Industrial Demand Side Management Formulation for Simultaneous Electricity Load Commitment and Future Load Prediction

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Abstract

Large consumers’ electricity bills depend on many factors including: different electricity purchasing contracts and markets, deviation penalties, and grid fees. Two key markets are the intraday and the day-ahead markets. On the day-ahead market, the consumer commits to a load of electricity that stacks on top of their longer-term contract commitments. The next day, the consumer must follow this demand profile to avoid paying deviation penalties. The demand curve can be modified on the existing day using the intraday market. A novel demand side response formulation is proposed that considers a two-day horizon for both the intraday and the day-ahead markets by a separate modeling approach. Results show that this formulation can effectively combine intraday and day-ahead market concerns and that the resulting demand profile from the two-day problem is more realistic than current models, which consider only a single-day problem.

1. Introduction

Demand Side Management (DSM) provides grid operators the opportunity to improve efficiency and stability of the power grid by flattening the electricity load curve and will play a crucial role in the improvement of grid efficiency and reliability for years to come. Simultaneously, DSM provides an opportunity for electricity consumers to lower their operating costs by responding to time-dependent electricity costs (Merkert, \textit{et al.}, 2015).

The bill for an electricity consumer is dependent on many factors. One factor is the type of electricity purchase contract. These contracts include: long-term (up to a year) base load (BL) contracts, short-term (a few months) Time-of-Use (TOU) contract, and the day-ahead market in which consumers can purchase hourly electricity loads at hourly prices up to 12 hours in advance of the first delivery the next day. The total load from these contracts represents the hourly committed load curve for a consumer for the next day (24 hours). This load curve must then be followed to within a tolerance else so-called deviation penalties must be paid. If a consumer experiences a major shift in electricity demand (for example, in the event of unit-breakdown) there exists an intraday market in which consumers can modify their committed loads to avoid paying deviation penalties. In addition, companies also need to pay various grid fees. One such grid free is a peak-pricing scheme in which a company must pay a fee based on their highest simultaneous electricity consumption over a given time-interval (Frontier Economics, 2016).
Due to the strong time-dependence of these electricity-related concerns, effective scheduling is essential in DSM, especially when a complex manufacturing process is involved. Several works have looked at DSM for scheduling, including Nolde & Morari, 2010 and Hadera, et al., 2015 who investigate scheduling of steel manufacturing based on a multi-contract variable electricity pricing load commitment problem using continuous-time precedence-based scheduling models. Castro, et al., 2013 also studied the load commitment problem for steel manufacturing but using a discrete-time Resource-Task Network (RTN) representation. The downside of only studying a 24-hour commitment problem is two-fold: the first is that this unrealistically makes the day-ahead and the intraday markets overlap by considering them to both be active at the same time, or by ignoring one of the markets. The second drawback is that the committed electricity load drops off towards the end of the schedule as the jobs are completed. This is unrealistic as production is performed on a continuous basis and is one of the factors hindering the application of DSM in industrial settings.

In this work, the current-day problem of load commitment (considering the intraday market) is combined with the problem of future load prediction (on the day-ahead market) in order to pay less deviation penalties and to achieve more realistic electricity-demand profiles that do not drop off towards the end of the scheduling horizon. In addition, this work considers penalties paid on the maximum electricity consumption. The problem is formulated as a discrete-time RTN (Pantelides, 1994) and is applied to the industrial problem of steel melt shop scheduling.

2. Problem Definition

This work looks at the problem of steel melt shop scheduling considering multiple electricity contracts and markets as well as peak-related grid-operator fees in order to minimize total cost. Stainless-steel production is an energy-intensive batch process with complicated processing constraints. The typical production process has four processing steps. The first involves melting the scrap in an Electric Arc Furnace (EAF) to form a so-called heat (a batch of liquid metal). This is a very energy intensive process and accounts for the majority of the electricity consumed. From there, the heat is transported to the next station where the carbon content of the steel is reduced in a process known as Argon Oxygen Decarburization (AOD). Next, the heat is transported to a Ladle Furnace (LF) to further adjust the chemistry and temperature of the heat. The final stage of the process is the Continuous-Casting (CC), where a group of several heats must be processed in an uninterrupted sequence according to a strict set of rules. The considered example here contains two parallel machines at each stage. A diagram of the process, including the RTN diagram of the process, can be viewed in Castro et al. 2013.

3. Model Formulation

A discrete-time model is chosen, as the location of every time point in the grid is known in advance allowing for straightforward modelling of intermediate events (such as changes in electricity pricing or power availability). Note that this formulation contains many different time intervals, but they are all matched to the underlying discrete grid.

An RTN model is applied, as it is general, yet simple, and has been shown to be both capable of handling problems of industrial relevance and expandable to account for DSM (Castro et al. 2013). The notation for the model can be viewed in Table 1. Note that all variables are non-negative continuous variables unless otherwise specified.
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Table 1: Model notation

| Index/Set | Description | Set | Description |
|-----------|-------------|-----|-------------|
| \( r \in R \) | Resources | \( \theta \) | Relative time to start of task |
| \( i \in I \) | Tasks | \( T_{rr} \) | Set of hours in the horizon |
| \( h \in H \) | Set of steel heats | \( T_{peak} \) | Set of times over which the peak is calculated |
| \( g \in G \) | Set of steel groups | \( T_{intra} \) | Set of times over which electricity is sold |
| \( k \in K \) | Set of processing stages | \( T \) | Parameter |
| \( t \in T \) | Set of time points | \( \delta_T \) | Time grid discretization size for the RTN |
| \( u \in U \) | Set of units | \( \delta_{T, peak} \) | Interval size for the peak and electricity selling times respectively |

Parameter Description

- \( t_i \): Duration of task \( i \) in time slots
- \( \mu_{r,i,\theta} \): Extent of discrete interaction of \( r \) with \( i \) at point \( \theta \)
- \( y_{HR}^{TOU} \), \( y_{HR}^{BL} \): Respectively, amount of electricity load from a TOU or baseline contract
- \( y_{CL} \): Total amount of current day committed electricity load
- \( p_{w,h,u} \): Power usage of \( h \) in \( u \)
- \( c_{DA} \): Penalty-free tolerance on load tracking

Variable Description

- \( \xi \): Maximum electricity peak
- \( \omega_T^r \): Free var. penalty free zone from day-ahead contract
- \( \sigma_{intra}^{DA} \): Free var. amount of day-ahead load sold or bought on the intraday market
- \( \sigma_{BL}^{TOU} \): Respectively amount of load sold from TOU or BL contract on the intraday market

3.1. Model Constraints

Resource availability over the time grid is managed by the excess resource balance given in Eq. (1).

\[
R_{r,t} = R_{r,t-1}^0 + \sum_{i=1}^{\sum_{i \in H} N_{i,t}} \mu_{r,i,\theta} N_{i,t} - \sum_{i=1}^{\sum_{i \in H} N_{i,t}} \mu_{r,i,\theta} N_{i,t-\theta} \quad \forall r, t \in T
\]  

(1)

Eq. (2) and (3) are used to ensure that all heats are processed exactly once at each stage, while Eq. (4) and Eq. (5) enforces transfer task tasks and times.

\[
\sum_{u \in U} \sum_{i \in H,t} u_i N_{i,t} = 1 \quad \forall h, k = 1,2,3
\]  

(2)

\[
\sum_{u \in U} \sum_{i \in H,t} u_i N_{i,t} = 1 \quad \forall g, k = 4
\]  

(3)

\[
\sum_{u \in U} \sum_{i \in H,t} u_i N_{i,t} = 1 \quad \forall h, k = 1,2,3
\]  

(4)

\[
\sum_{u \in U} \sum_{i \in H,t} u_i N_{i,t} = 1 \quad \forall h, k = 1,2,3
\]  

(5)

\[
R_{r,t} p_{w,h,u} = 0 \quad \forall t \in T
\]  

(6)

\[
\Pi_{r,t} p_{w,h,u} \leq \sum_{u \in U} p_{w,h,u} \quad \forall t \in T
\]  

(7)

\[
y_{h,t} \leq \sum_{u \in U} p_{w,h,u} \quad \forall h \in H \quad \forall t \in T
\]  

(8)
\[ \xi \leq \left| \frac{\delta_T}{\delta_{T_{peak}}} \right| \sum_h \sum_u p_{w,h,u} \]  

(9)

To prevent a buildup of electricity over time Eq. (6) is used. Eqs. (7), (8), and (9) set upper bounds on electricity consumption, predicted, and maximum electricity consumption. In order to calculate the deviations from the load that has been committed to within the current day, Eqs. (10) and (11) are used. Two equations are needed in order to account for the time before and after it is possible to trade on the intraday market.

\[ \Pi_{w,J}^{CL} = y_h^{CL} + \omega_t^{DA} - \Delta_t^{DA} - \Delta_t^{TOU} - \Delta_t^{BL} \forall t \in T_{hr}, T_{hr} < T^S \]  

(10)

\[ \Pi_{w,J}^{PL} = y_h^{PL} + \omega_t^{DA} - \Delta_t^{DA} - \Delta_t^{TOU} - \Delta_t^{BL} + \sigma_{t_{intra}}^{DA} + \sigma_{t_{intra}}^{TOU} + \delta_{t_{intra}}^{BL} \forall t \in t_{intra}, t_{intra} \in T_{hr}, T^S \leq T_{hr} \leq T^* \]  

(11)

The amount of load to commit on the day-ahead market is set by Eq. (12).

\[ \Pi_{w,J}^{PL} = y_h^{PL} + \omega_t^{DA} - \Delta_t^{DA} - \Delta_t^{TOU} - \omega_t^{BL} - \Delta_t^{BL} \forall t \in T_{hr}, T^* < T_{hr} \]  

(12)

Since the penalty-free region is a percentage of the contracted load, the upper and lower bounds on the penalty free region for the day-ahead contract are enforced through Eqs. (13) and (14). Note that because the BL and TOU contracts represent loads that should always be met there is no penalty free region for these contracts.

\[ -c_{pf}^{DA} * (y_h^{CL} - y_{hr}^{TOU} - y_{hr}^{BL} - \sigma_{t_{intra}}^{DA}) \leq \omega_t^{DA} \leq c_{pf}^{DA} * (y_h^{CL} - y_{hr}^{TOU} - y_{hr}^{BL} - \sigma_{t_{intra}}^{DA}) \forall t \in T_{hr}, T_{hr} \leq T^* \]  

(13)

\[ -c_{pf}^{DA} * (y_h^{PL} - y_{hr}^{TOU} - y_{hr}^{BL}) \leq \omega_t^{DA} \leq c_{pf}^{DA} * (y_h^{PL} - y_{hr}^{TOU} - y_{hr}^{BL}) \forall t \in T_{hr}, T^* < T_{hr} \]  

(14)

If the actual consumption strays outside of the penalty-free region defined above penalties must be paid. Eqs. (15) to (19) define the bounds on the magnitude of the deviations per contract. Note that because the contracts build on top of one another, deviations from ‘lower’ contracts are more costly than deviations from ‘higher’ contracts. Therefore, an extra variable is not needed to account for which contract is being violated, as the optimal solution will first penalize the higher contracts before proceeding to the lower ones.

\[ \Delta_t^{DA} \leq (1 - c_{pf}^{DA}) (y_h^{CL} - y_{hr}^{TOU} - y_{hr}^{BL} - \sigma_{t_{intra}}^{DA}) \forall t \in T_{hr}, T_{hr} \leq T^* \]  

(15)

\[ \Delta_t^{DA} \leq (1 - c_{pf}^{DA}) (y_h^{PL} - y_{hr}^{TOU} - y_{hr}^{BL} - \sigma_{t_{intra}}^{DA}) \forall t \in T_{hr}, T^* < T_{hr} \]  

(16)

\[ \Delta_t^{dl} \leq \sum_h \sum_u p_{w,h,u} \forall t \in T \]  

(17)

\[ \Delta_t^{TOU} \leq y_{hr}^{TOU} - \sigma_{t_{intra}}^{TOU} \forall t \in T \]  

(18)

\[ \Delta_t^{da} \leq y_{hr}^{BL} - \sigma_{t_{intra}}^{BL} \forall t \in T \]  

(19)

The last constraint given by Eq. (20) calculates the maximum peak power achieved.

\[ \xi \geq \sum_{t \in T_{peak}} \Pi_{r,t} \forall t_{peak} \in T_{peak} \]  

(20)

The objective function of the problem is to minimize the total cost of production. This includes cost of the electricity from each of the contracts, the cost of deviations from each of the contracts, revenue or costs incurred by trading on the intraday market, and a flat fee paid on the maximum peak attained during production.
4. Results

Three case studies were solved using GAMS 24.7.4/CPLEX 12.6.3.0. They are defined as follows: Case 1 considers a two-day commitment to a predetermined load with no consideration of the intraday market or the maximum peak. Case 2 is similar to Case 1 but it includes the intraday market. The aforementioned case studies were run with a daily production of 12 and 17 heats as two separate sub problems (SP1/SP2), one for each of the two days considered. Lastly, Case 3 is the proposed novel approach that highlights the importance of considering a longer horizon comprising current day load commitment and day-ahead prediction. In this case, it is not possible to trade on the intraday market to highlight the fact that fewer penalties can be paid simply by shifting production between the two days and changing the day-ahead consumption. This case was run with a time horizon of 54 hours (two days + six hours) with the total two-day forecasted production, plus two additional heats to account for production on the third day. The additional heats are necessary to highlight the fact that production should not drop off towards the end of the day, resulting in an unrealistic load profile. To facilitate a fair comparison, the total-two day production (24 and 34 heats respectively) was constrained to be completed by the end of day two, with the additional two extra heats exiting the last stage on the final day. A summary of the results is presented in Table 2 and Figure 1.

Results indicate that the novel formulation is able to avoid deviation penalties simply by transferring production across the current/next day boundary to better track the current day committed load while modifying the day-ahead demand to avoid future penalties. In the 12-heat case, this was accomplished by pushing production forward to the current day in order to avoid paying negative deviation penalties. In the 17-heat case, it was more favorable to slow down production to avoid paying positive deviation penalties. That being said, Case 3 cannot avoid as many deviations as the case that has no limit on selling or buying on the intraday market, however the intraday market is often avoided by large consumers unless it is necessary. In addition, the new formulation is able to manage the largest peak within the flexibility of production; in Case 2-12H when peak management was not considered, both EAFs were operated at the same time, resulting in a peak nearly twice as high as when the maximum peak was penalized. In the 17-heat case, peak management was more difficult due to the higher production amount; however, a smaller peak was still achieved. Figure 1 indicates that the two-day formulation is also able to avoid a drop off in production towards the end of the day when compared to considering two one-day problems. This presents a more realistic production scenario as each stage of the plant is operated constantly, as opposed to operating the first stages only until the daily production has been met. The major drawback of the new approach is that it results in very large models and it has difficulty in converging to a provably optimal solution.

Table 2: Comparison of results for the different cases.

| Case     | Deviations Paid (€) | Max Peak (MW) | CPU Time (s) [SP1/SP2] | Rel. Gap (%) [SP1/SP2] |
|----------|---------------------|---------------|-------------------------|-------------------------|
| Case 1-12H | 190,600             | 96            | 10,000/6,893            | <0.1/0                  |
| Case 2-12H | 120                 | 177           | 3,505/10,000            | 0/0.3                   |
| Case 3-12H | 25,100              | 94            | 10,000                  | 8.6                     |
| Case 1-17H | 305,400             | 185           | 265/10,000              | 0/0.1                   |
| Case 2-17H | 7,217               | 192           | 10,000/10,000           | 2.6/1.3                 |
| Case 3-17H | 16,500              | 177           | 10,000                  | 19.3                    |
5. Conclusions
A novel DSM model was presented in this work. The model differs from its predecessors, as it is able to effectively combine the problems of current day electricity load following considering the intraday market and day-ahead future load prediction considering the day-ahead market. Results show that this novel formulation is more realistic than its existing models as it is able to follow and predict more realistic load curves while minimizing maximum electricity peaks. The downside of this approach is that it results in very large, difficult to solve problems. Future work could investigate speed-up algorithms or decomposition approaches for such a formulation to ensure that good quality solutions can be found in industrially relevant time frames.

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References
Castro, P. M., Sun, L., & Harjunkoski, I. (2013). Resource-Task Network Formulations for Industrial Demand Side Management of a Steel Plant. Industrial and Engineering Chemistry Research, 52(2), 13046-16058.
Frontier Economics. (2016). METIS Technical Note T4 Overview of European Electricity Markets, Brussels: European Commission.
Hadera, H., Harjunkoski, I., Sand, G., Grossmann, I. E., & Engell, S. (2015). Optimization of steel production scheduling with complex time-sensitive electricity cost. Computers and Chemical Engineering, 76, 117-136.
Merkert, L., Harjunkoski, I., Isaksson, A., Saynevirta, S., Saarela, A., & Sand, G. (2015). Scheduling and energy - Industrial challenges and opportunities. Computers and Chemical Engineering(72), 183-198.
Nolde, K., & Morari, M. (2010). Electrical load tracking scheduling of a steel plant. Computers and Chemical Engineering, 34, 1899-1903.
Pantelides, C. C. (1994). Unified Frameworks for the Optimal Process Planning and Scheduling. Proceedings of the Second Conference on Foundations of Computer Aided Operations, Cache Publications: New York.