Energy Demand Management for Process Systems Through Production Scheduling and Control

Chudong Tong
Faculty of Electrical Engineering and Computer Science, Ningbo University, Zhejiang 315211, P.R. China

Dept. of Chemical Engineering and Materials Science, University of California, Davis, One Shields Avenue, Davis, CA 95616

Ahmet Palazoglu and Nael H. El-Farra
Dept. of Chemical Engineering and Materials Science, University of California, Davis, One Shields Avenue, Davis, CA 95616

Xuefeng Yan
Key Laboratory of Advanced Control and Optimization for Chemical Processes of Ministry of Education
East China University of Science and Technology, Shanghai 200237, P.R. China

DOI 10.1002/aic.15033
Published online September 24, 2015 in Wiley Online Library (wileyonlinelibrary.com)

Demand response (DR) is an integral part of the Smart Grid paradigm, and has become the focus of growing research, development, and deployment in residential, commercial and industrial systems over the last few years. In process systems, energy demand management through production scheduling is an increasingly important tool that has the potential to provide significant economic and operational benefits by promoting the responsiveness of the process operation and its interactions with the utility providers. However, the dynamic behavior of the underlying process, especially during process transitions, is seldom taken into account as part of the DR problem formulation. Furthermore, the incorporation of energy constraints related to electricity pricing and energy resource availability presents an additional challenge. The goal of this study is to present a novel optimization formulation for energy demand management in process systems that accounts explicitly for transition behaviors and costs, subject to time-sensitive electricity prices and uncertainties in renewable energy resources. The proposed formulation brings together production scheduling and closed-loop control, and is realized through a real-time or receding-horizon optimization framework depending on the underlying operational scenarios. The dynamic formulation is cast as a mixed-integer nonlinear programming problem based on a proposed discretization approach, and its merits are demonstrated using a simulated continuous stirred tank reactor where the energy required is assumed to be roughly proportional to the material flow. © 2015 American Institute of Chemical Engineers *AIChE J*, 61: 3756–3769, 2015
Keywords: demand response, scheduling and control, electricity pricing, renewable energy

Introduction

The development of efficient and cost-effective process operational strategies is an increasingly important goal in the context of energy demand management in the process industries. The increased emphasis on realizing this goal, especially in recent years, stems from a number of important developments, including the rising cost of energy, its increasingly diminishing and unpredictable supply, as well as the growing environmental awareness and climate change concerns that call for curbing the use of traditional fossilized fuels.[1,2] In the strategic plan of the International Energy Agency for 2008–2012, energy demand-side activities have been a focal point in nearly all energy policy decisions due to the significant benefits that can be realized through demand-side management, both at the economic and operational levels.[3] Indeed, the market price of electricity is the dominant incentive and heavily influences the electricity consumption of industrial customers. Typical examples of time-sensitive electricity prices are time-of-use (TOU) rates and real-time prices (RTPs). While TOU rates are usually specified in terms of on-peak, midpeak, and off-peak hours, RTP rates vary every hour and are quoted on a day-ahead or hourly basis.[1]

The electric-power grid is being transformed into a smarter network—one that could bring significant benefits to the chemical process industries.[4] An integral component of the current and future power systems is the concept of demand response (DR), which is a demand-side management solution that focuses on the operational level. DR refers to "changes in

Correspondence concerning this article should be addressed to N. H. El-Farra at nhelfarra@ucdavis.edu.
Current address of Chudong Tong: Faculty of Electrical Engineering and Computer Science, Ningbo University, Zhejiang 315211, P.R. China.

electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."[3] DR is achieved through mechanisms that discourage the energy load when the RTP is high and vice versa. Examples include demand reduction or demand shifting at a specific time for a specific duration. While the noncriticality of loads in residential and commercial applications may allow for demand reduction and/or shifting with relative ease, DR for industrial processes faces unique challenges due to production constraints, inventory constraints, maintenance schedules, and crew management, which are some of the many factors that need to be considered before DR is implemented.

Although the economic potential of DR for industrial processes has been recognized in a number of studies,[5–7] it is worth noting that, as DR requires by definition varying production levels and switching between different operating modes, consideration of the transition behavior between the operating modes remains a challenge. An examination of the existing body of research on DR for industrial processes shows that the transition behavior problem has not been adequately addressed in the literature. Mendoza-Serrano and Chmielewski,[8] for example, illustrated the potential opportunities of DR for a conceptual manufacturing facility. An important assumption of their study was the fact that the manufacturing facility could be operated at a continuum of production levels between which the process could switch instantly, with the transitional behavior ignored. Conversely, Mitra et al. presented an optimal production planning model for continuous power-intensive processes under time-sensitive electricity prices where transitions were considered. This study considered minimum stay constraints for describing ramp-up transitions and rate of change constraints for restricting transitions between operating points. However, the dynamic profile of the transition process between different operating modes was not taken into account in the optimization problem formulation. More recently, Wang et al. developed a methodology for incorporating DR in the production scheduling of a chlor-alkali plant powered by a combination of renewable energy (RE) resources and the grid.[9] The optimization formulation, which leads to a mixed-integer linear programming (MILP) problem, accounts for the time variations in electricity prices and the intermittency of RE resources, but does not consider the cost of transitions between the different operating modes or the closed-loop control necessary to realize the scheduled transitions.

From a DR standpoint, the main objective is to determine the optimal production level at any given time; thus the control problem is closely related to the responsive demand problem given that the major task of controllers is to determine the optimal values of the manipulated and controlled variables to achieve different production levels. Generally, production scheduling and control are addressed either sequentially or simultaneously.[10,11] Some early attempts to tackle the simultaneous scheduling and control problems were made by Flores-Tlacuahuac and Grossmann[12,13] who proposed an optimization formulation to address both steady-state production and dynamic product transitions in multiproduct continuous stirred tank reactors (CSTRs) using a mixed-integer nonlinear programming (MINLP) model. Baldea and Harjunkoski[14] recently reviewed the progress made thus far in the integration of scheduling and control activities and defined several directions for future development as well as a complement of promising applications. A literature review on the solution of simultaneous scheduling and control problems can be found elsewhere.[15] However, to the best of our knowledge, energy consumption and demand management issues were largely not considered in this line of studies. At this point, the incorporation of energy constraints related to electricity pricing[16] and energy resource availability into the plant scheduling problem remains a challenge.

In addition to responding to electricity price variability, another important dimension to the energy management problem is related to energy resource availability. Specifically, as environmental concerns, diminishing fossil fuel reserves, and economic pressures of efficient energy resource utilization continue to motivate governments, industrial, and academic communities to focus on substituting conventional resources by RE resources,[17,18] there is a greater need to investigate the variability of RE supply and its impact on process operation. The use of RE resources, such as solar plants and wind farms, has the potential to significantly reduce energy losses in transport, and hence the cost of energy;[19] however, integrating RE generation into the production scheduling problem poses a significant challenge due to the intermittent nature of these resources. The development of effective strategies for harnessing intermittent RE resources is an important prerequisite to their high penetration and has been actively studied in recent years,[20] most notably in the context of residential applications.[21] While insufficient attention has been paid to the potential of RE integration in industrial applications,[22] the emerging trends in distributed energy networks and smart grid applications make it plausible to envision manufacturing plants adopting on-site RE cogeneration in the future. This is also supported by the growing body of research work on the design and optimization of RE generation systems for industrial processes.[9,23] How to efficiently and reliably integrate intermittent renewable resources into production scheduling is a key goal of this study.

Motivated by the above considerations, the objective of this article is to present a new optimization formulation for energy demand management in the production scheduling and control of process systems to realize demand responsive operation. The formulation accounts explicitly for the cost and dynamics of transitions between the different operating modes, while handling time-sensitive electricity prices and uncertainties in RE availability at the same time. This study is exploratory, focusing on DR which takes into account the dynamic profile of the transition process under closed-loop control, time-sensitive electricity prices, and RE resource intermittency. For a proof of concept, the proposed formulation is applied to a simulated CSTR where the energy required is assumed to be approximately proportional to the material flow, and the process has to satisfy an hourly demand for the product.

To simplify the calculation of transition cost, the dynamic profile of the transition process is first discretized on the basis of the sampling interval, which is considered to be at a different time-scale compared with the time-scale of the scheduling phase. With the use of a transition indicator, the integration of transition behavior into the optimization model is then realized, and the resulting model is formulated as an MINLP problem. This is in contrast to conventional scheduling formulations where the transition states are typically ignored and the resulting problem is formulated as either a linear programming

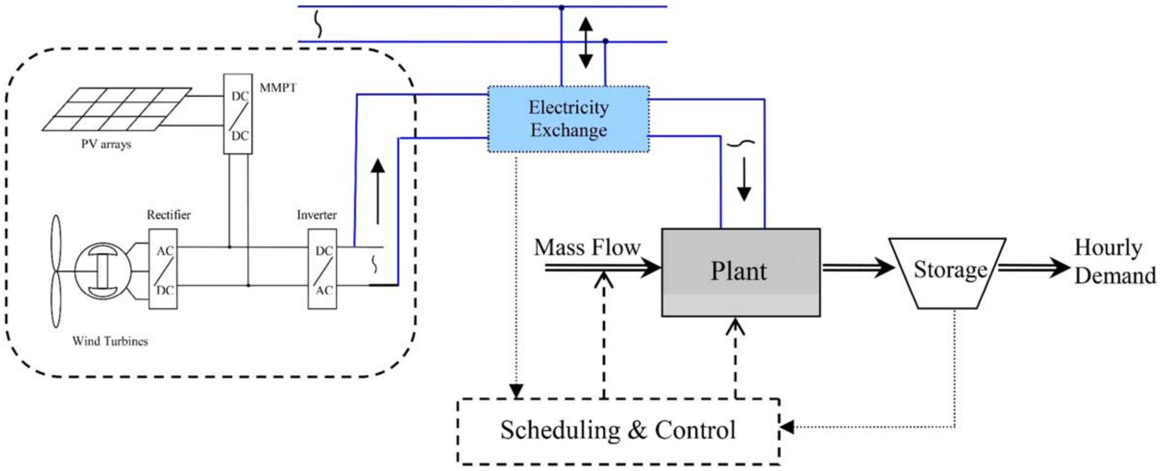

Figure 1. A schematic representation of the problem statement.

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

(LP) or an MILP model depending on the type of feasible operating region, which can be continuous or discrete. Given the absence of transition behaviors in such formulations, no transition indicator needs to be defined and the formulated model is easier to solve. However, the obtained solution may not be optimal or even feasible when transition cost and related production losses during transitions are considered. Consideration of transition costs, therefore, alters the optimization formulation from an LP to an MINLP.

Formulation Overview

Problem definition

The conceptual production system with the set of components considered for DR in this study is shown in Figure 1. The RE generation unit is operated by the plant. The system has to satisfy an hourly demand of the product, and a storage unit is installed to provide the needed flexibility. Surplus electricity can be sold to the power grid and electricity can also be purchased. The electricity prices vary on an hourly basis and the DR decisions are assumed not to influence the electricity prices. A lower bound on the product hourly demand is specified as a constant rate. The steady-state operating modes corresponding to different production levels are specified *a priori*, and so are the prices of the inventory and raw material costs. The problem then consists of the determination of the sequence of operating modes for the plant (i.e., production levels), the dynamic profile for the production changes under closed-loop control, and the electricity exchange between the plant and power grid. The key objective is to minimize the total production cost, which includes the transition cost (i.e., the cost associated with the raw material waste and electricity waste during transitions), inventory cost, electricity cost, and revenue from sold electricity.

Formulation of the scheduling and control problems

When the dynamic process model is incorporated into the constraints of the scheduling problem, this results in a mixed integer dynamic optimization (MIDO) formulation. Solution methods for general MIDO problems are presented in earlier studies.[24–27] A general decomposition-based framework was established by Allgor and Barton,[24] and Flores-Tlacuahuac and Biegler[26] proposed a methodology to transform the MIDO problem into an MINLP through the discretization of the dynamic model. Terrazas-Moreno et al.[27] extended the work by Flores-Tlacuahuac and Grossmann[12] and proposed a Lagrangean decomposition strategy to simplify the scheduling and control problem. In addition, heuristic-based approaches like agent-based simulations were also presented for the dynamic scheduling and control problem.[25,28]

To handle the dynamic optimization problem in this work, the steady state and transition states are treated differently. As shown in Figure 2, the system states x and the manipulated variables u are assumed to remain constant during the production period, while the manipulated variables change within the transition period and so do the system states. Given that the steady-state operating modes corresponding to different production levels are predefined, the steady-state values of the manipulated variables are known constants. However, to model the closed-loop state and manipulated input behavior during transitions, the transition period is discretized on the basis of the system sampling interval as shown in Figure 2. This sampling interval is considered to be much smaller than the discretization time step used in the scheduling phase calculations. With the aid of a detailed plant model and a suitable controller designed to steer the closed-loop process state during transitions, the approximate closed-loop transition profiles between the different operating modes can then be calculated off-line. In the absence of a mathematical model, the transition profile can still be obtained from historical plant data. Generally, the transition profile between the same pairwise operating

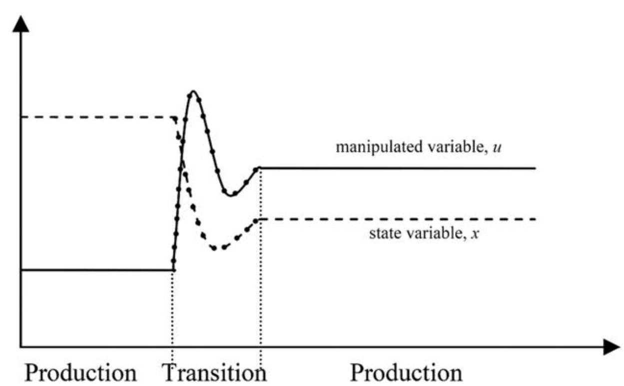

Figure 2. A schematic representation of dynamic system behavior during a transition.

modes is expected to follow a similar trajectory. From this point of view, the advantages of this method lie in the fact that the underlying differential equations are transformed into a set of data, and that the transition times between the different production levels become known parameters which are used as inputs to the scheduling problem.

Remark 1. The utilization of offline-fixed transition times is the conventional approach for accounting for process dynamics in the scheduling of batch and/or continuous processes.[14,29] The formulation proposed in this work, however, differs in that it integrates two discrete-time formulations—each with a different discretization time scale—to represent the transition and scheduling phases. Specifically, the detailed transition profiles are discretized using the system sampling interval whose size is considered to be smaller than that of the time step used in the scheduling phase. It should also be noted that the use of tabulated transition times does not constitute an integration of scheduling and control as the controller is designed *a priori* to allow determination of the transition profiles and times which are then, used as input in the solution of the scheduling problem. An integrated approach for scheduling and control would require treating the controller design parameters as decision variables in the optimization problem formulation and accounting for process dynamics in the scheduling layer, and is not pursued in this study.[30,31] The control problem considered here concerns mainly the manipulation of the manipulated variables, which is realized by sending different set-points to the controller at each scheduling time step. Traditional control-related issues, such as ensuring the desired output in the presence of disturbances, controller tuning, and fault-tolerance, are the subject of other research work.

Remark 2. The treatment of steady and transient periods in this study is inspired by the work of Flores-Tlacuahuac and Grossmann.[12] However, in that work no closed-loop control of the plant unit was considered. Chu and You recently proposed an integration method to solve the scheduling and control problems simultaneously.[29] In their integration framework, the control-related problem involves the selection of a set of offline-trained controller candidates for each possible transition. This sort of strategy can be adopted here to obtain better economic transition behaviors. Specifically, the controller used in this work can first be optimally tuned off-line for the available transitions to improve the corresponding economics, and then be activated when a transition occurs. This is possible and easily implementable because the feasible operating modes are defined beforehand. These possible extensions notwithstanding, the focus of our work is on accounting for the detailed transition profiles and scheduling calculations with different discretization time scales in the optimization formulation, and not on the integration of scheduling and control. Furthermore, energy demand management in response to varying electricity prices and intermittent RE generation is another target of this work, which was not considered in previous studies.

Model Formulation

Mathematical model of RE system

The models presented in the following subsections are available in the literature and cited below as appropriate. The data for wind speed, solar irradiation, and ambient temperature are sampled every hour and are available from Weather Analytics (http://www.weatheranalytics.com)

Photovoltaic Panel Model. The performance of a photovoltaic PV panel exhibits nonlinear current-voltage characteristic curves. The model presented by Belfkira et al.[32] allows calculating the current (I_{mpp}) and voltage (V_{mpp}) at the maximum power point using a maximum power point tracker (MPPT) as follows

$$I_{\mathrm{mpp}}=I_{\mathrm{SC}}\cdot\{1-C_1\cdot\left[\exp\left(\frac{V_{\max}}{C_2\cdot V_{\mathrm{OC}}}\right)-1\right]+\Delta I \tag{1}$$

$$V_{\mathrm{mpp}}=V_{\max}+\mu_{V,\mathrm{OC}}\cdot\Delta T \tag{2}$$

and the PV panel power is expressed as

$$P_{\mathrm{PV}}=V_{\mathrm{mpp}}\cdot I_{\mathrm{mpp}} \tag{3}$$

with

$$C_1=\left(1-\frac{I_{\max}}{I_{\mathrm{SC}}}\right)\cdot\exp\left(-\frac{V_{\max}}{C_2\cdot V_{\mathrm{OC}}}\right) \tag{4}$$

$$C_2=\left(\frac{V_{\max}}{V_{\mathrm{OC}}}-1\right)\cdot\left[\ln\left(1-\frac{I_{\max}}{I_{\mathrm{SC}}}\right)\right]^{-1} \tag{5}$$

$$\Delta I=I_{\mathrm{SC}}\cdot\left(\frac{G_T}{\mathrm{Gref}}-1\right)+\mu_{I,\mathrm{SC}}\cdot\Delta T \tag{6}$$

$$\Delta T=T_{\mathrm{c}}-T_{\mathrm{c,ref}} \tag{7}$$

T_{c} can be expressed as follows[33]

$$T_{\mathrm{c}}=T_{\mathrm{a}}+\frac{\mathrm{NOCT}-20}{800}\cdot G_T \tag{8}$$

where the normal operating cell temperature is usually between 42°C and 46°C.

Wind Turbine Model. The hourly output power of a wind generator is a function of wind speed v, which follows the relation

$$P_{\mathrm{WT}}=\begin{cases} a\cdot v^3-b\cdot P_{\mathrm{R}} & v_{\mathrm{ci}}<v<v_{\mathrm{r}} \\ P_{\mathrm{R}} & v_{\mathrm{r}}<v<v_{\mathrm{co}} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where $a=P_{\mathrm{R}}/(v_{\mathrm{r}}^3-v_{\mathrm{ci}}^3)$ and $b=v_{\mathrm{cl}}^3/(v_{\mathrm{r}}^3-v_{\mathrm{ci}}^3)$.

Scheduling constraints

The plant unit has a set of discrete operating modes corresponding to different production levels, $m\in M$. For every time period (hour h), we introduce two binary variables, y_m^h and $z_{m,m'}^h$ and one continuous variable s^h, which define the mode assignment, the transition status, and the storage level, respectively.

Mode Assignment Constraints. The constraints for the mode assignment are given by

$$\sum_{m\in M}y_m^h=1 \quad \forall h \tag{10}$$

$$\tilde{y}_m^h=y_m^{h-1} \quad \forall m,h\neq 1 \tag{11}$$

$$\tilde{y}_m^1=y_m^0 \quad \forall m \tag{12}$$

Equation 10 indicates that, within each time period h, only one mode can be active. Equation 11 defines a backward binary variable $\tilde{y}_m^h$, which takes the value assigned to the same binary variable but one time step backward. Equation 12 assigns the backward binary variable with the value of the same variable at the initial time step, y_m^0. The backward variable will be used later to determine the production transitions.

Logic Constraints for Transitions. The logic relationship that couples the binary transitional variable $z_{m,m'}^h$ with the binary variable y_m^h can be modeled with the following set of equality constraints

$$\sum_{m' \in M} z_{m',m}^h = y_m^h \quad \forall h \tag{13}$$

$$\sum_{m' \in M} z_{m,m'}^h = \tilde{y}_m^h \quad \forall h \tag{14}$$

with $z_{m,m'}^h = 1$ is true if and only if a transition from mode m to mode m' occurs from time step $h-1$ to h.

Storage Balance. The storage unit is supplied by the product from the plant and accommodates the hourly demand, d^h. Again, similar to the backward binary variable defined in Eq. 11, a backward variable ($\tilde{s}^h$) is defined for the storage level variable (s^h)

$$\tilde{s}^h = s^{h-1} \quad \forall h \neq 1 \tag{15}$$

$$\tilde{s}^1 = s^0 \tag{16}$$

The initial storage level (s^0) is assigned to $\tilde{s}^h$ at time index $h=1$. The storage level in the storage unit at the end of each time step is given by the following equation

$$s^h = \tilde{s}^h + \sum_{m \in M} (y_m^h \cdot p_m) \cdot \left[1 - \sum_{m',m \in M} (z_{m',m}^h \cdot t_{m',m})\right] - d^h \tag{17}$$

where p_m is the production level associated with operating mode m, and $t_{m',m}$ is the transition time period from mode m' to m. For self-transition, $t_{m,m}=0, \forall m \in M$. It is noted that a certain amount of off-specification product is generated and sent to waste when the process undergoes production level changes.

The storage unit has to satisfy an hourly demand for the product in each time step and has a maximum storage level, which is specified by

$$0 \leq s^h \leq s_{\max} \quad \forall h \tag{18}$$

Additionally, to avoid depleting the product in the storage unit, the storage level at the terminal time step (s^H) should not be less than the initial value of the storage level s^0, which is represented by

$$s^H \geq s^0 \tag{19}$$

The above terminal constraint on the storage level can be overly restrictive in cases when the chosen horizon, H, is too short. This is because the plant needs to operate for a certain time at high production levels to compensate for the losses during periods of under-utilization. If H is not long enough, the resulting production schedule could force the plant to operate at a constant mode. There are some studies on the impact derived from the length of the optimization horizon, especially in the area of economic model predictive control.[34,35] Adeodu and Chmielewski,[34] for example, have shown that short predictive horizons result in under-utilization of storage capabilities. Additionally, infinite-horizon-based optimization has also been considered in the literature.[35,36] In this work, different choices of H are investigated, and a discussion of the economic impact resulting from different horizon sizes are presented in the case study section.

Electricity balance

The electricity consumption can be divided into two parts: one associated with the production periods, and the other associated with the transition periods. Here, two auxiliary variables, ΔE^h and Δe_i^h, are introduced to capture the net electricity demand (demand less available generation) within hour h during the production and transition time periods, respectively.

Production Period. Given that the manipulated variables remain constant during the production period, the electricity required for the current operating mode also remains constant and can be computed from

$$d_{\mathrm{el}}^h = \alpha \cdot \sum_{m \in M} \left[y_m^h \cdot (\bar{u}_m^1 + \bar{u}_m^2 + \cdots + \bar{u}_m^n)\right] \cdot \left[1 - \sum_{m',m \in M} (z_{m',m}^h \cdot t_{m',m})\right] \tag{20}$$

Therefore, ΔE^h is calculated by

$$\Delta E^h = d_{\mathrm{el}}^h - (P_{\mathrm{PV}}^h + P_{\mathrm{WT}}^h) \cdot \left[1 - \sum_{m',m \in M} (z_{m',m}^h \cdot t_{m',m})\right] \tag{21}$$

where P_{PV}^h and P_{WT}^h represent the hourly generated power from the PV panels and wind turbines, respectively.

Transition Period. To determine the electricity consumption during production transitions, the transition profile obtained from the closed-loop model simulations or historical plant data is taken into account. Suppose there are total $N_{m',m}$ sampling points during the transition time period from mode m' to mode m, the net electricity consumption Δe_i^h ($i=1, 2, \ldots, N_{m'm}$) during each sampling interval (Δt) is then given by

$$\Delta e_i^h = \left\{ \alpha \cdot \sum_{m',m \in M} \left[z_{m',m}^h \cdot (u_{m',m}^{i,1} + u_{m',m}^{i,2} + \cdots + u_{m',m}^{i,n})\right] - (P_{\mathrm{PV}}^h + P_{\mathrm{WT}}^h) \right\} \cdot \Delta t \tag{22}$$

Note that the values of the manipulated inputs at each sampling time in the above expression are known from the closed-loop transition profile, which is determined off-line for all possible changes in production levels. The changes in the manipulated inputs during transitions are, therefore, taken into account in calculating the cost of energy consumption during transitions.

Electricity Exchange. Assuming that the plant has a self-operated RE system, the surplus electricity that could be generated from the renewables may be sold back to the power grid. To model this possibility, the variables ΔE^h and Δe_i^h are each divided into two parts: one part considering the electricity purchased, and the other considering the electricity sold, which are later used in the objective function to determine the cost or revenue

$$\Delta E^h = \Delta^+ E^h - \Delta^- E^h \quad \forall h \tag{23}$$

$$\Delta e_i^h = \Delta^+ e_i^h - \Delta^- e_i^h \quad \forall h \tag{24}$$

Note that if no RE system is considered, one can just set P_{PV}^h and P_{WT}^h to be 0 in Eqs. 21 and 22, and only the term that takes into account the amount of purchased electricity is used for determining the electricity cost. In the case study to be presented later, operational scenarios with and without RE resources will be presented and compared.

Additional transition cost

Within the transition period, a certain amount of off-specification product is produced and purged (possibly as fuel). Therefore, the cost of wasted raw material should be incorporated into the objective function when the process system undergoes a mode switching. This cost is given by

$$C^h_{\mathrm{raw}}=\vartheta_{\mathrm{r}}\cdot\sum_{m',m\in M}\left(z^h_{m',m}\cdot t_{m',m}\cdot p_m\right) \tag{25}$$

Objective function

To achieve an economically optimal operation of the process, the objective is to minimize the total cost, which is calculated as follows

$$J=\min\{\Phi_1+\Phi_2+\Phi_3-\Phi_4\} \tag{26}$$

with

$$\Phi_1=\sum_{h=1}^{H}\left(\Delta^+E^h\cdot\vartheta^h_{\mathrm{el}}\right) \tag{27}$$

$$\Phi_2=\sum_{h=1}^{H}\sum_{i=1}^{N_{m'm}}\left(\Delta^+e^h_i\cdot\vartheta^h_{\mathrm{el}}\right)+\sum_{h=1}^{H}C^h_{\mathrm{raw}} \tag{28}$$

$$\Phi_3=\sum_{h=1}^{H}s^h\cdot\vartheta_s \tag{29}$$

$$\Phi_4=\sum_{h=1}^{H}\left[\left(\Delta^-E^h+\sum_{i=1}^{N_{m'm}}\Delta^-e^h_i\right)\cdot\vartheta^h_{\mathrm{el}}\cdot\eta\right] \tag{30}$$

where Φ_1 is the cost of purchased electricity during production periods, Φ_2 is the transition cost which consists of the wasted energy and raw material costs, Φ_3 is the inventory cost, and Φ_4 is the revenue from sold electricity if the plant is equipped with a RE system. Note that the electricity price $\vartheta^h_{\mathrm{el}}$ is time-varying on an hourly basis, and that the sold electricity price is proportional to the current electricity price with a ratio η.

Remark 3. The incorporation of the RE system component models in the problem formulation potentially adds a certain degree of nonlinearity and complexity to the optimization model. To avoid this complexity, the outputs of the RE generation systems can be computed off-line and then used as inputs in the scheduling problem formulation; that is, the terms P^h_{PV} and P^h_{WT} become known parameters instead of intermediate decision variables. This is the approach used to determine the RE generation in the case study. Nonetheless, the availability of RE system component models is useful for analyzing the impact of different RE system sizes on the solution to the scheduling problem, which will also be illustrated in the case study.

Solution algorithm

The energy demand management problem considered in this work is cast as an MINLP problem which can be solved using standard techniques for solving MINLPs. Here, the solver DICOPT available in GAMS software was used. While a globally optimum solution cannot be guaranteed for MINLPs in general, useful solutions can still be obtained and analyzed as will be demonstrated in the next section.

It should be noted that given that the operating modes and controller parameters are fixed *a priori* in the proposed formulation, the transition time and profile between any pair of modes (obtained from the off-line closed-loop simulations) will be fixed and, if the plant-model mismatch is not significant, the values estimated off-line will be close to the actual values resulting when the controller is implemented on the plant. The main reason to prefer the strategy of off-line determination of the transition times as presented in this work—compared with the case in which the differential equations are discretized and incorporated directly as constraints into the optimization model[12,37,38], is because the resulting optimization model is simpler, and thus allows us to focus more on understanding the key ideas and implications of the proposed energy demand management scheme. With the precalculated transition profile, the involvement of discretized nonlinear differential equations is avoided, the nonlinearity and nonconvexity of the underlying optimization formulation are reduced to some extent, and the resulting optimization problem becomes easier to solve.

Remark 4. In the proposed formulation, the operating space is reduced to a discrete set of predefined production levels. This helps reduce the computational load of the scheduling problem, but it may also lead to suboptimal economic performance. As the number of discrete production levels is increased, one would expect a possibly improved economic performance—due to the larger feasible region—at the expense of increased computational cost. Ultimately, it would be best to find the optimal production level without *a priori* defining such levels; however, this can lead to a substantial increase in the computational complexity of the optimization problem, and is beyond the scope of the current study.

Case Study

To illustrate the application of the proposed DR optimization formulation, we consider in this section a single CSTR unit as shown in Figure 3, which conceptually represents a simplified version of the plant unit in Figure 1. Even though the CSTR is not a power-intensive process, it is still straightforward to illustrate the proposed formulation if we focus only on the management of energy demand, which is assumed to be roughly proportional to the material flow. Considering a single product that is produced by the reaction $A\rightarrow B$, the following model equations describe the dynamics of the CSTR

$$\frac{dC}{dt}=\frac{F}{V}(C_i-C)-k_0\cdot e^{-E/RT}\cdot C \tag{31}$$

$$\frac{dT}{dt}=\frac{-\Delta H\cdot k_0\cdot e^{-E/RT}\cdot C}{\rho C_{\mathrm{p}}}+\frac{F}{V}(T_i-T)+\frac{UA_{\mathrm{c}}\cdot(T_{\mathrm{c}}-T)}{\rho C_{\mathrm{p}}\cdot V} \tag{32}$$

$$\frac{dT_{\mathrm{c}}}{dt}=\frac{F_{\mathrm{c}}}{V_{\mathrm{c}}}(T_{\mathrm{ci}}-T_{\mathrm{c}})+\frac{UA_{\mathrm{c}}}{\rho_{\mathrm{c}}C_{\mathrm{pc}}\cdot V_{\mathrm{c}}}(T-T_{\mathrm{c}}) \tag{33}$$

The inlet concentration is $C_i=0.5$ mol/ft^3 (17.657 mol/m^3) and the concentration of the product is 0.0591 mol/ft^3 (2.087 mol/m^3). The model parameter values can be found in Feital et al.[39] The above equations are discretized using Euler's method,[40]and the sampling interval Δt is chosen to be 0.01 h. The CSTR is equipped with two cascaded proportional-integral (PI) controllers, in which the inner loop of the control structure manipulates the reactor coolant inlet flow rate F_{c} to track the set-point $F_{\mathrm{c,sp}}$ given by the outer loop

$$F_{\mathrm{c}}(k+1)=F_{\mathrm{c}}(k)+K_{\mathrm{p,c}}[e_{\mathrm{c}}(k)-e_{\mathrm{c}}(k-1)]+K_{I,\mathrm{c}}e_{\mathrm{c}}(k) \tag{34}$$

where $e_{\mathrm{c}}=F_{\mathrm{c,sp}}-F_{\mathrm{c}}$, $K_{\mathrm{p,c}}=0.08$, and $K_{I,\mathrm{c}}=0.4$. In practice, the realizable value of F_{c} is bounded due to physical limitations

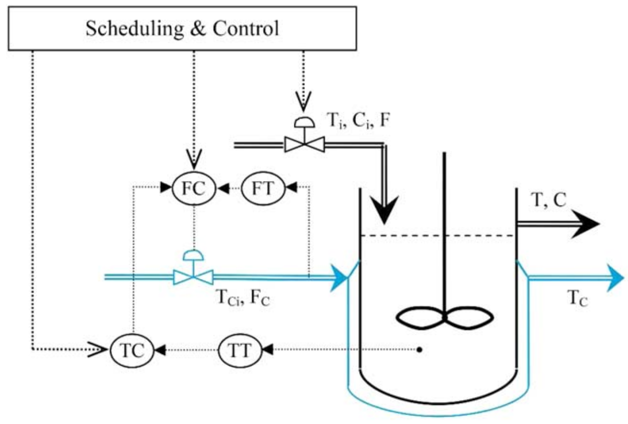

Figure 3. A CSTR equipped with feedback control.

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on the capacity of control actuators. The following bounds are considered

$$10\frac{\mathrm{ft}^3}{\mathrm{h}} \le Fc \le 80\frac{\mathrm{ft}^3}{\mathrm{h}} \tag{35}$$

The outer loop controller is responsible for stabilizing the reactor temperature T at the desired value $\bar{T}$ which is determined by the solution to the scheduling optimization problem

$$F_{\mathrm{c,sp}} = \bar{F}_{\mathrm{c}} + K_{\mathrm{p},T}[e_T(k) - e_T(k-1)] + K_{I,T}e_T(k) \tag{36}$$

where $e_T = \bar{T} - T$, $K_{\mathrm{p},T} = -1.8$, and $K_{I,T} = -4.2$. The controller parameters for both loops were tuned empirically by trial and error in this study. Other systematic methods, such as the ultimate-gain method,[41] for example, could be used instead, whenever appropriate. The solution to the scheduling problem provides the optimal set-points to the controllers and manipulates the feed flow rate F to realize the desired changes in production levels.

The feasible operating modes for the CSTR are specified in Table 1. The energy required for the different modes is proportional to the sum of the material flow rates (i.e., F and F_c). Operating mode 3 is considered as the nominal operating mode which is used to meet the hourly demand for the product, 35 ft^3/h (0.991 m^3/h) before any DR strategy is implemented. The transition times ($t_{m',m}$) for all possible transitions are tabulated in Table 2, which are obtained through running offline closed-loop CSTR simulations. The transition time depicted in Table 2 is defined as the time required for the concentration C to reach a value within 1% of the target value. It is important to emphasize that the transition times are obtained with fixed controller parameters. As stated earlier (see Remark 2), optimal controller parameters can be tuned individually off-line for each possible transition to improve the transition economics. However, this is not the focus of this work, and it is not pursued here. In the remainder of this section, two scenarios are investigated. In the first case, a simplified optimization model without RE generation is considered; and in the second case the full version of the proposed formulation is implemented.

Energy demand management under time-sensitive electricity prices

Given that RE generation is not considered in this case, that is, $P_{\mathrm{PV}}^{H}=0$ and $P_{\mathrm{WT}}^{h}=0$, the electricity required is purchased from the power grid and no revenue is generated. The objective function in Eq. 26 simplifies to the following one

$$J = \min\{\Phi_1 + \Phi_2 + \Phi_3\} \tag{37}$$

Table 1. Feasible Operating Modes for the CSTR Process

Operating Modes	Production Rates F (ft^3/h)	Jacket Flow F_c (ft^3/h)
6	50 (1.416 m^3/h)	58.227 (1.648 m^3/h)
5	45 (1.274 m^3/h)	54.040 (1.530 m^3/h)
4	40 (1.133 m^3/h)	49.747 (1.409 m^3/h)
3	35 (0.991 m^3/h)	45.327 (1.284 m^3/h)
2	30 (0.850 m^3/h)	40.752 (1.154 m^3/h)
1	25 (0.708 m^3/h)	35.985 (1.019 m^3/h)

Plant schedules are established for one day with electricity prices varying at three different levels: 69.999 \$/MWh, 94.789 \$/MWh, and 163.398 \$/MWh, as can be seen in Figure 4a. Figure 4 presents a comparison of the solutions obtained using three different optimization formulations, where Formulation (I) refers to an optimization formulation with a continuum of possible production levels ignoring the transitions, Formulation (II) corresponds to an optimization formulation with a set of discrete production levels, but with a fixed transition time, and Formulation (III) represents the proposed optimization model with transition behaviors and costs considered. Formulation I assumes that the plant can be operated at any production level that is bounded between 25 and 50 ft^3/h, and no transition process is considered (i.e., instant mode switching is assumed to be possible). The optimization model for this formulation reduces to an NLP problem, where the nonlinearity comes from the nonlinear process dynamics given in Eqs. 31–33. Formulation II is a simplified version of Formulation III with all transition times fixed at 0.3 h. The calculation of energy cost within this transition period is assumed to be the same as that during the production periods. Due to the fixed transition time, the transition cost for this formulation is also fixed. This formulation is useful for benchmarking the results of the proposed formulation against other formulations in the literature which typically assume a fixed transition cost. Despite the simplifications made in Formulation II, the resulting optimization model is still cast as an MINLP problem given that the binary variables y_m^h and $z_{m,m'}^h$ are still needed. The initial state of the operating mode is the nominal one, and the storage level is initialized at 10 ft^3 (0.283 m^3) as shown by the green dashed line in Figure 4c.

As expected, the process switches to a lower production level when the electricity price goes up and vice versa. Compared with the solutions obtain from Formulations II and III given in Figure 4b, more frequent mode switching is observed when Formulation I is implemented due to the assumed zero transition cost. For this case, the resulting solution tends to

Table 2. Transition Times for the Closed-Loop CSTR Process (h)

Operating Modes m	6	5	4	3	2	1
6	0	0.21	0.25	0.31	0.4	0.55
5	0.20	0	0.23	0.29	0.36	0.50
4	0.41	0.22	0	0.26	0.33	0.44
3	0.43	0.42	0.24	0	0.29	0.40
2	0.60	0.45	0.43	0.26	0	0.34
1	0.72	0.51	0.50	0.29	0.30	0

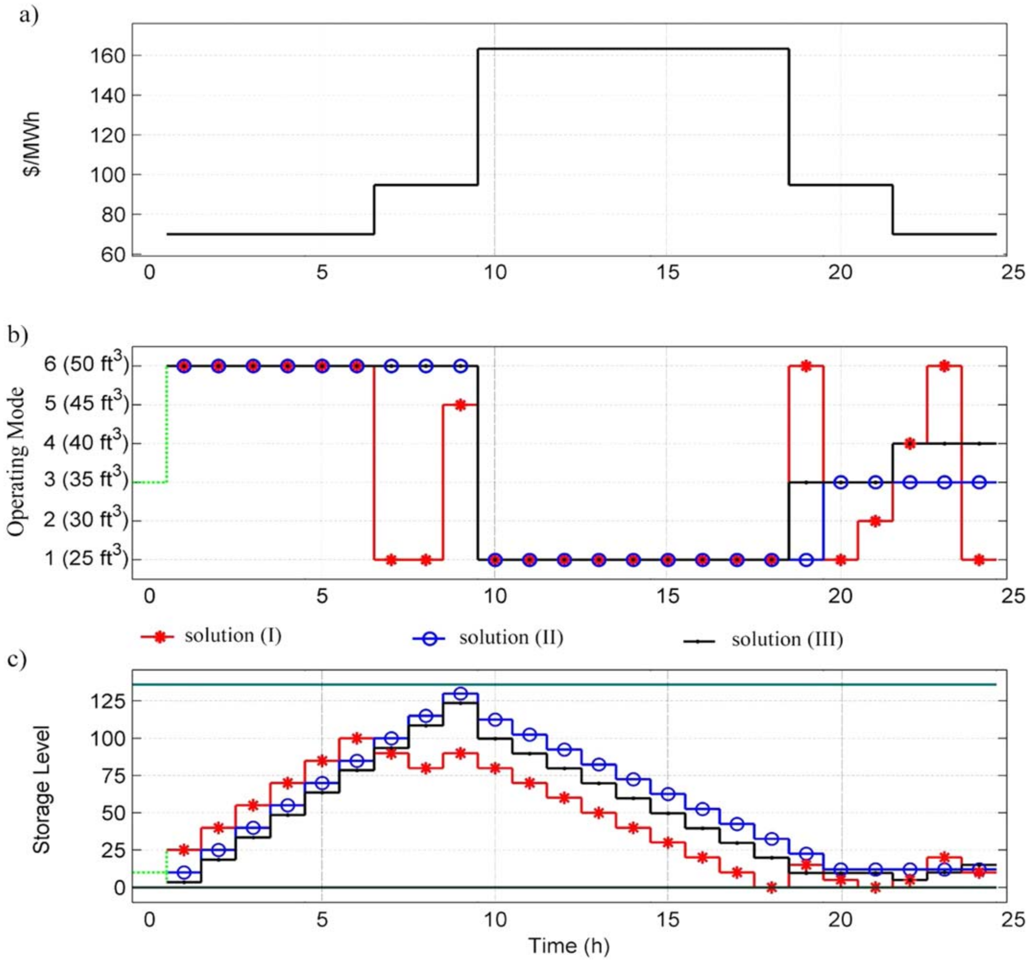

Figure 4. Production Scheduling when no RE generation is considered: (a) time-sensitive electricity prices; (b) the solutions obtained using different optimization formulations: (I) blue (star markers), (II) red (circle markers), and (III) black (dot markers); (c) inventory profiles.

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underutilize the storage tank to reduce inventory costs as shown by the red line (star markers) in Figure 4c. The profile of the solution corresponding to Formulation II, of course, is heavily dependent on the prefixed transition time. The fixed transition time of 0.3 h was deliberately chosen so that the deviation between Formulations II and III are small.

Given that instant mode switching does not exist in practice (i.e., actual transition time is always greater than zero), to compensate for the transition waste, the process should increase the time spent at the higher production level and reduce the hours at the lower production level, which can be observed from the solutions corresponding to Formulations II and III in Figure 4b. Moreover, it is important to note that the solution corresponding to Formulation III forces the plant to operate at a higher production level than that in the case of Formulation II within the last 3 h of the day. This is mainly due to the terminal constraint in Eq. 19. Additionally, the corresponding storage profiles for Formulations II and III are depicted in Figure 4c, together with lower and upper bounds on storage capacity. One can clearly observe how the product demand is met from the storage unit when the process operates at the low production level. However, it should be emphasized that due to their inadequate handling of transition behavior (Formulation I ignores transitions altogether, while Formulation II underestimates some of the transition periods), the solutions resulting from Formulations I and II cannot be truly realized in practice as the actual transition waste incurred during changes in production levels actually take place could make satisfaction of the hard hourly demand constraint impossible.

Figure 5 illustrates the variations of the manipulated and state variables in the closed-loop system, which correspond to the scheduled operating modes obtained from the proposed optimization model (Formulation III) in Figure 4b. To assess the economic performance of the different optimization models, a comparison of the total costs with a time horizon of $H = 24$ is provided in Figure 6, where Formulation IV represents an additional solution where only the nominal operating mode is active for all times (i.e., no DR is implemented). Not surprisingly, Formulation I achieves the lowest cost due to the absence of any transition cost in the objective function. The total cost achieved in Formulation II is smaller than the cost associated with the proposed formulation (Formulation III). This is due to the fact that the transition time is underestimated in Formulation II (some of the actual transition times are larger than the fixed value of 0.3 h as can be seen from Table 2). Under the proposed DR scheme, however, the total cost (Formulation III) is reduced compared with the cost in Formulation IV where no energy demand management is considered.

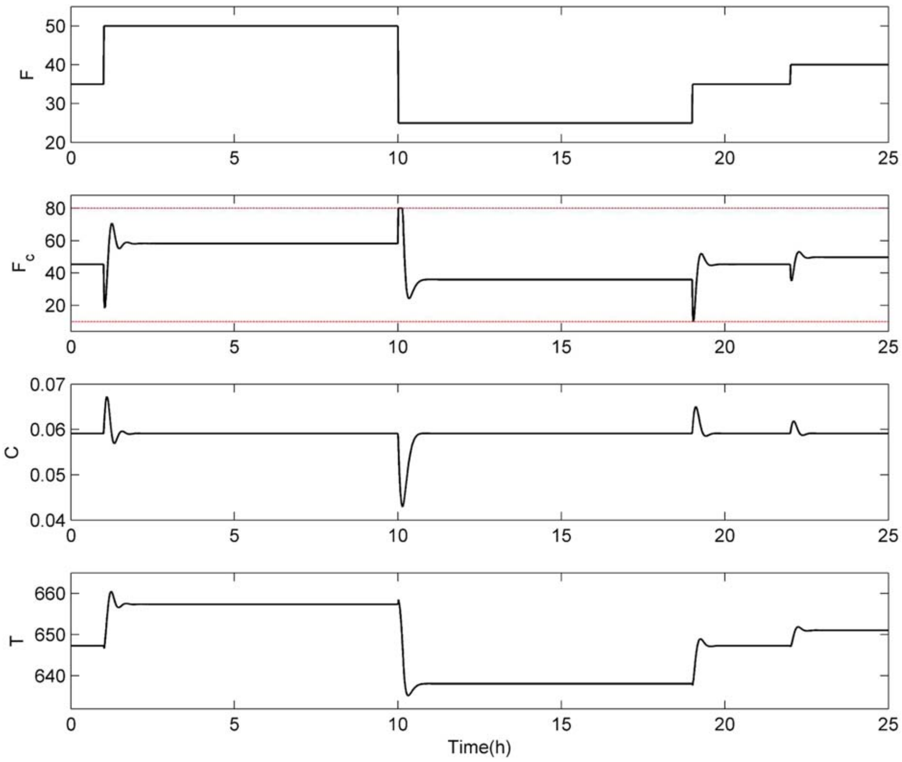

Figure 5. Time evolution of the closed-loop CSTR's manipulated and state variables under the proposed production scheduling formulation.

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As noted previously, the terminal constraint defined by Eq. 19 can be restrictive if the optimization horizon is small. To this end, an additional comparison is made with three different optimization horizons (i.e., $H = 24$, 48, and 72). Because of the different horizon sizes, the comparison for daily cost instead of total cost is illustrated in Figure 7. It is evident that the daily operating cost is reduced if the optimization horizon size is increased. It can then be concluded that the achieved economic benefits can be more optimal and less influenced by the terminal constraint with the increasing size of the optimization horizon.

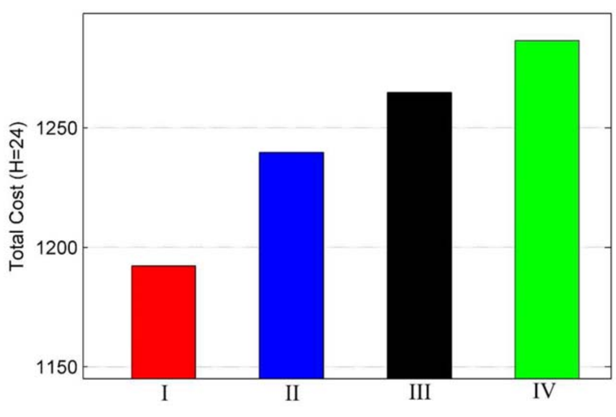

Figure 6. Total costs for (I) the continuum production formulation ignoring the transitions, (II) the discrete production formulation with a fixed transition time, (III) the proposed scheduling model with transition dynamics and costs considered, and (IV) the case when only the nominal operating mode is active.

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Energy demand management for process systems with RE cogeneration

In this subsection, the case when the RE system depicted in Figure 1 is used to provide some of the electricity demand is considered. Forecasting methods for predicting the output of RE resources have been the focus of extensive research and development.[42,43] In this article, the hourly weather data of current conditions and forecast are downloaded from Weather Analytics, which provides current and hour-by-hour seven-day

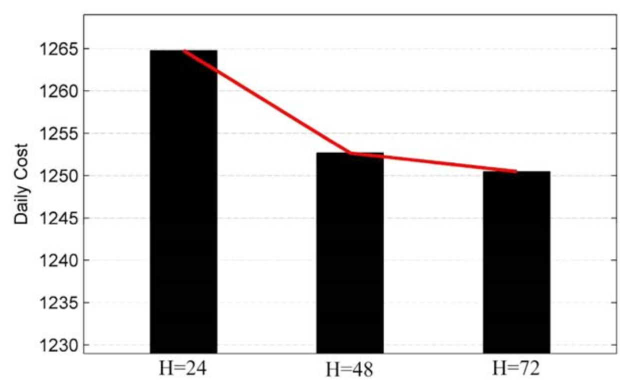

Figure 7. Daily operating cost as a function of horizon size.

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Table 3. Perfect Forecasting of RE Generation on an Hourly Basis (MW)

The First Day			The Second Day		
Time	PV	WT	Time	PV	WT
01:00	0.0000	0.0993	01:00	0.0000	0.3113
02:00	0.0000	0.0993	02:00	0.0000	0.4708
03:00	0.0000	0.0000	03:00	0.0000	0.4708
04:00	0.0000	0.0000	04:00	0.0000	0.4708
05:00	0.0000	0.0000	05:00	0.0000	0.0993
06:00	0.0000	0.6726	06:00	0.0000	0.0993
07:00	0.0000	0.0000	07:00	0.0000	0.0369
08:00	0.0000	0.0000	08:00	0.0000	0.0000
09:00	0.0000	0.0000	09:00	0.0000	0.0000
10:00	0.0985	0.3113	10:00	0.0711	0.0000
11:00	0.2508	0.1891	11:00	0.2258	0.0000
12:00	0.3437	0.0993	12:00	0.3265	0.0000
13:00	0.3752	0.0993	13:00	0.3872	0.0000
14:00	0.2795	0.0993	14:00	0.3817	0.0000
15:00	0.1698	0.0000	15:00	0.3114	0.0369
16:00	0.0645	0.0000	16:00	0.1470	0.0369
17:00	0.0000	0.0000	17:00	0.0000	0.0000
18:00	0.0000	0.0000	18:00	0.0000	0.0000
19:00	0.0000	0.0000	19:00	0.0000	0.0000
20:00	0.0000	0.0000	20:00	0.0000	0.0000
21:00	0.0000	0.3113	21:00	0.0000	0.0000
22:00	0.0000	0.0993	22:00	0.0000	0.0000
23:00	0.0000	0.7910	23:00	0.0000	0.0000
24:00	0.0000	0.4708	24:00	0.0000	0.0000

forecasted weather conditions. Once a good output forecast becomes available, the question is raised as to how to utilize the information from weather forecasting to better manage the energy demand of the process.

We first investigate the potential of using perfect weather forecasting data. In this case, no updating of the predicted RE system outputs is required; and real-time optimization (RTO) is adopted to generate an operating policy for the CSTR. Here, two factors, namely the electricity prices and available RE, are time-dependent. Generally speaking, depending on the size of the RE system, the RE generation can be a dominant factor and directly influences the solution of the production scheduling problem. Therefore, to explore the impact of varying RE system sizes, three cases are considered: under-sized, nominal-sized, and oversized. The perfectly forecasted outputs of the nominal-sized RE system are calculated using Eqs. 1–9 on an hourly basis, and are reported in Table 3, with an optimization horizon of $H = 48$. The outputs for the under-sized and the oversized RE systems are chosen to be proportional to those in Table 3 with factors of 0.25 and 2.0, respectively.

The solutions at each time index and the corresponding storage profiles are depicted in Figure 8. As expected, with different RE system sizes, the scheduled operating modes are different. Moreover, it is interesting to note that the solution for the under-sized RE system (i.e., Figure 8b) is the same as the one without any RE resources. This is because the electricity price is the dominant factor under these two conditions. When the RE system is oversized, the relatively high production level (i.e., Mode 4) is active even if the electricity price goes up, as can be observed by the red line (plus markers) in Figure 8b within the time periods [10, 14] and [34, 39]. This is made possible by the excess energy generated during the peak generation hours, and it becomes more economical to operate the process at a higher production level. For the nominal-sized

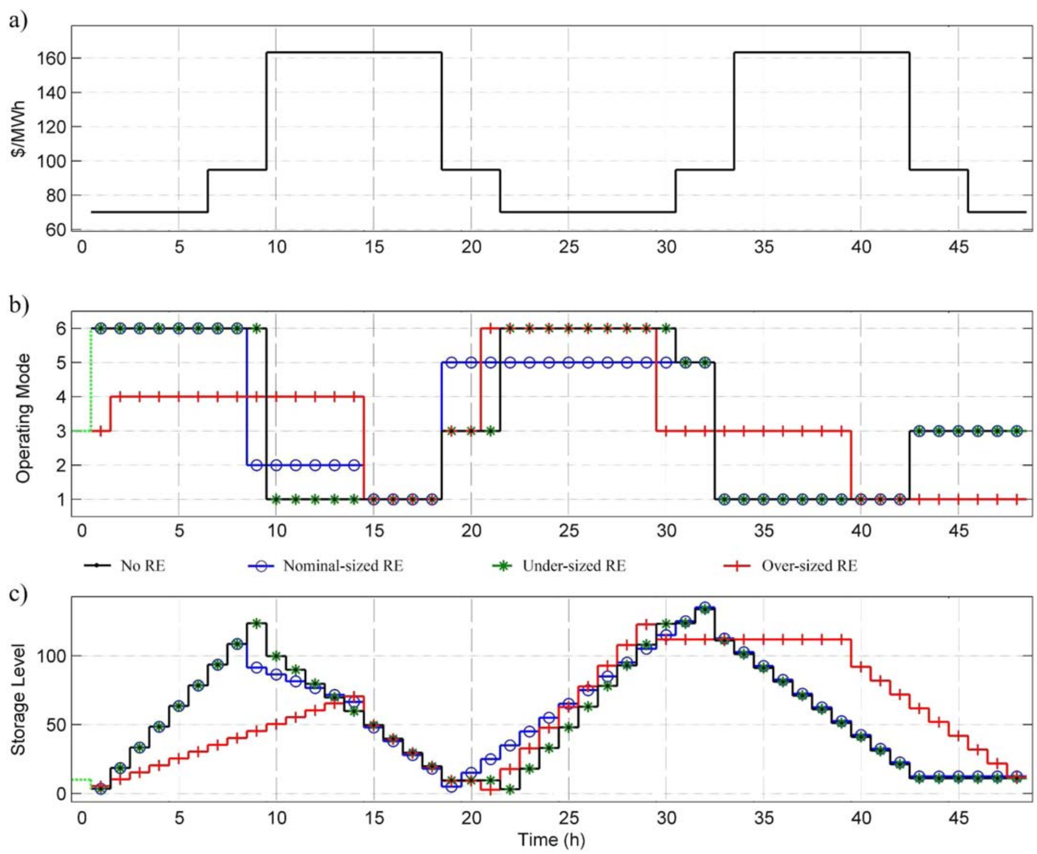

Figure 8. Production scheduling under perfect weather forecasting for different RE system sizes: (a) time-sensitive electricity prices, (b) operating modes, and (c) inventory profiles.

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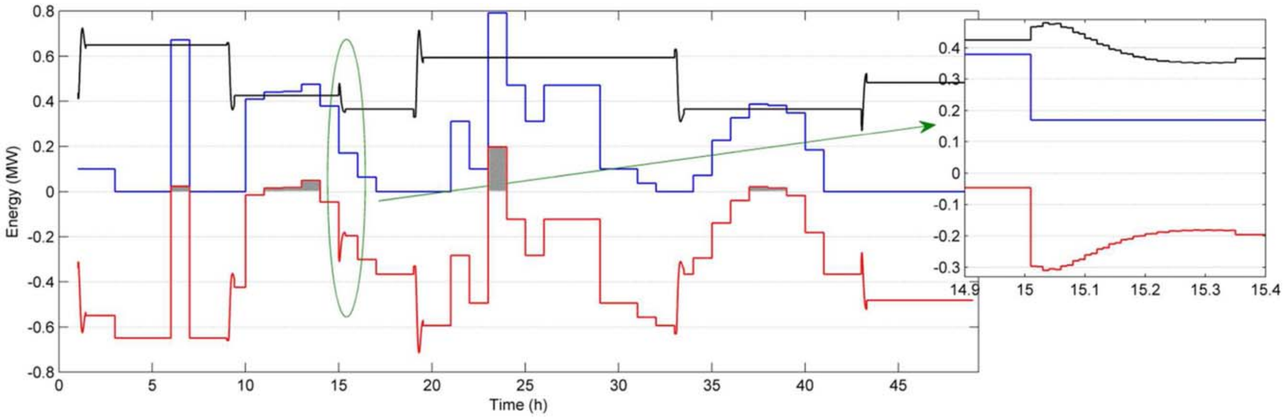

Figure 9. Energy balance profiles for the required energy (black, top profile), generated renewable energy (blue, middle profile), and the net energy demand (red, bottom profile).

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system, these two factors have comparable effects on the optimization model, and a tradeoff solution is obtained, as illustrated by the blue line (circle markers) in Figure 8b. During the peak RE generation hours in the first day, the available RE can only afford to operate the process at the second lowest production level with the consideration of relatively expensive electricity prices for a certain time period. Figure 8c illustrates the inventory profiles obtained for the different cases, from which one can see how the hourly demand is satisfied when the plant is under-utilized.

Given that the net energy loads within the production and transition periods are calculated on the basis of hour h and sampling interval Δt as defined in Eqs. 21 and 22, respectively, the profiles of the required energy, the generated RE, and the net energy demand shown in Figure 9 are presented to illustrate the energy balance. The black line (top profile) in Figure 9 shows the required energy for operating the plant unit according to the schedule given by the blue line (circle markers) in Figure 8b, where the plant unit with the nominal-sized RE is considered. The blue line (middle profile) in Figure 9 presents the hourly available RE for the whole horizon, which is plotted according to the values tabulated in Table 3. The red line (bottom profile) in Figure 9 shows the surplus and purchased electricity in the interaction with the power grid, of which the shadow areas display the energy sold to the power grid.

The above study illustrates how process operation can be made responsive to both time-varying electricity prices and intermittent renewable resources through a combination of production scheduling and closed-loop control. We now consider the uncertainty in predicting the weather data. Given that the forecasting weather data is updated hourly, it is important to explore new solutions to operate the process in the most efficient way. This motivates the use of a receding horizon optimization (RHO) strategy. The optimization problem is implemented within a receding horizon framework in the sense that the hourly forecasting data is updated at each time step, and only the solution of the first time step is implemented. In this case, the plant unit is equipped with a nominal-sized RE system.

As one would expect, the application of RHO results in operation similar to the RTO case, as shown in Figure 10. In

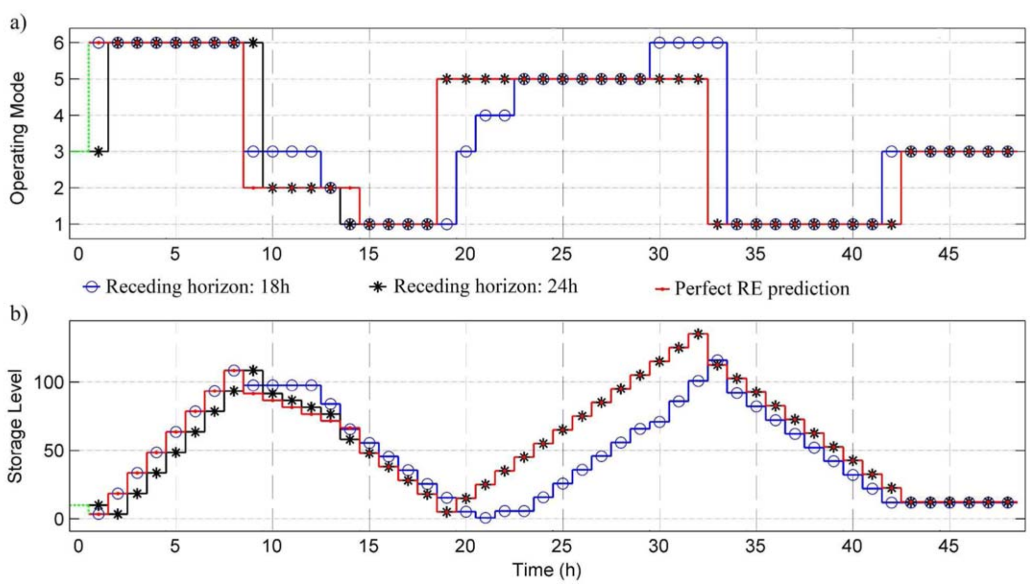

Figure 10. Production scheduling using RHO: (a) operating profiles, (b) inventory profiles.

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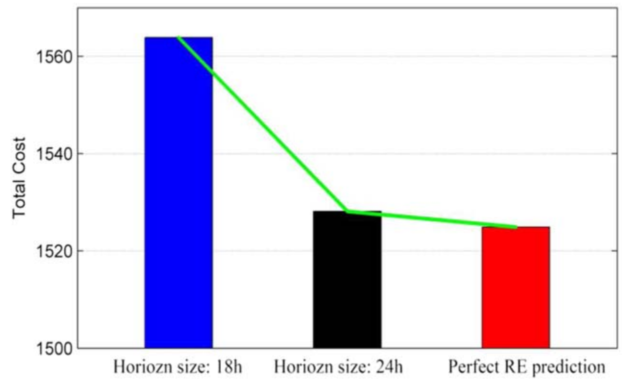

Figure 11. Total costs of different cases.

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this case, two different sizes of the receding horizon are investigated (e.g., $H=18$, $H=24$). Note that the terminal constraint given in Eq. 19 is not active until the receding horizon reaches the last hour of the entire optimization horizon (i.e., 48 h). Given that the purpose of Eq. 19 is to avoid depleting the storage tank at the end of the schedule, none of the hours—except the terminal one—is restricted. The profile resulting from RHO appears a bit more exaggerated because of the uncertainty in the forecasting of available RE resources. With a small receding horizon size (i.e., $H=18$), the obtained solution exhibits more variations compared with the other two, which results in more costly operation as shown in Figure 11. In comparison to the solution obtained under perfect RE output predictions, the longer the receding horizon is, the more similar the resulting schedules are and the more economically optimal the operation is.

Finally, it should be noted that in all the simulations presented in this section, the storage level was initially set at 10 ft^3 (0.283 m^3) of inventory to ensure the transition and still meet the hourly demand for product. The simulation results, of course, are sensitive to the prespecified parameters such as this initial level. Nevertheless, the values of the parameters in this case study were chosen to be as realistic as possible, and of course further studies can be performed to explore these points as well.

Conclusions

In this work, an optimization-based production scheduling approach was developed for the management of energy demand in process systems subject to time-sensitive electricity prices and intermittent RE resources. The proposed optimization model realized DR through switching between a set of prespecified production levels in a way that accounts explicitly for the cost and dynamics of the transitions between the different operating modes. Based on an off-line computation of the closed-loop transition profiles for all possible pair-wise mode switches, the production scheduling problem was cast as an MINLP problem. While consideration of transition costs leads to an MILP formulation, which is harder to solve compared with conventional LP or MILP formulations that result when transition costs are ignored, the MINLP formulation is more realistic as it accounts for the energy and raw material losses incurred during transitions in deciding the operationally optimal demand responsive production schedule. It should be noted, however, that in the face of highly nonlinear behavior, convergence toward the globally optimal solution is difficult to achieve in general, and the nonconvexity of the optimization formulation often leads to suboptimal solutions.

A key feature of the proposed DR approach is that it addresses the problem in a closed-loop manner (i.e., in the presence of controllers). However, the integration of scheduling and control was not attempted here, and the role of closed-loop control was limited mainly to the execution of the transitions prescribed by the solution of the scheduling problem. Given that the transition time and cost are dependent on the type of controller used and the way in which it is tuned, future work will explore more general scheduling and control formulations that would allow simultaneous determination of the optimal production schedule and the optimal controller parameters needed to drive mode transitions. Another direction for future work is to generalize the proposed formulation by relaxing the assumption of proportionality between energy consumption and material flow. While this assumption was made in this study mainly to simplify the calculations, there are situations where it does not hold (e.g., a variable part of the feed stream undergoing a phase transformation). In such cases, where there is no explicit relationship between material throughput and energy consumption, the full process model must be used to estimate energy use.

Notations

Indices

$m \in M$ = set of operating modes.
$h=1,2,\ldots,H$ = time index.
$1,2,\ldots,n$ = index of manipulated variables.
$i=1,2,\ldots,N_{m'm}$ = sampling points during transition period.

Parameters

$s_{\max}$ = maximum storage level, 140 ft^3 (3.964 m^3)
$\bar{u}^1,\ldots,\bar{u}_m^n$ = steady-state values of manipulated variables for mode m
$u_{m',m}^{i,2},\ldots,u_{m',m}^{i,n}$ = sampled values of manipulated variables from transition m' to m
Δt = sampling interval, 0.01 h
p_m = production rate for operating mode m
d^h = production hourly demand
α = energy required to material flow ratio, 0.006 MWh/ft^3
ϑ_r = unit price of raw material, 0.1 \$/ft^3
ϑ_{el}^h = time-sensitive electricity prices
ϑ_s = unit price of inventory cost, 0.01 \$/(ft^{3}h)
η = electricity sold price to electricity purchase price ratio, 0.1

Variables

y_m^h = binary variable to denote if mode m is active in time step h
$\tilde{y}_m^h$ = binary auxiliary variable
$z_{m',m}^h$ = binary variable to denote if a transition happens from mode m' to m at time h
s^h = storage level at time h
$\tilde{s}^h$ = auxiliary variable
Δ^+E^h = purchased electricity during production period
Δ^-E^h = sold electricity during production period
$\Delta^+e_i^h$ = purchased electricity during transition period at each sampling interval
$\Delta^-e_i^h$ = sold electricity during transition period at each sampling interval

Other symbols

I_{mpp} = PV panel current at the maximum power point
I_{SC} = short circuit current of PV panel
$V_{\max}$ = maximum voltage of PV panel at the reference operating conditions
V_{OC} = open circuit voltage of PV panel
V_{mpp} = PV panel voltage at the maximum power point

$\mu_{V,OC}$ = temperature coefficient for short circuit current
$\mu_{I,SC}$ = temperature coefficient for short circuit current
T_c = PV panel operating temperature
$T_{c,ref}$ = PV panel temperature at reference operating condition
G_T = hourly irradiance on a tilted surface
P_R = rated power of the wind turbine
v = wind speed
v_r = rated wind speed of the wind turbine
v_{ci} = cut-in wind speed of the wind turbine
v_{co} = cut-out wind speed of the wind turbine
C = reactant concentration, 0.0591 mol/ft^3
C_i = feed stream concentration, 0.5 mol/ft^3
V = reactor volume, 48 ft^3
ρ = density of the stream liquid, 50 lb$_m$/ft^3
ρ_c = density of the cooling liquid, 62.5 lb$_m$/ft^3
C_p = heat capacity of the process liquid 0.75 BTU/lb$_m$ R
C_{pc} = heat capacity of the cooling liquid, 1 BTU/lb$_m$ R
V_c = jacket volume, 3.85 ft^3
U = overall heat transfer in the jacket, 150 BTU/lb$_m$ R
A_c = heat transfer area, 250 ft^3
k_0 = pre-exponential factor, 7.08×10^{10} 1/h
E = activation energy, 30000 BTU/mol
R = universal gas constant, 1.99 BTU/mol R
ΔH = reaction enthalpy, -30000 BTU/mol
T_{ci} = inlet jacket temperature, 530 R

Acknowledgments

Financial support, in part by the National Natural Science Foundation of China (21176073), the China Scholarship Council (CSC), the US National Science Foundation (CBET-1438456), and the K.C. Wong Magna Fund of Ningbo University, is gratefully acknowledged. The authors would also like to thank the anonymous reviewers for their valuable comments and insights.

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Manuscript received Jan. 21, 2015, and revision received July 31, 2015.