Auction-based approach to resolve the scheduling problem in the steel making process

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Steel production is an extremely complex process and determining coherent schedules for the wide variety of production steps in a dynamic environment, where disturbances frequently occur, is a challenging task. In the steel production process, the blast furnace continuously produces liquid iron, which is transformed into liquid steel in the melt shop. The majority of the molten steel passes through a continuous caster to form large steel slabs, which are rolled into coils in the hot strip mill. The scheduling system of these processes has very different objectives and constraints, and operates in an environment where there is a substantial quantity of real-time information concerning production failures and customer requests. The steel making process, which includes steel making followed by continuous casting, is generally the main bottleneck in steel production. Therefore, comprehensive scheduling of this process is critical to improve the quality and productivity of the entire production system. This paper addresses the scheduling problem in the steel making process. The methodology of winner determination using the combinatorial auction process is employed to solve the aforementioned problem. In the combinatorial auction, allowing bidding on a combination of assets offers a way of enhancing the efficiency of allocating the assets. In this paper, the scheduling problem in steel making has been formulated as a linear integer program to determine the scheduling sequence for different charges. Bids are then obtained for sequencing the charges. Next, a heuristic approach is used to evaluate the bids. The computational results show that our algorithm can obtain optimal or near-optimal solutions for combinatorial problems in a reasonable computation time. The proposed algorithm has been verified by a case study.

Keywords: Combinatorial auction; Charges; Coherent scheduling

1. Introduction

For decades, the steel industry has been a powerful symbol of an increasingly global market economy, providing one of the most primary materials for many
other industries, including automobiles, aircraft, construction, machinery production, food services, beverage industries, etc. Modern iron and steel companies are heading towards continuous, fast and automated processes along with a large infrastructure to attain high-quality and low-cost products, just-in-time delivery and small lot sizes with a variety of products. The development and use of the computer integrated manufacturing system (CIMS) can improve the productivity, reduce the waiting time between two processes, enable efficient material and energy utilization, and also reduce the production costs (Balakrishnan and Brown 1996). Iron and steel production includes several processing stages, viz. iron making, steel making, continuous casting, and steel rolling, and has high investment and energy consumption. The most important characteristics of these processes are the high-temperature, high-weight material flow with complex technological processes.

To accommodate customer requirements for different types of finished products with varying demand, various rolling mills with sufficient production capacity in the steel rolling phase have been designed. Since the steel making process includes complicated technological processes that require expensive and energy-intensive equipment that runs in continuous mode, its capacity is always below the actual capacity of the rolling stage. Thus, the effective scheduling of steel making resources is a key component, especially in the highly competitive global steel market of today, in meeting customer requirements and improving the productivity of the entire production system.

Scheduling problems associated with steel making–continuous casting production are aimed at determining at what time, on which device and in what sequence the molten charge should be arranged at various production stages from the converter (steel making) to continuous casting. Three important aspects for a system to be applied in a real scheduling environment are the following.

- **Representation of the problem environment.** Due to the dynamic nature of demand, resources and organization are frequently changing. Therefore, environments and constraints pertaining to the problem should be modelled that are easy to represent and modify.
- **Different evaluation criteria.** A schedule is assessed according to many conflicting criteria. These criteria vary for different cases.
- **Efficient solution generation.** It is not only necessary but imperative to generate a scheduling sequence pertaining to different charges, without machine conflicts. Rescheduling capacity is also crucial when dealing with mechanical problems.

The whole scheduling problem of steel making–continuous casting (SMCC) consists of four steps:

- cast sequencing;
- scheduling of individual charge sets;
- merging of individual charge set scheduling to make a rough scheduling; and
- optimal scheduling that eliminates machine conflicts.

The first three steps are mainly dependent on the operational relationships and can be done relatively easily. The last step is crucial and needs to follow resource and machine constraints to ensure practical feasibility of the resulting schedule. This paper focuses on determining this optimal scheduling step.
Hence, it is essential to develop an efficient and effective scheduling algorithm for such a system. The problem addressed in this paper is the steel making–continuous casting production (SMCC) scheduling problem encountered in practice. However, due to its complexity, no efficient optimization algorithm can solve the problem in polynomial time. Iterative algorithms are good alternatives, but robustness, an important criterion in practical situations, is usually unattainable. In this paper we develop a combinatorial auction-based approach to resolve the scheduling problem in SMCC. In a combinatorial auction, bidders bid on a set of items via different bidding languages and the auctioneer allocates the set of items to the highest paid bid. The present study uses this property to determine the charge sequence. The steel making system acts as an auctioneer and all possible sequences of different charges act as bidders. A bid is the demand for a certain position in the charge sequence. Thus the bids determine the order in which the charges are to be processed on different machines. Each bid is then evaluated using a heuristic approach. A bid is feasible until it satisfies the various constraints related to the SMCC scheduling problem. Finally, the system allows a bid for steel production which gives a minimum waiting time and a maximum throughput. The computational results show that our algorithm can obtain optimal or near-optimal solutions for large-sized problems in a reasonable computation time. Therefore, the proposed algorithm may be implemented in real-life production systems.

The remainder of this paper is organized as follows. Section 2 provides a brief review of related work. Section 3 illustrates the scheduling problem in SMCC production. Section 4 deals with the combinatorial auction with different bidding rules. Section 5 presents the mathematical formulation of the problem and evaluation of the objective function. Section 6 presents the results and discussion. Finally, the general conclusions follow.

2. Background and related work

The main difficulty when dealing with a scheduling problem is combinatorial explosion, which is characterized by an $n$ machine, $m$ job problem having $(m!)^n$ possible schedules and a diversity of conflicting constraints. Due to combinatorial explosion, a prohibitively large number of cases must be checked without elaborate and intelligent methods. A scheduling problem is usually constrained by the due date, cost limits, production levels, machines, demand, resources and other factors.

Scheduling problems have been studied comprehensively using the Artificial Intelligence (AI) technique to obtain near-optimal solutions. Scheduling problems have also been studied extensively using the OR technique, which is an analytical method for obtaining optimal solutions by modeling. Johnson (1954) presented an algorithm for obtaining an optimal solution for two machines with the same order of jobs. Heller (1960) and Little et al. (1963) studied the scheduling problem using simulation and a branch-bound method. Fox and Smith (1984) and Smith et al. (1986) presented a knowledge-based system for factory scheduling.

Steel production scheduling is recognized as a difficult industrial scheduling problem (Cowling and Rezig 2000, Tang et al. 2002). It involves a variety of complex technological processes, each of which has many critical production constraints, and interacts with several others in an integrated fashion to produce a finished product.
Brown (1988) presented a rescheduling method to take care of disturbances and disruptions during processing. Roy et al. (2004) and Schreiber et al. (1999) developed a knowledge-based model for managing schedule disturbance in the steel making process. A mathematical programming model for scheduling steel making–continuous casting production was provided by Tang et al. (2000). An example of an off-line scheduling problem for steel production using dynamic mathematical programming was studied by Redwine and Wismer (1974). Petersen et al. (1992) developed a mathematical programming model to optimally schedule the slabs through the reheating furnace and the rolling mill for a steel production scheduling problem. This model was solved heuristically. Tang et al. (2002) resolved the problem of the steel making process using Lagrangian relaxation. Lally et al. (1987) constructed a simple model of a steel plant in which steel was started at an electric arc furnace, held in a ladle, and cast on a continuous caster, and established a simple mixed-integer linear programming solution to the problem of caster scheduling. However, the model did not consider all the complexities of a real continuous caster. Tong et al. (1994) constructed a complex mixed-integer linear programming model and solved it using heuristic techniques for a twin strand continuous slab caster scheduling problem at LTV and Geneva Steel Works. The model was intended to schedule caster production from customer orders while optimizing several key objectives such as maximizing caster productivity.

Jimichi et al. (1990) presented an expert system to determine the parameters and operational conditions to match slab production with customer orders. Another example of using expert system techniques for iron and steel production scheduling is provided by Sato et al. (1977). Numao et al. (1988), Numao and Morishita (1989, 1991) and Morishita et al. (1990) described an expert system application to perform cooperative scheduling in which the schedule was modified by the scheduler using a graphical user interface. They discussed the difficulties of maintaining the original short-term schedule due to the dynamic nature of the steel making process. The main justification for the use of expert systems came from reducing the waiting time from charge to charge and minimizing energy consumption. Stohl et al. (1993) established a hybrid cooperative expert system modelling to solve SCC scheduling problems, but they were unable to construct an optimized mathematical model. Epp et al. (1989) described an interactive scheduling system developed using the AI method for a SCC facility at Inland Steel Corporation. Hamada et al. (1995) presented a framework for solving complex steel making scheduling problems and then combined a rule-based expert system and genetic algorithm to produce efficient schedules.

In this paper, an attempt is made to adopt a heuristic procedure that is effective in minimizing a large search space, discontinuity and noise to obtain near-optimal solutions. The present paper presents a combinatorial auction-based heuristic that determines the optimal set from the pool of all possible solutions.

3. The scheduling problem in steel making processes

In this section, we describe the scheduling problem in steel making processes. An iron–carbon diagram used to determine the melting temperature of steel and cast iron is shown in figure 1. The major processing steps, steel making, refining and continuous casting, are the three main stages. Each stage further contains parallel
machines, as shown in figures 2(a) and (b). The various stages pertaining to the steel making process are described in the subsections below.

3.1 Iron making

The first link in the chain is the production of molten iron in the blast furnace by the reduction of iron ore. Iron ore is processed into pallets, or sinter, having more consistency and reducibility than the raw ore. Coal, another raw material for iron making, is baked in ovens to produce coke, a derivative product with a higher combustion efficiency. Each separate oven chamber holds a charge of up to 30 tons of coal. The coal is heated, or carbonized, in the ovens until it becomes coke. It is then removed from the oven, cooled and graded before use in the blast furnace. Coke, ore and sinter pellets are charged into the top of the blast furnace, together with limestone. A hot air blast is injected through tuyeres in the base of the furnace creating a temperature gradient in the furnace, from about 1400°C at the bottom to about 250°C at the top. As these ingredients fall through the furnace, several actions take place. The ore is smelted and reduced through combination with carbon from
the coke. The molten limestone serves as a flux, i.e. it forms a liquid slag that carries coke ash and other impurities away from the molten metal. At the base of the furnace, slag is drawn out for disposal, and hot molten iron is tapped out into ladles for steel making. Meanwhile, the raw material continues to be charged into the top of the furnace, and heated air blasted in at the bottom. This process is continuous and goes on throughout the life of the furnace, which can be 10 years or more. A blast furnace operates constantly, with the materials being fed continuously and the product tapped periodically. This is a necessary condition, since shutdown of the furnace could necessitate a rebuild (rehabilitating the furnace and replacing its refractory lining, a procedure that may cost 70 to 100 million dollars and require as long as a year). For this reason, hot iron produced by the blast furnace is viewed as a continuous supply, and the consumption of this continuous supply is an important constraint on the planning and scheduling of the next stage.

### 3.2 Primary steel making

Primary steel making accepts the supply of hot molten iron from the blast furnace and transforms it into semi-finished products (slabs, coils, billets, blooms, etc.)
in a variety of grades (specific metallurgical compositions of steel) and dimensions. The principal processes for primary steel making are a basic oxygen furnace or an electric arc furnace, a ladle treatment facility, continuous casters, and a hot strip mill.

3.2.1 Basic oxygen furnace or electric arc furnace. Hot molten iron arrives from the blast furnace in insulated vessels, often by rail, and is poured into the refining furnaces along with scrap steel. Further heat is then applied to melt the combined charge into a homogeneous liquid state, remove impurities, and reduce the carbon content to the desired level. During this refining process, alloying additives can be added to achieve the required metallurgical specifications for the particular grade produced. The basic oxygen furnace and electric arc furnace are two types of refining furnaces predominant in the steel industry: in high production operations, the basic oxygen furnace is more common. A typical production facility, or basic oxygen furnace shop, might consist of two vessels and produce about 35 heats per day, with each heat consisting of 200 to 300 tons of molten steel. On the input side, refining furnaces are constrained by the requirement that they collectively must consume all hot iron arriving from the blast furnaces, a continuous supply with little available variation. On the output side, each heat of steel produced by a refining furnace is of a single specific grade, and furnaces are normally run for complete heats only. Therefore, one challenge in scheduling primary production is to make efficient use of the material produced by the refining furnaces in full and grade-specific heat lots. Refining furnaces are also subject to certain constraints concerning the sequence in which different grades are made, and the number of consecutive heats of certain grades they can produce, since some grades may damage the refractory lining of the furnace if too many heats are scheduled.

3.2.2 Ladle metallurgical facility. From the refining furnaces, molten steel is transferred via ladles containing one heat of steel, which are transported by a crane to a ladle metallurgical facility. At the ladle metallurgical facility, a heat might undergo any of several refining processes, which aim to produce molten steel of the correct grade or chemistry by subjecting the steel to processes that reduce the carbon content, and add alloying additives such as nickel and manganese. Sometimes, degassing is also performed to remove the gases that may be trapped during various processes.

3.2.3 Continuous caster. Molten steel from the ladle metallurgical facility then moves to the casting step, where liquid steel is transformed into different semi-finished shapes, dimensions, weights, and grades. Common cast shapes include slabs, blooms, and billets used to make flat-coiled products and plates, etc. Each slab has several important characteristics: width, thickness, grade, weight, and length. The slabs are typically 150–320 mm thick, 500–3000 mm wide, and 10–20 m long. Blooms and billets have smaller width and thickness dimensions, and are used to make long products such as pipes. Liquid steel is produced in heats generally of a fixed size for a given plant (e.g. 300 tons), and each heat produces a number of slabs (a 300 ton heat can produce about 16 slabs) in the continuous caster, and all of the slabs cast will essentially have the same grade. In this paper, we consider only the production of
slabs. At a continuous caster, the ladles of molten steel or heats are drained into a tundish at the top of the machine. The ladle is lifted by a crane into a rotating turret, which contains a second empty ladle opposing it at 180°. The full ladle is rotated into place over the caster as the previous empty ladle is rotated out for return to the steel-making shop. A ceramic nozzle and slide gate is attached to the bottom of the ladle; the ladle is opened and molten steel flows into the tundish.

Owing to the above facts, it is very difficult to assess an optimal solution for scheduling various charges on different machines. It is imperative that every stage of the steel making process is at high temperature. Therefore, in order to achieve the minimum waiting time and maximum throughput, an efficient algorithm is required. In this paper, a combinatorial auction-based heuristics has been applied to obtain an optimal or near-optimal solution of the scheduling problem.

A few special terms have been used in this paper and their definitions are listed in Table 1. Figure 3 shows a diagrammatic representation of a few of the terms listed in the table. Here, the vertical line is for time, and each line represents a machine. One charge path includes units and handling times, which are represented by lines connecting the units. The waiting times are shown by dotted lines before the units.

| Term     | Definition                                                                 |
|----------|-----------------------------------------------------------------------------|
| Charge   | A unit of production that consists of a sequence of operations on a heat     |
| Charge set | A set of charges that produces the same dimension product                   |
| Billet   | A steel piece with square cross section, smaller than a bloom               |
| Bloom    | A steel piece with square cross section, larger than a billet               |
| Machine  | A production device that performs one operation at a time. Machines used for performing identical operations are called alternative machines. Different machines perform different operations: a converter converts pig iron into steel; a refining machine performs refining and alloying addition; and a continuous caster makes steel slab |
| EAF      | Electric arc furnace                                                       |
| BF       | Blast furnace                                                              |
| BOF      | Basic oxygen furnace                                                       |
| LMF      | Ladle metallurgical facility                                               |
| Tundish  | A receptacle at the top of the caster                                      |
| LF       | Ladle furnace                                                              |
| Grade    | Steel with a specified metallurgical composition                           |
| Heat     | Furnace-load of steel                                                      |
| Slab     | A steel piece with elongated rectangular cross section                     |
| Strand   | Stream of steel from a caster                                              |
| Unit     | An operation that specifies the machine, the starting time, and completion time |
An auction provides a mechanism to allocate a set of goods to a set of bidders on the basis of bids and requirements. When there are uncertainties in demand and supply, unresponsive suppliers, and demand uniqueness then auctions are frequently used for the allocation of multiple resources (Banks et al. 1989). In a sequential auction, the items are auctioned one at a time and the auctioneer always wants to allocate that item to the highest bidder among the group of bidders. But if the bidders are interested in a combination of items then it is very difficult for the bidders to submit bids because they do not know what items they will receive in a later auction. In a parallel auction, items are auctioned in parallel. Here, bidders face the same difficulties as in a sequential auction. In combinatorial auctions (CAs), multiple goods are auctioned simultaneously, i.e. each bid may claim any combination of goods. This characteristic helps to overcome the inefficiencies in allocation due to related uncertainties, because, in a combinatorial auction, the value of an item that a bidder wins greatly depends on the winning of other items. The concepts of complementarity and substitutability are very important in CAs.

- **Complementarity.** The property that shows the willingness of a bidder to pay more for the whole than the sum he is willing to pay for the parts is termed complementarity. Complementary goods have a superadditive utility function:

\[ V(\{a, b\}) > V(\{a\}) + V(\{b\}), \]  

where \( V(\{a,b\}) \) is the utility function for a combination of item a and b, \( V(\{a\}) \) is the utility function for item a, and \( V(\{b\}) \) is the utility function for item b.

- **Substitutability.** A bidder may only be ready to pay for the whole if it is less than the sum of what he is willing to pay for the parts. This is termed substitutability. Substitutable goods have a subadditive utility function:

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4. **Combinatorial auction: an overview**

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Figure 3. The scheduling terminology.
Numerous industrial applications for combinatorial auctions have been reported by different researchers. Spectrum auctions, collaborative planning, resource scheduling, train scheduling, airport slot allocation, supply chain management, and e-procurement are a few. In this paper, a combinatorial auction has been used for the steel scheduling problem to obtain coherent schedules for a wide variety of production steps in a dynamic environment.

In a manufacturing plant, a set of jobs is to be scheduled across a set of machines to minimize metrics such as tardiness or total delay, maximize throughput, etc. In auction-based manufacturing, various entities in the manufacturing system bid themselves, accept bids and select a bid based on some heuristic procedure from the available bids (Shaw 1987).

In a combinatorial auction, bidding languages and the allocation of bids to bidders are two important issues. Section 4.1 discusses the various bidding languages.

### 4.1 Bidding languages

A bidding language can be used for expressing valuations. Bidding languages should have the following characteristics:

- they must be expressive enough to represent every possible valuation;
- the representation should not be too long;
- simplicity;
- they should be easy for humans to understand; and
- it should be easy for the auctioneer algorithms to handle.

The various types of bidding languages are discussed below.

1. **Atomic bids.** In atomic bids, a bidder has to put forward a bid \((B_d)\) which contains two elements \((I, P)\), where \(I\) is the subset of items and \(P\) is the price that the bidder has to pay for \(I\). Conditions to be satisfied for subset \(A\):

\[
I \subseteq A, \quad C(A) = P, \quad \text{otherwise} \quad C(A) = 0;
\]

this means that the bidder has to pay price \(P\) if \(A\) items are to be taken from set \(I\).

2. **OR bids.** In OR bids, there is no restriction on the number of atomic bids to the bidder. The bidder is willing to obtain any number of atomic bids and the price of these atomic bids will be equivalent to the aggregate of their individual prices.

3. **XOR bids.** In XOR bids, the bidder can submit any number of atomic bids but he has to procure at most one of these atomic bids.

4. **OR of XOR bids.** In these bids, the choice of the number of XOR bids depends on the bidder and any number of these bids can be obtained by the bidder by paying the price of these bids, which is equal to the sum of their individual prices.

5. **XOR of OR bids.** In these bids, the bidder can submit any number of OR bids, but only one bid can be obtained by him.

6. **OR* bids.** Let there be \(Z\) sets of items for sale, and each bidder \(b\) has \(Z_b\) sets of phantom items, on which only he can bid. Each bidder \(b\) can submit an arbitrary number of pairs \((I_b, P_b)\), where \(I_b \subseteq Z \cup Z_b\), and \(P_b\) is the
maximum price that the bidder is willing to pay for that subset. The bidder is willing to obtain any number of disjoint bids for their respective prices.

4.2 Optimal subset determination

All bids are accepted in a combinatorial auction, unlike in other auctioning processes, because a bid may form a combination with other bids that may emerge a better combination for the auctioneer. The optimal subset is determined by optimizing some target value, generally the auctioneer revenue or the total economic efficiency. This problem is modelled as an integer linear programming model and the formulation is an instance of the weight set-packing problem. Karp (1972) proved that the weighted set-packing problem is an NP-complete problem. Therefore, many heuristics have been used to solve this problem (Rothkopf et al. 1998, Fujishima et al. 1999).

No fractional allocation is allowed in the combinatorial auction problem but, in some cases, the auction setting itself may allow fractions to bids to be won as opposed to complete bids. Possible examples of such auctions are for raw materials such as oil or electricity (Market Design Inc., http://www.marketdesign.com).

4.3 Motivation for the use of combinatorial auction theory

A steel making plant is a cluster of several interacting subsystems such as machines, raw materials, storage, order processing, etc. These systems work cooperatively with respect to the allocation of raw materials. Recently, a great deal of research has been directed towards new tools and techniques to obtain real-time solutions for planning and scheduling problems (Jeong and Kim 1998). One such approach is the mathematical programming model. Tang et al. (2000) have developed a mathematical programming model for scheduling steel making–continuous casting production. Redwine and Wismer (1974) presented an example of off-line scheduling for steel production using dynamic mathematical programming. Petersen et al. (1992) developed a mathematical programming model to solve the scheduling problem in steel making. The main goal of these mathematical programming models is to ensure the fulfillment of objectives: minimum price paid and maximizing the charged price to satisfy the charge’s requirement. The above bidding procedure has been organized using combinatorial auction theory and the model is developed for intelligent real-time operational control of a steel making plant.

5. Auction-based model for the scheduling problem in the steel making process

5.1 Problem characteristics

After the composition of charges and the size of casts have been defined, the task of the charge scheduler is to determine when and where (on which device) each charge should be processed at each production stage. The following general assumptions are made in the steel making process.

(a) All charges follow the same process route: steel making, refining, and then continuous casting. At each stage, a charge can be processed on any one of the machines at that stage, and the parallel machines at that stage are identical.
(b) A machine can process at most one job at a time.
(c) A job can be processed on at most one machine at any time.
(d) Job processing is non-preventive.

5.2 Integer programming formulation

The scheduling problem in steel making has been formulated as a linear integer program to determine the optimal charge sequence to assign various charges on different machines. In this auction model, the bids presented by each charge determine the order in which the different charges are to be processed on different machines. To evaluate each bid, a heuristic-based approach is then used.

The integer programming formulation for determining the optimal charge sequence from the charge pool is described below.

5.2.1 Notation.

- $k$: Machine 1, 2, 3, ..., $m$
- $CON$: Converter
- $REF$: Refining equipment
- $CC$: Continuous caster
- $W_i$: Waiting time for the $i$th charge
- $RT_k$: Resting time for the $k$th machine
- $UT_m$: Unit processing time of the $i$th charge on machine $m$
- $b_j(s)$: Bidder $j$‘s value for the bid for subset $s$ of the sequence
- $Y(s,j)$: 1, if charge sequence subset $s$ is selected and allocated to bidder, 0 otherwise
- $TH$: Throughput
- $NS$: Number of steel slabs

5.2.2 Evaluation criteria. The following criteria related to the quality of the charge scheduling have been used to solve the scheduling problem in the steel making process.

1. Minimization of waiting time. The process of steel making should be finished while the iron is still in the molten state. Otherwise, molten iron begins to solidify and goes into a mushy state, which would be very difficult to cast through a continuous casting machine. The initial temperature of the iron is assessed from the total waiting times on each machine during each charge processing. Therefore, the process waiting time should be minimized in order to reduce the heating cost. To evaluate the sequence with the objective of minimizing the waiting time by satisfying the problem constraints, the objective can be expressed as

$$\min f_1 = \sum_{k=1}^{m} W_{ik},$$

where $W_{ik}$ is the waiting time of the $i$th charge on machine $k$. 

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2. **Maximizing output.** Output is defined as the number of steel slabs of different cross section produced by the steel making plant without violating the problem constraints in one day. When the objective is to maximize output, charges are arranged in a sequence so as to ensure the maximum number of steel slabs produced by satisfying the system constraints

\[
\max f_2 = \sum_{k=1}^{n} NS_k.
\]

(4)

where \(NS_k\) is the number of steel slabs produced by the continuous caster machine and \(n\) is the number of continuous casting machines.

5.2.3 **Constraints.** The aforementioned evaluation criteria are subjected to the following constraints which are typical in the steel making process.

1. **Limitation of waiting time.** The process should be finished while the iron is in the molten state. Thus, the sum of the waiting times of each charge on different machines is limited to less than 30 min

\[
\sum_{i=1}^{n} \sum_{k=1}^{m} W_{ik} \leq 30,
\]

(5)

where \(n\) is the number of charges and \(m\) is the number of machines.

2. **Use of some machines continuously.** The continuous caster machine is known for its continuous operation. In the steel making process, all charges end with continuous casters, which should perform regularly, i.e. no resting time between operations, in order to maximize the throughput. Keeping in view this characteristic of the continuous caster machine the process of refining a charge must be completed before the previous casting process ends.

3. **Requirement of a resting time for some machines.** In the steel making process, the temperature of the steel handled by the various machines varies from 1200 to 1400°C depending on the percentage of carbon equivalent present in the steel. Therefore, some of the machines need regular repair. For example, damaged refractory tiles inside the converters need to be replaced by new tiles after a few continuous processing cycles. The scheduling of different charges should take this kind of resting time into account.

5.3. **Heuristic procedure**

To determine the winning condition for each bid, the stepwise heuristic method is described below.

**Step 1.** Construct a detailed table consisting of the charge number, the machines on which the charge will be processed, and the time required on that machine for various operations. Here, each bid stands for one possible charge routing.

**Step 2.** In order to determine the charge sequence, all possible combinations of two charges are formulated and, for each combination, the values of the objective functions are determined without violating the system constraints.
Step 3. The combination that gives the best value of the objective functions, that is minimum waiting time and maximum throughput, is set as one group. If there is a tie for any bid of the charge in the sequence, then the bid with the earlier charges is accepted as a group.

Step 4. The selected group is again combined with the rest of the charges and again the values of the objective functions are determined without violating the system constraints for each combination. The combination that gives the best value of the objective functions is again set as one group.

Step 5. Steps 3 and 4 are repeated until all charges would not be combined.

Step 6. For the determined charge sequence, the overall waiting time and the throughput are computed.

6. Case study

A combinatorial auction-based heuristic approach has been developed and applied to solve the scheduling problem in a steel making process that consists of four converters, four refiners, and four continuous casters. Table 2 shows the detailed problem description, which includes the unit processing time of each charge and the corresponding machine. The scheduling problem has been re-organized to suit the requirements of the proposed auction-based approach and is shown in table 3. To simplify the coding problem related to a machine, ‘C’ is assigned for converter, ‘R’ is assigned for refiner, and ‘CC’ is assigned for continuous caster. This is shown in table 3.

The planning horizon for this case study is 10 h. First, 15 bids can be generated from 15 bidders that are individual charges. The problem is then formulated for the XOR bidding language, and the heuristic procedure described in section 5.2 is applied to the problem given in table 2 and is described stepwise below.

Step 1. First, a detailed table is constructed consisting of charge numbers, and the time required on different machines for various charges for each bid (as listed in tables 2 and 3).

Step 2. All possible combinations of two charges are formulated and, for each combination, the corresponding waiting time is calculated.

Step 3. Since there are four converter machines, four charges can be scheduled at a time. From these combinations, 6–9, 3–5 and 12–11 offer a better objective function value, i.e. minimum waiting time and maximum output.

Step 4. The selected combinations are now set as one group separately and combined with the rest of the charges.

Step 5. Steps 3 and 4 are repeated until all charges would not be combined.

Step 6. Finally, a sequence is determined in detail and is described in figure 4, which gives the minimum waiting time (35 min) and also the maximum output (15 charges per shift).
Table 2. Processing times on various machines for different charges.

| Charge | Unit processing time in minute | Machine |
|--------|-------------------------------|---------|
| 1.     | 30                            | CON1    |
|        | 10                            | REF1    |
|        | 15                            | REF3    |
|        | 30                            | CC1     |
| 2.     | 30                            | CON4    |
|        | 15                            | REF1    |
|        | 60                            | CC3     |
| 3.     | 45                            | CON4    |
|        | 30                            | REF4    |
|        | 30                            | CC3     |
| 4.     | 30                            | CON2    |
|        | 45                            | REF1    |
|        | 45                            | CC1     |
| 5.     | 30                            | CON4    |
|        | 30                            | REF2    |
|        | 30                            | CC4     |
| 6.     | 45                            | CON3    |
|        | 30                            | REF3    |
|        | 30                            | CC4     |
| 7.     | 30                            | CON4    |
|        | 30                            | REF3    |
|        | 60                            | CC1     |
| 8.     | 30                            | CON1    |
|        | 15                            | REF3    |
|        | 60                            | CC4     |
| 9.     | 30                            | CON2    |
|        | 15                            | REF3    |
|        | 30                            | CC2     |
| 10.    | 30                            | CON1    |
|        | 15                            | REF3    |
|        | 30                            | CC2     |
| 11.    | 30                            | CON3    |
|        | 30                            | REF4    |
|        | 30                            | CC3     |
| 12.    | 15                            | CON2    |
|        | 30                            | REF2    |
|        | 30                            | CC2     |
| 13.    | 30                            | CON1    |
|        | 15                            | REF4    |
|        | 45                            | CC1     |
| 14.    | 30                            | CON3    |
|        | 15                            | REF4    |
|        | 30                            | CC2     |
| 15.    | 30                            | CON3    |
|        | 30                            | REF2    |
|        | 60                            | CC2     |

Where, CON1 = Converter 1, CON2 = Converter 2, CON3 = Converter 3, CON4 = Converter 4; REF 1 = Refiner1, REF 2 = Refiner2, REF 3 = Refiner3, REF 4 = Refiner4; CC 1 = Continuous Caster1, CC 2 = Continuous Caster2, CC 3 = Continuous Caster3, CC 4 = Continuous Caster4.
The results of the combinatorial auction-based heuristic approach are shown in figure 4. To demonstrate the efficacy of the proposed algorithm, the results are compared with those of standard scheduling rules such as SPT, LPT, FCFS, SPT/TOT, SPT.TOT, LPT/TOT, and LPT.TOT (table 4). The waiting times and outputs for the corresponding sequences of charges are shown in table 5. A comparative study of the results obtained using various scheduling rules as shown in figures 5 and 6 clearly demonstrates the superiority of the proposed algorithm, i.e. minimum waiting time and maximum output. The percentage improvement in the

The results of the combinatorial auction-based heuristic approach are shown in figure 4. To demonstrate the efficacy of the proposed algorithm, the results are compared with those of standard scheduling rules such as SPT, LPT, FCFS, SPT/TOT, SPT.TOT, LPT/TOT, and LPT.TOT (table 4). The waiting times and outputs for the corresponding sequences of charges are shown in table 5. A comparative study of the results obtained using various scheduling rules as shown in figures 5 and 6 clearly demonstrates the superiority of the proposed algorithm, i.e. minimum waiting time and maximum output. The percentage improvement in the
results obtained using the proposed auction-based approach compared with the other scheduling rules is shown in table 6. The percentage improvement was calculated according to the expression

\[
\frac{(O_T - A_C)}{O_T}
\]  

(6)
where $O_T$ is the performance measure of the other scheduling rules and $A_C$ is the performance measure of the auction-based approach.

### 7. Conclusion

In this paper, the scheduling of charges in the steel making process has been studied. To determine the optimal charge sequence, an integer programming model has been formulated that takes care of the waiting times of different charges along with the number of steel slabs produced in the system. The scheduling problem has been addressed using a combinatorial auction-based approach. The main objective of the scheduling problem is to minimize the waiting time and maximize the number of steel slabs produced. In the combinatorial auction-based approach, combinations of two charges are formulated; the combinations are evaluated as per the specified evaluation criteria, based on the performance value. The best combination is treated as a single group. The selected combinations are then considered as one separate
group and combined with the rest of the charges and the process is iterated until all charges are combined. Finally, a sequence is generated that gives the best value of the objective functions. The results obtained by the auction-based heuristics are compared with those from other existing approaches and the percentage improvement over the other results is presented.

Even if the numbers of scheduling methods are available to determine the optimum schedules, there is a need to develop an expert system, based on rules that can efficiently handle scheduling problems in steel making processes. In this article auction based algorithm is proposed, considering the future scope, in which different agents considered in a steel making shop floor situation can mediate/interact with each other. This can best be mapped using an auction based mechanism. Major breakthrough attained in implementing effective protocol and network architecture will enable the shop floor manager to witness the generation of effective schedules for complex and dynamic shop floor situations on a real time basis. The proposed approach also needs to be tested in a dynamic environment where multiple objectives and multiple constraints are present.

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