DTU Library

Integrating Distributed Flexibility into TSO-DSO Coordinated Electricity Markets

Tsaousoglou, Georgios; Junker, Rune; Banaei, Mohsen; Tohidi, Seyed Shahabaldin; Madsen, Henrik

Published in:
IEEE Transactions on Energy Markets, Policy and Regulation

Link to article, DOI:
10.1109/TEMPR.2023.3319673

Publication date:
2024

Document Version
Peer reviewed version

This article has been accepted for publication in IEEE Transactions on Energy Markets, Policy, and Regulation. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TEMPR.2023.3319673

Integrating Distributed Flexibility into TSO-DSO Coordinated Electricity Markets

Georgios Tsaousoglou, *Member, IEEE*, Rune Junker, Mohsen Banaei, Seyed Shahabaldin Tohidi, *Member, IEEE*, Henrik Madsen
Department of Applied Mathematics and Computer Science,
Technical University of Denmark

***Abstract*—The future of electricity markets is envisioned to be heavily based on renewable generation and distributed flexibility. Yet, integrating existing distributed flexibility into market decisions poses a major challenge, given the diversity of consumers' modeling frameworks and controllers. Moreover, in such a system, the market's decisions need to be predictive, adaptive, as well as TSO-DSO coordinated. In this paper, we present an iterative market procedure through which, in contrast to traditional electricity markets based on one-off bids, flexible participants can indirectly implement their model by repeatedly responding to tentative pricing signals. This, combined with a scheduling/forecasting grey-box agent introduced on the consumer side, allows for the seamless integration of existing flexible loads' control schemes into a holistic electricity market. The proposed market-operation policy inherently coordinates Transmission and Distribution System Operators' decisions in the presence of uncertain distributed flexibility and renewables' generation. The results demonstrate promising convergence properties and short execution times, which is encouraging towards the scheme's practical applicability.**

***Index Terms*—TSO-DSO coordination, flexibility, forecasting, electricity markets, demand response**

NOMENCLATURE

Sets:

$\mathcal{G}$	Set of generators
$\mathcal{C}$	Set of flexible consumers
$\mathcal{C}^{\mathtt{scdl}}$	Set of schedulable consumers
$\mathcal{C}^{\mathtt{fns}}$	Set of flexible, non-schedulable consumers
$\mathcal{T}$	Set of timeslots in a look-ahead horizon
$\mathcal{N}$	Set of distribution networks
$\mathcal{B}_n$	Set of buses in distribution network n
$\mathcal{C}_b$	Set of flexible consumers connected to bus b
$\mathcal{J}_b$	Set of buses directly descendant to bus b

System Parameters:

$\overline{\mathrm{y}}_g, \underline{\mathrm{y}}_g$	Generator's upper/lower bounds on energy generation
r_g	Generator's ramp
$\mathrm{w}_g^{\mathrm{l}}, \mathrm{w}_g^{\mathrm{q}}$	Generator's cost parameters
$\overline{\mathrm{P}}_c$	Consumer's connection capacity
$\mathrm{a}_c, \mathrm{b}_c$	Schedulable consumer's state transition coefficients
$\underline{\mathrm{u}}_c, \overline{\mathrm{u}}_c$	Schedulable consumer's upper/lower bounds
$\widetilde{\mathrm{x}}_c$	Schedulable consumer's ideal state value
$\mathrm{e}_{c,t}$	Schedulable consumer's elasticity parameter
R_{bj}	Resistance of line bj
X_{bj}	Reactance of line bj
$\mathrm{w}_b^{\mathtt{res}}$	RES cost parameter at b

Decision Variables:

$y_{g,t}$	Generator's dispatch at t
$u_{c,t}$	Schedulable Consumer's consumption change factor at t
$\rho_{c,t}$	Price faced by consumer c at t
$d_{c,t}$	Consumer's energy demand at t
$\gamma_{c,\tau}$	Non-schedulable consumer's power consumption at moment τ
$u_{c,\tau}$	Change in non-schedulable consumer's consumption
$p_{b,t}$	Active power absorption of node b at t
$q_{b,t}$	Reactive power absorption of node b at t
$\zeta_{b,t}$	RES curtailment factor for node b at t
$P_{bj,t}$	Active power flow in line bj at t
$Q_{bj,t}$	Reactive power flow in line bj at t
$I_{bj,t}$	Current (squared magnitude) flow in line bj at t
$V_{b,t}$	Voltage (squared magnitude) at node b at t

Random Variables:

$x_{c,t}$	Schedulable consumer's state at t
$w_{c,t}$	Schedulable consumer's disturbance at t
$\beta_{c,\tau}$	Non-schedulable consumer's expected power consumption at τ
$x_{c,\tau}$	Non-schedulable consumer's expected state at τ
$p_{b,t}^{\mathtt{res}}$	Active generation of RES at node b, timeslot t
$q_{b,t}^{\mathtt{res}}$	Reactive generation of RES at node b, timeslot t

Algorithm's Variables/Parameters:

λ_t	Dual variable of the system's power balance constraint for timeslot t
$\mu_{b,t}$	Dual variable of the active power balance constraint of node b, timeslot t
$\nu_{b,t}$	Dual variable of the reactive power balance constraint of node b, timeslot t
h	Number of timeslots in the look-ahead horizon
$\mathcal{H}_{\widetilde{t}}$	Set of timeslots comprising the look-ahead horizon of operational timeslot $\widetilde{t}$
$\rho_{c,t}$	Price faced by consumer c at t

This work was supported by Innovation Fund Denmark, through the project Flexible Energy Denmark (FED): 8090-00069B and Energy Cluster Denmark, through the project "Nordic Market Based Balancing System" (110368).

k	index of algorithm's iterations
$w_{c,t}$	Schedulable consumer's disturbance at t
$\beta_{c,\tau}$	Non-schedulable consumer's expected power consumption at τ
$x_{c,\tau}$	Non-schedulable consumer's expected state at τ
$p^{\mathrm{res}}_{b,t}$	Active generation of RES at node b, timeslot t
$q^{\mathrm{res}}_{b,t}$	Reactive generation of RES at node b, timeslot t

I. Introduction

A. Motivation and Background

The threatening advancement of climate change has constituted discussions and policy actions toward power systems' decarbonization, a matter of utmost urgency. There is increasing consensus that the next generation of power systems shall be heavily based on renewable energy sources (RES) and flexible demand [1]. In this context, the respective electricity markets face the challenge of integrating the flexibility capabilities of numerous distributed resources, such as flexible loads, smart buildings, electric vehicle charging facilities, smart water management systems, etc., into the market decisions.

In this direction, Transmission System Operators (TSOs) have started to incorporate Demand Response into the Day-Ahead and real-time Balancing procedures. A prominent example refers to Nord Pool's "Flexi Orders", which allow a flexible consumer to allocate its energy demands in the cheapest timeslots of the consumer's desired consumption period. With increasing penetration of flexibility at the demand side, however, a simultaneous shifting of loads into low-price times creates significant operational dangers for the distribution systems to which such loads are connected. Such dangers only add to the challenges created by increasing load electrification (predominantly referring to electric heating and electric vehicles), which also brings congestion and voltage issues for distribution systems.

As a result, two developments are now gaining significant importance. The first is around Distribution System Operators (DSOs) evolving into pivotal cogwheels of the system operation by developing and operating local, distribution-level flexibility markets [2], [3]; the second, most widely referred to as the issue of "TSO-DSO coordination", refers to the establishment of dispatch processes and architectures that integrate distributed flexibility into the wholesale (transmission-level) markets' operation, such that the economic efficiency of the overall system is effectively attended to.

One specialty of distributed flexibility resources is that, in contrast to traditional generators, they are only partially dispatchable due to their local primary objectives (i.e. serving their users' needs) and the uncertainties that come with user activity, weather, and also as a result of inevitable modeling inaccuracies. Such characteristics dictate that a market heavily based on renewables and flexibility, is necessarily operated in a *predictive* and *adaptive* manner, i.e. market decisions need to account for future system trajectories, while the market operator needs to continuously review the new information on the system's state and act adaptively by re-dispatching the system in an online manner (close to real-time), at each operational timeslot.

Moreover, and from a practical point of view, the multitude of small flexibility resources brings a virtually unlimited diversity of characteristics and control schemes, which hinders their massive integration into the wholesale market. Each building/facility/load features different operational characteristics, different type of flexibility capabilities, and different types of controllers, sometimes even custom-made. Naturally, an electricity market operator cannot accommodate customized models for each small resource, neither it can be re-configuring its software each time a new resource is to be integrated. This means that the market integration of distributed resources needs to be made in a scalable and interoperable way.

In conclusion of this subsection, we identify a research challenge revolving around four critical components:

- enabling DSOs to deal with distribution-level congestion and voltage issues via market-based dispatch procedures;
- designing TSO-DSO coordination schemes in the presence of distributed flexibility;
- establishing a sequential decision-making process such that the (coordinated, real-time) market decisions are made in a predictive and adaptive manner;
- integrating diverse sources of flexibility in a scalable, seamless and interoperable manner.

The next subsection discusses the research studies related to this challenge.

B. Related Work

The modeling and control problem of a distributed resource, has been dealt with in the literature through a diverse set of approaches. These, indicatively, include classical, model-based, feedback controllers for buildings [4], predictive techniques based on non-intrusive load monitoring [5], practical and easier-to-implement rule-based energy management systems [6], methods based on model predictive control [7], [8], as well as model-free controllers predominantly based on reinforcement learning [9], [10]. Notably, this big body of literature invariably suggests that, while it is unrealistic for distributed resources to communicate their detailed set of models upstream, they can however be very effective in self-dispatching themselves once provided with a (tentative) set of prices (this concept is often referred to as the transactive, or market-based control paradigm). This observation will play a key role in motivating the hierarchical market structure proposed later in this paper.

At the distribution network level, the main challenge refers to efficiently solving the well-studied AC Optimal Power Flow (OPF) problem in the presence of distributed flexibility. The AC-OPF problem is notoriously NP-complete, but there have been identified tractable reformulations, most notably in the form of convex relaxations. Research on convex relaxations of the OPF problem constitutes a community of its own, with [11] serving as a notable representative reference. The presence of distributed resources, in particular, motivates distributed solutions of the AC-OPF, an overview of which was surveyed in [12]. A special mention is relevant for the distributed optimization approach, in which each distributed resource solves its local problem in parallel, and coordination

This article has been accepted for publication in IEEE Transactions on Energy Markets, Policy, and Regulation. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TEMPR.2023.3319673

is achieved through the exchange of multipliers (acting as pricing signals) with the operator. Such pricing signals, that differentiate to the level of a distribution network's node, are also known as Distribution Locational Marginal Prices (DLMPs) [13]. Importantly, this approach features a naturally occurring market interpretation which, by-and-large, has inspired the recent discussions around distribution-level flexibility markets, including their peer-to-peer market counterparts [14]. On the practical side, toward supporting the computational requirements of multiple distribution networks, the work in [15] proposed an edge-fog-cloud resource allocation scheme for multiple, decomposed AC-OPF problems.

Recent studies have proposed online, adaptive decision-making policies for a DSO. In [16], the DLMP approach is adopted, with distributed resources adapting to the updated DSO signals in an online manner, such that the system is maintained within safe operational limits. A machine-learning-based OPF policy is presented in [17], which enables the DSO to make fast online dispatch decisions. The works in [18] and [19] combine the iterative DLMP approach with dynamic-programming, predictive decision policies at each distributed resource's level while, in [20], the DLMPs communicated by the DSO are also uncertainty-aware by encapsulating the information of future uncertainties through the assistance of a machine learning model. Note, however, that all these studies assume a predictive controller is available for each load, which can schedule the load's consumption profile by taking into account future prices for a look-ahead horizon. It is not clear how a simpler, non-predictive, load controller (which is the most common type currently used in practice) would be integrated into such market frameworks.

TSO-DSO coordination is a topic that received rapidly increasing attention in the latest years. One approach, closely aligned with how transmission systems are currently operated, is to capture the flexibility capabilities of distributed resources by identifying the relevant flexibility "envelopes" at each distribution system coupling point, as suggested in [21] and [22]. The authors in [23] propose a method for communicating the flexibility of a distribution network's resources upstream, in the case of a Distribution Company (i.e. an entity that acts as a distribution system operator and as a market-participating aggregator at the same time). The TSO, after receiving the DSOs' information can readily dispatch the system.

Data-driven methods for communicating the flexibility capabilities of distributed resources to the TSO, were proposed in [24] and [25] (for aggregators), while the work in [26] presents a data-driven method while also accounting for distribution network constraints. A different approach is adopted in [27] where the authors propose a decomposition algorithm through which the TSO's problem is decomposed down to resource-level local problems, while [28] a similar idea is adopted for a simultaneous TSO-DSO dispatch procedure, where coordination is achieved again by a DLMP-based scheme.

Notice that all cited studies around TSO-DSO coordination, deal with scheduling problems (e.g. day-ahead) without accounting for a full predictive and adaptive decision-making policy. Predictive approaches for uncertainty-aware transmission-level market dispatch are thoroughly discussed in [29], while the authors in [30] present a model for a so-called stochastic electricity market. In the context of uncertainty-aware TSO-DSO coordinated market dispatch, [31] accounts for uncertainty by probabilistically assessing a distribution network's flexibility in future time intervals, while the authors in [32] also consider practical perspectives (such as the TSO's security constraints) and present a decomposition algorithm for a TSO-DSO coordinated day-ahead market. Again, though, these works only fulfill the *predictiveness*, and not the *adaptive* requirement (unlike studies [16] - [20] discussed above, that present online dispatch policies but focus only on the distribution network level). Overall, the focal system levels and relevant considerations of the reviewed literature are summarized in Table I.

TABLE I: Classification of literature with respect to the aspects motivated

	Resource level	DSO level	TSO/ DSO	Uncertainty aware	Adaptive policy
[4], [6]	✔	×	×	×	✔
[5], [7], [8] , [9], [10]	✔	×	×	✔	✔
[15], [14]	✔	✔	×	×	×
[16]	×	✔	×	×	✔
[17]	×	✔	×	✔	✔
[18], [19], [20]	✔	✔	×	✔	✔
[21], [22], [23]	×	✔	✔	×	×
[24], [25]	×	×	✔	✔	×
[26], [31], [32]	×	✔	✔	✔	×
this work	✔	✔	✔	✔	✔

C. Research Gap and Contributions

The literature review of the previous subsection reveals that, while there have been various propositions for distribution-level markets for network management, TSO-DSO coordination schemes, and market-based control approaches for demand response, a holistic interconnecting scheme is boldly missing. Moreover, such a framework should not be bound to specific consumer models (e.g. buildings with model predictive controllers) but should be able to incorporate various types of consumers, including ones with non-predictive controllers or even consumers taking demand-response actions manually. Thus, in this paper, we present an adaptive, holistic (i.e. TSO-DSO coordinated) electricity market that integrates and utilizes the flexibility capabilities of diverse distributed consumers in a scalable and interoperable way.

Towards integrating distributed flexibility into the market's decisions, we combine two ideas: on one end (top-down), we adopt the powerful concept of communicating the system's state in the form of pricing signals (by utilizing a Lagrangian decomposition algorithm); on the other end (bottom-up), we introduce a consumer *agent* between the consumer's controller/energy management system and the power system operator, as in Fig. 1. The agent features a grey-box, state-space model of the consumer which is generic enough to model various types of consumers, but flexible enough to be configured for each consumer's special characteristics[1]. The system integration is achieved by a decomposition algorithm, where

[1] An elaborate report on implementation details can be found in [33].

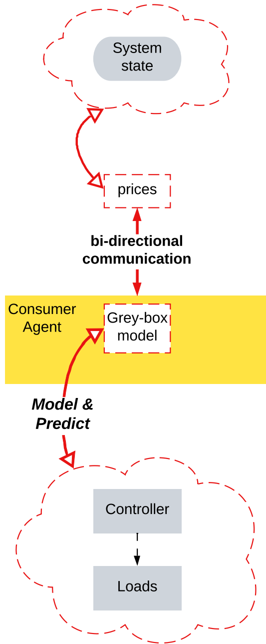


Fig. 1: A grey-box agent seamlessly integrates a distributed resource by modeling and predicting its reaction to price signals and communicating with the system on its behalf.

the operators iteratively send tentative pricing signals, and the consumer agents respond, on behalf of the consumers, with the consumers' forecasted consumption profile for those signals.

It is important to highlight that, while for many controllers and energy management systems it is not straightforward, or even realistic, to communicate their local model upstream (e.g. it could include a rule-based controller), it is however much easier for an agent to predict their reactions for a given set of pricing signals. Therefore, all the modeling difficulties are outsourced to the consumer agent, reducing the interoperability requirement to one of building a versatile grey-box model that can be tuned to represent different consumer types; a task that, fortunately enough, has been shown to be manageable [34].

Summarizing the elaborations above, this paper contributes to the literature by presenting a hierarchical (TSO-DSO coordinated) market scheme which, in contrast to (bid-once, then-clear) traditional electricity markets, takes the form of an iterative auction. This market format implements a predictive and adaptive decision-making policy, while integrating distributed flexibility and addressing the interoperability issue by introducing a consumer agent, able to represent a diverse set of resource-level controllers, and only asking it to answer price-demand queries (without communicating modeling details).

Section II presents the system model (including generators, consumers, and distribution level constraints) and market-motivating problem formulation as a problem of coordinated TSO-DSO decisions. Section III presents the proposed market-clearing algorithm and Section IV empirically assesses it in a simulation setting. Section V concludes the paper.

Notation: We use straight letters for parameters, italics for variables, and calligraphic fonts for sets. The index τ is used for moments of continuous time, whereas t is used to index discrete timeslots (periods of time).

II. System Model

We consider the operation of a power system, comprising a set $\mathcal{G}$ of generators and a set $\mathcal{C}$ of consumers, for a horizon $\mathcal{T} = \{0, 1, ...\}$ of timeslots of equal duration Δt.

A. Generator Model

A generator $g \in \mathcal{G}$ can be dispatched at a generation level $y_{g,t}$, which is a continuous variable subject to upper/lower bounds

$$\underline{\mathrm{y}}_g \le y_{g,t} \le \overline{\mathrm{y}}_g, \quad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{1}$$

as well as to ramp constraints

$$-\mathrm{r}_g \le y_{g,t} - y_{g,t-1} \le \mathrm{r}_g, \quad \forall g \in \mathcal{G}, t \in \mathcal{T}. \tag{2}$$

Each generator also faces an operational cost $C_{g,t}$ at t, modeled as

$$C_{g,t} = \mathrm{w}^{\mathrm{l}}_g \cdot y_{g,t} + \mathrm{w}^{\mathrm{q}}_g \cdot y^2_{g,t}, \quad \forall g \in \mathcal{G}, t \in \mathcal{T}, \tag{3}$$

where $\mathrm{w}^{\mathrm{l}}_g$ and $\mathrm{w}^{\mathrm{q}}_g$ are the coefficients of the linear and the quadratic term respectively.

B. Consumer Model

We consider three types of consumers: a set $\mathcal{C}^{\mathtt{infl}}$ of inflexible consumers, a set $\mathcal{C}^{\mathtt{scdl}}$ of flexible consumers whose loads can be *scheduled*, and a set $\mathcal{C}^{\mathtt{fns}}$ of flexible-but-not-schedulable consumers who only react to the current electricity price without scheduling for the future.

1) Schedulable Loads: For a schedulable consumer $c \in \mathcal{C}^{\mathtt{scdl}}$, connected to a distribution network, let $\beta_{c,t}\overline{\mathrm{P}}_c$ denote its forecast consumption, where $\beta_{c,t}$ is defined as a percentage of its connection capacity $\overline{\mathrm{P}}_c$ in the absence of purposeful adjustments. A schedulable load/consumer $c \in \mathcal{C}^{\mathtt{scdl}}$ is modeled using a state-space representation

$$x_{c,t+1} = \mathrm{a}_c \cdot x_{c,t} + \mathrm{b}_c \cdot u_{c,t} + w_{c,t}, \quad \forall c \in \mathcal{C}^{\mathtt{scdl}}, t \in \mathcal{T}, \tag{4}$$

where $x_{c,t}$ is the consumer's *state* (relating for example to a battery's or an electric vehicle's state of charge, or to a building's indoor temperature etc.), $w_{c,t}$ is a *disturbance*, and $u_{c,t}$ is the (controlled) energy consumption modification factor defined as a factor of the consumer's forecast demand; i.e., the consumer's consumption $d_{c,t}$ is given by

$$d_{c,t} = u_{c,t} \cdot \beta_{c,t}\overline{\mathrm{P}}_c, \quad \forall c \in \mathcal{C}^{\mathtt{scdl}}, t \in \mathcal{T}. \tag{5}$$

Finally, parameters $\mathrm{a}_c, \mathrm{b}_c$ are consumer-specific and relate to state inertia (e.g. building insulation and thermal mass) and energy conversion efficiency respectively.

The consumer's energy consumption factor $u_{c,t}$ can be controlled within the consumer's flexibility margins $0 \le \underline{\mathrm{u}}_c \le 1 \le \overline{\mathrm{u}}_c$, as in

$$\underline{\mathrm{u}}_c \le u_{c,t} \le \overline{\mathrm{u}}_c, \quad \forall c \in \mathcal{C}^{\mathtt{scdl}}, t \in \mathcal{T}. \tag{6}$$

The consumer's cost $C_{c,t}$ at t is defined based on its state's distance from the ideal state value $\widetilde{\mathrm{x}}_c$ and an electricity cost component $\rho_{c,t} \cdot u_{c,t} \cdot \beta_{c,t}$, where $\rho_{c,t}$ is the electricity price at t, as in

$$C_{c,t} = (1 - \mathrm{e}_{c,t}) \cdot (x_{c,t} - \widetilde{\mathrm{x}}_c)^2 + \mathrm{e}_{c,t} \cdot \rho_{c,t} \cdot d_{c,t}, \quad \forall c \in \mathcal{C}^{\mathrm{scdl}}, t \in \mathcal{T}, \quad (7)$$

where $\mathrm{e}_{c,t}$ is a user-specific elasticity parameter that balances electricity costs with user comfort, similar to the "transactive slider" proposed in [35]. Observe that this type of model is generic enough to capture various types of loads. Indicatively, for the case of thermostatically controlled loads, the state could represent the room's temperature and the ideal state value would represent the desired temperature. For electric vehicles, the state could represent the state-of-charge, and the ideal state would be equal to the desired state-of-charge upon departure; if the user is interested only in the final state-of-charge and not in its trajectory, then the parameter $\mathrm{e}_{c,t}$ would be set to zero for all timeslots except the one of departure.

2) Non-Schedulable Loads: A flexible but non-schedulable consumer $c \in \mathcal{C}^{\mathrm{fns}}$ features a controller that adjusts the consumption based on the current price and load state (without scheduling future consumption). Notably, this is the case for most energy management systems currently employed in actual flexible buildings. For this case, we consider an agent (grey-box model) that forecasts the consumer's consumption profile for a given set of prices ahead. This grey-box model, termed as the consumer agent is based on the concept of the so-called "flexibility function" [34], and is generic enough to adapt to different types of (possibly continuous-time) controllers the consumer may employ, thus fulfilling the interoperability requirement motivated in the introduction. Indeed, prior works (namely [34]) have successfully applied this model to represent real loads of different nature (e.g. buildings, water towers).

We define a consumer's instantaneous power consumption at moment τ (of continuous time) as $\gamma_{c,\tau}\overline{\mathrm{P}}_c$, where $\gamma_{c,\tau} \in [0,1]$ is a normalized variable denoting the consumer's demand as a percentage of its connection capacity. Accordingly, the consumer's (normalized) *energy* consumption in a timeslot t is denoted by $d_{c,t}$ and it is given by integrating the consumer's instantaneous power consumption within t:

$$d_{c,t} = \int_t^{t+\Delta t} \gamma_{c,\tau}\overline{\mathrm{P}}_c \mathrm{d}\tau, \quad \forall c \in \mathcal{C}^{\mathrm{fns}}, t \in \mathcal{T}. \quad (8)$$

The real-time consumer demand $\gamma_{c,\tau}$ consists of two parts: the consumer's forecast consumption $\beta_{c,\tau} \in [0,1]$, defined as a percentage of its connection capacity in the absence of purposeful adjustments, and its flexible consumption which is subject to control decisions within pertinent limits. Namely, for a baseline consumption level $\beta_{c,\tau}$, we regard that the consumer's consumption can be adjusted between $[\beta_{c,\tau} - \mathrm{w}_c\beta_{c,\tau}, \quad \beta_{c,\tau} + \mathrm{w}_c \cdot (1 - \beta_{c,\tau})]$, where $\mathrm{w}_c \in [0,1]$ denotes the percentage of the baseline consumption that is flexible. Thus, $\mathrm{w}_c\beta_{c,\tau}$ is the amount of the forecast consumption that can be curtailed and $\mathrm{w}_c(1-\beta_{c,\tau})$ is the amount of the unused connection capacity that can be used for inducing additional consumption. Let us define the consumption change induced by control actions as a factor $u_{c,\tau} \in [-1,1]$ (negative for curtailing consumption and positive for imposing additional consumption) of the relevant flexibility margin ($\mathrm{w}_c\beta_{c,\tau}$ for curtailment and $\mathrm{w}_c(1-\beta_{c,\tau})$ for additional consumption). The consumer's power consumption at τ can then be expressed as the result of adding the consumption change on top of the forecast consumption, i.e.,

$$\gamma_{c,\tau} = \beta_{c,\tau} + u_{c,\tau} \cdot \mathrm{w}_c \cdot \big(\beta_{c,\tau}\mathbb{1}(u_{c,\tau} < 0) + (1 - \beta_{c,\tau})\mathbb{1}(u_{c,\tau} > 0)\big), \quad \forall c \in \mathcal{C}^{\mathrm{fns}}, \quad (9)$$

where $\mathbb{1}$ is the indicator function.

The consumer agent is also characterized by its *state* $x_{c,\tau}$ which, similarly to section II-B1, encapsulates all the information relevant to the facility's functionality. The state dynamics model the way the state $x_{c,\tau}$ increases (decreases) when the facility's consumption is higher (lower) than its forecast demand, as in

$$\mathrm{d}x_{c,\tau} = \mathrm{w}^{\mathrm{fl}} \cdot (\gamma_{c,\tau} - \beta_{c,\tau})\mathrm{d}\tau + (1 - x_{c,\tau})x_{c,\tau}\sigma_s \mathrm{d}W_\tau, \quad \forall c \in \mathcal{C}^{\mathrm{fns}}, \quad (10)$$

where $\mathrm{w}^{\mathrm{fl}} \in [0,1]$ is the factor by which the curtailed/increased consumption affects the state, while the second term models the system's disturbance with σ_s denoting the noise intensity, W being a Wiener process, while the term $(1-x_{c,\tau})x_{c,\tau}$ makes sure that the disturbance goes to 0 as the state approaches its upper or lower limit (in order to keep the disturbance term from bringing the state below 0 or above 1).

A consumer features a controller that adjusts the flexible part of its consumption. The role of the agent (refer back to Fig. 1) is to simulate/predict the decisions of the consumer's controller regarding power consumption for a horizon ahead, as a function of the state $x_{c,\tau}$ and the price. For this purpose, the agent uses a policy, defined as $\pi_c : (x_{c,\tau}, \rho_{c,t}) \rightarrow u_{c,\tau}$, in the form of a function

$$u_{c,\tau} = \frac{2}{1 + e^{-\mathrm{a}\cdot(\eta(x_{c,\tau}) + \theta(\rho_{c,t}))}} - 1, \quad (11)$$

where $\eta(x_{c,\tau})$ is a decreasing function of the state, and $\theta(\rho_{c,t})$ is a decreasing function of the price. The functions η and θ link the demand to the consumer's state of charge and price respectively. Their purpose is to capture the consumer's inherent monotonicities; namely, the fact that a high amount of stored energy tends to reduce demand (η) and, similarly, a high price tends to reduce demand (θ) - and vice versa for low amounts of stored energy and low prices. The functions are constructed using I-splines, which are defined in terms of integrated normalized B-splines to ensure that the function is monotonously decreasing in a way that is computationally feasible. The set of equations (8)-(11) serves as a forecasting grey-box model of a consumer's consumption and it can generally be tuned to represent various types of consumers and controllers, as shown in [34].

C. Distribution Network

We assume that each consumer is connected to a bus $b \in \mathcal{B}_n$ of a radial distribution network $n \in \mathcal{N}$, where $\mathcal{N}$ is the set of the system's distribution networks and $\mathcal{B}_n$ is the set of buses of network n. Multiple consumers may be connected to a single node (e.g. apartments of a building complex). Let $\mathcal{C}_b$ denote the set of consumers connected to node b. The active power absorption $p_{b,t}$ of a bus within t is given by the demand of all consumers connected to that bus, minus the RES generation $\zeta_{b,t} p_{b,t}^{\mathrm{res}}$ coming from any renewable sources connected to b:

$$p_{b,t} = \sum_{c \in \mathcal{C}_b} d_{c,t} - \zeta_{b,t} p_{b,t}^{\mathrm{res}}, \quad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}, \quad (12)$$

where $p_{b,t}^{\mathrm{res}}$ is the RES output (i.e. a random variable) and $\zeta_{b,t} \in [0,1]$ is a RES curtailment factor, with $\zeta_{b,t} = 1$ meaning that no RES is curtailed and $\zeta_{b,t} = 0$ meaning that all of the RES production is curtailed.

The bus's reactive power is assumed to be unilaterally determined by the active power, through a constant power factor pf_b, (with its value depending on the type of resources connected to the node) as in

$$q_{b,t} = p_{b,t} \tan\left(\cos^{-1}\left(\mathrm{pf}_b\right)\right), \quad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}. \quad (13)$$

Moreover, let us denote a bus's parent node by i_b and its directly descendant nodes by the set $\mathcal{J}_b$. The active and reactive power flows from i_b to b are denoted as $P_{i_b b,t}$ and $Q_{i_b b,t}$ respectively. The active and reactive power balance constraints of each bus read as

$$P_{i_b b,t} - p_{b,t} - \sum_{j \in \mathcal{J}_b} \left(P_{bj,t} + \mathrm{R}_{bj} I_{bj,t}\right) = 0 \qquad \forall\, b \in \mathcal{B}_n, n \in \mathcal{N}, \, t \in \mathcal{T}, \quad (14)$$

and

$$Q_{i_b b,t} - q_{b,t} - \sum_{j \in \mathcal{J}_b} \left(Q_{bj,t} + \mathrm{X}_{bj} I_{bj,t}\right) = 0 \qquad \forall\, b \in \mathcal{B}_n, n \in \mathcal{N}, \, t \in \mathcal{T}, \quad (15)$$

respectively, where $I_{bj,t}$ is the squared magnitude of the current flowing through the line connecting b to $j \in \mathcal{J}_b$, the parameter R_{bj} is the line's resistance and X_{bj} is the line's reactance. Let $V_{b,t}$ denote a bus's voltage (squared magnitude). The voltage drop between i_b and b is given by

$$V_{i_b,t} - 2\left(\mathrm{R}_{i_b b} P_{i_b b,t} + \mathrm{X}_{i_b b} Q_{i_b b,t}\right) - \left(\mathrm{R}_{i_b b}^2 + \mathrm{X}_{i_b b}^2\right) I_{i_b b,t} = V_{b,t}, \quad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}. \quad (16)$$

Branch power flows are calculated using the inequality

$$V_{b,t} I_{i_b b,t} \geq P_{i_b b,t}^2 + Q_{i_b b,t}^2, \qquad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}, \quad (17)$$

as prescribed by the eminent second-order conic relaxation model [36], while voltages and currents should remain within safe operational bounds, i.e.,

$$\underline{\mathrm{V}} \leq V_{b,t} \leq \overline{\mathrm{V}} \qquad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}, \quad (18)$$

$$0 \leq I_{i_b b,t} \leq \bar{\mathrm{I}}_{i_b b} \qquad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}. \quad (19)$$

To maintain the distribution system's operational safety, the operator may need to curtail RES generation, which comes with a penalty instantiated as

$$C_{b,t} = \mathrm{w}_b^{\mathrm{res}} \cdot (1 - \zeta_{b,t})^2, \quad \forall b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{T}. \quad (20)$$

D. Problem Formulation

The overall system's balancing constraint reads[2]

$$\sum_{g \in \mathcal{G}} y_{g,t} = \sum_{n \in \mathcal{N}} p_{0,t}^{(n)}, \quad \forall t \in \mathcal{T}, \quad (21)$$

where $p_{0,t}^{(n)}$ is the power absorption at the root node of network n. Under these considerations, the market-motivating, optimal operation of the overall, flexibility-integrated system can be expressed as the optimal control problem OPT (for optimal control), which takes the form

$$\min_{\pi} \left\{ \mathbb{E}\Big[\sum_{t \in \mathcal{T}} \Big(\sum_{g \in \mathcal{G}} C_{g,t} + \sum_{c \in \mathcal{C}^{\mathrm{scdl}}} C_{c,t} + \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{B}_n} C_{b,t} \Big) \Big] \right\} \quad \text{(OPT)}$$

$$\text{subject to}$$

$$\begin{aligned} \text{Generators' constraints} &: (1)-(3), \\ \text{Schedulable Loads' models} &: (4)-(7), \\ \text{Non-schedulable Loads' models} &: (8)-(11), \\ \text{Distribution Networks' constraints} &: (12)-(20), \\ \text{Balancing constraint} &: (21), \end{aligned}$$

where the system cost expectation is over state-action trajectories of the (stochastic) demand, and the relevant solution concept is a policy π, i.e., a mapping of observed joined states $(x_{c,\tau})_{c \in \mathcal{C}}$, previous generator outputs $(y_{g,t-1})_{g \in \mathcal{G}}$, and RES generation $(p_{b,t}^{\mathrm{res}})_{b \in \mathcal{B}_n, n \in \mathcal{N}}$, to decisions

$$\begin{aligned} \mathcal{D}_t = \big\{&(y_{g,t})_{g \in \mathcal{G}}, \\ &(d_{c,t}, x_{c,t}, u_{c,t})_{c \in \mathcal{C}^{\mathrm{scdl}}, t \in \mathcal{T}}, (\gamma_{c,\tau}, u_{c,\tau}, x_{c,\tau}, d_{c,t})_{c \in \mathcal{C}^{\mathrm{fns}}, t \in \mathcal{T}}, \\ &(\zeta_{b,t}, p_{b,t}, q_{b,t}, V_{b,t}, P_{i_b b,t}, Q_{i_b b,t}, I_{i_b b,t})_{b \in \mathcal{B}_n, n \in \mathcal{N}} \big\}. \end{aligned}$$

Naturally, the multitude of small consumers constitutes the joint state space of problem (OPT) unmanageably large, which necessitates the design of a distributed policy. In the next Section, we present a market framework that implements a solution to problem (OPT) by allowing local transactive-control policies for consumers to be integrated with neighborhood (i.e. distribution system related) and global (balancing related) pricing signals that achieve system-wide coordination.

III. The Proposed Market Paradigm

In this Section, we present a market framework toward implementing a solution to problem (OPT). Fix a current operational timeslot $\tilde{t} \in \mathcal{T}$ and a look-ahead horizon $\mathcal{H}_{\tilde{t}} =$

[2]To avoid additional notational clutter, we refrain from modeling the transmission system's topology and power flows, assuming a sufficiently over-provisioned transmission network. Nonetheless, the elaborations to follow can be easily generalized for the case of per-node power balance constraints. We also refrain from explicitly modeling RES generation connected directly to the transmission network. Those could already be captured in the given model (1)-(3), by treating them as generators with zero operational cost.

This article has been accepted for publication in IEEE Transactions on Energy Markets, Policy, and Regulation. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TEMPR.2023.3319673

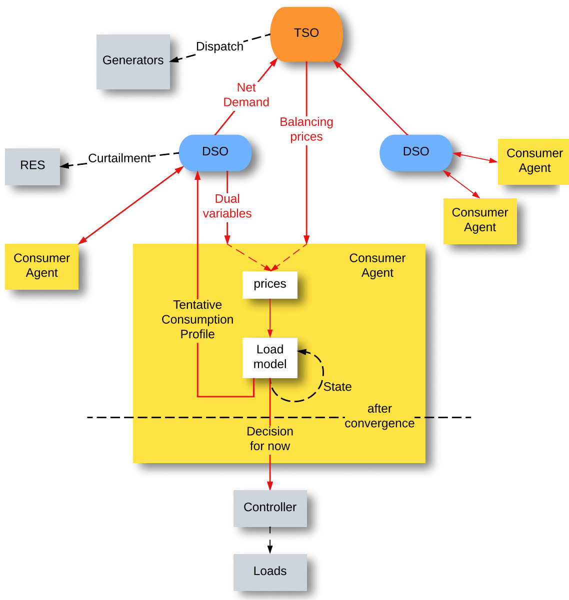


Fig. 2: Schematic diagram of the information exchange and decision process

$\{\widetilde{t}, \widetilde{t}+1, ..., \widetilde{t}+\mathrm{h}\} \subseteq \mathcal{T}$, where h is the number of look-ahead timeslots. We consider a set of tentative consumer prices $(\rho_{c,t})_{t\in\mathcal{H}_{\widetilde{t}}}$. We will exploit the capability of consumers to adapt their consumption in response to prices to integrate them into an iterative market-clearing algorithm where each consumer is informed about the state of the constraints affected by it, via pricing signals. The high-level procedure, to be elaborated in this Section, is demonstrated in Fig. 2.

Let $\left(\rho_{c,t}[k]\right)_{t\in\mathcal{H}_{\widetilde{t}}}$ denote the prices faced by a consumer at iteration k and $\left(d_{c,t}[k]\right)_{t\in\mathcal{H}_{\widetilde{t}}}$ denote its expected demand profile at k. The schedule of consumer $c \in \mathcal{C}^{\mathtt{scdl}}$ is given by

$$\min_{\mathcal{D}_c^{\mathtt{scdl}}} \Big\{ \sum_{t\in\mathcal{H}_{\widetilde{t}}} C_{c,t} \Big\} \quad (22)$$
$$\text{s.t. } (4)-(7),$$

where the decision variables are

$$\mathcal{D}_c^{\mathtt{scdl}} = (d_{c,t}, x_{c,t}, u_{c,t})_{t\in\mathcal{H}_{\widetilde{t}}}, \quad \forall c \in \mathcal{C}^{\mathtt{scdl}}, \quad (23)$$

while the respective expected consumption of a non-schedulable consumer $c \in \mathcal{C}^{\mathtt{fns}}$ is forecasted by the consumer's grey-box agent[3] by solving the set of stochastic differential equations (8)-(11).

Consumer demands $\left(d_{c,t}[k]\right)_{t\in\mathcal{H}_{\widetilde{t}}, c\in\mathcal{C}_b, b\in\mathcal{B}_n}$ are aggregated (per node) and communicated[4] to the local distribution system's n coordinator, namely the DSO, which determines whether these demands are feasible for the distribution network, possibly by necessitating RES curtailments. The DSO's optimal power flow problem reads as

$$\min_{\mathcal{D}_n^{\mathtt{dso}}} \Big\{ \sum_{t\in\mathcal{H}_{\widetilde{t}}} \sum_{b\in\mathcal{B}_n} C_{b,t} \Big\} \quad (24)$$
$$\begin{aligned} \text{s.t. } & (12)-(13), \\ & (14) : \mu_{b,t}, \\ & (15) : \nu_{b,t}, \\ & (16)-(20), \\ & (d_{c,t})_{c\in\mathcal{C}_b, b\in\mathcal{B}_n, t\in\mathcal{H}_{\widetilde{t}}} = \left(d_{c,t}[k]\right)_{c\in\mathcal{C}_b, b\in\mathcal{B}_n, t\in\mathcal{H}_{\widetilde{t}}}, \end{aligned}$$

where the decision variables of n are

$$\mathcal{D}_n^{\mathtt{dso}} = (\zeta_{b,t}, p_{b,t}, q_{b,t}, V_{b,t}, P_{i_b b,t}, Q_{i_b b,t}, I_{i_b b,t})_{t\in\mathcal{H}_{\widetilde{t}}, b\in\mathcal{B}_n}.$$

Note that the consumer demands are fixed, by the last constraint, to the consumers' own decisions, and the dual variables $\mu_{b,t}, \nu_{b,t}$ express the objective function's sensitivity to a marginal change in the node's active and reactive consumer demand. These duals come with an eminent interpretation of pricing signals and their optimal values $\mu_{b,t}[k], \nu_{b,t}[k] \in (24)$ shall be communicated back to the consumers so that the later can adjust their demand profiles. Intuitively, in our context, if the demand causes excessive RES curtailments or excessive energy absorption from the feeder, the sensitivity of the objective function to the demand will be high (due to the quadratic nature of Eqs. (20) and (3)), causing aggressive prices (positive or negative) that incentivize the consumers to adjust the demand in the right direction.

After problem (24) is solved by each DSO, the resulting net demands $\left(p_{0,t}^{(n)}[k]\right)_{n\in\mathcal{N}}$ are communicated to the TSO, which dispatches the generators such that the overall system demand is met. Upon receiving the system's net demand, the TSO solves the economic dispatch problem

$$\min_{\mathcal{D}^{\mathtt{tso}}} \Big\{ \sum_{t\in\mathcal{H}_{\widetilde{t}}} \sum_{g\in\mathcal{G}} C_{g,t} \Big\} \quad (25)$$
$$\begin{aligned} \text{s.t. } & (1)-(3) \\ & (21) \ : \lambda_t, \\ & p_{0,t}^{(n)} = p_{0,t}^{(n)}[k], \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \end{aligned}$$

where the decision variables are

$$\mathcal{D}^{\mathtt{tso}} = (y_{g,t})_{g\in\mathcal{G}, t\in\mathcal{H}_{\widetilde{t}}}$$

and the dual variables $\lambda_t[k] \in (25)$ instantiate the widely understood concept of system marginal prices[5].

Given the results from the TSO and DSO problems, a consumer's pricing signal is updated as

$$\rho_{c,t}[k+1] = \mu_{b,t}[k] + \nu_{b,t}[k] + \lambda_t[k],$$

[3]In practice, an agent can be configured for a consumer by a third party that fills the gap of forecasting and communicating the consumer's flexibility capabilities to the system operator.

[4]Note that, epsecially in distribution networks, a flexible consumer can take advantage of the local network constraints and the market conditions (low liquidity), and act strategically towards deliberately creating and solving congestion problems in order to benefit from manipulating the market. This issue not considered in this paper. The reader is referred to related mechanism-design-inspired studies (e.g. [37]) that treat such issues.

[5]Note that, in problems (25) and (24), we implicitly assume that the TSO and DSO respectively can readily dispatch the generators (respectively, RES) based on their bids (and registered characteristics), as is the case in current systems. This is just for the brevity of the exposition and in order to be more aligned with current practices. This, however, is without loss of generality, and the generators (and/or the RES) could also self-dispatch, similarly to the consumers, based on the tentative prices, if deemed purposeful.

Algorithm 1 The proposed distributed control policy

1: Set $\widetilde{t} = 0$
2: Initialize h, and $\mathcal{H}_{\widetilde{t}}$
3: **while** $\widetilde{t} \leq |\mathcal{T}|$:
4: Set $\mathrm{h} = \min\{\mathrm{h}, |\mathcal{T}| - \widetilde{t}\}$ and update $\mathcal{H}_{\widetilde{t}}$
5: Update RES output forecasts
6: Initialize $k = 0, (\rho_{b,t}[1])_{c\in\mathcal{C},t\in\mathcal{H}_{\widetilde{t}}}$
7: **repeat:**
8: $k = k + 1$
9: **for** $c \in \mathcal{C}^{\mathtt{scdl}}$:
10: Observe consumer's current state
11: calculate $(d_{c,t}[k])_{t\in\mathcal{H}_{\widetilde{t}}}$ by solving (22)
12: communicate $(d_{c,t}[k])_{t\in\mathcal{H}_{\widetilde{t}}}$ to the regional DSO
13: **for** $c \in \mathcal{C}^{\mathtt{fns}}$:
14: calculate $(d_{c,t}[k])_{t\in\mathcal{H}_{\widetilde{t}}}$ by solving (8)-(11)
15: communicate $(d_{c,t}[k])_{t\in\mathcal{H}_{\widetilde{t}}}$ to the regional DSO
16: **for** $n \in \mathcal{N}$:
17: calculate $\left(\zeta_{b,t}[k], \mu_{b,t}[k], \nu_{b,t}[k]\right)_{b\in\mathcal{B}_n,t\in\mathcal{H}_{\widetilde{t}}}$ by solving (24)
18: communicate $\left(p_{0,t}^{(n)}\right)_{t\in\mathcal{H}_{\widetilde{t}}}$ to the TSO
19: calculate $(y_{g,t}[k])_{g\in\mathcal{G},t\in\mathcal{H}_{\widetilde{t}}}$ and $(\lambda_t[k])_{t\in\mathcal{H}_{\widetilde{t}}}$ by solving (25)
20: set $\rho_{c,t}[k+1]$, for each c, t, as in (26)
21: **until** $|\rho_{c,t}[k+1] - \rho_{c,t}[k]| < \varepsilon, \forall c, t$
22: **apply:** $\rho_{c,\widetilde{t}}[k]$ to each $c \in \mathcal{C}$ and $y_{g,\widetilde{t}}[k]$ to each $g \in \mathcal{G}$
23: [time transitions] $\widetilde{t} = \widetilde{t} + 1$

$$\forall c \in \mathcal{C}_b, b \in \mathcal{B}_n, n \in \mathcal{N}, t \in \mathcal{H}_{\widetilde{t}}, \quad (26)$$

and the demand calculation is updated accordingly, thus closing the loop. The procedure repeats until all price changes fall below a tolerance parameter ε. The exact algorithm is described in Algorithm 1. Notice that the policy of Algorithm 1 solves a look-ahead optimization problem at each timeslot, by using decomposition. In constrast to standard dual decomposition methods that update the dual variables using a (constant or adaptive) step, this method updates the duals by setting them directly to the values obtained by solving the operators' optimization problems. This update rule, in contrast to standard dual decomposition methods, gives rise to convergence properties even for non-convex problems. The reader is referred to [38] for a more elaborate discussion and to [39], Proposition 7.2.1, for the original source.

Another important observation for Algorithm 1 is that it decomposes the problem down to the agent level, i.e. one sub-problem per agent (cf. line 11 of Algorithm 1) and that these subproblems are solved in parallel. Therefore, as the number of nodes/agents grows, the computational time will not be significantly higher since all subproblems are solved in parallel.

IV. Simulation Setting and Results

A. Simulations' Setting

The proposed policy was applied to a system consisting of eight generators and four IEEE 33-bus distribution networks, the characteristics of which are set as in [40]. The simulations were run for a period of 12 timeslots.

TABLE II: Schedulable Consumers' parameters

Parameters	Values
$\underline{\mathrm{u}}_c$	$\mathcal{N}(0.6, 0.1)$
$\overline{\mathrm{u}}_c$	$\mathcal{N}(1.2, 0.2)$
$\widetilde{\mathrm{x}}_c$	$\mathcal{N}(0.6, 0.1)$
a_c	$\mathcal{U}(0.5, 0.75)$
b_c	$\mathcal{U}(0.5, 0.75)$
$\mathrm{e}_{c,t}$	$\mathcal{U}(0.1, 1)$

The generators' upper and lower bounds were set in equally-spaced, decreasing order, in $[4, 2]$ MWhs and in $[0.5, 0]$ MWhs respectively. Their cost parameters $\mathrm{w}_g^{\mathrm{l}}$ were set in increasing order in $[1, 5]$ to capture the usual mix of expensive small generators and cheaper and bigger base generators. The quadratic cost parameters $\mathrm{w}_g^{\mathrm{q}}$ were set in $[0.5, 0.1]$ and the ramping parameters r_g in $[3, 1.5]$.

Each distribution network was assumed to have ten flexible nodes (unless stated otherwise), and the rest are inflexible. Each node's demand was set as specified by the IEEE 33-bus standard but multiplied by a factor df_t such that the demand exhibits some peaks and valleys across time. To simulate demand forecast inaccuracy, at each operational timeslot $\widetilde{t}$ the demand factors were updated by sampling from $\mathcal{N}(\mathrm{df}_{\widetilde{t}}, 0.05)$, i.e. the new forecast is normally distributed around the previous forecast. Of the network's flexible nodes, half were considered schedulable and the other half non-schedulable, with two flexible consumers per node.

The schedulable consumers' parameters were set as defined in Table II, where $\mathcal{N}(\mu, \sigma)$ represents the normal distribution and $\mathcal{U}(x, y)$ represents the uniform distribution. The disturbances $w_{c,t}$ for each $t \in \mathcal{H}_0$ were sampled from $\mathcal{N}(0, 0.05)$. At each subsequent operational timeslot $\widetilde{t}$ the disturbance forecasts were updated as $(w_{c,t})_{t\in\mathcal{H}_{\widetilde{t}}} = (\delta w_{c,t} \cdot w_{c,t})_{t\in\mathcal{H}_{\widetilde{t}-1}}$, where $\delta w_{c,t} \in \mathcal{N}(1, 0.05)$. The non-schedulable consumers' flexibility functions were parameterized as described in [34]. Their actualized state was again assumed to be normally distributed around zero with a standard deviation of 5% from the previously forecasted one. The same assumption was adopted for consumer baseline consumptions and for the RES output forecasts, unless stated otherwise. Note that these models were only used for the purpose of having a particular testbed for the algorithm's experimental evaluation; but the grey-box models and methods of this paper are transparent to load models and are not restricted by assumptions over them.

Finally, the RES cost parameters $\mathrm{w}_b^{\mathtt{res}}$ were sampled from $\mathcal{N}(1, 0.1)$ and their capacity was assumed normally distributed around the node's demand. For each distribution network, ten random nodes were selected to feature RES generation.

B. Simulation Results

This subsection presents insights from the market's empirical simulation. We first present a characteristic example of the system's demand and RES modification, with respect to their would-be baseline consumption and generation, across time. Fig. 3 showcases the algorithm's resulting modifications, where it can be observed the tendency to fill valleys and flatten

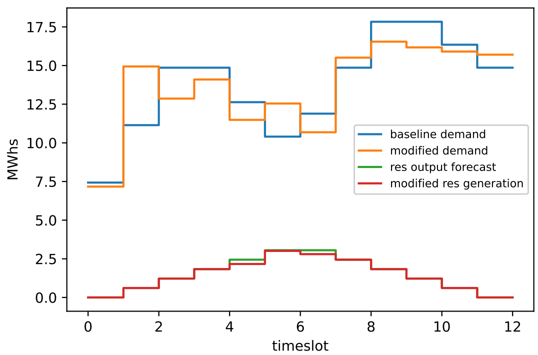


Fig. 3: System demand and RES generation modification across time

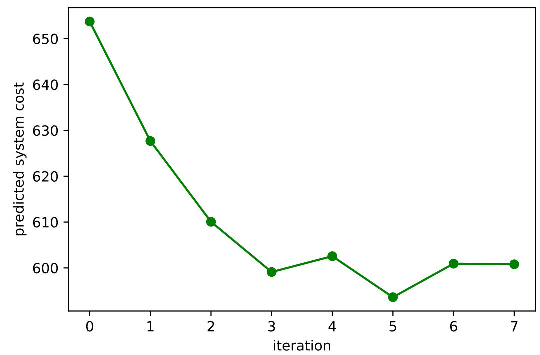


Fig. 5: System's expected cost across iterations

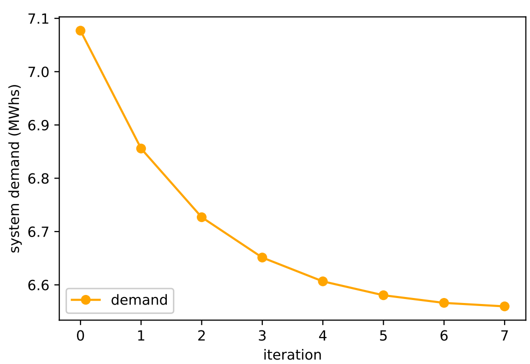


Fig. 4: System's net demand (demand minus RES generation) across iterations

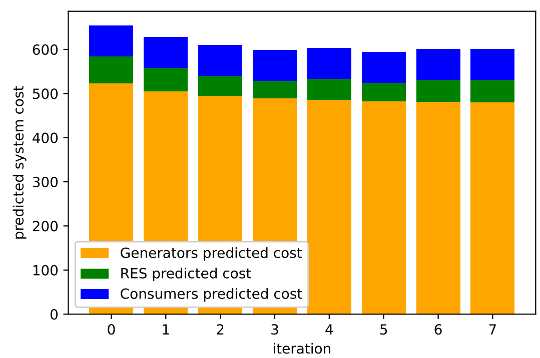


Fig. 6: System's cost allocation to generators, RES, and consumers, across iterations

peaks, as well as the tendency to move the demand into times with more RES generation (e.g. timeslot 5), in order to absorb more RES generation when it is available.

Next, we study the clearing algorithm's convergence properties. For a look-ahead horizon of six timeslots and a tolerance of $\varepsilon = 0.1$, Figs. 4 and 5 present the system's net demand (i.e. the total aggregated demand minus the total aggregated RES generation) and expected cost, across the algorithm's iterations[6]. Moreover, Fig. 6 shows how the cost is allocated to generators, RES, and consumers across iterations.

The rest of the results that follow were obtained by averaging values over 20 experiments, where in each experiment a different sample was drawn from the random distributions described in the previous subsection. We first investigate the effect of the look-ahead horizon's length on the system's cost and on the algorithm's computational time for one iteration. Fig. 7 demonstrates the trade-off between optimality loss (defined as the percentage increase of system cost with respect to the minimum one achieved) and computational time for different horizon lengths.

Initially, the optimality loss decreases with increasing horizon length, with a 4-timeslots' look-ahead exhibiting the lowest average system cost. Interestingly, for longer look-ahead horizons the performance worsens. This can be explained by the fact that we have considered systematic forecasts errors at each time; so, when looking too far ahead, the system accumulates larger forecast errors that outweigh the benefits of prediction-informed decisions. Although this is the case for this particular simulation setup, it should not be interpreted as an indication that long-term forecasts are not helpful in general. Sophisticated forecast methods readily account for such effects, e.g. by using a discount factor for the weights of variables further down the horizon.

The computational time per iteration, on the other hand, increases monotonically with longer look-ahead horizon, as expected. Note though that the iteration times are remarkably short[7], which verifies and quantifies the benefit of the algorithm's advantageous feature of enabling the parallel execution of the consumers' sub-problems.

Next, we assess how the degree of flexibility penetration affects the system's cost. For this purpose, we run simulations with increasing numbers of flexible nodes and obtained the corresponding average (over experiments) system cost. Fig. 8

[6]Note that the algorithm converged in only 7 iterations. This is not a specialty of this particular problem instance; it is, rather, a typical convergence behavior across various problem instances.

[7]All experiments were run in a i5-7300U CPU, 2.60GHz laptop computer with 8GB of RAM, calling the Gurobi (for the TSO and consumer problems) and Ipopt (for the DSO problem) solvers from the Pyomo environment.

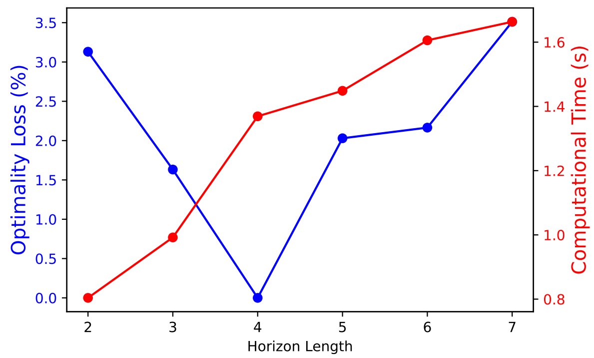


Fig. 7: System's cost and algorithm's computational time per iteration as a function of look-ahead horizon length

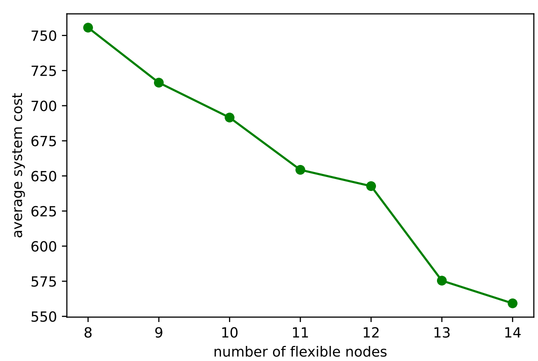


Fig. 8: Average system's cost as a function of the number of flexible nodes in each distribution network

demonstrates the expected effect of diminishing system cost with higher numbers of flexible consumers.

Last, we perform a sensitivity analysis with respect to the inaccuracy of RES forecasts. Specifically, at an operational timeslot $\tilde{t}$, we set the forecasted RES generation $(p^{\mathrm{res}}_{b,t})_{t\in\mathcal{H}_{\tilde{t}}}$ over the look-ahead horizon as

$$(p^{\mathrm{res}}_{b,t})_{t\in\mathcal{H}_{\tilde{t}}} = (\delta p_{b,t} \cdot p^{\mathrm{res}}_{b,t})_{t\in\mathcal{H}_{\tilde{t}-1}}, \tag{27}$$

where $\delta p_{b,t} \in \mathcal{N}(1, \sigma^{\mathrm{res}})$. Fig. 9 demonstrates the average (over experiments) system cost for different values of σ^{res}, i.e. for different levels of forecast inaccuracies. Seeing that the loss only increases from 678 to 715 when going from perfect foresight to a standard deviation of 10%, it can be concluded that the method exhibits a satisfactory level of robustness against RES forecast errors.

V. Conclusions and Implications

In this paper, we motivated the problem of coordinating TSO and DSO decisions in a predictive and adaptive manner, while integrating the flexibility capabilities of diverse distributed resources. The formulated problem motivated a market-based approach, suggesting a shift from traditional markets where participants bid their whole model (i.e. cost function and constraints) upstream, to an iterative market

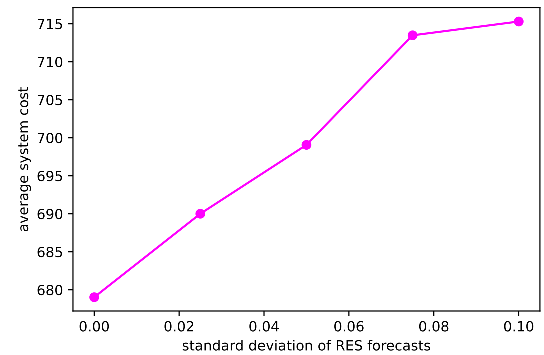


Fig. 9: Average system's cost as a function of the RES forecast inaccuracy factor

procedure where flexible participants indirectly implement their model by repeatedly responding to tentative pricing signals. This, combined with a scheduling/forecasting grey-box agent introduced between the system operation layer and the consumer's control layer, allows for the seamless integration of existing flexible loads' control schemes into a holistic electricity market.

Importantly, the proposed market scheme allows for a distinction of system operation from consumer modeling: designing consumer agents is no longer constrained by specific modeling requirements; instead, by only requiring agents to respond to price queries, much room is left for innovation and competition. This, in combination with our promising results of fast coordination times, can be a powerful concept that can pave the way for massive integration of distributed flexibility.

In the simulation study, the proposed policy took an average of 0.8 seconds per iteration. The demonstrated convergence in less than 10-20 iterations together with the result on computational time per iteration being in the order of seconds, indicate that the proposed market framework can reach a decision in less than one minute (modulo communication delays, which are not expected to be significant according to [15]). In view of the fact that the main impactful distributed resources (e.g. buildings' heating, water towers, etc.) exhibit dynamics of significantly slower order (cf [7]), we regard the market's short decision times as an encouraging result toward potential consideration for practical applicability. Future work can put this potential to the test, by implementing the proposed framework in real pilot systems. Also, more research is required to incorporate other types of agents (e.g. based on reinforcement learning) into the proposed framework and address issues of strategic agent behavior.

References

[1] P. Pinson, "What may future electricity markets look like?" arXiv preprint arXiv:2302.02833, 2023.
[2] G. Tsaousoglou, J. S. Giraldo, and N. G. Paterakis, "Market mechanisms for local electricity markets: A review of models, solution concepts and algorithmic techniques," Renewable and Sustainable Energy Reviews, vol. 156, p. 111890, 2022.
[3] X. Jin, Q. Wu, and H. Jia, "Local flexibility markets: Literature review on concepts, models and clearing methods," Applied Energy, vol. 261, p. 114387, 2020.

This article has been accepted for publication in IEEE Transactions on Energy Markets, Policy, and Regulation. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TEMPR.2023.3319673

[4] E. Vrettos, E. C. Kara, J. MacDonald, G. Andersson, and D. S. Callaway, “Experimental demonstration of frequency regulation by commercial buildings—part i: Modeling and hierarchical control design,” IEEE Transactions on Smart Grid, vol. 9, no. 4, pp. 3213–3223, 2016.

[5] S. Lai, J. Qiu, Y. Tao, and J. Zhao, “Customized pricing strategy for households based on occupancy-aided load disaggregation,” IEEE Transactions on Energy Markets, Policy and Regulation, 2023.

[6] X. Zhang, M. Pipattanasomporn, T. Chen, and S. Rahman, “An iot-based thermal model learning framework for smart buildings,” IEEE Internet of Things Journal, vol. 7, no. 1, pp. 518–527, 2019.

[7] C. A. Thilker, H. Madsen, and J. B. Jørgensen, “Advanced forecasting and disturbance modelling for model predictive control of smart energy systems,” Applied Energy, vol. 292, p. 116889, 2021.

[8] C. Finck, R. Li, and W. Zeiler, “Economic model predictive control for demand flexibility of a residential building,” Energy, vol. 176, pp. 365–379, 2019.

[9] D. Azuatalam, W.-L. Lee, F. de Nijs, and A. Liebman, “Reinforcement learning for whole-building hvac control and demand response,” Energy and AI, vol. 2, p. 100020, 2020.

[10] X. Xu, Y. Jia, Y. Xu, Z. Xu, S. Chai, and C. S. Lai, “A multi-agent reinforcement learning-based data-driven method for home energy management,” IEEE Transactions on Smart Grid, vol. 11, no. 4, pp. 3201–3211, 2020.

[11] S. H. Low, “Convex relaxation of optimal power flow—part i: Formulations and equivalence,” IEEE Transactions on Control of Network Systems, vol. 1, no. 1, pp. 15–27, 2014.

[12] D. K. Molzahn, F. Dörfler, H. Sandberg, S. H. Low, S. Chakrabarti, R. Baldick, and J. Lavaei, “A survey of distributed optimization and control algorithms for electric power systems,” IEEE Transactions on Smart Grid, vol. 8, no. 6, pp. 2941–2962, 2017.

[13] A. Papavasiliou, “Analysis of distribution locational marginal prices,” IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 4872–4882, 2017.

[14] Y. Zhou, J. Wang, Y. Zhang, J. Wei, W. Sun, and J. Wang, “A fully-decentralized transactive energy management under distribution network constraints via peer-to-peer energy trading,” IEEE Transactions on Energy Markets, Policy and Regulation, 2023.

[15] G. Tsaousoglou, P. Soumplis, N. Efthymiopoulos, K. Steriotis, A. Kretsis, P. Makris, P. Kokkinos, and E. Varvarigos, “Demand response as a service: Clearing multiple distribution-level markets,” IEEE Transactions on Cloud Computing, vol. 10, no. 1, pp. 82–96, 2021.

[16] G. Qu and N. Li, “Optimal distributed feedback voltage control under limited reactive power,” IEEE Transactions on Power Systems, vol. 35, no. 1, pp. 315–331, 2019.

[17] M. K. Singh, V. Kekatos, and G. B. Giannakis, “Learning to solve the ac-opf using sensitivity-informed deep neural networks,” IEEE Transactions on Power Systems, vol. 37, no. 4, pp. 2833–2846, 2021.

[18] M. Chertkov, D. Deka, and Y. Dvorkin, “Optimal ensemble control of loads in distribution grids with network constraints,” in 2018 Power Systems Computation Conference (PSCC). IEEE, 2018, pp. 1–7.

[19] Z. Pan, T. Yu, J. Li, Y. Wu, J. Chen, J. Lu, and X. Zhang, “Multi-agent learning-based nearly non-iterative stochastic dynamic transactive energy control of networked microgrids,” IEEE Transactions on Smart Grid, vol. 13, no. 1, pp. 688–701, 2021.

[20] G. Tsaousoglou, P. Ellinas, J. Giraldo, and E. Varvarigos, “Distributed sequential optimal power flow under uncertainty in power distribution systems: A data-driven approach,” 2022.

[21] F. Capitanescu, “Tso–dso interaction: Active distribution network power chart for tso ancillary services provision,” Electric Power Systems Research, vol. 163, pp. 226–230, 2018.

[22] S. Riaz and P. Mancarella, “On feasibility and flexibility operating regions of virtual power plants and tso/dso interfaces,” in 2019 IEEE Milan PowerTech. IEEE, 2019, pp. 1–6.

[23] Z. Yuan and M. R. Hesamzadeh, “Hierarchical coordination of tso-dso economic dispatch considering large-scale integration of distributed energy resources,” Applied energy, vol. 195, pp. 600–615, 2017.

[24] S. Taheri, V. Kekatos, S. Veeramachaneni, and B. Zhang, “Data-driven modeling of aggregate flexibility under uncertain and non-convex device models,” IEEE Transactions on Smart Grid, vol. 13, no. 6, pp. 4572–4582, 2022.

[25] J. Saez-Gallego, J. M. Morales, M. Zugno, and H. Madsen, “A data-driven bidding model for a cluster of price-responsive consumers of electricity,” IEEE Transactions on Power Systems, vol. 31, no. 6, pp. 5001–5011, 2016.

[26] X. Chen, E. Dall’Anese, C. Zhao, and N. Li, “Aggregate power flexibility in unbalanced distribution systems,” IEEE Transactions on Smart Grid, vol. 11, no. 1, pp. 258–269, 2019.

[27] R. Halvgaard, L. Vandenberghe, N. K. Poulsen, H. Madsen, and J. B. Jørgensen, “Distributed model predictive control for smart energy systems,” IEEE Transactions on Smart Grid, vol. 7, no. 3, pp. 1675–1682, 2016.

[28] M. Caramanis, E. Ntakou, W. W. Hogan, A. Chakrabortty, and J. Schoene, “Co-optimization of power and reserves in dynamic t&d power markets with nondispatchable renewable generation and distributed energy resources,” Proceedings of the IEEE, vol. 104, no. 4, pp. 807–836, 2016.

[29] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, Integrating renewables in electricity markets: operational problems. Springer Science & Business Media, 2013, vol. 205.

[30] J. Kazempour, P. Pinson, and B. F. Hobbs, “A stochastic market design with revenue adequacy and cost recovery by scenario: Benefits and costs,” IEEE Transactions on Power Systems, vol. 33, no. 4, pp. 3531–3545, 2018.

[31] D. M. Gonzalez, J. Hachenberger, J. Hinker, F. Rewald, U. Häger, C. Rehtanz, and J. Myrzik, “Determination of the time-dependent flexibility of active distribution networks to control their tso-dso interconnection power flow,” in 2018 Power Systems Computation Conference (PSCC). IEEE, 2018, pp. 1–8.

[32] M. Usman, M. I. Alizadeh, F. Capitanescu, I.-I. Avramidis, and A. G. Madureira, “A novel two-stage tso–dso coordination approach for managing congestion and voltages,” International Journal of Electrical Power & Energy Systems, vol. 147, p. 108887, 2023.

[33] A. Dognini, C. Challagonda, E. Moro, K. Helmholt, H. Madsen, L. Daniele, L. Schmitt, L. Temal, O. Genest, P. Calvez, R. Ebrahimy, R. Riemenschneider, R. Böhm, and S. Abbes, Data Spaces for Energy, Home and Mobility. RWTH Aachen University, 2022.

[34] R. G. Junker, C. S. Kallesøe, J. P. Real, B. Howard, R. A. Lopes, and H. Madsen, “Stochastic nonlinear modelling and application of price-based energy flexibility,” Applied Energy, vol. 275, p. 115096, 2020.

[35] A. Singhal, S. Hanif, B. Bhattarai, F. B. dos Reis, H. Reeve, and R. Pratt, “Designing a transactive electric vehicle agent with customer’s participation preference,” International Journal of Electrical Power & Energy Systems, vol. 151, p. 109147, 2023.

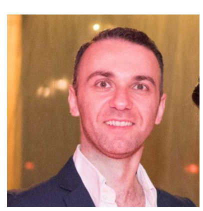
[36] S. H. Low, “Convex relaxation of optimal power flow—part ii: Exactness,” IEEE Transactions on Control of Network Systems, vol. 1, no. 2, pp. 177–189, 2014.

[37] G. Tsaousoglou, J. S. Giraldo, P. Pinson, and N. G. Paterakis, “Mechanism design for fair and efficient dso flexibility markets,” IEEE transactions on smart grid, vol. 12, no. 3, pp. 2249–2260, 2021.

[38] P. Andrianesis, M. Caramanis, and N. Li, “Optimal distributed energy resource coordination: A decomposition method based on distribution locational marginal costs,” IEEE Transactions on Smart Grid, vol. 13, no. 2, pp. 1200–1212, 2021.

[39] D. Bertsekas, “Nonlinear programming, athena sci,” Optim. Comput. Ser., 3rd ed., Athena Scientific, Belmont, MA, 2016.

[40] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Power Engineering Review, vol. 9, no. 4, pp. 101–102, 1989.



Georgios Tsaousoglou received his PhD from the National Technical University of Athens (NTUA) in 2019. He then joined the Greek Transmission System Operator as an electricity markets expert. Soon after, he became a postdoctoral researcher and Marie Curie Fellow at the Eindhoven University of Technology. Since October 2022, he has been an Assistant Professor at the Department of Applied Mathematics and Computer Science, Technical University of Denmark (DTU). His research interests include decision-making under uncertainty, multi-agent systems, and algorithmic game theory, applied to power and energy systems.

Rune Junker received his PhD from the Technical University of Denmark (DTU) in 2020. He has since continued with DTU, initially as a postdoctoral researcher, but he was quickly appointed assistant professor in 2021. His work is centered around developing mathematical models of energy flexibility, that can be used for both characterization and control. Meanwhile, he teaches time series analysis, and forecasts quantities of the energy system professionally at the company ENFOR A/S.

Mohsen Banaei received Ph.D. in power electrical engineering from the Ferdowsi University of Mashhad (FUM), Mashhad, Iran, in 2020. From 2019 to 2020, he was a guest Ph.D. student and then research assistant at Aarhus University (AU), conducting research on advanced control strategies of marine power systems. He is currently a Post-Doc researcher at Technical University of Denmark (DTU). His research interests include operation and planning of power systems, renewable energy resources, electricity markets, energy flexibility, and energy management.

Seyed Shahabaldin Tohidi received his Ph.D. degree in Mechanical Engineering from Bilkent University, Turkey, in 2021. He then joined Applied Mathematics and Computer Science Department in Technical University of Denmark, where he is currently a Postdoctoral researcher. He received his M.Sc. degree in Electrical engineering from K. N. Toosi University of Technology, Iran, in 2014. He has been a member of Control Systems Society (CSS). His research interests include control of energy systems, adaptive control, thermal dynamics modelling and control, model predictive control, safety-critical systems, cyber-physical human systems.

Henrik Madsen received his PhD from the Technical University of Denmark (DTU) in 1986. Since then he has been employed by DTU first as assistant professor, 1986, assoc. prof, 1989, and he has been a full professor in stochastic systems since 1999. In June 2016, he was appointed Knight of the Order of Dannebrog by Her Majesty the Queen of Denmark, and he was appointed Doctor HC at Lund University in June 2017. His research is primarily on modeling, forecasting and control. He has a special focus on applications related to dynamics and flexibility in energy systems.