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Flexibility Service Providers' Gaming Potential and its Impact on TSO-DSO Coordinated Markets

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***Abstract*—This paper introduces a game-theoretic framework under bounded rationality to analyze the impact of strategic behavior of flexibility service providers (FSPs) on the efficiency of TSO-DSO coordinated flexibility markets. Four market structures are analyzed considering either joint, independent, or sequential DSO-TSO procurement. For each market model, a mathematical formulation is introduced for clearing the market and optimally meeting the congestion management and balancing needs of the different system operators. Then, best response models of the FSPs are developed to define their optimal bidding behavior. Finally, a k-level algorithm is proposed to simulate the gradual bidding behavior of the FSPs using the derived best response functions. As a result, the FSPs' strategic bids are obtained, enabling the analysis of their impact on the different markets. The proposed approach is applied to four case studies, which showcase that all markets can be affected negatively by strategic behavior, but a joint procurement of services is less affected by such behavior. The results highlight the increasing effects of strategic bidding in situations with restrained liquidity, market fragmentation, or market power due to congestion.**

***Index Terms*—TSO-DSO coordination, flexibility markets, strategic behavior, bounded rationality.**

I. Introduction

The increasing penetration of variable renewable energy sources and the growing electrification of end-users' appliances (e.g., e-mobility and electric heating) is driving countries around the world to establish new market models for the procurement of flexibility from the different voltage levels. Both transmission (TSO) and distribution (DSO) system operators can use those flexibility sources to balance their networks, manage congestion, and control voltage, among others. In this respect, a key challenge arises in terms of defining efficient and coordinated market-based flexibility procurement processes between the different system operators (SOs).

Several studies in the literature have tackled this challenge. For instance, multiple TSO-DSO coordination market models to allow SOs to procure flexibility have been proposed, both conceptually [1], [2] and mathematically [3]–[6]. Their applicability has been tested in various international demonstration projects such as in [7], [8]. Some of their properties have also been analyzed, e.g., the efficiency of the different market models [9], [10], the financial settlement when system operators jointly procure flexibility [11], the impact of interface flow pricing on the optimality of the market models [9], and the solution mechanisms and communication aspects of the coordination models [9], [12].

One key aspect that has not yet been adequately evaluated is how different bidding behaviors of the flexibility service providers (FSPs) impact the efficiency of the TSO-DSO coordination mechanisms. The efficiency analyses of different TSO-DSO coordination models performed so far in the literature assume truthful bidding, but market designs can open space for participants, being profit maximizers, to act strategically in a way that can be harmful to the market efficiency. Indeed, market participants can be expected to behave in their self-interest when choosing their actions (e.g., setting bids), based on their own subjective evaluation of likely events (e.g., market rules, grid status, flexibility needs, etc.), and on the possible actions of competitors (e.g., other FSPs) [13]. This economically rational strategic behavior can be misaligned with the market objectives, reducing its overall efficiency (e.g. FSPs bidding higher than their marginal cost will increase the systems' flexibility procurement costs). As a result, understanding how market participants behave is key to: 1) check if a designed market structure gives rise to market power or any other behavior harming the optimality of the market; 2) identify the reasons as to which those markets can lead to such strategic behaviors; and 3) propose countermeasures to avoid efficiency-decreasing behaviors.

To understand and measure the impact of strategic behavior of market participants in the new TSO-DSO coordinated market models, this paper proposes a game-theoretic methodology based on bounded rationality to model FSPs bidding behavior when engaging in those markets. We assume a bounded rationality scenario because, given the complexity of the proposed coordination market models, FSPs might not have the computational capabilities and information needed to calculate and play their Nash Equilibrium [14]–[16] strategies. Therefore, such bounded rationality is more likely to take place in practice, making the presented analysis more realistic. Moreover, to the best of our knowledge, this is the first study analysing the impact of strategic behavior in TSO-DSO coordinated markets. Four types of markets for balancing and congestion management are analyzed: common, disjoint, fragmented and multi-level markets, which vary according to the levels of coordination between the TSO and the DSOs seeking to procure flexibility, and the access of SOs to flexibility outside their own grids. As such, these four markets have different relevance and applicability, as shown in [1], [7], [8], meaning they suit different flexibility procurement contexts.

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For each of the markets, and considering nodal pricing in a pay-as-cleared mechanism, best response functions are derived to represent the FSPs' optimal bidding behaviors. Then, a k-level approach to simulate the FSPs behavior under different levels of rationality is proposed. The approach is inspired by k-level reasoning [15], in which an FSP's strategic bid is derived based on its observation of the bids submitted by the opponents in the previous market round, i.e., FSPs best respond to the opponents bids in the last level (i.e., $k-1$). At the end of the k-level run, FSPs' strategic bids are defined for each market, which allows the calculation and comparison of the different markets' efficiency when subjected to FSPs' strategic behavior. This methodology is tested in four case studies.

The rest of this paper is organized as follows: Section II presents the methodology, market models, best response functions, and the k-level approach), Section III present the case studies, and Section IV concludes the paper.

II. Methodology

A. Systems and Notation

A nomenclature table is available in [17]. We consider an interconnected network composed by one transmission system T, operated by a TSO, connected to $\mathcal{S}=[1,\ldots,S]$ distribution systems, each operated by a DSO. All systems are denoted by a graph $G^m(\mathcal{I}^m,\mathcal{L}^m)$, in which $\mathcal{I}^m$ is the set of nodes and $\mathcal{L}^m$ is the set of lines of system $m\in\mathcal{M}=\{T\}\cup\mathcal{S}$. In the case of the transmission system T, a subset $\mathcal{I}^S\subseteq\mathcal{I}^T$ represents the TSO nodes that are connected to a distribution system. For the distribution systems $m\in\mathcal{S}$, we define $i_0^m\in\mathcal{I}^m$ as the root node (connecting DSO-m to the transmission system).

To denote the different parameters and variables within the systems, we use the following notation: 1) p_i^m for the net real power injection at nodes $i\in\mathcal{I}^m$; 2) a_i^m and b_i^m denote, respectively, the vectors of anticipated base injection and load at all transmission/distribution systems nodes; 3) F_{ij}^m denote the real power flow over line $\{i,j\}\in\mathcal{L}^m$; 4) $F_{ij}^{m,\max}$ are the maximum thermal limits of those lines; 5) $F^{T\to m}$ denotes the power transfer to the distribution system DSO–m from a transmission node; 6) $F_{\text{min}}^{T\to m}$ and $F_{\text{max}}^{T\to m}$ are, respectively, the minimum and maximum limits of the interface flow; and 7) λ_i^m denotes the nodal prices.

All systems are represented by the linearized power flow model using generation shift factors [18] ($\mathcal{G}_{(i,j),l}^m$), capturing the change in the active power flow over line $\{i,j\}$ due to a change in injection or offtake at node l.

FSPs can be located in any of the systems' nodes, and we distinguish between upward and downward flexibility offers. We denote $\mathcal{U}(i)$ and $\mathcal{D}(i)$ the sets of, respectively, upward and downward offers from FSPs located in node i. They have associated bid price $\pi_{n,i}^m$, maximum offered quantity $x_{n,i}^{m,\max}$, dispatch level $x_{n,i}^m$, and marginal cost $c_{n,i}^m$ for $n\in\mathcal{U}(i)\cup\mathcal{D}(i)$.

B. TSO-DSO Coordinated Market Models

Four types of market models are considered, which vary according to the levels of coordination between the TSO and the multiple DSOs seeking to procure flexibility for balancing and congestion management. In the first type, SOs jointly procure flexibility from all voltage levels. Their congestion and balancing needs are solved together, in one optimization model, using the FSPs' bids originating from the different systems. In the other types, sequential sub-markets are defined, where priority access to local flexibility is given to DSOs, who procure flexibility to solve their local congestion needs first. Then, the TSO clears its sub-market, in the second layer, to resolve its congestion and balancing needs. As such, each of the sub-markets requires its own market clearing which is formulated based on separate (but linked) optimization problems. Those models are differentiated by the level of co-ordination and resources sharing between the layers. For more information about the concepts behind TSO-DSO coordination market models, the reader is referred to [1], [9], [11].

1) Common Market Model: This market represents the setting in which all SOs jointly procure flexibility from a common pool of resources, while abiding by the constraints of all systems involved. The mathematical description of this market clearing is formulated as follows:

$$g^{\text{CM}}(\boldsymbol{\pi})=\min_{\boldsymbol{x}}\left[\sum_{m\in\mathcal{M}}\sum_{i\in\mathcal{I}^m}\left(\sum_{n\in\mathcal{U}(i)}\pi_{n,i}^m x_{n,i}^m-\sum_{n\in\mathcal{D}(i)}\pi_{n,i}^m x_{n,i}^m\right)\right] \tag{1a}$$

Subject to:

$$p_i^m=a_i^m-b_i^m+\sum_{n\in\mathcal{U}(i)}x_{n,i}^m-\sum_{n\in\mathcal{D}(i)}x_{n,i}^m:(\lambda_i^m),\quad \forall m\in\mathcal{M},\forall i\in\mathcal{I}^m\setminus\{\mathcal{I}^S\cup\{i_0^m\}_{m\in\mathcal{S}}\}, \tag{1b}$$

$$p_i^T=a_i^T-b_i^T+\sum_{n\in\mathcal{U}(i)}x_{n,i}^T-\sum_{n\in\mathcal{D}(i)}x_{n,i}^T-F^{T\to m}:(\lambda_i^T),\quad \forall i\in\mathcal{I}^S,m\in\mathcal{S}, \tag{1c}$$

$$p_i^m=a_i^m-b_i^m+\sum_{n\in\mathcal{U}(i)}x_{n,i}^m-\sum_{n\in\mathcal{D}(i)}x_{n,i}^m+F^{T\to m}:(\lambda_i^m),\quad \forall m\in\mathcal{S},i=i_0^m, \tag{1d}$$

$$\sum_{i\in\mathcal{I}^m}p_i^m=0,\forall m\in\mathcal{M}, \tag{1e}$$

$$F_{ij}^m=\sum_{l\in\mathcal{I}^m}p_l^m\mathcal{G}_{(i,j),l}^m,\forall m\in\mathcal{M},\forall\{i,j\}\in\mathcal{L}^m, \tag{1f}$$

$$-F_{ij}^{m,\max}\le F_{ij}^m\le F_{ij}^{m,\max},\forall m\in\mathcal{M},\forall\{i,j\}\in\mathcal{L}^m, \tag{1g}$$

$$0\le x_{n,i}^m\le x_{n,i}^{m,\max},\forall m\in\mathcal{M},\forall i\in\mathcal{I}^m,\forall n\in\mathcal{U}(i)\cup\mathcal{D}(i), \tag{1h}$$

$$F_{\text{min}}^{T\to m}\le F^{T\to m}\le F_{\text{max}}^{T\to m},\forall m\in\mathcal{S}. \tag{1i}$$

Equation (1a) is the objective function of this markets and calculates the total cost of the flexibility procurement $g^{\text{CM}}(\boldsymbol{\pi})$, when a vector of bid prices $\boldsymbol{\pi}$ is sent to the market. This function is subjected to all networks' constraints and bids' limits. As such, constraints (1b), (1c), and (1d) calculate the injection of, respectively, non-interface nodes, interface nodes of the transmission system, and interface nodes of the distribution systems. Constraint (1e) indicates that each system should be balanced (including imports from/exports to other systems). Constraint (1f) captures the power flow over the lines, and (1g) imposes the thermal limits to the lines. Constraint (1h) represents the limits of the bids. Finally, constraint (1i) establishes the limit of the interface flows. Note that nodal prices λ_i^m are associated to constraints (1b)–(1d).

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2) Disjoint Market Model: This market represents the setting in which no coordination between system operators exists, nor resources are shared between the different SOs. Each SO clears its market independently, using bids originating only from its own system. To impose an alignment between the operators in terms of interface flow, $F^{T\to m}$ is fixed (i.e. taken as a constant). As such, each DSO $m \in \mathcal{S}$ solves the following:

$$g_m^{\mathrm{DI}}(\boldsymbol{\pi^m}) = \min_{\boldsymbol{x}} \left[\sum_{i\in\mathcal{I}^m} \left(\sum_{n\in\mathcal{U}(i)} \pi_{n,i}^m x_{n,i}^m - \sum_{n\in\mathcal{D}(i)} \pi_{n,i}^m x_{n,i}^m \right) \right] \tag{2a}$$

Subject to:

$$\text{(1b), (1d)–(1h)}, \tag{2b}$$

$$F^{T\to m} = \text{constant}; \tag{2c}$$

while TSO solves the following problem:

$$g_T^{\mathrm{DI}}(\boldsymbol{\pi^T}) = \min_{\boldsymbol{x}} \left[\sum_{i\in\mathcal{I}^T} \left(\sum_{n\in\mathcal{U}(i)} \pi_{n,i}^T x_{n,i}^T - \sum_{n\in\mathcal{D}(i)} \pi_{n,i}^T x_{n,i}^T \right) \right] \tag{3a}$$

Subject to:

$$\text{(1b), (1c), (1e)–(1h)},\ m = T, \tag{3b}$$

$$F^{T\to m} = \text{constant}. \tag{3c}$$

One should note that, since $F^{T\to m}$ are constant, no links between the SOs' problems exist, which means that they are separable and can be solved in parallel. Moreover, the total cost of the disjoint market can be defined as:

$$g^{\mathrm{DI}}(\boldsymbol{\pi}) = g_T^{\mathrm{DI}}(\boldsymbol{\pi^T}) + \sum_{m\in\mathcal{S}} g_m^{\mathrm{DI}}(\boldsymbol{\pi^m}). \tag{4}$$

3) Fragmented Market Model: This market represents the setting in which a sequential coordination in two layers exists, but SOs have direct access only to bids coming from their own systems. It resembles the disjoint market model, with the difference that DSOs can indirectly use resources from the transmission system by modifying the interface flow (which induces limited imbalances to the TSO). This is done in the first layer of the market. Afterwards, the TSO solves its own needs while rectifying the generated imbalances by the first layer. As such, the fragmented market model can be formulated as follows:

Layer 1 (cleared for each DSO $m \in \mathcal{S}$):

$$g_m^{\mathrm{FR}}(\boldsymbol{\pi^m}) = \min_{\boldsymbol{x}} \left[\sum_{i\in\mathcal{I}^m} \left(\sum_{n\in\mathcal{U}(i)} \pi_{n,i}^m x_{n,i}^m - \sum_{n\in\mathcal{D}(i)} \pi_{n,i}^m x_{n,i}^m \right) \right] \tag{5a}$$

Subject to:

$$\text{(1b), (1d)–(1h), and interface: (1i)}. \tag{5b}$$

Layer 2 (cleared for the TSO):

$$g_T^{\mathrm{FR}}(\boldsymbol{\pi^T}) = \min_{\boldsymbol{x}} \left[\sum_{i\in\mathcal{I}^T} \left(\sum_{n\in\mathcal{U}(i)} \pi_{n,i}^T x_{n,i}^T - \sum_{n\in\mathcal{D}(i)} \pi_{n,i}^T x_{n,i}^T \right) \right] \tag{6a}$$

Subject to:

$$\text{(1b), (1c), (1e)–(1h)},\ m = T, \tag{6b}$$

$$F^{T\to m} = \text{solution of DSO-}m,\ \forall m \in \mathcal{S}. \tag{6c}$$

The total cost of the fragmented market can be defined as:

$$g^{\mathrm{FR}}(\boldsymbol{\pi}) = g_T^{\mathrm{FR}}(\boldsymbol{\pi^T}) + \sum_{m\in\mathcal{S}} g_m^{\mathrm{FR}}(\boldsymbol{\pi^m}). \tag{7}$$

4) Mulit-level Market Model: This market is a sequential market composed by two layers that provides priority access for DSOs to distribution-level flexibility in the first layer, while also giving access to such resources to the TSO in the second layer. To capture this setting, the first layer is equal to the first layer of the fragmented market, but the second layer resembles the common market model with updated needs and bids based on the outcomes of Layer 1. As such, the multi-level market model can be formulated as follows:

Layer 1 (cleared for each DSO $m \in \mathcal{S}$): same as (5)

$$g_m^{\mathrm{ML}}(\boldsymbol{\pi^m}) = g_m^{\mathrm{FR}}(\boldsymbol{\pi^m}). \tag{8}$$

Layer 2 (cleared for the TSO):

$$g_T^{\mathrm{ML}}(\boldsymbol{\pi^T}) = \min_{\boldsymbol{x}} \left[\sum_{m\in\mathcal{M}} \sum_{i\in\mathcal{I}^m} \left(\sum_{n\in\mathcal{U}(i)} \pi_{n,i}^m x_{n,i}^m - \sum_{n\in\mathcal{D}(i)} \pi_{n,i}^m x_{n,i}^m \right) \right] \tag{9a}$$

Subject to:

$$\text{(1b)–(1i)}, \tag{9b}$$

$$a_i^m = a_i^{m^*} + \sum_{n\in\mathcal{U}(i)} x_{n,i}^{m^*}, \forall m \in \mathcal{S}, \forall i \in \mathcal{I}^m, \tag{9c}$$

$$b_i^m = b_i^{m^*} + \sum_{n\in\mathcal{D}(i)} x_{n,i}^{m^*}, \forall m \in \mathcal{S}, \forall i \in \mathcal{I}^m, \tag{9d}$$

$$x_{n,i}^{m,\max} = x_{n,i}^{m,\max^*} - x_{n,i}^{m^*}, \forall m \in \mathcal{S}, \forall i \in \mathcal{I}^m, \forall n \in \mathcal{U}(i) \cup \mathcal{D}(i). \tag{9e}$$

Constraints (9c) and (9d) are, respectively, the update of the base injection and load of the distribution systems nodes, considering $a_i^{m^*}$ and $b_i^{m^*}$ as the original injection and load, and $x_{n,i}^{m^*}$ as the optimal dispatch of resources of layer 1. Similarly, constraints (9e) is the update of the distribution upward and downward bid limits, considering $x_{n,i}^{m,\max^*}$ as the original bid limits sent to the market. Moreover, the total cost of the fragmented market can be defined as:

$$g^{\mathrm{ML}}(\boldsymbol{\pi}) = g_T^{\mathrm{ML}}(\boldsymbol{\pi^T}) + \sum_{m\in\mathcal{S}} g_m^{\mathrm{ML}}(\boldsymbol{\pi^m}). \tag{10}$$

C. Best Response Functions

In the four types of TSO-DSO coordinated market models under analysis, the offers to fulfil the SOs needs are provided by FSPs, which are market participants seeking for sustainable profitability. To analyze their strategic behavior, the market clearing problem must be examined from their point of view, instead of from the point of view of the SOs procuring flexibility at a minimal cost. The FSPs, when entering the TSO-DSO markets and offering their flexibility as bids, are expected to aim at maximizing their profits (constituting a rational economic behavior). Moreover, their revenue, as well as their optimal bids, will be influenced by what other FSPs are bidding, the market structure, and the network configuration.

To represent those aspects, we propose best response (BR) models, in which FSPs determine their best bid (strategy) as a response to opponents' bids. In mathematical terms, consider the set of all FSPs $\mathcal{N} = \bigcup_{\substack{m\in\mathcal{S}\\ i\in\mathcal{I}^m}} \mathcal{U}(i) \bigcup_{\substack{m\in\mathcal{S}\\ i\in\mathcal{I}^m}} \mathcal{D}(i)$ offering flexibility to the four different markets $\sigma = \{\text{CM, DI, FR, ML}\}$. Each FSP $n \in \mathcal{N}$ has a marginal cost/value $c_{n,i}^m$. Their bid prices are their strategies (i.e., each FSP aims at choosing its optimal bid price), which are represented by $\pi_{n,i}^{m,\sigma}$. The opponents' vector of bid prices is denoted as $\boldsymbol{\pi^{\sigma}_{-n}}$. Nodal prices ($\lambda_i^{m,\sigma}$) and the cleared quantities ($x_{n,i}^{m,\sigma}$ and $\boldsymbol{x^{\sigma}_{-n}}$) are a result of the market σ, when a vector of bid prices ($\pi_{n,i}^{m,\sigma}, \boldsymbol{\pi^{\sigma}_{-n}}$) is submitted. Using this generalized notation, the best responses for FSPs offering flexibility in market σ can be defined as:

$$BR_n^{\sigma}(\boldsymbol{\pi^{\sigma}_{-n}}) = \pi_{n,i}^{m,\sigma^*} = \underset{\pi_{n,i}^{m,\sigma}}{\operatorname{argmax}} |\lambda_i^{\sigma,m} - c_{n,i}^m| x_{n,i}^{m,\sigma}, \quad (11a)$$

$$\text{Subject to:} \qquad \pi_{n,i}^{m,\sigma} = [\pi_{n,i,1}^{m,\sigma}, \dots, \pi_{n,i,\Pi}^{m,\sigma}] \quad (11b)$$

$$\lambda_i^{\sigma,m}, x_{n,i}^{m,\sigma} = f^{\sigma}(\pi_{n,i}^{m,\sigma}, \boldsymbol{\pi^{\sigma}_{-n}}) \quad (11c)$$

Objective function (11a) refers to the utility of FSP n, which is calculated by the absolute value[1] of the nodal price from the node where the FSP is submitting the bid minus its marginal cost/value, times its cleared quantity. This function is subject to the vector of possible bid prices FSP n can send to market σ, defined in constraint (11b), and to the result of the market clearing of σ when an specific bid $\pi_{n,i}^{m,\sigma}$ together with opponents' bids $\boldsymbol{\pi^{\sigma}_{-n}}$ are sent to the market, defined in constraint (11c). Function $f^{\sigma}(\cdot)$ is calculated using model (1) when $\sigma =$ CM, models (2) and (3) when $\sigma =$ DI, models (5) and (6) when $\sigma =$ FR, and models (8) and (9) when $\sigma =$ ML.

D. K-Level Approach

In a strategic bidding setting as the one analyzed in this paper, each FSP's revenues are impacted not only by their own bidding behavior but also by the bidding behavior of the opponents, as described by the best response functions defined in (11), giving rise to a game-theoretic framework. Under fully rationality, standard game theory analyzes and seeks a Nash equilibrium (NE) [14]: a context in which each player plays optimally against the optimal decision of others. However, in practice, this considers that all players will be playing their Nash equilibrium strategy. As such, if one player diverges (due to, e.g., limited computational power or information, not allowing the player to compute its NE strategy), different players can be better off diverging as well [15], [16], [19]. In addition, this full rationality assumption considers fundamentally that all players have the computational capabilities and information to reach their NE strategies, which can face practical challenges.

Therefore, we consider strategic bidding in the TSO-DSO market models under bounded rationality, which is more likely to take place in practice [15]. The approach is inspired by k-level reasoning [15], in which players are rational and best respond to opponents who they believe are (k-1) rational. Following this logic, an FSP's strategic bid is derived based on its observation of the bids submitted by the opponents in the previous market round. Under this approach, at each level k, the FSPs choose the bid that optimizes their profit, considering that the other FSPs bid at the previous level (i.e., at level $k-1$). As such, this provides gradual levels of rationality in the derivation of the optimal bidding strategy, through the increase in k.

In mathematical terms, the players solve the best responses developed in Section II-C taking into account $\boldsymbol{\pi^{\sigma}_{-n}}$ being equal to the opponents' best responses in the past level, which correspond to, and is revealed through, their submitted bids in the previous market round. Considering that FSPs have K levels of thinking, the rationalization process of the FSPs is represented in Algorithm 1. This process returns the set of optimal bids $\pi_{\mathbf{K}}^{\sigma^*}$ that the FSPs would submit to market type $\sigma \in$ {CM, DI, FR, ML} after K levels of thinking. By running market σ with this set of bids, it is possible to measure the impact on the market efficiency due to the strategic behavior of its participants.

Algorithm 1 K-level Approach to Simulate FSPs Strategic Behavior in the TSO-DSO Markets

Input: Levels of thinking (K), market model ($\sigma \in$ {CM, DI, FR, ML}), grid parameters

Output: Best bid vector at level K of market model σ ($\pi_{\mathbf{K}}^{\sigma^*}$), market σ efficiency measurement when best bids of level K are sent ($g_K^{\sigma}(\pi_{\mathbf{K}}^{\sigma^*})$)

```
1: Initialize bid vector π_0^{σ*} with FSPs' marginal cost/value (c);
2: for k = {1, ..., K} do
3:   for all n ∈ N do
4:     Calculate FSP n best response π_{k,n,i}^{m,σ*} = BR_n^σ(π^{σ*}_{k−1,−n})
       using (11) for market model σ;
5:   end for
6: end for
7: Run market model σ to calculate g_K^σ(π_K^{σ*}) of K (models (1),
   (4), (7) and (10));
8: return π_K^{σ*}, g_K^σ(π_K^{σ*});
```

III. Numerical Results

The proposed k-level approach is applied to four case studies considering an interconnected transmission-distribution system. The transmission network is represented by the IEEE 14-bus system, which is connected to two distribution networks, represented by the Matpower 69-bus (DN_69) and 141-bus (DN_141) systems [20]. An initial base case is considered, in which injections and loads of the nodes are adapted to create an anticipated negative imbalance (total load surpassing total generation) in the interconnected system, resolved by upward flexibility. In addition, the lines' upper limits are adjusted to create anticipated congestion in the networks. Upward and downward flexibility bids are randomly generated and allocated to the nodes. Their quantities are aligned with the nodes' base injection/load and their marginal values are in the range [10, 26] €/MW for downward, and marginal costs in the range [30, 73] €/MW for upward, totaling 536 bids. This is the base case, i.e., $k = 0$ (the truthful bidding setting in which the prices comprise the marginal costs/values) from which bids are modified in accordance to the strategic behavior of the FSPs for higher k levels. We then identify the resulting

[1] We use absolute value to cover both upward and downward offers, given that the profit of upward offers is a function of the nodal price minus their marginal cost, and the profit of downward offers is a function of their marginal value minus the nodal price. Notice that an FSP n bids either upward or downward flexibility.

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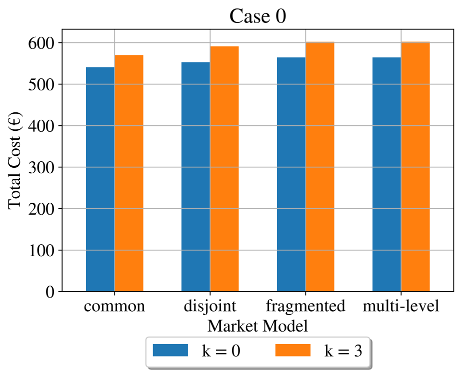

Fig. 1. Impact of strategic behavior on market efficiency under high liquidity

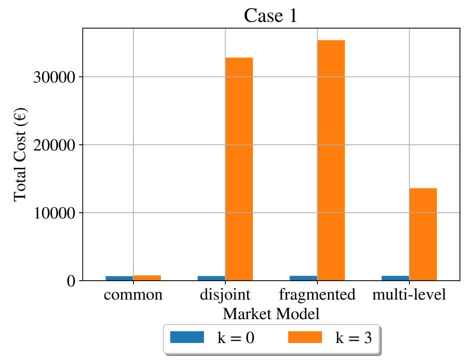

Fig. 2. Impact of strategic behavior on market efficiency in a case of low liquidity in the transmission system

impacts on the TSO-DSO coordinated market efficiency. The full data set is available in [17].

We consider three levels of thinking (third-order rationality), which was chosen to comply with empirical measures of the levels of rational thinking. For instance, experiments in [21] show that most of the subjects have a level $k = 3$ reasoning. Moreover, we consider that each FSP n chooses the possible bid prices vector in (11b) according to its opponents' best bid prices with the same sense (i.e., upward or downward) in $k-1$ ($\boldsymbol{\pi}^{\boldsymbol{\sigma}^*}_{\boldsymbol{k-1,-n}}$) as follows: for an upward FSP n, the vector of possible bid prices includes all upward opponents prices that are higher than its marginal cost, together with those values minus a small epsilon (i.e. 10 ¢), a price cap for upward offers (i.e. 3,000 €/MWh) – which can be imposed by the market operator platform as e.g., in [22] – and this cap minus epsilon; for a downward FSP n, the vector of possible bid prices also includes all downward opponents prices that are lower than its marginal value, together with those values plus a small epsilon (i.e. 10 ¢), a price cap for downward offers (i.e. 0 €/MWh), and this cap plus epsilon. The addition of values plus or minus epsilon is done as a tie-break rule, i.e. when two FSPs are bidding the same value, only one of them might be selected, which can encourage them to bid a slightly lower (for upward) or higher (for downward) price than the opponent.

A. Case 0: High Liquidity

In this case, all 536 bids from the different systems are kept, and efficiency results of running the k-level described in Algorithm 1 for the four TSO-DSO coordination market models are shown in Fig. 1. As can be seen, the strategic behavior of the FSPs leads to an increased cost in all market models, as some in-the-money FSPs have the opportunity to bid higher than their marginal cost (or lower than their marginal value). However, this increase is dampened by the high liquidity available in the markets, as the the last in-the-money FSPs can not bid higher (for upward) or lower (for downward) than the next opponent's bid price, as they would otherwise no longer be cleared. The total cost of the SOs when FSPs behave strategically ($k = 3$) is 1.05 times higher than the truthful case ($k = 0$) in the common market, and 1.07 times higher in the disjoint, fragmented, and multi-level markets.

B. Case 1: Low Liquidity in Transmission System

In this case, the same network and distribution bids list of case 0 are used, but 40% of the bids located in the transmission system were deleted. Efficiency results of running the k-level to this case are shown in Fig. 2. Here it is possible to see that, when the market liquidity at transmission level is reduced, the effect of strategic behavior further increases. For instance, the total cost to the SOs when FSPs behave strategically ($k = 3$) is 1.17 times higher than the truthful case ($k = 0$) in the common market, 48.05 times higher in the disjoint, 50.45 times higher in the fragmented, and 19.39 times higher in the multi-level. The impact is more pronounced in the disjoint and fragmented markets due to the additional market fragmentation, which creates opportunities to some FSPs to exert market power (e.g. bidding at price cap) in the second (transmission) layer. Although the multi-level is also a two layers market, the effect is reduced if compared to the disjoint and fragmented, since its second layer pools bids from the different grids, which increases its liquidity. Nonetheless, the impact is higher than if all needs were solved jointly, as in the common market.

C. Case 2: Limited liquidity in Distribution Systems

In this case, the same network and transmission bids list of case 0 are used, but 98% of the bids located in the distribution systems were deleted. This deletion is not done randomly, but rather considers the congestion present in the distribution systems to capture the effects of low liquidity. In this regard, the bids in case 0 which were needed to solve the congestion were kept in the list, in order to avoid infeasibilities, and some additional bids were also kept to increase competition. Efficiency results of running the k-level to this case are shown in Fig. 3. As can be seen, when the market liquidity at distribution level is reduced, the effect of strategic behavior increases when compared to case 0. However, this increase is not as high as compared to the increase in cost at low liquidity in the transmission system (case 1). For instance, the total cost to the system operators when FSPs behave strategically ($k = 3$) is 1.12 times higher than the truthful case ($k = 0$) in the common market, 1.16 times higher in the disjoint, and 1.14 times higher in the fragmented and multi-level.

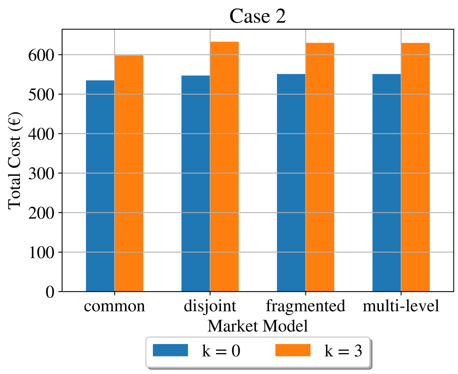

Fig. 3. Impact of strategic behavior on market efficiency in a case of limited liquidity in the distribution systems

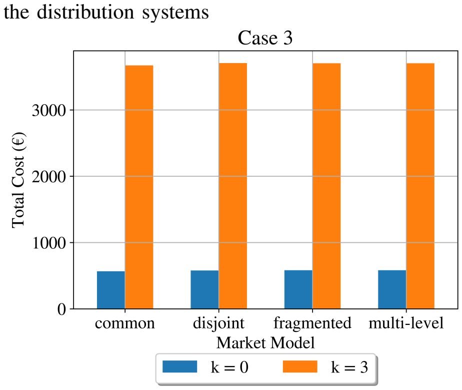

Fig. 4. Impact of strategic behavior on market efficiency in a case with critically low liquidity in the distribution systems

D. Case 3: Low Liquidity in Distribution Systems leading to Market Power due to Congestion

This case is a variation of case 2 in which only the necessary bids of the distribution systems are kept in the bids list. Efficiency results of running the k-level to this case are shown in Fig. 4. Here, it is possible to see that, when the market liquidity at distribution level is critically low, the effect of strategic behavior is significant, and impacts all market models similarly. For instance, the total cost to the SOs when FSPs behave strategically ($k = 3$) is 6.47 times higher than the truthful case ($k = 0$) in the common market, 6.40 times higher in the disjoint, and 6.35 times higher in the fragmented and multi-level. The impact is more pronounced in the common market due to: 1) it is the most efficient market when FSPs bid truthfully (leading to a lower denominator in the calculation), and 2) the FSPs which are necessary for the congestion management of the distribution systems strategically bid at the price cap (exerting market power) in all market models, which means that the final cost is comparable in all the markets. The common market is still slightly more efficient under $k = 3$ than the rest of the market models, but the difference is less pronounced as compared to the case under truthful bidding.

IV. Conclusion

In this paper we proposed a game-theoretic methodology based on bounded rationality to analyze the impact of the FSPs' strategic behavior on the efficiency of TSO-DSO coordinated market models for the procurement of system services (balancing and congestion management). Four types of market models were analyzed (common, disjoint, fragmented, and multi-level), which vary according to the levels of coordination between the TSO and the DSOs seeking to procure flexibility. Best response functions were derived for each market model, and a k-level approach was proposed to simulate the bidding behavior of the FSPs when joining those markets. The methodology was applied to four case studies, showcasing that: 1) all markets can be affected negatively by the FSPs' strategic behavior, but the common market can be less affected, 2) the impact of strategic behavior is higher in situations with restrained liquidity, specially in the transmission system, and 3) the impact of strategic behavior can be significant in situations of market power due to available congestions.

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