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Estimating Energy Market Schedules using Historical Price Data

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Abstract

The global climate crisis is expected to reshape the energy generation landscape in the coming decades. Increasing integration of non-dispatchable renewable energy resources into energy infrastructures and markets creates uncertainty as well as new opportunities for flexible energy systems. To conduct proper economic evaluation of flexible energy systems, such as integrated energy systems (IES), advancements in modelling of market interactions, such as bidding, is crucial. This work presents a shortcut algorithm which uses two mixed integer linear programs to compute dispatch schedules (e.g., hourly power production targets) that are constrained by the resource's bid information and characteristics (e.g., minimum up and down times) based on historical locational marginal price (LMP) data. The proposed algorithm is approximately 100 times faster and uses orders of magnitude less data than a full production cost model (PCM). We find the shortcut simulator recapitulates generator dispatch signals for the Prescient PCM with approximately 4% error for the RTS-GMLC test system.

Keywords: Electricity Generation, Energy Markets, Integrated Energy Systems, Multiscale Simulation

1. Introduction

Governments around the world have pledged to lower their carbon emissions in response to climate change. Incorporating more variable renewable energy (VRE) sources, such as wind and solar, into power systems is critical to meet these goals. While VRE resources have many benefits such as low to zero emissions and operating costs, their unpredictable nature is challenging for electric grid operations. They increase price variability (Seel et al. 2018) and create strong incentives for more flexible energy generation and consumption. Using historical market price data, Dowling et al. 2017a showed that energy systems can more than double their profits by participating in faster market timescales. Many new promising technologies, including integrated energy systems (IES) which exploit the synergy between multiple technologies (e.g., renewables, nuclear, fossil-based with CO_2 capture, energy storage) by tightly coupling them into single systems (Arent et al. 2021) can provide flexibility to enhance grid reliability and resilience with high VRE utilization. But properly valuing the flexibility of these new technology concepts requires analysis that directly considers interactions between IESs and energy markets. Traditional energy system value metrics, such as levelized cost of electricity (LCOE), do not capture the value created in the market (Dowling et al. 2017b).

Wholesale energy markets coordinate the generation and consumption of electricity from an increasingly diverse set of technologies. The markets set energy prices in a two-settlement system: a day-ahead market (DAM) to meet forecasted demand and a balancing real-time market (RTM) for fast adjustments. Market participants, providing energy generation or ancillary services (various reserves or frequency regulation), can interact with the market via self-scheduling or bidding. A resource that self-schedules creates its own power generation schedule over its preferred planning horizon and is subject to the cleared market price. In contrast, bidding requires participants to submit a set of power-price pairs to the independent service operator (ISO). The power-price pairs reflect the resource’s marginal costs and generation flexibility to the ISO. With all the submitted bids, generation is scheduled by optimizing the bids and clearing the market in order of cost. Once enough generation has been scheduled to meet forecasted energy demand for the considered horizon (following day for DAM or following hours for RTM), the locational marginal price (LMP), or price per MWh produced, is set by the highest cost resource to clear the market. Ela et al. 2014 found self-scheduling, although popular for market-based technoeconomic analysis, results in lower profits than bidding. Despite this fact, much of the current technoeconomic analysis of novel, more flexible energy concepts are done via self-schedule and their value may not be fully estimated.

Bids submitted by generators enable flexibility in the system’s power output and schedule, and with more flexibility, the market has more options to meet ever-increasing demand. Therefore, for the technoeconomic analysis of flexible energy system concepts, simulating their market performance while bidding is essential. But this evaluation requires models to predict energy dispatch calculated from resource bids. Unfortunately, Production Cost Models (PCMs), which mimic market clearing by ISOs, are ‘data-hungry’; they require knowledge of all generation resources in the grid, network topology, demand, and renewables forecasts, etc. Much of this required data is private or protected, which makes PCMs challenging to use for economic evaluation.

To address this challenge, we propose a shortcut algorithm to estimate dispatch schedules for individual market participants, requiring only generator characteristics, bid curves, and historical LMPs. Figure 1 shows the three-step process, which includes solving two mixed integer linear programs (MILP). To evaluate the proposed method, we simulate a single generator in the open-source RTS-GMLC data set (“GridMod/RTS-GMLC") over a month-long horizon using a rolling-horizon algorithm. The resulting dispatch is then compared to results from conducting a full market clearing using the open-source Pyomo-based PCM Prescient (“Prescient”).

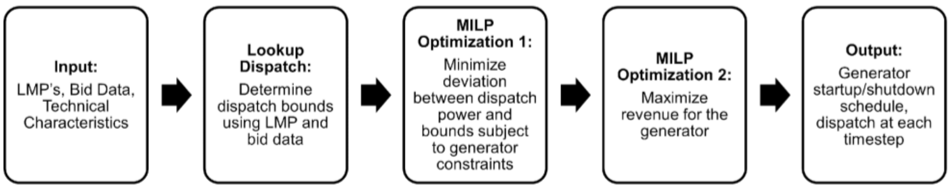

Figure 1: Shortcut Market Simulator Process

2. Methods

Figure 1 summarizes the proposed shortcut market simulator algorithm. The input data are: π_h^{real}, historical LMPs; piecewise "bid curve", a set of power, B_{hl}, and price, π_{hl}, pairs that communicate the total operational costs for the generator; and, technical characteristics including minimum and maximum power output, uptime and downtime constraints, and ramping limits. The latter are used in the thermal generator MILP model adapted from Arroyo and Conejo (2000) and Carrión and Arroyo (2006). The MILP optimization problems shown in Figure 1 are described below. The full simulation can be conducted in one-shot or using a rolling horizon algorithm. The rolling horizon algorithm solved a 24-hour horizon subproblem (from hour 0 to hour 23), saving the results of the first timestep, fixing that timestep, and solving another 24-hour horizon beginning at the next hour (from hour 1 to hour 24 with hour 1 fixed).

2.1. Sets and Variables

All equations in the MILP models are indexed over 2 sets: set $h \in H$ represents the timesteps in the horizon and set $l \in L$ represents the points on the bid curve, or each individual power-price pair. The MILP models include five sets of decision variables. Variable p_h represents the power output of the generator and time h. Variable B_h represents the bid power (bound by the lookup dispatch algorithm) for the generator at time h. Both p_h, and B_h are continuous variables. The remaining three variables are discrete: y_h represents the on/off state of the generator at timestep h (0 is off, 1 is on), y_h^{SU} represents if the generator *is* starting up at timestep h, and y_h^{SD} represents if the generator is shutting down at timestep h.

2.2. Lookup Dispatch Algorithm

The lookup dispatch algorithm compares the LMP, π_h^{real}, to the generator's bid curve prices, π_{hl}, at each timestep of the horizon (the bid curves may be either static, i.e., time-invariant, or indexed by time). The algorithm sets upper and lower bounds, $\underline{B_h}$ and $\overline{B_h}$, on the bid power at that timestep, B_h, according to where on the bid curve the LMP falls. If the LMP is larger than the highest price on the bid curve, the generator has low marginal costs and has cleared the market for that timestep, therefore will be constrained to maximum power output,P^{max}. If the LMP is lower than the lowest point on the bid curve, the generators marginal costs are higher than electricity price at that timestep, so the generator is constrained to either shutdown (zero power output) or operate at minimum power,P^{min}. If the LMP falls between two points on the bid curve, the dispatch of that generator is expected to fall between the associated power values of those points $(B_{hl} \leq B_h \leq B_{h(l+1)})$.

2.3. MILP Optimization Problem

After the bid power bounds are set, a multiobjective optimization problem is solved for the final dispatch of each generator:

min $$\Delta \tag{1a}$$

max $$\sum_{h \in H} \underbrace{\pi_h^{real} p_h}_{A} - \underbrace{(\pi_h^0 B_h^0) y_h}_{B} - \underbrace{\sum_{l=1}^{N} \pi_h^l \delta_{hl}}_{C} - \underbrace{c^{SU} y_h^{SU}}_{D} \tag{1b}$$

s.t. $$\underline{B_h} \leq B_h \leq \overline{B_h} \;\; \forall h \tag{1c}$$

$$\Delta = \sum_{h \in H} |p_h - B_h| \tag{1d}$$

$$0 \leq \delta_{hl} \leq B_{hl} - B_{h(l-1)} \quad \forall h, l \tag{1e}$$

$$p_h = P^{min} y_h + \sum_{l=1}^{N} \delta_{hl} \quad \forall h \tag{1f}$$

$$\sum_{h} |p_h - B_h| \leq \Delta^* + \varepsilon \quad \forall h \tag{1g}$$

The first objective function Eq.(1a) minimizes the sum of deviations for the generator, Δ. The second objective function Eq.(1b) maximizes the revenue of the generator over the entire horizon. Term A represents the profit from the final dispatch, term B represents the minimum operating costs which are represented by the first point on the bid curve, term C is a linear representation of the bid curve of the generator, and term D is the start-up cost (this term is zero if generator is not starting up at timestep h i.e. $y_h^{SU} = 0$) It is constrained by Eq.(1c), bounds on the bid power for each timestep, and Eq.(1d), the definition of deviation between final dispatch, p_h, and bid power, B_h. The continuous auxiliary variable δ_{jhl} is a linear correction for the piecewise bid curve. Eq.(1e) and Eq.(1f) describe the variable's behavior, which allows the selection of the proper segment of the piecewise bid curve when π_{hl} is increasing in l, i.e., the piecewise cost curve is convex. The thermal generator model also adds constraints to the problem and includes all the discrete decisions for the generator (whether it is on/off, starting up, or shutting down at each timestep). To solve the problem, objective functions are solved using lexicographic ordering, placing full priority on Eq.(1a) first, then optimizing with the second objective. To ensure the minimum deviation value is enforced in the second objective, constraint Eq.(1g) is added to constrain the deviation between the optimized first objective, Δ^*, and a small number ε (approximately 10^{-2}).

3. Results and Discussion

To test the shortcut market simulator algorithm, we analyze a single node from the RTS-GMLC data set named "Adams". One month of the node's dispatch was simulated using a rolling horizon algorithm. The historical LMPs came from a full market clearing simulation in Prescient. The dispatch results from the shortcut simulation and Prescient were then compared. Problems M1 and M2 were formulated in Pyomo (Hart et al. 2017) and solved using Gurobi. The optimization problem contained 194 variables (122 continuous, 72 binary) for the 24-hour sub problem solved during the rolling horizon. The total 31-day shortcut market simulator algorithm took ~532 seconds. In small-scale tests, we found the shortcut market simulator algorithm was approximately 100-times faster than conducting a full market clearing in Prescient.

Comparing the results of Prescient with the shortcut simulation revealed the accuracy of our proposed approximation. Figure 2 (left) shows the generator dispatch schedules from the shortcut simulator (solid line) and Prescient (dotted line) for one quarter of the 31-day rolling horizon case study (hours 186-372). Only three time periods in this portion of the simulation, circled in red, show differences in the dispatch profiles. When analyzing the points where the shortcut simulator's dispatch did not match Prescient's dispatch, we observed two main trends. First, the shortcut simulator heavily

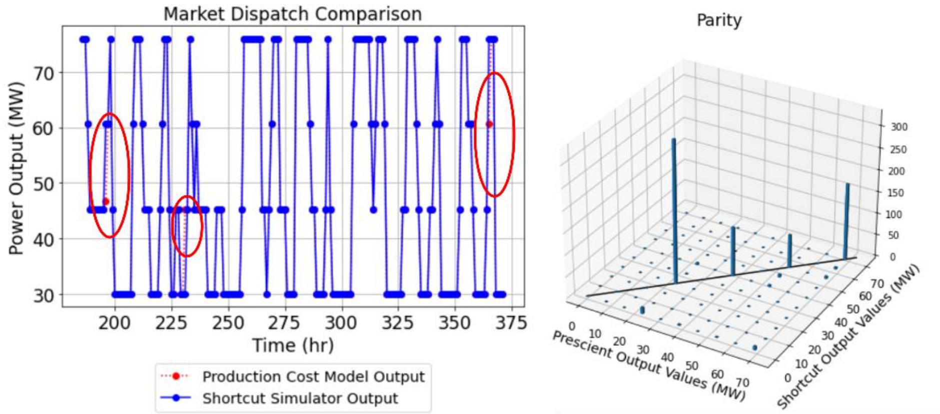

Figure 2: (left) generator dispatch schedule, comparing dispatch results from production cost model (red, dotted line) and shortcut market simulator (blue, solid line) for hours 182-372 of the 31-day simulation. The three red ovals show small discrepancies between output of the shortcut simulator and Prescient PCM. (right) parity between dispatch results from production cost model and shortcut market simulator.

favors the upper bound on bid power, set in the lookup dispatch step. Second, because Prescient makes unit commitment decisions (start-up/shut-down) in the DAM, the shortcut simulator finds different unit commitment while considering RTM prices. Figure 2 (right) shows a 3D parity plot, demonstrating the frequency of timesteps that match exactly. Approximately 67% of the dispatch points match. Overall, the shortcut simulator predictions had approximately 4% error in cumulative power output (summed over the entire horizon) as compared to Prescient.

4. Conclusions and Future Work

The case study provides initial validation of the proposed shortcut simulator to approach dispatch schedules using only historical LMPs, bid curves, and generator characteristics. Coupled with market participation optimization formulations (e.g., Dowling, 2017a), this can enable new approaches to estimate the economic performance of new technologies such as integrated energy systems when participating in markets. Ongoing work includes analysing all nodes of the RTS-GMLC dataset to further benchmark the accuracy of this proposed method. Moreover, the proposed shortcut simulator can be used to improve the realism of technoeconomic evaluations by considering bidding, the dominant mode to participating in markets, instead of the common self-schedule assumption.

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References

Arent, Douglas J., Shannon M. Bragg-Sitton, David C. Miller, Thomas J. Tarka, Jill A. Engel-Cox, Richard D. Boardman, Peter C. Balash, Mark F. Ruth, Jordan Cox, and David J. Garfield. 2021. "Multi-Input, Multi-Output Hybrid Energy Systems." *Joule* 5 (1): 47–58.

Arroyo, J. M., and A. J. Conejo. 2000. "Optimal Response of a Thermal Unit to an Electricity Spot Market." *IEEE Transactions on Power Systems* 15 (3): 1098–1104.

Carrión, Miguel, and José Manuel Arroyo. 2006. "A Computationally Efficient Mixed-Integer Linear Formulation for the Thermal Unit Commitment Problem." *IEEE Transactions on Power Systems* 21 (3): 1371–78.

Dowling, Alexander W., Ranjeet Kumar, and Victor M. Zavala. 2017. "A Multi-Scale Optimization Framework for Electricity Market Participation." *Applied Energy* 190 (March): 147–64.

Dowling, Alexander W., Tian Zheng, and Victor M. Zavala. 2017. "Economic Assessment of Concentrated Solar Power Technologies: A Review." *Renewable and Sustainable Energy Reviews* 72 (June 2016): 1019–32.

Ela, E, M Milligan, A Bloom, A Botterud, A Townsend, and T Levin. 2014. "Evolution of Wholesale Electricity Market Design with Increasing Levels of Renewable Generation," no. September: 1–139.

"GridMod/RTS-GMLC: Reliability Test System - Grid Modernization Lab Consortium." n.d. https://github.com/GridMod/RTS-GMLC.

Hart, William E., Carl D. Laird, Jean-Paul Watson, David L. Woodruff, Gabriel A. Hackebeil, Bethany L. Nicholson, and John D. Siirola. 2017. *Pyomo — Optimization Modeling in Python*. Vol. 67. Springer Optimization and Its Applications. Cham: Springer International Publishing.

"Prescient." n.d. https://github.com/grid-parity-exchange/Prescient.

Seel, Joachim, Andrew Mills, Ryan Wiser, Sidart Deb, Aarthi Asokkumar, Mohammad Hassanzadeh, and Amirsaman Aarabali. 2018. "Impacts of High Variable Renewable Energy Futures on Wholesale Electricity Prices, and on Electric-Sector Decision Making." https://emp.lbl.gov/publications/impacts-high-variable-renewable.