{n',t}^{\theta} \quad \forall n',t \quad (\text{C.ii.22a})$$

$$\theta_{n',t} \leq m \cdot \left(1 - B_{n',t}^{\theta}\right) \quad \forall n',t, \quad (\text{C.ii.22b})$$

$$dem_{n',t}^H + \epsilon - \sum_{\hat{t} \leq t} H_{n',\hat{t}}^{mca} \leq m \cdot B_{n',t}^{\bar{\theta}} \quad \forall n',t \quad (\text{C.ii.23a})$$

$$\bar{\theta}_{n',t} \leq m \cdot \left(1 - B_{n',t}^{\bar{\theta}}\right) \quad \forall n',t, \quad (\text{C.ii.23b})$$

Day-ahead market clearing operator

$$G_{p,t}^{mca} \leq m \cdot B_{p,t}^{\varrho} \quad \forall p,t \quad (\text{C.ii.26a})$$

$$\varrho_{p,t} \leq m \cdot \left(1 - B_{p,t}^{\varrho}\right) \quad \forall p,t, \quad (\text{C.ii.26b})$$

$$c_{p,t}^G - G_{p,t}^{mca} \leq m \cdot B_{p,t}^{\bar{c}} \quad \forall p,t \quad (\text{C.ii.27a})$$

$$\bar{c}_{p,t} \leq m \cdot \left(1 - B_{p,t}^{\bar{c}}\right) \quad \forall p,t, \quad (\text{C.ii.27b})$$

$$\sum_n d_{n,t} + \sum_{n'} H_{n',t}^{mca} - \sum_p G_{p,t}^{mca} \leq m \cdot B_t^{\Pi^{mc}} \quad \forall t \quad (\text{C.ii.28a})$$

$$\Pi_t^{mc} \leq m \cdot \left(1 - B_t^{\Pi^{mc}}\right) \quad \forall t, \quad (\text{C.ii.28b})$$

Appendix D. Figures

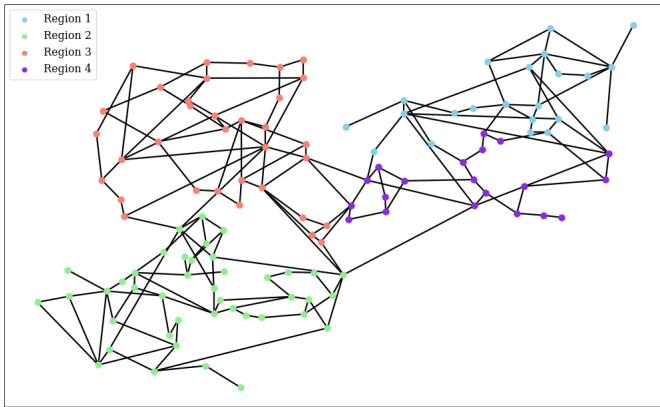


Figure D.10: Grid regions.

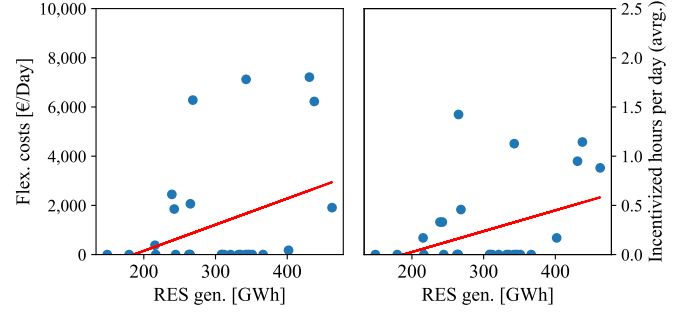


Figure D.11: correlation RES vs. PO.P- b).

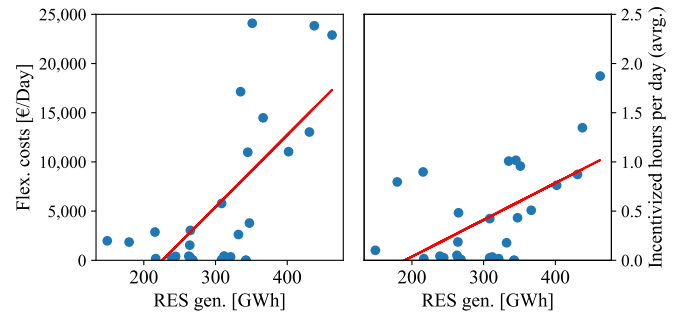


Figure D.12: correlation RES vs. PO.P- c).

References

- Avau, M., Govaerts, N., & Delarue, E. (2021). Impact of distribution tariffs on prosumer demand response. *Energy Policy*, 151. doi:10.1016/j.enpol.2020.112116.
- Barrios, H., Roehder, A., Natemeyer, H., & Schnettler, A. (2015). A benchmark case for network expansion methods. In *2015 IEEE Eindhoven PowerTech*. IEEE. doi:10.1109/PTC.2015.7232601.
- Bundesnetzagentur (2024). smard. URL: <https://www.smard.de/home>.
- Burger, S., Chaves-Ávila, J. P., Batlle, C., & Pérez-Arriaga, I. J. (2017). A review of the value of aggregators in electricity systems. doi:10.1016/j.rser.2017.04.014.
- Entsog, & Entso-e (2022). Tyndp 2022 scenario report — version. april 2022.
- Gabriel, S. A., Conejo, A. J., Fuller, J. D., Hobbs, B. F., & Ruiz, C. (2013). *Complementarity Modeling in Energy Markets* volume 180. Springer New York. doi:10.1007/978-1-4419-6123-5.
- Ghaemi, S., Li, X., & Mulder, M. (2023). Economic feasibility of green hydrogen in providing flexibility to medium-voltage distribution grids in the presence of local-heat systems. *Applied Energy*, 331. doi:10.1016/j.apenergy.2022.120408.
- Godron, P., Herrndorff, M., Müller, S., Schaber, K., Zackariat, M., Jooss, N., Köppl, S., Müller, M., Reinhard, J., von Roon, S., & Weiss, A. (2023). Haushaltsnahe flexibilitäten nutzen. wie elektrofahrzeuge, wärmepumpen und co. die stromkosten für alle senken können (using household-related flexibility. how electric vehicles, heat pumps and the like can reduce electricity costs for everyone). URL: <https://www.agora-energiewende.de/publikationen/haushaltsnahe-flexibilitaeten-nutzen>.
- Hartmann, T., Mühlhaus, T., Neumann, H., Reuter, H., & Röschmann, H. (2003). Lastprofile für unterbrechbare verbrauchseinheiten (load profiles for interruptible consumption units). URL: <https://www.bdew.de/media/documents/LPuVe-Praxisleitfaden.pdf>.
- Hobbie, H., Mehlem, J., Wolff, C., Weber, L., Flachsbarth, F., Möst, D., & Moser, A. (2022). Impact of model parametrization and formulation on the explorative power of electricity network congestion management models - insights from a grid model comparison experiment. *Renewable and Sustainable Energy Reviews*, 159. doi:10.1016/j.rser.2022.112163.
- Jin, X., Wu, Q., & Jia, H. (2020). Local flexibility markets: Literature review on concepts, models and clearing methods. doi:10.1016/j.apenergy.2019.114387.

- Kerscher, S., & Arboleya, P. (2022). The key role of aggregators in the energy transition under the latest european regulatory framework. doi:10.1016/j.ijepes.2021.107361.
- Meyer, J. T., Daam, C., & Gemassmer, J. (2022). Realise flexibility potential of ev fleets through grid-serving charging strategies. In *6th E-Mobility Power System Integration Symposium (EMOB 2022)*. IET. doi:10.1049/icp.2022.2716.
- Rebenaque, O., Schmitt, C., Schumann, K., Dronne, T., & Roques, F. (2023). Success of local flexibility market implementation: A review of current projects. *Utilities Policy*, 80. doi:10.1016/j.jup.2023.101491.
- Sensfuß, F., Maurer, C., Blömer, S., De, S. B., Pehnt, M., De, M. P., Mellwig, P., De, P. M., Müller-Kirchenbauer, J., & Auftraggeber, J.-B. D. (2021). Langfristszenarien für die transformation des energiesystems in deutschland 3 (long-term scenarios for the transformation of the energy system in germany 3). URL: <https://www.langfristszenarien.de/enertile-explorer-wAssets/docs/LFS-Gebaeude.pdf>.
- Stute, J., & Klobasa, M. (2024). How do dynamic electricity tariffs and different grid charge designs interact? - implications for residential consumers and grid reinforcement requirements. *Energy Policy*, 189. doi:10.1016/j.enpol.2024.114062.
- Zemkoho, A. B. (2016). Solving ill-posed bilevel programs. *Set-Valued and Variational Analysis*, 24, 423–448. doi:10.1007/s11228-016-0371-x.