Evaluating Demand Response Particibility Potential of Process Systems using Levelized Cost Analysis

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Abstract: This work examines the impact of process design decisions on the ability of a process to participate in Demand Response (DR) activities. Focusing on load shifting capabilities, the DR particibility potential of a given process design is evaluated using the notion of levelized cost of the load-shifting capacity, which is taken as a measure of an overall cost of the design decisions over the lifetime of the process. Initially, the concept of levelized cost of energy (LCOE), or levelized cost of electricity, is introduced and adapted to capture the levelized cost of load-shifting (LCOL). Then, a bottom-up approach to calculate the load-shifting capacity for a given process design, and the associated levelized cost, is developed based on an MILP scheduling model. The implementation of the proposed approach is demonstrated using a conceptual case study involving a reactor-storage process with a discretized scheduling model. The case study investigates the differences in load-shifting capacities when considering DR participation in a day-ahead electricity market versus participation in a five-minute market.

Keywords: Demand Response, Process Design, Process Scheduling, Process Control, Supply Curves.

1. INTRODUCTION

Demand Response (DR) has become an increasingly important tool for balancing power supply and demand under an ambitious renewable portfolio standard, keeping the electric grid stable and efficient; deferring upgrades to generation, transmission and distribution systems; and providing tangible economic benefits to customers. The economic potential of DR operation in energy-intensive industrial processes has been studied extensively (see, e.g., Wang et al. (2017); Brée et al. (2019)). Early works formulated the problem using mixed-integer linear programming (MILP) models, where the optimal process scheduling sequence that minimizes the total operating cost under time-varying electricity prices is determined (see, e.g., Mitra et al. (2012)). Subsequent efforts focused on the integration of the scheduling problem with process dynamics (see, e.g., Pattison et al. (2016); Tong et al. (2017)) and on the optimal design of processes under demand-side management (see, e.g., Pattison and Baldea (2014); Cao et al. (2015)). A framework for the design and operation of process networks that meet DR objectives through both operational and configurational changes was also developed in Wang et al. (2015) and Liu et al. (2020).

While the above works have investigated the participation of processes in the time-varying electricity markets, the potential for demand flexibility of a process from the design perspective remains an open question. Specifically, the impact of process design (and the associated costs) on the ability of the process to participate in certain DR services (DR particibility) needs to be assessed. One metric that can be used to assess the DR particibility potential of a process is its load-shifting capacity. Load shifting refers to a DR approach that involves moving electrical loads from one time to another to better match either the availability of low-cost power or to "valley fill" grid-level load requirements (i.e., peak-clipping), while providing equivalent energy service to the end user. Naturally, a process can serve as a shift resource by adjusting its consumption pattern. A key motivating question here is whether different designs can be compared in terms of how much load shifting they could enable. If one could quantify the load-shifting potential, would it be worthwhile to perform the process design from this perspective?

In a previous study (Liu et al. (2021)), a model-based framework was proposed to assess the potential of a process to participate in load-shifting services based on the capital cost of various design alternatives through the use of supply curves. However, the full life-time costs of a process, including the investment, the operation and maintenance, and the profit of the process over the investment period, were not considered in the evaluation of the design alternatives. Furthermore, the assessment was limited to participation in the day-ahead electricity market. The operation of processes that participate directly in the short-term electricity market (which requires a fast response from the process to the price signals) has received increasing attention in recent years (see, e.g., Dowling and Zavala (2018); Schäfer et al. (2018); Teichgraeber and Brandt (2020)).

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The objective of this work is to develop a systematic, and more comprehensive, approach for analyzing the impact of process design decisions on the DR particibility potential. The notion of levelized cost of the load-shifting capacity of a process, which takes account of both the capital and operating costs of the design decisions, is used to assess the cost-effectiveness of process design alternatives when considering participation in different time-varying DR markets. A bottom-up approach is developed, whereby a first-principles dynamic model is used first to construct a high-fidelity process operating range. The scheduling model is then implemented to quantify and analyze the load-shifting capacity, together with the associated levelized cost, under a specific electricity price profile. The results are illustrated using a simulated process example.

2. OVERVIEW OF METHODOLOGICAL FRAMEWORK

To assess the potential of a certain process design to enable participation in the DR market, we present in this work a bottom-up approach that starts with a first-principles dynamic process model which is used to construct a high-fidelity process operating range. A discrete MILP scheduling model is then developed and implemented to determine the load-shifting capacity and evaluate the cost-effectiveness of the process design.

The first step in this framework is to generate the feasible region for the operation-related decision variables. To this end, a first-principles dynamic process model is used to provide the scheduling model with a feasible operating range as well as the mode transition profile information. The feasible region also provides information on whether specific operational adjustments will violate system constraints such as safety constraints and production requirements.

The second step is to develop a scheduling-oriented operating model to evaluate the load shifting potential under a specific process design or capacity. We define the base load of the process and then calculate the load-shifting capacity for each design (e.g., with different inventory sizes or different capacity).

The last step is to construct the supply curve to demonstrate the "cost-effectiveness" of the various design alternatives. The scheduling model under different design parameters, such as process or inventory capacity, is implemented repeatedly, and the results are used to construct the supply curve. The supply curve, which is widely used in the field of economics, is a graphical representation of the correlation between the cost of a good or service and the quantity supplied for a given period.

In the following sections, we elaborate on the various components of the proposed framework. In the next section, we beginn by defining the *load-shifting capacity* metric which is used to quantify the DR capability of a process. The *load-shifting capacity* metric is then calculated using a scheduling-based model integrated with process dynamics.

3. QUANTIFYING DR PARTICIPATION POTENTIAL

3.1 Load-shifting capacity

A metric that can be used to quantify the DR capability of a process and assess its potential to participate in the time-varying electricity market (DR particibility) is the load-shifting capacity which can be defined as follows:

$$E^{shift} = \sum_t E_t^{shift} = \sum_t \frac{|E_t^b - E_t^s|}{2} \qquad (1)$$

where E^{shift} is the shifted load at time t; E_t^b is the base load at time t; and E_t^s is the real scheduled load at time t. In this study this metric is used to evaluate the load-shifting capacity only under the real-time electricity market (RTM), such as the day-ahead market (DAM) and the five-minute market (FMM). Theoretically, over a certain period of time, if the production requirement does not change and the operation remains unchanged, the total energy consumption over this period should be unchanged. However, the load-shifting capacity can be different if a different control strategy is used.

3.2 Levelized cost of load-shifting

The levelized cost of electricity (LCOE) is a measure of the average net present cost of electricity generation for a generating plant over its lifetime. This measure is used for investment planning and to compare different methods of electricity generation on a consistent basis, and is calculated as the ratio of all the discounted costs over the lifetime of an electricity generating plant to a discounted sum of the actual energy amounts delivered. By definition, LCOE is generally applied to the electricity generation unit, such as different renewable generation resources, and is computed as follows:

$$LCOE = \frac{\sum_{t=1}^{n}\left(\frac{I_t+M_t+F_t}{(1+r)^t}\right)}{\sum_{t=1}^{n}\left(\frac{G_t}{(1+r)^t}\right)}, \qquad (2)$$

where n is the lifespan of the system in years, r is the discount rate, G_t is the electricity generated in year t; I_t, M_t and F_t stand for investment expenditure, operation and maintenance, and fuel expenditures in year t, respectively.

While the LCOE concept has been widely used in energy system design, to the best of the authors' knowledge its application to chemical process design has not been reported previously. Note that LCOE, by definition, requires knowledge of the anticipated energy generation over a period of time. However, the majority of chemical processes - particularly energy intensive processes such as the chlor-alkali and air separation processes - are energy consuming. Therefore, the term G_t in Eq.2 cannot be specified if the LCOE metric were to be used directly to evaluate the cost-effectiveness of a certain process design. To address this problem, we adapt the LCOE concept to processes that have the potential to participate in DR services by defining a new metric, which is referred to as the levelized cost of load-shifting (LCOL).

The key idea is to use the load-shifting capacity of a process, as defined in Eq.1, to replace the term G_t in the LOCE metric in Eq.2. The modified metric (i.e., the LCOL) can then be used to quantify the cost associated with the load shifting capacity, and to compare different process designs in terms of their DR particibility potentials, or more specifically, their load-shift capacities. The LCOL is defined as follows:

$$LCOL = \frac{I + \sum_{t=1}^{n} \left(\frac{OM_t - Pro_t}{(1+r)^t}\right)}{\sum_{t=1}^{n} \left(\frac{E_t^{shift}}{(1+r)^t}\right)}, \tag{3}$$

where I is the investment capital, OM_t is the total operating cost, Pro_t is the profit generated by selling the product, and E_t^{shift} is the load-shifting capacity. The above expression incorporates all the elements required to determine the full life-time cost of a chemical process: investment, operation and maintenance (OM) as well as the profit of the process divided by electricity load shifted during the investment period. It assumes that all investment costs are incurred in the first year, and sums ongoing costs in each year up to the system lifetime. By utilizing this metric, we can better compare the design and operation of different processes while having a better understanding of how much DR potential a chemical process could provide to the grid as a "grid-level" battery.

The LCOE could be interpreted as the cost for the generation system to provide 1 MWh of electricity. Therefore, if the electricity price is higher than the LCOE, the generation system would be considered profitable. A similar interpretation can be made for the LCOL as how much it costs for a chemical process to provide 1 MWh of load-shifting capacity to the grid. While currently the grid does not directly provide payment for such service, one could still compare this metric to the levelized cost of a battery. For a battery, the levelized cost can be defined as how much it costs to store 1 MWh of electricity. A chemical process can therefore be compared with a battery in terms of the load-shifting capacity.

4. PROBLEM STATEMENT

We consider a conceptual production system where the process has the potential to participate in load-shifting DR services by scheduling production levels in response to variations in the electricity prices. The process has to satisfy an hourly product demand; and a storage unit is installed to provide the operational flexibility needed. DR decisions are assumed not to influence the electricity prices. We consider the capacity of the plant to be determined by two factors: the process capacity (e.g., reactor volume, column size) and the inventory (storage) capacity. The capacity of the process is typically the dominant factor; however, the inventory can still have a substantial impact on the choice of the operational level. Assuming the process will participate in the wholesale electricity market, with a certain required hourly demand, we would like to determine the required capacity of the process as well as the inventory size. To assess the LCOL of the plant under different market conditions, we first define two different discrete time sets: $t \in T$ and $st \in ST$. The set $T := \{1, 2, ..., N\}$ denotes the day-ahead market layer, where the time interval Δt is 1 hour, whereas the set $ST := \{1, 2, ..., N^{ST}\}$ specifies the 5-minute market layer, where Δst is an interval of 5 minutes. The overall time set T^* can then be defined as $T^* := T \times ST = \{(1, 1), (2, 1), ..., (N^{ST}, N)\}$.

5. FORMULATION OF SCHEDULING MODEL

We consider a discrete scheduling model in which a set of discrete operating modes are pre-defined. Once the process dynamic model is solved, the transition times and transition profiles among the different operating modes are determined. Such an approach, which utilizes fixed transition times that are computed a priori (off-line) is common for capturing process dynamics in process scheduling. The discrete model used here extends the one introduced in Tong et al. (2015), where a convexification of the bilinear term is performed to convert the model into a mixed-integer linear program (MILP) model.

5.1 Transition and mode constraints

We consider a set of discrete operating modes, each denoted by $m \in M$, and a set of different equipment, each denoted by $e \in E$. Defining $t \in T$ as the discrete time, we have:

$$\sum_{m \in M} y_m^{e,t} = 1, \tag{4}$$

where, $y_m^{e,t}$ is a mode-assignment binary variable that specifies whether equipment e is operating in mode m at time t. This constraint ensures that, at any time t, only one mode could be selected. Additionally, we have:

$$\sum_{m_1 \in M} z_{m_1,m_2}^{e,t} = y_{m_2}^{e,t}, m_2 \in M, e \in E, t \in T, \tag{5}$$

$$\sum_{m_2 \in M} z_{m_1,m_2}^{e,t} = y_{m_1}^{e,0}, m_1 \in M, e \in E, t = 1, \tag{6}$$

$$\sum_{m_2 \in M} z_{m_1,m_2}^{e,t} = y_{m_1}^{e,t-1}, m_1 \in M, e \in E, t > 0, \tag{7}$$

where $z_{m_1,m_2}^{e,t}$ denotes a transition binary variable that indicates whether a transition is occurring from operating mode m_1 to operating mode m_2 at time t. Eqs.5-7 are a group of transition constraints that specify whether there is a transition occurring between two modes for equipment e at time t, where $z_{m_1,m_2}^{e,t} = 1$ is true if and only if a transition from mode m_1 to mode m_2 occurs from time step $t-1$ to time step t.

5.2 Production constraint

The production rate for the plant at time t is computed as follows:

$$Q^t = \sum_{e \in E} \sum_{m_1 \in M} (y_{m_1}^{e,t} \frac{V^e}{\theta_{m_1}^e}) \left[1 - \sum_{m_2, m_1 \in M} (z_{m_2,m_1}^{e,t} \cdot tt_{m_2,m_1}^e)\right] \tag{8}$$

where Q^t is the total production rate at time t, $y_{m_1}^{e,t} \frac{V^e}{\theta_{m_1}^e}$ defines the production rate of equipment e operating in mode m_1, V^e is the capacity of equipment e, and $\theta_{m_1}^e$ is a time constant. The terms in the bracket define the total production time which excludes the times during which mode transitions take place. The term tt_{m_2,m_1}^e denotes the transition time from mode m_2 to mode m_1 in units of hours. It is noted that, when expanding Eq.8, a bilinear term that involves the mode assignment binary variable, $y_{m_1}^{e,t}$, and the transition binary variable, $z_{m_2,m_1}^{e,t}$, will appear. To eliminate the bilinear term, we perform a convexification as follows:

$$yz^{e,t}_{m_1,m_2} \leq y_{m_2};\ m_1, m_2 \in M, e \in E, t \in T, \tag{9}$$
$$yz^{e,t}_{m_1,m_2} \leq z^{e,t}_{m_1;\,m_2}, m_1, m_2 \in M, e \in E, t \in T, \tag{10}$$
$$yz^{e,t}_{m_1,m_2} \geq y^{e,t}_{m_2} + z^{e,t}_{m_1,m_2} - 1;\ m_1, m_2 \in M, e \in E, t \in T, \tag{11}$$

where $yz^{e,t}_{m_1,m_2}$ is the convexified term that will replace the bilinear term $y^{e,t}_{m_1} \cdot z^{e,t}_{m_2,m_1}$. With this convexification, Eq.8 can be replaced by the following convex linear constraint:

$$Q^t = \sum_{e\in E}[F^{e,t} - \sum_{m_2\in M}(\sum_{m_1\in M} yz^{e,t}_{m_1,m_2} \cdot tt^e_{m_1,m_2} \cdot \frac{V^e}{\theta^e_{m_2}})], \tag{12}$$

where the term $F^{e,t}$ is defined as

$$F^{e,t} = \sum_{m\in M} \frac{y^{e,t}_m \cdot V^e}{\theta^e_m}. \tag{13}$$

5.3 Inventory constraint

The inventory constraint relates the storage capacity S^t, the production rate Q^t and the hourly demand D^t, and is given by

$$S^t = S^{t-1} + Q^t - D^t,\ t > 0, \tag{14}$$

The storage capacity will be limited by the design size:

$$S^t \leq S^{max} \tag{15}$$

5.4 Objective function

The objective function for the scheduling problem is given as follows:

$$J_{schedule} = \min(\Phi_1 + \Phi_2 + \Phi_3), \tag{16}$$

where

$$\Phi_1 = \sum_{e\in E}\sum_{t\in T}\sum_{st\in ST} \pi^t_{st} \cdot P^{e,t}_{st}, \tag{17}$$

$$\Phi_2 = \sum_{e\in E}\sum_{t\in T} \delta^{raw} F^{e,t}, \tag{18}$$

$$\Phi_3 = \sum^{T} \delta^s S_t. \tag{19}$$

The term Φ_1 represents the power consumption cost, where $P^{e,t}_{st}$ is the power consumption for equipment e during the time interval (t, st), and π^t_{st} is the electricity price for the interval (t, st). In the case of the DAM, the price should be the same within the interval $t \in T$; thus, we could have $\pi^{t^*}_{st} = \pi^{t^*}$, where $st \in ST$. However, this is not true for the case of the FMM. The terms Φ_2 and Φ_3 represent the raw materials cost, and the inventory cost, respectively. δ^{raw} and δ^s denote the cost coefficients for that material and inventory costs, respectively.

5.5 Definition of the capital cost

The capital cost is calculated as follows:

$$\log_{10} C = K_1 + K_2 \log_{10}(A) + K_3[\log_{10}(A)]^2 \tag{20}$$

where C is the capital investment, A is the capacity or size parameter for the equipment, and K_1, K_2, and K_3 are the cost coefficients. The equation and the values of the parameters are taken from Turton et al. (2018).

6. CASE STUDY

For an illustrative case study, we consider a jacketed non-isothermal CSTR connected to a storage (inventory) system (see Tong et al. (2015)). The cost parameters of the CSTR system are taken from Turton et al. (2018).

6.1 Dynamic model and power consumption

The dynamic model of the CSTR is obtained from standard mass and energy balances, and consists of the following equations (Flores-Tlacuahuac et al. (2008)):

$$\frac{dc}{dt} = \frac{1 - c(t)}{\theta} - k_0 \exp\left(-\frac{n}{T}\right) c(t), \tag{21}$$
$$\frac{dT}{dt} = \frac{y_f - T(t)}{\theta} - k_0 \exp\left(-\frac{n}{T}\right) c(t) + \alpha u(t)(y_c - T(t)), \tag{22}$$

where c is a dimensionless reactant concentration, T is a dimensionless reactor temperature, and u is the coolant flow rate which is used as the manipulated variable. The process parameters include the time constant θ, the reaction rate constant k_0, a dimensionless activation energy n, and a dimensionless coolant temperature y_c. The values of the process parameters are taken from Flores-Tlacuahuac et al. (2008). Furthermore, the dimensionless reactor temperature is subject to the following constraint:

$$0 \leq T(t) \leq 1,\ \forall t. \tag{23}$$

We consider the main source of power consumption to be the reactor cooling duty which is given by:

$$Q_c = \alpha \Delta H V u(T - y_c). \tag{24}$$

where ΔH is the heat of reaction and V is the reactor volume. Based on this model, the cooling load scales with the CSTR volume, and the power consumption can then be calculated as follows:

$$P^{e,t}_{st} = \gamma(V) \sum_{m_2\in M}\sum_{m_1\in M} yz^{e,t}_{m_1,m_2} \cdot u^e_{m_1,m_2,st} \cdot (T^e_{m_1,m_2,st} - T_c), \tag{25}$$

where $P^{e,t}_{st}$ is the power consumption at st; $yz^{e,t}_{m_1,m_2}$ is the relaxed binary variable and $u^e_{m_1,m_2,st}$ specifies the power-related manipulated variable, and $\gamma(V)$ is the scaling factor where $\gamma(V) = \alpha\Delta HV$.

To calculate the baseline power consumption of the process, we first specify a base value for θ under a specific product demand for a CSTR size V. For example, for a CSTR size of 500 L, to satisfy an hourly demand of 50 L/hr, θ is 10 hr. This θ value is then used to calculate the required cooling power, which is used as the base power consumption for a 500 L-CSTR.

Transitions between different operating modes are enforced by means of a dynamic optimization-based controller. The objective function for the optimal control problem is given by:

$$obj = \Sigma_t[\beta(c(t) - c_s)^2 + \gamma(u(t) - u(t-1))^2], \tag{26}$$

where β and γ are the penalty weights, c_s is the target concentration of the desirable product. The objective function penalizes changes in the control action, as well as concentration set-point errors. The above dynamic optimization problem is solved using Pyomo Hart et al. (2017) and using the differential-algebraic equation package Nicholson et al. (2018). The parameter β is set at 1×10^6, whereas γ is chosen to be 1 in this case study.

6.2 Feasible mode transitions

To generate data points for the transition time profiles, the transition between two steady states corresponding to different θ values, ranging from 8 to 80 hr, is simulated via dynamic optimization. The selection of the operating modes can be arbitrary; however, since the scheduling model is an MILP, depending on the number of operating modes considered, a large number of modes can increase the complexity of the model. Additionally, given that the goal of this study is to compare the load-shifting capacities for different CSTR sizes, it is important to use the same transition profile for all CSTR sizes. As a result, we choose to fix the range of θ values since the transition profiles are determined by θ. With the range of θ values fixed for the different modes, the operating flow rate, or the production rate F^t, will be different for different CSTR sizes, leading to different feasible operating ranges under different designs. One could also consider varying the operating flow rate (instead of θ) for the different modes; however, in such a scenario the dynamic transition profiles will be different as the volume V is varied and θ changes for different designs, increasing the number of dynamic optimization results. In this study, we choose to fix θ for the different CSTR sizes considered. The selection of θ values for the different modes are based on a reactor size of 400 L. For a range of θ values between 8 and 80 hr, the flow rate is in the range from $\frac{400}{80}$ to $\frac{400}{8}$. The flow rates in this range are equally sampled and then converted back to θ values. Therefore, varying θ can be realized under this framework.

6.3 Seasonal representation

The LCOL calculation intrinsically considers a long-term design and operation up to years, yet the variations in electricity prices occur are at much shorter time scales (on the order of 1 hour and 5-minute intervals in the DAM and FMM, respectively). To account for the multi-scale nature of the problem, we leverage the seasonality of the electricity price profiles (see, e.g., Zhang et al. (2018)). Electricity prices for both the DAM and FMM are separated into four different seasons and then averaged over the period of that season. The seasonal electricity price profiles in the year 2018 of a node in the California Independent System Operator (CAISO) market were used in this study. Based on these seasonal profiles, the scheduling and operation problem is solved for each market under each season, and the operating cost and the shifted load are calculated accordingly.

7. RESULTS AND DISCUSSION

The scheduling model described above is solved using the Gurobi solver (Gurobi Optimization, LLC (2021)), and the results are used in this section to assess the impact of different design capacities on the ability of the process to participate in load-shifting DR services in different time-varying electricity markets. The material and inventory costs, as well as the profit of selling the potential product, are ignored for simplicity. Also, a period of 2 years and a discount rate of 5% are assumed in the calculation of the LCOL. These simplifications allow treating the process like a battery, so that the LCOL calculation involves only the electricity consumption cost and the load-shifting capacity.

Figures 1 and 2 present a comparison between the performance of a process with a 500 L CSTR and 250 L storage and a process with 700 L CSTR and 250 L storage, under the FMM.

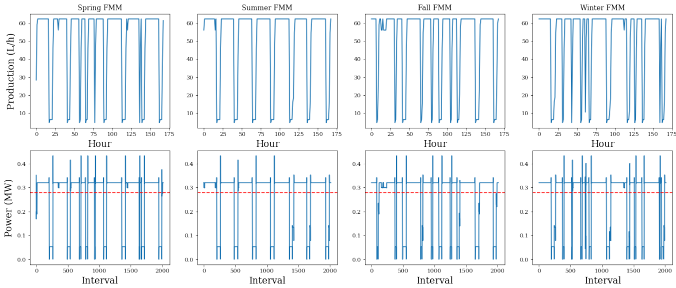

Fig. 1. Production level (top) and power consumption profiles (bottom) for a 500-L CSTR with 250-L storage unit, for different seasons, under the FMM.

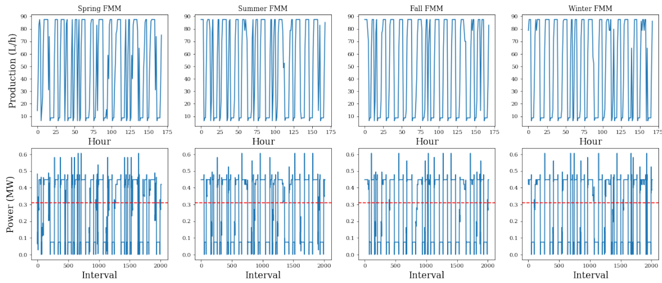

Fig. 2. Production level (top) and power consumption profiles (bottom) for a 700-L CSTR a 250-L storage unit, for different seasons, under the FMM.

In both figures, the top panel shows the production levels in different seasons, while the bottom panel shows the power consumption. The red dotted lines specify the baseline power consumption for the corresponding CSTR size. It can be seen that the load-shifting activity is more frequent for the 700-L CSTR than it is for the 500-L CSTR. The loads shifted for both cases are given in Table 1. It is worth noting that, for both cases, the power consumption tends to fluctuate between the minimum and maximum, and as a result the load-shift capacity, by definition, is maximized.

Table 1. Weekly power shifted for a 500-L CSTR and a 700-L CSTR, for different seasons.

Weekly power shifted (MW)	$V_{CSTR} = 500$ L	$V_{CSTR} = 700$ L
Spring	79.5974	166.1959
Summer	80.3108	172.0224
Fall	78.0487	175.3420
Winter	79.1334	175.3995

Figure 3 compares the LCOL associated with a given CSTR capacity under two different electricity markets, namely the DAM and FMM. In this figure, the LCOLs for different CSTR capacities are plotted against the discounted shifted energy over the year. The dotted lines correspond to the case of the FMM, while the solid lines represent the DAM case. As can be seen, the dotted lines are consistently below the solid lines, suggesting that when scheduling under the FMM the LCOL for a given CSTR capacity is lower than under the DAM. Using the FMM for scheduling can lower the LCOL.

Another important trend that can be seen in Figure 3 is that as the shifted load increases, the LCOL, under a given market and for a given CSTR capacity, initially decreases and then increases. This increase is also very

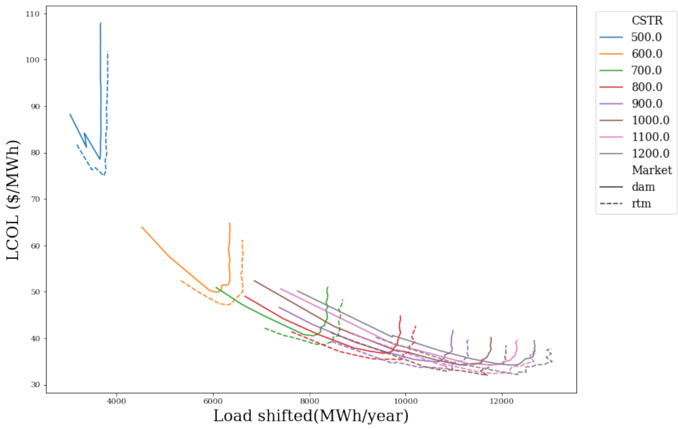

Fig. 3. LCOL for different CSTR sizes under the DAM (solid lines) and under the FMM (dashed lines).

steep. An implication of this behavior is that there exists a limitation on the load-shifting capacity associated with a CSTR of a given capacity in both markets (even when different storage sizes are used). The limitation of the load-shifting capacity is determined by the reactor capacity. Another implication of the trends displayed is that one could lower the LCOL while simultaneously maximizing the load-shifting capacity per year. For example, when the CSTR size is increased from 500 to 600 L, a significant drop in the LCOL is observed, and this drop is accompanied by a rightward shift in the load-shifting capacity. However, this trend starts to diminish with increasing CSTR sizes.

8. CONCLUSION

In this work, a model-based optimization framework was developed to evaluate and compare process design alternatives in terms of their potential to facilitate participation in load-shifting DR activities. The DR particibility potential of a given process design was assessed using the levelized cost of load-shifting capacity (LCOL). Utilizing this metric, a chemical process could be viewed as a grid-level battery and compared with other energy generation units or batteries to assess the economic benefits that load-shifting could provide over the lifetime of the process. A conceptual case study involving a reactor-storage system was used to illustrate the proposed framework.

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