

Opportunities for Price Manipulation by Aggregators in Electricity Markets

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ABSTRACT

Aggregators are playing an increasingly crucial role for integrating renewable generation into power systems. However, the intermittent nature of renewable generation makes market interactions of aggregators difficult to monitor and regulate, raising concerns about potential market manipulations. In this paper, we address this issue by quantifying the profit an aggregator can obtain through strategic curtailment of generation in an electricity market. We show that, while the problem of maximizing the benefit from curtailment is hard in general, efficient algorithms exist when the topology of the network is radial (acyclic). Further, we highlight that significant increases in profit can be obtained through strategic curtailment in practical settings.

1. INTRODUCTION

The increasing penetration of renewable generation poses new challenges for controlling the future grid. In particular, aggregators such as SolarCity [4, 8] are playing an increasingly crucial role in managing renewable generation and demand response for Independent System Operators (ISOs). Such aggregators have generation resources at multiple locations in the network and, crucially, can manage these resources in a coordinated manner. Further, unlike traditional generation resources, the ISO cannot verify the availability of the generation resources of aggregators. While the repair schedule of a conventional generator can be made public, the downtime of a solar generation plant and the times when solar generation is not available, cannot be scheduled or verified after the fact. Thus, aggregators have the ability to strategically curtail generation resources without the knowledge of the ISO, and this potentially creates significant opportunities for them to manipulate prices.

In order to understand the impact of aggregators in the electricity market, market operators need to quantify the potential profit that aggregators can gain by strategically curtailing generation. In this paper, we address this goal in a two-stage market setting where the first stage is the *ex-ante* (or day-ahead) market that decides the generation schedule and the second stage is the *ex-post* (or real-time) market to perform fine adjustment based on updated information.

Summary of Contributions: This paper makes three main contributions. *First*, we quantify opportunities for price manipulation and gauge the profit that aggregators can potentially make through strategic curtailment (Section 2.2). *Second*, we focus on the aggregator's optimization problem, which is hard to solve in general. We develop an efficient algorithm that can be used by the aggregators

in radial networks, to approximate the optimal curtailment strategy and maximize their profit (Section 3). Such algorithms can also be used by the operator to assess the potential for strategic curtailment in distribution networks. *Third*, we show that in practical scenarios, strategic curtailment can indeed impact the prices and yield much higher profits for the aggregators.

Related Work: There is a large volume of literature that focuses on identifying and measuring market power for generators in an electricity market, see [11] for a survey. Early works on market power analysis emerged from microeconomic theory suggest measures that ignore transmission constraints and do not capture renewable producers, e.g., [5, 10]. There is relatively limited literature on market power of renewable generation producers. Existing works such as [13] and [12] study market power of wind power producers ignoring transmission constraints. However, line congestion is an important source of market power for electricity market suppliers. Thus, more recently measures have emerged that take into account transmission constraints, e.g., [3]. None of these study the impact of strategic curtailment by aggregators of renewable generation.

2. SYSTEM MODEL

We begin by describing how we model the way the Independent System Operator (ISO) computes the Locational Marginal Prices (LMPs). Locational marginal pricing is adopted by the majority of power markets in the United States, and our model mimics the operation of two-stage markets like ISO New England, PJM Interconnection, and Midcontinent ISO, that use ex-post pricing strategy for correcting the ex-ante prices [9, 14].

We consider a power system with n nodes (buses) and t transmission lines. The generation and load at node i are denoted by p_i and d_i respectively, with $p = [p_1, \dots, p_n]^T$ and $d = [d_1, \dots, d_n]^T$. Our focus is on the behavior of an aggregator, which owns generation capacity at multiple nodes. The aggregator has the ability to curtail generation without penalty, e.g., by curtailing the amount of wind/solar generation or by not calling on demand response opportunities. Let $N_a \subseteq \{1, \dots, n\}$ be the nodes where the aggregator has generation and denote its share of generation at node $i \in N_a$ by p_i^a (out of p_i). The curtailment of generation at this node is denoted by α_i , where $0 \leq \alpha_i \leq p_i^a$. Together, the net generation delivered to the grid is represented by $p - \alpha$, where $\alpha_j = 0 \forall j \notin N_a$. The flow of lines is denoted by $f = [f_1, \dots, f_t]^T$, where f_l represents the flow of line l . We have $f = G(p - \alpha - d)$, where $G \in \mathbb{R}^{t \times n}$ is the matrix of generation shift factors [1]. We define $B \in \mathbb{R}^{n \times t}$, the link-to-node incidence matrix that transforms line flows back to the vector of net injections as $p - \alpha - d = Bf$.

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2.1 ISO's Program

At the end of each dispatch interval, in real time, the ISO obtains the current values of generation, demands, and flows from the state estimator. Based on this information, it solves a constrained optimization problem for market clearing. The objective of the optimization is to minimize the total cost of the network, based on the current state of the system. The ex-post LMPs are announced as a function of the optimal Lagrange multipliers of this optimization. Mathematically, the following program has to be solved.

$$\underset{f}{\text{minimize}} \quad c^T Bf \quad (1a)$$

subject to

$$\lambda^-, \lambda^+ : \quad \underline{\Delta p} \leq Bf - p + \alpha + d \leq \overline{\Delta p} \quad (1b)$$

$$\mu^-, \mu^+ : \quad \underline{f} \leq f \leq \overline{f} \quad (1c)$$

$$\nu : \quad f \in \text{range}(G) \quad (1d)$$

In the above, c_i is the offer price for the generator at node i . f_l is the desired flow of line l , and $Bf = p + \Delta p - \alpha - d$, where Δp_i is the desired amount of change in the generation of node i . Constraint (1b) enforces the upper and lower limits on the change of generations, and constraint (1c) keeps the flows within the line limits. The last constraint ensures that f_l are valid flows, i.e. $f = G\tilde{p}$ for some generation \tilde{p} . Variables $\lambda^-, \lambda^+ \in \mathbb{R}_+^n$, $\mu^-, \mu^+ \in \mathbb{R}_+^t$ and $\nu \in \mathbb{R}^{t-\text{rank}(G)}$ denote the Lagrange multipliers (dual variables) corresponding to constraints (1b), (1c) and (1d).

DEFINITION 1. *The ex-post LMP of node i at curtailment level of α , denoted by $\lambda_i(\alpha)$, is a function of the optimal dual variables of the problem (1), and is defined as*

$$\lambda_i(\alpha) = c_i + \lambda_i^+ - \lambda_i^-, \quad (2)$$

for all $i = 1, \dots, n$.

We assume that there is a unique optimal primal-dual pair, and therefore the LMPs are unique. There are several ways that the ISOs ensure such condition, for instance by adding a small quadratic term to the objective.

2.2 Profit-Maximizing Aggregator

The key feature of our model is the behavior of the aggregator. Aggregators have generation resources at multiple locations in the network and can curtail generation resources without the knowledge of the ISO. Of course, such curtailment may not be in the best interest of the aggregator, since it means offering less generation to the market. But, if through curtailment prices can be impacted, then the aggregator may be able to receive higher prices for the generation offered or make money through arbitrage of the price differential.

DEFINITION 2. *The Curtailment Profit (CP) is the difference between the profit that aggregator makes after curtailment and at the normal condition:*

$$\gamma(\alpha) = \sum_{i \in N_a} (\lambda_i(\alpha) \cdot (p_i^a - \alpha_i) - \lambda_i(0) \cdot p_i^a) \quad (3)$$

A natural model for a strategic aggregator is one that maximizes CP, subject to LMPs and curtailment constraints. Since LMPs are solution to an optimization problem themselves, the aggregator's problem is a nested optimization problem. Using the KKT conditions of ISO's program (1),

the aggregator's problem can be formulated as follows.

$$\gamma^* = \underset{\alpha, f, \lambda^-, \lambda^+, \mu^-, \mu^+, \nu}{\text{maximize}} \quad \gamma(\alpha) \quad (4a)$$

subject to

$$0 \leq \alpha_i \leq p_i^a, \quad i \in N_a \quad (4b)$$

$$\alpha_j = 0, \quad j \notin N_a \quad (4c)$$

$$\text{KKT conditions of (1)} \quad (4d)$$

The objective (4a) is the curtailment profit defined in (3). Constraints (4b) and (4c) indicate that the aggregator can only curtail generation at its own nodes, and the amount of curtailment cannot exceed the amount of available generation to it. Constraint (4d) enforces the locational marginal pricing adopted by the ISO.

We have assumed the aggregator has complete knowledge of the network topology (G), and state estimates (p and d). This is, perhaps, optimistic; however one would hope that the market design is such that aggregators do not have profitable manipulations even with such knowledge. The results in this paper indicate that this is not the case.

3. AGGREGATOR'S MARKET POWER

The aggregator's profit maximization problem described above is a bilevel optimization, which is challenging to analyze. In fact, bilevel linear programming is NP-hard to approximate up to any constant multiplicative factor in general [7]. Furthermore, the objective of the program (4) is even quadratic (bilinear) in the variables, rather than linear. The combination of difficulties means that we cannot hope to provide a complete analytic characterization of the behavior of a profit maximizing aggregator in general. However, we can give a tractable algorithm for the case when the network is radial (acyclic). Hence the result is relevant to strategic aggregators since most distributed renewable resources are in distribution networks, and majority of distribution networks are acyclic.

In particular, in the following we show that an ϵ -approximation of the optimal curtailment profit can be obtained using an algorithm with running time linear in the size of the network and polynomial in $\frac{1}{\epsilon}$ in the case of radial networks.

Before we state the main result of this section, we introduce the notion of an approximate solution to (4):

DEFINITION 3. *A solution $(\alpha, f, \lambda^-, \lambda^+, \mu^-, \mu^+, \nu)$ is an " ϵ -accurate solution" if the constraints of (4) are violated by at most ϵ and $\gamma(\alpha) \geq \gamma^* - \epsilon$.*

Note that if one is simply interested in approximating γ^* (as a market regulator would be), the ϵ -constraint violation is of no consequence, and an ϵ -accurate solution of (4) suffices to compute an ϵ -approximation to γ^* .

THEOREM 1. *An ϵ -accurate solution to the optimal aggregator curtailment problem (4) for an n -bus radial network can be found by an algorithm with running time $cn(\frac{1}{\epsilon})^9$ where c is a constant that depends on the parameters $p_i^a, B, d, p, \underline{f}, \overline{f}$. On a linear (feeder line) network, the running time reduces to $cn(\frac{1}{\epsilon})^6$.*

It can be shown that the problem on any arbitrary acyclic network can be expressed as one on a binary tree (see the extended version of this paper [2]). So we focus on binary trees here. For a node i , let $c_1(i), c_2(i)$ denote its children (where $c_1 = \emptyset, c_2 = \emptyset$ is allowed since a node can have fewer than two children). Defining $x_i = (\lambda_i, f_i, \alpha_i)$ for each node i allows us to write all the constraints of problem (4)

(in particular the KKT conditions of (1)) in a “local” form. The problem can then be expressed as

$$\begin{aligned} \max_x \quad & \sum_{i=1}^n g_i(x_i) \\ \text{s.t.} \quad & h_i(x_i, x_{c_1(i)}, x_{c_2(i)}) \leq 0 \end{aligned}$$

for some functions $g_i(\cdot)$ and $h_i(\cdot)$. This form is amenable to dynamic programming. Define $\kappa_n(x) = g_n(x)$ and for $i < n$ define κ_i recursively as

$$\kappa_i(x) = \max_{x'_1, x'_2} \sum_{j=1,2} g_{c_j(i)}(x'_j) + \kappa_{c_j(i)}(x')$$

$$h_i(x, x'_1, x'_2) \leq 0$$

Then, the optimal value can be computed as $\gamma^* = \max_x \kappa_1(x) + g_1(x)$. The above recursion, however, requires an infinite-dimensional computation at every step since the value of κ_i needs to be calculated for *every* value of x . However, the variables λ_i, f_i, α_i are bounded, and hence x_i can be discretized to lie in a certain set \mathcal{X}_i such that every feasible x_i is at most ϵ_i away from some point in \mathcal{X}_i . The discretization error can be quantified precisely, and this error bound can be used to relax the constraint to $h_i(x_i, x_{i+1}) \leq \delta(\epsilon)$ guaranteeing that any solution to (4) is feasible for the relaxed constraint.

Algorithm 1 Dynamic Programming on the Binary Tree

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S ← {i : c1(i) = ∅, c2(i) = ∅}
κi(x) ← gi(x) ∀ x ∈ Xi, i ∈ S
while |S| ≤ n do
  S' ← {i ∉ S : c1(i), c2(i) ∈ S}
  ∀ i ∈ S':
    κi(x) ← max_{x'_1 ∈ X_{c_1(i)}, x'_2 ∈ X_{c_2(i)}, h_i(x, x'_1, x'_2) ≤ δ(ε)} ∑_{j=1,2} g_{c_j(i)}(x'_j) + κ_{c_j(i)}(x')    ∀ x ∈ Xi
  S ← S ∪ S'
end while
γ ← max_{x ∈ X1}} κ1(x) + g1(x)

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The algorithm essentially starts at the leaves of the tree and proceeds towards the root, at each stage updating κ for nodes whose children have already been updated (stopping at root). The analysis of the algorithm can be found in the full version [2].

4. CASE STUDIES

We now illustrate the impact of strategic curtailment by an aggregator using extensive simulations in a number of networks with realistic settings. We use IEEE 30- and 57-bus test cases, and their enhanced versions from NICTA Energy System Test case Archive [6].

We simulate the behavior of aggregators with different sizes, i.e. different number of buses, in a number of different networks. In order to examine the profit and market power of aggregator as a function of its size, we assume that the way aggregator grows is by sequentially adding random buses to its set (more or less like the way e.g. a solar firm grows). Then, at any fixed set of buses, it can choose different curtailment strategies to maximize its profit. In other words, for each of its nodes it should decide whether to curtail or not (assuming that the amount of curtailment has been fixed to a small portion). We assume that the total generation of the aggregator in each bus is 10 MW and it is able to curtail 1% of it without detection (0.1 MW).

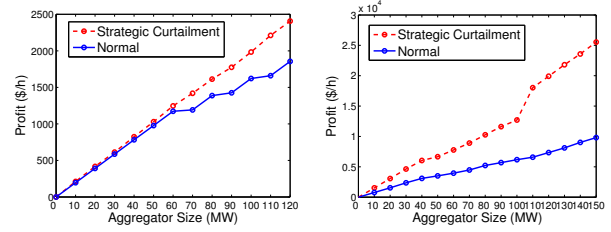


Figure 1: The profit under the normal (no-curtailment) condition and under (optimal) strategic curtailment, as a function of size of the aggregator in IEEE test case networks: a) IEEE 30-Bus Case, and b) IEEE 57-Bus Case.

For the two networks, Fig. 1 shows the profit for a random sequence of nodes. Comparing the profit with and without strategic curtailment reveals an interesting phenomenon. As the size of the aggregator (number of its buses) grows, not only does the profit increase (which is expected), but also the difference between the two curves increases, which is the “curtailment profit.” More specifically, the latter does not need to happen in theory. However in practice, it is observed most of the time, and it points out that larger aggregators have higher incentive to behave strategically, and they can indeed gain more from curtailment.

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