A Demand Response Strategy for Continuous Processes Using Dynamic Programming Approach

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Abstract: This work considers the problem of optimizing the energy management in the operation of dynamic continuous processes subject to demand response objectives. A dynamic programming approach that aims to lower the operating cost is developed and presented. The dynamics of process transition between operating modes, as well as the time-sensitive energy profiles, are incorporated into the optimization formulation. The merits of the proposed approach are demonstrated using a jacketed continuous stirred tank reactor where the energy required is assumed to be proportional to the material flow.

Keywords: Demand Response, Dynamic Programming, Process Operation, Process Scheduling and Control

1. INTRODUCTION

Demand response (DR) operation of chemical processes can help increase grid stability and plant profitability by overproducing and storing products when the grid demand is low and reducing the production levels and satisfying the product demand using storage when the grid demand is at peak (Baldea (2017)). Although the economic potential of DR for industrial processes has been well-recognized in several studies (e.g. Wang and Li (2013); Paulus and Borggreve (2011); Kwag and Kim (2012)), as DR requires changing production levels from time to time, the consideration of transitions between different operating modes remains a challenge. Mendoza-Serrano and Chmielewski (2013) demonstrated the potential opportunities of DR for a conceptual manufacturing facility with the assumption that the production levels of the facility could switch instantaneously and thus the dynamic profile was ignored. Mitra et al. (2012) studied the optimal production scheduling for a continuous energy intensive air separation plant under time-varying electricity prices. While plant transition behavior was considered in that study, the dynamic profiles between different operating modes were not included.

In our previous work (Tong et al. (2015)), a DR problem was formulated as a mixed-integer nonlinear programming (MINLP) problem, where the optimal operating policies were found in response to varying energy profiles, including time-sensitive electricity prices and onsite renewable energy generation, while the off-line generated transition profiles between different operating modes were also included. The uncertainty in the energy profiles was handled via a receding horizon optimization framework, where the optimization problem was solved at every time step with given forecasting renewable energy data. In the MINLP model, the operating mode assignments at different time periods were treated as binary variables, and the different operating modes were predefined. Therefore, as the number of discrete operating modes or time length increased, the number of binary variables also increased. At the same time, due to the nonlinearity and nonconvexity of the proposed models, convergence towards the global optimum is not guaranteed in general. Moreover, the receding horizon optimization framework required the repeated solution of a MINLP model, and potentially a large-scale problem needed to be solved at every time-step which could pose computational challenges for real-time implementation.

Motivated by the above considerations, the objective of this work is to develop a dynamic programming optimization framework and solution strategy that can manage the nonlinearity and nonconvexity in the DR operation problem. The proposed formulation explicitly accounts for the dynamic behavior of the transition between operating modes, time-varying electricity prices, and varying energy generation profiles. The proposed formulation is then applied to a CSTR example where the energy consumption is assumed to be proportional to the material flow, and the process needs to meet hourly varying product demand.

2. MODEL FORMULATION

2.1 Problem description

The conceptual system considered in this study is depicted in Figure 1. The system includes several components: onsite energy generation (solar and wind), power grid, production system and the storage.

The production system has a set of pre-defined operating modes, \( i \in I \), and is operated over a given time horizon, \( H \). For every time period, \( h \in H \), if the mode \( i \) is operated, then the total energy consumption is denoted as \( E^h_i \), the total material requirement is denoted as \( M^h_i \) and the total
production rate is $F^h$. The production system is required to meet the hourly product demand $d^h$ and can utilize storage to provide operational flexibility. The storage level of the unit is denoted by $S^h$. Surplus electricity generated by the onsite sources, $E_y$, can also be sold back to the grid. The problem can then be stated as follows: given the varying energy profiles and production demands, determine the sequence of operating modes for the process and the electricity exchanged with the grid. The goal is to minimize the total operating cost including the energy cost, storage cost, and the raw material cost.

### 2.2 Model formulation

**Electricity consumption** The electricity consumption can be divided into two parts: one associated with the production periods which correspond to the steady-state operation and the other with the transition periods. We introduce mode $i$ and $j$, and the transition time for changing from mode $j$ to $i$ at period $h$ is denoted as $t_{i,j}$. The energy related to the steady-state operation is defined as $E_i$ and the transition energy waste from mode $j$ to $i$ is $e_{i,j}$. Thus, the total energy consumption at period $h$ and target mode $i$ is expressed as:

$$E_i^h = e_i^h (1-t_{i,j}^h) + e_{i,j}^h - E_y^h. \quad (1)$$

The onsite energy generation $E_y^h$ is used by the process units once available, and if $E_y^h$ is negative, this implies that the extra electricity can be sold back to the grid. Also, one should note that $e_{i,j}^h$ is basically the electricity required during time $t_{i,j}^h$.

**Material consumption** The material cost can also be divided into two parts as the energy consumption. We define $m_i^h$ as the material used for the steady-state operation and $m_{i,j}^h$ as the wasted material amount during transition. Thus, the total material used for operating mode $i$ at period $h$, $M_i^h$, is given as:

$$M_i^h = m_i^h(1-t_{i,j}^h) + m_{i,j}^h. \quad (2)$$

**Storage constraints** The storage unit is supplied by the production from the system and meets the hourly product demand. The storage level at every time step is bounded by the minimum requirement and the maximum storage capacity; thus,

$$0 \leq S^h \leq S_{\text{max}}^h. \quad (3)$$

Additionally, the storage, the production amount and the product demand together should meet the mass balance, which is represented by

$$S^h - S^{h-1} = F^h - d^h, \quad (4)$$

where the initial storage level is defined as $S^0$.

**Objective function** The total cost $J^h$ at each time step includes the electricity cost, the material cost as well as the inventory cost. The electricity price at every time step is given as $C_e^h$, and therefore, we can express the total energy cost, $\phi_e^h$, as:

$$\phi_e^h = C_e^h \cdot E_i^h. \quad (5)$$

However, if the onsite energy generation exceeds the energy required by the production, then the extra electricity is sold back at a cost ratio $\eta$. The cost for electricity will then be given by

$$\phi_e^h = \begin{cases} C_e^h \cdot E_i^h, & \text{if } E_y^h \geq 0 \\
\eta C_e^h \cdot E_i^h, & \text{otherwise} \end{cases}. \quad (6)$$

The material cost at every time step, $\phi_m^h$, which is given by

$$\phi_m^h = C_m^h \cdot M_i^h, \quad (7)$$

where $C_m^h$ is the material cost at every time period.

Finally, the storage cost $\phi_s^h$ is defined as

$$\phi_s^h = \delta^h \cdot S^h, \quad (8)$$

where $\delta^h$ is the hourly storage cost coefficient.

The total cost over the horizon will then be given as:

$$J(\sigma) = \sum_{h \in H} \{\phi_e^h + \phi_m^h + \phi_s^h\}, \quad (9)$$

where $\sigma$ is the operating mode sequence throughout the time horizon $H$, which can be denoted as $[i_0, i_1, i_2, ..., i_T]$. The objective is to find the $\sigma$ that minimizes the total operating cost.

### 2.3 Solution strategy

The determination of the operating sequence is naturally a multistage decision-making process, where a dynamic programming (Bellman (2013)) approach is applicable. A branch-and-cut algorithm is developed to solve the above formulation and the related pseudocode is provided in Algorithm 1. The algorithm is applied to determine the optimal operating sequence. At every time step $h$, the current feasible state is described using $F_i(h)$ and the possible action to be taken is described with $U(h)$. The branch procedure checks all the feasible states in $F_i(h)$ and all the possible actions in $U(h)$ to determine the feasible action using the constraints in the model (e.g., (3) and (4)), which is then defined as $A(h)$.

Next, the cut procedure will evaluate all the possible actions $a_{h,p}$ in $A(h)$ to determine the potentially optimal state for the next time step $F_i(h+1)$. To distinguish the feasible action in $A(h)$, we define $a_{h,p}$ and $a_{h,q}$ where $p \neq q$. The cut procedure also removes excessive feasible actions and the number of the states to be evaluated is
thus reduced. Two criteria are used to remove the feasible action. The first one is the cumulative cost $J(a_{h,p})$ by taking action $a_{h,q}$; the second one is the storage levels $S_{h,p}$ by taking action $a_{h,q}$. If $J(a_{h,p}) \leq J(a_{h,q})$ and $S_{h,p} \geq S_{h,q}$, then the action $a_{h,q}$ is removed from the set $A(h)$ and will not be used to calculate the feasible state $F(h+1)$. The cut procedure can decrease the number of possible states and therefore prevents the number of computations from increasing exponentially in time.

\begin{algorithm}
\textbf{Algorithm 1} Branch-and-cut
\begin{algorithmic}
\State $h \leftarrow 0$, given initial state $F(0)$
\While{$h \leq H$}
\ForAll{feasible state $f_h \in F(h)$}
\ForAll{possible action $u_h \in U(h)$}
\If{$u_h$ satisfies the constraints}
\State Store the $u_h$ in the feasible action set $A(h)$
\EndIf
\EndFor
\EndFor
\ForAll{feasible action $a_{h,p}$ and $a_{h,q}(p \neq q) \in A(h)$} 
\State Calculate the cumulative cost $J(a_{h,p})$ and $J(a_{h,q})$ 
\If{$J(a_{h,p}) \leq J(a_{h,q})$ and $S_{h,p} \geq S_{h,q}$}
\State Remove $a_{h,q}$ from $A(h)$
\EndIf
\EndFor
\State Determine $F(h+1)$ based on $A(h)$
\State $h \leftarrow h + 1$
\EndWhile
\end{algorithmic}
\end{algorithm}

At the last time period, the minimum cumulative cost is found, and the related operating mode sequence can then be determined. Compared to the MINLP formulation considered in Tong et al. (2015), the solution strategy developed here has the benefit that instead of solving a deterministic mixed-integer optimization problem, which might be nonlinear and non-convex, at every time step, an evaluation of the function value is used.

3. CASE STUDY

3.1 CSTR dynamics and transition profiles

To illustrate the proposed dynamic programming scheme, a CSTR example, as shown in Figure 2 is used. Even though a CSTR is not an energy-intensive process, it is helpful to illustrate the energy management scheme if we assume the energy consumption to be proportional to the material flow. The CSTR considers a single production reaction $A \rightarrow B$, and the model dynamics can be described by the following mass and energy balances:

\begin{align}
\frac{dC}{dt} &= \frac{F}{V}(C_i - C) - C \cdot k_0 \cdot \exp(-E/RT), \\
\frac{dT}{dt} &= -\Delta H \cdot k_0 \cdot \exp(-E/RT) \cdot C \\
&\quad + \frac{F}{V}(T_i - T) + \frac{UA_c \cdot (T_c - T)}{\rho C_p V}, \\
\frac{dT_c}{dt} &= \frac{F_c}{V_c}(T_{ci} - T_c) + \frac{UA_c T_c - T_c}{\rho C_{pc} \cdot V_c}.
\end{align}

Fig. 2. CSTR process with a PI controller.

The inlet concentration is denoted as $C_i = 0.5 \text{ mol/ft}^3$ and the steady state concentration of the product is $C = 0.0591 \text{ mol/ft}^3$. All the model parameters can be found in Feitai et al. (2013). The above equations are discretized using Euler’s method, and the interval of time, $\Delta t$, is chosen to be 0.002h. A cascade of PI controllers are used, where the inner loop manipulates the inlet coolant flowrate $F_c$ to track the set-point $F_{c,sp}$ given by the outer loop: $F_c(k+1) = F_c(k) + K_{p,c}[e_{c}(k) - e_{c}(k-1)] + K_{I,c} e_{c}(k)$ (13) where $e_{c} = F_{c,sp} - F_{c}, \ K_{p,c} = 0.08$ and $K_{I,c} = 0.4$. In practice the flow rate is bounded by physical limitations and in this case study, $F_c$ lies in the interval $[10, 80]$.

The outer loop controller stabilizes the temperature $T$ at the desired temperature $T$:

\begin{align}
F_{c,sp} = \bar{F}_c + K_{p,T}[e_{T}(k) - e_{T}(k-1)] + K_{I,T} e_{T}(k),
\end{align}

where $e_{T} = T - T_{p}, \ K_{p,T} = -1.8$ and $K_{I,T} = -4.2$. The parameters for both loops in this study are tuned empirically. Different feasible operating modes are specified in Table 1. Operation mode 4 with material flow rate of $35 \text{ mol/ft}^3$ is considered as the nominal mode. Table 2 shows the closed-loop transition time for each mode transition. Here, the transition time is defined as the time required when the norm of consecutive 10 sampling points is less than $10^{-4}$ and the concentration $C$ reaches a value within 1% of the target value. These transition time values are computed off-line and are based on fixed controller parameters. We note here that the simultaneous optimization of the controller parameters and the operating schedule is not the focus of this study.

The energy consumed by the CSTR is related to the material flow. Here, both the raw material flow and coolant flow are included. For simplicity, we define $e_i^h = \alpha \cdot F_i^h$, (15)
Table 2. Transition times for the closed-loop CSTR Process (h)

<table>
<thead>
<tr>
<th>Mode</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0.48</td>
<td>0.43</td>
<td>0.39</td>
<td>0.67</td>
<td>0.64</td>
</tr>
<tr>
<td>2</td>
<td>0.59</td>
<td>0</td>
<td>0.42</td>
<td>0.38</td>
<td>0.64</td>
<td>0.61</td>
</tr>
<tr>
<td>3</td>
<td>0.62</td>
<td>0.48</td>
<td>0</td>
<td>0.37</td>
<td>0.34</td>
<td>0.59</td>
</tr>
<tr>
<td>4</td>
<td>0.64</td>
<td>0.50</td>
<td>0.41</td>
<td>0</td>
<td>0.33</td>
<td>0.32</td>
</tr>
<tr>
<td>5</td>
<td>0.67</td>
<td>0.51</td>
<td>0.43</td>
<td>0.37</td>
<td>0</td>
<td>0.31</td>
</tr>
<tr>
<td>6</td>
<td>0.70</td>
<td>0.53</td>
<td>0.44</td>
<td>0.38</td>
<td>0.33</td>
<td>0</td>
</tr>
</tbody>
</table>

where $\alpha$ is the flow-to-power coefficient and $F_{tot}^h$ is the sum of raw material flow and coolant flow. $\alpha$ is set to be 0.006 MWh/ft$^3$.

Similarly, the material cost is defined as

$$m^h = \mu \cdot F_{tot}^h, \quad (16)$$

where $\mu$ is the unit material cost and is set to be 0.1 $/ft^3$.

3.2 Results and discussion

First, to validate the proposed algorithm, the plant schedule is established for 2 days with varying electricity prices at different levels: 69.999 $/MWh, 94.789 $/MWh and 163.398 $/MWh, as shown in Figure 3(a), with no onsite energy generation and a constant product demand, 30 ft$^3$/h, as shown in Figure 3(c).

The result for the demand responsive operation with constant product demand and no onsite energy generation is presented in Figure 4. As one would expect, the operating levels vary in response to the electricity price profiles shown in Figure 3(a). When the electricity price reaches peak level, the production rate decreases and the highest production rate occurs during the lowest electricity price level. The inventory levels also change accordingly and the cumulative cost is $2,344.5. The dynamic operating profiles show that the proposed dynamic programming approach is indeed valid.

Next, we consider the onsite renewable energy generation and the time-varying product demand. The onsite renewable energy generation is shown in Figure 3(b) for 48 hours. The product demand is given in Figure 3(c), where we stipulate three different demand levels: 20 ft$^3$/h, 30 ft$^3$/h and 40 ft$^3$/h.

Figure 5 presents the dynamic programming solution for the demand responsive operation case while Figure 6 illustrates the results when the process unit is operated at the nominal operating level during the 48-hour period. The cumulative cost for the demand responsive operation is $1,484.9 , generating a 12.9% savings, while the nominal operation has a cost of $1,705.1.

As shown in Figure 3(b), the renewables generation is abundant during the first 24 hours due to the wind energy while the latter 24 hours have less available wind energy. As one would expect, the operating levels decrease when the electricity price is high, while the production level increases during the low price period. The significant cost savings in the DR operation is owing to the operating level adjustment in the latter 24 hours when the onsite energy generation is low, and the electricity price is still very high. As one could see in the operating mode in Figure 5(a), the operating level is kept as low as possible, and most of the product demand is satisfied using the storage. While in Figure 6(c), since the operating level is constant, the storage level remains at a very high level, which not only increases the inventory cost but also the operating cost.
Finally, we note that the optimization results are sensitive to the model parameters, and the values of parameters in this study are chosen to be as realistic as possible, but further studies can be performed to explore these parameters as well. However, the proposed dynamic programming can easily incorporate the parameter tuning. For example, if the control laws or the control parameters which are predefined and fixed in the current study are allowed to change at a certain period, the dynamic programming framework can simply re-evaluate the transition time and corresponding transition data at that period and thus the optimal sequence can be updated. Also, finer operating levels could be used under the proposed dynamic programming approach, which can provide a more accurate operating sequence; however, finer operating levels in the original MINLP formulation will lead to more integer variables and thus can become more computationally challenging.

4. CONCLUSIONS

A dynamic programming approach was successfully implemented to find the optimal operating sequence for a DR problem. The application of the proposed methodology to a CSTR model resulted in a 12.9% operating cost savings. For future work, a detailed comparison between the MINLP solution and the dynamic programming approach in the DR operation study will be carried out. Additionally, a stochastic dynamic programming framework to address the problem will be explored. A stochastic framework is a natural choice to incorporate the uncertainty in the formulation instead of solving a deterministic MINLP using receding horizon at every time step.

REFERENCES