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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

Operations Research Transforms Baosteel's Operations

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Shanghai Baoshan Iron and Steel Complex (Baosteel) is China's largest and the world's third-largest steel company. In 2005, our research team was tasked with developing advanced operations research-based planning tools to improve the operational efficiency of Baosteel's Shanghai plant. In the following six years, we developed novel optimization algorithms and tailored metaheuristics, and implemented four decision support systems (DSSs) to replace the manual planning methods at the Shanghai plant. The DSSs have brought scientific operations management to Baosteel and transformed the plant's production and final-product delivery operations. Baosteel estimates that from 2007 to 2012, they provided a cumulative economic benefit of $77 million. Based on their current usage at this plant, they also estimate that these DSSs will continue to provide an annual economic benefit of $20 million, which represents a 17 percent improvement of Baosteel's information technology and operations management capability. They have also reduced Baosteel's carbon dioxide emissions by 585,770 tons annually.

Keywords: iron and steel industry; production planning; batch planning; logistics scheduling; integer programming; branch and price; metaheuristics; decision support system.

For decades, the iron and steel industry has been a powerful symbol of an increasingly global market economy, leading the development of other industries, such as construction, automotive, shipbuilding, and home appliances. Over the past 30 years, China's iron and steel industry has grown rapidly, as has the Chinese economy. China has been the largest steel producer in the world for the past 15 years. Figure 1 compares the annual crude steel production by China and the rest of the world from 2004 to 2011. In 2011, China's steel output was 695 million tons, 46 percent of the world's total output. The iron and steel industry has been one of the pillar industries in China's national economy, accounting for about 12 percent of the industrial sector's share of China's gross domestic product. Of the hundreds of large and medium iron and steel enterprises in China that have an annual throughput of over one million tons, the Shanghai Baoshan Iron and Steel Complex (Baosteel) is the largest.

Baosteel Overview

The construction of Baosteel started in December 1978, the same month in which China decided to reform its way of doing business and open its doors to the outside world. By 1995, Baosteel had developed as the largest and most technologically advanced iron and steel enterprise in China. Within 20 years of its

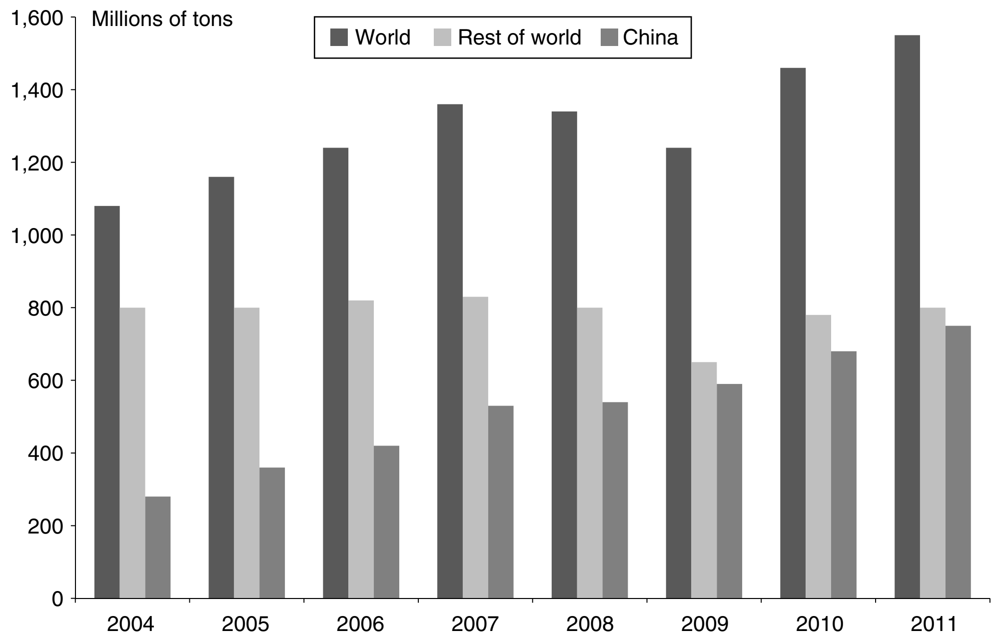

Figure 1: The graph shows the annual crude steel production by China, the rest of world, and the entire world including China (in millions of tons).

first production run in 1985, Baosteel became one of the world's top 500 enterprises (by revenue). With production output of 44 million tons in 2011, Baosteel was ranked third among all iron and steel enterprises in the world. Its development trajectory reflects the rapid growth of China's steel industry and symbolizes the country's fast economic development over the past 30 years. Baosteel has become a flagship of China's state-owned enterprises. Headquartered in Shanghai, the company has four steel production sites in China, including Shanghai, Ningbo, Guangdong, and Xinjiang. The Shanghai plant is the largest, accounting for 61 percent of Baosteel's steel output.

Although producing high-quality steel products remains its core business, Baosteel also does business in six other areas, including resource development and logistics, steel in-depth processing, engineering technology services, coal chemical engineering, financial investment, and production services. In 2011, Baosteel's net profit was \$2.9 billion, of which the net profit from its core steel business was \$1.2 billion.

Baosteel has several competitive advantages over other steel manufacturers in China. First, it uses the most advanced manufacturing facilities, processing technologies, and automatic control systems, which together enable it to make a wide variety of high-quality products. Second, its large size and leading business position give it bargaining power to acquire raw materials in bulk at lower prices than its competitors. Third, Baosteel has an excellent information technology (IT) infrastructure that allows seamless data communication and data management across the entire enterprise. Since it was established in 1978, Baosteel has taken full advantage of its manufacturing facilities, technological strengths, and bargaining power in the marketplace to maximize its profit. However, until our collaboration, the company had not utilized its IT infrastructure to its full potential. It needed to improve in one critical area: fully leveraging its advanced IT infrastructure to improve its decision-making and operations management capabilities. Baosteel estimated that its operations management and information capabilities indirectly contributed about 10 percent of the total profit from its core steel business (i.e., about \$118 million). Therefore, even a small improvement in its operations management capability could bring significant economic benefits.

Challenges Baosteel Faced

In recent years, fierce global competition and the slowdown of the global economy have resulted in a decrease in steel prices. However, the price of iron ore, and the costs of coal, electricity, water, and transportation have continued to rise, causing the profit margins of companies in the iron and steel industry to shrink. Furthermore, most Chinese iron and steel enterprises have lacked scientific and systematic management methods for production and logistics planning, and have long relied on simple rules and the experience of experts to make complex planning decisions. This has resulted in both frequent late orders and high costs for production, inventory, and logistics. Because of these challenges, iron and steel manufacturing businesses have become less profitable (or unprofitable) for some companies in recent years.

Before our collaboration, Baosteel had been using fairly advanced management information systems to keep relevant order data and necessary information about its production processes. However, these were transactional systems that did not have built-in decision-making capabilities. Baosteel's expert planners had to manually make planning and scheduling decisions based on greedy rules and personal experience, and then type the decisions into the company's manufacturing management system. Because of the large scale and highly complex nature of the underlying planning and scheduling problems, planners usually spent six to eight hours each day in making these decisions. Furthermore, because of the myopic nature of the manual planning methods used, their decisions were often ineffective. Consequently, Baosteel often had low resource and energy utilization, low levels of production and logistics efficiency, and high levels of work-in-process inventory. The company's products frequently had quality problems and its orders were often late. In addition, the planning quality depended highly on the experience and preferences of the individual planners involved. Thus, the production schedule often varied significantly from day to day with little robustness and stability, which resulted in operational inefficiency and increased quality and cost uncertainty. Baosteel realized that to improve its competitiveness in worsening market conditions, it had to shorten its production cycle, decrease work-in-process inventory levels, cut material and energy consumption, reduce production costs, and improve product quality. To achieve these objectives, in 2004 Baosteel started to identify the major bottlenecks of the production process at its Shanghai plant; its goal was to streamline the plant's operations by removing these bottlenecks. It also realized that it had to change how it manages operations and makes decisions. The company started to search for more systematic planning and scheduling methods.

Challenges the Research Team Faced

In 2004, Baosteel invited Professor Lixin Tang, the leader of our research team, to submit a proposal on how to improve its in-plant operations. He proposed that Baosteel use rigorous operations research (OR)-based decision-making approaches to replace its manual planning methods. We developed optimization models and tools in our earlier research in the steel industry (Tang 1999, Tang et al. 2001), and were confident that we could extend these models and tools to enable Baosteel to make better planning and scheduling decisions. However, many people at the company knew little about OR and optimization; they doubted that any optimization-based algorithm could find a better solution than their well-trained and experienced planners, given the complex and large-scale problems they were facing. Most planners were also reluctant to change how they make decisions.

During 2004, we spent considerable time communicating with Baosteel's planners and managers, introducing the OR tools to them, and sharing OR success stories from other steel companies. We also used OR techniques on several of their small-scale research projects, and successfully demonstrated the significant economic benefits that they could achieve by using our decision-making approaches, rather than their manual approaches. This, coupled with the knowledge that an increasing number of international and domestic companies had embraced OR-based decision support systems (DSSs) to improve their productivity, gradually made the planners more receptive to using OR tools and boosted the managers' confidence in OR.

In 2005, Baosteel started systematic collaboration with our research team to streamline its operations across the entire production process at its Shanghai plant through advanced OR techniques. We were tasked with developing effective decision-making tools to handle the planning and scheduling problems in four bottleneck areas within the production process, which the company had identified during a year-long investigation. These four bottleneck areas had significantly affected this plant's production efficiency, the associated production, inventory, logistics, and energy costs, and the quality of its steel products.

To facilitate collaboration, Baosteel formed a project team of experts, including three Baosteel authors of this paper, several planners, and managers. In the following three years (2006–2008), the research team worked closely with the Baosteel team. Each bottleneck area required tackling one or two major decision-making problems. The research team faced several challenges. One challenge was modeling and formulating these problems. Each problem consisted of multiple objectives and complex technology and management constraints. Baosteel was interested in not only maximizing productivity and minimizing costs, but also in maximizing product quality and customer satisfaction. Therefore, even mathematically formulating these problems was not straightforward. Another challenge was developing computationally efficient algorithms to solve these difficult problems. Each problem had characteristics that had not been previously studied in the literature; thus, we could not directly apply or generalize existing algorithms. These problems were technically intractable (i.e., they were strongly NP-hard), and finding optimal solutions for them would be time consuming. They were large-scale problems, some of which had to be solved several times daily. Therefore, we had to be creative in (1) formulating these problems so that the resulting formulations were more tractable and yet closely reflected the issues and complexity of Baosteel's practice, and (2) designing solution algorithms that could generate optimal or near-optimal solutions in a short time.

We developed a number of novel optimization and sophisticated heuristic solution algorithms by exploiting the structures of the problems and taking advantage of their unique characteristics. To guarantee the optimality or near optimality of the solutions for such difficult problems within a reasonable amount of computation time, we used a number of optimization techniques, including branch and bound (B&B), column generation, valid inequalities (cutting planes), variable reduction techniques, very large neighborhood-based metaheuristics, and novel dynamic programming algorithms. We then developed a number of computerized DSSs in which we embedded our algorithms. Baosteel implemented the DSSs at some production lines of its Shanghai plant from 2006 to 2008 to replace its manual planning methods.

During the next three years (2009–2011), we continued working with Baosteel to fine-tune the DSSs and install them at similar production lines of the Shanghai plant. As of this writing, they have been running smoothly for more than two years. Their successful launch has profoundly transformed the company's daily production operations, brought huge economic and other benefits, and helped make Baosteel one of the most competitive steelmakers in the global market.

Next, we describe the scope of the project, the problems we tackled, and the OR solution approaches we developed. We also summarize the DSS implementation and the benefits to Baosteel.

Project Scope

Iron and steel production is a complicated multistage system (see Figure 2), which consists of four major stages—iron making, steelmaking, hot rolling, and cold rolling. In the iron-making stage, raw materials, including iron ore, coke, and limestone, are transformed into molten iron. In the steelmaking stage, the converter first transforms the molten iron into molten steel with the required steel grade of specific customer orders. The continuous caster then transforms the molten steel into slabs, which are dimensioned to meet customer requirements. Sequentially, in the hot-rolling stage, suitable slabs are selected, rolled into steel sheets with the required specifications, and coiled. Finally, the hot-rolled coils are cold rolled into thinner strips and then coiled again. Cold-rolled coils can be used as final products to fulfill customer orders or processed further to make customer-required final products through operations such as batch annealing. Tang (1999) and Tang et al. (2001) provide additional details on the steelmaking process.

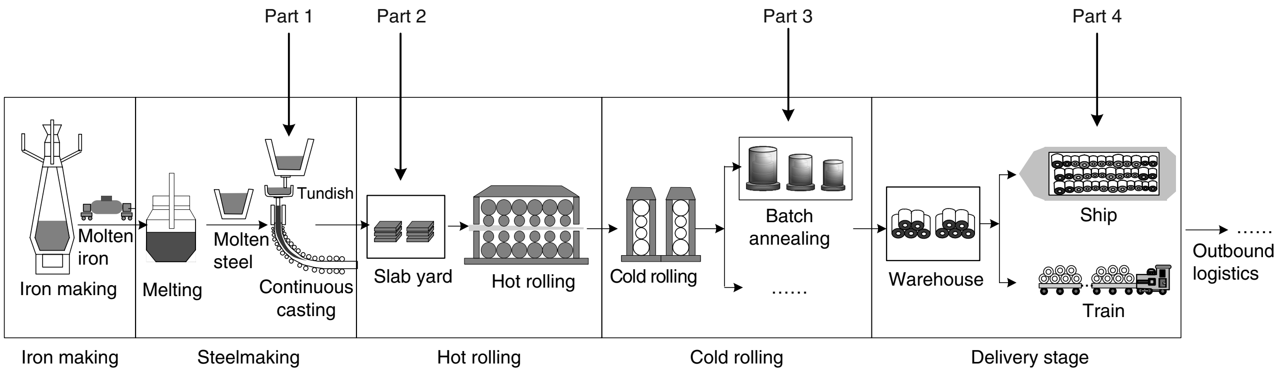

Figure 2: This figure shows four main stages of iron and steel production, the finished-product delivery stage, and the areas of the process we address in the four parts of our OR project.

In the delivery stage, which follows the completion of the production process, the finished steel products are delivered from the plant to nearby ports or train stations for transport to the final customer destinations.

The project consisted of four parts, which we implemented over six years (2006–2011). Each part was a multiyear subproject focusing on one specific area of the steel production and final-product delivery process at Baosteel's Shanghai plant (see Figure 2). Next, we list the corresponding decision-making problems in these four parts, which we illustrate in Figure 3 and describe in detail in later sections.

Part 1: Integrated charge-batching (i.e., batching and sequencing a set of available charges to form casts) and casting-width selection (i.e., selecting a casting width for each charge in a cast) decisions in the continuous-casting operation of the steelmaking stage.

Part 2: Open-order slab-allocation and slab-reallocation decisions in the slab yard of the hot-rolling stage.

Part 3: Coil batching decisions in the batch annealing operation of the cold-rolling stage.

Part 4: Ship-consolidation and ship-stowage planning in the final-product delivery stage.

These four problem areas were an integral part of Baosteel's operations-improvement project. Each area had to be improved to maximize the enterprise-wide benefit. However, because of the complexity and large scale of the decision problems, considering all four problem areas as a unit and solving them as one integrated problem would be unrealistic. In addition, the four areas were physically separated by work-in-process storage areas (e.g., storage yards or facilities), and each problem was relatively independent of the others in terms of the decisions involved. Therefore, we addressed them separately. From an implementation perspective, considering them separately was also beneficial. Making changes in all four areas simultaneously would have been too disruptive to Baosteel's operations.

The decision problems we addressed in this project are more complex than similar problems facing other steel companies. First, Baosteel deals with a larger variety of products, because it seeks to have a specific market share for almost every high-end steel product to keep its leading position in the market. Second, the models we developed for Baosteel jointly consider multiple sets of decisions, whereas most models reported in the literature do not. For example, Baosteel jointly considers charge-batching and casting-width selection decisions to achieve better solutions; in the literature, these decisions are considered separately and sequentially (Chang et al. 2000, Tang and Wang 2008), which can result in ineffective solutions. Third, Baosteel considers multiple objectives, whereas most models in the literature involve a single objective. All of these factors increase the complexity of Baosteel's production and logistics operations problems.

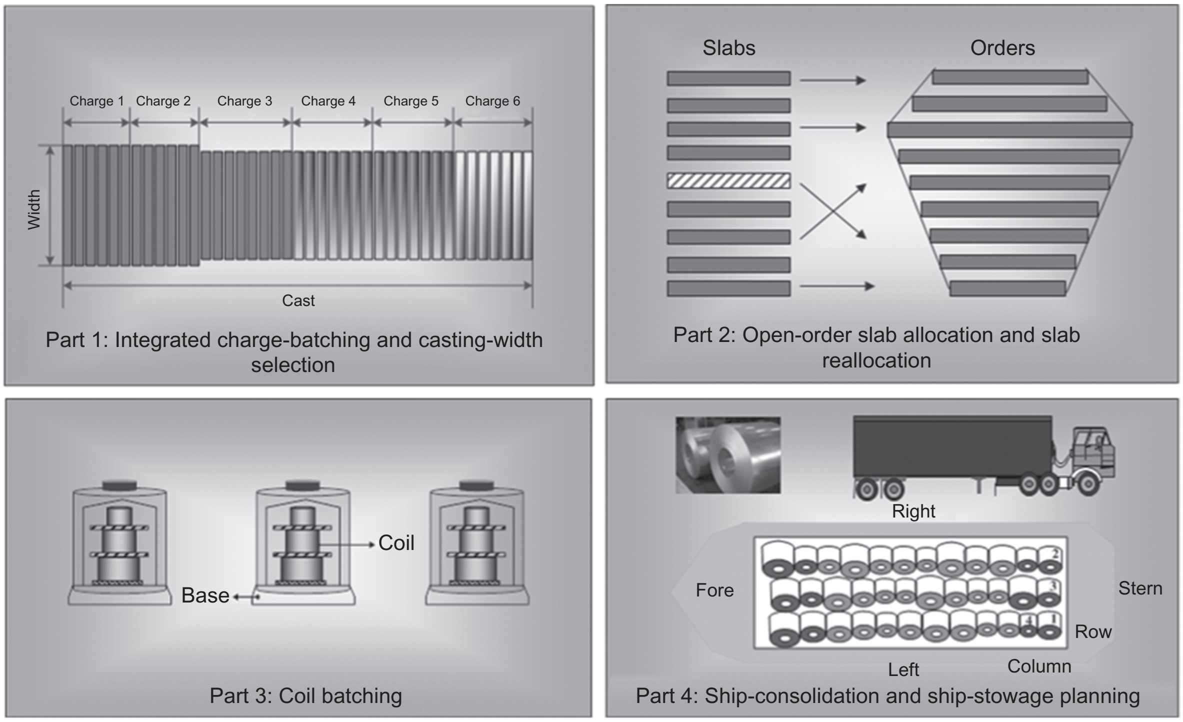

Figure 3: This figure illustrates the decision-making problems in the four parts of this project: integrated charge-batching and casting-width selection, open-order slab allocation and slab reallocation, coil batching, and ship-consolidation and ship-stowage planning.

Integrated Charge-Batching and Casting-Width Selection in the Steelmaking Stage

The steelmaking stage is often the biggest bottleneck in the steel production process. In this stage, the molten iron from blast furnaces is converted at the converter and refining furnace into the molten steel with the required steel grade of specific customer orders. A full furnace or ladle load of molten steel (about 250–300 tons), called a charge, is then transferred to the continuous caster, where molten steel flows from the ladle via a tundish—a broad open container with a pipe emanating from its bottom—into water-cooled copper molds that simultaneously contain it, cool it, and move it forward. The steel strand is completely solidified at the bottom of the continuous caster and immediately cut into slabs of required lengths. The tundish acts as a buffer between the ladle and the continuous caster, so that an empty ladle can be removed and a new, full ladle can be positioned without interrupting the continuous-casting process. Once the heat-resistant material coated at the lining of the tundish is burned out by high-temperature molten steel, the tundish must be replaced by a new tundish. When a tundish is replaced, the caster must be shut down and cleaned; this incurs both a setup time, which varies from one to two hours and results in productivity loss, and a setup cost of about $4,000 to repair the used tundish. To improve productivity and reduce production costs, a steel company must increase the tundish utilization, which is measured as the average number of charges cast in each tundish.

The two main decisions that a steel company such as Baosteel faces in its daily planning for the continuous-casting operations are charge-batching and casting-width selection. As we define previously, charge-batching is batching and sequencing a set of available charges to form casts, one for each available tundish. A cast is a set of charges in the planning level, which is represented by multiple ladles of molten steel consecutively processed in a tundish. Casting-width selection is selecting a casting width for each charge in a cast.

When making these decisions, the company must consider a number of technological constraints and restrictions imposed on the continuous-casting operation. The first constraint, called a grade-switch constraint, requires that only the charges with the same steel grade or compatible steel grades can be consecutively cast within a tundish. In addition, a grade-switch cost is incurred to account for the resulting low-quality slab between the two neighboring charges whenever a charge with one grade is followed by a charge with a different grade. The second constraint, called a width-switch constraint, requires that the width of the nozzle located at the bottom of a tundish can be adjusted at most once per cast and only from the current width to the smaller adjacent width. In addition, a width-switch cost is incurred to account for the resulting low-quality slab between the two neighboring charges whenever a width change occurs. Finally, each tundish lining has a limited life span; hence, the total casting time of the charges processed within a tundish must not exceed this life span.

In addition to maximizing the tundish utilization, Baosteel also wants to maximize product quality by minimizing the total grade-switch and width-switch cost of all the casts formed. These objectives often conflict. In practice, however, the first objective is much more important than the others because repairing a tundish is substantially more expensive than the cost of a grade switch or width switch. Thus, we need to maximize the number of charges packed first, and then minimize the total grade- and width-switch cost. Mathematically, we can do this by combining these three objectives into one by assigning a sufficiently large reward ρ to each charge packed and using the total net reward (total reward minus total grade-switch and width-switch cost) in the objective function.

Baosteel's Shanghai plant has two steelmaking shops (Number 1 and Number 2), which have three and two continuous casters, respectively. These steelmaking shops are managed separately. For each steelmaking shop, Baosteel makes charge-batching and casting-width selection decisions once per weekday for the following day's plans; it makes the decisions for Saturday, Sunday, and Monday on Friday afternoon because the planners are unavailable over the weekend. It makes daily decisions by considering the available tundishes and the available charges generated by solving an order-batching problem, which it considers separately.

The daily integrated charge-batching and casting-width selection problem can be formulated as a mixed-integer program (MIP) (see the appendix). For an average-size practical problem, however, the MIP formulation has about 3,000 binary integer variables, 100 continuous variables, and 3,000 constraints. More than 80 percent of the constraints are conditional constraints used to represent the logical relationship of the finishing times between each pair of adjacent charges within a case. Consequently, the linear programming (LP) relaxation is very weak and the MIP formulation is extremely difficult to solve. A direct commercial MIP solver, such as CPLEX, would fail to solve it to optimality within several hours.

As a result, we chose not to directly use a commercial MIP solver. Instead, we reformulated the MIP model as a set-packing model, which contains an extremely large number of columns but has a very tight LP relaxation, and we developed a column-generation-based B&B exact algorithm for solving the set-packing model. We used the column-generation approach to decompose the LP relaxation of the set-packing model into a much smaller master LP problem and two single-cast subproblems. In each iteration of the column-generation procedure, we first solve a restricted master problem with the columns generated so far. We then efficiently solve the subproblems using dynamic programming algorithms that exploit subproblem structures to generate columns with the most positive reduced costs. We next add the newly generated columns to the restricted master problem and update it. When no new columns with a positive reduced cost can be found in solving the subproblems, the procedure terminates and the LP relaxation is solved to optimality. In addition, we proposed valid inequalities to strengthen the LP relaxation. We designed branching strategies in a way that ensures that after each stage of branching, the structures of the subproblems are preserved. Tang et al. (2012) provide more information on this solution.

We conducted a pilot test based on 14 days of real production (i.e., March 3–March 16, 2006) at the Number 2 steelmaking shop. The computational experiment showed that using our B&B exact algorithm, for every problem instance tested, (1) at most 8,388 columns are generated, (2) the integrality gap is less than 0.07 percent, and (3) an optimal solution is found in less than one minute. However, using the direct MIP solver of CPLEX, the objective value of the best feasible solution obtained in two hours still has 3.73–11.13 percent of gap relative to the optimal objective value. This shows that our B&B exact algorithm is more effective than the direct MIP solver of CPLEX.

Open-Order Slab Allocation and Slab Reallocation in the Hot-Rolling Stage

Slab production is planned based on customer orders. Ideally, the number of slabs produced for an order should be exactly equal to the required quantity of the order. To fully use the capacity of a steelmaking furnace, which is often required because steelmaking furnace capacity is a major bottleneck, slabs for multiple orders may have to be produced together in a furnace by sharing a charge (i.e., a full furnace load) of molten steel. However, because a charge of molten steel can only be used to produce slabs with the same dimension and chemical composition requirements, only orders with the same requirements can be batched together. In the current iron and steel market, orders tend to be large in variety and low in volume. Consequently, the total quantity of the orders that can be batched together to form a charge is frequently not enough to fill up a furnace load. Thus, to fill up the capacity of a furnace, an excess number of slabs, called open-order slabs (i.e., slabs that have not yet been assigned to any orders), may have to be produced together with the customer-order slabs (i.e., slabs that are produced for specific orders). Order cancellations also lead to open-order slabs. Open-order slabs are stored in the hot-rolling slab yard as surplus inventory. Prior to our collaboration, the surplus inventory at the Shanghai plant accounted for one-quarter of the total inventory in the hot-rolling slab yard. The generation of surplus inventory greatly increases production and inventory costs. One way to solve this problem is to allocate open-order slabs to some unfulfilled orders (i.e., the orders whose order quantity is not completely satisfied) whenever possible. This can reduce the surplus inventory, hence saving production costs, and reduce the need to produce new separate slabs for the unfulfilled orders, hence speeding up the completion of these orders.

We call the decision to allocate open-order slabs to unfulfilled orders the open-order slab-allocation problem. In this problem, we must consider a number of matching and allocation constraints. First, Baosteel has a requirement that a slab can be allocated to an order only if the steel grade of the slab is the same as, or compatible with, the grade required by the order, and the slab dimensions (including width, length, and thickness) are in the ranges that the order requires. In addition, if the steel grade or a dimension of a slab differs from the order's requirements, a mismatching cost between the slab and the order will result. Second, because customers usually pay a lower price for the excess slab weight of an order, defined as the weight of the slabs allocated to this order less the required weight of the order, Baosteel requires that the excess slab weight of each order not exceed the weight of the lightest slab allocated to that order. Finally, each slab can be allocated to at most one order. To decrease energy consumption, increase resource utilization, and improve customer satisfaction, Baosteel tries to maximize the amount of allocated open-order slabs, minimize the total weight loss caused by the width and length mismatch of the open-order slabs and the orders (which we call trim loss), maximize the total amount of the hot open-order slabs allocated to the orders, minimize the total excess slab weight of the orders, minimize the number of unfulfilled orders, maximize the proportion of open-order slabs that are allocated to urgent orders, and minimize the mismatching cost between the open-order slabs and their allocated orders.

Steel production is a complex process. In many cases, even a small process variation may cause the slabs produced to deviate from the design specifications of an order to the extent that the slabs cannot be used to fulfill the order. Therefore, in addition to allocating open-order slabs to unfulfilled orders, to improve the matching relationship between the slabs and orders, planners may need to reallocate the customer-order slabs among all the orders on hand. We call this decision problem the slab-reallocation problem.

In the slab-reallocation problem, we consider the same performance measures as in the open-order slab-allocation problem. In addition to the same set of constraints, we must satisfy an additional constraint. All slabs are first rolled into strips at the hot-rolling stage and then processed at different production lines in the cold-rolling stage, based on the customer requirements. To ensure the continuous operation of equipment and to keep balanced production at the cold-rolling stage, the total weights of the slabs flowing through different production lines must be balanced. The total slab weight flowing through each production line cannot exceed a given upper limit. This constraint does not exist in the open-order slab-allocation problem because this constraint arises in the actual production, which starts only after slab-reallocation decisions are made.

Previous studies (Kalagnanam et al. 1998, 2000) consider similar open-order slab-allocation problems. However, they consider only the total weight of allocated slabs and trim loss of slabs in their objectives. The objectives and constraints in our problem are more complex, because the additional production balance constraint in Baosteel's production lines makes the problem different from the ones studied in the previous research.

By assigning (positive or negative) weights to the performance measures and adding them together to form a single objective function, these two problems can be formulated as MIPs. The resulting formulation for the open-order slab-allocation problem has on average about 2.3 million binary integer variables, 2,000 continuous variables, and 12,000 constraints, whereas the formulation for the slab-reallocation problem has on average about 3.5 million binary integer variables, 3,000 continuous variables, and 36,000 constraints. Clearly, directly using a commercial MIP solver to solve these formulations is impossible.

Finding an optimal solution for these problems in a reasonable time is unlikely. Hence, we developed tailored metaheuristics to quickly find near-optimal solutions for them. Based on the matching constraint that the steel grade of a slab should be the same as, or compatible with, the grade required by its matched order, we proposed a steel grade-based decomposition strategy to divide the original open-order slab-allocation problem into several independent subproblems. We then proposed a hybrid heuristic that combines scatter search and variable-depth search to solve the subproblems. In the heuristic, scatter search operates as a diversification mechanism, while variable-depth search provides intensification for further exploration. We developed some strategies to accelerate the search procedure and improve the solution quality. To evaluate the solution performance, we developed a column-generation algorithm to find the lower bound of the problem's objective function by optimally solving the LP relaxation of the problem. Our computational experiment showed only a very small gap between the objective value of the solution obtained by the heuristic and the lower bound, implying that the heuristic is capable of generating near-optimal solutions.

Similarly, for the slab-reallocation problem, we developed a steel-grade-based decomposition strategy that divides the problem into several independent subproblems, which we solve using a tabu search heuristic. To further improve the solution during the tabu search procedure, we proposed an innovative search method based on the neighborhoods generated by a series of pairwise exchanges of slabs in a sequence of assignments to orders. The computational results show that all the tested practical problem instances can be solved in about two minutes, and all the performance measures after reallocation improve significantly over those before reallocation.

Coil Batching in the Batch Annealing Operation of the Cold-Rolling Stage

The batch annealing operation consists of the following steps. First, a batch of coils is loaded onto the empty base of a furnace. Next, the inner cover of the furnace is placed over the coils, a protective gas atmosphere is added to prevent oxidation, and the outer cover of the furnace is loaded. Finally, a series of heating and cooling operations are executed following a temperature control curve. Although each coil has its own ideal annealing curve for achieving quality requirements, only one temperature control curve can be set for batch annealing in a furnace. Therefore, one coil in each batch is selected as the median coil whose ideal annealing curve is used to set the temperature control curve of the furnace.

The decisions the planners must make include selecting suitable coils from the available coils to form batches, each of which will be loaded into an empty furnace for annealing, and selecting one coil in each batch to be the median coil, based on which coil the temperature control curve of the furnace is set. In making these decisions, the following technological constraints must be satisfied. First, the outer diameter of each coil in a batch must be smaller than the inner diameter of the furnace, and the total height of a batch must not exceed the height of the furnace. Second, the coils loaded in the same batch must have similar characteristics in terms of annealing curve, thickness, outer diameter, surface flatness, and steel grade. In addition, a coil-coil mismatching cost is incurred if a coil in a batch has different characteristics than the median coil in the batch. Third, the coils and the protective gas atmosphere in a furnace have matching requirements. A coil-furnace mismatching cost is incurred if a mismatch occurs between the annealing curve index of a coil and the protective gas atmosphere of the furnace.

The most important performance measure in making coil batching decisions is the furnace utilization, which we define as the total weight of coils annealed in a furnace. Higher furnace utilization means less energy and resource consumption for annealing the same set of coils. Hence, furnace utilization should be maximized. Another performance measure is the annealing quality of coils. To ensure that each coil receives the level of annealing required and hence guarantee the quality of annealing coils, the total coil-coil and coil-furnace mismatching cost should be minimized. In addition, Baosteel must consider some management issues regarding customers and internal logistics; these include order due dates, relationships between coils, contract accumulation times, and storage times of coils. We quantify these issues and determine a collective priority value for each coil. Baosteel wants to maximize the total priority value of the coils annealed.

Although most steel companies commonly encounter the coil batching problem, we are not aware of any study in the literature that addresses a coil batching problem with a similar structure to our problem. The literature does not discuss the concept of median coils in a batching problem in the steel production process; this does not mean that nobody has considered this problem; it only means that nobody has published results on it. Our problem can be viewed as a combination of the multiple-knapsack problem and the p-median problem, and inherits the complexity of both problems.

Baosteel runs three shifts in a workday. Coil-batching decisions are made once per shift for the batch annealing production in the next shift. New coils come in and new furnaces become available continuously. Such new information is incorporated into the next coil-batching decision problem to be solved. The unfinished work that began in an earlier shift will continue in the later shifts. Depending on the market demand for batch-annealed coils, two demand seasons occur each year—low-demand and regular seasons. The low-demand season lasts about four months, including a period of approximately one month (usually from mid-January to mid-February) that covers the Chinese Spring Festival, and the three-month quiet season of the automobile industry (July, August, and September). The remaining eight months are the regular-demand season. During this season, about 100–300 coils and 8–30 available furnaces need to be considered for each shift.

By combining the multiple-objective functions using weights and treating them as a single objective function, we can formulate the coil-batching problem as a binary integer program. The formulation for the regular-demand season has about 100,000 binary integer variables and 40,000 constraints. A commercial IP solver, such as CPLEX, cannot deal with such large-scale instances because of memory overflow. Even for the formulation during the low-demand season, the commercial IP solver cannot find an optimal solution within two hours. This motivated us to design specialized solution methods to solve it.

To solve the problem for the low-demand season, we developed a column-and-row generation-based B&B exact algorithm. This algorithm involves a different set of techniques than the ones used in the algorithm for solving the integrated charge-batching and casting-width selection problem in the first part of the project. The pilot test results showed that the average computation time to solve the problem instances with a practical size (about 80 coils and eight furnaces) in the low-demand season was about 17 minutes. However, solving some difficult instances could take more than two hours, which would exceed Baosteel's maximum allowable planning time (i.e., two hours). Hence, we had to develop new strategies to improve the computational efficiency. By exploring the problem structure, we proposed some valid inequalities to tighten the LP bound during the column-generation procedure so that in each iteration of the procedure, columns and rows are generated alternately until no column or row can be generated. The introduction of the row-generation procedure significantly reduces the integrality gap. Consequently, it reduces the number of B&B nodes that need to be explored and shortens the computation time. We also employed a variable reduction strategy to identify columns that can never be included in the optimal solution. The strategy effectively reduces the solution space and thus further reduces the run time of the algorithm. After we applied these techniques, the average computation time needed to optimally solve the problem instances with a practical size in the low-demand season decreased from 17 minutes to six minutes—a reduction of 65 percent.

The coil-batching decisions in the regular season typically involve up to 300 coils and 30 furnaces, making it impossible to optimally solve this difficult large-scale problem in a short time. Therefore, we designed a tailored tabu search heuristic to obtain near-optimal solutions for the problem, and developed three simple search neighborhoods and a sophisticated variable-depth neighborhood-search strategy. The computation time of the tabu search heuristic is always less than three minutes for all test instances with a practical size in the regular-demand season. The average gap between the solution obtained by tabu search heuristic and the upper bound is only three percent.

Ship-Consolidation and Ship-Stowage Planning in the Final-Product Delivery Stage

Because of large volume and heavy tonnage, steel products are transported to customer sites by ship or by train wherever possible. At Baosteel's Shanghai plant, more than 50 percent of the steel coils are transported by ship to customers at different destination ports. For each arriving ship, Baosteel must develop a two-phase loading plan. In the first phase, planners select the final coil products from the warehouse to be delivered to customers according to the destinations of available ships, required quantities and due dates of customer orders, and positions of the coils in the warehouse. We call this decision problem the ship-consolidation planning problem. Its objectives are to maximize the loading rate of the ships and minimize the number of destinations of each ship, the number of late orders, and the number of shuffling operations in the warehouse. In addition to the capacity constraint of the ships used, Baosteel requires that some finished coils belonging to the same order must be simultaneously transported to the terminal. The coils selected in the ship-consolidation planning problem are transported from the final-product warehouse to the storage yard of the terminal. We can view this problem as a knapsack problem with complex constraints; hence, it is NP-hard. No such practical consolidation problems have been previously reported in the literature.

In the second phase, for a given set of coils to be loaded onto a ship, planners need to decide the position of each coil on the ship, and consider all the necessary constraints, such as the weights and diameters of coils and the balance of the ship. We call this decision problem the ship-stowage planning problem. Its objectives are to minimize the moment imbalance of the ship, the total number of shuffling operations that will be needed for unloading, and the dispersion of coils for the same destination, considering the following Baosteel structural and operational restrictions: (1) coils at the lower layer in each row must be placed from the stern to the fore with no space between adjacent coils, and the sum of diameters of coils at the lower layer in each row cannot exceed the length of the ship; (2) the width, diameter, and weight of a coil at the upper layer cannot exceed those of any of the two coils underneath it; (3) to keep stability, the sum of the moment contributions of coils along the length of the ship and across the width of the ship, respectively, must be within a given small range, which is near zero.

Most existing research on ship-stowage planning focuses on container ships. The cylindrical shape of steel coils makes stowage planning for these coils different from that of rectangular containers. Few studies (Hvattum et al. 2009) on ship-stowage planning problems involve cargos with a cylindrical shape. Because of the nature of the cargo considered, these studies do not consider stacking and shuffling. Instead of using estimated distances to calculate the moment, we created a new method to calculate the moments of the coils using precise distances.

Each workday, about a dozen ships arrive at the port that the Shanghai plant uses. Each arriving ship requires a consolidation plan and a stowage plan. Hence, the ship-consolidation problem and the ship-stowage problem are solved about 12 times per workday.

We formulated the ship-stowage planning problem as a MIP and derived five valid inequalities to tighten the problem. We tried to solve the resulting formulation using the CPLEX MIP solver, and found that we could obtain optimal solutions within acceptable times only for instances of small and medium sizes. The computation time to solve the models increases exponentially with the number of coils. For instances with a practical size (e.g., 200 coils), the MIP formulation of the stowage planning problem is very large; on average, it has about 80,000 binary integer variables, 1,000 continuous variables, and 90,000 constraints. This motivated us to develop effective metaheuristics to obtain near-optimal solutions in a short time. We developed a tabu search algorithm with a tabu list of variable length. We first use an optimality property to construct a heuristic for generating an initial solution. Then, we use shift moves (i.e., moving a loaded coil to an available position) and ring-swap moves (i.e., swapping several coils with correlative coils) to improve the initial solution within the framework of the tabu search. For further improvement, we use two acceleration strategies to accelerate the search procedure.

We formulated the ship-consolidation planning problem as a pure integer program. For instances with a practical size (i.e., about 20,000 coils), this problem has about 20,000 binary variables and 20,000 constraints on average. We found that solving it with a commercial solver is also impossible. Therefore, we developed a hybrid metaheuristic, which combines variable-depth search and scatter search, to solve it. The computational results on the practical instances show that the proposed hybrid intelligent search algorithm can solve the problem within one minute.

Implementation of the Decision Support Systems

As we mention previously, before we started this project, Baosteel's Shanghai plant already had a sophisticated management information system. Human-machine interactive editors allowed Baosteel's expert planners to manually make planning and scheduling decisions, based on greedy rules and their experience, by entering their decisions into the management information system. A major goal of our collaboration with Baosteel in this project was to streamline its decision-making processes and replace the manual planning approaches by optimization-based DSSs. In this project, we developed four DSSs, one for each of the four parts of our project. We developed all the DSSs in the Microsoft Visual C++ 6.0 integrated development environment, coded the optimization algorithms for all the planning problems in C++, and solved all the LP problems with the LP solver of IBM CPLEX.

To protect the management information system security and to make our DSSs portable, our DSSs neither replace Baosteel's management information system nor are imbedded within it. Instead, they run on top of it through a data interface. Each DSS consists of similar functional modules and includes separate modules for data downloading, technological data management, parameter configuration, optimization, human-machine interactive editing, and data uploading (see Figure 4). The main difference among the four DSSs is that they call different optimization solvers, which we have customized for different planning problems using different algorithms.

We keep our DSSs and the management information system separate and link them through a data interface; therefore, they are highly portable and can easily link to the existing information systems at Baosteel's other plants. Other steel companies in China face similar daily operational challenges to those we describe for Baosteel's Shanghai plant. Therefore, these steel companies could readily use these DSSs by modifying the company-specific parameters for some functional modules.

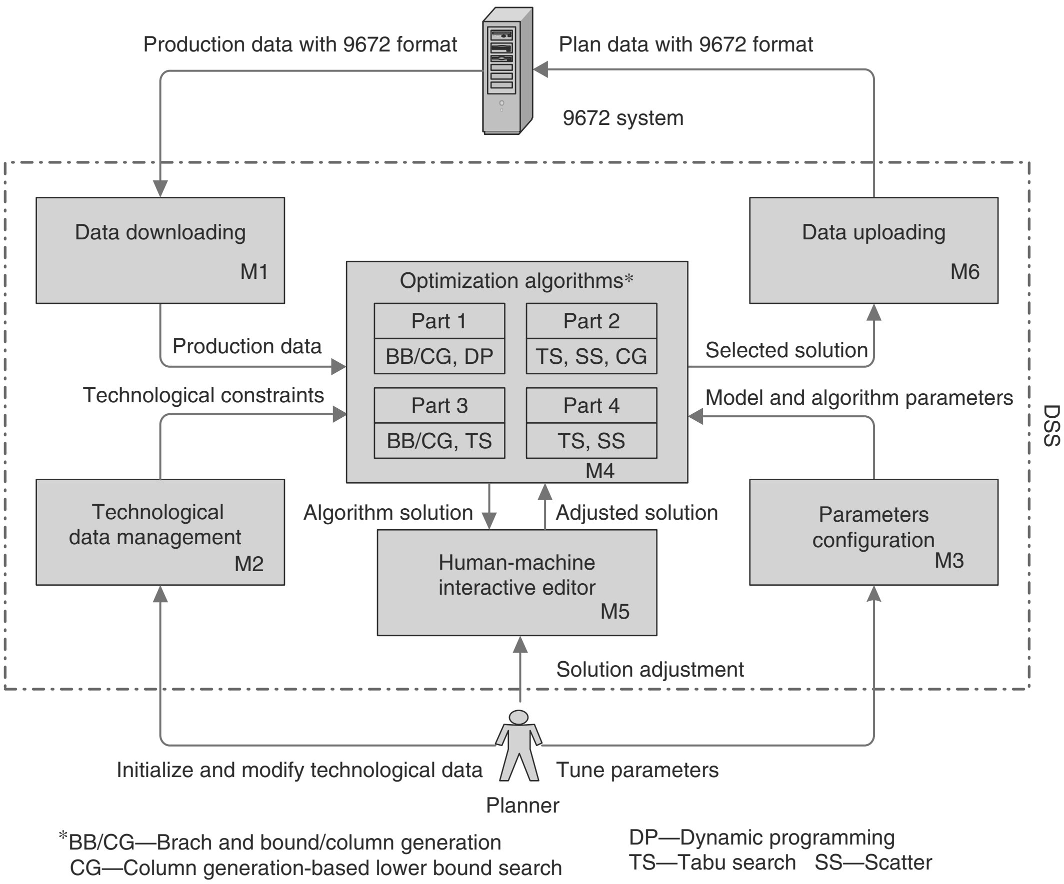

Figure 4: Each DSS consists of similar functional modules; however, we use different algorithms to optimize each of the four parts. The DSSs are built on top of Baosteel's previously existing 9672 management information system.

Each DSS consists of six modules (see Figure 4), and each has a specific function, as we describe next.

(1) The data downloading module is the data interface between the DSS and the management information system. When using the DSS for daily planning, the production data (e.g., information about orders, charges, slabs, coils) is downloaded from the management information system and uploaded to the DSS each day through this module.

(2) The technological data management module is used to initialize, add, update, or delete some of the infrequently updated data related to production technology (e.g., steel grades, casting widths, steel-grade compatibility, furnace capacity, tundish lining life span). Such data rarely change, but can be dynamically updated whenever necessary.

(3) The parameters configuration module is used to tune the values of some parameters in the mathematical models and algorithms. We collaborated with Baosteel's expert planners to tune these parameters to ensure that the models closely reflect practical technological restrictions and management requirements. In addition, for some metaheuristics such as tabu search, the algorithm parameters (e.g., tabu list length, population size, aspiration criteria) are also tuned in this module.

(4) The optimization algorithms module is the engine of the DSS in which our solution algorithms reside. Its task is to generate optimal or near-optimal solutions for a particular planning problem.

(5) The human-machine interactive editor module is a graphical interface in which the solution can be

displayed in both visual graphics and data tabulation format. This editor allows the planners to evaluate and modify a solution according to their personal experience and preferences.

(6) The data uploading module is a data interface that converts the resulting solution data into the management information system-defined format and then uploads the data to the management information system.

We developed and implemented the four DSSs at various production lines and related sites of the Shanghai plant across a six-year period, 2006–2011.

Impact and Benefits

The successful implementation of the DSSs using advanced OR techniques has transformed Baosteel's operations across its entire production process and final-product delivery from its plant to ports, thus bringing significant tangible and intangible benefits to the company.

In today's volatile steel market, in which many steel companies operate on a slim profit margin or even at a loss, Baosteel's steel output and net profit continue to grow at a steady rate. This can be attributed not only to Baosteel's use of advanced manufacturing equipment and production technology, but also to its adoption of advanced OR-based planning tools, which result in significantly improved operational efficiencies. Next, we elaborate on the various benefits associated with using the DSSs.

Tangible Benefits

We can quantify the monetary impact of this project based on a number of key performance measures. Baosteel estimates that from 2007 through 2012, the DSSs at the Shanghai plant have provided a cumulative benefit of $77 million. Based on their current usage at this plant, Baosteel also estimates that they will continue to provide an annual economic benefit of $20 million. As previously mentioned, Baosteel's IT and operations management contribute almost 10 percent of Baosteel's annual profit of $1.2 billion from the steel business (i.e., $118 million). Therefore, the current estimate of the annual economic benefit of the DSSs ($20 million) represents a 17 percent improvement in Baosteel's IT and operations management capability. As a result of the substantial benefits that the DSSs have brought, Baosteel plans to extend and implement them at its other plants in the next several years; it estimates that this will result in an annual economic benefit of more than $50 million.

Table 1 summarizes the cumulative direct and indirect economic benefits that the DSSs have provided in the impacted areas of the production process from 2007 through 2012. We calculate the direct economic benefits based on the improvement of technical measures that have a direct impact on cost or revenue (e.g., increased tundish utilization, increased production rate, reduced scrap steel), and the indirect economic benefits based on the improvement of technical measures that have an indirect impact on cost or revenue (e.g., improved product quality, reduced inventory space usage).

The use of the DSSs has also significantly reduced the time that planners spend in making decisions (see Table 2). The improved planning efficiency allows planners to spend more time doing what-if analyses to gain meaningful managerial insights.

Other tangible benefits include an annual reduction of 293,967 tons of standard coal consumption, an annual reduction of 585,770 tons (or equivalently 12 percent) of carbon dioxide emissions, and a nine percent reduction in inventory.

Baosteel calculated the tangible benefits previously reported based on the actual improvement of corresponding technical measures, such as increased tundish utilization, reduced scrap steel, increased charging rate, and reduced trim loss.

Intangible Benefits

The use of OR-based planning tools has also provided Baosteel with benefits that are difficult to quantify,

DSSs	Production line	Total direct economic benefits (million $)	Total indirect economic benefits (million $)	Total economic benefits (million $)
DSS for part 1	Steelmaking shops	14.73	1.92	**16.65**
DSS for part 2	Hot-rolling lines	43.41	0.75	**44.16**
DSS for part 3	Batch annealing line	11.00	0.80	**11.80**
DSS for part 4	Final-product warehouse	4.20		**4.20**
Total		73.34	3.47	**76.81**

Table 1: Baosteel estimates the cumulative economic benefits it gained from using the DSSs from 2007 through 2012 to be about $77 million.

Decision problems	Computation-time comparison (for an average-size problem instance) Manual methods	DSSs	Efficiency improvement
Part 1	1 hour	$\leq$2 minutes	About 30 times
Part 2	7 to 10 hours	$\leq$15 minutes	About 40 to 56 times
Part 3	3 hours	$\leq$8 minutes	About 22 times
Part 4	5 hours	$\leq$10 minutes	About 30 times

Table 2: Replacing Baosteel's manual planning methods with the DSSs has improved the efficiency of Baosteel's planning process by more than 30 times, on average.

but are equally (or even more) important from a long-term perspective. Next, we summarize these intangible benefits.

• Improved product quality and customer satisfaction. Increased customer satisfaction has helped Baosteel enhance customer loyalty and grow market share, benefits that are strategically important in the long run.

• Reduction in Baosteel's annual carbon dioxide emissions and hence its environmental impact. This sends an important message to China's steel industry, which has been one of the major industries responsible for pollution and other environmental problems in China. Baosteel has demonstrated that by using OR-based operations management tools, it can improve its profitability and also reduce its environmental impact.

• Increased understanding of the important role that OR-based models and planning tools play in daily production and logistics operations planning at Baosteel. Its planners have changed from being skeptical about OR to fully embracing it. This project has been a great learning experience for everyone involved. Baosteel learned about the true value of OR, and the research team gained additional real-world experience.

• Baosteel's realization that it must maximize operational efficiency to stay competitive. By replacing its decades-old rules and experience-based manual planning methods with computerized DSSs, the company is starting to embrace rigorous scientific operations management approaches to improve its planning and operations management capability. This change in management culture is undoubtedly the biggest benefit that this project has given Baosteel.

• Positive external impact. As a large, well-respected state-owned company and a role model for other steel companies in China, Baosteel's initiatives and practices will attract the attention of other Chinese companies. Many Chinese companies rely on simple rules and expert opinions to make planning decisions. Baosteel's success story is likely to motivate other Chinese companies to adopt more systematic OR-based planning tools to improve their profitability. The optimization models and algorithms that we have developed in this project can be almost directly applied to similar problems at other steel companies.

Conclusion

In the six years of close collaboration between Baosteel and the research team, this project has transformed the production process at its Shanghai plant and made a significant impact on the plant's operational efficiency, product quality, energy and resource consumption, and environmental footprint. The DSSs we developed will continue to improve Baosteel's operations management capability and enhance its competitiveness. The successful adoption of our OR-based planning tools could also have a positive impact on other steel and nonsteel manufacturing companies in China who face similar problems. This project is an example of how OR can successfully solve complex real-world problems and create value.

Appendix. The Mixed-Integer Programming Formulation for the Integrated Charge-Batching and Casting-Width Selection Problem

The MIP formulation consists of the following components.

Parameters

$N = \{1, 2, \ldots, n\}$, the set of charges.
$m =$ the number of available tundishes.
$G =$ the set of steel grades involved.
$R =$ the set of possible casting widths.
$g_i =$ the steel grade of charge $i \in N$.
$R_i = \{l_i, l_i + 1, \ldots, u_i\}$ the set of possible casting widths for charge $i \in N$.
$G_k =$ the set of steel grades that are compatible with grade k.
$T =$ the tundish lining's life span.
$t_j =$ the casting time of a charge using width j.
$\Gamma_j = \{i \in N \mid l_i \leq j \leq u_i\}$, the set of charges for which j is an allowable casting width.
$\Delta^+_{ij} = \{h \in \Gamma_j \backslash \{i\} \mid g_h \in G_{g_i}\}$, the set of charges h that can be sequenced immediately before charge i in a cast where both charges i and h use width j.

$\Delta_{ij}^{-} = \{h \in \Gamma_j \backslash \{i\} \mid g_h \in G_{g_i}\}$, the set of charges h that can be sequenced immediately after charge i in a cast where both charges i and h use width j.

$\Pi_{ij}^{+} = \{h \in \Gamma_{j+1} \backslash \{i\} \mid g_h \in G_{g_i}\}$, the set of charges h that can be sequenced immediately before charge i in a cast where charge h uses width $j+1$ and charge i uses width j.

$\Pi_{ij}^{-} = \{h \in \Gamma_{j-1} \backslash \{i\} \mid g_h \in G_{g_i}\}$, the set of charges h that can be sequenced immediately after charge i in a cast where charge i uses width j and charge h uses width $j-1$.

$\alpha_{kk'} =$ the grade-switch cost between adjacent charges associated with grades k and k'.

$\beta =$ the width-switch cost.

$\rho =$ the reward for packing a charge.

$BigM =$ a large positive constant.

Decision variables

$x_{hij}^{1} = 1$ if charge h is sequenced immediately before charge i, and both h and i use width j, 0 otherwise.

$x_{0ij}^{1} = 1$ if charge i is the first charge in a cast and uses width j, 0 otherwise.

$x_{i0j}^{1} = 1$ if charge i is the last charge in a cast and uses width j, 0 otherwise.

$x_{hij}^{2} = 1$ if charge h using width $j+1$ is sequenced immediately before charge i using width j, 0 otherwise.

$y_j^1 =$ number of casts using one width j.

$y_j^2 =$ number of casts using two widths $(j+1, j)$.

$Q_i =$ the time when charge i finishes dispensing from a tundish.

Objective Function

Maximize the total reward of packed charges minus the total grade-switch cost and total width-switch cost:

$$\rho \sum_{i\in N}\sum_{j\in R_i}\left(\sum_{h\in\Delta_{ij}^{+}\cup\{0\}} x_{hij}^{1} + \sum_{h\in\Pi_{ij}^{+}} x_{hij}^{2}\right) - \sum_{i\in N}\sum_{j\in R_i}\left(\sum_{h\in\Delta_{ij}^{+}} \alpha_{g_h g_i} x_{hij}^{1} + \sum_{h\in\Pi_{ij}^{+}} \alpha_{g_h g_i} x_{hij}^{2}\right) - \beta\sum_{j\in R} y_j^2. \quad (1)$$

Constraints

Assignment constraint requires that each charge is assigned to at most one cast:

$$\sum_{j\in R_i}\sum_{h\in\Delta_{ij}^{+}\cup\{0\}} x_{hij}^{1} + \sum_{j\in R_i}\sum_{h\in\Pi_{ij}^{+}} x_{hij}^{2} \le 1, \quad i \in N. \quad (2)$$

Flow conservation constraint is similar to that of typical network problems:

$$\sum_{h\in\Delta_{ij}^{+}\cup\{0\}} x_{hij}^{1} + \sum_{h\in\Pi_{ij}^{+}} x_{hij}^{2} = \sum_{h\in\Delta_{ij}^{-}\cup\{0\}} x_{ihj}^{1} + \sum_{h\in\Pi_{i,(j-1)}^{-}} x_{ihj}^{2}, \quad j \in R,\ i \in \Gamma_j. \quad (3)$$

Variables relationship constraint to ensure that the number of times that a charge is sequenced at the first position of a cast and uses width j is equal to the number of casts using one width j and using two widths $(j, j-1)$:

$$\sum_{h\in\Gamma_j} x_{0hj}^{1} = y_j^1 + y_{j-1}^2, \quad \forall j \in R. \quad (4)$$

Variables relationship constraint to ensure that the number of times that a charge is sequenced at the last position of a cast and uses width j is equal to the number of casts using one width j and using two widths $(j+1, j)$:

$$\sum_{h\in\Gamma_j} x_{h0j}^{1} = y_j^1 + y_j^2, \quad \forall j \in R. \quad (5)$$

Variables relationship constraint to ensure that the number of times switching from width $j+1$ to j is equal to the number of two-width casts using widths $(j+1, j)$:

$$y_j^2 = \sum_{h\in\Gamma_j}\sum_{i\in\Pi_{hj}^{-}} x_{hij}^{2}, \quad \forall j \in R. \quad (6)$$

There are m tundishes available:

$$\sum_{j\in R}\sum_{h\in\Gamma_j} x_{0hj}^{1} = \sum_{j\in R}\sum_{h\in\Gamma_j} x_{h0j}^{1} = m. \quad (7)$$

Logical relationship of the finished times between each pair of adjacent charges within a cast:

$$Q_i \ge t_j + (x_{0ij}^{1} - 1)BigM, \quad \forall j \in R, i \in \Gamma_j, \quad (8)$$

$$Q_i \ge Q_h + t_j + (x_{hij}^{1} - 1)BigM, \quad \forall j \in R, h \in \Gamma_j, i \in \Delta_{hj}^{-}, \quad (9)$$

$$Q_i \ge Q_h + t_j + (x_{hij}^{2} - 1)BigM, \quad \forall j \in R, h \in \Gamma_{j+1}, i \in \Pi_{hj}^{-}. \quad (10)$$

Nonnegativity and integrality requirements for variables:

$$0 \le Q_i \le T, \quad \forall i \in N, \quad (11)$$

$$x_{hij}^{1}, x_{i0j}^{1}, x_{i0j}^{1} \in \{0, 1\}, \quad \forall j \in R,\ i \in \Gamma_j,\ h \in \Delta_{ij}^{+}, \quad (12)$$

$$x_{hij}^{2} \in \{0, 1\}, \quad \forall j \in R,\ h \in \Gamma_j,\ i \in \Pi_{hj}^{-}, \quad (13)$$

$$y_j^1, y_j^2 \ge 0, \quad \forall j \in R. \quad (14)$$

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