Industrial Demand Response by Steel Plants with Spinning Reserve Provision

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***Abstract*—Demand response has gained significant attention in recent years as it demonstrates potentials to enhance the power system's operational flexibility in a cost-effective way. Industrial loads such as steel manufacturing plants consume large amounts of electric energy, and their electricity bills account for a remarkable percentage of their total operation cost. Meanwhile, lots of industrial loads are very flexible in terms of adjusting their power consumption rate, e.g. through switching the transformer tap position. Hence, industrial loads such as the steel plants have both the motivation and the ability to support power system operation through demand response. In this paper, we focus on the steel plant and optimize its scheduling to maximize its profits from both the energy and the spinning reserve markets.**

***Index Terms*—Demand response, spinning reserve, industrial load, resource-task network (RTN), steel plant.**

I. Introduction

Increased operational flexibility is an inherent characteristic of what is commonly referred to as the smart grid. This is because a large share of renewable generation resources such as wind and solar generation are expected to be deployed to enable a sustainable energy future. However, the power output of these renewable resources is intermittent and uncertain which requires significant amounts of balancing resources to increase the operational flexibility of the grid. Traditionally, the power system relies on generators to provide such flexibility, but it is not economical for generators to frequently change their output. Hence, demand response has gained significant attention in recent years as it demonstrates potentials to enhance the power system's operational flexibility in a cost-effective way [1]–[3]. There have been intensive discussions and promising solutions for demand response provided by buildings [4], storage [5], data centers [6], [7], residential areas [8], as well as industrial loads [9]–[11].

Within the realm of demand response, industrial loads have the following advantages [12], [13]: the magnitude of power consumption by an industrial manufacturing plant and the change in power it can provide are generally very large; besides, the industrial plants usually already have the infrastructures for control, communication and market participation, which enables the provision of demand response; moreover, some industrial plants are able to offer fast and accurate adjustments in their power consumption [9], [14]. Among these industrial loads, steel manufacturing is a highly energy-intensive process and also has the required consumption flexibility. A steel plant with electric arc furnaces has a limited capability to schedule its production activities to follow a desired energy consumption profile over time. A steel plant can reduce its loading level drastically by controlling the transformers that supply power for its equipment, which enables the provision of spinning reserves.

Besides their capability, industrial plants also have the incentive to actively contribute to the electricity markets through demand response programs. Nowadays, with the needs for industrial materials slowing down, and the competition from all over the world, industrial plants such as aluminum smelters and steel manufacturing plants have experienced a hard time in recent years, especially in developed countries [15], [16]. Demand response could be an opportunity for these industrial plants to make use of their assets and increase their profits. For instance, the industrial plants can move the most energy-intensive activities to off-peak hours thereby reducing their electricity bills; in addition, they can also sell ancillary services to the electricity markets by effectively utilizing their operational flexibility.

In this paper, we study the participation of the steel plants in demand response. The steel plant is assumed to be a participant in the day-ahead electricity markets, both energy and spinning reserve markets, and we want to optimize its scheduling of production activities to maximize its revenues from the electricity markets. The remaining of the paper is organized as follows: Section II introduces the scheduling problem that we are interested in; Section III explains the resource task network approach that we use to model the steel plant scheduling problem; in Section IV, the optimal scheduling model is proposed and described; the case study of a typical steel plant is discussed in Section V, based on which the conclusions are drawn in Section VI.

II. Problem Statement

The considered steel production process is illustrated in Fig. 1. There are four stages in the production. In the first stage, the solid metal scrap (e.g. recycled from abandoned cars) is transformed to molten metal in the electric arc furnaces

The authors would like to acknowledge the financial support by ABB.

(EAF); then, the impurities in the molten steel such as carbon elements are extracted by the argon oxygen decarburization (AOD) units in the second stage; in the ladle furnaces (LF) stage, the molten metal gets refined and the quality of the metal is further improved; and finally, the molten metal is casted into slabs by the continuous casters (CC). The slabs are the final products of the melt-shop production, and they can be classified into different categories according to their steel grade, slab width, slab thickness and so on.

For the first three stages, the equipment processes a particular amount of metal at one time. That particular amount depends on the size of the equipment units, e.g. the volume of the furnace. Each such amount of metal is termed as a *heat*. Using the definition of heats, we can quantify the throughput of the steel plant, e.g. a medium-sized steel plant produces around 20 heats a day. For the fourth stage, the casters operate continuously but subject to certain critical constraints: the casters are only allowed to process a limited number of heats after which they need maintenance (e.g. changing the caster mold and tundish). Usually a campaign of several heats sharing the same or very similar features such as steel grade and slab shape are casted together as a campaign group, and the casters can be maintained between these campaign groups. The casting order for the heats within one group should follow certain rules and the casting sequence must not be interrupted.

The power consumption rate of the EAFs can be adjusted very quickly by switching the on-load tap changers (OLTCs) of the transformers which supply power to the EAFs. This qualifies the steel plant to be a valid demand response resource for providing spinning reserve. The amount of spinning reserve it can provide depends on the melting power profile, i.e. the power consumption rate of the melting process, and the sustaining (minimal) power the furnace requires to keep the molten metal from solidification.

The payment structures for spinning reserve are different across different electricity markets. In most North American electricity markets, e.g. the Midwest Independent System Operator (MISO) where demand response is actively encouraged and where an aluminum smelter (Alcoa's Warrick Operation) has participated as a regulation provider for the first time, spinning reserve is compensated by both reserve capacity and actual allocation. In other words, the spinning reserve provider gets paid for the capacity it has committed to provide independent of if this reserve capacity is dispatched or not; and if it does get dispatched, it receives an additional payment as the allocation compensation. However, the actual dispatch of spinning reserve is very rare. According to Alcoa's Warrick

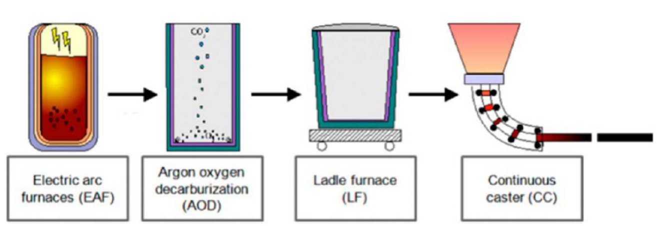

Fig. 1: Production process of steel manufacturing [17]

Operation, the regulation provider we previously mentioned who is also offering spinning reserve to MISO, their so-called interruptible load (i.e. spinning reserve) only gets 55 deployments annually with an average length of 42 minutes, resulting in an actual dispatch rate of only around 0.44% [14]. Even if the capacity payment rate is fairly low, the spinning reserve providers still find it profitable as they earn money simply by standing by and waiting.

In this paper, we consider the participation of the steel plant in a day-ahead electricity market, from the perspective of the steel plant scheduling. The scheduling horizon is one day. The daily production activities, i.e. the heats to produce, are known ahead according to the business contracts and the long-term scheduling. The hourly prices of the day, both energy and spinning reserve, are assumed to be known ahead: these prices may be part of a given demand response program contract or they could also be obtained by prediction techniques. Given the production activities and their power profile, the steel plant optimizes the scheduling to minimize its net cost - the cost of electric energy minus the revenue from spinning reserve provision. Of course, the steel plant endures other aspects of cost such as labor, metal scraps, chemical ingredients and so on. But all these costs are fixed in the daily operation and therefore we do not take them into account in the operation optimization process. Furthermore, the impact of actual dispatch of spinning reserve is not considered in this daily scheduling problem, as the dispatch rate is very low and it should be taken into account in a longer term, e.g. weekly or monthly, optimization problem.

III. Resource Task Network Modeling

We model the steel plant and its production activities through a resource task network (RTN) approach. Figure 2 provides an illustration of the RTN of a steel plant. The circles represent resources such as equipment units used in different stages, intermediate and final products for different heats, electric energy usage and spinning reserve provision. As intermediate products are transferred from one stage to the next, they are super-indexed with s or d to specify their current locations (start or destination, respectively). For example, $\mathrm{EA}_h^{\mathrm{d}}$ represents the intermediate product between stage EAF and AOD that has already been transferred to the AOD stage and is waiting to be processed. The RTN modeling in this paper also employs resources of electric energy (EN) and spinning reserve (SP) to help accumulate the plant's energy usage and reserve provision. The set of resources in the steel plant is denoted by $\mathbb{S}$, i.e. $\mathbb{S} = \{\text{EAF, AOD, LF, CC}\} \cup \{\mathrm{EA}_h^{\mathrm{s}}, \mathrm{EA}_h^{\mathrm{d}}, \mathrm{AL}_h^{\mathrm{s}}, \mathrm{AL}_h^{\mathrm{d}}, \mathrm{LC}_h^{\mathrm{s}}, \mathrm{LC}_h^{\mathrm{d}}, \mathrm{H}_h | h \in \mathbb{H}\} \cup \{\text{EN,SP}\}$ with $\mathbb{H}$ as the set of heats to produce. We use a matrix $Y \in \mathbb{R}^{|\mathbb{S}| \times T}$ to denote the amount of each resource available at all time slots, in which $|\mathbb{S}|$ is the size of $\mathbb{S}$; we use a discrete time grid with uniform time slot width of t_0, and T is the total number of time slots. Each element of Y is a continuous variable, $y_{s,t}$, which stands for the available amount of resource s at time t. For example, $y_{\mathrm{EAF},t} = 2$ means there are two furnaces available at time slot t; $y_{\mathrm{EA}_h^{\mathrm{d}},t} = 0$ means either intermediate product $\mathrm{EA}_h^{\mathrm{d}}$ has not been transported to AOD yet or has

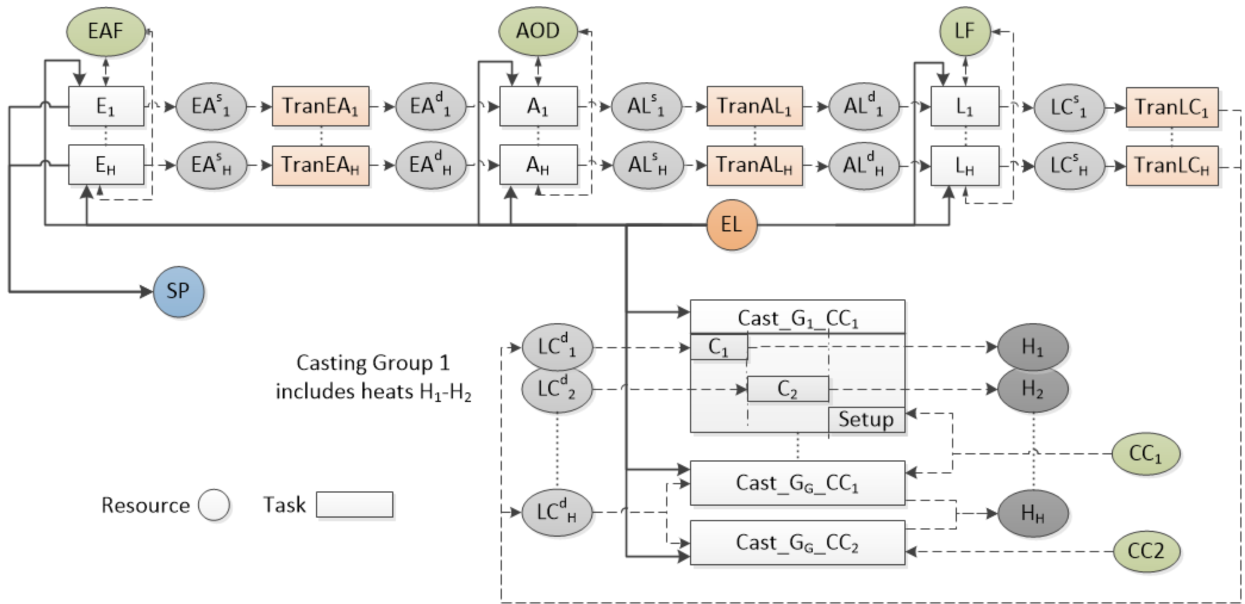

Fig. 2: Resource task network for a steel plant.

already been processed by AOD, while $y_{\mathrm{EA}^{\mathrm{d}}_h,t} = 1$ means $\mathrm{EA}^{\mathrm{d}}_h$ is there waiting to be processed; $y_{\mathrm{EN},t} = 100$ MWh means the steel plant uses 100 MWh electric energy during time slot t; $y_{\mathrm{SP},t} = 50$ MW means the plant provides 50 MW of spinning reserve to the power system. Actually, most $y_{s,t}$ can only take discrete values such as 0, 1, or 2. However, we model them as continuous variables for computational considerations, but as discussed later the constraints in the optimization model will enforce them to take discrete values.

The tasks are denoted by rectangles in Fig. 2. There are two types of tasks: the operational tasks at each of the four stages and the transfer tasks between the stages. There is one task for every heat h for each type of operation and transfers except for the casting; these tasks are denoted by the task type sub-indexed with the corresponding heat, e.g. E_h stands for the melting of heat h in the EAF stage, and EA_h (without super-index s or d) denotes the transfer of heat h between stage EAF and AOD. Unlike the first three stages where parallel units are not distinguished, we treat the casters individually because different casters are designed for casting different slabs. Besides, as mentioned before, the tasks in the CC stage are executed by group instead of by heat. Therefore, the casting task is denoted by $\mathrm{C}_{g,u}$ which corresponds to the casting of group g by caster unit u. Note that C_{g_1,u_1} is different from C_{g_1,u_2}. For example, their casting durations might be different due to the different casters. Of course, only one of C_{g_1,u_1} and C_{g_1,u_2} will actually take place as group g_1 should be casted exactly once. We use $\mathbb{K}$ to denote the set of tasks, i.e. $\mathbb{K} = \{\mathrm{E}_h, \mathrm{EA}_h, \mathrm{A}_h, \mathrm{AL}_h, \mathrm{L}_h, \mathrm{LC}_h | h \in \mathbb{H}\} \cup \{\mathrm{C}_{g,u} | g \in \mathbb{G}, u \in \mathbb{CC}\}$, with $\mathbb{G}$ and $\mathbb{CC}$ as the set of casting campaign groups and available casters, respectively.

A $|\mathbb{K}|$-by-T binary matrix X is used to denote the starting times of tasks, in which $|\mathbb{K}|$ is the size of $\mathbb{K}$. Each element of X is a binary variable $x_{k,t}$ that denotes whether task k starts at time slot t. For instance, $x_{\mathrm{E}_h,t}$ denotes whether the processing (melting) of heat h in stage EAF starts at time slot t or not. Hence, only one out of $x_{E_h,t}, t = \{1, \ldots, T\}$ is non-zero.

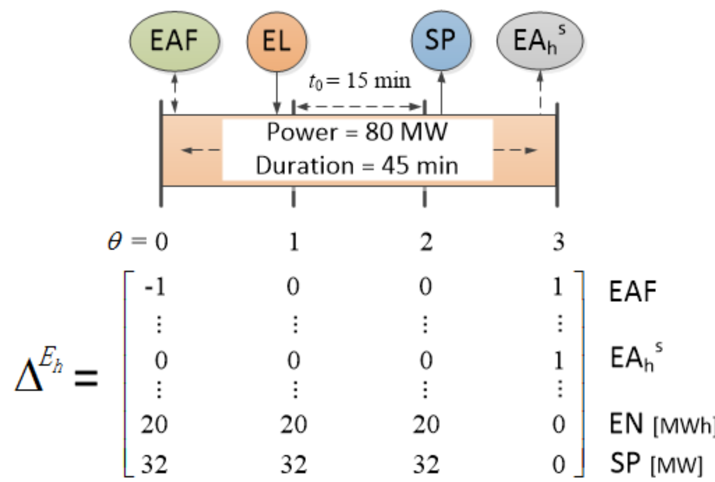

Fig. 3: Illustration of interaction parameters for a melting task.

In Fig. 2, the networks are represented by arrows which indicate how each task interacts with each resource. For each task $k \in \mathbb{K}$ whose duration is τ_k time slots, the interaction parameter Δ^k is a $|\mathbb{S}|$-by-$(\tau_k + 1)$ matrix that quantifies how much task k consumes or generates of each of the resources as it proceeds. For instance, its element $\Delta^k_{s,1}$ quantifies the interaction between task k and resource s at the beginning of the first time slot during this task, and Δ^k_{s,τ_k+1} quantifies the interaction at the end of the last time slot. Δ^k is very sparse and a zero element means that there is no interaction. The interaction parameters for a melting task are illustrated in Fig. 3. The time slot width in Fig. 3 is $t_0 = 15$ minutes. The duration of the melting task is 45 minutes. Therefore, the melting spans 3 time slots. This task interacts with resources EAF, EN, SP and $\mathrm{EA}^{\mathrm{s}}_h$, and its interaction parameter matrix only has four rows with nonzero elements. At the very beginning, the task reduces EAF by one as it uses one furnace. After the completion of the melting process, EAF is increased by one as that furnace is freed up. Also, $\mathrm{EA}^{\mathrm{s}}_h$ is increased by one to promote the execution of the following transfer. The melting task consumes electric energy continuously during its entire duration. The sustaining power is assumed to be 48 MW, hence, it can provide 32 MW spinning reserve for each time slot.

IV. Optimal Scheduling

The scheduling model in this section is based on the Aggregated Equipment Resource and Simple Transfer Tasks model from [17], and has been updated to incorporate spinning reserve provision. As discussed in Section II, the following scheduling model does not consider the impact of actual dispatch of spinning reserve, as the actual dispatch is very rare and we assume that there is no actual dispatch in the scheduling horizon.

A. Constraints

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

$$y_{s,t} = y_{s,t-1} + \sum_{k\in\mathbb{K}} \sum_{\theta=0}^{\tau_k} \Delta^k_{s,\theta} \cdot x_{k,t-\theta} \quad \forall s \in \mathbb{S}_{\neg\{\text{EN},SP\}}, \forall t \quad (1)$$

in which the value of resource s at time step t is equal to its previous value at $t-1$ adjusted by the amounts generated/consumed by all the tasks. Only nonzero $\Delta^k_{s,\theta}$ implies actual interaction and the interaction only occurs when task k is proceeding, i.e., the interaction occurs at time slot t only if task k starts θ earlier than t ($x_{k,t-\theta} = 1$) and $\Delta^k_{s,\theta} \neq 0$. $\mathbb{S}_{\neg\{\text{EN,SP}\}}$ stands for the set of all the resources except EN and SP. For any resource $s \in \mathbb{S}_{\neg\{\text{EN},SP\}}$, its initial value is integer: the initial value is zero for any intermediate or final product, and the initial value for any equipment equals to the number of units available in the steel plant. Since the interaction parameters $\Delta^k_{s,\theta}$ for these resources are integers and $x_{k,t-\theta}$ are binary variables, the $y_{s,t}$ can only take integer values due to constraint (1). As mentioned before, even though $y_{s,t}$ only take integer values, we model them as continuous variables to reduce the computation burden for this mixed integer programming problem.

The electric energy usage of the steel plant is calculated as

$$y_{\text{EN},t} = \sum_{k\in\mathbb{K}} \sum_{\theta=0}^{\tau_k} \Delta^k_{\text{EN},\theta} \cdot x_{k,t-\theta} \qquad \forall t \qquad (2)$$

where $\Delta^k_{\text{EN},\theta}$ is the electricity used by task k at the θ-th time slot duration of its execution. We assume that only the EAF can provide spinning reserve, and the provided spinning reserve should be upper bounded by its availability, as given by

$$y_{\text{SP},t} \leq \sum_{k\in\{E_h|h\in\mathbb{H}\}} \sum_{\theta=0}^{\tau_k} \Delta^k_{\text{SP},\theta} \cdot x_{k,t-\theta} \qquad \forall t \qquad (3)$$

with $\Delta^k_{\text{SP},\theta}$ denoting the available spinning reserve.

2) Task Execution: We use the following constraints to make sure that the tasks are executed the proper number of times, as in

$$\begin{aligned} &X_{\mathbb{K}_{\neg\mathbb{CC}}} \mathbb{1}_T = \mathbb{1} \\ &\mathbb{1}' X_{\mathbb{C}_u} \mathbb{1}_T = 1 \quad \forall u \in \mathbb{CC} \end{aligned} \qquad (4)$$

in which $X_{\mathbb{K}_{\neg\mathbb{CC}}}$ denotes X without the rows involving the casting tasks; $X_{\mathbb{C}_u}$ denotes the rows of X corresponding to casting tasks by caster u; $\mathbb{1}_T$ means a vector of 1s with length T and $\mathbb{1}$ stand for vectors of 1s with appropriate lengths. The above constraints ensure that each heat is processed exactly once by all types of tasks within the scheduling horizon.

3) Waiting Time: In steel plant operations, it is common to enforce the transfer task to be executed immediately after the completion of its preceding processing task. This requirement is reflected by enforcing

$$Y_{\text{EA}^\text{s}} = \mathbf{0} \qquad (5)$$

in which Y_{EA^s} stands for the rows of Y corresponding to the intermediate products EA^s; $\mathbf{0}$ is a zero matrix with the same dimensions as Y_{EA^s}. Similar constraints apply for the intermediate products AL^s and LC^s.

The transfer time of the intermediate products, w_{EA}, w_{AL}, and w_{LC}, are assumed to be independent of the specific heats and the exact locations of the units. We use $\bar{w}_{\text{EA}}$, $\bar{w}_{\text{AL}}$, and $\bar{w}_{\text{LC}}$ to denote the maximum allowable transportation times that ensure that the intermediate products are processed by the next stage in time before the cooling effects adversely affect the product quality. Therefore, the maximum waiting time constraint for intermediate products should be satisfied,

$$Y_{\text{EA}^\text{d}_h} \mathbb{1}_T \leq \frac{(\bar{w}_{\text{EA}} - w_{\text{EA}})}{t_0} \mathbb{1} \qquad (6)$$

in which Y_{EA^d} stands for the rows of Y corresponding to intermediate products EA^d before the transfer. The left side of the constraint corresponds to the number of time slots during which the intermediate product is waiting before being processed. Similar constraints apply for intermediate products AL^d and LC^d.

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

$$y_{\text{H}_h,T} = 1 \qquad \forall h \qquad (7)$$

in which $y_{\text{H}_h,T}$ stands for the availability of the final product for heat h at the end of the scheduling horizon.

5) Spinning Reserve Provision: Spinning reserve is traded hourly in most electricity markets. The time slot width in the discrete time formulation is usually smaller than the trading window. Once the reserve provider has committed to the market an hourly quantity, it is obligated to guarantee that amount of reserve for any time slot in that hour. In other words, the time slots belonging to the same hour ($\mathbb{T}_{hr}$) should provide the same amount of spinning reserve, as enforced by

$$y_{\text{SP},t} - y_{\text{SP},t'} = 0 \qquad \forall t, t' \in \mathbb{T}_{hr} \qquad (8)$$

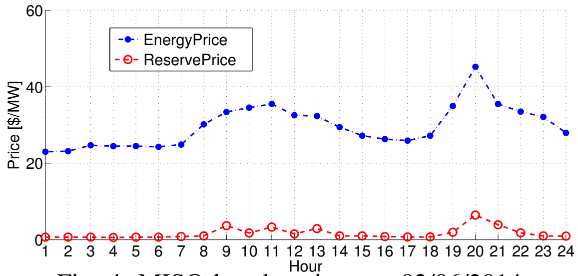

Fig. 4: MISO hourly prices on 02/06/2014.

B. Objective Function

The objective of the scheduling is to minimize the net cost of the steel production, i.e. the electric energy cost minus the spinning reserve revenue. Given the energy and spinning reserve price vectors $\lambda_{\text{EN}}, \lambda_{\text{SP}} \in \mathbb{R}_T$, the overall optimization problem is formulated as

$$\begin{aligned} \underset{X}{\text{minimize}} \quad & Y_{\text{EN}}\lambda_{\text{EN}} - Y_{\text{SP}}\lambda_{\text{SP}} \\ \text{subject to} \quad & (1) - (8) \\ & x_{s,t} \in \{0,1\}, \;\; y_{s,t} \in [0, \bar{y}_s], \;\; \forall s, \forall t \end{aligned}$$

in which $\bar{y}_s$ is the upper bound for the available amount of resource s. For example, $\bar{y}_{\text{EAF}}$ equals to the number of EAF furnaces and $\bar{y}_{\text{EN}}$ equals to the summation of energy usage by all the equipment units in one time slot.

V. Case Study

In this section, we present the study of the daily scheduling for a typical steel plant to demonstrate the effectiveness of the optimal scheduling model.

A. Problem Parameters

The hourly energy and spinning reserve prices for the case study are taken from MISO, as displayed in Fig 4. Note that the spinning reserve (capacity) prices follow the trend of energy prices, but are much lower. In practice, the hourly prices are obtained either from demand response contracts, e.g. time-of-use pricing programs, or price prediction techniques. For the latter case, the prices are uncertain and are decided by the markets, and we have to rely on price prediction tools. We could simply use the point-wise price prediction or the expected price if its distribution is available. Note that the constraints in Section IV do not involve any price information.

The steel plant layout and parameters are taken from the typical scheduling example in [17] and are restated here. There are two parallel units for each of the four stages, and the nominal power consumption rates of the units are given in Table I. The group correspondences of the heats to produce are given in Table II, and their nominal processing times are shown in Table III. It can be observed from these tables that the EAF is the most energy-intensive process stage. The transfer times w_{EA}, w_{AL}, and w_{LC} are 10, 4, and 10 minutes respectively, and the maximum waiting times $\bar{w}_{\text{EA}}$, $\bar{w}_{\text{AL}}$, and $\bar{w}_{\text{LC}}$ are 240, 240, and 120 minutes. The caster setup times are 70 minutes for CC1 and 50 minutes for CC2, which are the times needed for equipment maintenance between casting two groups of heats. The sustaining power needed for spinning reserve provision is assumed to be 60% of the nominal EAF melting power.

TABLE I. Nominal power consumptions [MW] [17]

equipment	EAF_1	EAF_2	AOD_1	AOD_2	LF_1	LF_2	CC_1	CC_2
power	85	85	2	2	2	2	7	7

TABLE II. Steel heat/group correspondence [17]

group	G_1	G_2	G_3	G_4	G_5	G_6
heats	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 III. Nominal processing times [min] [17]

heats	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 model in Section IV are given in Table IV, in which t_0 is set as 15 minutes. The four rows correspond to different scenarios with respect to how many and which groups are being scheduled and processed in the simulation. The column *Groups* gives the campaign groups to produce, e.g. the first row denotes scheduling group 1, 2, and 3 with the heats as indicated in Table II; *w/o SP* stands for the scheduling model without spinning reserve provision, which corresponds to the above model but without the resource SP and only minimizing electric energy cost; *with SP* is the scheduling model described in Section IV including spinning reserve; the column *Obj* represents the final objective value of the optimization problem; the column *EN* stands for the electric energy cost while the *SP* represents the spinning reserve revenue. All these optimization problems are mixed integer linear programming problems and we solve them in MATLAB by TOMLAB/CPLEX on a linux 64 bit machine. The relative optimality tolerance is set as 10^{-6}, and all these optimization problems are solved to optimality within three minutes. With spinning reserve participation, the electric energy cost increases a little bit, but the net cost of the steel plant operation is reduced because of the spinning reserve revenues. The decrease for the case studies here are around 1%.

We also set t_0 as 10 minutes to study the scheduling with a finer time grid. The optimal scheduling results are listed in Table V. The time limit for CPLEX is set to 2 hours. For scheduling groups 1-5 under both *w/o SP* and *with SP*, the relative objective gap between the best integer objective (by a feasible solution) and the best bound remaining in the iteration process are 0.02%. Compared with the results in Table IV, the final objective values in Table V are slightly improved because the rounding error due to discrete-time formulation is reduced

TABLE IV. Optimization results with t_0 = 15min

	w/o SP	with SP		
Groups	Obj(k$)	Obj(k$)	EN Cost(k$)	SP Revenue(k$)
1-3	39.307	39.002	39.321	0.319
1-4	57.824	57.357	57.864	0.507
1-5	69.731	69.157	69.897	0.741
1-6	86.346	85.508	86.474	0.966

TABLE V. Optimization results with t_0 = 10min

	w/o SP		with SP	
Groups	Obj(k$)	CPU Time(s)	EObj(k$)	CPU Time(s)
1-3	39.041	397.7	38.651	739.7
1-4	57.517	637.8	57.009	1094.7
1-5	69.162	7200.0	68.468	7200
1-6	85.228	916.0	84.164	3569.7

by using a finer time grid. However, the computation time in Table V grows drastically as the number of variables (both integer and continuous) increases by a factor of 1.5.

The equipment assignment chart for scheduling 24 heats with spinning reserve provision is displayed in Fig. 5. The rectangles denote the tasks. Different heats are represented by different colors. From Fig. 5 we can observe that the scheduling solution is valid: each heat is processed sequentially by each stage; each campaign group of heats are casted together without any interruption, and there is enough time for caster maintenance between each two campaign groups on the same caster; for any time slot, each equipment is occupied by one single task and there is no conflict in equipment assignment. Figure 5 also shows that the RTN model is able to generate detailed and practical schedules that can be easily understood by the steel plant operators. The corresponding spinning reserve provision schedule is displayed in Fig. 6. The maximum spinning reserve provided is around 70 MW. The spinning reserve provision cannot always stay at the maximum value due to constraint (8). The hourly spinning reserve provision should be less or equal to the available spinning reserve in any time slot of that hour.

VI. Conclusion

The RTN-based scheduling model for the steel plant is able to optimize the steel plant's production activities such that it can benefit the most from electricity markets. The steel plant is able to make use of the electric arc furnaces to offer spinning reserve services to the electricity markets and earn revenues. With the provision of spinning reserve, the steel plant could further lower its operation net cost. The proposed scheduling

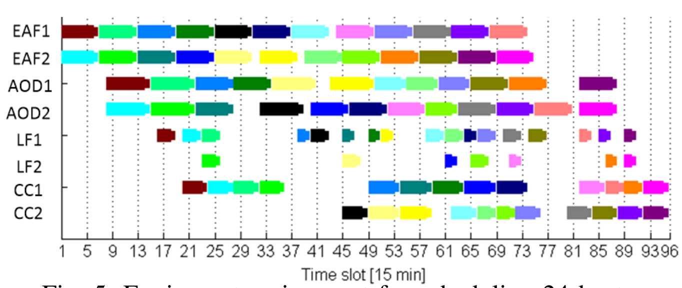

Fig. 5: Equipment assignment for scheduling 24 heats.

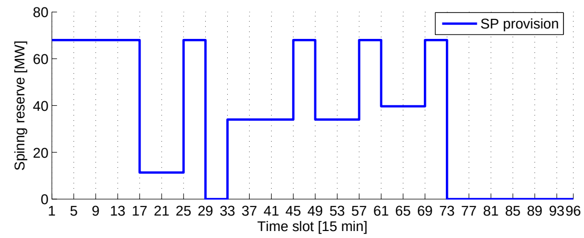

Fig. 6: Spinning reserve provision from scheduling 24 heats.

model is computationally effective and can generate detailed and practical production schedules.

Acknowledgment

We gratefully acknowledge the discussions with Marjia Zima and Xiaoming Feng from ABB and Dragoljub Gajic from ThyssenKrupp Acciai Speciali Terni Steel Plant.

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