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Multi-Objective Production Scheduling of a Steel Plant With Electric Arc Furnaces

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ABSTRACT

Energy costs constitute a significant expense for steel plants with electric arc furnaces (EAFs). To reduce energy costs, industrial processes actively participate in demand response by moving energy-consuming activities to low-price periods. On the other hand, conventional production scheduling mainly cares about the makespan via weighing the product demand and inventory. However, minimising energy costs and makespan are usually conflicting objectives. Therefore, we present a multi-objective mixed-integer linear programming (MOMILP) model for addressing the production scheduling problem of a steel plant with EAFs. The Normal Boundary Intersection (NBI) method is used to derive an evenly distributed Pareto frontier for better evaluating the trade-off between electricity costs reduction and the time saving of production completion. The effectiveness of the proposed model is demonstrated in the case study.

Keywords: industrial demand-side management, multi-objective optimisation, production scheduling, steel manufacturing

1. INTRODUCTION

Significant growth in the global end-of-life scrap availability, as much as more than 500 Mt, will be reached in the next 30 years [1]. Melting steel scrap as a circular-economy strategy could potentially help suppress industrial emissions and resource consumption. One promising option for melting recycling scraps is steelmaking with the electric arc furnaces (EAFs), where electrical energy is used for remelting charges of up to 100% to make new steel products [2].

Meanwhile, steel manufacturing is recognised as one of the most challenging industrial processes for scheduling due to the involvement of parallel equipment and critical production-related constraints [3]. Production scheduling of steel plants is a decision-making process, where the assignment of resources, sequence of production and timing to execute production tasks are decided [4]. Enormous advances have been seen in production scheduling solutions in recent decades with innovations in scheduling models and solution methods. The scheduling models can be categorised as precedence-based and time-grid-based models, or continuous-time and discrete-time models, or linear and nonlinear scheduling models. The solution methods include mathematical programming methods, heuristics and evolutionary algorithms, artificial intelligence methods, as well as stochastic optimisation approaches for tackling uncertainty [4].

However, applying optimisation methods for scheduling still face several challenges in practice, such as large numbers of coupling constraints and high computational burden [4]. Most existing work focuses on industrial demand response programs but mainly from the perspective of power grid management, while little attention has been paid to the industrial production processes. In this case, Pedro et al. spearheaded the development and continual refinement of the resource-task network (RTN) for production scheduling under energy constraints [5], reducing energy costs by participating in the industrial demand-side management programs under fluctuating energy prices. Based on this work, Xiao et al. extended the RTN models by incorporating the EAFs' flexibilities for further reducing energy costs [6]. However, although the above-mentioned scheduling models achieve the reduction of energy costs, they may be more easily affected by the disruption caused by unexpected events or result in a high overhead burden to steel plants because they sacrifice the makespan for cost-saving [7].

This paper presents a multi-objective production scheduling (MOPS) model for steel plants with EAFs considering both electricity costs and production completion time. The problem is formulated based on the RTN model in [5] as a multi-objective mixed-integer linear programming (MOMILP) problem. Specifically, the main contributions of this paper include the following:

(1) The MOPS model is proposed to explore the trade-off between minimising electricity costs and completion time.

(2) Renewable energy sources (RES) are integrated into the production scheduling framework. Therefore, more benefits can be earned by leveraging renewable energy and industrial demand-side management.

(3) The Normal Boundary Intersection (NBI) method is adopted for the MOPS model to obtain well-distributed Pareto solutions. Additionally, the optimal scheduling solution (OSS) is identified by applying the Entropy Weight Method (EWM).

2. THE MOPS MODEL FOR STEEL PLANTS WITH EAFS

2.1 RTN-based steelmaking process

The typical process of steelmaking in the melt shop is illustrated in Fig. 1. First, solid metal scraps from recycled steel are molten in the EAFs, then further processed in the argon oxygen decarburisation (AOD) unit to reduce the carbon content. Next, the molten steel is refined in the ladle furnace (LF) to give its steel characteristics and finally transported to the continuous casters (CC) to be cast into slabs which are the final products of the steelmaking process [6].

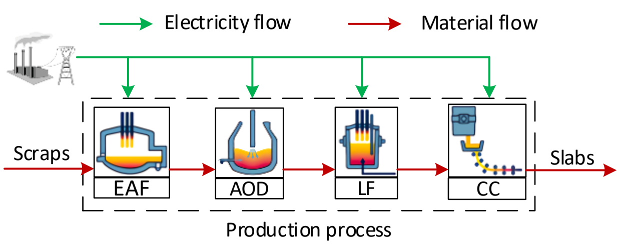

Fig. 1 The Scheme of Steel Production Process

The production scheduling problem is addressed by using the discrete-time RTN formulation [5]. The RTN for production scheduling of a steel plant is illustrated in Fig. 2. The RTN model involves two types of nodes: resources and tasks, as well as two kinds of interactions: discrete interaction and continuous interaction. The resource nodes include equipment resources like EAFs, AODs, LFs, CC1 and CC2; intermediate products such as $EA^s\_H_h$ and $EA^d\_H_h$, $AL^s\_H_h$ and $AL^d\_H_h$, $LC^s\_H_h$ and $LC^d\_H_h$, where s and d denote the intermediate product of the specific heat h located at the transfer start and destination, respectively. Final products are marked by $H_1,\dots,H_H$, as well as electricity resource as EL. The task nodes include production tasks for different heats in the first three stages, i.e., EAF_H_h AOD_H_h and LF_H_h. The last casting task, which needs a unit index in conjunction with the heat group index, is represented by $Cast\_G_g\_CC_1$ and $Cast\_G_g\_CC_1$. The transfer tasks between the stages are like $T_{EA}\_H_h$, $T_{AL}\_H_h$ and $T_{LC}\_H_h$. Moreover, the network flowchart in Fig. 2 shows that processing tasks interact discretely with related equipment resources, only consuming the resource at the start and releasing it at the end, while the production tasks consume the EL resource continuously throughout the production process.

2.2 Mathematical formulation

In this section, we integrate the interdependencies of the steelmaking process into the MOPS optimisation problem by using the RTN model to determine the daily schedule of the melt shop in a steel plant.

The MOPS model considers two objectives, i.e., minimisation of electricity costs and production completion time. Objective 1 is to minimise the electricity costs (EC) as calculated by daily electricity purchasing costs minus the profits of selling electricity to the grid. The time-varying wholesale electricity tariff λ_t^{Buy} is considered as the electricity buying price, and the feed-in tariff λ_t^{Sell} is considered constant, shown by Eq. (1).

$$O_1: \quad Min \quad EC = \sum_{t\in\{1,\dots,T\}} \left(\frac{P_t^{BUY}}{\eta^T}\cdot\lambda_t^{Buy}\right) - \left(P_t^{SELL}\cdot\eta^T\cdot\lambda_t^{Sell}\right) \tag{1}$$

where η^T is the efficiency of the transformer connecting the steel plant to the external power grid. P_t^{BUY} and P_t^{SELL} are amounts of energy bought from and sold to the power grid at time slot t.

Objective 2 is to minimise the production completion time (CT) as defined by the latest completion time of the final products, which are processed in the CC as shown in Eqs. (2) and (3). The CT is calculated by the starting time of the caster task $(t-1)\delta$, adding the processing time $\tau_i\delta$ and subtracting the setup time $setup_u$ [5]. The domain of Eq. (3) considers all possibilities of all groups. Therefore, all groups g and the last stage units u are considered with the summation over all the tasks belonging to $N_{g,u}$.

$$O_2: \quad Min \quad CT \tag{2}$$

$$\begin{aligned} s.t. \quad CT \geq \sum_{i\in N_{g,u}} \sum_t I_{i,t}^{Task}\left((t-1)\delta + \tau_i\delta - setup_u\right) \\ \forall g, k=4, u\in U_k \end{aligned} \quad (3)$$

In Eq. (3), $I_{i,t}^{Task}$ indicates the binary variable representing whether the task i starts at time slot t; δ is the duration time of every time slot t; τ_i is the length (in time slots) of the task i.

Constraints are considered, such as the steelmaking process and power balance constraints. The steelmaking process constraints are formulated by the RTN model from [5] to ensure the sequential steelmaking process, incl. resource evolution constraints and task execution constraints. Power balance constraints should also be respected to prevent violating the power limit of the transformer between the steel plant and the utility grid.

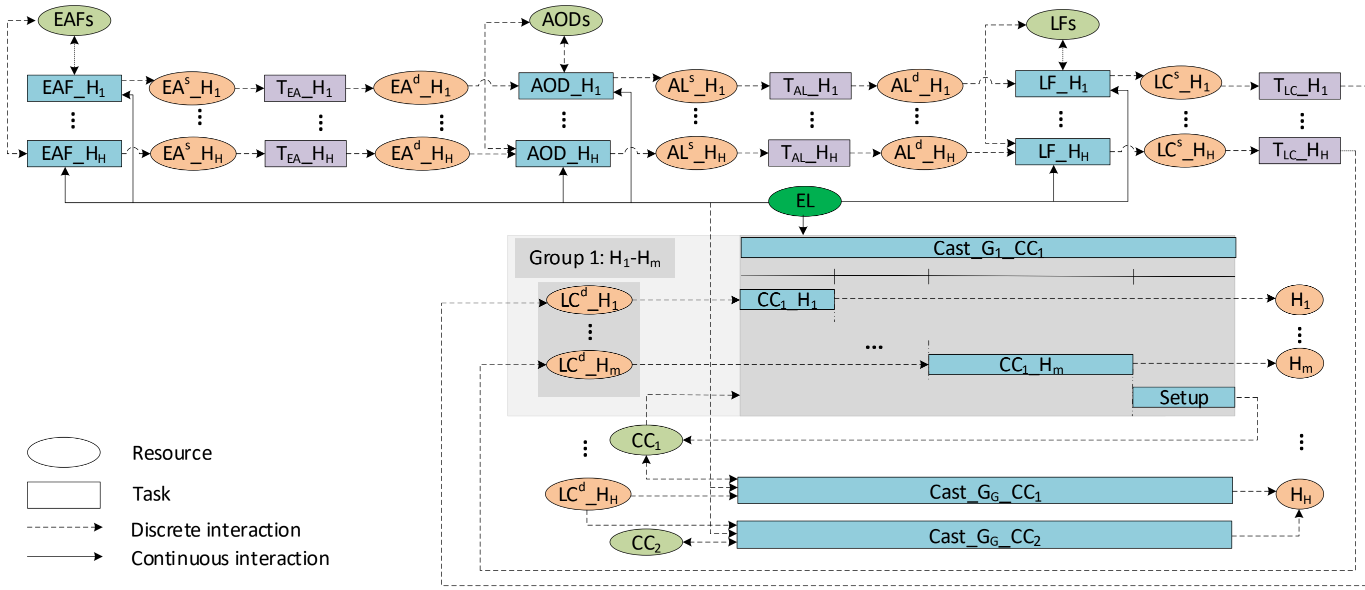

Fig. 2 Resource Task Network for Production Scheduling of a Steel Plant

3. NBI METHOD FOR SOLVING THE MOPS MODEL

The multi-objective optimisation problem involves multiple and conflicting objectives to be optimised simultaneously, which can be abstractly represented as Eq. (4), whose feasible region is Ω.

$$\begin{aligned} &Min \quad \{O_1(\chi), O_2(\chi)\} \quad \chi \in \Omega \\ &s.t. \quad g(\chi) \le 0; \quad h(\chi) = 0 \end{aligned} \tag{4}$$

The NBI method is widely adopted to obtain an evenly distributed Pareto frontier, even with a non-convex Pareto optimal set [8]. Referring to the NBI method, the multi-objective optimisation problem can be solved in four steps: (1) normalising objective functions; (2) generating evenly distributed points on the Utopia line; (3) obtaining the Pareto frontier; (4) selecting the optimal scheduling strategy.

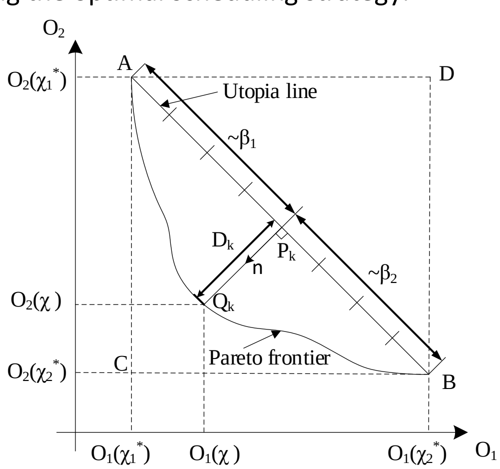

Fig. 3 Pareto Frontier for a Bi-objective Problem

3.1 Normalising objective functions

Due to differences in dimension and magnitude of different objective functions, each of the objective functions is normalised in the NBI method as Eq. (5):

$$\overline{O_i}(\chi) = \frac{O_i(\chi) - O_i(\chi_i^*)}{O_i(\chi_j^*) - O_i(\chi_i^*)} \quad i, j \in \{1,2\}, i \ne j \tag{5}$$

where $O_1(\chi_1^*)$ and $O_2(\chi_2^*)$ represent the optimal value by individually optimising $O_1(\chi)$ and $O_2(\chi)$ in Eq. (6); $O_2(\chi_1^*)$ and $O_1(\chi_2^*)$ indicates the values of the other objective functions at χ_1^* and χ_2^*; $\overline{O_i}(\chi)$ represents the normalised value of the objective function. As shown in Fig. 3, the line connecting the point $A(O_1(\chi_1^*), O_2(\chi_1^*))$ and $B(O_1(\chi_2^*), O_2(\chi_2^*))$ is referred to as the Utopia line.

$$\begin{cases} O_1(\chi_1^*) = Min \quad O_1(\chi) \\ O_2(\chi_2^*) = Min \quad O_2(\chi) \end{cases} \quad \chi \in \Omega \tag{6}$$

3.2 Generating evenly distributed points on the Utopia line

As shown in Fig. 3, the Utopia line *AB* is divided equally to get m_k evenly distributed point. Any point P_k on this line is expressed as Eq. (7) according to the NBI method.

$$\bar{\boldsymbol{\Phi}}\boldsymbol{\beta} = \begin{bmatrix} \overline{O_1}(\chi_1^*) & \overline{O_1}(\chi_2^*) \\ \overline{O_2}(\chi_1^*) & \overline{O_2}(\chi_2^*) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \tag{7}$$

where $\bar{\boldsymbol{\Phi}}$ indicates normalised payoff matrix defined in Eq. (8) considering Eq. (5); $\boldsymbol{\beta} = [\beta_1, \beta_2]^T$ is the parameterised vector corresponding to different points on the Utopia line and satisfies constrains $\beta_1 + \beta_2 = 1, \quad \beta_{1,2} \in [0,1]$.

$$\bar{\boldsymbol{\Phi}} = \begin{bmatrix} \overline{O_1}(\chi_1^*) & \overline{O_1}(\chi_2^*) \\ \overline{O_2}(\chi_1^*) & \overline{O_2}(\chi_2^*) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \tag{8}$$

3.3 Obtaining the Pareto frontier

A point Q_k corresponding to P_k can be expressed as

$$\boldsymbol{Q_k} = \bar{\boldsymbol{\Phi}}\boldsymbol{\beta} + D_k\boldsymbol{n} \tag{9}$$

so that $\overrightarrow{P_k Q_k}$ is a vector that is perpendicular to the Utopia line, where $\boldsymbol{n} = [n_1 \quad n_2]^T = [-1 \quad -1]^T$ is the normal unit vector to the Utopia line, starting from the point P_k and D_k indicates the distance between the points Q_k and P_k. Eq. (9) can be equivalently expanded as Eq. (10) considering Eq. (7) and Eq. (8) [9]:

$$\boldsymbol{Q_k} = \begin{bmatrix} \bar{\boldsymbol{O}}_1(\chi_k) \\ \bar{\boldsymbol{O}}_2(\chi_k) \end{bmatrix} = \begin{bmatrix} \overline{O_1}(\chi_1^*) & \overline{O_1}(\chi_2^*) \\ \overline{O_2}(\chi_1^*) & \overline{O_2}(\chi_2^*) \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \end{bmatrix} + D_k \begin{bmatrix} n_1 \\ n_2 \end{bmatrix} = \begin{bmatrix} \boldsymbol{\beta}_2 - D_k \\ \boldsymbol{\beta}_2 - D_k \end{bmatrix} \tag{10}$$

When $\overrightarrow{P_k Q_k}$ is extended (by increasing D_k gradually from zero) to intersect the Pareto frontier at the point Q_k, a Pareto optimal solution (Q_k) corresponding to P_k can be obtained. This can be obtained by solving the optimisation problem below:

$$Obj: \quad Max \quad D_k \tag{11}$$

$$s.t. \begin{cases} \overline{O_1}(\chi_k) = \beta_2 - D_k \\ \overline{O_2}(\chi_k) = \beta_1 - D_k \\ \beta_1 + \beta_2 = 1, \beta_{1,2} \in [0,1] \\ g(\chi_k) \le 0; \quad h(\chi_k) = 0 \end{cases} \tag{12}$$

Q_k can be calculated for each P_k obtained in Section 3.2, so that a total number of m_k evenly distributed points can be obtained on the Pareto frontier.

3.4 Selecting the optimal scheduling strategy

Generally, the scheduler needs to identify the optimal scheduling strategy from the Pareto frontier to get the desired compromise between each objective. We adopt the comprehensive evaluation method to use the score s_k for evaluating the $k-th$ solution on the Pareto frontier. The score s_k can be obtained by calculating the weighted sum of the normalised value of each objective function in Eq. (13). The Pareto optimal solution with the maximum s_k can be deemed the optimal scheduling strategy.

$$s_k = \sum_{i=1}^{2} w_i \cdot f_{ik} \tag{13}$$

where f_{ik} is the normalised value of the $i-th$ objective function for the $k-th$ Pareto optimal solution, with the smaller objective value being assigned closer to 1, as shown in Eq. (14); w_i is the entropy weight of the $i-th$ objective function, which is calculated by EWM in Eqs. (15) and (16).

$$f_{ij} = \frac{O_i(\chi_j^*) - O_i(\chi)}{O_i(\chi_j^*) - O_i(\chi_i^*)} \quad i, j \in \{1,2\}, i \ne j \tag{14}$$

$$w_i = (1 - E_i) / \sum_{i=1}^{2}(1 - E_i) \tag{15}$$

$$\begin{cases} E_i = -\dfrac{1}{\ln(2)} \sum_{j=1}^{m} p_{ij} \ln(p_{ij}) \\ p_{ij} = O_{ij} / \sum_{j=1}^{m} O_{ij} \end{cases} \quad i = 1,2 \quad j = 1,2,\cdots,m \tag{16}$$

where E_i indicates the entropy value of the $i-th$ objective function; m indicates the amount of Pareto optimal solutions considered.

4. CASE STUDY

In this section, we present a case study to illustrate the effectiveness of the proposed model. We consider the daily production scheduling for an EAF steel plant producing 12 heats a day. The data of the steel plant is generated from a real industrial case in [5]. Electricity prices [10] and RES generation profiles [11] come from publicly available data.

The numerical results are presented in Fig. 4, where we can see that the 11 Pareto solutions are well-distributed on the Pareto line by applying the NBI method, which contains comprehensive and abundant information for deciding the optimal production schedule for the steel manufacturing. Furthermore, the OSS is identified in Fig. 4 for deciding the final production schedule.

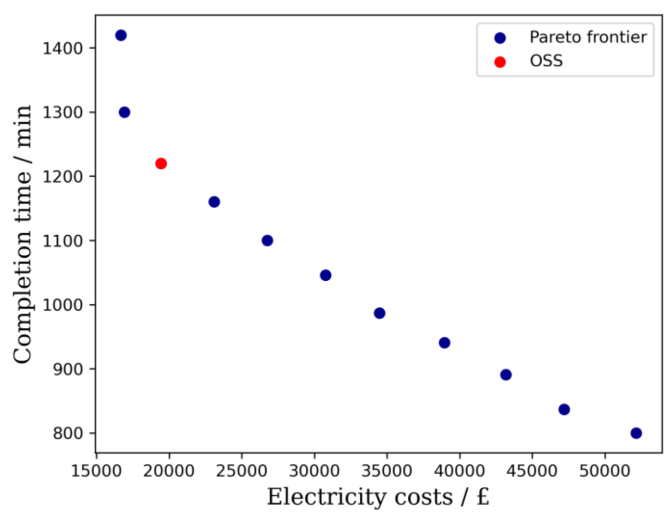

Fig. 4 The Pareto frontier of the MOPS problem

Moreover, the OSS is compared with the results of two classical single-objective scheduling approaches, i.e., shortest completion time (SCT) and minimal electricity cost (MEC). The comparison result is listed in Table 1, from which we can see that the EC of the OSS and MEC are 62.5% and 68% less than that of the SCT, while the RES consumption is 13.81% and 12.97% higher than that of the SCT. The reason is that the MEC and OSS both assign the most energy-consuming activities to low-price periods and improve local consumption of RES to reduce EC. On the other hand, the OSS completes the production 14% earlier than the MES at the cost of 5.5% higher EC. As a result, the risk related to the disruption caused by unexpected events and the overhead burden on the steel plant could be reduced.

Table 1 Performance of the results of the SCT and MEC models compared to the OSS

Index	SCT	MEC	OSS
CT/min	800	1420	1222
EC/£	52153	16689.1	19549.09
RES consumption	43.07%	56.04%	56.88%

5. CONCLUSIONS

In this work, MOMILP was formulated for the MOPS problem of steel plants with EAFs. The NBI method was used to derive well-distributed Pareto solutions, which can better evaluate the trade-off between electricity cost reduction and the time saving of production completion.

ACKNOWLEDGEMENT

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