Simulating GenCo bidding strategies in electricity markets with an agent-based model

by

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In this paper we use an agent-based simulation model, EMCAS, to analyze market power in electricity markets. We focus on the effect of congestion management on the ability of generating companies (GenCos) to raise prices beyond competitive levels. An 11-node test power system is used to compare a market design based on locational marginal pricing with a market design that uses system marginal pricing and congestion management by counter trading. Bidding strategies based on both physical and economic withholding are compared to a base case with production cost bidding. The results show that unilateral market power is exercised under both pricing mechanisms. However, the largest changes in consumer costs and GenCo profits due to strategic bidding occur under the locational marginal pricing scheme. The analysis also illustrates that agent-based modeling can contribute important insights into the complex interactions between the participants in transmission-constrained electricity markets.

1. INTRODUCTION

The ongoing restructuring of the electrical power industry and the introduction of competitive markets for electricity has resulted in a number of challenges for participants in the electricity market. New analytical approaches are needed in order to address some of the issues arising from the new, market-based organization of the power system, as discussed in Dyner and Larsen [1]. One of the major concerns in the emerging electricity markets is the potential exercise of market power by generating companies (GenCos). A number of approaches have been used to study market power. For instance, the Herfindahl-Hirschman Index (HHI) is a measure for market concentration. However, it is well accepted that concentration measures, such as the HHI, do not give a reliable diagnostic aid to the potential exercise of market power in the wholesale electricity sector (see Bunn and Martoccia [2]). Such measures do not take into account the effect of the transmission network and its influence on participants' ability to exercise market power. Other indexes, such as the Lerner index and the pivotal supplier index, can be very useful for analyzing market power in retrospect, but they also suffer from the inability to directly take into account the transmission constraints in the power system.

The traditional models of market power from game theory are usually based on equilibrium solutions, such as the Cournot, Bertrand, or supply function equilibriums. These modeling approaches are useful for determining theoretical equilibrium points, to which actual market performance can be compared. A number of market power models for electricity markets have been developed on the basis of these equilibrium concepts[2]. However, several simplifications must usually be made in order to find the equilibrium solutions, both in terms of the bidding behavior of the market participants and the technical and economic operation of the power system. As an alternative to the equilibrium approaches, agent-based modeling (ABM) is a field that is gaining increased interest for analyzing the complex interactions in restructured electricity markets. Agent-based models can simulate systems that

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[2] As an example, Chen and Hobbs [3] present a recent application of the Cournot game for analyzing the interaction between the electricity market and the market for tradable NO_x permits.

are outside of the traditional competitive or game-theoretic equilibrium solutions. In addition, the ABM paradigm allows for agents to learn and adapt their strategies during a simulation, thereby possibly converging toward equilibrium under certain assumptions. However, just as in real-world markets, convergence is not guaranteed. An important advantage of using ABM for simulating electricity markets is that this approach allows for including a number of details concerning the operation of the market and power system. This is important because electricity markets tend to have a highly complex set of rules and regulations, which affect the strategies of the participants.

In this paper, we present an analysis of GenCo bidding strategies based on simulations with an agent-based model, EMCAS. In particular, we analyze the effect of congestion management and pricing rules on the GenCos' ability to exercise market power. A number of systems are in use for congestion management in restructured power systems: solutions include nodal pricing, zonal pricing, explicit and implicit auctions, and counter trading. Clearly, the market design for congestion management will affect the GenCos' ability to exercise market power, since the prices and profits in the system can be highly dependent on how congestion is handled. In this paper, we use agent-based simulations to compare a market design based on locational marginal prices (LMPs) with a market design in which generators receive the uncongested system marginal price (SMP) and congestion management is handled through counter trading.

The paper has the following structure. In section 2, we present a brief overview of literature on some agent-based models of restructured and competitive electricity markets. In section 3, we briefly present the agent-based simulation model EMCAS, with emphasis on how GenCo bidding strategies can be represented. In section 4, the model is used to analyze an 11-node test power system under different assumptions about the GenCos' bidding strategies. The simulations are performed for both the LMP and SMP market designs, and results are compared. Finally, in section 5, conclusions and directions for further work are given.

2. AGENT-BASED MODELING OF ELECTRICITY MARKETS

ABM has been used to study several questions regarding the electricity market design in England and Wales. Bower and Bunn [4] used ABM to analyze whether the uniform price or the discriminatory auction format is better for the electricity market auction mechanism. The background for their work was the introduction of new electricity trading arrangements (NETA) in England and Wales. Generating companies are modeled as autonomous adaptive agents that develop their own bidding strategies using a reinforcement learning algorithm. Bower and Bunn find that the discriminatory auction results in higher market prices than the uniform-price auction because of the informational advantage given to large GenCos under the discriminatory auction scheme. Bunn and Oliveira [5, 6] developed a detailed multi-agent simulation model of the NETA market. The bidding behavior of both GenCos and demand companies (DemCos) in the bilateral market and the real-time balancing markets are simulated. Again, the agents' adaptive strategies are based on reinforcement learning. The market is simulated as a repeated game using a constant daily load pattern. Hence, the market dynamics emerge from the simulations as the agents learn and adjust their bidding strategies. The model is used to study market power and market design issues in the England/Wales market. However, the transmission network is not represented in any of these models, nor do the analyses address congestion management or transmission pricing.

There are also several more theoretical applications of ABM, where the models are used to analyze bidding behavior in hypothetical electricity markets; the agents learn and adjust their strategies through a repeated set of market interactions. Nicolaisen et al. [7] studied experimental market power and efficiency outcomes for a wholesale electricity market based on discriminatory midpoint pricing under systematically varied concentration and capacity conditions. Buyers and sellers use a modified Roth-Erev reinforcement learning algorithm to determine their price and quantity offers in each auction round. It is shown that high market efficiency is attained and that market microstructure is strongly predictive for the relative market power of buyers and sellers in the system; however, transmission is not considered in the model. Krause et al. [8] studied the bidding behavior of generating companies in an electricity market based on LMPs. Results from an agent-based model with reinforcement learning are compared with those for a computed Nash equilibrium on a five-node test power system. Ernst et al. [9] also used ABM to analyze generators' bidding strategies in an LMP market. In this approach, it is assumed that the generators choose their strategy by maximizing their expected profits, based on available information about current and future market conditions. In a simulation of a two-node system, the influence of line transfer capacity and number and size of generators and GenCos is analyzed.

3. ELECTRICITY MARKET COMPLEX ADAPTIVE SYSTEMS (EMCAS)

EMCAS uses an ABM approach to model the interactions among all major agents in a restructured electricity market, including GenCos, transmission companies, distribution companies, demand companies, consumers, system operator, and regulator. The model, developed over the last three years, includes a detailed representation of the bidding, dispatch, and settlement in the day-ahead and real-time (balancing) electricity markets. For a detailed description of the EMCAS model, see Conzelmann et al. [10, 11]. The most relevant features with regard to the case study presented here are:

- Chronological simulation of market prices over short or long time periods
- Hourly bid-based dispatch and market clearing based on Direct Current Optimal Power Flow (DC OPF) algorithm in day-ahead and real-time markets
- Simulation of several GenCo bidding strategies (further discussed below)
- Inclusion of stochastic forced outages in market simulations
- Possibility of specifying different market rules (e.g., regarding congestion management and pricing mechanisms)
- Calculation of prices and profits based on the "two-settlement system" (i.e., day-ahead price for day-ahead schedule, and real-time price for deviations between real-time dispatch and day-ahead schedule)
- Calculation of cost, revenues, and profits for all relevant agents in the system

Several other aspects can also be included in an EMCAS simulation, such as planned outages, GenCo level unit commitment, etc. However, these features are not included in the case study presented in this paper.

3.1 GenCo bidding strategies

The bidding strategies of GenCos usually receive most of the attention in discussions related to market power exercise in electricity markets. A number of different bidding strategies can be simulated in EMCAS by specifying parameters for the capacities and prices to be bid into the market for the different generation plants in the system. The strategies can be either static or dynamic (i.e., changing during the course of the simulation), and they will typically vary by generation technology and GenCo. In the case study presented in this paper, we only include thermal plants in the power system, and GenCos submit bids once a day (i.e., we assume that there is no re-bidding in the real-time market). The bidding strategies that are used in the analysis are further described below.

Production cost bidding (Base)

Under the production cost strategy, the GenCo acts as a pure price-taker in the market, bidding according to the marginal production cost of its plants as specified by the heat rate curve. Note that if a generating unit is being bid into the market according to its marginal production cost, and if its bid clears the market, it might not cover the total production cost, because the marginal production cost (and heat rate) is usually lower than the average production cost (and heat rate) for thermal plants.

Physical withholding based on system reserve (PWSR)

In this strategy, the GenCo tries to increase the market price by withholding units during hours when the expected system reserve is low. The GenCo forecasts the system reserve for the next day, based on projections of load (we use a perfect load forecast) and available system capacity (which might be in error because of unforeseen forced outages). If the expected system reserve is below a certain trigger point, the GenCo tries to reduce the system reserve further with a specified target amount. However, a limit is set for how much of its own capacity the GenCo is willing to withhold.

Economic withholding – fixed increment price probing (FIPP)

Under this strategy, the GenCo tries to probe its influence on market prices by changing its bidding strategy with a simple algorithm, which takes into account the outcome of last day's dispatch. If the bid for a unit in a certain hour was accepted, the GenCo will increase the bid price with a specific percentage for the same unit in the same hour for the following day. By doing this, the GenCo hopes to be able to raise the market price for that hour. In contrast, if the unit was not dispatched, the GenCo will reduce its bid with the same percentage, hoping that it will be dispatched the following day. A lower limit can be specified for the bid price to avoid bidding at unrealistically low levels.

4. CASE STUDIES

4.1 Assumptions for 11-node test power system

In our simulations, we use an 11-node transmission network configuration based on Christie et al. [12]. The technical specifications and the topology for the transmission lines are shown in Figure 1. We assume that there is only one transmission company (TransCo) in the system, which owns the entire transmission network. The operation of the transmission network is done by an independent system operator (ISO).

Representation of the supply side

There are eight GenCos in the system, located at various nodes in the grid (Figure 1). All the GenCos have the same set of generating units: one base load coal plant (CO), one combined cycle plant (CC) to cover intermediary load, and one gas turbine (GT) peaking unit. For each GenCo, all three generating units (CO, CC, and GT) are connected to the same node. The parameters for the plants are shown in Table 1 and Table 2. Note that the bidding blocks for each generating unit are based on the blocking of the heat rate curves described in Table 2. In the base scenario, the GenCos bid according to their incremental production cost, as shown in the table.

Forced outages are included in the simulations. These are distributed randomly among the generators, based on expected forced outage rates and durations. This makes it difficult to directly compare the profits for each of the GenCos, because one GenCo might have more outages than another. However, the same forced outages are used in all the simulations. Hence, the differences in GenCo results between scenarios can still be analyzed and compared, without correcting for the differences in forced outages.

Representation of the demand side

We use an aggregate representation of the demand side of the market. Five aggregate consumers are included, representing total demand in the node where they are connected. The loads are connected to nodes 1, 3, 4, 10, and 11. We are simulating the month of July, which is assumed to be the peak load month of the year. The five hourly load series are shown in Figure 2. The highest load is clearly in node 11.

All the consumers buy their electricity from a Demand Company (DemCo). The transmission network is split into four zones: A (nodes 1–3), B (nodes 4–7), C (nodes 8–10), and D (node 11). We have assumed that there is one DemCo in each of the zones. Note that in EMCAS, the consumers pay all charges to the DemCo, including both energy and transmission and distribution (T&D) charges. The DemCo, in turn, passes the respective charges on to the GenCos and T&D companies. A mark-up can be added to the price paid by the consumers in order to represent DemCo profits. However, in this study we focus on the GenCos and consumers and set the DemCo mark-up to zero. Furthermore, we do not include any T&D charges, except for the congestion charges, which depend on the congestion mechanism (explained below).

Line no.	*From node*	*To node*	*Circuit reactance (per unit)*	*Line capacity (MW)*
1	1	2	0.02	2000
2	1	3	0.025	1600
3	2	3	0.08	250
4	2	4	0.01	3000
5	2	5	0.02	1000
6	3	8	0.04	1000
7	3	9	0.05	400
8	4	5	0.01	2000
9	4	6	0.02	2000
10	4	7	0.01	3000
11	5	7	0.015	2000
12	6	7	0.01	2000
13	8	10	0.025	1600
14	8	9	0.03	1000
15	9	10	0.04	500
16	6	11	0.02	1500
17	7	11	0.025	1200
18	10	11	0.04	500

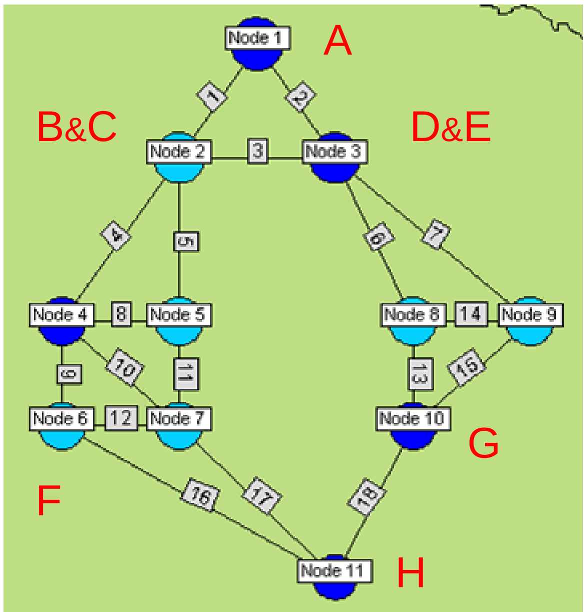

Figure 1. Transmission network in 11-node case study. The letters in the map refer to GenCos.

Table 1. Description of generating units in 11-node case study.

Parameter/Plant	*Unit*	*Base Coal (CO)*	*Comb. Cycle (CC)*	*Gas Turbine (GT)*
Capacity	*MW*	500	250	125
Fuel		Coal (BIT)	Natural Gas	Natural Gas
Fuel price	*$/MMBtu*	1.5	5	5
Variable O&M	*$/MWh*	1.75	2.8	8
Fixed O&M	*$/kWmonth*	2.1	0.6	0.7
Start-up time	*min*	720	180	0
Minimum down time	*min*	480	120	0
Warm start-up cost	*$*	7000	2000	50
Cold start-up cost	*$*	20000	5000	150

Table 2. Heat rates for generating units (Capacity and Bid block in MW, Heat Rates in MMBtu/MWh, Costs in $/MWh).

Base Coal (CO)

Cap-acity	Bid block	Heat rate	Incr. heat rate	Cost	Incr. Cost
250	N/A	12000	N/A	19.8	N/A
350	350	10500	6750	17.5	11.9
400	50	10080	7140	16.9	12.5
450	50	9770	7290	16.4	12.7
500	50	9550	7570	16.1	13.1

Combined Cycle (CC)

Cap-acity	*Bid block*	*Heat rate*	*Incr. heat rate*	*Cost*	*Incr. Cost*
100	N/A	9000	N/A	47.8	N/A
150	150	7800	5400	41.8	29.8
200	50	7200	5400	38.8	29.8
225	25	7010	5490	37.9	30.3
250	25	6880	5710	37.2	31.4

Gas Turbine (GT)

Cap-acity	*Bid block*	*Heat rate*	*Incr. heat rate*	*Cost*	*Incr. Cost*
50	N/A	14,000	N/A	78.0	N/A
100	100	10,600	7200	61.0	44.0
110	10	10,330	7630	59.7	46.2
120	10	10,150	8170	58.8	48.9
125	5	10,100	8900	58.5	52.5

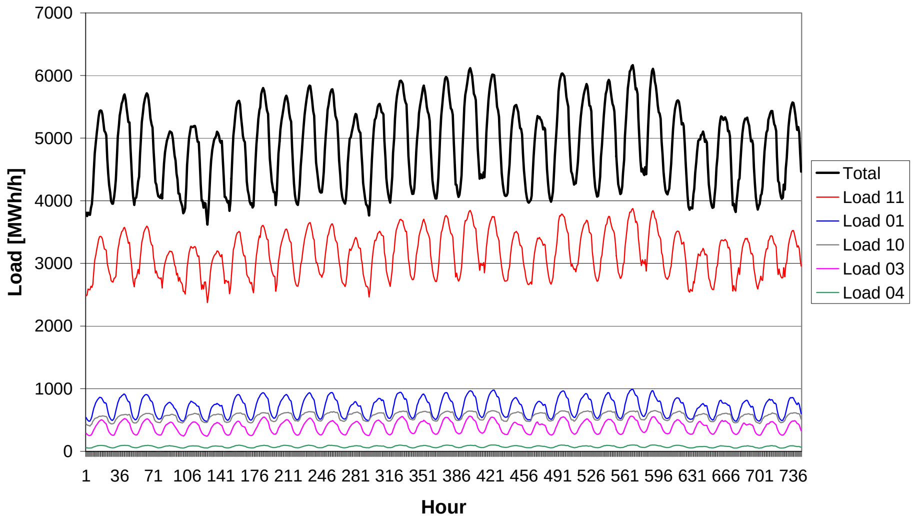

Figure 2 Hourly consumer loads in 11-node case study. Period: July 1-31.

The prices in the day-ahead and real-time energy markets depend on the congestion mechanism. In the LMP case, the consumers pay the load-weighted average of the LMPs in their zone, including both the energy and congestion costs. When the SMP approach is used, the consumers pay the uncongested system marginal price for their energy consumption. The congestion charge, which arises from the redispatch of generating units, is distributed evenly among the consumers in proportion to their loads. The consumer costs shown in the tables in the next section contain both the energy price and the congestion charges.

In the case studies, we assume that there is no price elasticity of demand (i.e., there is no demand-side bidding in the market). If supply cannot meet demand, the ISO will curtail load and set the price to the value of lost load (VOLL), which is assumed to be $999/MWh. This effectively caps the price in both the day-ahead and real-time markets. In the simulations, there is no difference between the day-ahead and real-time loads. Hence, the only effects that can cause a difference between the day-ahead and real-time prices are the forced generator outages.

4.2 Scenarios

A number of scenarios were run in order to analyze the impact of GenCo bidding strategies on the performance of the GenCos and consumers in the system. The scenarios can be grouped into base case, physical withholding, and economic withholding. We present main results from seven scenarios for each of the two congestion management mechanisms (LMP and SMP). In the results, we focus on the differences between the LMP and SMP results.

The base scenario assumes bidding strategies based on the incremental production cost of all the generating units in the system, as shown in Table 2. In the PWSR scenarios, we assume that one GenCo withholds parts of its generation capacity based on the system reserve, as explained in section 3.1. The parameters in the strategy are set to 30% for the system reserve trigger point, 6% for the target reduction in system reserve, and 40% for the maximum capacity to be withheld from the market. The last parameter implies that the GenCos are willing to withhold the CC and GT plants from the market and that the base plant will never be withheld. The strategy is simulated for GenCos A, G, and H, respectively, always assuming that the remaining GenCos bid according to their production cost. In the FIPP strategy, we used a 10% price adjustment, with a lower limit equal to the incremental production cost. The FIPP strategy was also simulated for GenCos A, G, and H, with production cost bidding assumed for the other GenCos. The scenarios presented in the paper are summarized in Table 3.

Table 3. Overview of simulated scenarios.

Scenario name	*LMP*	*SMP*
Base	Prod. cost for all GenCos	Prod. cost for all GenCos
PWSR_A	PWSR for GenCo A	PWSR for GenCo A
PWSR_G	PWSR for GenCo G	PWSR for GenCo G
PWSR_H	PWSR for GenCo H	PWSR for GenCo H
FIPP_A	FIPP for GenCo A	FIPP for GenCo A
FIPP_G	FIPP for GenCo G	FIPP for GenCo G
FIPP_H	FIPP for GenCo H	FIPP for GenCo H

4.3 Results

The first thing to note is that the dispatch of the system does not depend on the pricing mechanism used in the market clearing process (LMP or SMP). In the base case, GenCos bid marginal production cost in both LMP and SMP market designs, resulting in identical bids and dispatch. In PWSR, the bidding behavior depends on the load and available system generation capacity, which are identical under LMP and SMP, again resulting in identical bids and dispatch. In FIPP, on the first simulation day, the bids are identical and the same bids will be either rejected or accepted under LMP and SMP. As the bidding behavior depends on the previous day's dispatch, the subsequent days' dispatches are also identical under LMP and SMP. However, GenCo profits and consumer costs change due to the different settlement prices used under the two pricing mechanisms. Below, we focus on the financial results from the simulations.

Table 4 shows the average day-ahead (DA) and real-time (RT) prices for all the nodes with generation and/or load in the base case. The SMP is the same in all the nodes, since this is the unconstrained market clearing price. However, we can clearly see that there is congestion in the network, since the LMPs differ between the nodes. The highest LMP is at node 11; the lowest LMP is at node 10. The reason for this is that line 18, which connects nodes 10 and 11, is frequently congested because of the high net load at node 11, which can only be met by importing electricity from other nodes. In fact, line 18 is operating at full capacity (i.e., 500 MW) as much as 50.8% of the time in the base case, and it is the only congested line in the network in the base case.

Table 4. Average monthly prices (SMP and LMP) in DA and RT markets in base case.

	Node 1	Node 2	Node 3	Node 4	Node 6	Node 10	Node 11
SMP (DA)	29.9	29.9	29.9	29.9	29.9	29.9	29.9
SMP (RT)	31.3	31.3	31.3	31.3	31.3	31.3	31.3
LMP (DA)	30.5	31.0	29.8	31.4	31.7	28.1	32.2
LMP (RT)	31.9	32.6	30.9	33.1	33.5	28.5	34.2

Table 4 shows that the LMPs are higher than the SMPs in all nodes except node 10 (DA and RT) and node 3 (DA). This is because the LMPs include the cost of congestion, which can be either positive or negative depending on whether additional load at the node would contribute to increasing or decreasing congestion in the network. For instance, at node 10 a higher load would actually alleviate congestion in the network, since more power could be transmitted to node 11 from nodes 6 and 7. This explains why the LMP is lower than the SMP in node 10. The SMP does not account for congestion. With SMP market clearing, therefore, there is an additional cost for the redispatch of generating units in order to resolve congestion. However, since this cost is distributed equally to all the consumers it does not depend on the location of the load. Hence, all the consumers are facing the same hourly price under the SMP scheme, whereas they are paying locational prices when LMPs are used. The GenCos, on the other hand, also have a locational difference under the SMP scheme, because the generators being dispatched out of merit order to resolve congestion are paid their bid price, which will be higher than the SMP. However, the locational differences in GenCo profits are likely to be lower under SMP than LMP, since all generating capacity is paid a locational price in the LMP scheme.

Table 5 summarizes the total GenCo profits and consumer energy costs for all the scenarios, and it shows the percentage change between the SMP and LMP cases. We see that the total GenCo profit is higher in all the LMP cases, including both the physical and economic withholding scenarios. The consumer energy costs are always higher under the LMP scheme. The difference between the SMP and LMP results is particularly high for the PWSR A and PWSR H scenarios. In these cases, there is curtailment in the system for some hours due to transmission constraints (a total of 480 MWh and 2770 MWh in PWSR A and H, respectively). Therefore, the curtailment price will appear under the LMP settlement in hours with congestion, whereas the price remains at the point where the unconstrained supply meets demand with SMP. The resulting difference in prices during the hours of congestion explains the large difference in results for these two cases. From Table 5, we can also see that the total GenCo profits and consumer costs are increasing compared with the base case in all the strategic scenarios under both settlement mechanisms. The relative changes in profits and costs are further discussed below.

Table 5. Total GenCo profits (left) and total consumer energy costs (right) in $\$10^6$.

Scenario	*SMP*	*LMP*	*% Change*
Base	19.6	22.6	15.0
PWSR A	23.2	53.4	130.2
PWSR G	23.5	23.7	0.9
PWSR H	22.3	86.1	285.3
FIPP A	23.6	25.9	10.2
FIPP G	21.7	23.5	8.5
FIPP H	25.1	28.1	11.7

Scenario	*SMP*	*LMP*	*% Change*
Base	110.2	115.7	5.0
PWSR A	114.4	154.1	34.8
PWSR G	114.3	116.7	2.1
PWSR H	114.5	224.6	96.2
FIPP A	114.3	119.7	4.7
FIPP G	112.2	116.2	3.6
FIPP H	116.4	126.4	8.6

In Table 6, we present in more detail how the individual GenCo profits change under the SMP settlement rules when strategic bidding is applied by GenCos A, G, and H. We see that the total profits increase considerably in both the physical and economic withholding scenarios. However, the increase in GenCo profits differs between the individual companies, because the dispatch changes with respect to the base case. Furthermore, payment from congestion management depends on the location in the network, as discussed above. We can see from the table that differences between the GenCos' individual profit increases are highest in the economic withholding (FIPP) and PWSR H scenarios.

The ideal strategy for a single GenCo would be to bid in a manner that increases its own profit more than the profits of other companies. This is referred to as *unilateral market power* [2]. In contrast, if other GenCos increase profits more than the one who bids strategically, this would serve as a disincentive to exercise market power, since the result would be that other companies benefit more. We see from Table 6 that GenCo H can exercise unilateral market power with both the physical and economic withholding strategies, since the other GenCos increase their profits less than GenCo H in scenarios PWSR H and FIPP H. GenCos A and G have unilateral market power only by applying the economic withholding FIPP strategy.

Table 6 Percentage change in individual GenCo profits compared to base case (SMP).

Scenario	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*Total*
PWSR A	19.6	17.5	20.1	18.2	17.1	**20.2**	14.2	19.7	18.2
PWSR G	19.9	19.2	22.4	19.6	18.3	**24.6**	13.8	22.1	19.7
PWSR H	14.9	12	14.4	17	15.6	13.1	-1.3	**<u>25.8</u>**	13.9
FIPP A	**<u>32.2</u>**	17.9	20.3	18	16.7	26.2	13.5	20.4	20.1
FIPP G	9.8	8.1	9.7	8.5	7.9	14.5	**<u>15.9</u>**	11	10.5
FIPP H	27.8	20.6	24.8	26.6	24.3	28.4	20.2	**<u>54.1</u>**	28

Table 7 shows the same results as Table 6, but for the LMP settlement rule. We can clearly see that, compared to the base case, the percentage change varies much more between the individual GenCos than under the SMP scheme because of the locational prices. For instance, we see that GenCos G and E in some scenarios reduce their profit compared to the base case, probably due to lower locational prices. The differences between the GenCos are particularly high in the two scenarios with curtailment in node 11 (PWSR A and H). Also, unilateral market power appears to be easier to obtain with the economic withholding strategy under the LMP scheme; all three GenCos are able to increase their profits more than the rest when applying the FIPP strategy. For the physical withholding strategy, only GenCo G is able to exercise unilateral market power.

Table 7 Percentage change in individual GenCo profits compared to base case (LMP).

Scenario	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*Total*
PWSR A	51.1	162.1	180.7	126.0	124.3	179.4	12.4	**181.3**	136.6
PWSR G	3.3	3.9	4.5	8.8	6.8	2.1	**15.0**	1.0	5.1
PWSR H	315.8	340.8	**361.3**	235.3	229.7	301.6	-53.8	361.0	281.4
FIPP A	**22.1**	13.8	15.2	13.5	12.0	19.8	6.8	15.5	15.0
FIPP G	3.0	1.3	1.7	6.2	5.4	0.7	**25.8**	-0.7	4.3
FIPP H	22.2	30.9	35.6	0.5	-1.4	69.1	-54.3	**55.2**	24.4

Table 8 and Table 9 show the relative change in individual consumer costs for the strategic scenarios compared to the base case under SMP and LMP settlements. The cost increase is relatively modest in the SMP scenarios, and the cost increases are almost the same for all consumers. In fact, the only reason for the small differences between the individual consumers is that they have different hourly load profiles; the hourly energy and congestion costs are the same. In the LMP case, we again see more distinct differences between the consumers because of the locational prices. For instance, Load 10 reduces its cost by more than 10% when GenCo H applies either physical or economic withholding. Load 11, on the other hand, has a cost increase of more than 100% when GenCo H withholds capacity and causes curtailment to occur.

Table 8 Percentage change in individual Consumer costs compared to base case (SMP).

Scenario	*Load 1*	*Load 3*	*Load 4*	*Load 10*	*Load 11*	*Total*
PWSR A	4.0	4.1	3.9	3.7	3.7	3.8
PWSR G	3.9	4.0	3.8	3.6	3.7	3.7
PWSR H	4.3	4.3	4.1	3.9	3.8	3.9
FIPP A	3.9	4.0	3.8	3.6	3.7	3.7
FIPP G	1.9	1.9	1.8	1.7	1.8	1.8
FIPP H	6.0	6.1	5.8	5.4	5.6	5.7

Table 9 Percentage change in individual Consumer costs compared to base case (LMP).

Scenario	*Load 1*	*Load 3*	*Load 4*	*Load 10*	*Load 11*	*Total*
PWSR A	26.7	27.8	36.2	2.8	39.8	33.2
PWSR G	1.5	1.5	0.8	2.7	0.4	0.9
PWSR H	49.1	50.8	75.1	-10.9	125.3	94.1
FIPP A	3.1	3.2	3.6	1.8	3.8	3.4
FIPP G	1.1	1.2	0.3	2.5	-0.1	0.4
FIPP H	3.2	3.3	10.5	-11.4	14.4	9.3

4.4 Discussion

In general, we can see from Table 6 and Table 7 that, on average, GenCo H tends to benefit the most from the simulated strategic behavior under both the SMP and LMP schemes. GenCo G, on the other hand, appears to benefit the least. This is because of the location of these two GenCos, on each side of a congested line. However, the relative differences between the GenCos are much more amplified by the LMP market settlement as compared to SMP. The same is observed on the demand side of the system (Table 8 and Table 9), where the increase in consumer energy cost due to strategic behavior is almost the same for all consumers in the SMP case but varies greatly under the LMP design. The load in node 11 tends to see a high increase in costs, whereas the consumer in load 10 sees only a small increase or even a reduction in costs compared to the base case. An advantage of the LMP mechanism is that it gives efficient locational price signals to the agents in the system in a competitive setting, as indicated by the LMPs in Table 4. However, these signals might easily be distorted if market power is exercised in the system. The SMP approach, on the other hand, does not give the correct locational price signals; most of the generation receives the unconstrained market clearing price, and all consumers pay the same energy and congestion cost. However, the SMP approach appears less vulnerable than the LMP scheme to locational distortions from market power exercise.

The results from the case study show that it is possible to exercise market power in the 11-node system. Unilateral market power, which was also identified, appeared to be easiest to obtain using an economic withholding strategy. It is interesting to compare the results to the traditional HHI index for market concentration. The HHI index for the supply side of the system based on installed capacity is 1250, which is likely to be regarded as relatively low[3]. The case study clearly illustrates the importance of taking the transmission constraints into account when assessing market power in electricity markets. A clear advantage of using an agent-based model to simulate market power is that the transmission network can easily be represented in the model. In addition, it is possible to include more realistic assumptions (stochastic outages, supply function bidding, two settlement system, etc.) than are usually possible in a traditional market power model based on game-theoretical equilibrium approaches. A challenge when using agent-based simulations is, however, to assign reasonable strategies to the agents in the system. A high number of simulations can be necessary before realistic results emerge from the analysis, unless the agents have very intelligent and adaptive strategies that quickly approach realistic market behavior.

5. CONCLUSIONS

The results from our case study show that most GenCos are able to manipulate the prices and increase their profits under both the LMP and SMP designs, despite a fairly low market concentration in the 11-node test power system. However, because of the transmission constraints, the ability to raise prices is very dependent on the GenCos' location in the grid. The largest changes in GenCo profits and consumer costs due to strategic behavior occur under the LMP scheme. However, unilateral market power, found under both pricing mechanisms, occurs more frequently for economic than physical withholding strategies.

Of course, one should be careful in generalizing the results from a simple 11-node case study, where only a limited number of strategies are simulated. However, the analysis underlines the importance of taking the transmission network into account when assessing market power in electricity markets. Simple market concentration measures, such as the HHI Index, are not adequate in transmission-constrained electricity markets. Furthermore, the analysis shows that agent-based simulation models, which can facilitate a detailed representation of the rules in the electricity market in addition to the transmission constraints, can bring insights beyond the results from the traditional equilibrium models typically used to analyze market power issues.

We see a number of potential extensions of the work presented in this paper. For instance, it would be interesting to simulate alternative bidding strategies, where the GenCos have a better capability for learning and adapting their strategies during the simulation. Another important aspect is to represent demand-side response to prices, together with the possibility of simulating demand-side bidding as a counterweight to the potential market power exercise by GenCos. Bilateral contracts can also reduce the participants' ability to exercise market power; this is an important aspect to include in future simulations. Furthermore, it would be interesting to analyse the effect of using alternative congestion management mechanisms to nodal pricing and counter trading (e.g., zonal pricing, explicit and implicit auctions). In the end, instead of simulating a chronological time series of load, we could simulate the power market as a repeated game (i.e., using the same daily loads for all time steps), analyzing market stability and whether or not the market solution converges towards an equilibrium point.

[3] A HHI of 1800 is commonly used as a lower limit for concerns about market power abuse in the US (Stoft [13]).

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