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IFAC-PapersOnLine 48-25 (2015) 108–113

A Multiagent Framework for the Scheduling of Steel-making and Continuous Casting Process with Lagrangian Relaxation Neural Networks

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Abstract: **The steel-making and continuous casting process (SCCP) is the bottleneck in iron and steel production. SCCP often involves various uncertainties such as emergency customer orders, inaccurate estimate of processing time or unpredictable machine breakdown. All these dynamic disturbance factors disturb the rhythm of the regular production and results in the reduction of productivity. How to make a robust and adaptable dynamic reactive scheduling in a computationally efficient manner and be able to assess the quality of the schedule to improve the steel production during SCCP are the key factors for iron and steel manufacturing productivity. This problem is difficult due to various processing routs selection, complicated dynamic disturbances, and combinational explosion of the optimization search space. This paper presents a novel Lagrangian relaxation neural network (LRNN) for the scheduling of SCCP by combing recurrent neural network optimization ideas for constraint handling. An improved multiagent framework (IMAF) with an emphasis on robustness, adaptability, and optimization speed is introduced, and then a combinatorial auction mechanism based on improved surrogate subgradient algorithm with an emphasis on computational efficiency is applied in the mulitagent system architecture. The neuron-based stochastic dynamic programming (NSDP) method is adapted to obtain the subproblems. The approach provides both a theoretical basis and some experimental justifications for a dynamic scheduling combining real-time and predictive decision making. It resolves various disruptions as flexibly as dispatching rules while providing more stability. The approach has been tested by using practical data from Shanghai Baoshan Steel Plant of China. Numerical results demonstrate solution quality, computational efficiency, and values of new features in the IMAF architecture.**

1. INTRODUCTION

SCCP is the connection between the iron process and the hot/cold rolling process. SCCP is a high temperature, high energy expenditure, and large-scale logistics machining process. The modern integrated stage of steel-making, refining, and continuous casting directly connects the basic oxygen furnaces, refining furnaces, and casters and makes a synchronized production, as shown in Figure 1.1. Companies have been putting consistent emphasis on scheduling technology advances in the SCCP to increase productivity and to save energy. According to the statistics from Shanghai Baoshan Steel Plant of China, saving one second of SCCP scheduling calculation time will bring approximate 5,800 US dollars in profits for the steel enterprise [1].

The scheduling of SCCP is to determine the process sequence, the process beginning time, and the process machine of the molten steel, then the molten steel will be arranged to enter into various production stages from steel-making to continuous casting. Unlike general production scheduling in machinery industry, the scheduling of SCCP has to meet special requirements of steel production process. The products being processed are handled at high temperature and converted from liquid into solid (drawn billets). There are strict requirements on material continuity and flow time (including processing time, transportation time and waiting time). After the static schedule is released, SCCP often involves various uncertainties such as emergency customer orders, inaccurate estimate of processing time, or unpredictable machine breakdown. It is immediately subject to such random disruptions that may render the initial schedule obsolete and result in degraded system performance [2]. In order to maintain a smooth operation and ensure the least energy consumption, the calculation time of reactive scheduling is limited to seconds. Thus, the key issue for SCCP in terms of improved productivity is to design a robust and adaptable dynamic scheduling system in a limited time. The schedule is required to well organize the rhythm of the whole production and be able to assess the quality of the schedule.

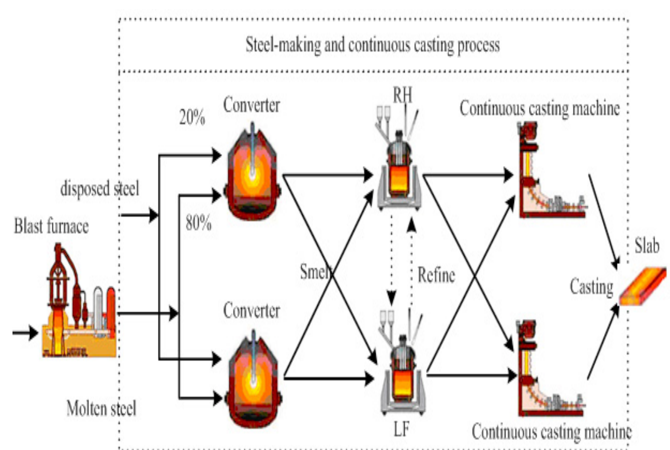

Fig. 1.1 The process of Steel-making and Continuous Casting

2. LITERATURE REVIEW

In SCCP, the scheduling of SCCP is a multi-objective, multi-machine, multi-stage and multi-process and NP-

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2015.11.068

hardness job shop problem to be solved. For this kind of scheduling optimization problem, historically, neural networks were developed based on the "Lyapunov stability theory" of dynamic systems: if a network is "stable," its "energy" will decrease to a minimum as the system approaches its "equilibrium state."[3]. The Hopfield-type recurrent networks have been based on the well-known "penalty methods," which convert a constrained problem to an unconstrained one by having penalty terms on constraint violations [4]. The problem is then solved by neural networks. Generally, a solution to the converted problem is the solution to the original one only when penalty coefficients approach infinity. As coefficients become large, however, the converted problem becomes ill conditioned [5]. To overcome the above difficulties, this paper sets up a network maps the objective function of the scheduling of SCCP problem onto an "energy function" for efficiently constraint handling, then the solution is a natural result of network convergence and can be obtained at a very fast speed.Meanwhile, less calculation time of making an optimized scheduling of SCCP will bring more economic benefits for the whole iron and steel production. Since many stages process activities are now tightly coupled in a complicated fashion and the entire process units are coupled in a complicated manner. New orders of significant urgency may interrupt those already scheduled, rendering their planned processes delayed. The breakdown of a single operation or uncertainties processing time will cause the disorder of subsequent operations belonging to the same part and the delay of other parts sharing the same machines, even though affect the whole production. In order to maintain a smooth operation and ensure the least energy consumption, the calculation time of reactive scheduling is limited to seconds; however the reactive scheduling is also always time-consuming, which cannot satisfy the reactive scheduling calculation time and the high qualified schedule results requirement. Previous approaches propose control strategies which are based on the Lagrangian relaxation (LR) or augmented LR for constraint handling [6]–[10], such as surrogated subgradient method. Although the application of the surrogate subgradient can get a proper direction in a limited time without solving all the separated subproblems' schedule to optimize dual functions for separable SCCP schedule problems which are relaxed by lagrangian relaxation method [10]–[14]. The difficulty of the standard surrogate optimization method primarily arises due to the lack of prior knowledge about the optimal dual value, which is used in the definition of a step size. In this paper, the ISSG algorithm is applied with an emphasis on computational efficiency. In order to overcome this difficulty, ISSG algorithm is proposed. The main purpose of the ISSG algorithm is to obtain a "good" direction quickly and independently of the optimal dual value. It is achieved by introducing a formula for updating the multipliers such that the exact minimization of the Lagrangian leads to a convergent result. Then an approximate formulation for updating the multipliers is developed so that the exact optimization of the Lagrangian leads to a convergent result under certain optimality conditions. Lastly, the notion of the surrogate subgradient is used for ensuring the convergence.

3. FORMULATION and SOLUTION of SSCP PROBLEM

A. Problem Formulation and LR

This section presents the LNRR providing the mathematical formulation of the SCCP. Based on the description of the SCCP in [1], after introducing two non-negative lagrangian multipliers $\{\pi_{hk}\}$ and $\{\psi_{sgp}\}$ respectively, the SCC schedule problem could be changed into the following formulation,

$\min_{\{c_{ij},h_{ij}\}} L$, with

$$L(\varphi_{s_{gp}},\pi_{\mathrm{hk}}) \equiv \sum_{g=0}^{G-1}\sum_{p=0}^{|\Omega_g|-2}\alpha_g W_g + \sum_{i=0}^{I-1}\beta_i T_i + \sum_{i=0}^{I-1}\sum_{j=0}^{J_i-2}\gamma_{ij}U_{i(j,j+1)}$$
$$+\sum_{g=0}^{G-1}\sum_{p=0}^{|\Omega_g|-2}\varphi_{s_{gp}}(c_{s(gp+1)(J_i-1)} - p_{s(gp+1)(J_i-1)} - c_{s(gp)(J_i-1)})$$
$$+\sum_{k=0}^{K-1}\sum_{j=0}^{J_i-1}\pi_{\mathrm{hk}}(\sum_{i=0}^{I-1}\delta_{ijhk} - M_{hk}). \quad (1)$$

The relaxed problem can be decomposed into sbuproblems, divide by each charge in each stage, the subproblem for charge i is given as follows:

$$\min_{\{c_{ij},h_{ij}\}} L_i, with L_i \equiv \beta_i T_i + \sum_{j=0}^{J_i-2}\gamma_{ij}U_{i(j,j+1)} + \sum_{k=0}^{K-1}\sum_{j=0}^{J_i-1}\pi_{\mathrm{hk}}\delta_{ijhk} + \mu(\mathrm{i}). \quad (2)$$

In the above, from the definition of cast, the charge in the same cast S_{gp} has the correspondence with charges i. The definition of $\mu(i)$ is shown below:

$$\mu(i) \equiv (\varphi_{s(gp)} - \alpha_g)c_{s(gp)(J_i-1)}, \text{for } s_{gp} = i \text{ and } p = 0, \quad (3)$$

$$\mu(i) \equiv (\varphi_{s(gp)} - \alpha_g)c_{s(gp)(J_i-1)}$$
$$+(\alpha_g - \varphi_{s(gp-1)})(c_{s(gp)(J_i-1)} - P_{s(gp)(J_i-1)})$$
$$\text{for } s_{gp} = i \text{ and } p = 1,\ldots,|\Omega_g| - 3, \quad (4)$$

$$\mu(i) \equiv (\alpha_g - \varphi_{s(gp-1)})(c_{s(gp)(J_i-1)} - P_{s(gp)(J_i-1)})$$
$$\text{for } s_{gp} = i \text{ and } p = |\Omega_g| - 2.$$

(5)

Because the sequence of charges in each cast has been assigned. The process unit of the whole process could be unified here. The subproblems could be solved by the unit of charge. Let L^*_i denote the minimal subproblem cost of charge i with given multipliers, the Lagrangian dual problem is then obtained as:

$$\max_{\{\pi_{hk},\varphi_{s(gp)}\}} D, with D \equiv \sum_i L_i^* - \sum_{h,k} M_{hk}\pi_{hk}. \quad (6)$$

The lagrangian dual function D is concave, and piece-wise linear, and consists of many "facets". The optimal solution is denoted as $D^* = D(\pi_{hk}^*, \varphi_{sgp}^*)$.

B. Largangian Relaxation Neural Networks:

In this part, LR is introduced to combine with neural networks to solve constrained schedule optimization. Since