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Grid-level "battery" operation of chemical processes and demand-side participation in short-term electricity markets

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HIGHLIGHTS

- Analysis of participation of electricity-intensive chemical processes in short-term electricity markets.
- Engagement managed via a two-tiered optimal scheduling approach.
- Considers speed of response of chemical process and market constraints.
- Extensive case study demonstrates real economic incentives for implementing this framework.

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ABSTRACT

The participation of power-intensive industrial chemical processes in short-term electricity markets (STMs) in addition to long-term markets (LTMs) is considered. STMs are highly volatile with dynamics of the order of seconds to minutes. It is thus imperative that production scheduling for chemical process participation in such markets (1) be carried out repeatedly to reflect ongoing changes in market conditions (2) account for process dynamics to guarantee feasibility, since frequent changes in production rate targets imply transient plant operation. To address these challenges, a novel production scheduling framework is formulated, consisting of a fixed-horizon scheduling problem for the LTM and a shrinking-horizon scheduling problem for response to STM changes. A case study illustrates that unused demand response (DR) potential from the LTM can be strategically deployed in STMs to improve grid operations and increase profit for the chemical process.

1. Introduction

Electricity generation from renewable resources has increased significantly over the past decade [1]. The introduction of intermittent sources like wind and solar generation into the power generation portfolio has complicated the already challenging task of balancing power demand and supply. One way to offset instantaneous electricity demand-supply mismatch is the use of energy storage, whereby batteries can be charged during off-peak hours when there is an excess supply of electricity and discharged during peak electricity demand hours. Other means of resolving the resulting grid variability challenge entails the participation of end users. Time-sensitive electricity pricing schemes for example, have been adopted to encourage demand response (DR) from both industrial users, and residential and commercial consumers. In this context, electricity is typically sold at higher rates during peak hours (when grid demand is high) and at lower rates during off-peak hours (when demand declines). Users can voluntarily modify their consumption patterns to incur less cost. In *incentive-based* DR programs, participants provide ancillary services to the grid, and are typically rewarded on a per occurrence basis for helping improve grid reliability by offering system operators handles with which real-time power generation and load can be balanced [2–5].

DR programs achieve different levels of engagement from the target participants. For industrial users, the extent of participation is highly dependent on the operational flexibility of the industrial plant [6–8]. Engagement in incentive-based programs is particularly demanding in terms of flexibility and agility, since these programs are designed to sustain grid reliability in the event of short-term supply-demand imbalances [2,9] and typically require fast and abrupt changes in the operating pattern of the production facility.

In the present study, we distinguish between long-term and short-term energy markets based on how far in advance electricity prices are known with certainty and the frequency at which prices change. We define these markets based on the operation of the Electricity Reliability Council of Texas (ERCOT), as described in [10]. Under this definition, we refer to the day-ahead market (whereby electricity prices

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are established once a day and known for 24 h in the future with hourly granularity) as a *long-term market (LTM)*. Conversely, in this work, the *short-term market (STM)* covers frequent, sub-hourly (specifically, fifteen minute) changes in electricity tariffs, which are known at most one hour in advance of the tariff becoming effective.

Electricity prices exhibit varying amounts of volatility (defined as the price rate of change, or the difference in price between two subsequent time intervals), as illustrated in Fig. A.1. The STM is typically more volatile. Also, there can be significant discrepancies between STM and LTM prices at any given point in time. STM prices could be lower than the corresponding LTM price, spike to values that are more than one order of magnitude higher than the LTM counterpart or even decline to negative values. While participation in the STM carries risks, these variations can be exploited by users to save cost or earn revenue.

Being aware of this electricity price variations is paramount for industries with high power usage. Industrial chemical processes that incur significant operating expenses from electricity purchases (e.g. air separation, aluminum smelting, chlor-alkali) can lower their energy costs by scheduling production in response to variable electricity prices. Effectively, energy intensive industries offer load reductions earning income as “electricity storage” providers in the energy market. By overproducing during off-peak demand hours and storing excess product to supplement a reduced production rate during peak hours, a chemical plant can serve as a “grid-level storage battery”. This production pattern requires that both excess production capacity and product storage facilities be available. Recent studies indicate that industrial plants can improve their economic performance 40–100% significantly [11] and mitigate risks associated with uncertain electricity price [12] by engaging in multiple electricity markets simultaneously. Scheduling plant production to allow for participation in both long-term and short-term markets will likely lead to greater cost savings compared to sole engagement in LTMs.

This work aims to explore the benefits of the participation of energy intensive processes in STMs in addition to LTMs. To do this, we focus on continuous (rather than batch) processes and propose a two-tier scheduling formulation. In the top level problem, an optimal production schedule for the process is computed over a fixed time horizon based on LTM price. This optimal profile may not necessarily imply operation at the limits of the plant and additional production and storage capacity may be available. Thus, in the lower tier problem, we compute the maximum load reduction available per sub-hourly interval that can be attained by the process with consideration of process dynamics and safety. This extra load reduction is defined as the plant “DR headroom”. Based on incentives presented in the STM, this DR headroom if available, will be deployed (i.e. production schedules from the lower tier formulation will be implemented). The lower level problem is repeatedly solved over a shrinking time horizon to accommodate changes in the STM and plant production profile, e.g., ramping up production to make up for down times. Throughout this work, we neglect any constraints related to the power grid, and assume that the grid is able to fully utilize the DR capabilities of the industrial facility.

The paper is organized as follows: we present a background on the modeling of chemical process systems for fast DR and the paradigm of employing industrial processes as grid-level storage batteries through relevant scheduling. In the context of existing literature (which we review in the next section), we highlight the key contributions of our work:

- definition of a utility-relevant process variable called “DR headroom” for aiding “battery"-like operation of industries, chemical processes
- development of a multi-level scheduling framework for the engagement of continuous energy intensive plants in multiple electricity markets including active engagement in STMs,
- employing dynamic process models in the scheduling framework developed above and highlighting the impact of the dynamic agility of the process (represented by its time constant) on its ability to participate meaningfully in STMs.

We present the overarching problem statement and solution approach based on the underlying assumptions of the problem presented. Finally, we illustrate the given solution approach with simulation case studies based on a large set of electricity price data collected from ERCOT, the Texas grid operator.

2. Modeling industrial processes for fast demand response

The engagement of process industries in DR has gained increased attention in recent times [13–16]. Research [17–24] shows that industrial DR can potentially facilitate the integration of variable renewable energy sources into the power grid. Diverse DR mechanisms for manufacturing industries have thus been investigated, including incorporating energy storage devices [25,26] and leveraging time-varying day-ahead market (DAM) prices for flexible plant operation [27–32].

More recently, efforts have been made to extend industrial DR to include response in faster-paced markets such as spot markets [33]. Frequent schedule changes over time horizons that overlap the process time constant lead to transient plant operation. A consequent important question regards how much of the process dynamics should be modeled to represent adequately the transient plant response [34,35]. Conventional plant production scheduling approaches (Table 2) which rely on steady state plant models [36,37] (possibly along with transition time arrays or rate of change constraints [38–41]) cannot predict adequately the dynamic response of the plant [42].

A modification to conventional scheduling [44] in which detailed transition profiles are computed off line from dynamic process models is similarly unsuitable for adequately representing the transient plant behavior since this formulation still assumes that steady state is attained between production target changes which very often, is not the case in fast DR.

On the one hand, detailed, first-principles process models can be used to express the dynamic response of the process. However, such models are typically of high order and nonlinearity, requiring significant computational time. This becomes a challenge when the model has to be repeatedly solved to provide updated schedules that reflect the current market conditions. This is very often the case when engaging in STMs. With scheduling for STM engagement the problem size is enlarged with more decision variables since schedules change on a sub-hourly basis. Data-driven surrogate models have been proposed to define a (convex) feasible operating region in the space of the process variables [45], thereby reducing the size of the scheduling problem.

The concept of Scale Bridging Models (SBMs) has been proposed [46] as a dynamic modeling framework for DR scheduling calculations. SBMs are a set of low-order representations of the closed-loop dynamic behavior of a chemical process, that is relevant to scheduling calculations (including, e.g., the evolution of production rate and product quality following changes in production targets, and hence, electricity consumption). Unlike conventional models utilized for scheduling, SBM are adapted for use in scheduling calculations geared towards DR participation. By incorporating process dynamics in the scheduling framework, SBMs guarantee feasibility of process operations even during transient operation of a plant. The associated scheduling models exhibit good computational performance. For example, SBMs developed for cryogenic air separation process have been shown to reduce computation time by two orders of magnitude compared to using a full-order, first-principles model of the plant [42,47]. SBMs that capture the evolution of process input variables (manipulated variables) that affect the economic objective function have also been identified and incorporated into scheduling calculations for sample processes [48].

In this work, we capitalize on the benefits of SBMs to develop a novel framework for the computation of the operating schedule of an