A real-time decision model for industrial load management in a smart grid

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HIGHLIGHTS

• Propose a real-time decision model for industrial energy consumption management.
• Consider both current and future load control in the scheduling horizon.
• Adopt robust optimization to model the future price uncertainty.
• Conduct a case study over an entire steel powder manufacturing process.

ABSTRACT

The potential impacts of evolving industrial load management into demand response (DR) programs have been widely acknowledged. This paper proposes a real-time decision model for the load management of an industrial manufacturing process in the face of ever-changing real-time prices (RTPs). Due to the inherent dependence between consecutive tasks in a manufacturing process, the decision model must take future load management into consideration. The challenge lies in the uncertainty that future RTPs cannot be known in advance. In view of this, robust optimization was adopted to deal with future price uncertainties, such that the proposed model is able to make timely decisions for industrial load control when receiving the RTP for the current time slot, while considering load scheduling in future time slots. The case study was conducted on a steel powder manufacturing process; simulation results validated the effectiveness of the proposed real-time decision approach from various perspectives.

1. Introduction

Ever-increasing electricity demand causes a huge burden on the power grid; the traditional solution is to build new generation capacity to match the supply and demand while suffering the escalating costs of burning fuels and carbon emission issues [1]. With the advent of the smart grid [2], demand response (DR) has started to play an active role in improving grid efficiency and reliability due to the ability to react quickly to supply-demand mismatch by adjusting flexible loads on the demand side [3–5]. Industrial DR management is often concerned with power-intensive industrial processes, for which the potential impact has been widely acknowledged [7].

There are still few efficient DR mechanisms designed for the energy management of industrial manufacturing processes. The works in [8–12] were built as day-ahead deterministic models: that is, assuming next-day electricity prices (e.g., time of use (TOU) prices or day-ahead real-time prices (DA-RTP)) are available to the industrial facility, the optimal energy consumption scheduling for the next day can be predefined accordingly through minimizing daily costs. Recently, an incentive-based real-time demand bidding strategy has been proposed for energy management of discrete manufacturing process [13], however, the period that the incentive was issued to the industrial facility was assumed to be known in advance. To some degree, the model in [13] is still deterministic and cannot accommodate the uncertainty under the context of dynamic smart grid environment. Overall, the above deterministic models face the challenges of unforeseeable incidents that might occur during the real-time stage. Moreover, along with deregulation of the electricity industry, power can be injected into the grid from various locations at different times, and the involvement of demand-side resources in the electricity market further exacerbates real-time imbalances between supply and demand. All of these factors cause inaccuracies in day-ahead price forecasts; that is, DA-RTP cannot catch up with the real-time
situation of ever-changing wholesale electricity prices. Given this, it is imperative to devise innovative DR mechanisms that can accommodate the volatility or uncertainty of dynamic real-time prices (RTPs).

Several portable real-time DR energy management schemes were proposed in [14–16], which can aid residential users in making timely decisions for controlling the loads as a response to received RTPs. These DR schemes focused on the instantaneous load control of equipment in the current time slot without considering the future price uncertainty, which cannot be applied directly to an industrial facility. Because a manufacturing process is usually composed of different consecutive tasks that inherently function together and cannot be treated independently, an extended scheduling horizon (e.g., 1 day) is needed when modeling the load management issues of an industrial manufacturing process.

The studies in [17–19] proposed DR approaches for various applications by formulating a 1-day time horizon, which not only made real-time energy management decisions for the present time slot (when provided with the RTP), but also took future price uncertainty into consideration. Broadly, two effective approaches have been applied to deal with price uncertainty: scenario-based stochastic programming models [17,20–24] and robust optimization [18,19,25]. With the former approach, multiple scenarios need to be generated; then, scenario-dependent operation decisions are derived in response to electricity price uncertainties in each scenario. This requires using probability distributions to generate scenarios, where fitting probability distributions to uncertain data (e.g., future prices) is complex. Moreover, the number of scenarios required to describe the uncertain data is usually quite large, which may cause severe computational burdens and result in intractability, especially when the application is complex [19].

As an alternative solution, robust optimization has been adopted to model price uncertainty in [18,19,25,26]. Robust optimization is a useful tool to tackle optimization problems with uncertain parameters, where an uncertainty set (e.g., intervals) is used to describe the variability of uncertain parameters that can be readily generated using existed forecasting techniques [27–29]. With the uncertainty set, robust optimization guarantees feasibility for all realizations of the uncertain parameters within this set, and results in a much lighter computational burden compared with a stochastic programming model. However, the above works [17–19,25,26] were all designed for residential load control or grid-level demand-response operations. No reported study has examined managing real-time energy consumption in an industrial manufacturing process in the face of instantaneously varying electricity prices.

Considering the dynamic features of RTPs, in this paper, we sought to address the issue of making timely load control decisions for an industrial manufacturing process, each time receiving the RTP for the present time slot and adopting robust optimization to handle future price uncertainty. The main contributions are as follows:

- Propose a real-time DR decision framework for managing the energy consumption of an industrial manufacturing process in a timely manner.
- Formulate an extended scheduling horizon by bridging current and future time slots together, where robust optimization is adopted to model the future price uncertainty.
- Proposing a method to aid the system designer in specifying the robustness level by estimating a tuning parameter (named the “reference percentage” (RP)) on a daily basis, with the intention of lowering daily electricity costs.
- An entire steel-powder manufacturing process was adopted as a case study; simulation results validated the effectiveness of the proposed real-time decision approach from various perspectives.

The remainder of this paper is organized as follows. Given the problem formulation of industrial load scheduling in Section 2, the robust optimization based real-time decision model is presented in Section 3. In Section 4, the proposed model is applied to a case study of a steel powder manufacturing process. Finally, Section 5 concludes the paper.

2. Problem formulation

This section provides a real-time decision model for an industrial facility that is supposed to participate in an RTP-based DR program. The energy management center (EMC) of the facility receives the RTP from its subscribed power provider several minutes ahead of the upcoming slot, and then manages the energy consumption of the industrial manufacturing process in response to the RTP received: such activity will be repeated every time a new price is provided to the EMC. The mathematical formulation of the decision model, including the process modeling, various operation constraints and objective function, is described in the following subsections.

2.1. Industrial load modeling

2.1.1. Operation constraints of different tasks

Industrial loads can be regarded as a complex of different consecutive tasks. For each task, let denote the operation state during slot , which is defined as a binary variable: if task is operated, and otherwise. According to the specific operating conditions, tasks are classified into three types: (1) A task is a non-shiftable (NS) task: once it starts operation, it must work continuously. Thus, is always equal to “1”. (2) A shiftable (ST) task has two operating states, of “on” and “off”; i.e., “1” and “0”. (3) Different than an ST task, a controllable (CRT) task can work at different operating levels during a pre-defined set . Denote as the binary variable, indicating the status of operating level of task during slot . During one slot, a task can only execute at one operating level, , which is constrained as follows:

\[
\sum_{m \in M_k} y_{m,k,t} = I_{k,t} \quad (1)
\]

2.1.2. Material storage constraints

Between every two consecutive tasks, there is supposed to be a storage space, denoted as . The material storage during slot is calculated as follows:

\[
S_{k,t} = S_{k,t-1} + \sum_{k' \in K_t} P_{k,k'} - \sum_{k' \in C_{k,t}} C_{k,k',t} \quad \forall t \in T \quad (2)
\]

where denotes the set of tasks that produces (consumes) material for (from) storage , and is the produced (consumed) quantity of storage by task during slot , defined as follows:

\[
P_{k,k,t} = \sum_{m \in M_k} y_{m,k,t} \cdot p_{m,k,t} \quad (3)
\]

\[
C_{k,k',t} = \sum_{m \in M_{k'}} y_{m,k',t} \cdot c_{m,k',t} \quad (4)
\]

where denotes the production (consumption) rate of task at operating level .
Fig. 1 gives an illustration of storage s where task k produces material for s and task k' consumes material from s. During any slot, to satisfy the operation of processing machines, it is sometimes necessary to maintain a minimum amount of material flow. Moreover, the stored material cannot exceed a maximum capacity limitation. Therefore, $S_{s,t}$ should be constrained as follows:

$$S_{s}^{\text{min}} \leq S_{s,t} \leq S_{s}^{\text{max}}$$ (5)

2.1.3. Final product constraints

For an industrial application, it is usually necessary to keep a minimum amount of final product when the scheduling horizon finishes. Denote the required final output as $F$, which should satisfy the following requirement:

$$\sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{m=1}^{M} y_{m,k,t} \cdot p_{m,k,t} \geq F$$ (6)

where $F$ denotes the set of tasks that produce the final product. In case a task k is not a CRT task, then $y_{m,k,t}$ in (6) will be simply replaced by $k_{t}$.

2.1.4. Electricity demand of the process

For any task $k$, the electricity demand during slot $t$ as $e_{k,t}$, and let $e_{k}$ be the power consumption rate of task $k$, according to the classification of tasks in 2.1.1. Then, the electricity demand of each task type is modeled as follows:

For an NS task:

$$e_{k,t} = e_{k}$$ (7)

For an ST task:

$$e_{k,t} = e_{k} \cdot L_{k,t}$$ (8)

For a CRT task, according to the binary variable determined in (1), its electricity demand can be modeled using (9):

$$e_{k,t} = m \cdot e_{m,k}$$ (9)

where $e_{m,k}$ denotes the power consumption rate of task $k$ at operating level $m$.

Accordingly, the total electricity demand ($E_{t}$) during one slot can be obtained by aggregating the demand of each task $k$.

$$E_{t} = \sum_{k_{t} = \text{NS}} e_{k,t} + \sum_{k_{t} = \text{ST}} e_{k,t} + \sum_{k_{t} = \text{CRT}} e_{k,t}$$ (10)

2.2. ESS modeling

An energy storage system (ESS) is assumed to exist at the industrial facility, aiming to help mitigate the grid burden by providing energy to the facility during electricity shortages. The state of ESS during slot $t$ is modeled using (11), which is calculated from the state of the previous slot and also considers the charged or discharged electricity amount into or from the ESS [30].

$$e_{t}^{\text{ESS}} = e_{t-1}^{\text{ESS}} + \frac{e_{t}^{\text{ESS}} - e_{t}^{\text{ESS}}}{\eta_{\text{dis},t}}$$ (11)

which is subject to the following constraints

$$0 \leq e_{t}^{\text{ESS}} \leq E_{t}^{\text{ESS}}$$ (12)

$$E_{t}^{\text{ESS},ch,t} \leq E_{t}^{\text{ESS},ch,t} \cdot \eta_{\text{ch},t}$$ (13)

$$E_{t}^{\text{ESS},dis,t} \leq E_{t}^{\text{ESS},dis,t} \cdot (1 - \eta_{\text{dis},t})$$ (14)

$$E_{t}^{\text{ESS},use,t} + E_{t}^{\text{ESS},sold,t} = E_{t}^{\text{ESS},use,t} \cdot \eta_{\text{dis},t}$$ (15)

where the state of ESS ($E_{t}^{\text{ESS}}$) during any slot should be within the capacity ($E_{t}^{\text{ESS}}$), as constrained by (12). Constraints (13) and (14) dictate that the feasible charged or discharged electricity ($e_{t}^{\text{ESS},ch,t}$ or $e_{t}^{\text{ESS},dis,t}$) during unit time (or one slot) should not exceed the charging or discharging rate ($E_{t}^{\text{ESS},ch,t}$ or $E_{t}^{\text{ESS},dis,t}$), and $\eta_{\text{dis},t}$ is a binary variable controlling the switching between charging and discharging modes. Eq. (15) divides the discharged electricity into two portions, where $E_{t}^{\text{ESS},use,t}$ denotes the portion used for satisfying industrial loads, and $E_{t}^{\text{ESS},sold,t}$ is the other portion, sold back to the grid for profit. $\eta_{\text{ch},t}$ and $\eta_{\text{dis},t}$ are the charging and discharging efficiencies.

2.3. DER modeling

The industrial facility is also supposed to be equipped with a distributed energy resource (DER), where the solar energy is taken as the example in this study. The produced energy ($E_{t}^{\text{DER,pro}}$) is decomposed into two portions: one for satisfying industrial loads ($E_{t}^{\text{DER,use}}$) and the other for selling back to the grid ($E_{t}^{\text{DER,sold}}$), which is modeled using (16).

$$E_{t}^{\text{DER,use},t} + E_{t}^{\text{DER,sold},t} = E_{t}^{\text{DER,pro}}$$ (16)

2.4. Power balance

During slot $t$, the electricity demand of the industrial manufacturing process ($E_{t}$) and the charging demand on the ESS ($E_{t}^{\text{ESS},ch,t}$) is either supplied by the grid ($E_{t}^{\text{grid}}$), or by a combination in which the energy is provided in part by ESS ($E_{t}^{\text{ESS},use,t}$) and DER ($E_{t}^{\text{DER,use}}$) and in part by the grid ($E_{t}^{\text{grid}}$)

$$E_{t}^{\text{grid}} + E_{t}^{\text{ESS},use,t} + E_{t}^{\text{DER,use}} = E_{t} + E_{t}^{\text{ESS},ch,t}$$ (17)

2.5. Maximum demand constraint

Peak demand is usually considered as an important factor in designing industrial load scheduling because many industrial facilities are subjected to maximum electricity demand restrictions. Thus, the electricity drawn from the grid ($E_{t}^{\text{grid}}$) should not exceed the maximum limitation ($L_{1}$).

$$E_{t}^{\text{grid}} \leq L_{1}$$ (18)

2.6. Total power injected into the grid

The total power that can be sold back to the grid comes from two sources: ESS and DER.

$$E_{t}^{\text{sold},t} = E_{t}^{\text{ESS},sold,t} + E_{t}^{\text{DER,sold},t}$$ (19)

2.7. Power transaction constraints

Beyond the maximum demand constraint (18), during one slot, drawing power from the grid or injecting power into the grid are exclusive of each other; this can be constrained using (20) and (21).
\[ E_{\text{grid}} \leq L_1 \cdot y_{t, \text{grid}} \]
\[ E_{\text{sold}} \leq L_2 \cdot (1 - y_{t, \text{grid}}) \]

where \( y_{t, \text{grid}} \) is a binary variable (taking value “0” or “1”) used to control switching between the two options and \( L_2 \) denotes the maximum amount of electricity that can be sold back to the grid.

### 2.8. Objective function

The objective is to minimize the total cost of electricity consumption throughout the whole time horizon (which is decomposed into the current slot \( t \) and future slots \( t + 1, \ldots, T \)), where the total costs include the cost of the current slot (given the RTP \( \pi_t \) at slot \( t \)) and the aggregate costs of future slots (with the assumption of future prices \( \pi_{t'} \forall t' \in [t+1,T] \)). The reason for considering the remaining \( T-t \) slots of the scheduling horizon is to maintain adaptability, because the consecutive tasks of a manufacturing process are interdependent and cannot be treated independently. Using an extended scheduling horizon, the proposed model could avoid a possibly jumpy, infeasible, and hard-to-implement solution [19].

\[
\min \left\{ E_{t, \text{grid}} \cdot \pi_t - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right\} \\
+ \sum_{t' = t}^{T} \left( E_{t', \text{grid}} \cdot \pi_{t'} - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right)
\]

Taking the current slot \( t \) as an example, the cost is calculated as the difference between the expenses for purchasing \( E_{t, \text{grid}} \) from the grid at price \( \pi_t \), and the profit of selling energy \( E_{\text{sold}} \) back to the grid at price \( \pi_{\text{sold}} \). The terms \( e_1 \cdot E_{\text{sold}} \) and \( e_2 \cdot E_{\text{grid}} \) are defined as artificial penalties imposed on the different energy resources [31], where \( e_1 \) and \( e_2 \) are assumed to be sufficiently small positive values (e.g., \( 10^{-7} \) or \( 2 \cdot 10^{-7} \)) so as to guarantee that the total cost is unaffected. By adding these two penalty terms, the priorities in selling energy for different resources can be distinguished. That is, a smaller value of \( e \) forces the EMC to first sell all the available energy from that resource before considering another resource. In this paper, we assume \( e_1 < e_2 \) because the energy cost from DER is usually regarded to be lower than that from ESS.

### 3. Robust optimization methodology

#### 3.1. Robust optimization model

Note that the objective function in (22) is not formally defined because the future electricity prices \( \pi_t \) are unknown values. In this paper, robust optimization is adopted to handle the future price uncertainties. The core concept of robust optimization is to minimize the overall costs in (22) without knowing exact values of \( \pi_t \). Without losing generality, the price interval is adopted to model the uncertainty of future prices [26], denoted as \( [\pi_{\text{min}}^t, \pi_{\text{max}}^t] \), where \( \pi_{\text{min}}^t \) and \( \pi_{\text{max}}^t \) are the lower and upper bounds of the interval in which \( \pi_t \) may vary during future slot \( t \). The price interval can be provided by the subscribed power provider, or derived using existing price forecasting models (e.g., time series models and neural networks) [27–29]. Note that this paper focuses on exploring the feasibility of adopting robust optimization in making real-time decisions for the load management of an industrial manufacturing process; price forecasting, which can be adopted from existing technologies, is beyond the scope of this paper.

Provided with the price interval, the robust counterpart of problem (22) is formulated as follows [17,18]:

\[
\min \left\{ E_{t, \text{grid}} \cdot \pi_t - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right\} \\
+ \sum_{t = t+1}^{T} \left( E_{t, \text{grid}} \cdot \pi_{t'} - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right)
+ \max_{\{\pi_{t'} \mid \pi_{\text{min}}^t \leq \pi_{t'} \leq \pi_{\text{max}}^t\}} \left( \sum_{t = t+1}^{T} E_{t, \text{grid}} \cdot (\pi_{t'}^\text{max} - \pi_{t'}^\text{min}) \right)
\]

In (23), \( \Gamma \) is a parameter specified by the system designer that controls the robustness level of the solution with respect to the uncertainties in future prices. The value of \( \Gamma \) can be adjusted from 0 to \( T-t \) (maximum number of future slots). For a specified value of \( \Gamma \), it indicates the maximum number of price deviations that can be tolerated. Specifically, \( \Gamma = 0 \) denotes the most optimistic case that completely ignores the influence of price deviations in the objection function, whereas \( \Gamma = T-t \) represents the most conservative case, which considers the simultaneous impacts of price deviations (or uncertainties) at all future time slots.

When looking into the inner maximization of (23), \( T_0 \) is a subset of future time slots (i.e., \( T_0 \subseteq [t+1,T] \)), where the number of elements in \( T_0 \) must be less than or equal to \( \Gamma \). This means the maximal number of price deviations that can be tolerated is \( \Gamma \). The inner maximization tries to simulate the worst-case realization of uncertain prices: that is, it tries to find the worst-case condition of uncertainty in prices that would maximally influence the total costs (or cause the maximal increase in total costs) [26]. The outer minimization of (23) then aims to find an optimal solution that optimizes against all cases, and such a solution is robust in the sense that the number of prices being allowed to vary in their respective interval \( [\pi_{\text{min}}^t, \pi_{\text{max}}^t] \) is up to \( \Gamma \).

Note that the problem in (23) is a min-max problem, which is usually hard to solve. According to the duality gap theory [26,32], this min-max problem can be transformed into a single-level optimization problem as follows:

\[
\min \left\{ E_{t, \text{grid}} \cdot \pi_t - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right\} \\
+ \sum_{t = t+1}^{T} \left( E_{t, \text{grid}} \cdot \pi_{t'} - E_{\text{sold}} \cdot \pi_{\text{sold}} + e_1 \cdot E_{\text{sold}} + e_2 \cdot E_{\text{grid}} \right)
+ \lambda \cdot \Gamma + \sum_{t = t+1}^{T} \zeta_t
\]

Subject to constraints (1)–(21)

\[
\lambda + \zeta_t \geq (\pi_{t'}^\text{max} - \pi_{t'}^\text{min}) \cdot \eta_t \quad \forall t' \in [t+1,T]
\]

\[
\zeta_t \geq 0 \quad \forall t \in [t+1,T]
\]

\[
\eta_t \geq 0 \quad \forall t \in [t+1,T]
\]

\[
\lambda \geq 0 \quad \forall t \in [t+1,T]
\]

\[
E_{t, \text{grid}} \leq \eta_t \quad \forall t \in [t+1,T]
\]

Variables \( \lambda \) and \( \zeta_t \) are the dual variables of the initial problem (22) that are used to take the price bounds into consideration, and \( \eta_t \) is an auxiliary variable used to obtain equivalent linear expressions. In (24), \( \Gamma \) can take any real number, ranging from “0” to the number of all unknown prices, where a greater value of \( \Gamma \) indicates a greater robustness level at the expense of a higher cost.

The objective function in (24), together with the constraints of (1)–(21) and (26)–(30), formulate a mixed-integer linear program-
ming (MILP) optimization problem that can be solved effectively using commercial software packages. Note that the problem is solved for each slot $t$ to obtain energy consumption decisions for the current and remaining slots, as well as the decisions for switching control variables such as $y^{\text{ESS}}_t$ and $y^{\text{grid}}_t$. However, only the decisions for the current slot are implemented, which provides the industrial facility with optimal energy management instructions for the present slot.

From (24), it can be seen that different values of $\Gamma$ will result in different daily costs. In the next subsection, a method will be introduced to aid the system designer in specifying the robustness level, with the intention of lowering daily electricity costs.

### 3.2. Method for specifying the robustness level

Ideally, the robustness level $\Gamma$ in (24) can take any real number between “0” and the maximum number of unknown prices ($T-t$), e.g., by multiplying a percentage with $T-t$ [18]. In this subsection, a method is proposed to aid the system designer in specifying $\Gamma$ by means of estimating a tuning parameter, $RP$, on a daily basis, with the implication of controlling daily costs at the lowest level. Then, the value of $\Gamma$ can be determined by multiplying $RP$ with $T-t$, as follows:

$$\Gamma = RP \times (T - t) \quad \forall t \in T \quad (31)$$

Before describing the estimating method in detail, we first introduce a distinguishable parameter – the actual optimal percentage ($AOP$) – upon which the specified robustness level can cause minimal daily costs. In practice, $AOP$ cannot be known in advance, but it can be acquired in a backward direction: i.e., a variety of percentages can be enumerated at the end of a day; for each enumerated percentage, the daily costs can be reversely calculated, and then the percentage that results in the minimal daily cost is regarded as the $AOP$. The $AOP$ would differentiate day to day because it is dependent on the ever-changing electricity price and electricity demand. In view of this, an exponential smoothing model is adopted for estimating the $RP$ of the current day $d$ based on historical data of $RP$ and $AOP$, as follows [14]

$$RP_d = \beta \times RP_{d-1} + (1 - \beta) \times AOP_{d-1} \quad (32)$$

where $RP_{d-1}$ and $AOP_{d-1}$ denote the $RP$ and the actual optimal percentage of the previous day $(d-1)$, respectively, and $RP_d$ is the $RP$ for the present day $d$. $\beta$ is the smoothing factor $(0 < \beta < 1)$ of the exponential smoothing model, which is designated by the system designer.

According to (32), the $RP_d$ will be estimated on a daily basis, which then is used for specifying the robustness level $\Gamma$ at the beginning of each slot $t$ when the scheduling horizon is rolling forward.

### 4. Case study

#### 4.1. Case configuration

To validate the effectiveness of the proposed robust optimization-based methodology in responding to RTPs, a steel-powder manufacturing process composed of multiple tasks was adopted to conduct a case study, as shown in Fig. 2 [34]. According to the functionality and characteristics of each task, they are classified into three types, including two NS tasks (Blast Furnace, Finish-reduction Furnace), four ST tasks (Spraying Atomization, Dehydration, Drying, and Magnetic separation), and five CRT tasks (Crushing, Classification, Blending, Water Cooling, and Nitrogen Generating), where the last two CRT tasks provide cold water and nitrogen for the tasks of Spraying Atomization, Dehydration, Drying, and/or Finish-reduction Furnace. The Blast Furnace is an energy-intensive steel stack used to feed liquid iron for multiple production lines simultaneously [35]. The energy consumption of the Blast Furnace was excluded from this use case study because we focused on modeling a single production line.

Tables 1 and 2 list the parameters of the three types of tasks as illustrated in Fig. 2, where the parameter values were generally referred to [11,36–38] and the minimum storage requirements of all the tasks in Table 1 are set to zero for this manufacturing process, because the latter tasks would stop operating if the material produced by the former tasks is not available. The parameters of ESS are provided in Table 3 [11]. For simplicity, we assume that the DER under this use case is represented by a solar panel. The quantity of electricity generated during each time slot is shown in Fig. 3, based on common sense that the electricity generation
rate was greatest at noon when the solar irradiance was largest, and no electricity was generated during the night. In practice, the stochastic nature of solar energy can be predicted using sophisticated methods based on weather forecast information.

The final product requirement $H$ was chosen as 90 tons; the maximum amount of electricity $L_1$ ($L_2$) that can be drawn from (sold back to) the grid was set at 500 (100) kWh for this case study. In practice, they usually vary from application to application and should be set by the facility designer or the power supplier side.

The entire time horizon is divided into 24 time slots representing the 24 h of a day. It was assumed that the time horizon started at 00:00, then, the simulation was conducted on a rolling basis. For each slot, supposing the RTP is received a short time in advance (e.g., 5 min), then the proposed robust optimization problem in (24)–(30) was solved using Gurobi on a Windows PC with four processors clocking at 3.2 GHz and with 8 GB of RAM. The computation time for solving a single slot optimization problem was 1 s. Such a short time can fully meet the requirements for deploying real-time DR management for an industrial manufacturing process.

The simulation was run from July 1 to August 11, 2015, based on RTPs provided by ComEd [39]. For the first day, $RP_{d,1}$ was assumed to be 50%; in the following days, $RP_d$ was estimated using (32), where $\beta$ was set at 0.5 to give non-discrimination over $RP_{d,1}$ and $AOP_{d,1}$. Fig. 4 shows the $AOP$ and estimated $RP$ on different days. It can be seen that the $RP$ followed quite a similar trend to $AOP$, validating that the method proposed in Subsection 3.2 was effective in estimating $RP$ by specifying the robustness level.

Table 2 gives the RTPs on August 11, where the second column provides the actual prices, and the third and fourth columns are the corresponding price bounds, which were formulated via a percent around the actual prices [17], i.e., $\left(1 \pm x\right)$.

In this simulation, $x$ was set at 20%. Next, we will analyze the simulation results by focusing on this representative day. The price for selling surplus electricity back to the grid was assumed to be 10% lower than the respective RTP.

4.2. Results with and without real-time demand response

To demonstrate the performance of the model established, a benchmark without a real-time DR was designed where a fixed flat price ($\pi_{flat}$) was applied to the model: i.e., the objective function in
would simply minimize the daily costs by aggregating the cost of each slot (i.e., $E_{\text{grid}}^{\text{pflat}}$). This is regarded as Case 1 – No DR.

Compared with the benchmark, we first examined the purified performance of the established real-time decision model using robust optimization (this is regarded as Case 2 – DR with robust optimization). Here, “purified” means the model only considered the energy demand of the manufacturing process itself, whereas ESS and DER were not taken into account.

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Compared with the benchmark, we first examined the purified performance of the established real-time decision model using robust optimization (this is regarded as Case 2 – DR with robust optimization). Here, “purified” means the model only considered the energy demand of the manufacturing process itself, whereas ESS and DER were not taken into account.

Figs. 5 and 6 show the aggregated electricity demand of all tasks under Cases 1 and 2, respectively. Clearly, the industrial facility had no incentive to reduce or shift its energy demand when the fixed flat price (the value took the average of RTPs in Table 4) was applied, but simply scheduled the electricity demand at the beginning slots to finish the daily production target (referring to constraint (6)) as early as possible. In comparison, electricity demand was scheduled appropriately under Case 2 when the robust optimization-based real-time decision model in Section 3 was used. Specifically, most of the electricity demands of CRT and ST tasks were scheduled to off-peak slots. Thus, the overall demand was maintained at quite a low level during peak slots, because only the NS tasks needed to operate and the other two types of tasks were all ceased, confirming that the established model can respond to RTPs properly.

To gain insights into the manufacturing process, two CRT tasks (Water Cooling and Nitrogen Generating) were selected to illustrate the production procedure throughout the time horizon. Fig. 7 shows the accumulating and consuming processes of cold water and nitrogen; it can be seen that storage of each increased continuously when RTPs were low. Such a stacking process was correlated with the optimal load scheduling result in Fig. 6, because the major electricity demand was scheduled during a low-price period. Specifically, it was found that the storage of nitrogen increased slightly during slot 11: the reason for this was because the RTP decreased suddenly compared with slot 10. Thus, such a slight increase in nitrogen storage further confirmed that our established optimization model was able to respond to the instantaneous varying of RTP in an effective way.
4.3. Results considering ESS and DER

In this subsection, the effects of ESS and DER were taken into consideration. Accordingly, two more cases were specified: Case 3 – DR with robust optimization and ESS, and Case 4 – DR with robust optimization and ESS and DER. Fig. 8 compares demand (purchased from the grid) for the four cases. It can be seen that more demand was shifted from peak time to off-peak time in Case 3 compared with Cases 1 and 2, because ESS was scheduled to store energy when RTPs were low (resulting in more demand during off-peak time) and provide electricity for the system requirement when RTPs were extremely high. With the help of ESS, the peak demand of the industrial facility was kept at a very low level (e.g., in slots 12, 14, 15, and 16), which is believed to be able to significantly release the grid burden. When DER was also considered in the model in Case 4, the demand during peak time was further reduced or even zero during slots 12, 14, 15, and 16, where the surplus electricity was sold back to the grid to earn profits during slots 12 and 15, as represented by the negative values in Fig. 8.

Moreover, Case 4 was analyzed extensively by decomposing the total load of the industrial facility into different portions. As shown in Fig. 9, the red and green bars denote the electricity that was purchased from the grid and used for the manufacturing process and charging the ESS, respectively; the purple bar represents the electricity discharged from the ESS, and the blue bar illustrates how the energy generated by DER was distributed in the facility. Clearly, the electricity drawn from the grid was appropriately controlled as a response to the RTPs: i.e., the major portion of electricity (red
and green bars) was purchased from the grid during the off-peak period, and only a small portion needed to be drawn from the grid during the peak period because the system requirement was satisfied mainly by DER and the stored energy in ESS. The energy generated by DER (referring to Fig. 3) was sufficiently used either for satisfying the system requirement or for selling back to the grid to earn profits during slots 12 and 15. Moreover, the electricity sold back to the grid came only from DER, not ESS, because the priorities in selling energy of different resources were distinguished by the objective function in (22).

### 5. Conclusions and future work

In the face of dynamic RTPs, this paper proposes a real-time decision framework for the load management of an industrial manufacturing process. The load scheduling horizon not only considered the current time slot, but also took future slots into account so as to maintain the interdependence of consecutive tasks, wherein robust optimization was adopted to handle future price uncertainties. Moreover, a method was proposed to facilitate the system designer in specifying the robustness level by means of estimating a tuning parameter (the RP) on a daily basis, with the intention of keeping daily electricity costs to a minimum. The proposed model was applied to a case study of a steel-powder manufacturing process: the simulation results demonstrated that the approach presented can make optimal real-time decisions for managing the loads of the illustrated manufacturing process. In future, the presented model will perform a further analysis towards the stochastic feature of renewable energy resources as well as how they will impact the energy management of the industrial manufacturing process.

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### References


