Sustainable Energy, Grids and Networks 38 (2024) 101399

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Electricity market equilibria analysis on the value of demand-side flexibility portfolios' mix and the strategic demand aggregators' market power

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ARTICLE INFO

Dataset link: https://github.com/FlexGrid/DA_EPEC

Keywords:
Market equilibrium
Strategic demand aggregator
Demand-side flexibility
EPEC
MPEC
Market power

ABSTRACT

Electricity market equilibrium analysis is becoming increasingly important within the today's liberalized electricity market and regulatory context for both market participants and policy makers. The former ones want to make informed business decisions to optimize their market position, while the latter need to promote efficient equilibria that satisfy both supply and demand-side requirements and optimize social welfare. In this paper, we focus on modeling the strategic demand aggregators' (DA) behavior via an Equilibrium Problem with Equilibrium Constraints (EPEC) formulation. We model typical demand flexibility portfolios that comprise of several types of distributed flexibility assets and renewable energy resources. We then quantify the value of demand flexibility portfolios' mix and respective value of market power that a strategic DA may exercise with respect to each DA's cost decrease and social welfare as a function of time for a day-ahead market use case. Simulation results show that: (i) there is an optimal equilibrium point where overall DAs' costs decrease, while social welfare's deteriorates negligibly, (ii) there may be a trade-off between the rate of a certain DA's cost decrease and the rate of market power (or else % share of total demand flexibility) that this DA possesses, so the strategic DA should take this into account in order to find its optimal CAPEX/OPEX balance for its portfolio, (iii) competition among strategic DAs at the demand-side can mitigate grid congestion problems and serve as a counter-balance to the strategic behavior of the supply-side market participants.

1. Introduction

Demand-side flexibility (DSF) is becoming increasingly valuable in today's liberalized electricity markets, because it can be exploited for many novel applications by several market actors in the context of energy transition goals [1]. Indicatively, DSF can be used to: (i) decrease the overall system cost by flattening the demand curve, (ii) provide ancillary services to the transmission grid, (iii) decrease system's balancing/re-dispatch costs in close-to-real-time markets, (iv) provide flexibility services to the distribution grid to deal with local congestion and over/under-voltage issues avoiding/postponing thus grid reinforcement costs, (v) support the political goals for higher renewable energy (RES) penetration levels, (vi) mitigate the increasing volatility of wholesale market prices, etc.

The Demand Aggregator (DA) is a key market actor for all above-mentioned applications. A DA represents a portfolio of numerous small-scale Distributed Flexibility Assets (DFAs) and Distributed Energy Resources (DERs) in the wholesale electricity market by bidding on the portfolio's behalf and scheduling the portfolio's flexibility activation [2]. Recent regulatory frameworks (e.g. [3]) promote a level-playing field for DAs and provide market incentives to them in order to make their business economically sustainable and also incentivize end prosumers to invest in new DER and DFA technologies in collaboration with the grid operators (see more details in [4] and references therein). At the same time, new digital technologies facilitate those DER/DFA investments. For example, smart buildings, being a major source of DSF, are equipped with sophisticated Home/Building Energy Management Systems (HEMS/BEMS), while Internet-of-Things (IoT) technologies enable remote monitoring and control of heavy-load electric appliances such as Thermostatically Controlled Loads (TCLs), Shiftable Loads (SLs), etc. (see more details in [5] and references therein). Another emerging DSF source are Electric Vehicles (EVs), which may use a smart charging infrastructure with vehicle-to-grid (V2G) capabilities in order

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https://doi.org/10.1016/j.segan.2024.101399
Received 4 December 2023; Received in revised form 22 March 2024; Accepted 23 April 2024
Available online 26 April 2024

Nomenclature

Sets

N	Set of transmission buses
H_i^{EV}	Operating horizon of prosumer i's EV, $H_i^{EV} = [t_i^{arr}, t_i^{dep}]$
L_n^{EV}	Set of prosumers with EVs located at bus n
G	Set of generators' buses, $G \subseteq N$
H	Set of timeslots in the scheduling horizon, indexed by t.
L_n^{INL}	Set of prosumers with inflexible loads located at bus n
L	Set of transmission lines
L_n^{RES}	Set of prosumers with RES units located at bus n
D^c	Set of buses with competing DAs' assets, $D^c \subseteq N$
L_n^{SL}	Set of prosumers with SLs located at bus n
H_i^{TCL}	Operating horizon of prosumer i's TCL
L_n^{TCL}	Set of prosumers with TCLs located at bus n
$X_{U/L}$	Set of upper/lower-level problem variables

Decision Variables

b_{nt}/o_{nt}	Strategic DA's quantity bid/offer (MW)
$p_{nt}^{\uparrow}/p_{nt}^{\downarrow}$	Power the DA sells/buys to/from the market at time t (MW)
λ_{nt}	Locational marginal price at bus n and time t (€/MW)
ϕ_{it}	Binary variable indicating the operation mode of prosumer i's EV battery at time t
$p_{it}^{EV,\downarrow}/p_{it}^{EV,\uparrow}$	Charging/Discharging power of prosumer i's EV battery at bus n and time t (MW)
SOC_{it}	State-of-Charge of prosumer i's EV battery at bus n and time t
g_{nt}	Power produced by generator i at bus n and time t (MW)
p_{it}^{INL}	Power consumed by prosumer i's inflexible load (MW)
h_{nt}	Binary variable indicating whether strategic DA submits a demand bid or a supply offer at time t
p_{it}^{RES}	Power produced by prosumer i's RES unit (MW)
$\overline{d}_{nt}^{o}/$	Quantity offer/bid submitted by competing DA at bus n and time t (MW)
ψ_{it}	Binary variable indicating the On/Off status of prosumer i's SL at time t
p_{it}^{SL}	Power consumption of prosumer i's SL at bus n and time t (MW)
p_{it}^{TCL}	Power consumption of prosumer i's TCL at bus n and time t (MW)
θ_{it}	Indoors temperature of prosumer i at time t (° C)
θ_{nt}	Voltage phase angle of bus i

Parameters

θ_{it}^{0}	Outdoor (ambient) temperature of prosumer i at time t (° C)
$\mathcal{W}$	Large positive constant value.
$\eta_i^{\downarrow}/\eta_i^{\uparrow}$	Charging/discharging efficiency of prosumer i's EV battery
COP_i	Coefficient of performance of prosumer i's TCL
C_i	Thermal capacitance of prosumer i's TCL (kWh/°C)
$\overline{T}_{ij}$	Capacity limit of transmission line ij (MW)
c_{nt}^{g}	Marginal production cost of generator i at bus n and time t (€/MW)
$\overline{G}_n$	Maximum production of generator i (MW)
Pr_{it}^{INL}	Forecasted inflexible load profile of prosumer i's inflexible load
SOC_{i0}	Initial state-of-charge of prosumer i's EV battery
SOC^{target}	Requested state-of-charge level of prosumer i' EV battery at the end of the scheduling horizon
$\overline{P}_i^{EV,\downarrow}/\overline{P}_i^{EV,\uparrow}$	Maximum charging/discharging power limit of prosumer i's EV battery (MW)
$c_{nt}^{DA,\downarrow}$	Marginal utility of the strategic DA for consuming power at bus n and time t (€/MW)
$c_{nt}^{DA,\uparrow}$	Marginal cost of the strategic DA for producing power at bus n and time t (€/MW)
y_{nj}	Admittance of transmission line ij
Pr_{it}^{RES}	Forecasted power production profile of prosumer i's RES unit
d_{nt}^{b}	Demand bids submitted by competing DA at bus n and time t (MW)
d_{nt}^{o}	Supply offer submitted by competing DA at bus n and time t (MW)
$c_{nt}^{d,b}$	Marginal utility for consuming power of competing DA at bus n and time t (€/MW)
$c_{nt}^{d,o}$	Marginal cost for supplying power of competing DA at bus n and time t (€/MW)
R_i	Thermal resistance of prosumer i's TCL (°C/kW)
Pr_{it}^{SL}	Power consumption profile of prosumer i's SL for each working cycle (MW)
$\overline{SOC}_i/\underline{SOC}_i$	Upper/Lower limits on state-of-charge of prosumer i's EV battery
$\overline{P}_i^{TCL}$	TCL consumption power limit (MW)
$\overline{\theta}_i/\underline{\theta}_i$	Maximum/minimum desired indoors temperature of prosumer i (° C)
θ_{ref}	Voltage phase angle of the reference bus
D_i	The non-interruptible work cycle duration of prosumer i's SL

Dual Variables

ϕ	Dual variables of the lower-level problem

to intelligently schedule their charging/discharging towards meeting the QoS requirements of the end users (see more details in [6] and references therein).

Despite the afore-mentioned advancements, there are also important economic and technological barriers for DA's business, namely [2]: (i) large initial capital expenditures (CAPEX) are required by DFA owners, (ii) inadequate subsidization of DSF-related assets, (iii) high penalization for DA's portfolio imbalances, (iv) lack of a widespread, standardized and interoperable ICT infrastructure as well as smart grid-ready electric appliances/buildings. Hence, despite the efforts towards reducing the barriers to entry, in today's markets there is an apparent tendency of concentrating large portfolios under only a few DAs, constituting the electricity market oligopolistic. Indeed, historical experience from the supply-side oligopolistic markets documented in [7], coincides with this tendency. In these so-called imperfect competition markets, market power is concentrated within the hands of few strategic participants, who aim at maximizing their individual profits. Market manipulation problems are amplified in systems heavy in non-dispatchable renewable supply and in energy crisis cases, because a relatively small number of dispatchable generators become critical for fulfilling the system's operational needs [8].

Within this context, it is easy to understand that DAs' strategic behavior affects the supply-side profits, too. Although this is desirable (to the extent that the most expensive and environment-unfriendly generation assets are phased out), there is a need to analyze the new electricity market equilibria that emerge. Indeed, there is a need for digital tools and regulatory sandboxes for energy market equilibria analysis to act as an enabler for a fair energy transition for both supply-side and demand-side market actors.

In this paper, we propose an Equilibrium Analysis with Equilibrium Constraints (EPEC) model that consists of several Mathematical Problems with Equilibrium Constraints (MPEC), one for each one of the four strategic DAs that are assumed.

- We compare EPEC vs. MPEC vs. competitive market settings with respect to the social welfare and strategic DAs' cost.
- We quantify the impact of a single DA's portfolio mix (i.e. quantify DA's market power as a function of time within a typical day-ahead market participation use case).
- We quantify the impact of competing DAs' portfolio mixes (i.e. quantify each DA's market power according to the strategic investments of other competing DAs, too)
- We quantify the impact of grid congestion on EPEC results showing that the congestion cost (i.e. DAs' payments minus generators' revenues) is decreased because of the increased ability of the demand side to lower the prices acting thus as a counter-balance to the strategic behavior of the supply-side generation assets.

The remainder of the paper is organized as follows: Section 2 summarizes the related works from the international literature ending up with explicitly stating this paper's novel contributions. In Section 3: (i) the system model is described together with all the mathematical formulation of the proposed bi-level problem (cf. Section 3.1), (ii) this bi-level problem is converted into a tractable Mixed Integer Linear Program (MILP) in Section 3.2, and (iii) in Section 3.3, the EPEC formualtion is explained. In Section 4, the performance evaluation results are demonstrated and explained. Finally, concluding remarks and future work is provided in Section 5.

2. Related works and paper's contributions

There are three main related research threads in the recent international literature: (i) MPEC-related works for strategic DAs with large-scale centralized FAs, (ii) MPEC-related works for strategic DAs with many distributed FAs, and (iii) EPEC-related works for modeling competition among several strategic market participants.

2.1. MPEC-related works for a strategic DA with large-scale centralized FAs

All papers that fall within this research thread consider MPEC models in which a strategic DA (or a strategic energy storage operator) competes with conventional generation. They all assume a generic model for their strategic demand-side management or storage portfolio, while all other demand-side participants are price takers. [9] considers a strategic large consumer that seeks to derive bidding curves to manipulate the energy-only day-ahead market for its own benefit. [10] is a similar work that assumes a more complex market participation model (i.e. day-ahead and real-time balancing market) to optimally exploit wind power production uncertainty. In both papers, only one large consumer is modeled without explicitly modeling the various types of FAs that may belong to its portfolio. [11–14] are all works that assume an MPEC model tailored to a strategic large-scale energy storage operator. [11,12] consider market participation in the day-ahead market only, while [13,14] assume co-optimized participation in both day-ahead (energy and reserve) and real-time balancing markets. [15] is the most relevant paper with our work. It considers an MPEC model for a strategic generator incorporating a generic model for demand-side flexibility, too. However, the focus is on the impact of demand shifting on the market power potential of the generation side, and not on the market power potential of the demand side through the modeling of strategic DAs.

2.2. MPEC-related works for a strategic DA with many distributed FAs

All papers of this category assume an MPEC model for a strategic DA that operates a vast number of distributed FAs (either of the same type or of several types of DFAs). [16] assumes a price-maker EV aggregator that operates a fleet of distributed EVs with no vehicle-to-grid (V2G) capabilities. [17] assumes a strategic DA that operates a portfolio of distributed curtailable loads taking into account wind power uncertainties, too, but without modeling any other type of DFA or distributed energy resource (DER). Authors in [18–21] assume a price-maker energy storage aggregator that operates many distributed battery storage units (BSUs) across the entire grid and is thus able to exploit spatio-temporal arbitrage to maximize its total revenues. In particular, our work in [21] extends the pre-mentioned works by considering co-optimized participation in four different markets (i.e. day-ahead, reserve, balancing, and a novel distribution-level flexibility market). Other recent works assume a strategic DA [22,23] or Virtual Power Plant (VPP) operator [24–26] or distribution company (DISCO) [27] which operate several types of DFAs, DERs, BSUs and conventional generation units. [22] quantifies the negative impact on social welfare and operational expenditures' (OPEX) increase in other price-taker DAs. [23] considers a DA, whose DFAs' modeling is quite similar with our work. However, it neither models the competition among several DAs nor focuses on the quantification of DAs' market power for various portfolio mixes of the strategic DAs. Instead, [23] focuses on quantifying the market power impact due to the DA's participation in various markets. Similarly, all other papers assume only one strategic DA, while all other competing DAs are assumed to be price-takers, which is a rather strong assumption, which does not enable a thorough electricity market equilibria analysis.

2.3. EPEC-related works for modeling competition among several strategic market participants

This research thread includes papers that explicitly model several strategic market participants and their respective interaction/competition in the electricity markets. Similarly to our work, they all use an EPEC model, but none of them considers market interaction among several strategic DAs. [28] was the first related EPEC work that models several strategic conventional generators by using the diagonalization method in order to find Nash equilibria in an imperfect electricity market. Several papers like [29–31] followed up by proposing specific enhancements. For example, [29] considers more realistic step-wise offer curves for the strategic generators, authors in [30] were the first to consider a multi-period market as well as multi-block bidding, while [31] deals with a slightly different use case (other than the classical day-ahead market participation), which is the yearly maintenance scheduling problem of strategic generators. More recently, EPEC modeling has also been applied for strategic large-scale RES generators (mostly wind power producers) given the fact that their market share has significantly grown and even become dominant in specific geographical regions around the globe (e.g. northern Europe and several mid-west states in USA) [32–34]. These works include market uncertainties (i.e. various wind power penetration scenarios) and take into account grid constraints, but the demand is assumed to be totally inelastic. Some other works such as [35,36] focus on small-scale DERs that usually reside at the distribution grid and are represented by a Distribution Company (DISCO) in the wholesale day-ahead electricity market. This DISCO should also respect distribution-level grid constraints. However, these works only consider inelastic and/or interruptible loads that are not price-responsive and thus flexible. Other interesting works focus on the interaction between strategic conventional generators', RES generators' and storage operators' business portfolios [37] or interaction between a strategic storage operator and a strategic DA [38]. However, they only assume a generic model of a flexibility portfolio and do not model explicitly the various types of DFAs that belong to the DA's portfolio. [39,40] focus on equilibrium analysis for strategic storage operators that exploit their spatio-temporal arbitrage capability of their portfolios. Various types of storage assets and generators (i.e. thermal units, hydro units, RES units, lithium-ion batteries, etc.) are considered and various generation portfolio mixes are simulated to showcase the impact that each individual type of generation/storage asset has on the market equilibrium. To the best of our knowledge, the first paper that deals with the interaction among several strategic DAs is our recent work in [41]. The current paper extends this conference paper's work by providing more extensive mathematical formulation and performance evaluation results. We claim that this work is the first one that explicitly models various types of DFAs (i.e. shiftable/curtailable loads, TCLs, EVs, PVs) and the impact that each individual DFA type has on both the market equilibrium as well as on the market power that each strategic DA can potentially exercise.

2.4. Paper's novel contributions

In this paper, we consider an oligopolistic day-ahead wholesale electricity market comprising of a few strategic DAs that compete with each other. We pursue a market equilibrium analysis by quantifying the value that various aggregated demand flexibility portfolio mixes can offer to each DA's business profits as well as the corresponding impact to the social welfare. Similarly, we also quantify each DA's market power in various market contexts to intuitively derive respective policy implications. The paper's contributions can be summarized as follows:

- In contrast to existing MPEC-related works (cf. Sections Section 2.1, 2.2 above), which model strategic DAs with large-scale FAs or small-scale DFAs of a certain type (e.g. EVs only, shiftable loads only, etc.), we explicitly model several types of heterogeneous DFAs and we quantify the impact of a single DA's or multiple DAs' portfolio mixes on each DA costs' decrease and social welfare's decrease. We showcase that when a certain type of DFA prevails, this entails different results on DAs' costs and social welfare.
- In contrast to existing EPEC-related works (cf. Section 2.3 above), that focus on modeling equilibria for oligopolistic supply-side market (i.e. strategic generators'/storage operators' EPEC problem), we focus on the oligopolistic demand-side market (i.e. strategic DAs' EPEC problem). Interestingly, the DAs' portfolio mix can exercise dynamic market power as a function of time within a typical day-ahead market.
- By studying the impact of various competing DAs portfolios' mixes, we interestingly found that, in some of them, there may be a trade-off between the rate of a certain DA's cost decrease and the rate of market power (or else % share of total demand flexibility) that this DA possesses. This means that even though a future investment of a specific DFA type may be more beneficial for a DA in terms of its OPEX decrease, it may be less beneficial for the same DA in the long term, because of its decreased future ability to influence the prices in the long-term.

3. System model

In this section, we formulate a Nash-Cournot equilibrium problem between a set of competing strategic Demand Aggregators (DAs). Each DA operates a portfolio of diverse distributed assets, representing them into the day-ahead electricity market. Our primary objective is to cultivate a comprehensive understanding of the market interactions between the DAs in an oligopolistic market setting. To achieve this, we have consciously opted for a rather deterministic framework, wherein we deliberately neglect the uncertainties associated with the renewable energy production or the demand patterns. However, this assumption can be readily relaxed, but at the cost of increasing the model's complexity.

In the following Section 3.1, we describe the bilevel model that characterizes the bidding decision problem of a single price-maker DA. Next, in Section 3.2, we focus on the process of converting the formulated bilevel problem into a solvable Mixed Integer Linear Problem (MILP). Finally, in Section 3.3, we focus on the formulation of the EPEC problem, that we use to calculate the Nash-Cournot equilibrium between several competing strategic DAs.

3.1. Bilevel problem of a single DA

As mentioned above, in this paper, we consider a day-ahead nodal network-constrained electricity pool market with a 24-h time horizon (H), that governs the operation of a transmission system, which is characterized by a set of buses N and a set of transmission lines L. Generators and demand aggregators participate in the market, with the latter representing the interests of a set of prosumers. These prosumers own and operate various assets, with the DAs being responsible for their feasible operation, based on the prosumers' preferences. The set of transmission grid buses which generators are connected to is denoted by $G \subseteq N$, while the set of buses where the assets of DAs are located is denoted by $D^c \subseteq N$. In this subsection, we focus on the bilevel problem of a single strategic DA, which can represent prosumers in the market, whose assets can be located at a set of transmission buses ($N^m \subseteq N$). The DA's portfolio consists of EVs (L_n^{EV}), TCLs (L_n^{TCL}), shiftable loads (L_n^{TCL}), generic inflexible loads (L_n^{INL}) and RES unts (L_n^{RES}), each located at a specific bus indexed by $n \in N^m$. The DA aims to leverage the assets' flexibility so as to strategically participate in the market and maximize financial gains.

Upper-Level Problem

In the upper-level problem, the DA seeks to minimize its daily costs that result from its participation in a nodal electricity pool market, while respecting the operational constraints of its portfolio's assets. Hence, the objective function of the upper-level problem is the following:

$$\min_{\mathbb{X}_U} \sum_{n\in N^m} \sum_{t\in H} \lambda_{nt} \cdot (p_{nt}^{\downarrow} - p_{nt}^{\uparrow}) \tag{a.1}$$

In (a.1), λ_{nt} denotes the market price of bus $n \in N^m$ of the transmission network at hour t, while $p_{nt}^{\downarrow}$ and $p_{nt}^{\uparrow}$ denote the power that DA buys and sells respectively from/to the pool market at hour t. Both the market price (λ_{nt}) and the power traded by the DA ($p_{nt}^{\downarrow}, p_{nt}^{\uparrow}$) are obtained endogenously from the lower-level problem, i.e. the market clearing process.

$$0 \leq p_{it}^{EV,\downarrow} \leq \phi_{it} \cdot \overline{P}_i^{EV,\downarrow}, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV}, \tag{a.2}$$

$$0 \le p_{it}^{EV,\uparrow} \le (1-\phi_{it}) \cdot \overline{P}_i^{EV,\uparrow}, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.3}$$

$$\phi_{it} \in \{0,1\}, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.4}$$

$$SOC_{i(t+1)} = SOC_{it} + \eta_i^{\downarrow} \cdot p_{it}^{EV,\downarrow} - \frac{p_{it}^{EV,\uparrow}}{\eta_i^{\uparrow}},$$
$$\forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.5}$$

$$SOC_{it} = SOC_{i0}, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.6}$$

$$SOC_{it} = SOC^{target}, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.7}$$

$$\underline{SOC}_i \le SOC_{it} \le \overline{SOC}_i, \quad \forall i \in L_n^{EV}, n \in N^m, t \in H_i^{EV} \tag{a.8}$$

Constraints (a.2)–(a.8) concern the operation of the DA portfolio's EVs. We assume that each EV i owner has specifically set a preferred plug-in (t_i^{arr}) and departure time (t_i^{dep}), along with a desired battery State-of-Charge (SoC) at the end of the plug-in period ($H_i^{EV} = [t_i^{arr}, t_i^{dep}]$). The EV charging/discharging power limits ($\overline{P}_i^{EV,\downarrow}, \overline{P}_i^{EV,\uparrow}$) are set in (a.2) and (a.3), with binary variable ϕ_{it} preventing simultaneous charging and discharging. Constraint (a.5) defines the current SoC of EV i (SOC_{it}), which is calculated based on its value in the previous timeslot, as well as charging/discharging amounts ($p_{it}^{EV,\downarrow}, p_{it}^{EV,\uparrow}$) and efficiencies ($\eta_i^{\downarrow}, \eta_i^{\uparrow}$). Each EV's SoC is initialized in constraint (a.6), where SOC_{i0} denotes the EV SoC at the beginning of the charging process. Constraint (a.7) dictates that the SoC of EV i must reach the demanded by its owner level (SOC^{target}) at its departure time. Lastly, SoC is bounded in (a.8) by its lower and upper limits ($\underline{SOC}_i, \overline{SOC}_i$).

$$0 \le p_{it}^{TCL} \le \overline{P}_i^{TCL}, \quad \forall i \in L_n^{TCL}, n \in N^m, t \in H_i^{TCL} \tag{a.9}$$

$$\theta_{i(t+1)} = \beta_i \cdot \theta_{it} + (1-\beta_i) \cdot (\theta_{it}^0 + COP_i \cdot R_i \cdot p_{it}^{TCL}),$$
$$\beta_i = e^{-\frac{\Delta t}{C_i \cdot R_i}}, \quad \forall i \in L_n^{TCL}, n \in N^m, t \in H_i^{TCL} \tag{a.10}$$

$$\underline{\theta}_i \le \theta_{it} \le \overline{\theta}_i, \quad \forall i \in L_n^{TCL}, n \in N^m, t \in H_i^{TCL} \tag{a.11}$$

Constraints (a.9)–(a.11) represent the operating constraints of each TCL $i \in L_n^{TCL}$, which operates within a time interval $H_i^{TCL} \subseteq T$ that has been set by its owner. The upper bound of TCL's power consumption ($\overline{P}_i^{TCL}$) is set in Eq. (a.9). The indoor temperature in each household with a TCL dynamically evolves according to Eq. (a.10), based on parameters such as the thermal resistance R_i ($°C/kW$), capacitance C_i ($kWh/°$C) of the room, coefficient of performance COP_i and outdoors temperature θ_{it}^0. Moreover, Eq. (a.11) expresses that each TCL owner establishes temperature preferences, setting both the lowest ($\underline{\theta}_i$) and highest ($\overline{\theta}_i$) indoor temperatures for her/his house.

$$p_{it}^{SL} = \sum_{\tau=t-D_i+1}^{t} (\psi_{i\tau} \cdot Pr_{ik}), \quad \forall i \in L_n^{SL}, n \in N^m, t \ge T_i^{SL,a},$$
$$k = (t-\tau) \mod D_i \tag{a.12}$$

$$\psi_{it} = 0, \quad \forall i \in L_n^{SL}, n \in N^m, t < T_i^{SL,a}, t > T_i^{SL,b} - D_i + 2 \tag{a.13}$$

$$\sum_{t=T_i^{SL,a}}^{T_i^{SL,b}} \psi_{it} = 1, \quad \forall i \in L_n^{SL}, n \in N^m \tag{a.14}$$

The non-interruptible operation of each SL $i \in L_n^{SL}$ is characterized by a consumption profile $\mathbf{Pr_i}$ and a working cycle with duration D_i. For example, let the task of a SL lasting 2 h and within each hour the SL consumes 2 kW. Then, its consumption profile would be [2 kW (hour 1), 2 kW (hour 2)]. Each SL owner sets its preferences, regarding the earliest hour that the SL can start its task ($T_i^{SL,a}$) and the hour until which the SL must have completed its corresponding task ($T_i^{SL,b}$). Constraint (a.12) defines the electric power consumption of the SL i at each hour $t \in [T_i^{SL,a}, T_i^{SL,b}]$, with binary variable ψ_{it} determining whether SL i starts operating at hour t. Eq. (a.13) states that the SL cannot start neither outside the period set by its owner ($[T_i^{SL,a}, T_i^{SL,b}]$), nor at an hour that would not allow the completion of the SL's task before $T_i^{SL,b}$. Lastly, Eq. (a.14) expresses that the SL can only begin once its working cycle within the scheduling horizon.

$$0 \le p_{it}^{RES} \le Pr_{it}^{RES}, \quad \forall i \in L_n^{RES}, n \in N^m, t \in H \tag{a.15}$$

$$p_{it}^{INL} = Pr_{it}^{INL}, \quad \forall i \in L_n^{INL}, n \in N^m, t \in H \tag{a.16}$$

The renewable energy produced by each RES unit $i \in L_n^{RES}$ is constrained by the forecasted RES profile (Pr_{it}^{RES}) as shown in Eq. (a.15). It is important to note that we allow for renewable energy to be spilled by the DA. Furthermore, Eq. (a.16) specifies that the power consumed by each inflexible load $i \in L_n^{INL}$ should match its forecasted power profile (Pr_{it}^{INL}).

$$p_{nt}^{\downarrow} - p_{nt}^{\uparrow} = \sum_{i \in L_n^{EV}} (p_{it}^{EV,\downarrow} - p_{it}^{EV,\uparrow}) + \sum_{i \in L_n^{TCL}} p_{it}^{TCL} +$$
$$+ \sum_{i \in L_n^{SL}} p_{it}^{SL} + \sum_{i \in L_n^{INL}} p_{it}^{INL} - \sum_{i \in L_n^{RES}} p_{it}^{RES}, \quad \forall n \in N^m, t \in H \tag{a.17}$$

$$0 \le b_{nt} \le h_{nt} \cdot \mathcal{W}, \quad \forall n \in N^m, t \in H \tag{a.18}$$

$$0 \le o_{nt} \le (1-h_{nt}) \cdot \mathcal{W}, \quad \forall n \in N^m, t \in H \tag{a.19}$$

$$h_{nt} \in \{0,1\}, \quad \forall n \in N^m, t \in H \tag{a.20}$$

Eq. (a.17) establishes that the final DA dispatch at each hour t and bus $n \in N^m$ must be equal with the combined power output of its constituent assets that are located at this specific bus. Constraints (a.18) and (a.19) serve to prohibit the simultaneous submission of demand (b_{nt}) and supply (o_{nt}) bids in the market. Within these constraints, $\mathcal{W}$ is a large constant value. Lastly, Eq. (a.20) defines the binary nature of the auxiliary variable h_{nt}. Finally, the optimization variable vector of the upper-level problem is
$\mathbb{X}_U = \{o_{nt}, b_{nt}, h_{nt}, p_{it}^{EV,\downarrow}, p_{it}^{EV,\uparrow}, \phi_{it}, SOC_{it}, p_{it}^{TCL}, \theta_{it}, p_{it}^{SL}, \psi_{it}, p_{it}^{RES}, p_{it}^{INL}\}$.

Lower-Level Problem

The lower-level problem represents the day-ahead electricity market clearing process, which determines the participants' operating points and the market clearing nodal prices based on the submitted offer/bids. Note that we use a DC approximation of the transmission system.

$$\min_{\mathbb{X}_L} \sum_{t \in H} \Bigg\{ \sum_{n \in G} c_{nt}^g \cdot g_{nt} + \sum_{n \in D^c} (c_{nt}^{d,o} \cdot d_{nt}^o - c_{nt}^{d,b} \cdot d_{nt}^b)$$
$$+ \sum_{n \in N^m} (c_{nt}^{DA,\uparrow} \cdot p_{nt}^{\uparrow} - c_{nt}^{DA,\downarrow} \cdot p_{nt}^{\downarrow}) \Bigg\} \tag{b.1}$$

Subject to

$$-g_{nt} + d_{nt}^b - d_{nt}^o + p_{nt}^{\downarrow} - p_{nt}^{\uparrow} + \sum_{j \ne i} y_{nj} \cdot (\theta_{nt} - \theta_{jt}) = 0; \quad (\lambda_{nt})$$
$$\forall n \in N, t \in H \tag{b.2}$$

$$0 \le g_{nt} \le \overline{G}_n; \quad (\underline{\phi}_{nt}^g, \overline{\phi}_{nt}^g) \;\; \forall n \in G, t \in H \tag{b.3}$$

$$0 \le p_{nt}^{\uparrow} \le o_{nt}; \quad (\underline{\phi}_{nt}^{DAo}, \overline{\phi}_{nt}^{DAo}) \;\; \forall n \in N^m, t \in H \tag{b.4}$$

$$0 \le p_{nt}^{\downarrow} \le b_{nt}; \quad (\underline{\phi}_{nt}^{DAb}, \overline{\phi}_{nt}^{DAb}) \;\; \forall n \in N^m, t \in H \tag{b.5}$$

$$0 \le d_{nt}^o \le \overline{d}_{nt}^o; \quad (\underline{\phi}_{nt}^{do}, \overline{\phi}_{nt}^{do}) \;\; \forall n \in D^c, t \in H \tag{b.6}$$

$$0 \le d_{nt}^b \le \overline{d}_{nt}^b; \quad (\underline{\phi}_{nt}^{db}, \overline{\phi}_{nt}^{db}) \;\; \forall n \in D^c, t \in H \tag{b.7}$$

$$-\overline{T}_{ij} \le y_{nj} \cdot (\theta_{nt} - \theta_{jt}) \le \overline{T}_{ij}; \quad (\underline{\phi}_{(nj)t}^l, \overline{\phi}_{(nj)t}^l) \;\; \forall (n,j) \in L, t \in H \tag{b.8}$$

The objective of the Market Operator (MO) is to maximize *Social Welfare*, or in other words minimize *Social Cost*, i.e. the cost of energy generated minus the willingness of the demand to pay for that energy (Eq. (b.1)), which is calculated based on the generators' marginal costs (c_{nt}^g) and the DAs' marginal cost/utility ($c_{nt}^{DA,\uparrow}, c_{nt}^{d,o}/c_{nt}^{DA,\downarrow}, c_{nt}^{d,b}$). Power balance at each bus $n \in N$ and hour $t \in H$ is expressed in Eq. (b.2), with the respective dual variables representing the nodal LMPs (λ_{nt}).

The maximum available generation capacity of each generator $n \in G$ is set in Eq. (b.3). The dispatch (sold or bought power) of the strategic DA ($p^{\uparrow}_{nt}$ or $p^{\downarrow}_{nt}$) is bounded in Eqs. (b.4) and (b.5) based on the DA's submitted offers and bids. Eqs. (b.6) and (b.7) concern the competing DAs (D^c) and limit the power that they offer (d^o_{nt}) or draw (d^b_{nt}) from the transmission grid based on their respective quantity offers ($\overline{d}^o_{nt}, \overline{d}^b_{nt}$). Finally, Eq. (b.8) constraints power flow to the transmission lines' capacity limits ($\overline{T}_{ij}$). The dual variables pertaining to each constraint of the lower-level problem are specified at each constraint following a semicolon. The voltage phase angle of the reference bus is set to zero throughout the whole scheduling period ($\theta_{ref} = 0$). The set of decision variables of the optimization problem (b) is $\mathbb{X}_L = \{g_{nt}, d^o_{nt}, d^b_{nt}, p^{\uparrow}_{nt}, p^{\downarrow}_{nt}, \theta_{nt}\}$.

3.2. Converting the bi-level problem into a tractable MILP

The formulated non-convex bi-level problem can be recast into a Mathematical Program with Equilibrium Constraints (MPEC). To this end, we replace problem (b) with its Karush-Kun-Tucker (KKT) conditions. Note that problem (b) is a continuous linear optimization problem, and hence its KKT conditions are necessary and sufficient optimality conditions [42]. Therefore, solving the following nonlinear system of equations is equivalent to solving problem (b):

$$-g_{nt} + d^b_{nt} - d^o_{nt} + p^{\downarrow}_{nt} - p^{\uparrow}_{nt} + \sum_{j \neq i} y_{nj} \cdot (\theta_{nt} - \theta_{jt}) = 0; \quad (\lambda_{nt})$$

$$\forall n \in N, t \in H \tag{b.2}$$

$$c^g_{nt} - \lambda_{nt} - \underline{\phi}^g_{nt} + \overline{\phi}^g_{nt} = 0, \quad \forall n \in G, t \in H \tag{c.1}$$

$$c^{d,o}_{nt} - \lambda_{nt} - \underline{\phi}^{do}_{nt} + \overline{\phi}^{do}_{nt} = 0, \quad \forall n \in D^c, t \in H \tag{c.2}$$

$$-c^{d,b}_{nt} + \lambda_{nt} - \underline{\phi}^{db}_{nt} + \overline{\phi}^{db}_{nt} = 0 \quad \forall n \in D^c, t \in H \tag{c.3}$$

$$c^{DA,\uparrow}_{nt} - \lambda_{nt} - \underline{\phi}^{DAo}_{nt} + \overline{\phi}^{DAo}_{nt} = 0, \quad \forall n \in N^m, t \in H \tag{c.4}$$

$$-c^{DA,\downarrow}_{nt} + \lambda_{nt} - \underline{\phi}^{DAb}_{nt} + \overline{\phi}^{DAb}_{nt} = 0, \quad \forall n \in N^m, t \in H \tag{c.5}$$

$$\sum_{j \neq n, (n,j) \in L} y_{nj} \cdot (\lambda_{nt} - \lambda_{j,t}) - \sum_{j > n} y_{nj} \cdot (\underline{\phi}^l_{(nj)t} - \overline{\phi}^l_{(nj)t}) +$$

$$+ \sum_{j < n} y_{nj} \cdot (\underline{\phi}^l_{(nj)t} - \overline{\phi}^l_{(nj)t}) = 0, \quad \forall n \in N, t \in H \tag{c.6}$$

$$0 \leq \underline{\phi}^g_{nt} \perp g_{nt} \geq 0, \quad \forall n \in G, t \in H \tag{c.7}$$

$$0 \leq \overline{\phi}^g_{nt} \perp -g_{nt} + \overline{G}_n \geq 0, \quad \forall n \in G, t \in H \tag{c.8}$$

$$0 \leq \underline{\phi}^{do}_{nt} \perp d^o_{nt} \geq 0, \quad \forall n \in D^c, t \in H \tag{c.9}$$

$$0 \leq \overline{\phi}^{do}_{nt} \perp -d^o_{nt} + \overline{d}^o_{nt} \geq 0, \quad \forall n \in D^c, t \in H \tag{c.10}$$

$$0 \leq \underline{\phi}^{db}_{nt} \perp d^b_{nt} \geq 0, \quad \forall n \in D^c, t \in H \tag{c.11}$$

$$0 \leq \overline{\phi}^{db}_{nt} \perp -d^b_{nt} + \overline{d}^b_{nt} \geq 0, \quad \forall n \in D^c, t \in H \tag{c.12}$$

$$0 \leq \underline{\phi}^{DAo}_{nt} \perp p^{\uparrow}_{nt} \geq 0, \quad \forall n \in N^m, t \in H \tag{c.13}$$

$$0 \leq \overline{\phi}^{DAo}_{nt} \perp -p^{\uparrow}_{nt} + o_{nt} \geq 0, \quad \forall n \in N^m, t \in H \tag{c.14}$$

$$0 \leq \underline{\phi}^{DAb}_{nt} \perp p^{\downarrow}_{nt} \geq 0, \quad \forall n \in N^m, t \in H \tag{c.15}$$

$$0 \leq \overline{\phi}^{DAb}_{nt} \perp -p^{\downarrow}_{nt} + b_{nt} \geq 0, \quad \forall n \in N^m, t \in H \tag{c.16}$$

$$0 \leq \underline{\phi}^l_{(nj)t} \perp y_{nj} \cdot (\theta_{nt} - \theta_{jt}) + \overline{T}_{ij} \geq 0, \quad \forall (n,j) \in L, n < j, t \in H \tag{c.17}$$

$$0 \leq \overline{\phi}^l_{(nj)t} \perp -y_{nj} \cdot (\theta_{nt} - \theta_{jt}) + \overline{T}_{ij} \geq 0, \quad \forall (n,j) \in L, n < j, t \in H \tag{c.18}$$

Eqs. (b.2), (c.1)–(c.18) are the KKT conditions of problem (b). The formulated MPEC problem contains the following non-linearities:

- The multiplication of the dual variable λ_{nt} by the primal variables $p^{\uparrow}_{nt}$ and $p^{\downarrow}_{nt}$ in the objective function,
- The complementarity conditions (c.7)–(c.18).

In order to convert the non-linear MPEC into a tractable MILP, at first we deal with the non-linear complementarity conditions using the well-known Big-M approach [43], replacing the complementarity conditions $0 \leq \alpha \perp \beta \geq 0$ by the following set of linear equations:

$$0 \leq \alpha \leq y \cdot M$$

$$0 \leq \beta \leq (1 - y) \cdot M$$

where y is a binary variable and M is a large enough constant. The computational time increases with the value of M, while infeasibility problems might occur with low values of M. Thus, in our model, we carefully select a proper constant to achieve a good balance M.

In addition, towards linearizing the objective function, multiplying Eqs. (c.4) and (c.5) by $p^{\uparrow}_{nt}$ and $p^{\downarrow}_{nt}$ respectively, adding them up and using the complementarity conditions (c.13)–(c.16), we have:

$$\lambda_{nt} \cdot (p^{\downarrow}_{nt} - p^{\uparrow}_{nt}) = c^{DA,\downarrow}_{nt} \cdot p^{\downarrow}_{nt} - c^{DA,\uparrow}_{nt} \cdot p^{\uparrow}_{nt} + \overline{\phi}^{DAb}_{nt} \cdot b_{nt} + \overline{\phi}^{DAo}_{nt} \cdot o_{nt}$$

Then, making use of the Strong Duality Theorem for problem (b), we obtain the final linear objective function:

$$\min \sum_{t \in H} \Bigg(\sum_{n \in G} (c^g_{nt} \cdot g_{nt}) + \sum_{n \in D^c} (c^{d,o}_{nt} \cdot d^o_{nt} - c^{d,b}_{nt} \cdot d^b_{nt}) + \sum_{n \in G} (\overline{\phi}^g_{nt} \cdot \overline{G}_n) +$$
$$\sum_{n \in D^c} (\overline{\phi}^{do}_{nt} \cdot \overline{d}^o_{nt} + \overline{\phi}^{db}_{nt} \cdot \overline{d}^b_{nt}) + \sum_{n < j, (n,j) \in L} \left(\overline{T}_{ij} \cdot \underline{\phi}^l_{(nj)t} + \overline{T}_{ij} \cdot \overline{\phi}^l_{(nj)t} \right) \Bigg)$$

3.3. EPEC formulation

In the previous subsection, we formulated the bi-level bidding problem of a single strategic DA, assuming that the rest of them form a competitive fringe. In this subsection, we break the above assumption, as we consider several strategic DAs. To this end, we formulate an EPEC structure, in which each DA solves its own MPEC problem.

An EPEC corresponds to a multiple-leader-common-follower game [44]. The goal of this game is to find a Nash equilibrium, if one exists, such that none of the players is able to increase its payoff unilaterally by changing its decision. In general, EPECs present challenges regarding the existence and uniqueness of equilibrium solutions, primarily due to their non-convex and nonlinear nature [45]. As discussed in several relevant studies, Nash equilibrium is not guaranteed to exist or to be unique [46–48].

In this work, in order to determine the oligopolistic market equilibrium stemming from the interactions of multiple strategic DAs, the iterative diagonalization algorithm, which was introduced in [49] and employed in various studies (e.g. [28,32–34,36,48] among others). The diagonalization algorithm involves iteratively solving each DA's MPEC problem by fixing the other DAs' bidding decisions to their current optimal solutions. The vector of all DAs' bidding variables at iteration i is compared to the one at iteration $i-1$. If their distance is lower than ϵ, the iterative procedure terminates (see Algorithm 1). In other words, the optimal solution determined by each DA should be identical to the value that the other DAs assume as a model parameter of their own MPEC problems.

The diagonalization method is not generally guaranteed to converge, even if equilibrium exists [45,46,50], since the feasible region of each DA's MPEC is non-convex. Therefore, a cycling behavior may be encountered [38]. In the context of this work, however, the DAs' bidding decisions can oscillate usually among different values within a relatively small range, as shown in Fig. 4. For more information on the EPEC structure and its solution method, the interested reader is referred to [51].

4. Performance evaluation

4.1. Simulation setup

For our market equilibrium analysis, we simulate an IEEE 6-bus transmission system topology. Four large generators (i.e. G1-G4) and

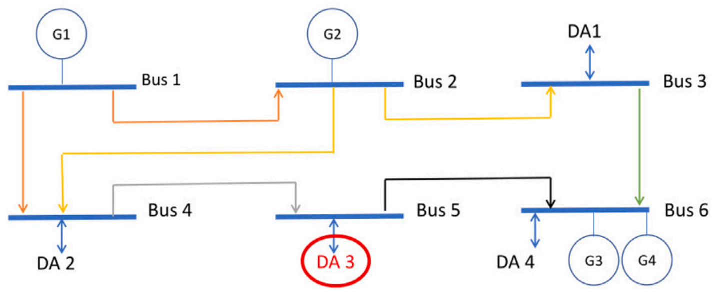

Fig. 1. IEEE 6-bus transmission topology: DA 3 at bus 5 is assumed to be the strategic player in the MPEC model.

Algorithm 1 Diagonalization algorithm

1: *Initialization*:

- Set convergence criterion ϵ.
- Set maximum number of iterations K.
- Set iteration counter $\kappa \leftarrow 1$.
- DAs' offers/bids ($\hat{d}^{o}_{n,t}/\hat{d}^{b}_{n,t}$) are initialized.

2: For $j = 1, ..., |D^c| + 1$

- DA j solves its MPEC problem, considering the offers/bids of the other DAs as fixed parameters ($\hat{d}^{o}_{j',t}/\hat{d}^{b}_{j',t}$ where $j' \in D^c$), equal to their values at iteration $\kappa - 1$.
- DA j obtains $o^{(\kappa)}_{n,t}, b^{(\kappa)}_{n,t}$, where $n \in N^m_j$.

3: If $|o^{(\kappa)}_{n,t} - o^{(\kappa-1)}_{n,t}| \leq \epsilon$ and $|b^{(\kappa)}_{n,t} - b^{(\kappa-1)}_{n,t}| \leq \epsilon$ for all $j \in \{1, .., |D^c| + 1\}$, $n \in D^c$, $t \in H$ then quit and report the last solution from Step 2.
4: if $\kappa = K$ quit and report that the algorithm has failed to converge. Report the last solution from Step 2.
5: Set $\kappa \leftarrow \kappa + 1$ and return to Step 2.

four large Demand Aggregators (DAs) reside at the various buses shown in Fig. 1. Without a lack of generality, we assume that all the end energy prosumers that are a given DA's customers reside at one specific bus (e.g. all end prosumers that belong to DA 3's portfolio reside at bus 5). As already analyzed in Section 3 above, each DA consists of EVs, TCLs, SLs, INLs, and PV units and participates in a typical day-ahead electricity market, where it should place its hourly bids (i.e. 1-24 timeslots denote 1:00 am to 12:00 pm). In scenario 1 (also called baseline scenario from now on), we assume that:

- Total inflexible loads are 1013.19 MW for DA 1, 1015.37 MW for DA 2, 1013.97 MW for DA 3 and 993.22 MW for DA 4. We have deliberately chosen the total loads to be similar for each one of the four competing DAs and for each one of the DFA categories in order to make fair comparisons (cf. market power) in the various simulation scenarios described below.
- All EVs have no vehicle-to-grid (V2G) capability. EVs' arrival takes place between 1-10 am and departure time is between 6-12 am. EVs' maximum flexibility is 2-4 h (randomly), which means that the departure time can be 2-4 h after the time when the task of EV charging would end if it was uninterruptedly charged at full rate. Total EV loads are 65.5 MW for DA 1, 66.5 MW for DA 2, 66.89 MW for DA 3, and 67.87 MW for DA4.
- SLs have no flexibility (i.e. cycles are equal to the distance between start and stop times). SLs' start time is distributed between 1-11 am and 15-22 am, while SLs' finish time based on the cycle are distributed between 2-13 and 16–24 pm. Total shiftable loads are 127.54 MW for DA 1, 130.03 MW for DA 2, 125.39 MW for DA 3, and 129.26 MW for DA 4.
- Regarding TCLs, the indoor temperature's lower and upper bounds are randomly selected to be 19-23 °C and 26-30 °C correspondingly to reflect the end user's preferences with respect to the TCLs' operation.
- Each DA manages PV units with an installed capacity that equals to the 20% of its peak load demand.
- DAs' marginal utility values are set to 150€/MW for energy purchase from the grid and 0€/MW for selling energy back to the grid. Thus, we avoid the cases in which DAs' bids are not cleared (i.e. rejected) in the market.

All the input data (i.e. transmission grid, conventional/PV generation, load data, etc.) as well as the technical specifications of all types of DFAs together with all simulation results incorporated in this paper can be found in [52].

4.2. EPEC vs. MPEC vs. competitive market settings

As a first step, we compare the three main market settings, namely: (i) competitive market, (ii) MPEC market, and (iii) EPEC market. In the first market setting, all DAs act as price takers in a perfect competition market context. This means that every DA must accept the equilibrium price at which it purchases the net electricity from the grid (or else if a price taker DA attempts to bid even a tiny amount less than the equilibrium price, then it will be unable to purchase the respective quantity of electricity). In the MPEC market setting, we assume that DA 3 acts strategically (see the outlined area in Fig. 1) by solving the bi-level problem formulated in Section 3.1 above, while the other 3 DAs are price takers. In other words, the price maker DA 3 is able to lower the market equilibrium price in specific day-ahead hourly timeslots by exploiting its DSF portfolio. Finally, in the proposed EPEC market setting, we assume that all DAs are price makers by solving the EPEC problem (via the diagonalization algorithm) described in Section 3.3.

The DAs' market costs and the market's social welfare (SW) in each one of the above-mentioned market settings are presented in Table 1. First of all, we see that market costs for every DA in the competitive market setting are very similar and this is explained by our deliberate choice to assume similar DSF portfolios for all DAs in order to ensure a fair comparison. In the MPEC setting, the strategic DA 3 achieves a 9.1% decrease in its market costs. As shown in Fig. 2(a), this happens because DA 3's strategic bidding lowers the market price in timeslots 2-5 and 15. Fig. 3 explains even further this cost decrease. For instance, we can see that DA 3's net loads (i.e. inflexible loads minus PV generation) are decreased in several early morning timeslots as well as at 15:00 mainly due to the increase of PV generation during mid-day. TCLs are also decreased in early morning timeslots as well as at 15:00, while EV charging is appropriately scheduled, too. SLs remain the same in both competitive and MPEC settings, because in the baseline scenario, SL flexibility is assumed to be zero. It is interesting to observe that the other price taker DAs realize cost decrease of around 7%, too, which is explained by the fact that they take advantage of the DA 3's strategic behavior that lowers the market prices for the whole system.

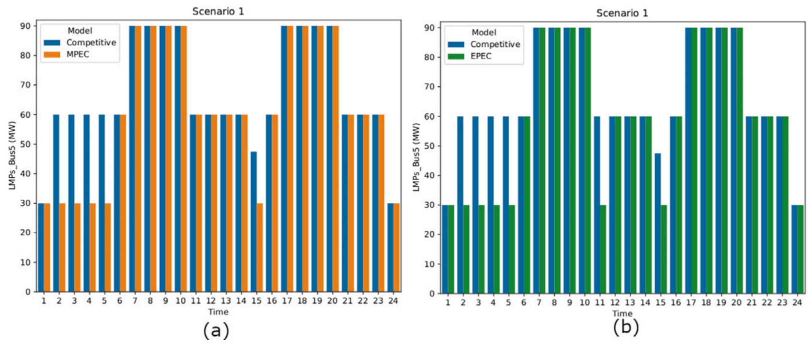

Fig. 2. LMPs at bus 5 in the 3 market settings for scenario 1 (baseline scenario).

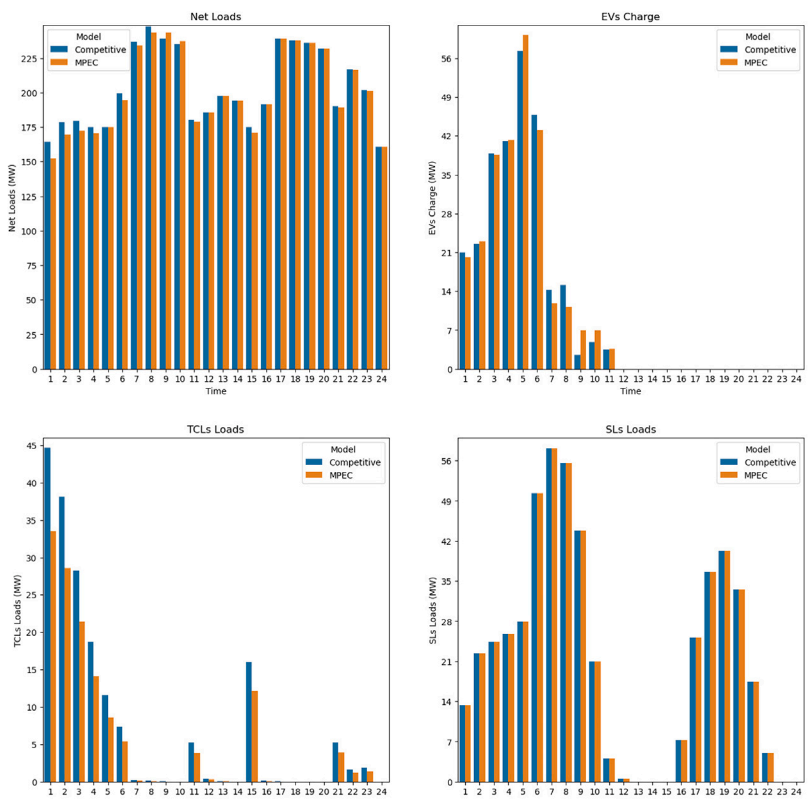

Fig. 3. MPEC load scheduling in baseline scenario for strategic DA 3.

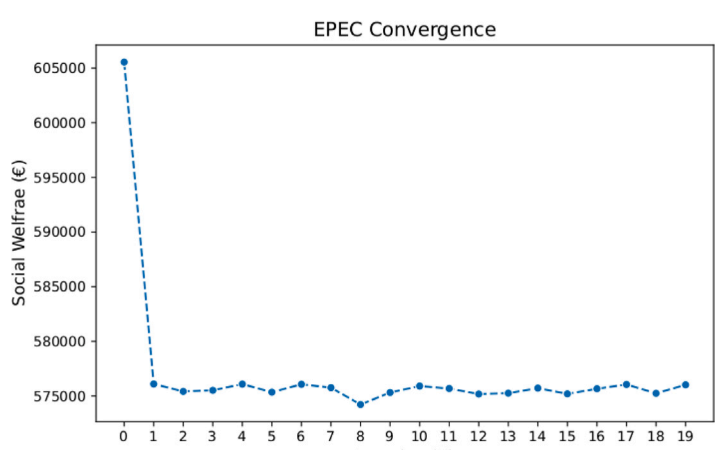

Fig. 4. Evolution of the episodic average market social welfare.

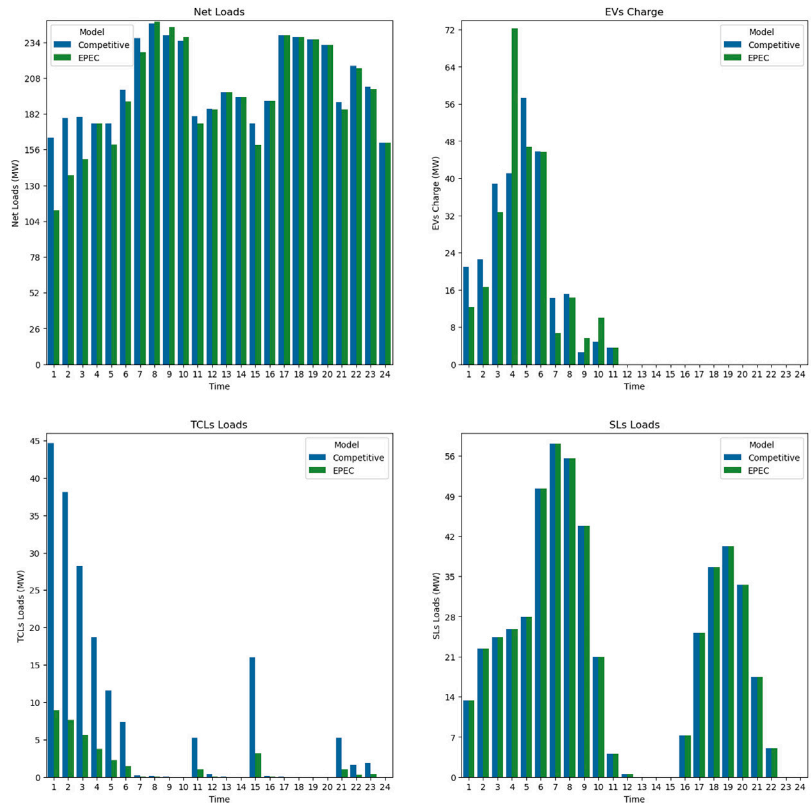

Fig. 5. EPEC load scheduling per type of DFA in baseline scenario.

Table 1
DA Costs & Electricity Market Social Welfare.

DA	Competitive market costs (€)	Strategic DA 3 - market costs (€)	EPEC - market costs (€)	Competitive market SW (€)	Strategic DA 3 - SW (€)	EPEC - SW (€)
1	84 403.36	78 305.04	75 390.93	615042.92	605556.17	575603.55
2	84 876.10	78 892.74	75 906.92			
3	984 697.27	76 970.55	75 813.42			
4	83 445.27	77 341.76	74 889.55			

In the EPEC market setting, the costs of all strategic DAs decrease even more (10.5% compared to the competitive market setting). As shown in Fig. 2(b), this happens because there is one more hourly timeslot (i.e. 11:00 am) compared to the MPEC setting, in which the market price decreases due to the increased demand-side flexibility that is available from all strategic DAs. In Fig. 5, one may see the greater load decrease of net loads and TCLs at 11:00, while EV and SL schedules remain the same.

On the other hand, we observe that DAs' cost decrease comes at the expense of social welfare (SW) decrease. In the EPEC setting, the SW is 6.4% lower than the competitive market setting, while in MPEC the decrease is 1.5%. This implies that generators' revenues are decreased at the supply side of the market. This market equilibrium may be acceptable (to the extent that most expensive and environmentally-unfriendly generators are gradually phased out), but it could also raise policy-related concerns about the incentivization for new generation investments.

Finally, concerning the convergence of the diagonalization algorithm, Fig. 4 demonstrates the evolution of the episodic average market social welfare. Note that the algorithm was forced to terminate after 20 iterations. As the algorithm progresses, the average social welfare oscillates, before stabilizing after a modest number of iterations. More specifically, in the last few iterations, the fluctuations in the DAs' bidding decisions diminish, leading to the average social welfare to oscillate within a small range (0.07%–0.14%). Hence, a market equilibrium has been reached.

4.3. Impact of a single da's portfolio mix

In this section, we focus on DA 3 considering various DSF portfolio mixes. In particular, we compare the baseline scenario (i.e. scenario 1) of the previous subsection with three more scenarios, namely:

1. **Scenario 2**: DA 3 invests in V2G technology. As a result, 50% of its end prosumers have EVs that can inject (discharge) power back to the grid (the prosumers are chosen randomly).
2. **Scenario 3**: DA 3 invests in Demand Side Management (DSM) technology (i.e. ICT to monitor and control shiftable electric appliances). Hence, the maximum flexibility for EV charging is now increased to 12 h and for SL cycles is 10 h.
3. **Scenario 4**: DA 3 invests in PV. Hence, the percentage of end prosumers that have on-site installed PVs has now increased from 20% to 50%.

Fig. 6 demonstrates the increased market power that the strategic DA 3 can exercise as a result of its above-mentioned DFA/DER investment scenarios assuming that the other competing DAs' portfolios

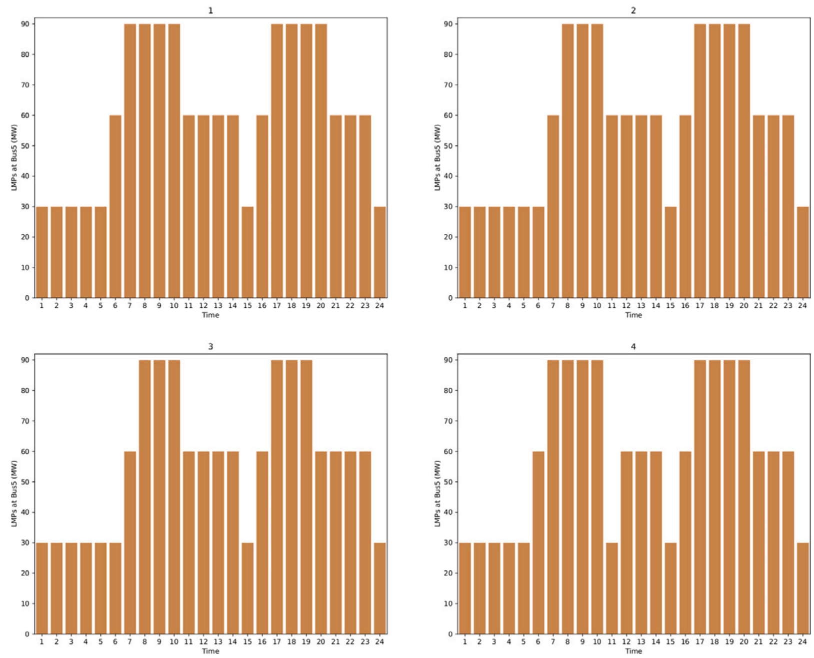

Fig. 6. LMPs (bus 5) in scenarios 1 to 4 when only DA3 plays strategically its MPEC.

remain the same. More specifically, in scenario 2, we can see that the equilibrium price is decreased in two consecutive morning timeslots (i.e. 06:00-08:00). Indeed, DA 3 exploits the V2G capability of the EVs in the morning in order to discharge a portion of the available EVs' power upon their arrival in the charging station (e.g. at work) without violating the end users' preference constraints about their EVs' state-of-charge upon their departure from the charging station later within the day (e.g. when leaving from workplace). Regarding 06:00-08:00 period, we can see a similar situation in scenario 3, while there is also an LMP decrease in timeslot 20, too. This is explained by the fact that in scenario 3, we not only have V2G capability and SLs in the morning, but also SLs, whose evening start time is 15:00-22:00 and their end time is 16:00-24:00. Finally, when we compare scenario 1 with scenario 4, we can see that at 11:00-12:00, the LMP is decreased from 60 €/MW to 30 €/MW. Indeed, in this timeslot, DA 3 realizes a higher PV production, which lowers its need for net load in order to serve its customer portfolio. Thus, DA 3 is able to strategically decrease its demand bid quantity in timeslot 11 by optimally exploiting its available flexibility within the whole day, too.

From now on, we focus on the EPEC case. Similarly to Table 1 above, Table 2 compares EPEC vs. competitive market setting with respect to the DAs' market participation costs and the social welfare for the three DA 3's investment scenarios. First of all, we observe that in the EPEC setting, all DAs' costs are significantly decreased (12% on average for all scenarios), while social welfare is also decreased (7% on average for all scenarios). In scenario 3, we observe the greatest DA costs' decrease (14.8%), which is explained by the fact that the overall available DSF is greater (across time and space) than all other scenarios. Scenario 3 also achieves the best trade-off between all DA costs' decreases and social welfare decreases (6.3%), so it is the best market equilibrium from a policy maker's perspective.

Fig. 7 elaborates even more on the impact of DA 3's portfolio mix on LMPs at bus 5. Regarding scenario 2, we can observe that in timeslots 8 and 11, the price is decreased compared to the MPEC market setting (cf. Fig. 6), while in timeslot 7 the price is increased. This explains the fact that DA 3 has not only more market power due to its available V2G flexibility, but also takes advantage of the other competing DAs' strategic behavior, too. In scenario 3, we see that in timeslot 11, the price is decreased compared to the same scenario in the MPEC setting. Similarly, in scenario 4, we see one price increase in timeslot 5 and one price decrease in timeslot 6. Even in this situation, DA 3 achieves a greater cost decrease, because the net load demand quantity of its portfolio is greater at 06:00-07:00 in comparison to 05:00-06:00.

In the next figures, the dispatch decisions for the various types of DFAs are illustrated. In scenario 2 (cf. Fig. 8), we can clearly see the changes in the EV charging schedule and TCL decrease compared to Fig. 5 (EPEC load scheduling for scenario 1). No changes in SL dispatch schedule take place, which is rational as no SL changes take place in scenario 2. However, as shown in Fig. 9, the SL dispatch schedule is significantly modified in scenario 3 for EPEC setting, because DA 3 exploits the added value of its DSM-related investment in order to decrease its market participation costs (see also Table 2 above). Finally, in Fig. 10, the new PV investment made by DA 3 changes significantly the EV charging/discharging schedule (compared to the other scenarios), because DA 3 has even more degrees of freedom for its multi-period scheduling within the day-ahead period.

4.4. Impact of competing das' portfolio mixes

Elaborating on the results of the previous subsection, we now assume that DA 3 makes an investment on a specific type of DFA and we investigate several scenarios in which the other competing DAs invest in the same or in another type of DFA. In particular, we consider the following scenarios:

1. **Scenario 5**: DA 3 invests in PV technology and other rivals invest in PVs, too.
2. **Scenario 6**: DA 3 invests in PV technology and other rivals invest in V2G technology.
3. **Scenario 7**: DA 3 invests in PV technology and other rivals invest in DSM technology.

From Table 3, we can see that in scenarios 5-7, the sum of DAs' costs are considerably lowered (up to 17.5%), which is rational because now the aggregated DSF portfolios' size is increased; hence the DAs can exercise more market power by acting as a coalition. Interestingly, this does not have much negative impact on social welfare, which is explained by the fact that DSF can both decrease the DAs' costs and also decrease the overall supply-side costs by flattening the demand curve. This happens

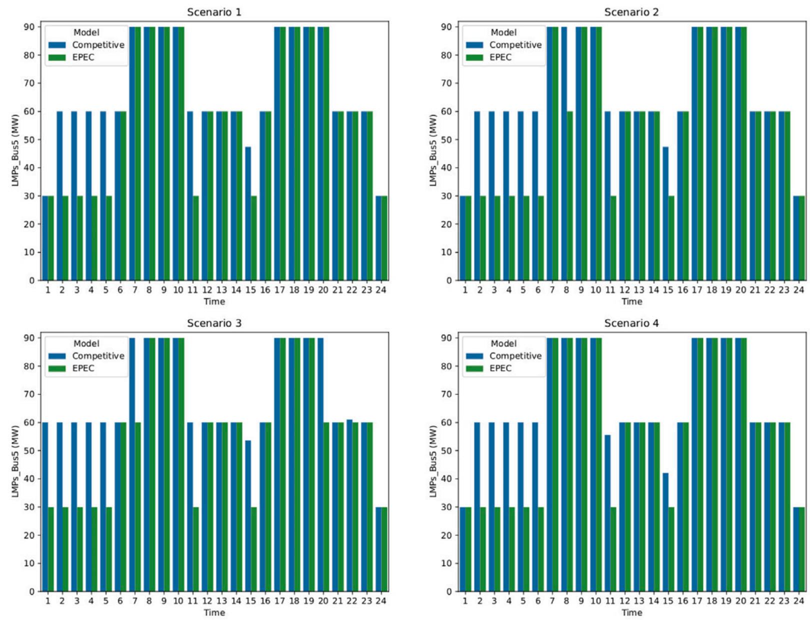

Fig. 7. EPEC vs. competitive market LMPs (bus 5) for scenarios 1 to 4.

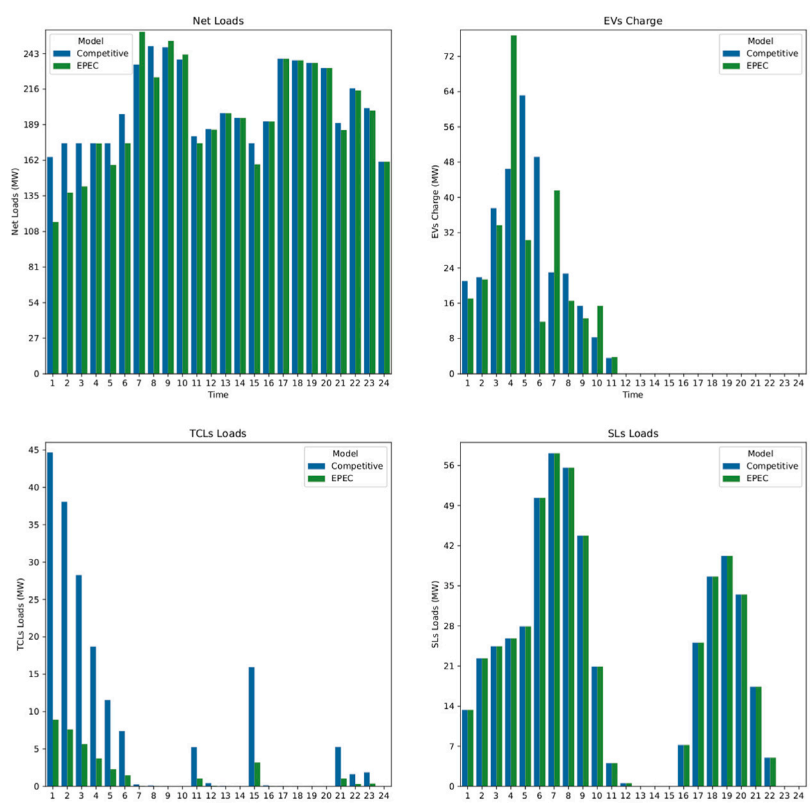

Fig. 8. EPEC load scheduling per type of DFA in scenario 2.

especially in scenario 7, in which the SW is slightly increased by 0.7% (compared to scenario 4), while in scenario 6 remains the same. In scenario 5, the SW is slightly decreased by 2.1%, because all the new investments are non-dispatchable PVs that decrease the overall DSF. From a policy maker's/regulator's perspective, scenario 7 seems the most beneficial one, because it has the highest SW, while the DAs' costs are the lowest. This ensures that profit-oriented DA companies are incentivized to make DSF/DER-related investments without disincentivizing large-scale supply-side investments on generation assets at the transmission grid. At the same time, scenario 7 seems to be the best for DA 3, too, even though it cannot control its rivals' investments.

Fig. 11 depicts the EPEC equilibrium prices for scenarios 4-7. As expected from Table 3 results, in scenario 7, we have the most timeslots, in which the LMP has decreased compared to scenario 4. More specifically, within 17:00-21:00 period, SLs are scheduled to consume less by shifting their demand in preceding or next timeslots. In the early morning (i.e. timeslots 5 and 7), we also observe the same context. In scenario 5, we also have several timeslots of LMP decrease during

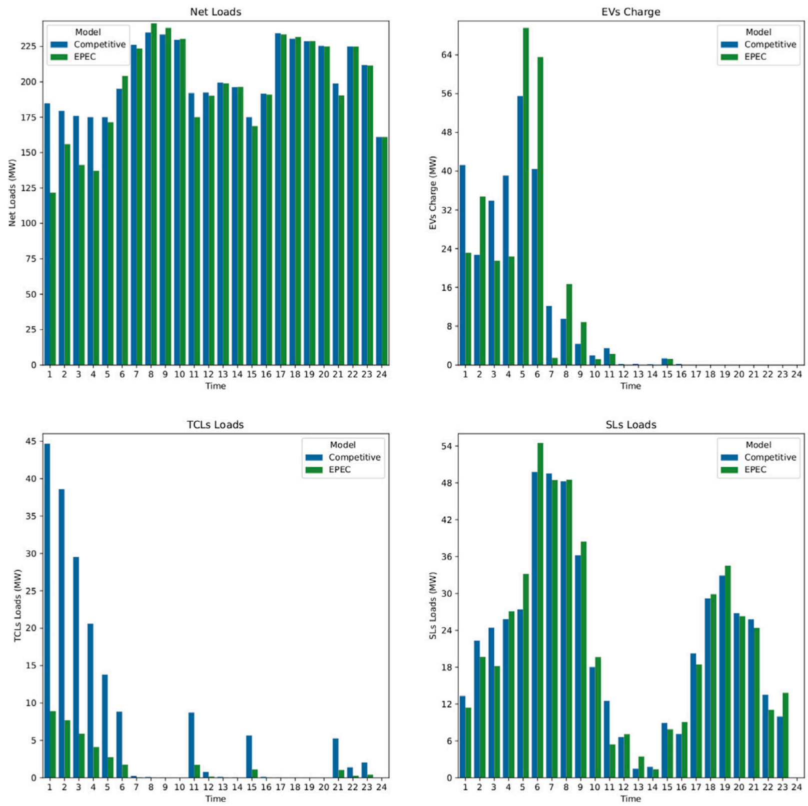

Fig. 9. EPEC load scheduling per type of DFA in scenario 3.

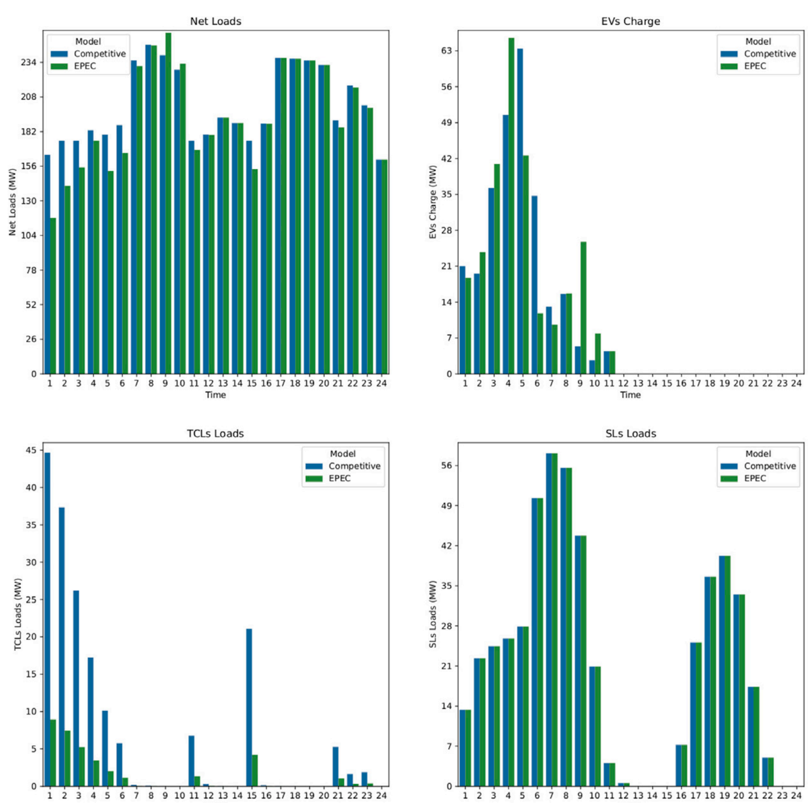

Fig. 10. EPEC load scheduling per type of DFA in scenario 4.

Table 2
DA Costs & Electricity Market Social Welfare per Scenario 1–4.

	Competitive market				EPEC			
	Scen. 1	*Scen. 2*	*Scen. 3*	*Scen. 4*	*Scen. 1*	*Scen. 2*	*Scen. 3*	*Scen. 4*
DA 1 Costs (€)	84 403.36	84 403.792	86 021.21	83 935.46	75 390.93	75 249.18	73 064.33	75 392.61
DA 2 Costs (€)	84 876.10	84 876.108	86 502.71	84 381.78	75 906.92	75 987.74	74 220.56	76 069.14
DA 3 Costs (€)	84 697.27	85 017.312	84 324.35	81 258.81	75 813.42	76 892.98	71 685.50	73 167.26
DA 4 Costs (€)	83 445.27	83 445.276	85 064.36	82 982.35	74 889.55	74 459.03	72 455.33	74 899.45
Total Costs (€)	337 422	337 742.5	341 912.6	332 558.4	302 000.8	302 588.9	291 425.7	299 528.5
SW (€)	615 042.92	621 565.31	617 292.12	618 057.24	575 603.55	575 339.85	578 120.96	571 431.84

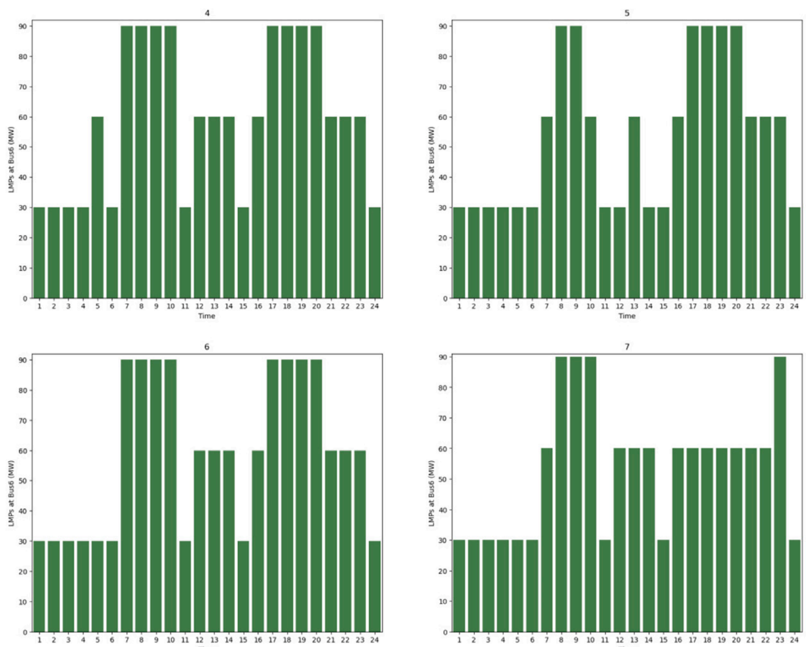

Fig. 11. EPEC LMPs (bus 5) for scenarios 4 to 7.

Table 3
DA Costs & Electricity Market Social Welfare per Scenario 4 to 7.

	EPEC			
	Scen. 4	*Scen. 5*	*Scen. 6*	*Scen. 7*
DA 1 Costs (€)	75 392.61	66 743.47	72 475.12	62 235.77
DA 2 Costs (€)	76 069.14	67 581.65	73 430.85	63 785.76
DA 3 Costs (€)	73 167.25	67 590.13	69 940.76	61 032.73
DA 4 Costs (€)	74 899.45	66 654.66	71 941.56	62 631.64
Total Costs (€)	299 528.5	268 569.9	287 788.3	249 685.9
SW (€)	571 431.84	559 007.32	571 278.94	575 444.29

Table 4
DA Costs & Electricity Market Social Welfare per Scenario 2, 8, 9, 10.

	EPEC			
	Scen. 2	*Scen. 8*	*Scen. 9*	*Scen. 10*
DA 1 Costs (€)	75 249.18	66 563.05	75 078.77	70 531.63
DA 2 Costs (€)	75 987.73	66 918.58	76 141.08	72 373.30
DA 3 Costs (€)	76 892.98	69 705.65	76 037.33	71 294.30
DA 4 Costs (€)	74 459.03	66 448.83	74 413.76	70 976.55
Total Costs (€)	302 588.9	269 636.1	301 671	285 175.8
SW (€)	575 339.85	563 238.71	574 494.26	577 737.28

day-time when the PVs are generating energy reducing thus the net load of the DAs (cf. timeslots 5, 7, 10, 11 and 14). Finally, in scenario 6, we only see one timeslot of LMP decrease (i.e. timeslot 5), which explains the relatively small difference in DAs' cost decrease compared to scenario 4 as shown in Table 3.

For complementarity reasons, we also consider three more scenarios, in which DA 3 invests in V2G technology and its rivals invest in: (1) PVs (cf. scenario 8), (2) V2G (cf. scenario 9), (3) DSM (cf. scenario 10). As shown in Table 4, scenario 10 seems to be the most beneficial for a policy maker, because it achieves the best SW, while total DA costs are considerably decreased, too. Actually, scenario 10 has the best SW across all scenarios 5-10. Scenario 8 is the best from the DAs' perspective, but also causes the lowest SW (only scenario 5 is worse than 8 for the reasons mentioned above). Interestingly, scenario 9, in which all DAs invest in V2G technology, experiences the lowest DA costs' decrease, even though the size of the total DSF capacity increases a lot. This can be explained because each strategic DA's bidding cancels the potential market power of its rivals given the fact that we assumed similar EV operational preferences and constraints for all DAs. This led to a situation, in which the DAs compete with each other during the morning timeslots without being able to act as a coalition. This can also be verified via Fig. 12, which depicts that there are two early morning timeslots (i.e. 4 and 6), in which the equilibrium price of scenario 9 increases compared to scenario 2. On the other hand, LMP figures of scenarios 8 and 10 confirm the results of Table 4.

4.5. Impact of network congestion on the market equilibria

In this subsection, we quantify the impact of possible grid congestion contexts on market equilibria results. For testing purposes, we changed the capacity of the line between bus 2 and 3 (i.e. from 150MW to 90MW) in order to incur a grid congestion event. In Table 5, we can see all locational marginal prices (LMPs) per timeslot for baseline scenario #1. As a result of the grid congestion, there are several

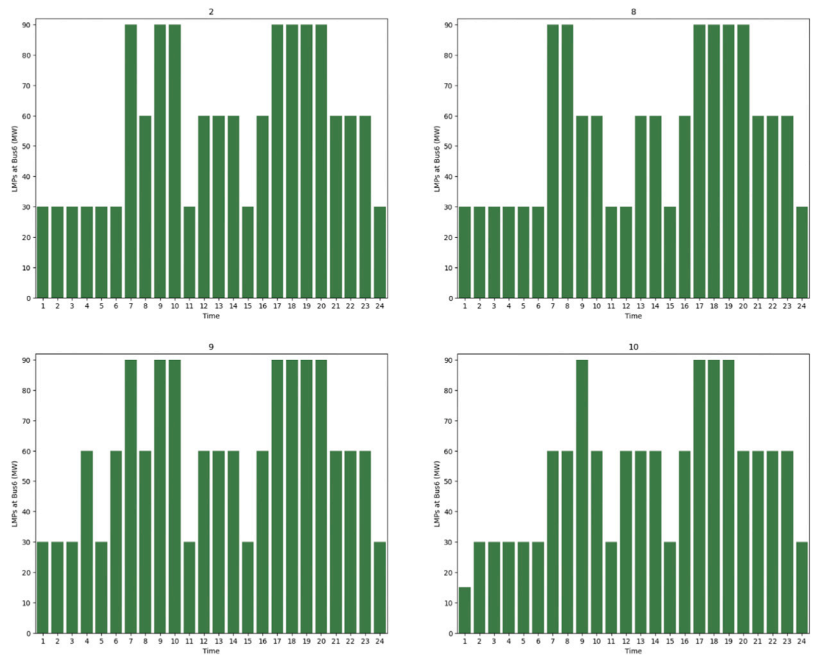

Fig. 12. EPEC LMPs (bus 5) for scenarios 2, 8, 9, 10.

Table 5
Baseline Scenario (#1) prices in congested network case per bus and per timeslot.

	Bus1 Price		Bus2 Price		Bus3 Price		Bus4 Price		Bus5 Price		Bus6 Price	
Time	*Comp*	*EPEC*	*Comp*	*EPEC*	*Comp*	*EPEC*	*Comp*	*EPEC*	*Comp*	*EPEC*	*Comp*	*EPEC*
1	30	30	30	30	30	30	30	30	30	30	30	30
2	35.15	30	30	30	61.73	30	42.97	30	46.53	30	60	30
3	35.15	30	30	30	61.73	30	42.97	30	46.53	30	60	30
4	35.15	35.15	30	30	61.73	61.73	42.97	42.97	46.53	46.53	60	60
5	35.15	30	30	30	61.73	30	42.97	30	46.53	30	60	30
6	35.15	30	30	30	61.73	30	42.97	30	46.53	30	60	30
7	90	90	90	90	90	90	90	90	90	90	90	90
8	90	90	90	90	90	90	90	90	90	90	90	90
9	90	90	90	90	90	90	90	90	90	90	90	90
10	90	90	90	90	90	90	90	90	90	90	90	90
11	60	60	60	60	60	60	60	60	60	60	60	60
12	60	60	60	60	60	60	60	60	60	60	60	60
13	60	60	60	60	60	60	60	60	60	60	60	60
14	60	60	60	60	60	60	60	60	60	60	60	60
15	37.18	30	32.44	30	61.59	30	44.36	30	47.63	30	60	30
16	60	60	60	60	60	60	60	60	60	60	60	60
17	90	90	90	90	90	90	90	90	90	90	90	90
18	90	90	90	90	90	90	90	90	90	90	90	90
19	90	90	90	90	90	90	90	90	90	90	90	90
20	90	90	90	90	90	90	90	90	90	90	90	90
21	60	60	60	60	60	60	60	60	60	60	60	60
22	60	60	60	60	60	60	60	60	60	60	60	60
23	60	60	60	60	60	60	60	60	60	60	60	60
24	30	30	30	30	30	30	30	30	30	30	30	30

timeslots within the day (i.e. 2:00-7:00 and 15:00-16:00), when the LMPs differ among the six buses. The gray-highlighted cells indicate the buses and timeslots at which the EPEC prices are lower than the competitive market setting. This happens because of the increased aggregated market power of DAs in the EPEC case compared to the competitive market setting, where all DAs are price-takers and thus potentially vulnerable to the strategic behavior of generators.

Table 6 depicts the whole network's congestion cost, which is calculated as the total DAs' payments minus the total generators' revenues. We can see that the EPEC market setting achieves a considerable decrease in congestion costs ranging from 39% (cf. scenario #4) to 83% (cf. scenario #1). Moreover, congestion costs are much higher in scenario #4 (compared to scenarios #1-3) because of the higher PV penetration, which decreases the available DSF capabilities across time as well as the market power capability of DAs.

Table 6
Network's congestion cost (DAs' payments minus generators' revenues).

Scenario #	Competitive market cost (€)	EPEC market cost (€)	% decrease
1	20 051.05	3387.84	83.10%
2	20 051.05	6775.69	66.20%
3	21 137.27	6775.69	67.94%
4	27 806.55	16 939.23	39.08%

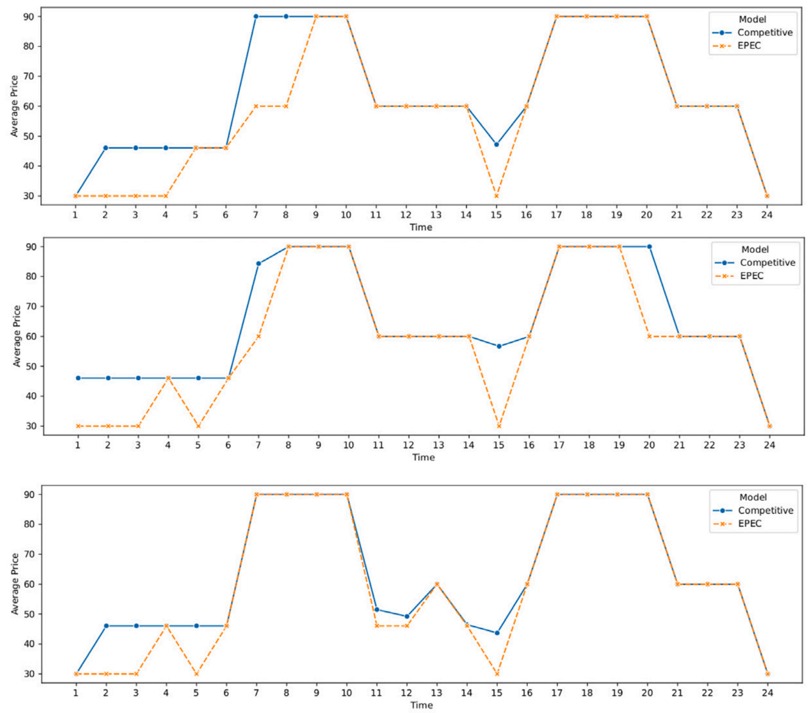

Fig. 13. Congestion case: Average price (across all 6 buses) for Scenarios 2, 3 and 4.

Fig. 13 illustrates the average price (across all 6 buses) for scenarios #2-4. Again, in all subfigures, we clearly see how the strategic behavior of all DAs can lower the average prices. Interestingly, the aggregated DSF portfolio mix directly affects the market power exercised by the demand-side of the market. For example, in scenario #2, most of the price decreases happen in the early morning hours when the V2G capability of the aggregated DSF portfolio is exploited. Scenario #3 demonstrates a similar trend; however, we also see a price change in the evening (20:00-21:00), when flexibility from SLs is exploited, too. Finally, in scenario #4, we can see the relatively limited capability of the aggregated DSF portfolio to change the prices within the whole day. However, the increased distributed PV generation in scenario #4 lowers the net load, and this in turn lowers the average price and aggregated DA costs during midday hours (11:00-16:00), when the greatest PV generation takes place.

5. Conclusion, policy implications and future work

In this paper, we conducted a thorough market equilibria analysis considering an oligopolistic demand-side electricity market comprising of a few strategic DAs. We formulated the relevant EPEC problem, using the diagonalization algorithm, i.e. an iterative best-response algorithm where each DA solves its own MPEC problem as if the bids of other rival DAs were fixed in their latest update. Simulation results demonstrate the impact that the proposed tool may have for both a DA's business as well as for a policy maker/regulator. Policy makers may incentivize new DSF investments in order to both support the DA's business and smoothly support the phasing out of the most expensive and environmentally-unfriendly generators. Furthermore, policy makers may also provide appropriate market signals to the DAs so as the latter can invest in the most profitable type of DSF investments, which can in turn lower the total system's cost. These market signals could be continuously updated in a way that the competition among several strategic DAs is effectively coordinated in a seamless manner and grid's congestion phenomena are proactively encountered deferring thus the need for costly grid reinforcements by the system operators.

Regarding our future work, we elaborate on one strong assumption that we have made in this paper, that is a DA myopically best-responds to the latest update of the other participants' bids (cf. diagonalization algorithm). A more realistic assumption would be that a DA observes the market participation strategies of other participants and gradually learns to anticipate their bidding strategies. As a result, our future work focuses on the interaction of strategic DAs with learning capabilities introducing the class of Coarse Correlated Equilibria (CCE) by using the Fictitious Play and the Smooth Fictitious Play algorithms to model the DAs' learning dynamics. Finally, our study can be extended by exploring the interactions between strategic Demand Aggregators and conventional generators. Investigating these interactions would offer deeper insights into the complex dynamics of electricity markets and contribute to the development of more comprehensive models for optimizing renewable energy integration and demand-side management strategies.

CRediT authorship contribution statement

Alireza Khaksari: Writing – review & editing, Visualization, Validation, Software, Resources, Formal analysis, Conceptualization. **Konstantinos Steriotis:** Writing – review & editing, Validation, Software, Methodology, Conceptualization. **Prodromos Makris:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Conceptualization. **Georgios Tsaousoglou:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Nikolaos Efthymiopoulos:** Writing – review & editing, Formal analysis, Conceptualization. **Emmanouel Varvarigos:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alireza Khaksari reports financial support was provided by the European Union's Horizon 2020 research and innovation program under the grant agreement No. 863876 in the context of FLEXGRID project. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to infuence the work reported in this paper.

Data availability

https://github.com/FlexGrid/DA_EPEC.

Acknowledgments

This work received funding from the European Union's Horizon 2020 research and innovation program under the grant agreement No. 863876 in the context of FLEXGRID project.

References

[1] F. D'Ettorre, M. Banaei, R. Ebrahimy, S. Ali Pourmousavi, E.M.V. Blomgren, J. Kowalski, Z. Bohdanowicz, B. Łopaciuk-Gonczaryk, C. Biele, H. Madsen, Exploiting demand-side flexibility: State-of-the-art, open issues and social perspective, Renew. Sustain. Energy Rev. 165 (2022) 112605.
[2] F. Plaum, R. Ahmadiahangar, A. Rosin, J. Kilter, Aggregated demand-side energy flexibility: A comprehensive review on characterization, forecasting and market prospects, Energy Rep. 8 (2022) 9344–9362.
[3] EU, DIRECTIVE (EU) 2019/944 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 5 June 2019 on common rules for the internal market for electricity and amending directive 2012/27/EU, 2019, [Online], Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019L0944.
[4] K. Steriotis, P. Makris, G. Tsaousoglou, N. Efthymiopoulos, E. Varvarigos, Co-optimization of distributed renewable energy and storage investment decisions in a TSO-DSO coordination framework, IEEE Trans. Power Syst. 38 (5) (2023) 4515–4529.
[5] G. Tsaousoglou, N. Efthymiopoulos, P. Makris, E. Varvarigos, Multistage energy management of coordinated smart buildings: A multiagent Markov decision process approach, IEEE Trans. Smart Grid 13 (4) (2022) 2788–2797.
[6] A. Khaksari, G. Tsaousoglou, P. Makris, K. Steriotis, N. Efthymiopoulos, E. Varvarigos, Sizing of electric vehicle charging stations with smart charging capabilities and quality of service requirements, Sustainable Cities Soc. 70 (2021) 102872.
[7] John Wiley & Sons, Ltd, Fundamentals of Power System Economics, ISBN: 978-1-119-21325-3, 2018.
[8] C. Heussaf, S. Tagliapietra, G. Zachmann, et al., An assessment of Europe's options for addressing the crisis in energy markets, Bruegel Policy Rep. (2022) Available at: https://apo.org.au/node/320426.
[9] S. Kazempour, A. Conejo, C. Ruiz, Strategic bidding for a large consumer, IEEE Trans. Power Syst. 30 (2015) 848–856.
[10] A. Daraeepour, S. Kazempour, D. Patiño-Echeverri, A. Conejo, Strategic demand-side response to wind power integration, IEEE Trans. Power Syst. 31 (2016) 3495–3505.
[11] Y. Wang, Y. Dvorkin, R. Fernández-Blanco, B. Xu, T. Qiu, D. Kirschen, Look-ahead bidding strategy for energy storage, IEEE Trans. Sustain. Energy 8 (2017) 1106–1117.
[12] H. Cui, F. Li, X. Fang, H. Chen, H. Wang, Bilevel arbitrage potential evaluation for grid-scale energy storage considering wind power and LMP smoothing effect, IEEE Trans. Sustain. Energy 9 (2018) 707–718.
[13] E. Nasrolahpour, J. Kazempour, H. Zareipour, W. Rosehart, A bilevel model for participation of a storage system in energy and reserve markets, IEEE Trans. Sustain. Energy 9 (2018) 582–598.
[14] K. Pandžić, K. Bruninx, H. Pandžić, Managing risks faced by strategic battery storage in joint energy-reserve markets, IEEE Trans. Power Syst. 36 (2021) 4355–4365.
[15] Y. Ye, D. Papadaskalopoulos, G. Strbac, Investigating the ability of demand shifting to mitigate electricity producers' market power, IEEE Trans. Power Syst. 33 (2018) 3800–3811.
[16] M. González Vayá, G. Andersson, Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty, IEEE Trans. Power Syst. 30 (2015) 2375–2385.
[17] X. Fang, Q. Hu, F. Li, B. Wang, Y. Li, Coupon-based demand response considering wind power uncertainty: A strategic bidding model for load serving entities, IEEE Trans. Power Syst. 31 (2016) 1025–1037.
[18] H. Mohsenian-Rad, Coordinated price-maker operation of large energy storage units in nodal energy markets, IEEE Trans. Power Syst. 31 (2016) 786–797.
[19] E. Mortaz, Portfolio diversification for an intermediary energy storage merchant, IEEE Trans. Sustain. Energy 11 (2020) 1539–1547.
[20] K. Šepetanc, H. Pandžić, A cluster-based operation model of aggregated battery swapping stations, IEEE Trans. Power Syst. 35 (2020) 249–260.
[21] K. Steriotis, K. Šepetanc, K. Smpoukis, N. Efthymiopoulos, P. Makris, E. Varvarigos, H. Pandžić, Stacked revenues maximization of distributed battery storage units via emerging flexibility markets, IEEE Trans. Sustain. Energy 13 (2022) 464–478.
[22] S. Wang, X. Tan, T. Liu, D. Tsang, Aggregation of demand-side flexibility in electricity markets: Negative impact analysis and mitigation method, IEEE Trans. Smart Grid 12 (2021) 774–786.
[23] Y. Jia, Z. Mi, Y. Yu, Z. Song, C. Sun, A bilevel model for optimal bidding and offering of flexible load aggregator in day-ahead energy and reserve markets, IEEE Access 6 (2018) 67799–67808.
[24] E. Kardakos, C. Simoglou, A. Bakirtzis, Optimal offering strategy of a virtual power plant: A stochastic bi-level approach, IEEE Trans. Smart Grid 7 (2016) 794–806.
[25] L. Baringo, M. Freire, R. García-Bertrand, M. Rahimiyan, Offering strategy of a price-maker virtual power plant in energy and reserve markets, Sustain. Energy Grids Netw. 28 (2021) 100558.
[26] K. Steriotis, K. Smpoukis, N. Efthymiopoulos, G. Tsaousoglou, P. Makris, E. Varvarigos, Strategic and network-aware bidding policy for electric utilities through the optimal orchestration of a virtual and heterogeneous flexibility assets' portfolio, Electr. Power Syst. Res. 184 (2020) 106302.
[27] S. Bahramara, M. Yazdani-Damavandi, J. Contreras, M. Shafie-Khah, J. Catalão, Modeling the strategic behavior of a distribution company in wholesale energy and reserve markets, IEEE Trans. Smart Grid 9 (2018) 3857–3870.
[28] X. Hu, D. Ralph, Using EPECs to model bilevel games in restructured electricity markets with locational prices, Oper. Res. 55 (2007) 809–827.
[29] C. Ruiz, A. Conejo, Y. Smeers, Equilibria in an oligopolistic electricity pool with stepwise offer curves, IEEE Trans. Power Syst. 27 (2012) 752–761.
[30] D. Pozo, J. Contreras, Finding multiple Nash equilibria in pool-based markets: A stochastic EPEC approach, IEEE Trans. Power Syst. 26 (2011) 1744–1752.
[31] H. Pandzic, A. Conejo, I. Kuzle, An EPEC approach to the yearly maintenance scheduling of generating units, IEEE Trans. Power Syst. 28 (2013) 922–930.
[32] S. Kazempour, H. Zareipour, Equilibria in an oligopolistic market with wind power production, IEEE Trans. Power Syst. 29 (2014) 686–697.
[33] T. Dai, W. Qiao, Finding equilibria in the pool-based electricity market with strategic wind power producers and network constraints, IEEE Trans. Power Syst. 32 (2017) 389–399.
[34] E. Tsimopoulos, M. Georgiadis, Nash equilibria in electricity pool markets with large-scale wind power integration, Energy 228 (2021) 120642.
[35] H. Haghighat, S. Kennedy, A bilevel approach to operational decision making of a distribution company in competitive environments, IEEE Trans. Power Syst. 27 (2012) 1797–1807.
[36] A. Naebi, S. SeyedShenava, J. Contreras, C. Ruiz, A. Akbarimajd, EPEC approach for finding optimal day-ahead bidding strategy equilibria of multi-microgrids in active distribution networks, Int. J. Electr. Power Energy Syst. 117 (2020) 105702.
[37] A. Shahmohammadi, R. Sioshansi, A. Conejo, S. Afsharnia, Market equilibria and interactions between strategic generation, wind, and storage, Appl. Energy 220 (2018) 876–892.
[38] Y. Dvorkin, Can merchant demand response affect investments in merchant energy storage? IEEE Trans. Power Syst. 33 (2018) 2671–2683.
[39] P. Zou, Q. Chen, Q. Xia, G. He, C. Kang, A. Conejo, Pool equilibria including strategic storage, Appl. Energy 177 (2016) 260–270.
[40] K. Pandžić, H. Pandžić, I. Kuzle, Virtual storage plant offering strategy in the day-ahead electricity market, Int. J. Electr. Power Energy Syst. 104 (2019) 401–413.
[41] A. Khaksary, K. Steriotis, G. Tsaousoglou, P. Makris, N. Efthymiopoulos, E. Varvarigos, Electricity market equilibrium analysis for strategic demand aggregators: The value of demand flexibility portfolios' mix, in: 2023 IEEE Belgrade PowerTech, 2023, pp. 01–06.
[42] S. Boyd, L. Vandenberghe, Convex Optimization, Cambridge University Press, New York, USA, 2004.
[43] J. Fortuny-Amat, B. McCarl, A representation and economic interpretation of a two-level programming problem, J. Oper. Res. Soc. 32 (1981) 783–792.
[44] S. Leyffer, T. Munson, Solving Multi-Leader-Common-Follower Games, Argonne National Laboratory, 2005.
[45] S. Gabriel, A. Conejo, J. Fuller, B. Hobbs, C. Ruiz, Complementarity Modeling in Energy Markets, Springer, New York, NY, USA, 2013.
[46] J.D. Weber, T.J. Overbye, An individual welfare maximization algorithm for electricity markets, IEEE Trans. Power Syst. 17 (2002) 590–596.
[47] T. Li, M. Shahidehpour, Strategic bidding of transmission-constrained GENCOs with incomplete information, IEEE Trans. Power Syst. 20 (2005) 437–447.
[48] B.F. Hobbs, C.B. Metzler, J.-S. Pang, Strategic gaming analysis for electric power systems: an MPEC approach, IEEE Trans. Power Syst. 15 (2000) 638–645.
[49] J.S. Pang, D. Chan, Iterative methods for variational and complementarity problems, Math. Program. 24 (1982) 284–313.
[50] S. Jin, S.M. Ryan, A tri-level model of centralized transmission and decentralized generation expansion planning for an electricity market—Part I, IEEE Trans. Power Syst. 29 (2014) 132–141.
[51] S. Che-Lin, Equilibrium Problems with Equilibrium Constraints: Stationarities, Algorithms, and Applications (Ph.D. thesis), Stanford University, 2005, [Online]. Available: https://web.stanford.edu/group/SOL/dissertations/clsu-thesis.pdf.
[52] [Online]. Available: https://github.com/FlexGrid/DA_EPEC.