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Carbon-based bidding structure in competitive electricity markets

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ABSTRACT

With changes to carbon output imminent as a result of governmental policies, the method by which energy generators in competitive markets are selected for operation can be called into question. We first simulated a bid-based day-ahead market with human participants and then analyzed generation asset owners' profits based on bid strategy. We then studied computing generator unit dispatch for this simulated market by introducing an environmental index related to the carbon intensity of the relevant fuel type, and computing dispatch via linear programming to either maximize or minimize this index subject to the constraint that average profits be the same as in the original market simulation. The results show that lower bids, even below cost, are most profitable for generators, and that adding an environmental weighting to the bid process has the potential to reduce carbon intensity of power generation without reducing overall average profitability to generators or increasing cost to consumers. This research concludes an environmental score should be explored as a potential weighting factor in bid-based electricity market dispatch.

1. Introduction

As the United States population grows, so does electricity demand and stress on existing electricity institutions and infrastructure. Increased demand, together with international commitments to reduce carbon emissions, are expected to lead to the increasing inclusion of novel and low-carbon energy-production technologies (Restuccia, 2015). Restructured electricity markets in the United States and abroad must meet changing demand and regulatory constraints while maintaining low-cost reliable power and a business environment that allows generators to operate profitably. This research analyzes a day-ahead bid-based dispatch market, and the implications of adding environmental weighting to dispatch optimization decisions.

2. Background—Electricity markets, PJM, and market simulation

One of these independent energy markets is the Pennsylvania, Jersey, and Massachusetts (PJM) energy market, which is used as a basis for the simulated system in this research. Responsible for managing over 67,000 MW of generating capacity, PJM is the world's largest competitive wholesale energy market (Ott, 2003). PJM began in 1927 as the first pooled resource generation system (PJM, n.d.), which allowed for three generation systems to be interconnected improving overall system reliability. This was a controlled system where PJM projected demand and dispatched capacity as needed. In 1997, this controlled system was changed as PJM became the first independent system operator (ISO). This independence allowed PJM to open the first bid market system in the United States (PJM, n.d.). This new bid system allowed anyone who generated electricity to place a bid to PJM, these bids were ranked lowest to highest by cost with the lowest bid units being selected by PJM first until the selectety -30ptd unit capacity met the projected demand, subject to transmission and reliability constraints. The market clearing price, the price which all units are paid, is selected by the bid price of the final unit selected to meet the necessary capacity (Ott, 2003). Soon after ISO's began operation, the Federal Energy Regulation Commission (FERC) began pushing these ISO's to consolidate into Regional Transmission Organizations (RTO) which are able to better process a larger number of generation and transmission transactions. In 2002, PJM became the United States' first RTO and has operated the expanding market of the Northeast United States ever since (PJM, n.d.).

PJM is currently composed of two energy markets, the real-time balancing market, and the day-ahead market (PJM, n.d.). The real-

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Nomenclature

Notation and Abbreviations

- c Capacity (MWh/h)
- φ Dispatch variable, fraction of available generation capacity that is dispatched
- f Forced out rate, probability that a particular generating unit will not be able to run
- ω Wind (MWh/h)
- ρ Profit ($)
- ψ Fuel cost ($)
- b Bid price ($/MWh)
- s Total environmental index
- t Time (hours)
- e Environmental index score for each fuel type
- h Heat rate (Btu/kWh)
- m Cost of operations and maintenance for electricity generating units ($/MWh)
- κ Market clearing price ($/MWh)
- u Generating unit
- p Time period (peak, shoulder, off-peak)

time balancing market actively manages the capacity, demand, and clearing price for the market every five minutes. This market allows for units priced out of the day-ahead market to find chances to remain active (Ott, 2003). The day-ahead market is calculated for each hour of the next day, and is based on generation offers, demand bids, virtual supply offers, virtual demand bids and bilateral transaction schedules which come from generators and are given to the PJM market operator. PJM then selects the units based on price and demand, producing a market clearing price which is a binding price for that time period. These binding prices allow for electricity producers to then sort out their transmission transactions based on transmission limitations and demand, producing a locational marginal price (LMP) for each location in the system (Ott, 2003).

While this bid-based system currently operates effectively to provide reliable power at reasonable prices to consumers, it is not known whether or not this is the most efficient system to reduce carbon outputs, or increase profits for generators (Ott, 2003). To analyze a bid-based system, a simplified version of a day-ahead energy market (based loosely on PJM day-ahead markets) was simulated in this research, as described in Section 4. The simulation included 762 generation units owned by nine generation companies. Proportional demand to capacity ratios were generated using information provided by PJM (PJM, n.d.). Fuel costs and wind energy generation varied from round to round, with each round simulating a single day of operation. Each round was broken into three time periods (peak, shoulder, and off-peak) as opposed to the hourly system used for the day-ahead market of PJM. Generation units included coal, natural gas, and nuclear plants, each with forced outage rates and operations and maintenance costs based on approximate industry-standard information (Ott, 2003; PJM, n.d.). These simplifications in assumptions and input parameters allow simplification of the calculations used to get meaningful results.

3. Problem statement and hypothesis

Since FERC Order 888 was issued in 1996, transmission providers have been required to provide equal access to the transmission grid to non-utility generators, effectively opening many electricity control areas to wholesale competition among traditional and independent power producers (Federal Energy Regulatory Commission, 2010). However, this process does not equate the “cleanest” method of energy production as that does not have priority to the decision making authority (Walden et al., 2015; Project Management Institute, 2008).

The competitive nature of the bidding process means that short-term profitability is not assured for any generation asset that is participating in a market. We hypothesize that average unit profitability could be maintained and carbon emissions substantially reduced if, instead, a fixed profit margin were allowed to each unit, and units were dispatched on an emissions-based rather than a cost-based score.

4. Methodology

In this work we compare the results of the optimization of dispatch of electricity generating assets using two approaches and models. The first uses a bid-based dispatch simulation, and relies on human actors to create profit-maximizing bid strategies. The second uses an optimization strategy with profitability as a constraint, rather than an objective function, and with minimizing an environmental index (a proxy for carbon emissions) as its objective. The following sections describe the methodology used in each of these optimization strategies

4.1. Profit Maximization—Human bids

To analyze the market participant behavior and resultant electric generation unit dispatch in a competitive market, we used a model simulating a day-ahead bid-based market, similar to that created by PJM, with simplifications to eliminate transmission and security constraints, and using three time steps per day rather than the more realistic 24 hourly time steps used in PJM and most day-ahead markets.

Table 1
Example of Market Plan for a single bidding cycle.

	Forecast			Real			
Round 1		$/MMBTU	Wind				Wind
fuel:	natural gas	$4		fuel	natural gas	$4	
	coal	$2.50			coal	$2.45	
	nuclear	$1.25			nuclear	$1.28	
demand:		MWh/h					
	peak	24000	no	demand	peak	26600	67
	shoulder	16000	no		shoulder	15600	134
	off-peak	8000	no		off-peak	8600	200
							f

Table 2
Snapshot from Market worksheet prepared for each owner.

Fill Out to Bid	=		Dispatch all? (Y or N)	
Fill Out to Score	=			

Fuel:	**forecast ($/MMBTU)**	**real ($/MMBTU)**	Round Profits =	
Natural gas			Total Profits =	
coal				
nuclear				

Demand:

	forecast (MWh/h)	**real (MWh/h)**	**# hours**	**Market Clearing Price (MCP)**	**Desired profit %**	+ for Seg 2	+ for Seg 3
peak			4				
shoulder			8				
off-peak			12				

Owner	**Type**	**Unit**	**Segment**	**Capacity, MW**	**Heat Rate, Btu/kWh**	**Forced Outage Rate**	**Fuel type**	**Variable O&M, $/MWh**	**Notes** *
Owner E	Combustion Turbine	100% Organic, Gluten Free	1	25	9,300	12.4%	Natural Gas	5.50	2
Owner E	Combustion Turbine	100% Organic, Gluten Free	2	25	7,840	12.4%	Natural Gas	5.50	
Owner E	Coal	Ace in the Coal	1	150	13,230	13.3%	Coal	3.72	
Owner E	Coal	Ace in the Coal	2	75	11,330	13.3%	Coal	3.72	
Owner E	Coal	Ace in the Coal	3	75	9,943	13.3%	Coal	3.72	
Owner E	Combustion Turbine	Bullet-Proof Gas	1	25	10,100	9.3%	Natural Gas	5.05	1
Owner E	Combustion Turbine	Bullet-Proof Gas	2	25	8,320	9.3%	Natural Gas	5.05	

The day-ahead market was simulated using an online web-based application called "EMM-App" being developed in Python at the Oregon Institute of Technology to support market simulation as a part of an electricity markets course (Hammond, 2016).

The EMM-App allows the creation of a virtual day-ahead electricity market with any number of users, referred to as owners, that are configured to possess a set of generating units (divided into up to three segments) with specified values of total capacity, forced outage rates, fuel types, operating efficiencies (i.e. heat rates), and fixed and variable costs. A market game may be configured through a web interface by an administrator logging into the EMM-App system, and uploading a set of specially formatted Excel spreadsheets determining the set of users, generating units, as well as forecast and actual values for electricity demand and fuel prices. A single market game may be configured with any number of bid rounds, each corresponding to a single model day, and each day may be segmented into any number of time periods (peak/off-peak, hourly, etcetera). Individual users interact with the EMM-App by logging in to the system through a standard web browser, after which they may upload bids (in the form of Excel spreadsheets) for their generating units for each bid round. At the close of each bid round, the administrator may run

Table 3
Example of time period worksheet calculations.

Off Peak						
forecast cost ($/hr)	Bid	Cap. Disp.	real unit cost	unit revenue	Unit profit	total profits
45.45	38.49	200	$8,085	$24,800	$16,715	$17,785
42.70	47.55	0	$0	$0	$0	$0
44.55	32.79	0	$0	$0	$0	$0
46.40	35.53	50	$2,065	$6,200	$4,135	$5,164
47.35	50.40	0	$0	$0	$0	$0
36.86	34.97	250	$8,642	$31,000	$22,358	$22,358
37.45	33.88	75	$2,622	$9,300	$6,678	$8,027
44.60	36.40	75	$3,005	$9,300	$6,295	$7,386
47.50	57.40	0	$0	$0	$0	$0
43.05	42.00	25	$965	$3,100	$2,135	$2,135
43.45	56.92	150	$5,765	$18,600	$12,835	$12,835
41.90	33.55	25	$992	$3,100	$2,108	$4,215
37.66	50.76	0	$0	$0	$0	$4,434
40.76	37.12	75	$2,865	$9,300	$6,435	$8,579
33.89	36.15	100	$2,856	$12,400	$9,544	$9,544
34.75	37.33	0	$0	$0	$0	$2,288
41.31	42.70	25	$974	$3,100	$2,126	$6,379
33.08	43.05	0	$0	$0	$0	$38,068
34.80	50.76	250	$8,102	$31,000	$22,898	$25,185
41.56	36.47	0	$0	$0.00	$0.00	$0.00
47.90	41.35	0	$0	$0.00	$0.00	$2,034.50

the market model, which has the effect of generating forced outages, then determining the market clearing price and generating unit dispatch, the results of which are saved to the internal EMM-App database. Following this, users may download individual market reports (as Excel spreadsheets) which show which of their own units were dispatched, but do not indicate the dispatch status of other users. The administrator may also download an overall market report showing the dispatch status of all generator units.

A total of 762 individual generation units were created and separated into nine "owner" packages of 32–34 units with 1–3 generation segments per unit (approximately 85 total per owner). Each generation package was given approximately the same percentage of unit types (coal, combustion turbine, natural gas combined cycle, and nuclear) for a total of 4750–4850 MW of total capacity per owner. Heat rates, forced outage percentages, variable O&M rates, and fuel types were chosen for each unit consistent with approximate industry standards (U.S. Department of Energy, n.d.).

A Market Plan as in Table 1 was developed with 10 "days" of forecasted demand for each applicable time period energy usage (peak: 4 h, shoulder: 8 h, and off-peak: 12 h) and forecast fuel costs for each fuel type available to the units. These "real" values were revised from forecast values after bids were submitted for demand and fuel costs. These values were chosen based on the ratio generation to demand in the real PJM area, as well as approximate industry values (PJM, n.d.).

Nine students in the Master of Science in Renewable Energy Engineering program at the Oregon Institute of Technology served as generation "owners" in this simulation. Excel worksheets were prepared for participants with their packaged units described in Table 2. Forecasted demand and fuel costs could be added to each round and the cost to operate each unit was automatically calculated (Eq. (1)). Bids could then be calculated for individual units by the "owner". A pre-programmed bid calculator (Eq. (2)) was also made available where a flat profit could be entered and all corresponding bids would be created automatically as in Table 3.

$$\lambda_{forecast} = \psi_{forecast}\frac{h}{1000} + m \qquad (1)$$

$$b = \lambda_{forecast}\left(1 + \frac{\rho}{100}\right)\text{Bid for Segment1} < \text{Segment2} < \text{Segment 3} \qquad (2)$$

4.1.1. Methodology

A total of 10 rounds were completed. "Real" values for fuel cost and demand were delivered after each bidding cycle with the dispatched capacity (whether the unit was "called" or not) (Fig. 1).

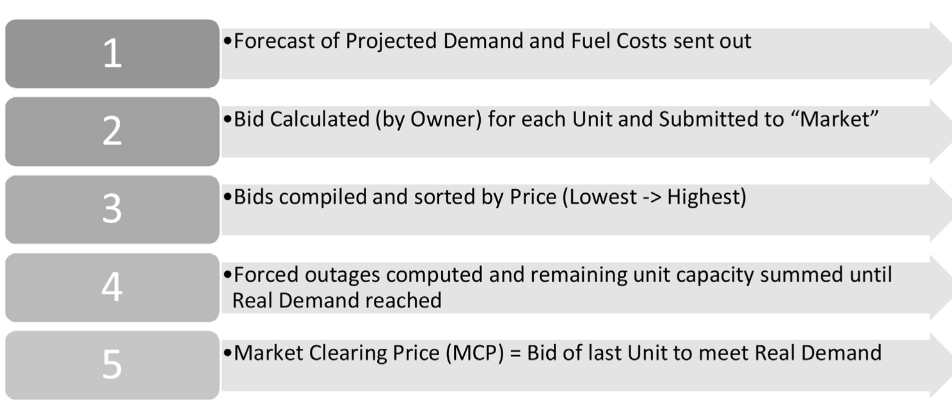

Fig. 1. Market simulation round process.

Table 4
Observed Bid strategies and per owner profit calculations, in millions.

	1	2	3	4	5	6	7	8	9	10	total
20%	$0.18	$0.17	$0.30	$0.35	$0.17	$0.34	$0.34	$0.21	$0.27	$0.12	$2.45
at cost	$0.95	$1.07	$1.27	$1.29	$1.30	$1.48	$1.41	$1.12	$1.67	$0.74	$12.29
≤1%	$0.56	$0.50	$0.85	$0.88	$0.58	$0.86	$0.75	$0.62	$0.71	$0.42	$6.72
1%	$0.53	$0.56	$0.73	$0.90	$0.54	$0.88	$0.77	$0.58	$0.67	$0.44	$6.58
at cost ≤ bid ≤ 5%	$0.60	$0.82	$0.90	$1.04	$0.75	$1.03	$0.91	$0.76	$1.01	$0.59	$8.93
−30% ≤ bid ≤ 8%	$0.62	$0.49	$0.71	$0.86	$0.48	$0.88	$0.98	$0.79	$0.83	$0.53	$7.17
8%	$0.43	$0.60	$0.53	$0.74	$0.34	$0.62	$0.60	$0.52	$0.48	$0.39	$5.27
−30%	$1.52	$1.66	$1.46	$1.61	$1.66	$1.91	$1.59	$1.30	$2.02	$1.48	$16.20
at cost	$1.57	$1.59	$1.73	$1.83	$1.66	$1.89	$1.72	$1.34	$1.66	$1.44	$16.44

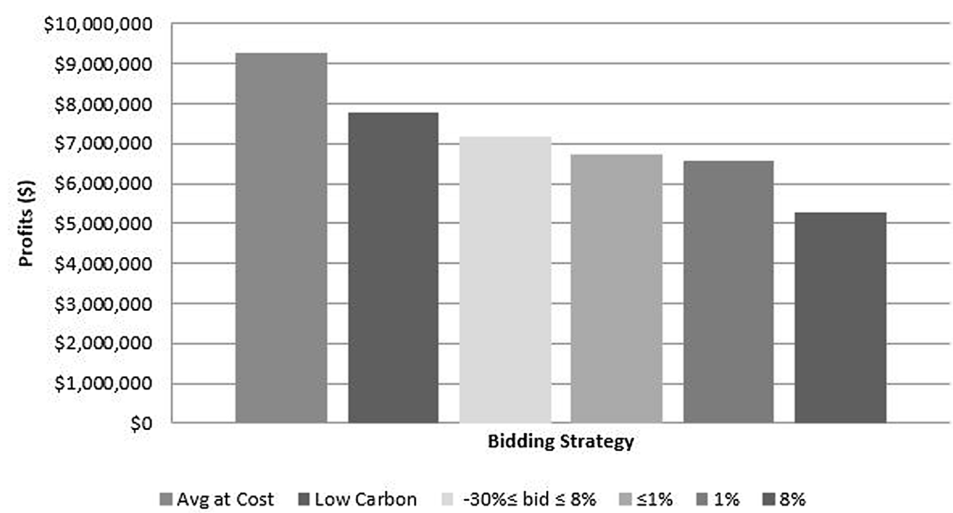

Fig. 2. Total profits for each owner by bidding practice.

Fig. 3. Environmental index e_u by Fuel Type for generator unit u.

Table 5
Decision Variables, Constraints, and Objective.

	Description	
Decision variables	$\phi_{u,p}$	The fraction of the capacity for unit (u) dispatched in time period (p)
Constraints	$0 \le \phi_{u,p} \le 1$	Unit dispatch cannot be negative or exceed total unit capacity
	$\Sigma_u \phi_{u,p} c_u (1 - f_u) + \omega_p = d_p$	Sum of the dispatched capacities plus wind power (ω_p) must meet demand
	$\frac{1}{N} \sum_{u,p} \phi_{u,p} t_p c_u (1 - f_u) \left(\kappa_p - \psi_u \frac{h_u}{1000} + m_u \right) = AP_i$	Average profit is the same as AP_i, the average profit from the ith human bid round
Objective function	$s(\phi) = \Sigma_{u,p} \varphi_{u,p} t_p e_u$	Total environmental index based on index scores (e_u) for fuel type of unit (u), see Table 19

Table 6
Legend for Excel.

INPUT	CONSTRAINT (Input)	OBJECTIVE

Table 7
Forecasted and Real Fuel Prices.

Type	*Natural gas*	*Coal*	*Nuclear*
Forecasted ($/MMBTU)	$ 4.00	$ 2.50	$ 1.25
Real ($/MMBTU)	$ 4.00	$ 2.45	$ 1.28

Table 8
Demand for Peak, Shoulder, and Off-Peak.

	Peak	Shoulder	Off-Peak
Forecast (MWh/h)	30,000	20,000	10,000
Demand (MWh/h)	33,250	19,500	10,750
Wind (MWh/h)	67	134	200
Non-wind Capacity Dispatched (MWh/h)	33,183	19,366	10,550

The profit $\lambda_{u,p}$ generated by unit u in time period p is given by (Eq. (3)), where κ_p is the market clearing price in time segment p, t_p is the duration of time segment p, $c_{u,p}$ is the dispatched capacity for unit u in time segment p, and ψ_u, h_u and m_u are the fuel prices, heat rate, and variable operating and maintenance costs for unit u. Total profits for each owner were then calculated by summing up $\lambda_{u,p}$ over all time periods, and over all units belonging to that particular owner.

$$\lambda_{u,p} = (k_p)(t_p)(c_{u,p}) - \left[\frac{\psi_u h_u}{1000} + m_u\right](c_{u,p}) \quad (3)$$

4.1.2. Results

After ten rounds, the collected data were analyzed. Despite the fact that generation owners did not work in concert, certain bidding strategies emerged as consistent across the rounds as in Table 4. Out of the 9 participants, 5 consistently bid at (or just above) marginal cost of dispatch for their units. Two participants bid well below cost and one bid at a profit level of 8%. A single participant bid at a high profit level of 20%, as shown in Table 4 and Fig. 2.

4.2. Energy Markets—Environmental optimization

The main result of our paper is to demonstrate that adjusting the unit dispatch selection procedure can give large changes in environmental impact, while still producing the same clearing price and the same average profit for all owners participating in the market as produced by the bid-based dispatch procedure described previously. We demonstrate this proof-of-concept by first introducing a simple ordinal scale for quantifying environmental impact. We then compute unit dispatch through an optimization procedure using this environmental index as an objective function, where we constrain average profits to be identical to those produced by the market simulation with human participants described previously. By comparing the environmental impact measures produced from optimization-based dispatch to those produced from the original bid-based dispatch, we quantify the possible environmental gains that may be achieved.

4.2.1. Methodology

Our optimization-based procedure relies on a quantitative measure of environmental impact for operating generator units of different types. We assign each generator unit u the environmental index e_u depending on its fuel type, as in Fig. 3. This ordinal ranking is not intended to illustrate the absolute difference in carbon emissions between each type of generation, but as proof of concept. We note that more refined scoring systems based on accurate carbon emission or other environmental impacts could be devised; however this is beyond the scope of the current work.

These scores are summed by unit and over all time periods to give the total environmental index (eq. 4) where we have introduced the dispatch fraction variables $\phi_{u,p}$ indicating the fraction of the capacity for unit u that is dispatched in time period p.

$$s = \sum_{u,p} \phi_{u,p} t_p e_u \quad (4)$$

For the optimization-based dispatch, we include some generation capacity from wind. We introduce wind independently of the owner units that are present in the market into the game. Wind was handled by randomly selecting a wind power production amount ω_p within each time segment p, dispatch of owner units was then required to meet the demand after subtracting the wind power.

Finally, forced outages were handled somewhat differently for the optimization-based dispatch. For simplicity, we did not randomly generate forced outages for each unit in each time-period, but instead modeled the effect of the forced outage probability by attenuating the capacity of each unit. This leaves each unit with total capacity c_u and forced outage probability f_u an effective capacity given by $c_u(1-f_u)$.

We may now describe the details of our optimization-based dispatch. The decision variables, constraints, and objective for the optimization are outlined in Table 5. For each of the 10 bid rounds, we ran two separate optimizations, seeking to find values for the dispatch fraction variables $\phi_{u,p}$ either minimizing or maximizing the environmental index s subject to the stated constraints. We note that all of the unit capacities (c_u), heat rates (h_u), fuel costs (ψ_u), demand values (d_p), variable operating and maintenance costs (m_u) and market clearing prices (κ_p) were the same as for the simulated markets using human bids.

As the objective function $s(\phi)$ described above is linear in the $\phi_{u,p}$, and all of the constraints are linear equalities or inequalities, both the minimization and maximization problems correspond to linear programs. These programs involved a total of 2286 variables.

Table 9
Market Clearing Price per Period.

Period	Peak	Shoulder	Off-Peak
Market Clearing Price (κ)	$ 44.85	$ 37.85	$ 34.54

Table 10
Dispatch fraction variables to determine whether a unit was turned on or off.

...	Called?			...
...	Peak	Shoulder	Off-Peak	...
...	1	0	0	...
...	1	1	0	...
...	1	1	0	...
...	0	1	0	...
...	1	1	0	...
...	1	1	0	...
...	0	0	0	...
⋰	⋮	⋮	⋮	⋱

```
---- Start Diagnose ----
No uncertain input cells.
Using: Full Reparse.
Parsing started...
Diagnosis started...
Convexity testing started...
Model diagnosed as "LP/MIP".
User engine selection: Gurobi Solver V6.5.0.0
Model: [OptimizedMarkets0845.xlsx]Opt1
Using: Psi Interpreter

---- Start Solve ----
No uncertain input cells.
Using: Full Reparse.
Parsing started...
Diagnosis started...
Convexity testing started...
Model diagnosed as "LP/MIP".
User engine selection: Gurobi Solver V6.5.0.0
Model: [OptimizedMarkets0845.xlsx]Opt1
Using: Psi Interpreter
Parse time: 0.81 Seconds.

Engine: Gurobi Solver V6.5.0.0
Setup time: 0.11 Seconds.

Engine Solve time: 0.05 Seconds.

Integer solution found within tolerance.
Solve time: 1.17 Seconds.
```

Fig. 4. Example Gurobi solver output.

Table 11
Round Profit.

Total round	$ 16,107,091.47
AVG per Owner	$ 1,789,676.83

We solved these linear programs using the Gurobi solver within Excel through Frontline's Premium Solver platform. Below we indicate the setup in Excel for round 1 of this simulation (Gurobi Optimization, 2016). Table 6 demonstrates how each cell is denoted. Table 7 indicates the forecasted and real fuel prices as given for round 1 of the simulation.

The forecasted demand is given prior to requiring bids to be submitted, but is not taken into account with this solver. The demand is a constraint that is generated by the round and matches that of the market game. We show the forecast demand, wind power and (non-wind) dispatched capacity in Table 8 for round 1.

Table 13
Market Clearing Prices and Profits.

Round	Market Clearing Price ($)			Profits ($)	
	Peak	Shoulder	Off-Peak	Total round	Average Profit (AP_i)
1	41	36	34	12,123,292	1,347,032
2	41	45	39	13,528,305	1,503,145
3	50	49	41	16,339,078	1,815,453
4	45	46	42	20,039,553	2,226,617
5	45	43	38	14,708,407	1,634,267
6	53	52	46	19,300,542	2,144,505
7	53	50	43	17,184,525	1,909,392
8	50	50	41	14,579,792	1,619,977
9	53	41	33	14,301,214	1,589,024
10	39	34	31	11,184,990	1,242,777

Market clearing prices were taken from the market game and are entered as in Table 9.

In order to maximize or minimize the objective, the solver changes the decision variables $\phi_{u,p}$ as in Table 10. We note that while these were not constrained to be binary, but only to lie between 0 and 1, in the computed solutions nearly all of the $\phi_{u,p}$ were either 0 or 1 (Fig. 4).

4.3. Results

In each round of the market simulation, the fuel cost, demand, and wind were randomized within specific parameters. To simulate the same conditions in each the markets simulation and environmental optimization, these conditions were taken directly from the markets simulation for the environmental optimization and are represented in Tables 11 and 12.

According to the bids given by each owner of units, the market clearing price is set at the highest bid necessary to meet the demand at that time segment and that price is used for all bids called in that time segment. These were taken directly from the markets game and utilized in the optimization to calculate the profits as in Table 13.

Fig. 5 shows the values of the largest and smallest environmental indices produced by the optimization procedure, as well as those from the human bid-based market game. We see clearly that the environmental indices from the human bid-based game are far from optimal.

This shows that if the market operator optimizes the units called to maximize the use of their more environmentally friendly units, the owners can still make the same profit. In each the market simulation as well as the minimal and maximum environmental optimization scenarios, the same demands and average profits were made by owners. Profit returns to generators would need to be the responsibility of the grid operator in this scenario.

Table 12
Fuel Cost, Demand, and Wind per round.

Round	Real ($/MMBTU)			Demand (MWh/h)			Wind (MWh/h)		
	Natural gas	Coal	Nuclear	Peak	Shoulder	Off-Peak	Peak	Shoulder	Off-Peak
1	4.0	2.5	1.3	26,600	15,600	8,600	67	134	200
2	5.3	2.5	1.5	26,200	17,000	7,760	167	334	500
3	5.5	2.3	1.8	24,600	18,000	9,000	0	0	0
4	4.3	2.5	1.8	25,800	24,000	13,800	133	266	399
5	5.8	2.8	1.5	21,200	17,200	11,400	90	180	268
6	6.0	2.3	1.5	26,000	21,400	8,800	0	0	0
7	6.0	2.8	1.8	26,000	17,200	9,720	33	66	98
8	7.0	2.8	2.0	22,200	16,400	8,400	123	246	367
9	5.8	2.8	1.8	27,640	15,800	8,800	50	100	149
10	5.0	2.3	1.5	23,920	14,840	9,600	0	0	0

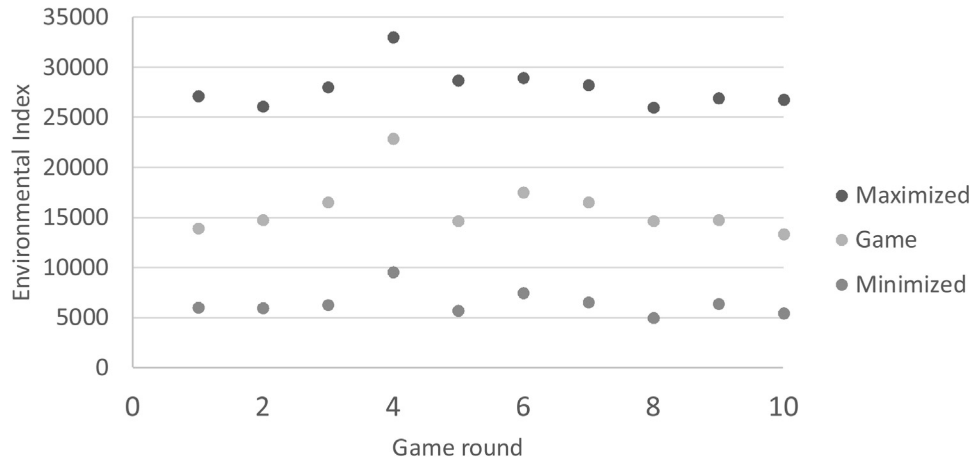

Fig. 5. Minimized and maximized environmental indices based on round.

Table 14
Magnitude greater environmental index maximized is than minimized.

Round	Score (Fuel Type*Called)		Maximized/minimized
	Maximized	Minimized	
1	27,139	6,025	4.50
2	26,133	5,992	4.36
3	28,022	6,292	4.45
4	33,025	9,593	3.44
5	28,714	5,725	5.02
6	28,970	7,469	3.88
7	28,234	6,543	4.31
8	26,034	5,008	5.20
9	26,964	6,398	4.21
10	26,803	5,444	4.92
AVG			4.43

The only difference is which particular units were chosen to be turned on during that particular round. Therefore, the bid system may not be the ideal manner of selecting generating units to meet the market demand. In order to demonstrate how significant of an environmental impact this could make either positively or negatively, Table 14 demonstrates the proportional difference per round.

Since the average is 4.43 for dividing the minimized score by the maximized score per round, this demonstrates that the grid can potentially be 4.43 more sustainably run than the worst use environmentally, based on the proxy ordinal scores used in this model.

5. Conclusion

Research into the relation between percentages of cost bid versus the profits yielded interesting results. Profits for generators were maximized when the bid was below cost, and profits were minimized when the bid was above cost. From our simulated market, it was in a generator's best interest to bid as low as possible to assure their units were selected for operation. The units which bid below cost relied on two primary factors: 1) other units would bid at or above cost and 2) the demand would be so large that at least one unit which bid at or above cost would need to be selected. These two factors assured the market clearing price would be above cost for the selected units, assuring profits for those who bid below cost. The problem with this system is how low efficiency and high carbon output units are selected above units which would be more efficient and safer for the environment. This system also discourages new or retrofitted units from being selected as after the capital costs are added to the unit cost, that total is likely to be above the market clearing price, leaving no way for the new or retrofitted unit to be profitable. While further study is necessary, this is a possible part of the answer as to why more efficient units are not being built and old units not being retrofitted to reduce carbon output.

The optimization of environmental score with standardized profit provided further insight into how low carbon output generators can profit in this market system. With profit being held constant and equal to the average profit from the simulation ($90,000 per unit; $8 million per owner) significant differences in the environmental impact score were evident. With an average maximized environmental score of 28,004 and a minimized environmental score of 6449 compared to the score of the simulated PJM market of 15,971, there are substantial opportunities for improvement of carbon output. This would simultaneously continue to provide the same average profits to generators as they are currently earning. This system would require a more accurate environmental impact scoring system and the inclusion of this score into the bid process used by PJM and other energy markets. Further, while profits would be maintained for generators, the cost of that generation could go up, which may result in increased electricity costs for consumers. As generators are most profitable when active, as shown by our research, then the addition of an environmental score into the bid system would heavily incentivize owners to shift to low carbon output methods. Carbon goals set forth by governmental policies are time dependent, and weighting of the environmental score to match carbon output goals would allow transitional period to these new bidding characteristics.

The energy market system used by PJM is capable of answering the increasing demand of the American people and meeting changing carbon output goals, but requires significant change to reach the necessary generation characteristics. By including a well-rounded environmental score to the bid selection system, this is a possible method to vastly reduce the carbon output of our current generation fleet but would require sacrifices. Sacrifices from generators as they would be required to front capital costs for carbon reduction retrofitting, and sacrifices for consumers as the additional cost of the cleaner units would be passed on to them. In the absence of a miracle generation technology we must find unique ways to use our current systems, while minimizing difficulties and maximizing opportunities for stakeholders.

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