Operations Research application technology

Decision Support Technology for Controlling Complex Manufacturing (Operations Research Technology)

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Abstract

Kobe Steel has developed its unique decision support technology based on Operations Research (OR) to manage quality, cost, and delivery (QCD) in complex manufacturing processes. In recent years, the scope of decision- making in manufacturing has expanded from single factories to interconnected networks of companies within supply chains, extending to considerations beyond QCD, including environmental impact. In such complex business ecosystems, the importance of decision support technology, or OR, as a foundation for creating new value has grown. This paper explains the foundational technologies that constitute decision support technology and their roles in KOBELCO's manufacturing processes. It also describes the value and possibilities offered by decision support technology through solutions developed for actual manufacturing facilities.

Introduction

The steel industry has always been a trailblazer in the use of computers in manufacturing.[1)] Kobe Steel in particular began using mainframe computers to optimize complex, large-scale steel mill operations in the 1970s. Initially, the objective was to optimize production planning in terms of individual processes such as steelmaking operations and docking operations in logistics. As processing power improved, computers made their way into production planning involving interrelated processes, devising plans entailing a level of complexity beyond what the human mind could process. The ability to simulate changes in production and logistics also brought computers into the processes of capital expenditure evaluation and logistics operation design.

Kobe Steel provides technology, products, and services in a wide range of fields. However, we operate on a relatively small scale in terms of our individual businesses compared with our competitors. Many manufacturing operations involve high-mix, mixed-model production, wherein a variety of products is manufactured on a limited number of production lines. Safeguarding QCD (quality, cost, delivery) under complex conditions necessitates scrupulous, data-driven decision making regarding capital expenditure, logistics, and production planning. This drove Kobe Steel to develop decision support technology based on the company's operations research (OR) technology in line with the group's business model.

Additionally, recent progress in digitalization and globalization has made the companies that make up supply chains increasingly intertwined, and in more complex ways. Against this backdrop is a growing desire to share and use data to optimize business ecosystems in ways that no individual company can achieve alone. Indices regarding what constitutes "optimal" have become multidimensional, supplementing the conventional factors of QCD with metrics for contributions to safe and secure manufacturing and a green society.

Today's manufacturing environment is complex and varied. Kobe Steel's decision support technology (OR technology) serves as a foundation for optimizing manufacturing in this environment through collaboration between our company, our partners, and our customers. This technology also adds value to society by using data to support the decision-making needs of various stakeholders.

This paper covers Kobe Steel's fundamental technologies that make up the decision support technology developed. Examples of this technology in use, demonstrating its practical value, are also covered alongside its future possibilities.

1. Overview of decision support technology (OR technology)

This section provides an overview of our decision support technology (OR technology).

Products go through a multitude of processes on their way through a factory. Mathematical models define the sequences and constraints of these processes in terms of formulas and rulesets. OR technology supports decision making by deriving optimal production conditions from mathematical models, or by predicting and evaluating future conditions based on chosen parameters. The former is mathematical optimization technology, and the latter is simulation technology.[2)]

1.1 Mathematical optimization technology

Mathematical optimization defines a set of decision variables that minimizes or maximizes an objective function based on given constraints and the search space (domain).

Linear programming models are one subset of mathematical optimization. Such models involve continuous variables (e.g., length, quantity), and their objective function and constraint equations have linear relationships. An example application of a linear programming model is that of defining the mixing ratios of raw materials (decision variables) so as to minimize cost (objective function) while adhering to quality specifications (domain). The range of applications for linear programming models is wide, including product configuration, personnel allocation, and inventory planning. Extensive research has been conducted to develop algorithms that can find optimal solutions within a reasonable time.

In the production planning activities of the metal industry, and thus within Kobe Steel, the main decision variables such as lot structure and processing sequence are discrete values. As such, the applicable optimization method is combinatorial optimization, which searches for an appropriate combination of decision variables. Combinatorial optimization generally cannot find the optimal solution in a reasonable time, necessitating an efficient search method that finds a suboptimal combination tailored to the characteristics of the problem. True optimization cannot be guaranteed, however. Furthermore, real-world operations entail constraints related to quality control and production equipment that are challenging to describe as mathematical models using formulas, even if they can be described in rules.

In developing mathematical optimization technology, Kobe Steel has constructed modeling and search methods coordinated to the characteristics of our manufacturing operations, such as high-mix, mixed-model production. We have combined these methods with methods that express constraint judgments and objective functions in a virtual operating model, or simulator, yielding an approach that is realistic and has high expressive power.

The heat treatment planning process for throws, a main component of the built-up type crankshaft in **Fig. 1**,[3)] involves defining the heat treatment timeframe (batch slot) for each heat treatment furnace. Combinatorial optimization determines the batch slot each throw is allocated to. Batch slot allocations and the arrangements in the furnace are based on a complex set of considerations. For instance, differences in throw size, whether throws can be stacked in the furnace, and constraints on positioning from a quality perspective are all critical factors. A provisional allocation plan for batch slots is determined first (top left of the figure). A simulator then determines the optimal furnace layout that satisfies the constraints (right). The weighted sum of heat treatment process deadline delays and energy intensities is evaluated as an objective function based on these results (bottom left). A new combination of throw allocations is explored, reinitiating a cycle that iteratively searches for the optimal heat treatment plan.

1.2 Simulation technology

Simulation technology can be used to predict and evaluate changes related to the decision variables of a problem. For example, mathematical models can predict changes in targets when there are changes to equipment, production plans, or staffing, or during the establishment of facilities. These results are then used to determine the suitability of various change proposals.

The hypothetical steelmaking plant in **Fig. 2** serves as an aid in explaining an example application of simulation technology.[4)] This plant has charging facilities for moving molten iron from the torpedo car to the ladle as well as a desulfurization

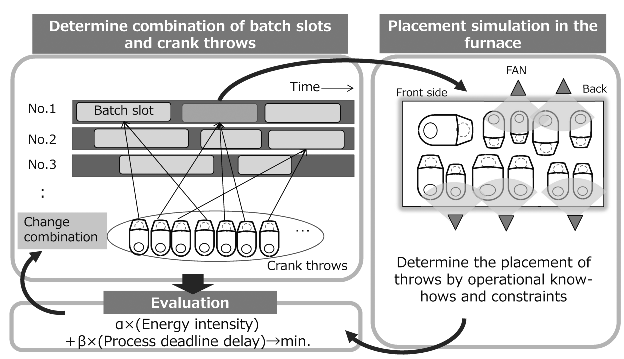

Fig. 1 Optimization of batch slot combination

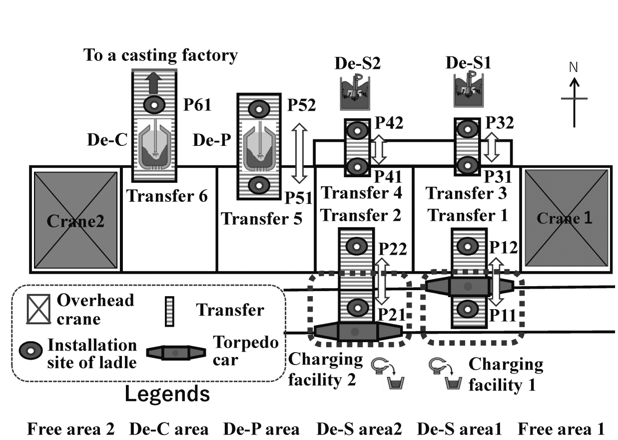

Fig. 2 Layout of steelmaking plant for example study

facility (De-S), a dephosphorization facility (De-P), and a decarbonization facility (De-C). Molten iron progresses through the facility in this order, the molten iron ladle being transported between facilities by crane.

The first step in setting up the simulator is to describe the operating conditions and processing times of each facility as rules, which are then treated as decision variables. Rules include the processing sequence, the status of the ladle at each facility, and constraints on transfer equipment such as cranes. An additional factor is that processing time is inconsistent. For example, the charging time when transferring molten iron to the ladle fluctuates based on the equipment, with a time distribution that has one peak when supplying the molten iron from one torpedo car and another when supplying it from two torpedo cars. A simulator based on this descriptive model calculates objective variables, such as the average tapping interval, a metric of productivity. This determines whether a facility's decision variables are achieving targets. If they are not, the simulator can analyze alternatives and can rank these alternatives by effectiveness.

There are two ways of applying simulation technology. The first is as a computational model, in which objective variables are derived from decision variables as one element of finding the optimal solution. The example in the previous section constitutes this type of application. The second is as a way of analyzing simulated results related to issues such as expanding facilities or improving operations to achieve targets. The immediately preceding example constitutes this type of application. When constructing a large-scale facility, it is not possible to determine the solution to every challenge in the initial stage of the project. However, sharing simulated results based on certain assumptions with all stakeholders makes it possible to iteratively analyze simulated conditions. This supports decision making in designing the operating conditions of Kobe Steel's built-for-purpose production facilities.

2. Example applications of decision support technology (OR technology)

This section introduces case studies in which decision support technology (OR technology) effected change in Kobe Steel's manufacturing processes and business models.

2.1 Allocation guidance system for steel wire rod and bar[5)]

In 2017, Kobe Steel consolidated the upstream processes of the Kakogawa and Kobe steelworks into Kakogawa Works. Alongside the restructuring, we introduced an "inventory replenishment" system into the process, in which semi-finished goods such as billet are first produced at Kakogawa Works, then transferred to Kobe Works (Kobe Wire Rod & Bar Plant of Kakogawa Works), and then allocated to production orders from stock. This operational transition entailed a fundamental shift in the nature of specialty wire production. Instead of the small-lot production of Kobe Works, these products would be manufactured in large lots with minimal semi-finished goods inventory. As such, new production management technology was needed.

Fig. 3 outlines the allocation guidance system and allocation optimization technology developed. Billet manufactured at Kakogawa Works (left side of the figure) is transferred to Kobe Works (right), where it is held as semi-finished goods for later allocation to production orders. Billet inventory is divided into lots of a few pieces to dozens of pieces, delineated not only by steel type, but also by

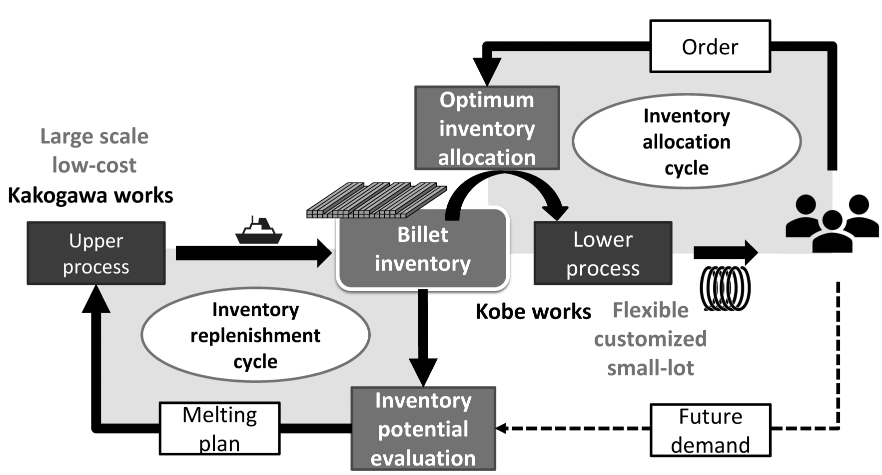

Fig. 3 Overview of inventory allocation guidance system

factors including casting time, weight, composition, and surface quality. Each production order has specifications related to these conditions, which determines which lots can be allocated to which orders. Billet is allocated to orders from stock (top right), and production planning for subsequent billet production is based on the remaining stock (bottom left). However, it takes time for the billet to be replenished from Kakogawa. As such, allocation is an issue of combination optimization, requiring fulfillment of current orders with existing inventory and maximal ability to respond to future orders with remaining inventory (i.e., inventory potential).

The optimization method of our system uses two indices: (1) current-order allocation fraction and (2) future-order inventory potential. The system combines two search concepts: (1) global search, which searches for a combination that prioritizes the current-order allocation fraction, and (2) local search, which optimizes the results of the global search to improve future-order inventory potential.

During implementation, we started with a global search to find a solution that could handle the current order. We then ran a local search to find a neighborhood solution that would improve inventory potential. The result was a practical solution that could be implemented within a reasonable time.

This system made it possible to link the economical, high-volume upstream process at Kakogawa Works to the small-lot special wire rod production of Kobe Works via billet inventory. In turn, we can now guarantee the supply of high-quality special steel customized to individual customer needs.

2.2 Takasago Machinery Plant production and logistics management system[6)]

Kobe Steel's Takasago Machinery Plant has around 200 pieces of equipment for running high-mix, mixed-model production of made-to-order products. The plant began experiencing the challenge of delays owing to temporary fluctuations in demand. In response, we developed iLiss (Innovation of Logistics and Intelligent Scheduling System), a production and logistics management system that achieves stable production by managing real-time progress and optimally allocating production resources. As shown in **Fig. 4**, this system consists of a scheduling system (iLiss-S, left side of the figure) and a logistics management system (iLiss-L, right). The scheduling system creates short- and long-term production plans (less than or greater than one month, respectively). The logistics management system issues operating instructions to the production floor based on the schedule and manages operational performance. Following is an explanation of the scheduling system's logic.

The scheduling system manages fluctuations in workload by first rearranging tasks in the long-term plan and then creating a short-term plan based on the adjustment. The long-term plan allocates work to machines and workers based on meeting delivery dates. Tasks beyond capacity (overload tasks) are extracted as candidates for outsourcing, and a contract assignment plan is drawn up with the service provider. After decisions regarding outsourcing are finalized, the short-term plan allocates resources to complete the remaining in-house work based on machine and worker

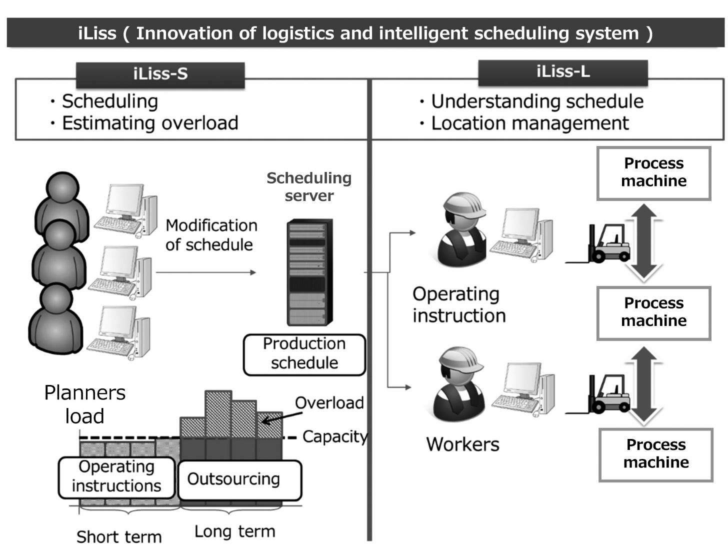

Fig. 4 Overview of iLiss

capacities.

The program's logic for managing overload tasks in the long-term plan is as follows:

(1) Task selection: The task with the smallest delivery margin is isolated from the unallocated tasks that are related to parts for which work has already been completed.
(2) Provisional allocation: The selected task is provisionally allocated within the constraints of machine and worker capacities. Specifically, the earliest available machine and the worker with the smallest number of available machines are allocated.
(3) Overload task allocation: If the provisionally allocated task will be completed before the delivery date (assuming standard working hours), the plan is confirmed. If the task would be completed after the delivery date, the overload task is allocated to the machine and worker that can meet the latest delivery date, disregarding capacity constraints.
(4) Steps 1-3 are repeated until all tasks are allocated.

Managing overload tasks during long-term planning has made it possible to coordinate decisions regarding outsourcing early in production planning. In addition, grasping overall progress and efficiently collaborating with outsourcers through the logistics management system have made it possible to respond to the large fluctuations in demand inherent to made-to-order production, and to handle high-mix, mixed-model production.

2.3 Carbon footprint of a product (CFP) calculation model

As part of the world's growing efforts to achieve carbon neutrality, Kobe Steel is researching a model for calculating and analyzing the CFP of each product in its metal materials business. This extension of the product cost management model to calculate CO_2 emissions goes beyond evaluating products based on the conventional metric of QCD by determining a product's future environmental burden.

Fig. 5 depicts the CFP calculation model Kobe Steel is researching. The scope of calculation covers everything from production at Kobe Steel to delivery to the customer (cradle-to-gate), and specifically includes energy consumption, waste management, subcontracted processes, and the procurement of raw materials, energy, consumables, and auxiliary materials.

Four inputs feed the calculation (left side of the figure):

(1) Energy consumption: energy used by the plant (e.g., electricity, LNG, kerosene). Calculated by equipment and department.
(2) Purchasing and procurement: raw materials, consumables by equipment and department, subcontracting by product, shipping destinations and methods. Categorized and then associated with CO_2 emissions factors in step 4.
(3) Manufacturing material flow: material streams, compositions, recycling, processing time and weight for each process based on data linked to manufactured products. Tabulated by product specifications and manufacturing process.
(4) CO_2 emissions factors: coefficient table for converting logistics and equipment information from Step 1 and Step 2 into CO_2 emissions values. Publicly available

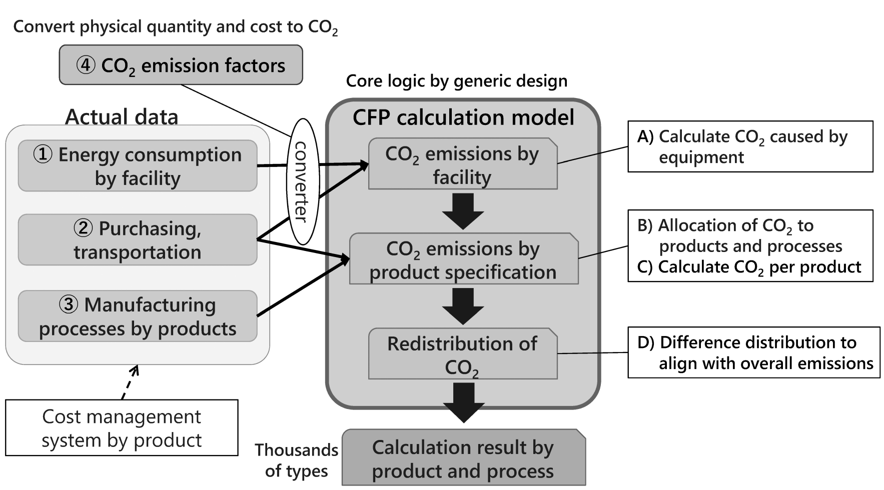

Fig. 5 Calculation model of CFP

information is used, such as IDEA, developed at the National Institute of Advanced Industrial Science and Technology.

The calculation is performed using the inputs above and the following procedure (right side of the figure). (A) Total CO_2 emissions are calculated by equipment. (B) Emissions values are allocated to each product based on historical consumption. (C) These values are combined with CO_2 emissions values per metal based on material streams to calculate CO_2 emissions by product. (D) If necessary, CO_2 emissions are redistributed for consistency throughout the operation.

Using such a model for the data-driven calculation of CO_2 emissions by product opens far-reaching possibilities. First, individual companies can evaluate equipment, process design, and product composition based on CO_2 emissions. And second, it will be possible to evaluate the entire manufacturing process based on data shared between companies throughout the supply chain. Our company will contribute to the reduction of CO_2 emissions throughout society as a whole by combining this type of computational model with decision support technology (OR technology) such as optimization and simulation technologies.

Conclusions

Kobe Steel has been using decision support technology based on OR technology in manufacturing for over 40 years. We began with simple simulations that optimized basic indicators such as the cost of a single process and the rate of on-time delivery. Our technology has since evolved to handle various indicators for the entire plant, with the ability to consider multiple processes and involve external stakeholders.

Historically, it was sufficient to consider only one's own QCD in manufacturing. In recent years, however, considering ESG has become non-negotiable. These increasingly complex issues must be addressed not only by us at Kobe Steel but also by the entire supply chain, including our partners and customers. Decision support technology (OR technology) must play a role in resolving these challenges.

Technological advances in ICT related to OR technology are underway. These include IoT technology that can newly obtain detailed, real-time operating status information; quantum computers that can quickly solve complex, previously unsolvable problems; and blockchain technology that enables multiple companies within a supply chain to share data.

In response to these changing circumstances, Kobe Steel will combine decision support technology (OR technology) with various new technologies to tackle increasingly complex and advanced societal challenges. Through these efforts, Kobe Steel will develop concrete solutions that add new value to society via our manufacturing operations.

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