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Strategic Bidding for a Large Consumer

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***Abstract*—The smart grid technology enables an increasing level of responsiveness on the demand side, facilitating demand serving entities—large consumers and retailers—to procure their electricity needs under the best conditions. Such entities generally exhibit a proactive role in the pool, seeking to procure their energy needs at minimum cost. Within this framework, we propose a mathematical model to help large consumers to derive bidding strategies to alter pool prices to their own benefit. Representing the uncertainty involved, we develop a stochastic complementarity model to derive bidding curves, and show the advantages of such bidding scheme with respect to non-strategic ones.**

***Index Terms*—Large consumer, mathematical program with equilibrium constraints (MPEC), strategic bidding, uncertainty.**

I. Introduction

A. Background, Methodology, and Aim

SMART grid technology enables an increasing level of demand response, and facilitates the strategic behavior of load serving entities [1], including large consumers and retailers. In fact, within a given legal framework, strategic consumers may seek to build bidding curves with the objective of manipulating market clearing prices to their own benefit.

We consider just one large consumer with the capability of exercising market power. All other consumers are assumed to be competitive and fairly inelastic, so their behaviors can be predicted accurately, which is the case of most real-world electricity consumers.

This paper proposes a complementarity bilevel model that allows the considered large consumer to build its optimal bidding curves. The upper-level (UL) problem of this bilevel model represents the utility of the large consumer and the lower-level (LL) ones the clearing of the market under different operating conditions. The UL problem influences the LL ones through the bidding curves, and the LL problems influence the UL one through the clearing prices. The joint solution of both problems (the solution of the complementarity problem) results in optimal bidding curves for the consumer and the subsequent clearing prices.

The considered framework is an electricity pool that clears once a day, one day ahead and on an hourly basis. The market operator seeks to maximize social welfare considering the stepwise supply function offers and the stepwise demand function bids submitted by producers and consumers, respectively, and using a lossless dc representation of the network. The market clearing results are hourly production/consumption levels and locational marginal prices (LMPs).

Note that the considered large consumer is assumed to be elastic enough to play strategically in the market, i.e., it does not need to be fully supplied. The strategic consumer selects its consumption level considering its own constraints, i.e., ramping limits and minimum energy consumption levels, so that it maximizes its expected utility. Therefore, the strategic consumer may or may not have to participate in additional trading floors to cover its unserved energy. Moreover, it may self-produce such energy.

Uncertainty regarding offers of producers and demand bids of consumers is represented through scenarios, which renders the complementary problem stochastic. In turn, this problem is transformed into a mixed-integer linear programming (MILP) problem. If the uncertainty representation requires many scenarios, the MILP problem may become computationally intractable for pools involving many agents. For such a case, a heuristic solution technique is proposed that generally renders solutions close to the optimal one.

B. Literature Review

Few papers are available in the technical literature considering bidding strategies for consumers. A demand-side bidding framework within a market environment is established in [2]. Pool bidding curves for non-strategic consumers are derived in [3] by using a highly risk-averse methodology. Reference [4] describes a methodology for purchase allocation and non-strategic demand bidding. In [5], a Monte Carlo-based algorithm is proposed to derive the day-ahead bidding curves for different coalitions of price-responsive demands. In addition, [6] considers two types of demand, i.e., price-based and must-serve, and then derives the optimal bidding functions for those types of demand.

Some other works address the bidding problem from an electricity retailer's perspective. Reference [7] considers a retailer view in Nord Pool and derives piecewise bidding curves using stochastic linear programming. Also considering the Nord Pool market, [8] analyzes the purchase of electricity in the Norwegian zone and establishes analytical conditions to derive optimal bidding curves. The long-term procurement of electric energy using risk-constrained stochastic programming is considered in [9]. Based on a heuristic approach, [10] addresses the problem of optimal bidding for a retailer that participates in a short-term electricity market.

Although not from a strategic point of view but related to this paper, some works report the impacts of demand-side elasticity on the market operation and its outcomes. For instance, [11] studies the benefits and challenges of electricity demand-side management. The analysis in [12] illustrates how an increasing

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level of demand-side price elasticity improves the operation of electricity markets. References [13]–[15] analyze the market efficiency under different levels of demand elasticity, while [16] and [17] study the impacts of demand response on LMPs. In addition, [18]–[21] analyze the value of price-responsive demands to increase the operational flexibility of a power system, which is crucial for renewable integration.

Finally, further mathematical details on the complementarity model used in this paper can be found in [22].

C. Contributions

Under the context of imperfect electricity markets, a number of works are reported in the literature pertaining to operation and planning problems for *strategic producers* (e.g., [23], [24], and [25]). However, to the best of our knowledge, no work in the literature considers *strategic consumers* that seek to derive bidding curves to manipulate the market to their own benefit. Accordingly, the contributions of this paper are fourfold:

1) To propose a complementarity model for deriving bidding curves for a strategic consumer that intends to manipulate pool prices to its own benefit.
2) To recast the proposed complementarity model as a stochastic complementarity problem that can be transformed into a MILP problem.
3) To propose an efficient heuristic solution technique that allows considering scenarios one at a time, and thus solving large-scale instances of the MILP problem.
4) To comprehensively study an example of small size, to provide and analyze results from a large case study, and to numerically illustrate how the strategic consumer impacts the market clearing outcomes.

D. Paper Organization

The rest of this paper is organized as follows. Section II states the assumptions and features of the proposed model to derive strategic bidding curves, which materializes in a stochastic complementarity problem. Section III describes the mathematical details of this complementarity problem, and the proposed solution technique to solve it. Section IV illustrates the functioning of the considered model using a simple example, and shows its validity and practical significance through a realistic case study. Finally, Section V provides some relevant conclusions.

II. Model Features

A. Model

A bilevel model is proposed to represent the strategic behavior of a large consumer, whose solution determines its optimal bidding curves. This model consists of an UL problem and a set of LL problems. The consumer behaves strategically through its bidding decisions made at the UL problem, with the objective of maximizing expected utility and subject to 1) UL problem constraints, and 2) the set of LL problems. The UL constraints include bidding curve conditions, ramping limits and minimum energy consumption levels for each demand of the consumer over the time periods considered. On the other hand, the set of LL problems represents the clearing of the pool under different operating conditions.

B. Network Representation

Most US electricity markets use a day-ahead market clearing that embeds a dc representation of the network. Such a network representation (dc, not ac) is generally deemed appropriate for day-ahead market clearing. On the other hand, most European electricity markets neglect the representation of the network in their market clearing algorithms, which requires ex-post heuristic approaches to attain network feasibility. This may result in optimality degradation and litigation among market agents. Our model resembles those used by European markets but includes network constraints using a lossless dc model as we consider that such constraints are important to accurately represent the physics of electricity transmission.

C. Uncertainty

To maximize its utility, the considered strategic consumer seeks to decrease market clearing prices through its strategic bidding decisions. In addition, that consumer faces an important number of uncertainties, e.g., the offering behavior of producers, the bidding behavior of other demands, the renewable power production levels, and others. Among those uncertainties, the most critical one corresponds to producers' offer curves, because that uncertainty directly affects market clearing prices. Note that the market is generally cleared at a price equal to the offer price of the last generating unit dispatched [23]. For the sake of simplicity, the uncertainty associated with the producers' offer curves is the only uncertainty considered in this paper, which is characterized through a set of scenarios. However, the proposed model can be easily extended to take into account other uncertainties through additional scenarios, but at the cost of higher computational burden.

Note that although renewable generating units and thus their corresponding production uncertainties are not explicitly represented in the proposed model, they are implicitly considered in the offering scenarios for the producers.

D. Bidding Curves

We consider the bidding decisions of the large consumer scenario-dependent variables [23]. Therefore, a set of additional conditions needs to be included in the model formulation to ensure that the resulting strategic bidding curves are decreasing in price, as required in most real-world electricity markets. This is enforced by conditions (1) below which guarantee that higher consumptions correspond to lower clearing prices (note that symbols are defined in the next section):

$$\left[\sum_k D^{\mathrm{L}}_{tdk\omega} - \sum_k D^{\mathrm{L}}_{tdks}\right]\left[\lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)\omega} - \lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)s}\right] \leq 0 \quad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall\omega, \forall s > \omega. \tag{1}$$

III. Model Formulation

This section provides the formulation of the bilevel problem, the resulting complementarity problem and the heuristic solution technique.

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NOTATION

A. Indices

t	Index for time periods running from 1 to T.
d	Index for the demands of the large consumer running from 1 to N_d.
q	Index for other demands running from 1 to N_q.
k	Index for demand blocks running from 1 to N_k.
i	Index for generating units running from 1 to N_i.
b	Index for generation blocks running from 1 to N_b.
n, m	Indices for nodes running from 1 to N_n, and from 1 to N_m, respectively.
ω, s	Indices for scenarios running from 1 to N_ω, and from 1 to N_s, respectively.

B. Sets

$\mathcal{D}^{\mathrm{L}}$	Set of demands of the large consumer.
$\mathcal{D}^{\mathrm{O}}$	Set of other demands.
$\mathcal{G}$	Set of generating units.
Ω_n	Set of nodes connected to node n.

Sets $\mathcal{D}^{\mathrm{L}}$, $\mathcal{D}^{\mathrm{O}}$, and $\mathcal{G}$ include subscript n if referring to the set of demands/units located at node n.

C. Constants

ϕ_ω	Probability of scenario ω.
β^{cap}	Price cap for bids [\$/MWh].
$\alpha_{tib\omega}$	Price offer by block b of generating unit $i \in \mathcal{G}$ in period t and scenario ω [\$/MWh].
U^{L}_{tdk}	Marginal utility of block k of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer in period t [\$/MWh].
β^{O}_{tqk}	Price bid by block k of demand $q \in \mathcal{D}^{\mathrm{O}}$ in period t [\$/MWh].
R^+_d	Load pick-up ramping limit for demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer [MW/h].
R^-_d	Load drop ramping limit for demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer [MW/h].
E^{T}_d	Minimum total energy consumption level of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer over time periods $t = 1, \ldots, T$ [MWh].
$P^{\max}_{ib}$	Capacity of block b of generating unit $i \in \mathcal{G}$ [MW].
$D^{\mathrm{L}^{\max}}_{tdk}$	Maximum load of block k of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer in period t [MW].
$D^{\mathrm{O}^{\max}}_{tqk}$	Maximum load of block k of demand $q \in \mathcal{D}^{\mathrm{O}}$ in period t [MW].
x_{nm}	Reactance of transmission line (n, m) [p.u.].
F_{nm}	Capacity of transmission line (n, m) [MW].

D. Variables

$P_{tib\omega}$	Power produced by of block b of generating unit $i \in \mathcal{G}$ in period t and scenario ω [MW].
$D^{\mathrm{L}}_{tdk\omega}$	Power consumed by block k of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer in period t and scenario ω [MW].
$D^{\mathrm{O}}_{tqk\omega}$	Power consumed by block k of demand $q \in \mathcal{D}^{\mathrm{O}}$ in period t and scenario ω [MW].
$\beta^{\mathrm{L}}_{tdk\omega}$	Price bid by block k of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer in period t and scenario ω [\$/MWh].
$\theta_{tn\omega}$	Voltage angle of node n in period t and scenario ω [rad].
$\lambda_{tn\omega}$	Locational marginal price at node n in period t and scenario ω [\$/MWh].

E. Bilevel Model

The proposed bilevel model is (2)–(3) below, where (2) is the UL problem, and (3) is the set of LL problems, one per time period and scenario. Note that dual variables associated with the LL problems are indicated at their corresponding constraints following a colon. The primal set of variables for each lower-level problem is $\Xi^{\mathrm{Primal}}_{t\omega} = \{P_{tib\omega}, D^{\mathrm{L}}_{tdk\omega}, D^{\mathrm{O}}_{tqk\omega}, \theta_{tn\omega}\}$, while its dual set of variables is $\Xi^{\mathrm{Dual}}_{t\omega} = \{\lambda_{tn\omega}, \mu^{\min}_{tib\omega}, \mu^{\max}_{tib\omega}, \eta^{\mathrm{L}^{\min}}_{tdk\omega}, \eta^{\mathrm{L}^{\max}}_{tdk\omega}, \eta^{\mathrm{O}^{\min}}_{tqk\omega}, \eta^{\mathrm{O}^{\max}}_{tqk\omega}, \xi_{tnm\omega}, \delta^1_{t\omega}\}$.

In addition, the primal set of variables for the UL problem (2) is $\Xi^{\mathrm{UL}} = \{\Xi^{\mathrm{Primal}}_{t\omega}, \Xi^{\mathrm{Dual}}_{t\omega}, \beta^{\mathrm{L}}_{tdk\omega}, y_{td\omega s}\}$. Note that the bidding decisions $\beta^{\mathrm{L}}_{tdk\omega}$ are variables within the UL problem, while they are parameters within the LL problems, i.e., the pool clearing mechanism treats them as fixed bidding parameters. This makes the lower-level problems (3) linear and thus convex:

$$\underset{\Xi^{\mathrm{UL}}}{\mathrm{Maximize}} \sum_{\omega} \phi_\omega \left[\sum_{t(d\in\mathcal{D}^{\mathrm{L}})k} D^{\mathrm{L}}_{tdk\omega} \left(U^{\mathrm{L}}_{tdk} - \lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)\omega} \right) \right] \tag{2a}$$

subject to

$$0 \le \beta^{\mathrm{L}}_{tdk\omega} \le \beta^{\mathrm{cap}} \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k, \forall \omega \tag{2b}$$

$$\beta^{\mathrm{L}}_{tdk\omega} \ge \beta^{\mathrm{L}}_{td(k+1)\omega} \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k < N_k, \forall \omega \tag{2c}$$

$$\sum_k D^{\mathrm{L}}_{(t+1)dk\omega} - \sum_k D^{\mathrm{L}}_{tdk\omega} \le R^+_d \qquad \forall t < T, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega \tag{2d}$$

$$\sum_k D^{\mathrm{L}}_{tdk\omega} - \sum_k D^{\mathrm{L}}_{(t+1)dk\omega} \le R^-_d \qquad \forall t < T, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega \tag{2e}$$

$$\sum_{tk} D^{\mathrm{L}}_{tdk\omega} \ge E^{\mathrm{T}}_d \qquad \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega \tag{2f}$$

$$(y_{td\omega s} - 1)\, M \le \left[\lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)\omega} - \lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)s} \right] \le y_{td\omega s} M \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega, \forall s > \omega \tag{2g}$$

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$$(y_{td\omega s}-1)\,M \le \left[\sum_k D^{\mathrm{L}}_{tdks} - \sum_k D^{\mathrm{L}}_{tdk\omega}\right] \le y_{td\omega s} M$$
$$\forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega, \forall s > \omega \qquad (2h)$$
$$y_{td\omega s} \in \{0,1\} \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall \omega, \forall s > \omega \qquad (2i)$$
$$\lambda_{tn\omega}, D^{\mathrm{L}}_{tdk\omega} \in \arg \underset{\Xi^{\mathrm{Primal}}_{t\omega}}{\text{minimize}} \Bigg\{ \sum_{(i\in\mathcal{G})b} \alpha_{tib\omega} P_{tib\omega} - \sum_{(d\in\mathcal{D}^{\mathrm{L}})k} \beta^{\mathrm{L}}_{tdk\omega} D^{\mathrm{L}}_{tdk\omega} - \sum_{(q\in\mathcal{D}^{\mathrm{O}})k} \beta^{\mathrm{O}}_{tqk} D^{\mathrm{O}}_{tqk\omega} \qquad (3a)$$
subject to:
$$\sum_{(d\in\mathcal{D}^{\mathrm{L}}_n)k} D^{\mathrm{L}}_{tdk\omega} + \sum_{(q\in\mathcal{D}^{\mathrm{O}}_n)k} D^{\mathrm{O}}_{tqk\omega} - \sum_{(i\in\mathcal{G}_n)b} P_{tib\omega} + \sum_{m\in\Phi_n} \frac{1}{x_{nm}} (\theta_{tn\omega} - \theta_{tm\omega}) = 0 : \lambda_{tn\omega} \qquad \forall n \qquad (3b)$$
$$0 \le P_{tib\omega} \le P^{\max}_{ib} : \mu^{\min}_{tib\omega}, \mu^{\max}_{tib\omega} \qquad \forall i \in \mathcal{G}, \forall b \qquad (3c)$$
$$0 \le D^{\mathrm{L}}_{tdk\omega} \le D^{\mathrm{L}^{\max}}_{tdk} : \eta^{\mathrm{L}^{\min}}_{tdk\omega}, \eta^{\mathrm{L}^{\max}}_{tdk\omega} \qquad \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k \qquad (3d)$$
$$0 \le D^{\mathrm{O}}_{tqk\omega} \le D^{\mathrm{O}^{\max}}_{tqk} : \eta^{\mathrm{O}^{\min}}_{tqk\omega}, \eta^{\mathrm{O}^{\max}}_{tqk\omega} \qquad \forall q \in \mathcal{D}^{\mathrm{O}}, \forall k \qquad (3e)$$
$$\frac{1}{x_{nm}} (\theta_{tn\omega} - \theta_{tm\omega}) \le F_{nm} \quad : \xi_{tnm\omega} \quad \forall n, \forall m \in \Phi_n \qquad (3f)$$
$$\theta_{t(n=1)\omega} = 0 \quad : \delta^{1}_{t\omega} \Bigg\} \quad \forall t, \forall \omega. \qquad (3g)$$

Objective function (2a) is the expected utility of the large consumer. Constraints (2b) and (2c) enforce the bid curve blocks for each demand of the large consumer to be non-negative, lower than the price cap and decreasing in price. Constraints (2d) and (2e) enforce the demand pick-up and drop ramping limits for each demand of the large consumer. Constraints (2f) impose a minimum total energy consumption level for each demand of the large consumer over the time periods considered. Set of constraints (2g)–(2i) is a mixed-integer linear form of conditions (1) described in Section II-D. Note that M is a large enough positive constant and $y_{td\omega s}$ is a binary variable.

Lower-level problems (3) represent the clearing of the pool per time period and scenario. Objective function (3a) is the negative social welfare of the corresponding pool clearing. Note that parameters $\alpha_{tib\omega}$ are indexed by ω to characterize the offering uncertainty of the producers. Constraints (3b), whose dual variables are the LMPs, enforce power balance at each node. Constraints (3c) bound the production of each generation block of the units. Constraints (3d) and (3e) bound the lower and upper limits for each consumption block of all demands. Constraints (3f) enforce transmission constraints. Finally, constraints (3g) identify node $n = 1$ as the voltage angle's reference.

F. MPEC

The linearity of LL problems (3) allows replacing them by their Karush-Kuhn-Tucker (KKT) optimality conditions. This transformation renders a mathematical program with equilibrium constraints (MPEC) as given by (4):

$$\underset{\Xi^{\mathrm{UL}}}{\text{Maximize}} \quad (2a) \qquad (4a)$$
subject to
$$(2b)-(2i), (3b), (3g) \qquad (4b)$$
$$\alpha_{tib\omega} - \lambda_{t(n:i\in\mathcal{G}_n)\omega} + \mu^{\max}_{tib\omega} - \mu^{\min}_{tib\omega} = 0 \qquad \forall t, \forall i \in \mathcal{G}, \forall b, \forall \omega \qquad (4c)$$
$$-\beta^{\mathrm{L}}_{tdk\omega} + \lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)\omega} + \eta^{\mathrm{L}^{\max}}_{tdk\omega} - \eta^{\mathrm{L}^{\min}}_{tdk\omega} = 0 \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k, \forall \omega \qquad (4d)$$
$$-\beta^{\mathrm{O}}_{tqk} + \lambda_{t(n:q\in\mathcal{D}^{\mathrm{O}}_n)\omega} + \eta^{\mathrm{O}^{\max}}_{tqk\omega} - \eta^{\mathrm{O}^{\min}}_{tqk\omega} = 0 \qquad \forall t, \forall q \in \mathcal{D}^{\mathrm{O}}, \forall k, \forall \omega \qquad (4e)$$
$$\sum_{m\in\Phi_n} \frac{1}{x_{nm}} (\lambda_{tn\omega} - \lambda_{tm\omega}) + \sum_{m\in\Phi_n} \frac{1}{x_{nm}} (\xi_{tnm\omega} - \xi_{tmn\omega}) + \left(\delta^{1}_{t\omega}\right)_{n=1} = 0 \qquad \forall t, \forall n, \forall \omega \qquad (4f)$$
$$0 \le P_{tib\omega} \perp \mu^{\min}_{tib\omega} \ge 0 \qquad \forall t, \forall i \in \mathcal{G}, \forall b, \forall \omega \qquad (4g)$$
$$0 \le (P^{\max}_{ib} - P_{tib\omega}) \perp \mu^{\max}_{tib\omega} \ge 0 \ \forall t, \forall i \in \mathcal{G}, \forall b, \forall \omega \qquad (4h)$$
$$0 \le D^{\mathrm{L}}_{tdk\omega} \perp \eta^{\mathrm{L}^{\min}}_{tdk\omega} \ge 0 \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k, \forall \omega \qquad (4i)$$
$$0 \le \left(D^{\mathrm{L}^{\max}}_{tdk} - D^{\mathrm{L}}_{tdk\omega}\right) \perp \eta^{\mathrm{L}^{\max}}_{tdk\omega} \ge 0 \qquad \forall t, \forall d \in \mathcal{D}^{\mathrm{L}}, \forall k, \forall \omega \qquad (4j)$$
$$0 \le D^{\mathrm{O}}_{tqk\omega} \perp \eta^{\mathrm{O}^{\min}}_{tqk\omega} \ge 0 \qquad \forall t, \forall q \in \mathcal{D}^{\mathrm{O}}, \forall k, \forall \omega \qquad (4k)$$
$$0 \le \left(D^{\mathrm{O}^{\max}}_{tqk} - D^{\mathrm{O}}_{tqk\omega}\right) \perp \eta^{\mathrm{O}^{\max}}_{tqk\omega} \ge 0 \qquad \forall t, \forall q \in \mathcal{D}^{\mathrm{O}}, \forall k, \forall \omega \qquad (4l)$$
$$0 \le \left[F_{nm} - \frac{1}{x_{nm}} (\theta_{tn\omega} - \theta_{tm\omega})\right] \perp \xi_{tnm\omega} \ge 0 \qquad \forall t, \forall n, \forall m \in \Phi_n, \forall \omega. \qquad (4m)$$

Constraint (4b) contains the upper-level constraints and the equalities included in the LL problems (3). Equalities (4c)–(4f) and the complementarity conditions (4g)–(4m) are the KKT optimality conditions of the LL problems.

G. MPEC Linearization

MPEC (4) above is nonlinear due to the following nonlinearities:

1) The bilinear term $\sum_{(d\in\mathcal{D}^{\mathrm{L}})k} D^{\mathrm{L}}_{tdk\omega} \lambda_{t(n:d\in\mathcal{D}^{\mathrm{L}}_n)\omega}$ in the objective function (4a), which is denoted below as $\Gamma_{t\omega}, \forall t, \forall \omega$.
2) The complementarity conditions (4g)–(4m).

It is important to note that MPEC (4) can be transformed into a MILP problem through the linearization techniques explained below: A linear expression for $\Gamma_{t\omega}$ can be obtained through the exact linearization approach proposed in [23]. This approach exploits the strong duality theorem and some of the KKT equalities. The application of that approach renders

$$\Gamma_{t\omega} = \sum_{(i\in\mathcal{G})b} \alpha_{tib\omega} P_{tib\omega} - \sum_{(q\in\mathcal{D}^{\mathrm{O}})k} \beta^{\mathrm{O}}_{tqk} D^{\mathrm{O}}_{tqk\omega} + \sum_{(i\in\mathcal{G})b} \mu^{\max}_{tib\omega} P^{\max}_{ib} + \sum_{(q\in\mathcal{D}^{\mathrm{O}})k} \eta^{\mathrm{O}^{\max}}_{tqk\omega} D^{\mathrm{O}^{\max}}_{tqk} + \sum_{n(m\in\Phi_n)} \xi_{tnm\omega} F_{nm} \quad \forall t, \forall \omega. \qquad (5)$$

In addition, each complementarity condition of the form $0 \le a \perp b \ge 0$ is equivalent to the set of mixed-integer linear conditions $a \ge 0$, $b \ge 0$, $a \le uM$, $b \le (1-u)M$, where u is an auxiliary binary variable, and M is a large enough positive constant [23], [26].

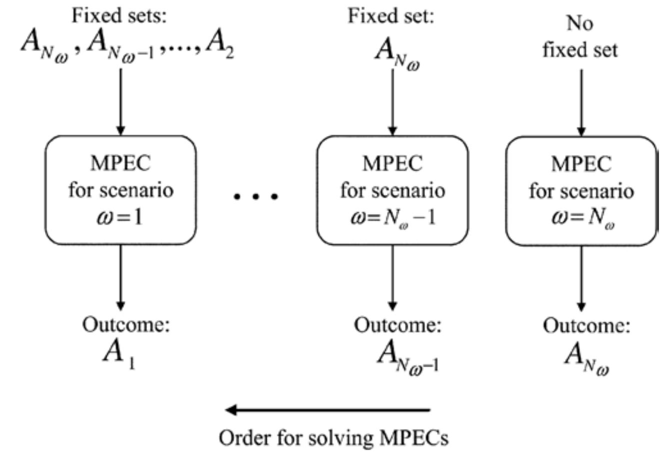

Fig. 1. Scheme of the proposed heuristic approach to solve the MPEC for each scenario individually.

Note that the variables of the resulting MILP are those included in the set Ξ^{UL} as well as the auxiliary binary variables used for the linearization of the complementarity conditions.

H. Heuristic Solution Technique: One MPEC per Scenario

The set of UL constraints (2g)–(2i) included in (4b) link together the LMPs $\lambda_{tn\omega}$ and the consumptions $D^{\mathrm{L}}_{tdk\omega}$ of different scenarios. Therefore, to solve MPEC (4) all scenarios need to be considered simultaneously (direct solution technique). However, this approach generally suffers from high computational burden and eventual intractability in cases with many agents or many scenarios.

To overcome such a drawback, we propose a coordinate descent algorithm [27]. This algorithm allows to solve the original MPEC by decomposing it by scenario, as illustrated in Fig. 1. Note that in this figure, the variable set A_ω consists of variables $\lambda_{tn\omega}$ and $D^{\mathrm{L}}_{tdk\omega}$. The functioning of the algorithm proposed is as follows: in the formulation of the MPEC corresponding to the last scenario, i.e., $\omega = N_\omega$, linking constraints (2g)–(2i) need not to be enforced since there is no scenario s whose ordering number is higher than scenario $\omega = N_\omega$. Therefore, in the first step, MPEC (4) is solved for scenario $\omega = N_\omega$ without imposing any condition related to other scenarios. In the next step, the MPEC corresponding to scenario $\omega = N_\omega - 1$ is solved, while constraints (2g)–(2i) are enforced based on the market outcomes obtained from the previously solved MPEC, i.e., A_{N_ω}. Since the optimal values for A_{N_ω} are known, the MPEC corresponding to scenario $\omega = N_\omega - 1$ can be also solved individually. In other words, there is no need to solve the MPECs corresponding to scenarios $\omega = N_\omega$ and $\omega = N_\omega - 1$, simultaneously. This procedure can be repeated for all scenarios up to the first one, so that for the first scenario $(\omega = 1)$, the corresponding MPEC is solved considering the optimal values $A_{N_\omega}, A_{N_\omega -1}, \ldots, A_2$ that are obtained from the solutions of the previous MPECs.

It should be emphasized that, although these types of algorithms (coordinate descent) are easy to implement, there is no guarantee of finding the global optimal solution if applied to non-convex problems, which is the case of the complementarity problem considered in this work. However, appropriate strategies can be used to find the best ordering of the scenarios that lead to solutions that are close to the global one. For the considered problem, we found through extensive numerical simulations that an ordering criterion based on average LMP is most effective. This scenario ordering procedure is as follows:

1) Solve MPEC (4) per scenario [where linking constraints (2g)–(2i) are not enforced], and then compute the average LMP over the nodes and time periods for each scenario.
2) Order scenarios from highest to lowest average LMP.

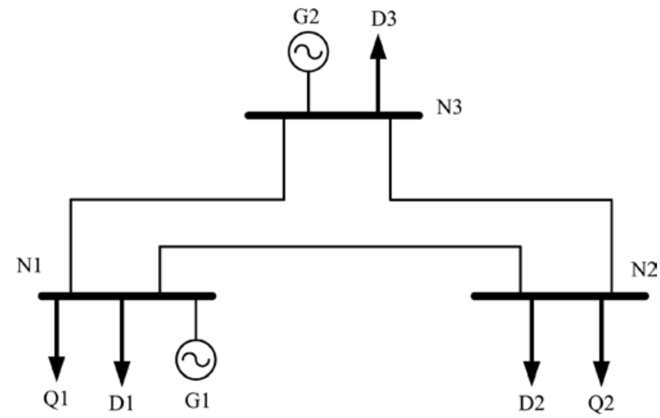

Fig. 2. Network of the illustrative example.

IV. Numerical Results

In this section, a simple example is used to illustrate the main features of the proposed model, as well as its consistent behavior. Additionally, a large scale case study is used to show the appropriate performance and the practical relevance of the proposed solution technique. The effectiveness of this technique is validated comparing the outcomes obtained using strategic bidding curves with those obtained using non-strategic ones.

For both the illustrative example and the case study, the resulting MILP described in the previous section is solved using CPLEX 12.1 [28] under GAMS [29] on a Sun Fire X4600 M2 with four processors clocking at 2.9 GHz and 256 GB of RAM.

A. Illustrative Example

In this section, results based on a three-node example are discussed. In addition, the effectiveness of the proposed heuristic algorithm is evaluated comparing its results to those obtained from a direct solution of the MILP version of MPEC (4), where all scenarios are considered simultaneously.

1) Data: Fig. 2 shows the network considered. Note that demands D1, D2, and D3 belong to the large consumer, while demands Q1 and Q2 belong to other consumers. In the uncongested cases, the capacity of each transmission line is 400 MW, and 100 MW in the congested ones. In addition, the reactance of each transmission line is assumed to be 0.01 p.u.

In this example, we consider three time periods, namely, t_1 (peak), t_2 (shoulder), and t_3 (off-peak). We also consider three generation blocks (blocks b_1 to b_3) for each unit and three demand blocks (blocks k_1 to k_3) for each demand. Table I gives the data for the generating units G1 and G2. Note that the total generation capacity of the system is 670 MW.

The offering uncertainty of the generating units is characterized through ten scenarios (ω_1 to ω_{10}), whose probabilities are identical and equal to 0.10. In each scenario, the offer prices

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TABLE I
DATA FOR GENERATING UNITS (ILLUSTRATIVE EXAMPLE)

Generating unit (i)	Unit capacity [MW]	Capacity of block b_1 [MW]	Capacity of block b_2 [MW]	Capacity of block b_3 [MW]	PC* of block b_1 [$/MWh]	PC of block b_2 [$/MWh]	PC of block b_3 [$/MWh]
G1	440	185	205	50	9.7	10.8	12.7
G2	230	110	60	60	15.0	15.9	16.8

* Production cost

TABLE II
FACTORS CHARACTERIZING THE OFFERING UNCERTAINTY OF THE PRODUCERS (ILLUSTRATIVE EXAMPLE)

Scenario	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9	ω_{10}
Factor for t_1	1.00	1.10	1.20	1.30	1.40	1.50	1.10	1.20	1.30	1.50
Factor for t_2	1.00	1.05	1.10	1.15	1.20	1.25	1.10	1.20	1.30	1.50
Factor for t_3	1.00	1.02	1.04	1.06	1.08	1.10	1.10	1.15	1.20	1.25

TABLE III
DATA FOR ALL DEMANDS IN PEAK TIME PERIOD t_1 (ILLUSTRATIVE EXAMPLE)

	Load level [MW]	Load of block k_1 [MW]	Load of block k_2 [MW]	Load of block k_3 [MW]	MU* of block k_1 [$/MWh]	MU of block k_2 [$/MWh]	MU of block k_3 [$/MWh]
D1	110	80	15	15	32.3	28.7	26.2
D2	100	65	15	20	29.8	25.1	24.0
D3	65	40	10	15	28.0	24.8	23.2
Q1	225	150	45	30	32.0	28.7	27.8
Q2	150	100	25	25	29.1	25.9	25.2

* Marginal utility

of each generating unit are its production costs (the last three columns of Table I) multiplied by a factor. Table II gives such factors.

Table III provides the data for the demands of the large consumer and other demands for the peak time period t_1. Note that in time period t_2 the load level and marginal utility of each demand are identical to those in time period t_1, but multiplied by 0.85 and 0.95, respectively. Similarly, in time period t_3, those factors are 0.70 and 0.90, respectively. We assume that each non-strategic demand (Q1 and Q2) bids in each time period at its corresponding marginal utility. According to Table III, the peak demand is 650 MW, 42% of it belonging to the large consumer.

Considering the electricity market of the Iberian Peninsula [30], we fix the bid price cap to 180 $/MWh. However, note that this cap is data that can be easily obtained from any market under consideration. Parameter E_d^{T} for demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer is assumed to be $0.7 \times \sum_{tk} D_{tdk}^{\mathrm{L}^{\max}}$. Finally, each pick-up and drop ramping limit of demand $d \in \mathcal{D}^{\mathrm{L}}$ of the large consumer is assumed to be equal to half of $\sum_k D_{tdk}^{\mathrm{L}^{\max}}$, evaluated for the peak time period, i.e., t_1.

2) Direct Solution versus Heuristic Solution: This section compares the strategic bidding results obtained using 1) a direct solution technique, where all scenarios are considered simultaneously for solving (4), and 2) using the proposed heuristic solution technique, where scenarios are considered one at a time. The corresponding results are presented in Table IV, and explained in the following:

a) For the uncongested case (second row), the results obtained from both solution techniques are identical. For this case, the value of the objective function, i.e., the expected utility of the large consumer is $6695.7, while the computational time for the direct solution technique (12.6 s) is comparatively higher than that of the heuristic one (1.7 s).

b) For the congested case (third row), the expected utility of the large consumer obtained from the direct solution technique is $6381.9, while that obtained from the heuristic one is $6289.4. Thus, the heuristic solution technique does not achieve global optimality for the congested case, but the results are close (1.4% error). However, the computational time required by the direct solution technique (2717.9 s) is dramatically higher than that of the heuristic one (4.0 s).

TABLE IV
BIDDING RESULTS THROUGH DIRECT AND HEURISTIC SOLUTION TECHNIQUES (ILLUSTRATIVE EXAMPLE)

Case	Solution technique	Expected utility of the large consumer (objective function) [$]	Computational time [s]
Uncongested case	Direct	6695.7	12.6
	Heuristic	6695.7	1.7
Congested case	Direct	6381.9	2717.9
	Heuristic	6289.4	4.0

This section concludes stating that with the heuristic solution technique there is no guarantee of achieving global optimality. However, this heuristic solution technique is relevant in practice due to its computational advantages if many scenarios are considered. This is further illustrated in Section IV-B.

3) Bidding Results: In this section, we compare the bidding results obtained from the proposed heuristic technique for two cases: 1) the large consumer behaves strategically, and 2) the large consumer bids at its marginal utility U_{tdk}^{L} (non-strategic). The impact of transmission congestion on the results is also analyzed.

The corresponding bidding results are provided in Table V, whose columns 2, 3, and 4 present the non-strategic uncongested, the strategic uncongested and the strategic congested cases, respectively. Rows 2, 3, and 4 of Table V provide expected utility, expected utility per MWh and expected unserved energy, respectively. Additionally, row 5 of Table V provides the market clearing prices for scenario ω_5 (a representative scenario). Note that for the cases in which the transmission lines are not congested (columns 2 and 3), the market clearing prices throughout the network are identical. However, they vary in the congested case (column 3). Finally, the last two rows of Table V give the total expected utility of all the other demands, and the total expected profit for all generating units. The following conclusions can be derived from the results presented in Table V:

a) As expected, the large consumer obtains a comparatively higher expected utility through bidding at strategic prices with respect to bidding at its marginal utility (row 2). Also, the expected utility of the large consumer per MWh in the strategic case is comparatively higher than that in the non-strategic case (row 3).

b) If the large consumer behaves strategically, a comparatively lower amount of energy is supplied with respect to the non-strategic case (row 4). The reason of this is that in the strategic case, the large consumer bids at comparatively lower prices with respect to its marginal utility.

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TABLE V
BIDDING RESULTS (ILLUSTRATIVE EXAMPLE)

		Non-strategic bidding case (uncongested)	Strategic bidding case (uncongested)	Strategic bidding case (congested)
EU* of the LC† [$]		5958.6	6695.7	6289.4
EU of the LC per MWh [$/MWh]		8.6	10.5	10.5
Expected unserved energy for the LC [MWh]		10.8	65.5	105.6
Market clearing prices	t_1	23.52	22.26	(13.97; 21.01; 17.49)
corresponding to scenario	t_2	19.08	18.00	(11.88; 22.05; 16.96)
ω_5 [$/MWh]	t_3	16.20	13.72	(11.88; 21.12; 16.50)
Total EU for all demands other than those of the LC [$]		8886.0	10309.8	10442.7
Total expected profit for all generating units [$]		12345.4	9770.3	5253.8

* EU: Expected utility; † LC: large consumer

Therefore, the market is cleared at comparatively lower prices (row 5), and thus the expected utility of the strategic consumer increases with respect to the non-strategic bidding case, in which a comparatively higher demand of that consumer is supplied, but at the cost of clearing the market at comparatively higher prices.

c) If all demands behave in a non-strategic manner, the market is cleared at comparatively higher prices. Therefore, the total expected utility of all demands decreases, while the total expected profit of all generating units increases (last two rows).

d) In the congested case (column 4), the market clearing prices throughout the nodes are different. The market clearing price corresponding to node N2 is the highest since no generating unit is connected to that node, while that of node N1 is the lowest because N1 is where the cheap unit G1 is located. In this case, congestion leads to a decrease in the expected utility of the large consumer. However, the impact of congestion on the utility/profit of the demands/generating units depends on their locations throughout the network.

4) Strategic Bidding Curve: As an example, we use the proposed heuristic technique to derive the strategic bidding curve of demand D3 in peak time period t_1 for the uncongested case. The corresponding market outcomes across scenarios are given in Table VI. The second row of this table includes the market clearing prices obtained, i.e., $\lambda_{tn\omega}, t = t_1, \forall n, \forall \omega$. In addition, the next three rows of Table VI contain the consumption of each block of demand D3, i.e., $D^{\mathrm{L}}_{tdk\omega}, t = t_1, d = \mathrm{D3}, \forall k, \forall \omega$. The strategic bidding curve corresponding to demand D3 in time period t_1 is plotted in Fig. 3. The stepwise shape of the resulting bidding curve can be explained as follows:

- For the first block (row 3 of Table VI), 28.3 MW is supplied across all scenarios, while the remaining load of block k_1, i.e., 11.7 MW is only supplied in scenarios ω_1 to ω_5 and ω_7 to ω_9. Thus, the large consumer bids 28.3 MW at a price within the highest market clearing price across all scenarios, i.e., 22.50 $/MWh, and the price cap, i.e., 180 $/MWh, while it bids the remaining 11.7 MW at the highest market clearing prices involving scenarios ω_1 to ω_5 and ω_7 to ω_9, i.e., 22.26 $/MWh. Note that in Fig. 3, the bid price of the first segment (28.3 MW) is arbitrarily set to 25 $/MWh, which is a price between 22.50 $/MWh and 180 $/MWh.
- Analogously, for the second block (row 4 of Table VI), the large consumer bids 5 MW at 22.26 $/MWh, and the remaining 5 MW at the market clearing price corresponding to the first scenario, i.e., 16.80 $/MWh.
- For the third block (row 5 of Table VI), the large consumer bids 15 MW at 16.80 $/MWh.

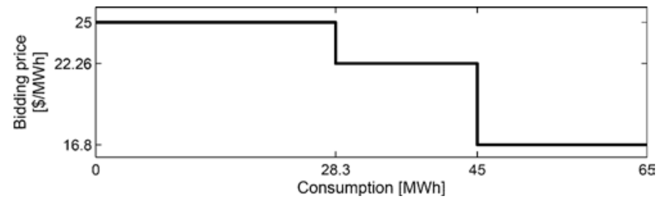

Fig. 3. Strategic bidding curve for demand D3 in peak time period t_1 in the uncongested case (illustrative example).

TABLE VI
MARKET CLEARING PRICES [$/MWh] AND CONSUMPTION LEVELS OF DEMAND D3 [MWh] IN PEAK TIME PERIOD t_1 ACROSS SCENARIOS (ILLUSTRATIVE EXAMPLE)

Scenario	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9	ω_{10}
Clearing price	16.80	17.49	19.08	20.67	22.26	22.50	17.49	19.08	20.67	22.50
Block k_1	40.0	40.0	40.0	40.0	40.0	28.3	40.0	40.0	40.0	28.3
Block k_2	10.0	5.0	5.0	5.0	5.0	0	5.0	5.0	5.0	0
Block k_3	15.0	0	0	0	0	0	0	0	0	0

TABLE VII
DATA FOR EACH TYPE OF GENERATING UNIT (CASE STUDY)

Type of generating unit	Unit capacity [MW]	Capacity of block b_1 [MW]	Capacity of block b_2 [MW]	Capacity of block b_3 [MW]	PC* of block b_1 [$/MWh]	PC of block b_2 [$/MWh]	PC of block b_3 [$/MWh]
Gas-12	12	3.2	4.6	4.2	20.5	21.1	21.9
Gas-20	20	5.4	8.3	6.3	19.6	21.2	22.1
Hydro-50	50	10.0	20.0	20.0	0.0	0.0	0.0
Coal-76	76	20.2	45.4	10.4	17.6	18.8	19.6
Gas-100	100	25.4	36.4	38.2	19.1	19.9	21.3
Coal-155	155	74.2	50.6	30.2	16.3	17.6	18.2
Coal-197	197	113.6	35.0	48.4	12.7	13.4	14.0
Gas-350	350	100.2	189.0	60.8	21.4	21.6	21.8
Nuclear-400	400	160.0	150.0	90.0	8.1	8.9	9.8

* Production cost

B. Case Study

In this section, the proposed heuristic approach is used in a case study based on the one-area IEEE reliability test system (RTS) [31]. A daily time horizon including off-peak hours t_1 to t_{10} and t_{24}, shoulder hours t_{11} to t_{17} and t_{23}, and peak hours t_{18} to t_{22} is considered. For the sake of simplicity, the capacity of each transmission line is considered to be 600 MW.

Table VII gives the data for each type of generating unit including its capacity and production cost per block. In addition, Table VIII provides the location and the number of each type of generating unit.

Table IX gives the data for the demands of the large consumer and other demands in peak hour t_{20}. Note that demands D1 to D7 belong to the large consumer, while demands Q1 to Q10 refer to other consumers. According to Table IX, the peak demand is 2850 MW, 36.6% of it belonging to the large consumer. Note also that the load level/marginal utility for each demand of

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TABLE VIII
LOCATION AND NUMBER OF EACH TYPE OF GENERATING UNIT (CASE STUDY)

Type of generating unit	Location and number of each type of unit
Gas-12	Node 15 (5 units)
Gas-20	Node 1 (2 units), node 2 (2 units)
Hydro-50	Node 22 (6 units)
Coal-76	Node 1 (2 units), node 2 (2 units)
Gas-100	Node 7 (3 units)
Coal-155	Node 15 (1 unit), node 16 (1 unit), node 23 (2 units)
Coal-197	Node 13 (3 units)
Gas-350	Node 23 (1 unit)
Nuclear-400	Node 18 (1 unit), node 21 (1 unit)

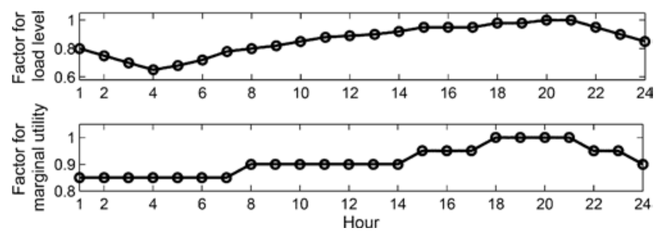

Fig. 4. Hourly factors corresponding to load level and marginal utility of each demand with respect to the ones in peak hour t_{20} (case study).

TABLE IX
DATA FOR ALL DEMANDS IN PEAK HOUR t_{20} (CASE STUDY)

	Load level [MW]	Load of block k_1 [MW]	Load of block k_2 [MW]	Load of block k_3 [MW]	MU* of block k_1 [$/MWh]	MU of block k_2 [$/MWh]	MU of block k_3 [$/MWh]	Demand location [node]
D1	108	65	28	15	28.9	23.0	21.0	1
D2	97	65	17	15	29.0	24.0	22.2	2
D3	180	100	45	35	29.6	24.5	23.3	3
D4	74	40	25	9	30.5	25.5	24.5	4
D5	71	39	17	15	29.8	25.0	24.1	5
D6	333	180	95	58	28.0	24.0	23.0	18
D7	181	98	51	32	27.0	23.7	22.8	19
Q1	136	80	35	21	32.0	26.0	25.0	6
Q2	125	75	30	20	31.0	27.0	24.0	7
Q3	171	120	30	21	31.2	23.5	21.0	8
Q4	175	105	40	30	31.0	26.5	23.0	9
Q5	195	135	40	20	26.0	23.0	21.0	10
Q6	265	160	70	35	28.0	24.0	22.0	13
Q7	194	140	30	24	29.0	23.0	21.5	14
Q8	317	210	60	47	31.9	26.5	22.5	15
Q9	100	70	20	10	32.5	26.0	24.0	16
Q10	128	80	30	18	31.1	27.0	22.5	20

* Marginal utility

the system in each hour is equal to the value given in Table IX multiplied by a factor. The considered factors are provided in Fig. 4.

We assume that each non-strategic demand (Q1 to Q10) bids in each hour at its corresponding marginal utility. Other conditions, e.g., bid price cap, ramping constraints and minimum energy consumption levels for each demand of the large consumer, are identical to those considered in the illustrative example (Section IV-A).

In this case study, 50 scenarios (ω_1 to ω_{50}) are considered. In each scenario, the offering prices of each generating unit are its production costs multiplied by their corresponding hourly factors. Fifty peak factors running from 1.00 to 1.49 (with a step

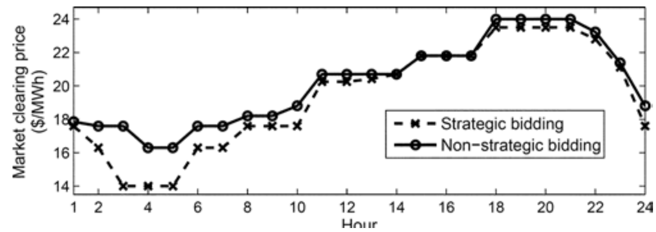

Fig. 5. Market clearing prices over a day corresponding to scenario ω_{18} considering strategic and non-strategic biddings of the large consumer (case study).

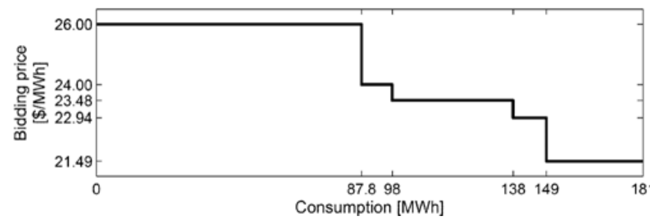

Fig. 6. Strategic bidding curve for demand D7 in peak hour t_{20} (case study).

of 0.01) as well as fifty shoulder factors running from 1.00 to 1.245 (with a step of 0.005) characterize the scenarios considered, while off-peak factors for all scenarios are 1.00. The probability of each scenario ω_1 to ω_{10} is 0.05, while that of each scenario ω_{11} to ω_{20} is 0.02. Finally, the probability of each scenario ω_{21} to ω_{50} is 0.01.

Regarding the results obtained from the proposed heuristic algorithm, the expected utility of the large consumer in the non-strategic case is $100 370.8, while such value increases 6.74%, i.e., $107 137.8, if the consumer bids strategically. Besides, the total expected unserved energy of the large consumer increases from 776.1 MWh in the non-strategic case to 2607.0 MWh in the strategic one.

As expected, the strategic behavior results in a decrease in the market clearing prices as Fig. 5 illustrates for a particular scenario. Note that the market clearing prices depicted in Fig. 5 are identical for all nodes of the system since there is no transmission congestion.

Additionally, as an example, Fig. 6 depicts the strategic bidding curve derived for demand D7 in peak hour t_{20}.

V. CONCLUSIONS AND FUTURE RESEARCH

This paper proposes a stochastic complementarity model to characterize the strategic behavior of a large consumer and to derive its strategic bidding curves. To make the proposed model computationally tractable in large instances involving many scenarios, a heuristic approach is proposed in which the scenarios are considered one at a time. The solution provided by this heuristic approach is generally close to the global optimal solution.

A simple example is used to illustrate the main features of the proposed model, as well as its consistent behavior. Additionally, a larger scale case study is used to show the appropriate working and the practical relevance of the proposed technique.

The numerical results show that a strategic consumer may bid at prices comparatively lower than its marginal utility. This behavior results in clearing the market at comparatively lower prices, and thus the expected utility of the large consumer increases. However, if the large consumer behaves in a non-strategic manner, a comparatively higher demand of that consumer is supplied, but at the cost of clearing the market at comparatively higher prices.

Risk management is generally a medium- or long-term issue, and thus is not modeled in the considered short-term bidding problem. Future work will address the involvement of strategic consumers in futures markets, which requires risk management.

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