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Cost-effective Scheduling of Steel Plants with Flexible EAFs

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***Abstract*—Electric arc furnaces (EAFs) in steel plants consume a large amount of electric energy, and the energy cost constitutes a significant proportion of the total costs in producing steel. However, a steel plant can take advantage of time-based electricity prices by optimally arranging energy-consuming activities to avoid peak hours. Besides, the EAFs' power rate can be adjusted by switching transformers' taps, which offers additional flexibility for arranging energy consumption and minimizing the cost of electricity. In this paper, we propose scheduling models based on resource-task network (RTN) formulations that incorporate the EAFs' flexibilities to reduce the electricity cost. The effectiveness of the model is demonstrated in multiple case studies.**

***Index Terms*—Resource task network, mixed integer programming, demand response, industrial load, steel manufacturing.**

I. NOMENCLATURE

Variables

$N_{i,t}$	binary variable indicating whether task i starts at time slot t
$R_{r,t}$	continuous variable representing the value of resource r at time slot t
$\Pi_{EL,t}$	continuous variable representing the energy usage (MWh) of the entire plant at time slot t
$S_{h,t}, P_{h,t}$	(in model Flex) the melting status (on/off) and melting power (MW) of heat h at time slot t

Parameters

τ_i	the length (in time slots) of task i
w_i, W_i	the time bounds (in time slots) of transfer i
$\mu_{r,i,\theta}$	the interaction quantity between task i and resource r at the θ-th time slot since the start of task i
δ	the duration (minutes) of every time slot
$price_{hr}$	the hourly electricity price (\$/MWh)
$m \in M_h$	(in model Modes) the index indicating different melting modes

Subscripts (tasks and resources)

i_{E_h}	the processing task of heat h in stage EAF
$i_{C_{g,u}}$	the casting task of group g by caster u
i_{EA_h}	the transfer task between stages EAF and AOD
EA_h^s, EA_h^d	the intermediate product resource between EAF and AOD (s: at source, d: at destination)
EAF	the equipment resource in stage EAF
EL	the electricity resource

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II. INTRODUCTION

Demand response (DR) or demand side management (DSM) is a popular topic that has been widely discussed and studied in recent years. It has been shown that the flexibility of loads can be used to provide valuable services to the electric power system [1]–[4]. Hence, electricity providers may offer economic incentives to encourage consumers to change their electricity usage behavior, and thereby help maintaining the supply-demand balance. This is particularly interesting for industrial plants for which the electricity cost constitutes a significant part of their operating costs. For example, they are able to reduce their electricity cost by shifting their consumption according to time-based energy prices. This on the other hand is beneficial for the power grid as it helps mitigating daily supply and transmission bottlenecks and slowing down the needs for constructing more generation capacity.

A recent study [5] investigated the potential of DSM for power-intensive industries such as electric arc furnaces, aluminum electrolysis, and cement milling in electricity markets in Germany, concluding that these industries potentially have significant impacts on electricity markets. In [6] and [7], the role of the industrial sector, also including food processing plants and greenhouses, in demand response is discussed. In [8], [9], the chemical engineering community has presented scheduling methods for industrial plants taking into account time-based energy prices. The result is that the electricity-intensive production activities are optimally arranged to minimize electricity costs. In addition to adjusting consumption according to price, the industrial plants can also make profits by providing ancillary services [10]–[12], such as spinning reserve that helps the power system operator to handle unexpected outages and regulation that compensates for minute-to-minute load fluctuations.

Industrial plants constitute a great portion of the total load. Compared to other loads such as buildings and residential areas [13], [14], industrial loads as demand response resource have the following advantages: the magnitude of power consumption by an industrial plant and the change in power it can provide are generally very large [15]; besides, the infrastructures for control, communication and market participation which enables demand response usually already have been installed at the plants; even more important, some industrial plants are able to offer fast and accurate adjustments in their power consumption [16], [17]; moreover, the industrial plants are generally more economically motivated to participate actively as demand response resource. However, the industrial processes such as steel manufacturing are generally complex to schedule, which needs to be addressed for these plants to actively take part in demand response.

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Electric arc furnaces (EAFs) in steel manufacturing plants are identified as having great potential for demand side management, since these furnaces not only consume large amounts of electric energy, but they operate in batch mode and are also fairly flexible in terms of changing their power consumption rate [5]. The EAFs are powered by transformers and their power consumption rate can be changed very quickly by adjusting the settings of the on-load tapchangers (OLTC). The objective for the optimal scheduling of steel plants has traditionally been to minimize the make-span, i.e. to produce as fast as possible to make the most utilization of the heavily invested facilities. However, in recent years the participation of steel plants in demand side management has been studied with a variety of emphases, such as peak load management [18], prespecified energy curve tracking [19], and electricity fee minimization [20], [21]. Meanwhile, it is recognized that steel plant scheduling is one of the most difficult industrial processes for scheduling, as steel manufacturing is a large-scale, multistage, multiproduct batch process which involves parallel equipment and critical production-related constraints [22]. A widely used technique to model and optimize the scheduling of such plants is resource-task network (RTN). The RTN modeling framework is able to explicitly represent the complex chemical processes in a systematic way, especially for processes with multiple stages and critical production requirements.

In this paper, we extend the RTN models in [20] to study the minimization of electricity cost for steel plants. Instead of merely shifting the tasks to time periods with cheaper electricity, we also integrate the furnaces' capability of adjusting the OLTC setting and thereby the instantaneous melting power rate. In this way, the steel plant gets more "flexibility" in arranging the production activities and reducing the electricity bill. With the word "flexibility" we refer to the ability of the steel plant to adjust its load curve in response to the electricity price curve: the more flexibility it has, the better it can adjust its load curve and save more money. Note that frequent switching at high currents potentially reduces the lifetime of the OLTCs. The benefit and cost analysis for switching OLTCs should be taken in a long time scale (e.g. several years) with a variety of practical considerations including the lifetime, expenditure and operational properties of the OLTCs, the sale price and yearly throughput of the final product, etc. In this paper, we provide an approach to optimize the benefits achieved, neglecting the lifetime reduction because this would require significant amounts of additional data which is beyond the scope of this paper.

The main contribution of this paper is the modeling of the steel plant enabling optimal scheduling with controllable transformers on the electric arc furnaces. Previous work has been devoted purely to optimally scheduling the tasks without consideration of such flexibilities within the tasks. Taking these flexibilities into account, however, increases the computational complexities of the scheduling problem which are addressed in this paper using a newly introduced modeling and solution approach. An additional contribution is the analysis of a typical steel plant that demonstrates the benefits achieved by controlling the OLTCs of these transformers. The remaining paper is organized as follows: Section III first describes the steel manufacturing and its ability to respond to time-based electricity prices, then proposes to solve the scheduling problem of the steel plant by RTN formulations. Section IV reviews the RTN model that minimizes energy cost only by shifting production tasks. Sections V and VI propose RTN models that take into account the EAFs' flexibilities in adjusting the power consumption rate to better respond to the variations in electricity prices. The effectiveness of the proposed models are demonstrated by case studies in Section VII. Section VIII draws the conclusion of this study and describes future research directions.

III. Problem Statement and Solution Method

The typical process of steel production is illustrated in Fig. 1. Solid metal scrap (from recycled steel such as discarded cars) is first molten in the electric arc furnace (EAF), then further processed in the argon oxygen decarburization unit (AOD) to reduce the carbon content. The molten steel is then refined in the ladle furnace (LF) and finally transported in ladles to the continuous casters (CC) to be casted into slabs - the final products of the steel manufacturing process. The steel can be characterized by grade, slab width, and thickness. Different kinds of products require different chemical ingredients and different casting procedures.

The first three processing stages operate in batch mode which means that a specified amount of metal is processed at a time. Each such amount of metal is called a *heat*. Meanwhile, the casting stage operates continuously and has some critical processing constraints. Due to the extreme conditions in the caster, it can only process a limited number of heats, after which it needs maintenance such as changing the caster mold and tundish before further operation. Several heats sharing the same or very similar grade characteristics and shape requirements form a campaign (a group of heats) and are casted sequentially. The method for forming casting campaigns is proposed and discussed in [22], and in this paper we assume the campaigns have already been formed. The casting order should follow certain rules and the casting sequence for the heats within one campaign must not be interrupted.

The steel manufacturing plant considered in this paper has parallel units for each of the four stages but the proposed methods can also be applied to a plant with any number of units and any number of stages. It is assumed that the processing abilities of the units for the first three stages are almost the same, i.e. the equipment units in the same stage have the same power consumption and the same processing

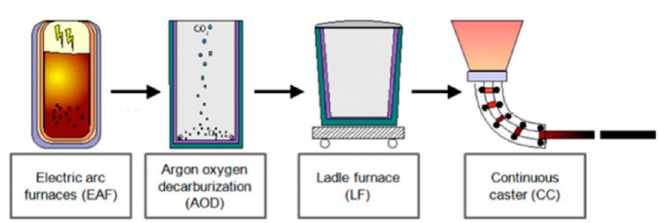

Fig. 1: Production process of steel manufacturing [20]

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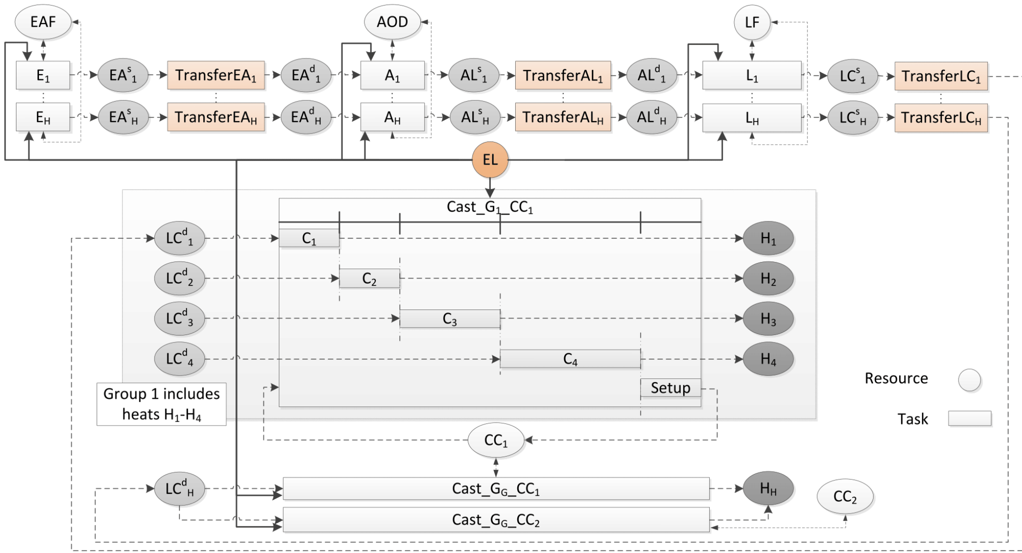

Fig. 2: Resource task network for basic scheduling of a steel plant.

time for each heat. Thus, the parallel units for the first three stages are assumed identical to simplify the problem. In contrast, casters need to be considered individually due to their different processing and setup times, and all the heats belonging to the same campaign group should be processed in the same caster sequentially.

In EAF-steel manufacturing, most of the electric energy is consumed by the furnaces in the melting stage. Hence, adding flexibility to the power consumption of this stage has the highest impact on the overall electricity cost. In existing steel plant scheduling literature like [20], the EAFs' power consumption rate and processing time are treated as constant parameters, and only the starting times of the melting tasks are moved in time to provide operational flexibility. However, according to practical operation, it is also possible to adjust the furnaces' power consumption rate very quickly by controlling the OLTC, which gives opportunities to further increase the flexibility of the steel plant's energy management. Hence, our goal is to incorporate this flexibility into the RTN model and exploit it to further reduce the electric energy cost of the steel manufacturing plant.

For the scheduling problem in this paper, we make the following assumptions about EAF's flexibility:

- the EAF can change its hourly energy consumption within given bounds without losing melting efficiency (tons of output per MWh of electricity) or jeopardizing operational safety.
- the total energy required for melting each heat is fixed, given by the product of nominal power and nominal processing time.
- the actual processing time depends on the actual power consumption and may vary within a given bound.

We address the scheduling problem by using a discrete-time RTN formulation. The RTN model involves two types of nodes: resources and tasks. The resource nodes represent all entities that are relevant to the process such as raw materials, intermediate and final products, equipment, and utilities. The task nodes include all tasks that take place during the production, such as a chemical process or the transportation of material. The task can change the amount of the product in a resource node and/or the status of the equipment (occupied or available). Resources are necessary to promote state changes or tasks' execution. For example, a certain task can only start if there is enough input material and equipment available. The network connecting these two types of nodes and the interaction parameters on the network describe the detailed interactions between resources and tasks.

The main difficulty of industrial scheduling problems arises from the large number of discrete variables in the model. For example, several thousands of binary variables are needed to denote the start of the tasks in a practical steel plant scheduling problem. Generally speaking, a more rigorous model which represents the process more accurately requires a larger number of variables, resulting in an optimization problem which is difficult to solve. Among the RTN models presented in [20], the Aggregated Equipment Resource and Simple Transfer Tasks (Basic RTN) model is the best selection for electricity cost minimization because of the reduced computational complexity and the negligible differences in the final solution compared to the solutions of more rigorous models which take a significantly longer time to run. We briefly provide an overview of this model in the next section and then present the extension to include the flexibility provided by OLTCs.

IV. Basic RTN

The Basic RTN model optimizes the electricity cost by shifting the time of production activities. Thereby, the EAF melting power is always equal to the equipment nominal value. The parallel units for the first three stages are assumed identical, while the casters are considered individually because

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different casters are designed for casting specific products. The model also overlooks the differences in transfer times between units from two successive stages: parallel units in the same stage might be located far away from each other, so that the transportation time between successive stages actually depends on the exact locations of the specific unit u in the previous stage and the unit u' in the next stage; the transportation time also depends on the transportation mode, e.g. by train or by crane. For instance, if there are 3 units for the first stage and 4 units for the second stage, then there are at least 12 possible transportation times. The Basic RTN assumes the transfers are independent of the units' locations, which is a simplification that might lead to an under- or over-estimation of the actual transfer time. With these assumptions, the Basic RTN achieves a relatively simple model with fast computation and reasonable results.

A. Resource Task Network

The Basic RTN is illustrated in Fig. 2. The tasks considered are the four main production stages, i.e. melting in the EAF, decarburization in the AOD, refining in the LF, and casting in the CC, as well as the transfer tasks between the stages.

Each task is indexed by i and the binary variable $N_{i,t}$ assigns the start of task i to time point t, i.e. $N_{i,t} = 1$ indicates that task i begins at time slot t. For the operational tasks of the first three stages and all the transfer tasks, there is one task for every heat h. For instance, if there are H heats that have to be produced, then we have H melting tasks to schedule: one melting task per heat. The tasks for the first three stages are therefore denoted by i_{E_h}, i_{A_h}, and i_{L_h}, respectively. Similarly, we denote the transfers by i_{EA_h}, i_{AL_h}, and i_{LC_h}.

Unlike the first three stages where we do not distinguish between parallel units, the casters are treated individually. Hence, we need to assign each casting job to a specific caster. A casting task is denoted by $i_{C_{g,u}}$ with a pair of indices (g, u), where g stands for the casting campaign group and u stands for a specific caster. This is because task $i_{C_{g_1,u_1}}$ is different from task $i_{C_{g_1,u_2}}$, e.g. these two tasks' durations are not equal due to the different setup times of the two individual casters. So, we have to consider both $i_{C_{g_1,u_1}}$ and $i_{C_{g_1,u_2}}$ in the problem formulation in order to take into account all possible caster assignments. Of course, casting g_1 will be assigned to just one caster. Consequently, only one of these two tasks will be scheduled, while the other one never takes place.

The transfer task is forced to be executed immediately after the completion of its preceding processing task, which is generally required in the steel manufacturing process. While on the other hand, after transferred to the next stage, heats may need to wait before the following processing step for the equipment to become available or for lower electricity prices.

The resources considered are equipment, electricity, intermediate products, and final products. As the intermediate products are transferred from one stage to the next, each intermediate product needs to be associated with the location where this heat of metal currently is. For example, EA_h^d denotes the intermediate product of the specific heat h located at the transfer destination (superscript d), i.e. the inlet of AOD, which is waiting to be processed by AOD; while EA_h^s denotes the same intermediate product located at the transfer start (superscript s) which is waiting to be transferred. The sets of resources considered in the model are processing units (EAF, AOD, LF, and CC), electric energy (EL), intermediate products (EA^s, EA^d, AL^s, AL^d, LC^s, and LC^d), and final product (H). Nonnegative continuous variables $R_{r,t}$ represent the value of resource r ($\forall r \notin EL$) at time t. For instance, $R_{EAF,t} = 1$ means there is one EAF available at time slot t. Nonnegative continuous variables $\Pi_{EL,t}$ are used to summarize the energy usage over all tasks in time slot t.

The network flowchart in Fig. 2 indicates how each task interacts with each resource. Processing tasks interact with electricity resources continuously, but interact with other resources discretely. Continuous interaction means that the task consumes or generates the resource continuously during the processing time of the task. For example, for simplification we assume that the melting task consumes electric energy continuously during the entire task. While discrete interaction means that the interaction only takes place at very distinct time points during the task. For example, the melting task occupies one EAF at the very beginning of the task and only returns the EAF at the end of the melting process. The melting task may last for several time slots, but it only interacts with the resource EAF in two time slots.

The detailed interactions are described by interaction parameters. Interaction parameter $\mu_{r,i,\theta}$ quantifies how much of resource r is consumed or generated by task i at the relative time slot θ - the time slot that is θ slots after the start of task i. The interaction parameters for the melting task with its interactive resources are illustrated in Fig. 3. There are three different time references: $Time$ stands for the actual hour of the day; t is the index for the uniform time grid; the relative time index θ is related to the start of the task. Discrete-time formulation assumes that the task can only start at the beginning of the time slot, but can end anywhere within the time slot. The slots' width of the time grid in Fig. 3 is $\delta = 30$ minutes. The time duration for melting is assumed to be 80 minutes. Hence, the melting spans 3 ($\lceil 80/30 \rceil$) time slots. Note that the melting is completed before the last time slot ends. This rounding error due to discrete-time formulation might underestimate the potential flexibility gained from rescheduling. Using a finer time grid can alleviate this issue but increases the computational complexity.

In Fig. 3, we assume that the melting task of heat h, i_{E_h}, starts at $t = 3$. This task interacts with resources EAF, EL, and EA_h^s. At the very beginning, the task reduces EAF by one as it uses the operation unit; after the completion of the melting process, EAF is increased by one as the EAF is freed up. Also, EA_h^s is increased by one to promote the execution of the following transfer; the melting consumes electric energy continuously during its entire duration. Note that the energy consumption of the last melting time slot is less than the previous slots because the task actually completes before the end of that slot.

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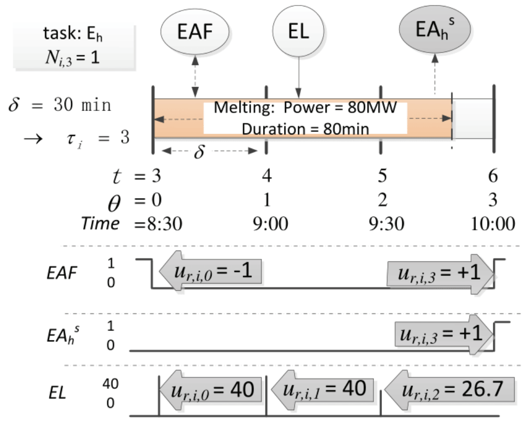

Fig. 3: Illustration of interaction parameters for a melting task.

B. Mathematical Formulation

In this section, we use the RTN model, formulate the dependencies mathematically and integrate it into an optimization problem to determine the daily schedule of a plant. The objective is to minimize the electricity cost, and the time-based electricity prices are assumed to be known ahead of time. In a time-of-use (TOU) pricing system, these hourly prices can be obtained easily; in a wholesale market, price forecast methods [23], [24] can be utilized to provide the forecast prices as the price signal for our model; in a tiered pricing system, we need to design an objective function with the detailed parameters in the tiered pricing. Since this paper is the first step in motivating these industrial loads to actively participate in demand/supply balancing and its focus is on modeling and optimization, we assume the price signal is known. The formulations in this section are based on [20], and have been updated for simplified presentation.

1) Resource Balance: Resource evolution over the time horizon is managed by the excess resource balance, as in

$$R_{r,t} = R_{r,t-1} + \sum_{i} \sum_{\theta=0}^{\tau_i} \mu_{r,i,\theta} N_{i,t-\theta} + \pi_{r,t} \quad \forall r \notin EL, t \quad (1)$$

in which the value $R_{r,t}$ of resource r at time slot t is equal to its previous value at $t-1$ adjusted by the amounts generated/consumed by all relevant tasks. The above constraint applies to all the resources described in Section IV-A except for the electricity resource.

Nonzero interaction parameters $\mu_{r,i,\theta}$ imply interaction and task i only interacts with resource r when the task is ongoing. In other words, the interaction takes place at time slot t only if the task i starts θ earlier than t ($N_{i,t-\theta} = 1$) with θ being less than τ_i - the duration of task i. Equipment maintenance can be modeled by adding parameters that influence the excess value of equipment in the balancing equation. For example, adding $\pi_{CC_1,5} = 1$ on the right side of (1) means caster CC_1 needs to be maintained and cannot be used at time slot 5.

Meanwhile, the electricity usage is calculated as

$$\Pi_{EL,t} = \sum_{i} \sum_{\theta=0}^{\tau_i} \mu_{EL,i,\theta} N_{i,t-\theta} \qquad \forall t \qquad (2)$$

where $\Pi_{EL,t}$ is equal to the electric energy usage by all possible tasks at time slot t; the right side of (2) first sums over all tasks and then for each task, it sums over all possible starting times of task i for which task i would still be running at time t.

2) Task Execution: Operational constraints (3), (4), and (5) are used to ensure that tasks are executed the proper number of times. The constraints

$$\begin{aligned} \sum_t N_{i_{E_h},t} &= 1 \qquad \forall h \\ \sum_t N_{i_{A_h},t} &= 1 \qquad \forall h \\ \sum_t N_{i_{L_h},t} &= 1 \qquad \forall h \end{aligned} \qquad (3)$$

ensure that all heats are processed only once by the first three stages. For the casting stage, we distinguish between individual casters and we need to assign one caster for each job. If we have C individual casters and G groups of heats, then the number of possible casting tasks is $C \times G$. But not all casting tasks are actually being executed. Each group of heats should be executed only once by any unit u from the available casters CCs. This is reflected in the following constraint

$$\sum_{u \in CCs} \sum_t N_{i_{C_{g,u}},t} = 1 \qquad \forall g \qquad (4)$$

Similarly, the intermediate products should only be transferred once between each of the stages, as defined by

$$\begin{aligned} \sum_t N_{i_{EA_h},t} &= 1 \qquad \forall h \\ \sum_t N_{i_{AL_h},t} &= 1 \qquad \forall h \\ \sum_t N_{i_{LC_h},t} &= 1 \qquad \forall h \end{aligned} \qquad (5)$$

3) Transfer Time: The transfer task is forced to be executed immediately after the completion of its preceding processing task, which is common in the steel manufacturing process. This requirement is embodied by enforcing

$$\begin{aligned} R_{EA_h^s,t} &= 0 \qquad \forall h, t \\ R_{AL_h^s,t} &= 0 \qquad \forall h, t \\ R_{LC_h^s,t} &= 0 \qquad \forall h, t \end{aligned} \qquad (6)$$

The variable $R_{EA_h^s,t}$ is either 0 or 1, and if it is equal to 1, then it indicates that the intermediate product EA_h^s is waiting at time slot t. The above constraint requires that there is no waiting time for any of the intermediate products with superscript s.

The transfer time of the intermediate products are assumed to be w_{EA}, w_{AL}, and w_{LC}, which are independent of the specific heats and the operation units. The maximum allowable transportation time W_{EA}, W_{AL}, and W_{LC} are also defined which makes sure that the cooling effect during transportation

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does not adversely affect the processing of each heat in the next stage, as the products' quality may be compromised by low temperature and would have to be compensated by expensive reheating. The transfer time constraints are therefore given by

$$\begin{aligned} \delta \sum_t R_{EA^d_h,t} + w_{EA} \leq W_{EA} \qquad \forall h \\ \delta \sum_t R_{AL^d_h,t} + w_{AL} \leq W_{AL} \qquad \forall h \\ \delta \sum_t R_{LC^d_h,t} + w_{LC} \leq W_{LC} \qquad \forall h \end{aligned} \tag{7}$$

in which δ is the time slot width. The $\sum_t R_{EA^d_h,t}$ is the total time slots that intermediate product EA_h waits before entering into the next stage. The constraint states that for each intermediate product, the transfer time plus the waiting time should be upper bounded to prevent adverse cooling effects.

4) Product Delivery: The final products should be deliverable by the end of the time horizon, which is enforced by

$$R_{H_h,T} = 1 \qquad \forall h \tag{8}$$

in which T is the last time slot of the time horizon.

5) Objective: The overall objective of the optimization is to minimize the total energy cost as given by

$$\min \quad \sum_{hr} price_{hr} \sum_{t \in T_{hr}} \Pi_{EL,t} \tag{9}$$

The hourly electricity prices $price_{hr}$ are given as inputs and T_{hr} is the set of time slots in hour hr. Here it should be noted that while we only optimize the electricity costs, all other production requirements are enforced through constraints.

V. Multiple Modes Melting

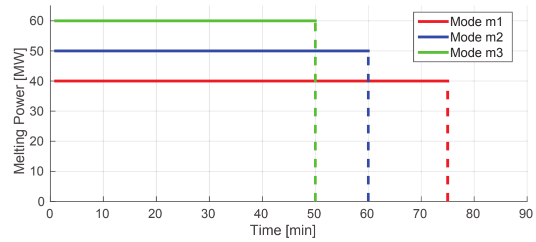
In the following, we integrate the flexibility of EAFs provided by the controllability of the transformer taps into the model described in the previous section. In this section, we limit such flexibility by making the following modeling assumptions:

- the OLTC setting and therefore the melting power for each heat can be chosen from a set of modes. This setting does not change until the melting of this heat completes.
- for each of these modes, the melting task of each mode fully spans the entire required time slots.

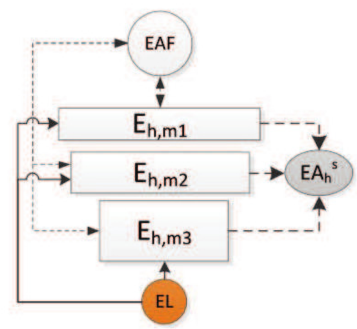
The second assumption makes it convenient to consider ancillary services such as spinning reserve for future research, as it has to be guaranteed that the service can be provided during the entire time slot.

A. Resource Task Network

Suppose the nominal melting power of the EAF is P. We assume that the melting power can be adjusted between P^L and P^U from its nominal value P. Note that P, P^L and P^U, as parameters of the EAF, are the same for all the heats. While on the other hand, suppose the nominal melting time for heat h is w_h, which depends on the specific heat. Then according to the nominal case, the electric energy needed to melt heat h



(a) Melting options



(b) Updated RTN

Fig. 4: Melting in stage EAF with 3 modes.

is equal to $w_h \cdot P$, and we assume that this amount of energy does not change when we adjust the melting power between P^L and P^U. Hence, the melting time of heat h is bounded between $w^L_h = w_h P/P^U$ and $w^U_h = w_h P/P^L$. The time slots spanned by the melting task of heat h is then bounded by $\tau^L_h = \lceil w^L_h/\delta \rceil$ and $\tau^U_h = \lfloor w^U_h/\delta \rfloor$[1]. We assume that we can change the OLTC settings so that the melting time of heat h is $\tau_m \delta$, where τ_m is a integer between τ^L_h and τ^U_h, and the corresponding melting power is $P w_h/(\tau_m \delta)$. In other words, there are $M_h = \tau^U_h - \tau^L_h + 1$ melting modes to choose from. For each mode, the melting duration τ_m is known, then the melting power and the OLTC setting can be calculated accordingly. In the example illustrated in Fig. 4, processing heat h in stage EAF has three melting options, i.e. power consumption rates at 60, 50, and 40 MW and lasting for 50, 60, and 75 minutes, respectively; the updated RTN graph for the modes modeling is displayed in Fig. 4b. Note that the areas under these three lines are the same and are equivalent to the total energy needed for melting the steel scrap. With the extra flexibilities given by the modes modeling, the plant operator can choose among different power consumption curves therefore has more options in minimizing its energy cost as well as helping the power grid to balance demand and supply.

Unlike the Basic RTN in the previous section, the melting tasks in the Multiple Modes Melting are denoted by $i_{E_{h,m}}$ in which h stands for the heat and m represents the melting mode. Hence, we have increased the number of tasks compared to the Basic RTN. The resources and the interaction parameters are still the same, except that we now need to update the

[1]Generally $\lceil w^L_h/\delta \rceil$ is smaller than $\lfloor w^U_h/\delta \rfloor$; if not, try to reduce the value of δ or formulate the melting modes differently.

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interaction parameters for each melting task $i_{E_{h,m}}$.

B. Mathematical Formulation

The formulations (1) - (9) still apply, except that the melting execution constraint in (3) needs to be replaced by the following constraint which incorporates the choice of the melting mode.

1) Melting Mode Choice: Only one mode should be chosen for melting each heat h, i.e.

$$\sum_{m=1}^{M_h} \sum_{t} N_{i_{E_{h,m}},t} = 1 \qquad \forall h \tag{10}$$

hence, only one $i_{E_{h,m}}$ from all possible modes $m = 1, \cdots, M_h$ should actually take place.

2) Demand Charge: As mentioned above, the objective for the Multiple Modes Melting is still the minimization of the total energy cost as given in (9). However, the modeling methods proposed in this paper are also able to consider the peak demand charge if that is being imposed. In order to take the peak demand into account, we can add a continuous variable P^k to denote the peak demand over the considered horizon, and then we can include this peak demand P^k in the minimization objective with the penalty price, $price_{dc}$ (\$/MW), as its coefficient. Since we already have the energy usage $\Pi_{EL,t}$ for every time slot, we can model the peak demand through the following constraint (given that we are minimizing P^k):

$$P^k \geq \Pi_{EL,t}/\delta \qquad \forall t \tag{11}$$

in which δ is the length of the time slot. In the objective function, we add the term $price_{dc} \cdot P^k$ to reflect the demand charge [25]. In the short-term scheduling problems considered in this paper, the plants optimize over a single day whereas demand charges are usually only charged for the one single maximum power consumption over the entire month. We can take this into account by setting the lower bound of P^k to be P^k_{max}, with P^k_{max} being a constant equal to the maximum power so far over all days in the ongoing month. The demand charge discussed here applies to all the three models presented in this paper.

VI. Arbitrary Flexible Melting

In this section, we further extend the EAFs' flexibility. Compared with Section V, here the EAFs are even more flexible by making the following assumption:

- the transformers' OLTC setting can be adjusted for every single time slot, thus the EAF power rate can change during the melting of each heat.

A. Resource Task Network

The consequence of allowing for adjustment of the melting power during the melting process is that the time duration of melting is not directly associated with a given melting power any more, but generally varies between τ_h^L and τ_h^U. This means that we need extra variables to denote the end of the melting tasks. However, since the heats are still required to be transferred immediately after having been processed, the end of the melting equals the start of the succeeding transfer. Thus, we use i_{EA_h} to denote the end of melting.

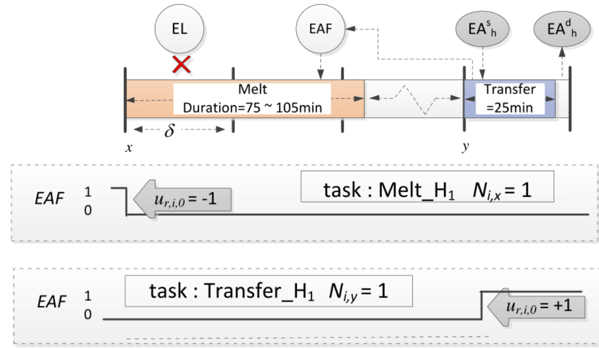

Fig. 5: Illustration of interaction parameters for a melting task for arbitrary flexible melting.

Furthermore, since the power consumption rate of the melting process is assumed to be adjustable, we cannot connect the melting task to the electric energy resource by fixed parameters. Hence, we introduce variables $P_{h,t}$ to denote the melting power of the melting task for heat h at time slot t. Accordingly, we remove the connection between the melting task and the electricity resource, which means that $\Pi_{EL,t}$ now only sums the energy consumption for the last three stages. The updated interaction parameters are illustrated in Fig. 5. Note that resource EAF interacts with both the melting task and the transfer task. The other tasks and resources remain the same as in Section IV.

B. Mathematical Formulation

Equations (1)-(8) still apply except for the parameter updates. In addition, we need the following constraints to enable the flexible scheduling.

1) Melting Duration Bounds: All melting tasks should be completed within given bounds, i.e.

$$\sum_{t'=t+\tau_h^L}^{t+\tau_h^U} N_{i_{EA_h},t'} \geq N_{i_{E_h},t} \qquad \forall h \tag{12}$$

Keep in mind that the start of the transfer equals the end of melting. Hence, the equation states that if melting task i_{E_h} starts at time slot t ($N_{i_{E_h},t} = 1$), then the transfer i_{EA_h} must start between time slots $t + \tau_h^L$ and $t + \tau_h^U$.

2) Melting Power Bounds: The melting power rate of the EAFs are constrained by the lower and upper bounds P^L and P^U as defined by

$$P^L \cdot S_{h,t} \leq P_{h,t} \leq P^U \cdot S_{h,t} \qquad \forall h \tag{13}$$

where $S_{h,t}$ is the melting status: $S_{h,t} = 1$ indicates the melting of heat h is taking place during t; $S_{h,t} = 0$ indicates that heat h is not in the melting stage at time t.

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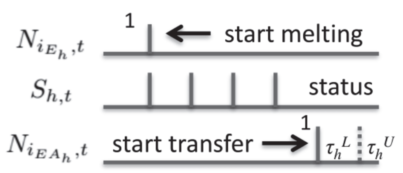

Fig. 6: Relation of melting status, start of melting and transfer.

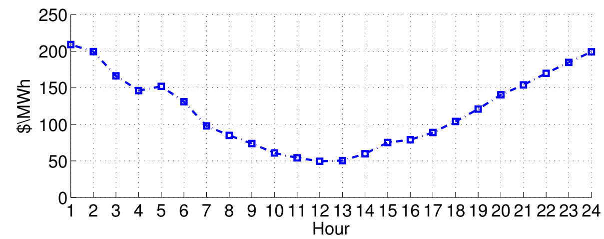

Fig. 7: Hourly electricity price [20]

3) Melting Status Evolution: The melting status evolves according to

$$S_{h,t} - S_{h,t-1} = N_{i_{E_h},t} - N_{i_{EA_h},t} \tag{14}$$

with initial condition $S_{h,0} = 0$. The evolution of the variables and their dependencies are visualized in Fig. 6: a change in the melting status is initiated by the start of the melting task and the start of the transfer. It is also worth to emphasize that variable $S_{h,t}$ is modeled as continuous variable to reduce the computational burden, but constraint (14) ensures it to be binary if all the other constraints hold.

4) Melting Energy Requirement: The total energy needed for melting heat h is assumed constant and can be calculated according to the nominal case. It is enforced by including the following constraint

$$\sum_t P_{h,t} \cdot \delta = P \cdot w_h \tag{15}$$

which states that the summation of the consumed energy over the time horizon is equal to the product of nominal power and nominal melting time.

5) Objective: Again, the objective is to minimize the total energy cost which is now defined as

$$\min \sum_{hr} price_{hr} \sum_{t \in T_{hr}} (\Pi_{EL,t} + \sum_h P_{h,t} \cdot \delta) \tag{16}$$

As stated in Section VI-A, $\Pi_{EL,t}$ only sums the last three stages' energy usage, the melting energy usage, i.e. $P_{h,t}$ times the duration δ, needs to be considered additionally in the objective function. The scheduling model in this section minimizes the objective function (16) while subject to constraints (1)-(8) and (12)-(15).

VII. Case Study

In this section, we carry out case studies to demonstrate the effectiveness of the proposed models. We consider the daily scheduling problem for an electric arc furnace steel plant.

A. Problem Parameters

The layout of the steel plant and the corresponding parameters are taken from the example in [20]. In particular, the plant considered has two EAFs, two AODs, two LFs and two CCs. Each heat belongs to a particular casting campaign group as given in Table I. The nominal power consumptions are provided in Table II, where the power consumption is independent of the specific heat. The nominal processing times are shown in Table III, where different heats require different processing times. Combining Table II and III, we observe that around 90% of the total electric energy consumption takes place at EAFs. The transfer times w_{EA}, w_{AL}, and w_{LC} are 10, 4, and 10 minutes for the three between-stage transfers successively; the maximum waiting time W_{EA}, W_{AL}, and W_{LC} are 240, 240, and 120 minutes, which are higher than practical values but help to provide more flexibilities in scheduling for testing purpose. The caster setup times are 70 minutes for CC_1 and 50 minutes for CC_2. The hourly-based electricity prices are given in Fig. 7. Recall that in a wholesale market, a price forecast is needed to provide the expected hourly prices. Note that the first hour in Fig. 7 is not necessarily 00:00-01:00 in the day, as we need to consider workers shift time and products' due time; that is why the hourly electricity prices are lower during the middle of the time horizon. Generally speaking, the larger the difference between peak price and non-peak price, the more benefits our methods bring to this industrial load.

For scheduling with flexible EAFs, the melting power rate are assumed to be adjustable between 75% to 125% of the nominal value. The melting times are changed accordingly, e.g. the heats with nominal processing time equaling 80 minutes now can be melted by a duration between 64 minutes and 106.7 minutes. With this assumption, the steel plant can obtain an extra flexibility of 80 MW (80MW$\cdot$50% $\cdot$ 2) for the hours when both furnaces are operating. The required energy for melting each heat is set as the product of the nominal power multiplied by the nominal processing time. In the simulations, we do not take demand charges into account because, as already mentioned, the case study spans one day which is the most reasonable time range for this application given the need for price predictions and also for practical operational reasons. Meanwhile, it can be assumed that for the majority of the months, the demand charges are equal to the demand charge price times the plant's power capacity, i.e. the total power consumption of all the equipment. This is because a well utilized plant often needs to use all the equipment concurrently.

TABLE I. Steel heat/group correspondence [20]

group g	G_1	G_2	G_3	G_4	G_5	G_6
H_g	$H_1 - H_4$	$H_5 - H_8$	$H_9 - H_{12}$	$H_{13} - H_{17}$	$H_{18} - H_{20}$	$H_{21} - H_{24}$

TABLE II. Nominal power consumptions [MW] [20]

$d_{h,u}$	EAF_1	EAF_2	AOD_1	AOD_2	LF_1	LF_2	CC_1	CC_2
$power_{h,u}$	85	85	2	2	2	2	7	7

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TABLE III. Nominal processing times [min] [20]

$d_{h,u}$	EAF_1	EAF_2	AOD_1	AOD_2	LF_1	LF_2	CC_1	CC_2
H_1-H_4	80	80	75	75	35	35	50	50
H_5-H_6	85	85	80	80	40	40	60	60
H_7-H_8	85	85	80	80	20	20	55	55
H_9-H_{12}	90	90	95	95	45	45	60	60
$H_{13}-H_{14}$	85	85	85	85	25	25	70	70
$H_{15}-H_{16}$	85	85	85	85	25	25	75	75
H_{17}	80	80	85	85	25	25	75	75
H_{18}	80	80	95	95	45	45	60	60
H_{19}	80	80	95	95	45	45	70	70
H_{20}	80	80	95	95	30	30	70	70
$H_{21}-H_{22}$	80	80	80	80	30	30	50	50
$H_{23}-H_{24}$	80	80	80	80	30	30	50	60

B. Scheduling Results

The optimal scheduling results of the three RTN models described above are given in Table IV. Different numbers of heats for daily scheduling are considered to simulate different production profiles for the steel plant. The more heats, the higher is the productivity of the plant, i.e. the higher is the amount of manufactured steel, but the less is the flexibility due to reduced free capacity. Obviously, model complexity and computation difficulty are directly related to the number of heats. Generally speaking, a larger number of heats to produce results in a more complex scheduling problem which is more difficult to solve, as the problem size depends on the number of heats. In Table IV, the column *Heats* lists the number of heats; the column *Model* compares the three models in which *Basic* stands for Basic RTN, *Modes* for Multiple Modes Melting, and *Flex* for Arbitrary Flexible Scheduling; the next three columns list the problem size - the number of binary variables, the number of total variables, and the number of constraints; the column *MIP* presents the final integer objective function value - the value of the objective function with the final integer (feasible) solution; the column *GAP* displays the relative objective gap, which is the relative distance between the best integer objective (by a feasible integer solution) and the objective of the best bound remaining (not necessarily an integer solution); the column *CPU* gives the final computation time by the solver. The maximum computation time is set to 7200s and the relative optimality tolerance is 10^{-6}. All of the models are implemented in Matlab and are solved by TOMLAB/CPLEX on a linux 64 bit machine.

From the results, we make the following observations:

- The flexibility increases the computation difficulty. For most cases, the computation times for *Modes* are larger than *Basic*. For $Heats = 12, 17, 20$, the *Flex* model does not converge to the optimal integer solution within two hours of computation.
- The flexibility reduces the electricity cost. For all cases, the final objective values of *Modes* are less than *Basic*. For $Heats = 4, 8, 12, 17$, the *Flex* model achieves the best integer solution; for $Heats = 20, 24$, the *Flex* model does not perform better than *Modes* due to computational difficulties.

The computation difficulty arises from the model's complexity: a large number of extra variables and constraints are needed to represent the EAF's flexibilities for the model *Flex*.

TABLE IV. Energy cost minimization with δ = 15min

Heats	Model	# bin	# var	# con	MIP(k$)	GAP	CPU(s)
4	Basic	2496	6048	3397	26.239	0	0.3
	Modes	3264	6816	3397	25.972	0	0.3
	Flex	2496	6816	4917	25.858	0	1.7
8	Basic	4992	11232	6122	60.173	0	0.8
	Modes	6528	12768	6122	57.501	0	1.1
	Flex	4992	12768	9162	57.332	0	31.1
12	Basic	7488	16416	8847	104.301	0	2
	Modes	10176	19104	8847	100.061	0	24
	Flex	7488	18720	13407	99.990	1.97%	7200
17	Basic	10560	22848	12253	171.615	0	4
	Modes	14208	26496	12253	159.454	0	170
	Flex	10560	26112	18713	160.896	3.72%	7200
20	Basic	12480	26784	14297	222.427	0	9
	Modes	16704	31008	14297	204.611	0	37
	Flex	12480	30624	21897	211.459	9.00%	7200
24	Basic	14976	31968	17022	299.782	0	320
	Modes	19968	36960	17022	277.283	0	83
	Flex	14976	36576	26142	287.077	11.36%	7200

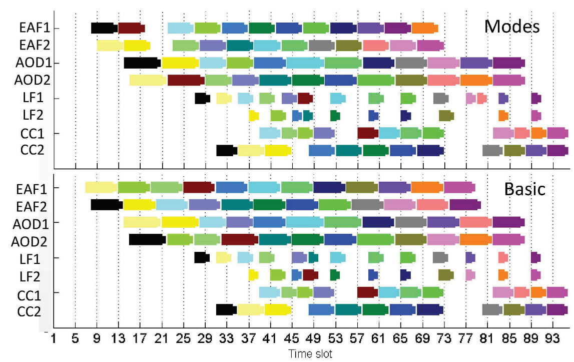

Fig. 8: Equipment occupancy for 24 heats.

The equipment occupancy charts for scheduling 24 heats by models *Basic* and *Modes* are displayed in Fig. 8, in which different heats are represented by different colors. We can observe that the solution is valid: each heat is processed sequentially by all four stages; each group of heats form a campaign and are casted continuously; there is no conflict in equipment assignment, i.e. each equipment is occupied by one single task for every time slot. It also demonstrates that the RTN model is able to generate detailed and practical schedules which can be clearly understood by the steel plant operators. Besides, compared with the scheduling results by the model *Basic*, the melting durations according to the model *Modes* are shorter, and the melting schedule wisely skips the locally high price in hour 5.

The hourly energy consumptions corresponding to the optimal schedule of 12 heats from the three models are compared in Fig. 9. We observe that as the flexibility increases, more of the energy is consumed during the price valley.

VIII. Conclusion

The resource task network models are derived and investigated in this paper to study the scheduling problem of steel

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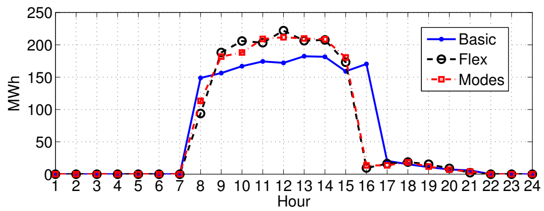

Fig. 9: Hourly energy consumptions for scheduling 12 heats.

plants with flexible EAFs. The objective for the scheduling problem is to minimize energy cost according to the electricity market signals by arranging its load curve, which not only lowers the plants' operation cost but also helps the power grid to mitigate the pressure of supplying the peak demand. Both of the Multiple Melting Modes and Arbitrary Flex Melting proposed in this paper enable the steel plants to participate more actively in the electricity market by exploiting the EAFs' capability to adjust their power consumption rate through controlling the OLTCs. Moreover, the numerical analysis of a typical steel plant demonstrates remarkable savings and could encourage the steel plants to participate more actively in the smart grid. as demand response resource. The proposed approach helps steel manufacturing loads to optimize their demand response participation therefore encourages the industrial load to be more active in demand response. With the help of this approach and similar methods targeting different industrial loads, we expect more active participation from the industrial loads and more interaction between the supply and demand sides in the smart grid.

Extended from the Basic RTN which optimizes the schedule merely through arranging the time and sequence of the tasks, the Multiple Melting Modes model enables controlling the transformers at the beginning of each EAF task, while the Arbitrary Flex Melting model allows the control of the transformers at every time slot within the EAF task. The Multiple Melting Modes model provides a good trade-off between enabling the exploitation of the flexibilities given by the OLTCs and computational complexity. The computation of the Arbitrary Flex Melting model is still difficult which remains as a problem to be solved in future research; more efficient modeling and parallel computing will be considered to alleviate the computational burden. We are also interested to combine the presented analysis with electricity price prediction methods and to take into account the impacts of price uncertainties. Besides, the models proposed in this paper can be extended to investigate the steel plants' participation in electricity ancillary service markets as spinning reserve provider. Practical concerns including the benefit-cost analysis of implementing the optimal scheduling, the degradation of the OLTCs from switching actions, the quality of the final steel products will also be studied in our future research.

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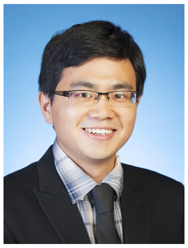

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