Demand Side Management Scheduling  
Formulation for a Steel Plant Considering  
Electrode Degradation  

Giancarlo Dalle Ave∗∗,∗∗∗ Jesus Hernandez∗∗,∗∗∗  
Iiro Harjunkoski∗ Luca Onofri∗∗∗ Sebastian Engell∗∗  

∗ ABB Corporate Research Center Germany, Wallstadter Str. 59, 68526 Ladenburg, Germany (email: iiro.harjunkoski@de.abb.com)  
** Process Dynamics and Operations Group, Department of  
Biochemical and Chemical Engineering, Technische Universität  
Dortmund, EmilFigge-Str. 70, 44221 Dortmund, Germany  
*** Acciai Speciali Terni S.p.A, Viale Benedetto Brin 218, 05100  
Terni, Italy  

Abstract: Stainless steel production consumes a large amount of electricity. Demand side management (DSM) has been identified as a key way to reduce costs in steel plant operations by responding to time-varying electricity prices. The electric arc furnace (EAF) is responsible for the majority of a steel plant’s electricity consumption and has been identified as having sufficient flexibility to participate in DSM schemes as it is run in batch mode with variable operating settings. Often neglected in steel plant scheduling is the degradation of the electrodes of the EAF units and the associated cost of replacing them. However, there exists a complex trade-off between the intensity at which the EAF is operated, and the lifetime of the electrode. This work proposes a novel scheduling formulation that explicitly considers DSM and its relation to electrode degradation. Results show on the one hand, that the novel formulation is able to more realistically model the EAF operations by explicitly considering electrode consumption. On the other hand, the model is also able to effectively balance the trade-offs between DSM-related costs and electrode replacement costs by extending the lifetime of the electrodes while still having the flexibility to be able to participate in DSM schemes.

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1. INTRODUCTION  

Demand Side Management (DSM) provides benefits to both electricity producers and electricity consumers. On the one hand, DSM provides grid operators the opportunity to improve the efficiency and stability of the power grid by flattening the electricity load curve. On the other hand, DSM enables electricity consumers to lower their operating costs by responding to time-dependent electricity prices.

The steel producing industry has been identified as a key industry to benefit from participation in DSM schemes. This is because the main consumer of the process, the Electric Arc Furnace (EAF), consumes large amounts of electricity, but has considerable operating flexibility. The EAF melts scrap by passing large amounts of electricity through a set of electrodes. DSM flexibility is provided by the EAFs as they are operated in batch mode, and are able to change their power consumption rates (Paulus and Borggreve, 2011). This enables the process to respond to time-varying prices by changing the timing of the batches and the intensity at which the batch is operated by adjusting the setting of the on-load tapchangers (OLTC). Due to the strong time-dependence of these electricity-rated concerns, effective scheduling is essential in DSM and as a result, the participation of steel plants in DSM schemes has been well studied. Nolde and Morari (2010) proposed a continuous-time scheduling formulation for electricity load tracking of a steel plant. The problem consists of scheduling the production tasks, with fixed power consumption, in order to track a pre-specified energy curve, and thus avoid paying penalties from the electricity providers. Hadera et al. (2015) also used a continuous time model for the same purpose, but expanded the formulation to account for multiple different electricity purchasing contracts while also using fewer binary variables than their predecessor’s work. Castro et al. (2013) studied a similar problem but using a discrete time Resource-Task Network (RTN) approach. The RTN framework is a widely used, generic technique to model and optimize the scheduling of complex processes in a systematic way (Pantelides, 1994). As a result, the model of Castro et al. (2013) was used as the basis of several other works including that of Dalle Ave et al. (2018) who expanded the model for more detailed consideration of the electricity markets and contracts. This
work focuses specifically on combining the load tracking problem (with consideration of the intraday market), with the day-ahead load prediction problem. A separate expansion of the same formulation by Zhang et al. (2017) enabled consideration of multiple operating modes of the EAF. The goal of that work is to minimize the total electricity cost of steel production. Additional flexibility is provided by not only shifting the times to periods with cheaper electricity, but also through accounting for the adjusting of the OLTC and thereby changing the instantaneous power consumption of the batch.

A major cost in steel production that is often neglected is the consumption, and replacement of the electrodes of the EAF, despite the fact that they carry a “premium price” (AISE Steel Foundation, 1998). As current is run through the electrodes, the high temperatures cause the electrodes to sublime. The higher the current, the greater the rate of sublimation. When an electrode is used up, a new electrode must be inserted for production to continue. In this work, the steel plant scheduling problem, under time-varying pricing (from the day-ahead market) is considered with explicit modeling of electrode consumption. This work features multiple EAF operating modes, which have an impact on batch timing, total and instantaneous electricity usage, and electrode consumption. As many of its predecessors, the problem is formulated as a discrete-time RTN.

2. PROBLEM STATEMENT AND ELECTRODE DEGRADATION INFORMATION

The first step in steel production is the melt shop, where solid scrap is melted, endowed with its steel characteristics and cast into slabs. The melt shop production process has four stages. The first involves melting the scrap in an EAF to form a so-called heat (a batch of liquid metal). An EAF generally consists of three electrodes, whereby an electric current is passed through in order to melt the steel. From the EAF a heat is transported to the Argon Oxygen Decarburization unit (AOD) where an argon-oxygen mixture is blown into the melt to endow the heat with its appropriate steel characteristics. From there, the heat is transported to the Ladle Furnace (LF) where final adjustments are made to the chemistry and temperature of the heat. The last stage in the melt-shop is the continuous caster (CC) where a group of heats are processed consecutively to form slabs of steel. The CC is operated continuously, and therefore corresponds to some critical processing constraints. Conversely, the first three stages of the melt shop are operated in batch mode.

The steel manufacturing plant considered in this work has two parallel machines at each stage, but the formulation is flexible and can be applied to various plant configurations. In this case, the AODs, LFs, and CCs are assumed to be identical. The EAFs on the other hand are considered unique, with each EAF having three electrodes. Additionally, the OLTC is assumed to have three different discrete settings. This corresponds to three operating modes for the EAF, henceforth referred to as low, medium, and high. Works in the past have noted that the different operating modes increased the flexibility of the steel scheduler to lower electricity costs (Zhang et al., 2017). However, they did not consider the interaction between operating mode and electrode consumption. In general, the low operating mode is characterized by a lower rate of power consumption, and thus increased batch time and decreased electrode wear. Conversely, the high operating mode is characterized by a high rate of power consumption corresponding to a decreased batch time and increased electrode wear (Madias et al., 2017). Degradation parameters considered in this work were calculated using the updated Bowman correlations (Bowman, 1995), with parameters and correlation results presented later in this paper. In this work it is assumed that every EAF task can be operated in one mode only, implying that the tap setting can only be changed in-between batches. The electrode consumption also provides the reason that each EAF needs to be tracked individually (as opposed to the other stages). This is because each EAF has three electrodes the consumption of which needs to be tracked separately. It is further assumed that an EAF processing task cannot be interrupted to replace an electrode and can only be scheduled if all the electrodes belonging to an EAF can complete the current task without being completely worn out.

Previous work has also assumed that the total energy required for melting is fixed, given by the product of nominal power and nominal processing rate. This unfortunately is not true, as industrial data shows that energy losses increase with the EAF power setting. A visualization of these energy losses can be viewed in Figure 1. Therefore, there is a further trade-off between the different operating modes and DSM; more intense operating modes can better take advantage of cheaper electricity times, however, have higher total energy consumption than less intense operating modes. The goal of this work is to expand the RTN formulation so that it can explicitly consider the complex trade-offs that exist in steel plant scheduling between electrode degradation, DSM considering multiple EAF operating modes, and task timing.

Fig. 1. Average power consumption per EAF operating mode determined from historical data.
3. MODEL FORMULATION

In this work, a discrete-time RTN model was chosen as the base model. A discrete-time model was chosen as the location of every time point in the grid is known in advance. This allows for straightforward modeling of intermediate events, such as changes in electricity pricing or power availability. The discrete-time formulation divides the scheduling horizon \( H \) into a set of intervals \( T \) of size \( \delta \).

The RTN formulation represents the entire scheduling models as a set of resources \( R \) and tasks \( I \). The resource nodes represent entities that are relevant to the process, including: equipment, utilities, and final products. The task nodes represent the operations that take place during production, such as the production operations themselves, or transport tasks. Tasks manipulate the quantities of resources through a discrete interaction parameter \( \mu \) to match the production layout (e.g., the consumption of raw materials and the production of final products). For this problem, the continuous interaction parameter \( \xi \) is omitted, because heats in steel production are discrete entities, so it is assumed that information about batch sizing is determined elsewhere. The network connecting these two types of nodes, and the corresponding interaction parameters describe the interaction between resources and tasks.

Resources are managed over the length of the time horizon through the non-negative continuous variable \( R_{r,t} \). The key equation in the RTN formulation is the excess resource balance. The excess resource balance ties the change in the quantity of the resource to the execution of a task, denoted by the binary variable \( N_{i,t} \). The task \( N_{i,t} \) represents the execution of a task and the excess resource balance can be viewed in Eq. (1). The variable \( \Pi_{r,t} \) in combination with the term \( R_{r,t-1} \) not applying to the energy balance for power enforces that electricity consumption can be properly tracked and that it does not propagate over time.

\[
R_{r,t} = R_{r,t+1} + \sum_{i \in I} \mu_{r,i} N_{i,t-\theta} + \Pi_{r,t} \quad \forall r \in R, t \in T \tag{1}
\]

3.1 Steel plant model extension

In order to model the complex operational constraints of steel making, additional constraints are needed. The first type of constraint needed are execution constraints, which enforce that a heat \( h \in H \) is executed in one unit \( u \in U \) at each production stage \( k \in K \). The units of a stage are denoted by \( U_k \). For the EAFs, an additional term is needed to indicate that the heat need to be processed on each machine, in one mode \( m \in M \). The same applies for a group of heats \( g \in G \) in the CCs. These execution constraints can be viewed in Eqs. (2) to (4).

\[
\sum_{u \in U_k} \sum_{i \in I_{h,u}} \sum_{m \in M} N_{i,t} = 1 \quad \forall h \in H, k = 2, 3 \tag{2}
\]

\[
\sum_{u \in U_k} \sum_{i \in I_g} N_{i,t} = 1 \quad \forall g \in G, k = 4 \tag{3}
\]

As noted in Castro et al. (2013), detailed wait times are difficult to model using the discrete time RTN, thus they need to be approximated. To model the transfer of a heat between stages, the intermediate resource between stages needs to be broken up into two parts. One to represent the resource at the outlet of a stage \( R_{h,u} \) and one to represent the heat at the inlet location to the subsequent stage \( R_{h+1,u} \), coupled with a task to transport the resources between the locations. For example, the execution of an EAF tasks produces an intermediate at the outlet location of the EAF, a transfer tasks is then executed to transport the intermediate heat from the outlet location of the EAF, to the inlet location of the AOD. A similar style of execution constraint is then used to enforce the minimum transportation time between stages, which can be seen in Eq. (5). The maximum transfer time of a heat between stages is approximated using Eq. (6). This constraint puts a limit on the inlet location resource lifetime. In conjunction with a constraint that sets the output location location lifetime to zero (thereby forcing execution of the transfer task), the maximum waiting time between stages is enforced.

\[
\sum_{u \in U_k} \sum_{i \in I_{h,u}} \sum_{m \in M} N_{i,t} = 1 \quad \forall h \in H, k \neq 4 \tag{5}
\]

\[
\sum_{u \in U_k} \sum_{r \in R_{h+1,u} \in T} R_{r,t} \leq \max(maxf_{u,u'} - minf_{u,u'})/\delta \quad \forall h \in H, k \neq 4 \tag{6}
\]

Eq. (7) is needed to connect the amount of electricity consumed, to the electricity markets. Electricity in this case is assumed to be bought from the day-ahead market in hourly chunks \( load_{4\text{hr}} \). Deviation penalties \( \Delta^+, \Delta^- \) are paid if the electricity consumed does not follow the load to be purchased to within a tolerance \( \Phi \) of the total load purchased (Eq. (8)). The percent allowable tolerance is denoted \( c_{pf} \). Electricity consumed within this hour range is purchased at the hourly consumption price. Deviations are penalized separately at a flat rate.

\[
\Pi_{r,t} = load_{4\text{hr}} + \Delta^+ + \Delta^- + \Phi_t \quad \forall t \in T \tag{7}
\]

\[
-c_{pf} \cdot load_{4\text{hr}} \leq \Phi_t \leq c_{pf} \cdot load_{4\text{hr}} \quad \forall t \in T \tag{8}
\]

3.2 Electrode degradation model

In order to model the different operating modes the task of running the EAF has to be split into several tasks; one for each operating mode. Each of the EAF sub-tasks consume an EAF unit at the start of the task and release it at the end. At the end of the task a heat is produced in the outlet location of the EAF. Additionally each EAF task requires
electricity, the quantity of electricity consumed depends on the mode it is operated in. A resource also needs to be created for the weight of each electrode. Similar to electricity, each operating mode of the furnace consumes a different amount of electrode weight. A new electrode replacement task then needs to be defined to replace a worn out electrode with a new one. The electrode replacement task also occupies the physical unit for its duration. An RTN diagram for a three mode EAF with a single electrode can be seen in Figure 2.

Fig. 2. RTN diagram for the EAFs with a single electrode. The thickness of the arrows indicates the magnitude of the interaction parameter for the EAF tasks.

The goal of the electrode replacement task is to take a used electrode, and replace it with a new one. There is a one-to-one correspondence between a maintenance task and an electrode. The problem introduced by the maintenance tasks is that a task cannot be interrupted to replace an electrode. This means that an electrode may not necessarily be replaced when its weight goes to zero, but rather when its weight is smaller than that required to run a single batch. This creates a problem as an RTN task can only consume and produce fixed amounts of resources. In order to account for this flexible range the excess resource balance for the electrodes needs to be broken up from a single equality constraint to a series of inequality constraints. These constraints can be viewed in Eqs. (9) to (12).

\[
R_{r,t} \leq R^0_{r|t=1} + R_{r,t-1} + \sum_{i \in I_{maint}} \sum_{\theta=0}^{\theta_t} \mu_{r,i,\theta} N_{i,t-\theta} \\
\forall r \in R_{electrode}, t \in T \tag{9}
\]

\[
R_{r,t} \geq R^0_{r|t=1} + R_{r,t-1} + \sum_{i \in I_{maint}} \sum_{\theta=0}^{\theta_t} \mu_{r,i,\theta} N_{i,t-\theta} \\
\forall r \in R_{electrode}, t \in T \tag{10}
\]

\[
R_{r,t} \leq R^\text{new}_{electrode} \forall r \in R_{electrode}, t \in T \tag{11}
\]

In the event an EAF task is executed, which consumes some of the electrode weight, Eqs. (9) and (10) are both active and calculate the appropriate remaining electrode weight. Conversely, if the maintenance task to replace an electrode is executed, both constraints are feasible but neither is active. Instead, Eqs. (11) and (12) are active which set the electrode weight after the maintenance task is executed, to the weight of a new electrode.

In order to improve the performance of the model, tightening constraints are introduced in order to limit the amount of maintenance tasks that can be executed over the scheduling horizon. These constraints can be viewed in Eqs. (13) and (14).

\[
\sum_{i \in T} N_{i,t} \leq \left[ \left( N_{Heats} \times \text{MaxConsume} - R^0_{r|t=1} \right) / R^\text{new}_{electrode} \right] \tag{13}
\]

\[
\sum_{i \in I_{maint}} \sum_{t \in T} N_{i,t} \geq \left[ \left( N_{Heats} \times \text{MinConsume} - \sum_{\theta \in U_3} \min(R^0_{r|t=1}) \right) / R^\text{new}_{electrode} \right] \times \text{NumElectrodesSameLiftime} \forall i \in I_{maint} \tag{14}
\]

Eq. (13) sets an upper limit on the number of maintenance tasks over a given horizon for each electrode. It accomplishes this by calculating the total electrode consumption of all heats if they were to be processed in the mode that consumes the most electrode weight. It then subtracts the initial weight of the electrode in order to determine the additional weight of electrode needed. This is divided by the weight of a new electrode and rounded up to ensure that enough maintenance tasks are considered.

The lower bound to the number of maintenance tasks is then provided by Eq. (14). Note that this is a limit to the total amount of maintenance tasks. It is necessary to do this, because it is the job of the scheduler to determine which machine processes which task; thus it is not known a priori how many heats will be processed by each EAF and each electrode beforehand. Therefore, the two EAFs, and their corresponding electrodes, need to be considered together in order to calculate the minimum consumption and the minimum total number of maintenance tasks. The minimum number of maintenance tasks is then calculated using a similar approach to the maximum number of maintenance tasks. In this case however, the minimum total consumption mode is used and the sum of the minimum electrode weights is used. The term can then be multiplied the total number electrodes in the EAF.
with the same lifetime (NumElectrodesSameLifetime). This can be determined using operator experience, or algorithmically by checking how many of the electrodes can perform the same amount of batches before needing replacement. This is done to account for situations where, for some reason, the electrodes do not degrade exactly evenly, or have been replaced for situations other than pure consumption. The objective function in this case is to minimize total cost. This consists of, total electricity costs considering hourly prices, and the cost of replacing electrodes.

4. COMPUTATIONAL STUDIES

The performance of the model is tested using a set of five case studies. The studies aim to characterize both the cost of electricity paid, as well as the number of maintenance tasks that need to be performed. The MILPs were implemented in GAMS 24.7.4 and solved using CPLEX 12.6.3.0.

4.1 Problem Data

The key problem data in this case are the operating conditions of the EAFs and the associated electrode consumption. In this work is is assumed that all steel heats have the same operating times in the EAF. The value of the scaled EAF parameters can be viewed in Table 1. This problem considers hourly electricity prices from an average day, with neither very large peaks nor very large valleys. These prices can be viewed in Figure 3. The remainder of the parameters are the same as in Castro et al. (2013).

Table 1. Scaled parameters for the three EAF operating modes considered in this problem.

| Operating Mode | Power Consumption | Batch Time | Electrode Consumption |
|----------------|-------------------|------------|-----------------------|
| Low            | 0.571             | 1          | 0.858                 |
| Medium         | 0.786             | 0.833      | 0.980                 |
| High           | 1                 | 0.667      | 1                     |

Fig. 3. Electricity prices considered in this work taken from the German day-ahead market. (EPEX, 2017).

4.2 Model Results

The five case studies considered in this work are as follows: the first case is the current state-of-the-art considering the aforementioned EAF operating modes outlined in Table 1 without any consideration of electrode replacement. The next three case studies are single operating mode cases with consideration of electrode degradation, one for each EAF operating modes. The last case study puts everything together, combining the flexible operating modes with consideration of electrode degradation. Each case study was run for a time horizon of 24 hours with a production target of 14 heats. Key results from the various test cases can be viewed in Table 2.

Looking at the results for the single mode cases versus the flexible operating mode case that considers maintenance, it is evident that the flexible operating modes is able to provide additional DSM flexibility within the additional degradation constraints. The flexible operating mode case was able to avoid replacing any electrodes, while the single medium and high operating mode cases were not. The low single operating mode case was also able to avoid any maintenances, however it resulted in a higher objective function value than the flexible mode case as it was unable to fully take advantage of the electricity pricing valleys. Comparing between the single mode medium and high cases shows that, despite the increased total energy consumption at more intense operating modes, there is still the potential for total cost savings from operating at a higher mode.

Comparing the flexible operating modes with and without electrode degradation illustrates why it is an important aspect to explicitly consider in the optimization. The two cases are identical except for their consideration of electrode consumption. Therefore, if no maintenance was required the two cases would have the same objective function values. In this case, the flexible modes with no regard for electrode weight had a lower objective function value. This implies that it is more advantageous, in regards to electricity cost, to operate in more intense modes when electricity is cheaper. However, this solution is infeasible if maintenance is considered indicating that the EAF is operated too harshly, and burns through the electrodes too quickly. This is confirmed by Figure 4, which shows that the electrode weight in the case that does not consider degradation, clearly becomes negative. This implies that in reality a maintenance task would be needed, showing that the operating mode sequence for this EAF is infeasible in regards to electrode weight constraints.

Lastly, it is worth comparing computation times between each of the cases. The flexible operating mode without consideration of degradation converges to an optimal solution in less than half a minute. All of the cases considering maintenance took considerably longer to solve, the majority of which were not able to converge to a global optimum within the allotted 3600s. That being said, the gap for all cases was relatively small. However, this still indicates that the consideration of the electrodes maintenance requirements makes the problem more difficult to solve. This is most likely due to the fact that the resource constraints for the electrodes need to be relaxed into a set of inequality constraints, which are not as tight as the standard equality resource balance.
Table 2. Computational results from each of the cases.

| Case                          | Objective Function (EUR) | Number of Maintenances | Computation Time (s) | Relative Gap (%) |
|-------------------------------|--------------------------|------------------------|----------------------|------------------|
| Flexible Modes - No Maint.    | 129,130                  | N/A                    | 22                   | 0                |
| Single Mode - Low             | 132,660                  | 0                      | 449                  | 0                |
| Single Mode - Medium          | 218,850                  | 1                      | 3600                 | 3.8              |
| Single Mode - High            | 205,400                  | 1                      | 3600                 | 0.1              |
| Flexible Modes - With Maint.  | 130,450                  | 0                      | 3600                 | 0.3              |

Fig. 4. Electrode weight for the flexible operating mode case with no electrode degradation considered (solid line) and for the case with electrode degradation (dashed line).

5. CONCLUSIONS

In this work, a novel DSM melt shop scheduling formulation was presented. This formulation explicitly considers the complex trade-offs between the batch timings, electricity usage, and electrode consumption of the different operating modes of the EAFs. The model is formulated as a discrete-time RTN, based on the models by Castro et al. (2013) and Zhang et al. (2017) with major modifications made to account for the tracking of electrode weight and for the electrode replacement tasks.

Results show that the novel formulation is able to take advantage of the flexibility provided by the different operating modes, within the constraints of electrode degradation. Furthermore, it was shown that it is necessary to explicitly consider the electrode degradation in the scheduling model or else the optimizer will attempt to operate the EAF too intensely, thereby violating the electrode weight constraints.

The drawback to this model is that it results in large computation times compared to the case when electrode degradation is not considered. Future work could focus on producing tighter models for the electrode weight tracking and replacement tasks, or by investigating potential speed-up algorithms such as decomposition-based approaches.

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