Demand Bidding Models for Chemical Processes: Conceptual Framework and a Chlor-Alkali Optimal Power Flow Example

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Abstract

In recent years, the integration of renewable energy resources has significantly increased the variability of power generation rates in the power grid. As a result, balancing power supply and demand has become more challenging. Price-based demand response programs partially address this problem in the sense that they incentivize (large) users to reduce their consumption during peak demand periods. However, the resulting load changes remain relatively unpredictable to the grid operator. Demand bidding has the potential to improve the predictability as large electricity consumers submit electricity load bids to the grid and adjust consumption during critical time intervals. In this work, we propose a demand bidding model for industrial plants and validate it using a prototype system comprising the IEEE 24 Bus reliability test case and chlor-alkali plant as the load entity.

Keywords

Demand response, Bid-in electricity, Optimal power flow, Chlor-alkali

1 Introduction

In recent years, the increased contribution of variable renewable energy resources (such as wind or solar photovoltaics) to the generation portfolio has significantly increased the variability of power generation in the power grid. Considering the inherent variability of demand, balancing power generation and demand has become more challenging. To some extent, energy storage can address this problem (Huggins, Huggins), but installing grid-level storage capacity remains costly. To mitigate this pressure, programs like price-based demand response (DR) (Vahid-Ghavidel et al., 2020) can engage the end-users, especially large consumers like industrial plants, to lower their electricity demand during peak hours (when electricity price is high). However, the users are not obligated to reduce demand even if prices are high, and the response of loads to price changes remains uncertain from the grid operator's perspective.

From the point of view of the grid operator, there is significant value in making load changes more predictable; intuitively, one way to do so is to establish the framework for large loads to behave similar to generators. Demand bidding programs are a means to this end (Li and Hong, 2016), and represent an option for (large-scale) users, such as industrial plants, that have the ability to vary their electricity usage, i.e., have flexible production schedule or operating modes. In this context, the industrial plants submit bids for electricity use at different time intervals. This is similar to the dispatch of power generators, with the notable difference that it involves dispatch of loads rather than of generation.

Demand bidding allows consumers to actively participate in the market and potentially set the market price. The strategy enables two-sided participation (both supply and consumption) in the electricity markets, which involves better communication and information exchange between both sides and the market operators. Compared to DR programs (which result in unpredictable load changes), demand bidding allows the grid operator to schedule flexible loads.

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Specifically, it enables access to the real demand curve, which adds more flexibility for finding an efficient market equilibrium. With demand bidding, users can reschedule, increase, or reduce their loads according to the bidding results at the grid level, which can help balance the demand and supply, maintain and improve the quality of supply, and improve the system reliability and resilience. Demand bidding not only allows the consumers to take control of their own electricity costs (Li and Hong, 2016; Mohsenian-Rad, 2014), but also makes the market more efficient and reliable (Iria et al., 2018).

Motivated by the above, in this work, we propose an incipient demand bidding model for chemical plants in day-ahead (DA) or real-time (RT) electricity market. Specifically, we discuss a linear demand bidding model considering an electricity-intensive plant with single product and constant product demand rate.

The manuscript is organized as follows: the general ideas of demand bidding models using simple one-period and multi-period scenarios are described. A case study is presented, consisting of a chlor-alkali plant load operating within a grid structure based on a modified IEEE 24-bus reliability test system (RTS) (Soroudi, 2017). The linear demand bidding model is integrated into the optimal power flow (OPF) formulation. Simulation results are discussed, and contrasted with those obtained using a previously-introduced linear cooperative DR scheduling model (Otashu et al., 2021). Directions for future work are also presented.

2 Demand Bidding Model: Framework and Formulation

Principles and Assumptions

As is the case in demand response programs, it is assumed that a user willing to engage in demand bidding will consume more electricity if the cost of consumption decreases. Users are expected to follow dispatch signals from the grid operator, but are not forced to. However, it is expected that consumption significantly outside of the dispatch signals may have much higher price. In fact, high deviation penalties are likely a key reason for the low participation rate for demand bidding – grid operators may even ban users failing to follow dispatch signals repeatedly participating in the RT market. Each user is assumed to have identified an electricity price threshold beyond which no consumption is the best option economically. Electricity price bids are expected to clear within a certain price range, but occasionally clear above an extreme upper limit, below the lower limit or may be negative. Extremely high clearing prices could occur during severe situations that cause major disruptions to generation/transmission/distribution capacity (e.g., the 2021 Texas winter storm ((EMP), 2021)), while extremely low clearing prices may occur due to renewable curtailment. It is also assumed that a participating user can modulate its consumption over a useful interval of time (i.e., "not too long") and operates continuously (i.e., without needing to shut-down completely and restart) within some production rate/ power demand bounds that are known.

Demand Bidding Concept

We illustrate our ideas with a simple one period case, a single load and a single generator. A bid is assumed to be the value of energy consumption cost for the user and the only avoidable cost. The goal is to maximize the market surplus $B_1P_1 - C_2P_2$ (i.e., revenue - cost) and the decision variable is the electricity consumption/generation $P_1 = P_2$. The price of selling products made with one unit of electricity consumption is B_1, the cost of generating one unit unit of electricity is C_2. Since the market model below is convex, the dual variable of the power balance equation (1b), λ, gives the locational marginal price (LMP). Upper and lower bounds are set on P_1, reflecting the range of operating capacity for the user, and an upper bound is set on P_2 reflecting the fact that generation capacity is limited.

$$\max_{P_1} B_1P_1 - C_2P_2 \tag{1a}$$

$$P_1 - P_2 = 0 \tag{1b}$$

$$P_1^{min} \le P_1 \le P_1^{max} \tag{1c}$$

$$0 \le P_2 \le P_2^{max} \tag{1d}$$

(1)

Depending on the relationship between the values of parameters B_1 and C_2, as well as the values of the consumption and generation bounds, the solution of problem (1a) broadly follows three cases as shown in Table 1. In the first case, the locational marginal price is the sale price of the product, the consumer breaks even, and the generator registers a surplus of $(\lambda - C_2)P_2$. In the second case the locational marginal price is the generation cost of the generator, the generator breaks even, and the consumer registers a surplus of $(B_1 - \lambda)P_1$. In the third case, the value derived from selling the product is lower than the cost of electricity needed to make it; production is set to zero and there is no profit for either party.

Table 1: Different outcomes of the one-period demand bidding model

B_1, C_2	P bounds	P	λ
$B_1 \ge C_2$	$P_1^{max} > P_2^{max}$ $P_2^{max} > P_1^{min}$	$P_1 = P_2 = P_2^{max}$	$\lambda = B_1$
$B_1 \ge C_2$	$P_1^{max} < P_2^{max}$ $P_2^{max} > P_1^{min}$	$P_1 = P_2 = P_1^{max}$	$\lambda = C_2$
$B_1 \le C_2$		$P_1 = P_2 = 0$	

This model serves to explain the bidding behavior of a participant, but its practical implementation becomes meaningful only when recognizing that total electricity use/generation cannot typically be set to zero (i.e., there will be a demand for product that must be satisfied, thereby requiring *some* electricity consumption to occur) and that the generation rates are set to meet the demand of a (large) set of consumers. Additionally, the product generated using electricity P_1 can be stored, and electricity consumption at a given time can exceed (or, indeed, drop below) the level of consumption required to meet instantaneous demand. We resolve these points by integrating these concepts within a multi-period optimal power flow problem below.

3 Case Study: Demand Bidding for Chlor-Alkali Production

Process Description

The core of the chlor-alkali production process is the electrolysis of brine (sodium chloride solution) to chlorine and sodium hydroxide, which accounts for roughly 50% of the total electricity consumption of the process. Other important production units are shown in Figure 1. The process model is based on the work of Otashu and Baldea (2019). The plant is designed to meet a daily demand of 55 tons of chlorine, although the maximum daily production capacity is slightly higher.

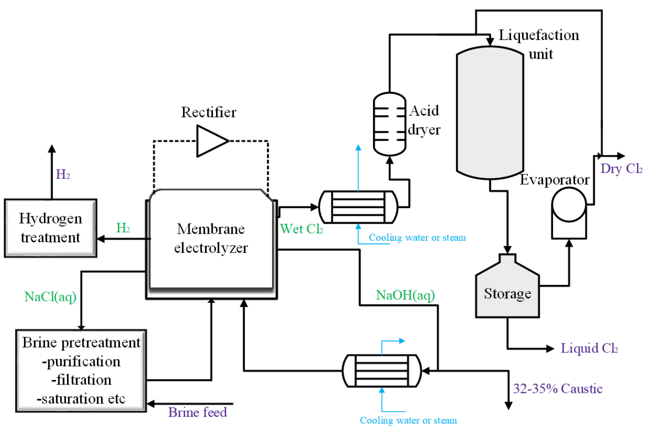

Figure 1: Process flow diagram of chlor-alkali production.

Optimal Power Flow Problem

In power systems, a typical short-term operation modeling problem is the optimal power flow problem (OPF) (Bakirtzis and Biskas, 2003; Zimmerman et al., 2010). The goal of OPF is to minimize the operating costs of the system by varying generation rates of generators while maintaining an active power balance and satisfying transmission constraints (Soroudi, 2017).

In this case study, a modified IEEE 24-bus Reliability test system (RTS) structure (Figure 2) that includes renewable power generation and battery energy storage is used as the support for setting up a DC-OPF (which has the benefit of resulting in a linear optimization problem). Each bus (i) has an associated power demand (Pd_i), and load shedding (LS_i) with the unit value of load loss being ($VOLL$). For wind power generation (P^w), wind curtailment (P^{wc}) is considered, with a unit value loss of wind curtailment (VWC). For battery operation, we consider the power for charging (P^c), power discharged (P^d), as well as state of charge (SOC). The problem involves several operating constraints including transmission line capacity, generator ramp rates, SOC limits, etc. The reader is referred to the original publication by Soroudi Soroudi (2017) for further details.

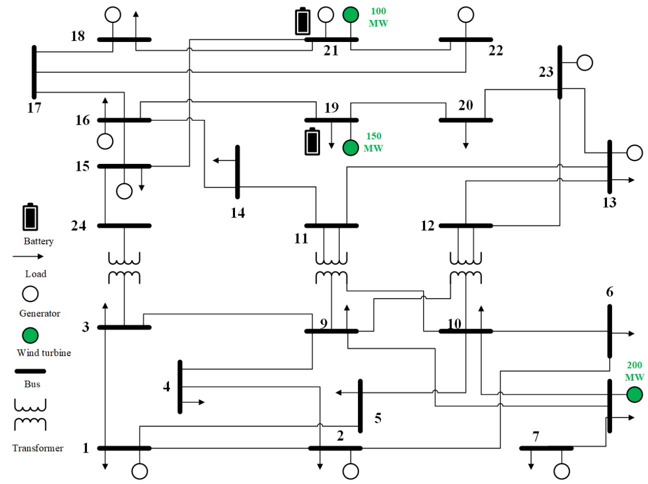

Figure 2: The IEEE 24-bus RTS with wind turbines and battery energy storage.

For the purpose of this case study, we focus on the active power balance and the objective function (OF), as formulated in Equations 2. Balancing active power requires the total production to equal total served demand at all times (discrete time interval t). The active power flow P_{ij} on line ij is calculated from voltage angles (θ) and the circuit susceptance (S) connecting bus i to j. In the linear case, the locational marginal price LMP (λ) will be obtained as the shadow price of the active power balance. The goal is to minimize the operating cost (OF) including the cost of power generation from generators (with unit generation cost of C_{2g} for generator g), transmission, and value loss of loads or renewables (wind curtailment in this case). OF can be expressed as a linear combination of the relevant variables as shown in Equation 2b.

$$\min_{P} OF(P_{2g,t}, LS_{i,t}, P^{wc}_{i,t}) \tag{2a}$$

$$OF = \sum_{g,t} C_{2g} P_{2g,t} + \sum_{i,t} VOLL \times LS_{i,t} + \sum_{i,t} VWC \times P^{wc}_{i,t} \tag{2b}$$

$$\sum_{g} P_{2g,t} + LS_{i,t} + P^{w}_{i,t} - Pd_{i,t} - P^{c}_{i,t} + P^{d}_{i,t} = \sum_{j} P_{ij,t} : \lambda_{i,t} \tag{2c}$$

$$P_{ij,t} = S_{ij}(\theta_{i,t} - \theta_{j,t}) \tag{2d}$$

(2)

Embedding Demand Bidding in OPF

Several modifications are needed to integrate demand bidding in the OPF problem. In the active power balance constraint, the power consumption of the bidding entity should be included as shown in Equation 3c. Then, according to the formulation of the demand bidding model, the objective function is updated to maximize the market surplus, i.e., minimize the total cost considering the profit derived from selling the product made by the bidding load (Equation 3b). Reflecting on the observation made earlier regarding the need to meet product demand, an integral constraint (3d), is introduced to ensure that the total production (Pt_{1i} over the time considered is equal to the product demand (D_i). This constraint is usually not considered in an OPF problem, and is to be expected to complicate the solution given its integral nature (i.e., the fact that it involves variables that span all time intervals).

There are two important bid-in parameters: B_1, the unit profit per unit electricity consumed by the plant which depends on the market prices of the products and reactants;H_1, unit production per unit electricity used, which is a function function of the plant efficiency.

$$
\begin{aligned}
&\min_P OF(P_{2g,t}, LS_{i,t}, P^{wc}_{i,t}, P_{1i,t}) && \text{(3a)}\\
&OF = \sum_{g,t} C_{2g}P_{2g,t} + \sum_{i,t} VOLL \times LS_{i,t} + \sum_{i,t} VWC \times P^{wc}_{i,t} \\
&\qquad - B_1 \times \sum_{i,t} P_{1i,t} && \text{(3b)}\\
&\sum_g P_{2g,t} + LS_{i,t} + P^{w}_{i,t} - Pd_{i,t} - P^{c}_{i,t} + P^{d}_{i,t} - P_{1i,t} \\
&\qquad = \sum_j P_{ij,t} : \lambda_{i,t} && \text{(3c)}\\
&Pt_{1i} = \sum_t H_1 \times P_{1i,t} = D_i && \text{(3d)}
\end{aligned}
\tag{3}
$$

For this case study, we assume that the chlor-alkali plant is connected to bus 7. The power demand of the plant is variable since the production rate can be varied by adjusting the current density in the electrolyzer cells. The plant power demand can vary between 3.7 and 9 MW, which are the lower and upper bounds defined in the bidding model. The value of parameter B_1 was determined to be 330 \$/MWh (Dwilkins, 2020) and H_1 was determined as 0.455 tons Cl_2/MWh (O'Brien et al., 2005). In principle, both vary with the operating conditions, but for this case study we assumed them to be fixed and we computed their values from plant performance and economic information that is publicly available.

Baseline Model: Cooperative DR scheduling with OPF

For comparison, a cooperative DR scheduling model from previous work Otashu et al. (2021) is considered. The cooperative model relies on solving the OPF problem by minimizing the overall cost of power generation, while at the same time accounting for the integral production constraint (4d). A linear state space model of the process dynamics is used to represent the relationship between production rate and power consumption. As in the case of the demand bidding model, the active power balance constraint includes the plant power consumption for the relevant node(s). However, here the grid operator is fully aware of the process dynamics and has full control over the process operation.

$$
\begin{aligned}
&\min_P OF(P_{2g,t}, LS_{i,t}, P^{wc}_{i,t}) && \text{(4a)}\\
&OF = \sum_{g,t} C_{2g}P_{2g,t} + \sum_{i,t} VOLL \times LS_{i,t} + \sum_{i,t} VWC \times P^{wc}_{i,t} && \text{(4b)}\\
&\sum_g P_{2g,t} + LS_{i,t} + P^{w}_{i,t} - Pd_{i,t} - P^{c}_{i,t} + P^{d}_{i,t} - P_{1i,t} \\
&\qquad = \sum_j P_{ij,t} : \lambda_{i,t} && \text{(4c)}\\
&Pt_{1i} = \sum_t H_1 \times P_{1i,t} = D_i && \text{(4d)}
\end{aligned}
\tag{4}
$$

4 Results and Discussion

The OPF problem modified using the two approaches (demand bidding and cooperative DR scheduling), was implemented in GAMS (Distribution 35.1.0) and solved using the CPLEX LP solver (version 20.1). Based on the results, we discuss the power consumption/production schedule of the plant, locational marginal prices (LMPs), as well as energy usage and cost (calculated from power consumption and LMP) below.

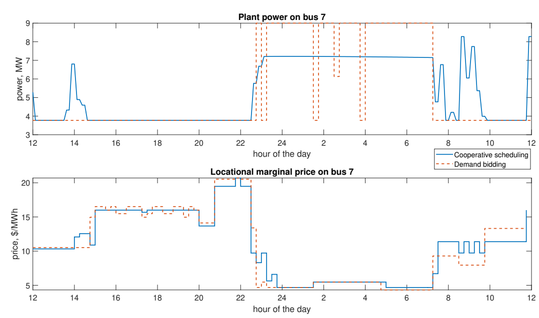

Figure 3: Plant power consumption and LMP for bus 7 for both demand bidding and cooperative DR scheduling ("cooperative scheduling") cases.

Figure 3 shows the chlor-alkali plant power consumption and the LMPs over the 24-hour time horizon for both demand bidding and cooperative DR scheduling cases. The evolution of plant power demand and LMP in demand bidding case is close to the corresponding values in the cooperative case. Because the bidding model is linear, the rapid changes in the decision variable – the power consumption of the plant – are akin to "bang bang" control, leading to abrupt transients. Note that this is not the case in the cooperative scheduling case, where the scheduling calculation includes a representation of the process dynamics. We thus expect that imposing realistic ramp rate constraints on production would mitigate the abrupt transients in the demand bidding case.

Table 2 shows the energy generation/consumption and associated costs. The total energy generated/consumed in the power system is 198,977 MWh in the cooperative scheduling model, which is quite close to the value predicted in the demand bidding case. Note that the objective function value in the cooperative scheduling case is the total operating cost, whereas in the demand bidding case the objective function involves market surplus and thus also considers the profit of the plant. If only the generation and loss costs are taken into consideration, the values of the objective function for both cases are similar. The total energy use and associated cost to the plant are similar as well. This indicates that demand bidding model is promising, resulting in solutions that are comparable to the baseline model using full plant dynamics, although far less plant information is used in the demand bidding model, and all the information except for the daily production demand, can be derived from public sources.

Table 2: Energy utilization and associated costs for the grid and plant

	Cooperative scheduling	Demand bidding
Total energy generation (MWh)	198,977	198,131
OF ($)	1,804,718	1,764,403
Generation and loss costs ($)	1,804,718	1,807,400
Energy utilization by plant (MWh)	127	130
Energy cost to the plant ($)	1,189	1,157

Finally, it is worth pointing out that this is not a fully equitable comparison, since in practice the electricity consumed per unit production changes as the operating conditions change, which is reflected in the dynamic model used in the baseline case; on the other hand, the demand bidding model assumes that this value is constant.

5 Conclusions

An increased contribution of renewable energy to the power generation portfolio requires that grid operators manage power generation and consumption more efficiently and flexibly. Large loads, such as flexible electricity-intensive industrial plants, are good candidates for demand-side management programs including price-based DR and demand bidding. In this work, we proposed a demand bidding model where industrial plants submit bids for electricity use to the grid, effectively acting as "virtual generators." An initial validation of the bidding model was accomplished through a comparison with a previous cooperative demand response approach, applied to a standard grid test case incorporating a chlor-alkali plant. The case study results suggest that demand bidding models have the potential to promote active participation of industrial plants as "virtual generators" without exposing extensive sensitive information regarding the plant dynamics, or ceding the control of plant operations to the grid. Further investigation of the demand bidding model should consider including necessary process constraints (such as ramp rates), testing in more complex scenarios (like a transmission congestion case or an industrial plant with a co-generation power plant), extending the approach to the case of multiple products, and developing distributed optimization algorithms that allow for protecting all relevant information of participating industrial entities.

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