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RESEARCH ARTICLE

Integrated Optimization Scheduling Model for Ship Outfitting Production with Endogenous Uncertainties

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Abstract

Ship outfitting is a key process in shipbuilding. Efficient and high-quality ship outfitting is a top priority for modern shipyards. These activities are conducted at different stations of shipyards. The outfitting plan is one of the crucial issues in shipbuilding. In this paper, production scheduling and material ordering with endogenous uncertainty of the outfitting process are investigated. The uncertain factors in outfitting equipment production are usually decision-related, which leads to difficulties in addressing uncertainties in the outfitting production workshops before production is conducted according to plan. This uncertainty is regarded as endogenous uncertainty and can be treated as non-anticipativity constraints in the model. To address this problem, a stochastic two-stage programming model with endogenous uncertainty is established to optimize the outfitting job scheduling and raw material ordering process. A practical case of the shipyard of China Merchants Heavy Industry Co., Ltd. is used to evaluate the performance of the proposed method. Satisfactory results are achieved at the lowest expected total cost as the complete kit rate of outfitting equipment is improved and emergency replenishment is reduced.

Keywords Ship outfitting; Production scheduling; Purchase planning; Endogenous uncertainty; Multistage stochastic programming

1 Introduction

Outfitting is an essential process in shipbuilding. Outfitting refers to the process of fabricating and installing nonstructural components. The ship outfitting process has three stages, namely, on-unit, on-block, and on-board outfitting. On-unit outfitting refers to the assembly of an interim product consisting of only outfitting materials independent of the hull structure. On-block outfitting refers to the installation of outfitting components, or units, on any structural subassembly or block before its erection on the ways. On-board outfitting refers to the assembly of outfitting materials during hull erection and after launching. On-unit outfitting enhances safety and reduces both required manhours and durations, which would otherwise be allocated to on-block and on-board outfitting (Dong et al., 2013; Dong et al., 2016). In the outfitting process, various mechanical, electrical, and electronic equipment are manufactured or purchased according to the hull structure (Karanassos, 2016; Wang et al., 2020). In general, this process is fairly chaotic and governed by complex interactions between the geometry of the vessel, time constraints, shipyard layout, building strategy, and different organizations (i. e., shipyard and all involved subcontractors; Rose and Coenen, 2015). Therefore, to minimize the task time and cost for outfitting work, the ideal planning strategy is to finish all of the outfitting work as early as possible. However, as a result of the system disruptions and variations, the delay of other schedules, capacity limitations, technical infeasibility, and the management of an effective system production rate, the ideal outfitting plan is not the reality. Because of unforeseen uncertainties involved in processing times and resource consumptions, as a key element in the manufacturing and purchasing of outfitting equipment, outfitting planning is faced with challenges in improving assembly and complete kit rate. This is one of the most significant challenges encountered in the outfitting production stage

Article Highlights

- A two-stage stochastic programming method is proposed to deal with the endogenous uncertainties in the purchasing and production of outfitting equipment.
- The model is completely consistent with the problems encountered during outfitting production in shipyards.
- The complete kit rate of outfitting equipment and emergency replenishments are improved under the minimum expected total cost.

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of shipbuilding (Dong et al., 2016; Lee et al., 2012). The uncertainties can directly affect the scheduling and replenishment processes and thus need to be considered when making decisions. The degree of autonomy is crucial for scheduling problems to deal with production uncertainties. When disruptions occur, the process is often rescheduled accordingly.

Solving a complex monolithic problem to optimize a single objective under disruptions specific to scheduling in each period is often impractical. Compared with the simultaneous methods, different objectives stemming from reactive scheduling are readily accommodated by the bi-level programming methods (Sha et al., 2021). The research presented in this paper mainly focused on ship outfitting production and purchasing with endogenous uncertainties and the production scheduling and material ordering involved (Wassick et al., 2012). Stochasticity and periodicity in outfitting equipment purchasing and production are considered in this study. First, the operational management of outfitting is divided into two stages. Then, a two-stage stochastic programming (SP) model with endogenous uncertainty is constructed. Furthermore, production schemes are generated based on the actual production data. Finally, the technique for order of preference by similarity to ideal solution (TOPSIS) method is introduced to select the optimal solution from the multi-production schemes.

In this study, a two-stage SP method is proposed to deal with the endogenous uncertainties in the purchasing and production of outfitting equipment. The planning process considers the uncertainties of processing time and resource consumption. A two-stage stochastic mixed-integer programming algorithm containing endogenous uncertainty is constructed to deal with the model. The total cost is used as the optimal goal. In addition, the model proposed in this study is completely consistent with the problems encountered during outfitting production in shipyards. The methods and results presented in this study have academic value and potential practical value for outfitting production in shipyards.

The remainder of the paper is organized as follows: In Section 1, the background and related research work are introduced. In Section 2, the definition of the production scheduling problem of outfitting equipment and the construction of a two-stage SP model are presented. In Section 3, the methodology is discussed in detail. In Section 4, a detailed outfitting scheduling and ordering decision case study is provided. In Section 5, the conclusions and future studies are outlined.

2 literature review

2.1 Production scheduling and material ordering

Traditionally, scheduling and ordering are sequential methods because of different objectives and time scales (Tang et al., 2019). Production scheduling is made by determining the daily and weekly production quantities according to the orders of the customers and is used as the input of the material ordering model. However, such separate models would lead to suboptimal solutions (Lucht et al., 2021). Integrated solutions for scheduling and ordering have long been investigated in manufacturing management. Aquilano and Smith (1980) introduced an integration of project scheduling and material ordering problems (PSMOP) and developed a hybrid model that includes critical path methods and material requirements programming. Smith-Daniels and Aquilano (1984) then proposed an improved heuristic procedure for large-scale project scheduling. Smith-Daniels and Smith-Daniels (1987) proved that an optimal solution can be achieved by decomposing the integration into the derivation of project progress and material batch under certain assumptions. Dodin and Elimam (2001) developed a model that considers different factors, including changes in activity duration, bonuses/penalties due to early/delayed completion of the project, and procurement quantity discounts. Sajadieh et al. (2009) determined an optimal activity duration and material ordering plan using a meta-heuristic algorithm. Najafi et al. (2011) proposed a new optimization model based on the joint replenishment strategy. Tabrizi and Ghaderi (2016) established a bi-objective model with maximum progress robustness and minimum project cost as objectives.

Because sustainable scheduling is attracting increasing attention from many manufacturing enterprises and energy consumption is a core problem regarding sustainability, the aim is to develop an energy-efficient scheduling method to fulfill material delivery tasks in mixed-model assembly lines (Zhou and Shen, 2018). This scheduling method is required if workers can flexibly fulfill tasks across stations of several lines; thus, the capacity of workers is shared among the lines. Rahman and Nielsen (2019) developed a methodology for scheduling automated transport vehicles to ensure the smooth flow of materials in production and container terminal environments. Elmughrabi et al. (2020) proposed an integrated model for collaborative construction supply chain planning that deals with joint project scheduling and material ordering decisions. Almatroushi et al. (2020) proposed an integrated approach that seeks to jointly optimize project scheduling and material lot sizing decisions for time-constrained project scheduling problems. A mixed-integer linear programming model, which utilizes the splitting of noncritical activities as a means of leveling renewable resources, was devised. Asadujjaman et al. (2021) proposed a mathematical model and solution approach for a resource-constrained PSMOP with discounted cash flows. Because the storage space for materials is often limited in reality in many construction sites, a bi-objective optimization model for the PSMOP with limited storage space is proposed (Zhang and Cui, 2021). Job scheduling incorporated with material ordering can better meet practical needs and lead to overall cost reduction. Sha et al. (2021) presented a stochastic approach for this joint optimization problem, considering uncertainties in job processing times and resource consumption. After the occurrence of major sudden disasters, the dispatching and distribution of disaster relief materials are particularly important; however, in the distribution process, there may be excessive distribution of similar emergency materials, unbalanced distribution volume of relief materials in different disaster-affected points, high distribution cost, and low effective distribution rate. To solve the aforementioned problems, based on the application of big data, Huo and Wang (2022) proposed a three-level network post-disaster material scheduling and distribution model and an improved non-dominated sorting genetic algorithm II algorithm.

2.2 Stochastic programming with endogenous uncertainties

The aforementioned studies mostly address the deterministic model of the scheduling and ordering plan (Tabrizi, 2018). However, the integrated model considering uncertainties has not received enough attention. Tabrizi and Ghaderi (2016) solved the procurement scheduling problem of construction projects by considering uncertain task duration and execution cost. They proposed a robust mixed-integer model to describe this problem and applied a metaheuristic algorithm to obtain the solution. To deal with the uncertainty of activity duration, Sha et al. (2021) proposed a two-stage optimization method, which first obtained baseline scheduling by finding a deterministic model and then generated robust scheduling by inserting buffer time. Bruni et al. (2015) presented a multistage SP to solve the uncertainty disclosure sequence of the model. Uncertainties in SP are divided into two categories, namely, exogenous and endogenous uncertainties (Apap and Grossmann, 2017). Several recent studies have considered exogenous uncertainty, which usually refers to market uncertainty, such as price changes, and is independent of production decisions. The SP methods with exogenous uncertainty include stochastic decomposition and stochastic dual dynamic programming (Higle and Sen, 1991; Pereira and Pinto, 1991). In contrast to exogenous uncertainty, endogenous uncertainty has an important impact on the decision-making process. A scenario tree model is used to realize the stochastic process of endogenous uncertainty. A scenario is composed of a series of stages. The scenario tree with endogenous uncertainty is dependent on decision-making, which leads to difficulties in creating models and solving problems. According to Goel and Grossmann (2004), decision-making affects the stochastic process in at least two aspects. The first is that the probability distribution of uncertainty may be changed by the decision, and the second is the uncertainty of revealed time.

Recently, a polynomial time algorithm, which can identify all redundant non-anticipativity constraints (NACs) in an SP problem with only endogenous uncertainty, has been proposed in the literature. Hooshmand et al. (2018) addressed a new variant of the daily operating room scheduling problem, in which surgeries have stochastic durations and simultaneously considered the initial scheduling and rescheduling decisions within a single optimization model to obtain a more flexible schedule. Zeng et al. (2019) considered large-scale multistage stochastic programs under a specific type of uncertainty, i.e., endogenous uncertainty and developed a general primal bounding framework based on extending the concepts of expected value solution and value of the stochastic solution from multistage stochastic programs under exogenous uncertainties. Bhuiyan et al. (2019) developed a methodology that provides the basis for a decision-making tool to help managers allocate limited cost−share resources among a set of landowners to maximize wildfire risk reduction by implementing a hazardous fuel reduction treatment. Bhuiyan et al. (2020) constructed a resource-constrained decision-maker seeking to optimally allocate protection resources to the facilities and construct links in the network to minimize the expected post-disruption transportation cost. Li and Grossmann (2021) reviewed the basic concepts and recent advances of a risk-neutral mathematical framework called "stochastic programming" and its applications in solving process systems engineering problems under uncertainty. For SP models with latently decision-dependent uncertainty, without any parametric assumption of the latent dependency, Liu et al. (2022) developed a coupled learning-enabled optimization (coherent light emission output) algorithm, in which the learning step of predicting the local dependency and the optimization step of computing a candidate decision are conducted interactively. Leo et al. (2022) addressed the challenge of integrating production planning and maintenance optimization for a process plant. Menon et al. (2021) proposed an integer programming model to solve the problem, whose key feature is that it does not require auxiliary binary variables or explicit NACs to ensure non-anticipativity. Yazdaninejad et al. (2021) presented a new operation optimization approach for an aggregator of distributed energy resources (DERs) considering the unavailability of DERs (as discrete uncertainty sources), as well as forecast uncertainties of electricity prices, solar powers, and wind powers.

3 Methodology

3.1 Problem formulation

Because multiple products are manufactured in a single period, the outfitting production process needs to be scheduled to meet the production quantities determined by the planning model within a scheduling horizon. Generally, the scheduling horizon is equal to the length of the corresponding planning period. The inputs of the scheduling problem are the production quantities determined by the planning problem. The task processing times are uncertain, which can affect the remaining unscheduled tasks. For example, a prolonged processing time can make the subsequent tasks fail to start at the predetermined time points.

In this study, a stochastic two-stage programming model with endogenous uncertainty is established to optimize the outfitting job scheduling and raw material ordering process, as shown in Figure 1. The model is treated as a random process. The random variables include job processing time and resource consumption. During the production and processing of ship outfitting parts, the production and procurement planning problem ensures that the production quantities assigned to all periods are fulfilled on time by solving a detailed scheduling problem for every period. Under production uncertainties, successful fulfillment becomes a probabilistic problem. Therefore, this uncertainty is regarded as endogenous uncertainty or decision-related uncertainty in this study. This uncertainty can be treated as NACs in the model. For simplicity, "jobs" is used in this study to refer to production planning jobs that require manufacturing. Each operation involves production tasks of various outfitting equipment, and each task requires different types of renewable and nonrenewable resources. A fixed number of renewable resources are available for production in each period, but nonrenewable resources (outfitting raw materials) need to be purchased and distributed to the outfitting workshop.

3.2 Uncertainty analysis

The uncertain factors of outfitting production are as follows:

1) Uncertainty of raw materials and resource consumption

All assembly jobs in each programming cycle are executed following the assembly plan. The outfitting equipment is finished through the process of warehousing, sorting, assembly, pre-outfitting, and forming the hull structure. The demand time and sequence of outfitting equipment are limited. However, the time and sequence of outfitting equipment requirements are changed if the plan is inaccurate or the production changes. The factors are divided into controllable and uncontrollable factors according to the characteristics of uncertainty. Controllable factors include auxiliary equipment, such as forklifts and flatbed trucks in the shipyard. Reasonable auxiliary equipment scheduling can reduce the impact of arrival time uncertainty. Uncontrollable factors are impossible to predict. These factors include weather, equipment failure, and urgent orders. Therefore, the resource consumption of auxiliary equipment and outfitting raw materials in operations are established as random variables.

2) Uncertainty of the processing time of outfitting equipment manufacturing

In the process of outfitting equipment manufacturing, equipment failure, supply delay of raw materials, and worker

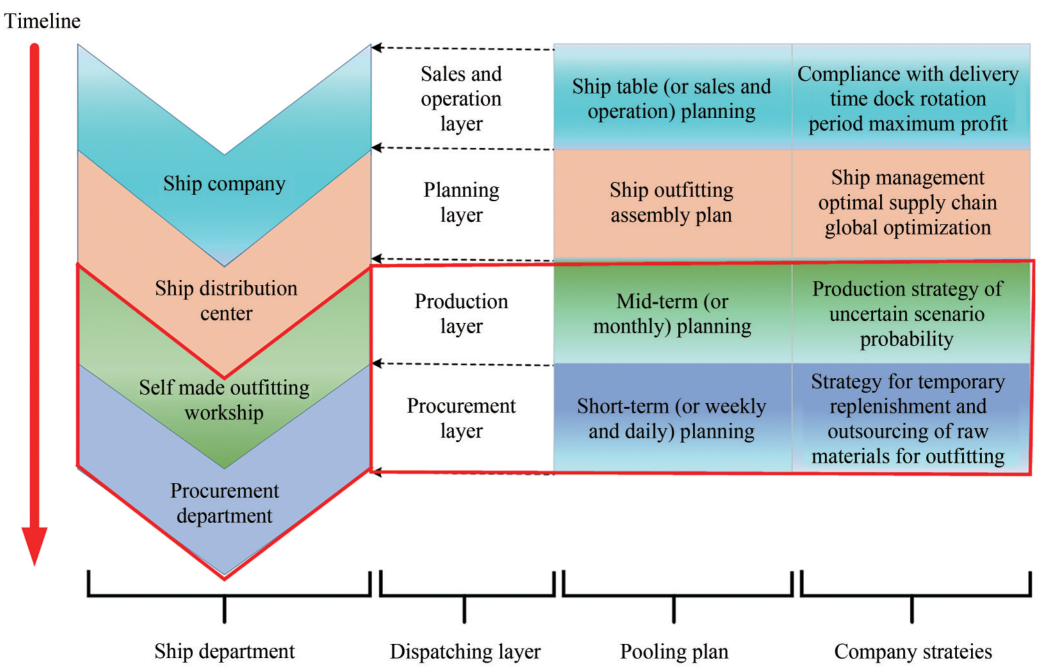

Figure 1 Two-stage production and purchasing model of outfitting equipment

scheduling operations have a strong impact on processing time.

(a) Equipment failure. If equipment failure occurs, then maintenance of the mechanical–electrical equipment of the outfitting equipment production line will be time-consuming and difficult.

(b) Supply delay of raw materials. If the outfitting of raw materials or the upstream semifinished products is not completed on time, then the processing time of the semifinished products will be lengthened.

3) Uncertainty of the delivery date of outfitting equipment

The production tasks for self-made outfitting equipment are categorized into three types, namely, tube, iron, and electric outfitting equipment.

The delivery time of tube and iron outfitting equipment is determined by the completion time required by the outsourcing and paint shops. The delivery time of electric outfitting equipment is determined by its required completion time. Uncertain factors in the scheduling of outfitting equipment production will lead to the failure of the original scheduling scheme, which will bring additional costs to the production or subsequent operations. The two types of time costs under uncertainty are lead time cost and delay cost. The lead time cost is the cost of outfitting equipment made in advance. Because the shipyard outfields are usually crowded, outfield scheduling will occur if the outfitting equipment is made in advance. To simplify the problem, the cost of outfield scheduling is used as the penalty cost for the outfitting equipment made in advance. By contrast, delayed delivery of materials will increase the assembly cost of outfitting. The delay cost is introduced to refer to the penalty cost of delayed delivery.

The concept of slack time is presented because of the uncertain delivery date of outfitting equipment. If the delay is within the slack time, then there will be no penalty cost. Otherwise, the cost will be considered based on the delay.

3.3 Model assumption

The main assumptions are as follows:

Assumption 1: The production plans of the outfitting shop are made according to the capacity limit of the shop inventory.

Assumption 2: The replenishment lead time of each nonrenewable resource (outfitting raw material) is constant.

Assumption 3: The inventory holding and shortage costs are linear, and the planning cost is fixed.

Assumption 4: The uncertainty of raw material delivery time, the processing time of outfitting equipment, and resource consumption will not be fully revealed until the job starts to be processed.

Assumption 5: A single period is considered in the problem, in which the demands of products are uncertain.

Assumption 6: The determined production quantities should meet the order demands and the capacity of the production process so the demanded products in every period can be delivered in the current period.

The first three assumptions simplify the formulation of the joint replenishment process. Assumption 1 is commonly used in dynamic lot sizing problems. Notably, in Assumption 2, replenishment lead time may be related to order quantity in practical applications. Thus, only a constant replenishment lead time is considered in the present study. Assumption 3 guarantees that the replenishment cost function is concave. Assumption 4 explains the progressive revelation of uncertainties. A specific examination will be conducted on each job at its starting time to determine the exact processing time and resource consumption. This updated information will provide an accurate basis for subsequent decision-making.

3.4 Model construction

The indices and sets used in the model are shown in Table 1. The model parameters are shown in Table 2. The decision variables are shown in Table 3.

Table 1 Indices and sets

Indices	Sets
t	Time, $t = 1, \cdots, T$
J	Set of outfitting production planning jobs, $J = \{1, \cdots, n\}$
i	Type of pallets, $i = \{1, \cdots, I\}$
v	Type of outfitting equipment, $v = 1, \cdots, V$
K_1	Different kinds of outfitting auxiliary equipment, $K_1 = \{1, \cdots, m_1\}$
K_2	Different kinds of outfitting processing raw materials, $K_2 = \{1, \cdots, m_2\}$
k	Type of resource, $k \in K_1 \cup K_2$
ω	Future scenario, $\omega \in \Omega$, where Ω is the collection of all future scenarios

Formulation (SIOSP):

$$\min \sum_{j=1}^{n} \sum_{t=1}^{T - \mathrm{pt}_j^{\max} + 1} c_{jt} x_{jt} + \sum_{\omega \in \Omega} p^{\omega} Q(x, \omega) \tag{1}$$

$$\text{subject to} \sum_{t=1}^{T - \mathrm{pt}_j^{\max} + 1} x_{jt} = 1, \quad \forall j \in J \tag{2}$$

$$Q(\boldsymbol{x}, \omega) = \min \sum_{t=1}^{T} \left[\sum_{k_1=1}^{m_1} b_{k_1 t} z_{k_1 t}^{\omega} + \sum_{k_2=1}^{m_2} \left(g_{k_2 t} s_{k_2 t}^{\omega} + b_{k_2 t} z_{k_2 t}^{\omega} + h_{k_2 t} \mathrm{in}_{k_2 t}^{\omega} \right) + \sum_{v=1}^{V} \left(h_{vt} \mathrm{in}_{vt}^{\omega} + g_{vt} q_{vt}^{\omega} \right) \right] \tag{3}$$

Table 2 Model parameters

Parameters	Definitions
c_{jt}	Cost of starting job j in period t
pt_j^{ω}	Processing time of job j in scenario ω
$\mathrm{pt}_j^{\max}$	Maximum processing time of job j in scenario ω
a_{vi}^{ω}	Number of outfitting equipment v required for pallets i
N_{vt}	Indexed set of pallets that requires outfitting equipment v during the period t in the pallets list
d_j	Due time of job j
r_{jk}^{ω}	Amount of resource k consumed by job j during a period in scenario ω
R_{k_1}	Initial amount of renewable resource k_1 available in the system
b_{kt}	Per-unit shortage cost of resource k in period t
g_{k_2t}	Production preparation cost of raw materials k_2 processed in the outfitting workshop during t period
h_{k_2t}	Per-unit holding cost of raw material k_2 in period t
g_{vt}	Processing cost of outfitting equipment v in the outfitting workshop during t period
h_{vt}	Supply hub inventory cost of unit outfitting equipment v during t period
p^{ω}	Probability of scenario ω
IN	Warehouse capacity
I_{k_2}	Initial inventory of raw material k_2
L_{k_2}	Fixed replenishment lead time for outfitting raw material k_2
L_v	Fixed replenishment lead time for outfitting equipment v
M	A large number

Table 3 Decision variables

Variables	Definitions
x_{jt}	Binary variable equal to 1 if job j starts in period t, and 0 otherwise
z_{kt}^{ω}	Amount of temporary expansion of resource k in time t in scenario ω
$s_{k_2t}^{\omega}$	Binary variable equal to 1 if there exists replenishment of raw material k_2 during time $t + L_{k2}$ in scenario ω, and 0 otherwise
$w_{k_2t}^{\omega}$	Amount of raw material k_2 arriving during time t in scenario ω
$\mathrm{in}_{k_2t}^{\omega}$	Inventory of raw material k_2 during time t in scenario ω
$\mathrm{in}_{vt}^{\omega}$	Supply hub inventory of outfitting equipment v during time t in scenario ω

$$z_{k_1t}^{\omega} \geqslant \mathrm{csmp}_{k_1t}^{\omega} - R_{k_1}, \quad \forall k_1 \in K_1, \forall \omega \in \Omega, t = 1, \cdots, T \tag{4}$$

$$\mathrm{in}_{v,t-1}^{\omega} + q_{v,t-L_v}^{\omega} - \sum_{i=N_{vt}}^{I} a_{vi}^{\omega} = \mathrm{in}_{vt}^{\omega}, v = 1, \cdots, V; \ t = 1, 2, \cdots, T \tag{5}$$

$$w_{k_2t}^{\omega} + z_{k_2t}^{\omega} + \mathrm{in}_{k_2,t-1}^{\omega} = \mathrm{in}_{k_2t}^{\omega} + \mathrm{csmp}_{k_2t}^{\omega}, \quad \forall k_2 \in K_2, \forall \omega \in \Omega, t = 1, \cdots, T \tag{6}$$

$$-Ms_{k_2t}^{\omega} + w_{k_2,t+L_{k_2}}^{\omega} \leqslant 0 \quad \forall k_2 \in K_2, \forall \omega \in \Omega, t = 1, \cdots, T - L_{k_2} \tag{7}$$

$$\sum_{k_2=1}^{m_2} \mathrm{in}_{k_2t}^{\omega} \leqslant \mathrm{INK}, \quad \forall \omega \in \Omega, t = 1, \cdots, T \tag{8}$$

$$\sum_{v=1}^{V} \mathrm{in}_{vt}^{\omega} \leqslant \mathrm{INV}, \quad \forall \omega \in \Omega, t = 1, \cdots, T \tag{9}$$

NACs:

$$Z_t^{\omega\omega'} = \sum_{j \in D(\omega,\omega')} \sum_{\tau=1}^{t} x_{j\tau}, \quad \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T \tag{10}$$

$$MZ_t^{\omega\omega'} + s_{k_2t}^{\omega} - s_{k_2t}^{\omega'} \geqslant 0, \quad \forall k_2 \in K_2, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T - L_{k_2} \tag{11}$$

$$MZ_t^{\omega\omega'} - s_{k_2t}^{\omega} + s_{k_2t}^{\omega'} \geqslant 0, \quad \forall k_2 \in K_2, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T - L_{k_2} \tag{12}$$

$$MZ_t^{\omega\omega'} + w_{k_2,t+l_{k_2}}^{\omega} - w_{k_2,t+L_{k_2}}^{\omega'} \geqslant 0, \quad \forall k_2 \in K_2, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T - L_{k_2} \tag{13}$$

$$MZ_t^{\omega\omega'} - w_{k_2,t+L_{k_2}}^{\omega} + w_{k_2,t+L_{k_2}}^{\omega'} \geqslant 0, \quad \forall k_2 \in K_2, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T - L_{k_2} \tag{14}$$

$$MZ_t^{\omega\omega'} + q_{v,t}^{\omega} - q_{v,t}^{\omega'} \geqslant 0,$$
$$\forall v \in V, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T \quad (15)$$

$$MZ_t^{\omega\omega'} - q_{v,t}^{\omega} + q_{v,t}^{\omega'} \geqslant 0,$$
$$\forall v \in V, \forall \omega, \omega' \in \Omega, \omega < \omega', t = 1, \cdots, T \quad (16)$$

Other constraints:

$$w_{k_2 t}^{\omega} = 0, \quad \forall k_2 \in K_2, \forall \omega \in \Omega, t = 1, \cdots, L_{k_2} \quad (17)$$

$$\mathrm{in}_{k_2 t}^{\omega} = I_{k_2}, \quad \forall k_2 \in K_2, \forall \omega \in \Omega, t = 0 \quad (18)$$

$$x_{jt}, s_{k_2 t}^{\omega} \in \{0,1\}, w_{k_2 t}^{\omega}, z_{k_1 t}^{\omega}, z_{k_2 t}^{\omega}, \mathrm{in}_{k_2 t}^{\omega} q_{vt}^{\omega}, \geqslant 0,$$
$$\forall j \in J, \forall k_1 \in K_1, \forall k_2 \in K_2, \forall \omega \in \Omega, t = 1, \cdots, T \quad (19)$$

The stochastic version of the integrated ordering and scheduling problem (SIOSP) is used in the present study to solve the two-stage SP model and minimize the expected constraints. The model is described as follows:

The SIOSP is a multistage SP model aiming to minimize its expected total cost. The objective function (Eq. (1)) is the sum of a deterministic first-stage cost and an expectation of the recourse function $Q(\boldsymbol{x}, \omega)$ of subsequent stages. The schedule of jobs (x_{jt}) is determined in the first stage, and $\boldsymbol{x}$ is used to denote the appropriately sized vector corresponding to x_{jt}. The first term in the objective function (Eq. (1)) represents the first-stage job scheduling cost. The term $T - \mathrm{pt}_j^{\max} + 1$ represents the latest start time of job j, which is set to ensure that job j can be completed by time T in all possible scenarios.

Given the schedule x and each possible scenario ω, the compensatory cost in subsequent stages expressed as recourse function $Q(x,\omega)$ in Eq. (3) is optimized. The compensatory decisions include resource expansion quantity (z_{kt}^{ω}), material replenishment demand variable $(s_{k_2 t}^{\omega})$, raw material ordering quantity $(w_{k_2 t}^{\omega})$, outfitting equipment processing batch (q_{vt}^{ω}), and inventory of raw material and outfitting equipment $(\mathrm{in}_{k_2 t}^{\omega}, \mathrm{in}_{vt}^{\omega})$ in each period of the planning horizon.

The compensatory cost expressed in Eq. (3) consists of the temporary renewable resource expansion cost, material setup, shortage and holding costs, and outfitting equipment processing and inventory costs (Wang et al., 2020). The probability of expedited production has been determined by related literature (Ghadimi et al., 2018; Mohammed et al., 2019). Temporary renewable and nonrenewable resources are allowed in the model to expand penalty costs, such as equipment outsourcing or renting. Temporary resource expansion is measured using the variable z_{kt}^{ω}. If b_{kt} is sufficiently large, then the variable z_{kt}^{ω} will be equal to 0 in the optimal solution, unless the resource k is inadequeate, which provides decision-makers with insights into which resources are scarce and bottlenecks.

Constraints (2) and (4) model the scheduling of production auxiliary equipment k_1 of shared jobs. Eq. (2) ensures that each job is completed by time T, and Inequation (4) guarantees the availability of resource k_1 in any period. Renewable resources of the same type are indistinguishable. Therefore, the tasks that need to be processed are randomly allocated on the idle resources. The right side of Inequation (4) is the resource expansion required by the resource k_1 in period t, where $\mathrm{csmp}_{kt}^{\omega}$ is the consumption of resource k in scenario ω in time t. The variable $\mathrm{csmp}_{kt}^{\omega}$ is calculated as follows:

$$\mathrm{csmp}_{kt}^{\omega} = \sum_{j=1}^{n} \sum_{\tau = \max(0, t - \mathrm{pt}_j^{\omega})}^{t} r_{jk}^{\omega} x_{j\tau},$$
$$\forall k \in K_1 \cup K_2, \forall \omega \in \Omega, t = 1, \cdots, T \quad (20)$$

In Eq. (20), job scheduling item $\sum_{\tau = \max(0, t - \mathrm{pt}_j^{\omega})}^{t} x_{j\tau}$ is equal to 1 if the job j is processed in time t; otherwise, it is equal to 0.

Constraints (5) to (9) indicate the material ordering process. Inequation (5) is the inventory equilibrium constraint of the supply hub. Inequation (6) is the buffer inventory equilibrium constraint. Inequation (7) guarantees the storage of raw materials in advance. Inequations (8) and (9) limit the inventory capacity.

In the model, uncertainties are described by different scenarios. Decisions in different scenarios are linked through unexpected constraints NACs (10) to (16). Unexpected constraints assume that scenarios ω and ω' are indistinguishable in time t. Therefore, for scenarios ω and ω', the compensation decision variables in this period should be the same. If two scenarios are distinguishable, then there is no correlation between two scenarios when making a decision. Set $D(\omega, \omega') \subseteq J$ is defined to make $j \in D(\omega, \omega')$, and $Z_t^{\omega\omega'}$ in Eq. (10) is used as an auxiliary variable if and only if the uncertain properties (processing time and resource consumption) of job j are not the same in scenarios ω and ω'. Constraints (10) to (16) indicate that if the jobs that cause scenarios ω and ω' do not start to differ within or before time $t\,(Z_t^{\omega\omega'} = 0)$ and there is no information to distinguish between scenarios ω and ω', then $s_{k_2 t}^{\omega} = s_{k_2 t}^{\omega'}$ and $w_{k_2 t, t + L_{k_2}}^{\omega} = w_{k_2 t, t + L_{k_2}}^{\omega'}$. If scenarios ω and ω' in time t are distinguishable, then $Z_t^{\omega\omega'} \geqslant 1$, and Eqs. (9) to (16) will no longer constrain the value of the corresponding decision variable. Notably, Constraints (10) to (16) are symmetrical for the pair of scenarios (ω, ω').

4 Case study

4.1 Scheme generation

The numerical example used in this study is generated by combining the actual data from the shipyard of China Merchants Heavy Industry Co., Ltd. with random schemes. The numerical example including two production scenarios ω and ω' is set, which represents the original traditional self-made outfitting equipment production workshop and the new laser center workshop of the shipyard. The conditions of the two workshops are different. Furthermore, the outfitting equipment processing time, resource consumption, and demand for outfitting equipment are different. In the numerical example, a monthly plan is considered. The processing operations of the 12 outfitting equipment ($v = 12$) required for 5 virtual pallets ($i = 5$) are divided into 25 planned periods ($T = 25$) with 30 jobs ($J = 30$). The corresponding relationships are shown in Table 4.

Table 4 Relationship table of pallet and outfitting equipment

unit: pcs

Pallet ID (i)	Outfitting equipment ID (v)	Demand quantity	Job serial number (j)
UD14C	UC14C-WA-PS01	510	Job1
UD14C	UC14C-WA-PS01	510	Job2
UD14C	UC14C-WA-PS01	510	Job3
UD14C	UC14C-WA-PS02	514	Job4
UD14C	UC14C-WA-PS02	514	Job5
UD14C	UC14C-WA-PS03	488	Job6
UD14C	UC14C-WA-PS03	488	Job7
UD14C	UC14C-WA-PS03	488	Job8
AMD02	AMD02-WA-PS01	506	Job9
AMD02	AMD02-WA-PS01	506	Job10
AMD02	AMD02-WA-PS01	506	Job11
AMD02	AMD02-WA-PS02	464	Job12
AMD02	AMD02-WA-PS02	464	Job13
SM18	SM18-WA-PS01	592	Job14
SM18	SM18-WA-PS01	592	Job15
SM18	SM18-WA-PS01	592	Job16
SM18	SM18-WA-PS02	532	Job17
SM18	SM18-WA-PS02	532	Job18
SM18	SM18-WA-PS03	584	Job19
SM18	SM18-WA-PS03	584	Job20
MM26	MM26-WA-PS01	554	Job21
MM26	MM26-WA-PS01	554	Job22
MM26	MM26-WA-PS01	554	Job23
MM26	MM26-WA-PS02	558	Job24
MM26	MM26-WA-PS02	558	Job25
MF21	MF21-WA-PS01	520	Job26
MF21	MF21-WA-PS01	520	Job27
MF21	MF21-WA-PS02	492	Job28
MF21	MF21-WA-PS02	492	Job29
MF21	MF21-WA-PS02	492	Job30

Other input data are displayed in Tables 5−7.

Table 5 Various costs related to raw materials except (t=1, k=3−14)

$\times 10^3$

Raw material (k)	Production preparation cost (g_k)	Per-unit holding cost (h_k)	Per-unit shortage cost (b_k)
3	77	3	1 408
4	67	3	553
5	44	5	1 340
6	57	1	1 300
7	95	2	163
8	20	5	1 373
9	44	4	1 369
10	66	2	623
11	64	5	556
12	25	6	876
13	15	8	192
14	86	2	927

Table 6 Various costs related to outfitting equipment except (t = 1, k=3−14)

$\times 10^3$

Outfitting equipment ID (v)	Preparing cost (g)	Holding cost (h)
1	111	59
2	167	75
3	164	58
4	104	86
5	109	69
6	121	70
7	193	61
8	119	75
9	174	97
10	166	99
11	117	84
12	180	91

Table 7 Random variables and initial scheme generation

Parameters	Scheme generation
Job processing time (pt)	U (1, T/5)
Resource consumption (r_{jk}^{ω})	U (1, 50)
Initial inventory of raw materials (I_{k_2})	0
Lead time of raw material purchase (L_{k_2})	U (2, 3)
Lead time of outfitting equipment production (L_v)	U (1, 7)
Inventory capacity of the buffer (INK)	1 000
Inventory capacity of the supply hub (INV)	100

4.2 Model results

Nine kinds of schemes (m = 1, 2, ⋯, 9) are hypothesized according to the numerical example data. These schemes correspond to different probability combinations ($p_\omega, p_{\omega'}$) of scenario pairs (ω, ω'). Each scheme is tested 10 times ($n = 1, 2, \cdots, 10$). The target value (c_{mn}) and model gap (g_{mn}) of each round are recorded in Table 8. The target and average values of the model gap for every scheme are drawn with a double Y-axis cylindrical point line diagram, as shown in Figure 2.

4.3 Scheme evaluation and selection

TOPSIS is used to select the optimal scheme (Bai et al., 2021). The basic principle of the TOPSIS evaluation method is based on the concept of normalizing the evaluation matrix of the original scheme. The best and worst schemes are identified. The distance between the evaluated object and the best scheme and the distance between the evaluated object and the worst scheme are calculated. The relative closeness between the evaluated object and the best scheme is obtained as the basis for evaluating the pros and cons.

Four evaluation indicators are selected based on the characteristics of outfitting equipment production and the opinions of ship experts. These indicators are total cost, model gap, replenishment frequency, and complete kit rate of outfitting equipment. Four experts from the shipyard brainstormed the methods to assign different weights to the four indicators, as shown in Table 8. The calculation methods of the four indicators are as follows:

1) Indicators (C) of total cost

The cost C_m can be obtained by averaging the data from 10 experiments. The calculation formula is expressed as follows:

$$C_m = \frac{\sum_{n=1}^{10} c_{mn}}{10} \tag{21}$$

2) Indicators (G) of model gap

The cost G_m can be obtained by averaging the data from 10 experiments. The calculation formula is expressed as follows:

$$G_i = \frac{\sum_{j=1}^{10} g_{ij}}{10} \tag{22}$$

3) Indicators (B) of replenishment frequency

The cost B_i can be obtained by averaging the replenishment frequency in 10 experiments. The calculation formula is expressed as follows:

$$B_m = \frac{\sum_{\omega=1}^{2}\sum_{t=1}^{T} s_{k_2 t}^{\omega}}{10} \tag{23}$$

4) Indicators (Θ) of the complete kit rate of the outfitting equipment

Table 8 Experimental results of the numerical examples

Schemes (m)	Scenario pairs (ω, ω')	Data	Number of experiments (n) 1	2	3	4	5	6	7	8	9	10
1	(0.9, 0.1)	Target value	799 800	849 244	850 758	849 079	835 913	881 030	895 279	869 931	831 480	799 707
		Gap	2.74%	3.76%	3.09%	2.90%	3.12%	2.77%	2.85%	3.78%	3.55%	3.75%
2	(0.8, 0.2)	Target value	752 199	800 654	752 590	747 486	773 496	790 312	752 234	768 909	801 367	773 657
		Gap	4.22%	3.56%	4.46%	4.06%	4.06%	4.41%	4.94%	4.93%	4.43%	4.60%
3	(0.7, 0.3)	Target value	653 827	606 201	648 563	599 952	579 538	607 173	619 305	631 766	624 497	606 770
		Gap	7.16%	6.38%	5.52%	6.81%	9.07%	7.27%	6.10%	9.50%	9.13%	9.64%
4	(0.6, 0.4)	Target value	599 952	610 330	598 104	582 110	561 472	639 668	582 076	562 138	580 050	589 311
		Gap	6.81%	5.18%	6.93%	6.24%	6.03%	6.09%	6.86%	6.92%	6.44%	6.22%
5	(0.5, 0.5)	Target value	573 967	563 107	557 978	572 637	556 939	537 712	555 935	544 996	577 405	568 589
		Gap	6.67%	6.04%	6.33%	6.12%	6.03%	6.87%	6.87%	6.91%	6.20%	6.75%
6	(0.4, 0.6)	Target value	542 097	570 881	587 294	534 769	535 775	527 119	504 771	545 677	525 532	517 210
		Gap	7.84%	7.47%	7.79%	6.86%	6.63%	7.59%	6.67%	6.60%	7.09%	7.64%
7	(0.3, 0.7)	Target value	618 698	634 170	652 562	605 870	603 825	626 527	602 261	617 953	635 617	630 303
		Gap	4.36%	3.72%	4.90%	4.34%	4.58%	4.56%	4.83%	4.13%	4.69%	4.27%
8	(0.2, 0.8)	Target value	682 161	600 737	642 986	615 636	687 783	685 775	625 490	660 408	653 472	606 126
		Gap	4.94%	6.24%	4.50%	4.60%	4.44%	4.68%	4.78%	4.93%	4.61%	4.72%
9	(0.1, 0.9)	Target value	756 032	738 601	795 482	781 278	788 346	747 846	752 268	758 745	760 459	752 288
		Gap	3.44%	3.99%	3.87%	3.74%	3.73%	3.55%	3.99%	3.73%	3.80%	3.18%

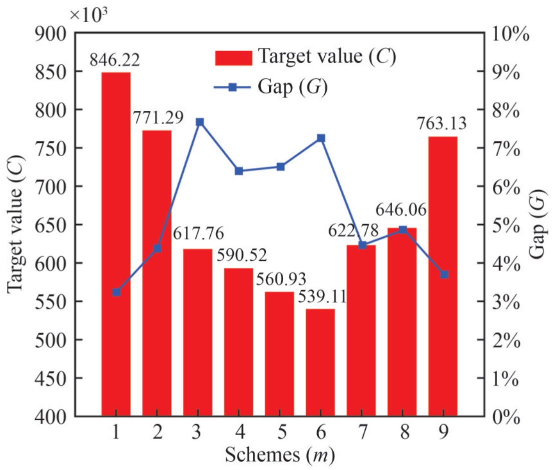

Figure 2 Comparison diagram of scheme operation results

The complete kit rate of outfitting equipment is an important indicator that reflects the quality of production. The cost Θ_i can be obtained by comparing the batch size and demand of the outfitting equipment in 10 experiments. The calculation formula is expressed as follows:

$$\Theta_m = \frac{\sum_{\omega=1}^{2}\sum_{i=N_{vt}}^{I} a_{v_i}^{\omega} - \sum_{t=1}^{T} q_{vt}}{10 \times \sum_{\omega=1}^{2}\sum_{i=N_{vt}}^{I} a_{v_i}^{\omega}} \tag{24}$$

The data of the four evaluation indicators of each scheme are shown in Table 9.

Table 9 TOPSIS comprehensive evaluation data

Scheme (m)	Total cost (C) weight = 0.3	Gap (G) weight = 0.1	Replenishment frequency (B) weight = 0.2	Complete set rate (Θ) weight = 0.4
1	846 222	3.23%	239	91.26%
2	771 290	4.37%	215	89.67%
3	617 759	7.66%	220	87.78%
4	590 521	6.37%	239	83.77%
5	560 927	6.48%	257	88.14%
6	539 113	7.22%	227	89.38%
7	622 779	4.44%	219	90.72%
8	646 057	4.84%	225	91.23%
9	763 135	3.70%	241	79.92%

The TOPSIS method is used to calculate the score and ranking of different schemes according to the previously presented data and weight. The calculation process is as follows:

1) Data forward processing

Different characteristics are used in data processing. The data characteristics of the four indicators used in this case and their forward processing method formulas are shown in Table 10.

2) Standardized data

Data standardization is conducted to eliminate the influence of different data index dimensions. In this step, the normalized matrix is standardized, where $z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$ is the standardized matrix.

Table 10 Data forward processing

Indicator name	Indicator characteristics	Forward processing
Total cost (C) Gap (G)	Minimum (cost) indicators	$\hat{x}_i = \frac{1}{x_i}$
Replenishment frequency (B) Complete set rate (Θ)	Maximum (beneficial) indicators	No need to process

$$\boldsymbol{Z} = \begin{pmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{pmatrix} \tag{25}$$

3) Best and worst solution calculations

Matrix z is scored after the first two steps of normalization and standardization. The best and worst solution vectors, i.e., the largest and smallest numbers in each column, are derived as follows:

$$\begin{aligned} z^+ = [z_1^+, z_2^+, \cdots, z_m^+] = [&\max\{z_{11}, z_{21}, \cdots, z_{n1}\},\\ &\max\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots,\\ &\max\{z_{1m}, z_{2m}, \cdots, z_{nm}\}] \end{aligned} \tag{26}$$

$$\begin{aligned} z^- = [z_1^-, z_2^-, \cdots, z_m^-] = [&\min\{z_{11}, z_{21}, \cdots, z_{n1}\},\\ &\min\{z_{12}, z_{22}, \cdots, z_{n2}\}, \cdots, \min\{z_{1m}, z_{2m}, \cdots, z_{nm}\}] \end{aligned} \tag{27}$$

4) TOPSIS score calculation

The distance of the ith scheme z_i from the best solution is calculated as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (z_j^+ - z_{ij})^2} \tag{28}$$

The distance of the ith scheme z_i from the worst solution is calculated as follows:

$$d_i^- = \sqrt{\sum_{j=1}^{m} (z_j^- - z_{ij})^2} \tag{29}$$

A high score for the ith scheme S_i indicates a good scheme.

$$S_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{30}$$

5) Implementation of the TOPSIS algorithm

The algorithm is designed according to the previously presented calculation process. The results are shown in Table 11 (Akatsu et al., 2020). The results are described in a radar chart, as shown in Figure 3.

Table 11 TOPSIS comprehensive evaluation results

Scheme (m)	Total cost (C) weight = 0.3	Gap (G) weight = 0.1	Replenishment frequency (B) weight = 0.2	Complete set rate (Θ) weight = 0.4	Score	Rank
1	846 222	3.23%	239	91.26%	0.59	4
2	771 290	4.37%	215	89.67%	0.64	3
3	617 759	7.66%	220	87.78%	0.46	6
4	590 521	6.37%	239	83.77%	0.47	5
5	560 927	6.48%	257	88.14%	0.45	7
6	539 113	7.22%	227	89.38%	0.51	8
7	622 779	4.44%	219	90.72%	0.78	1
8	646 057	4.84%	225	91.23%	0.70	2
9	763 135	3.70%	241	79.92%	0.52	9

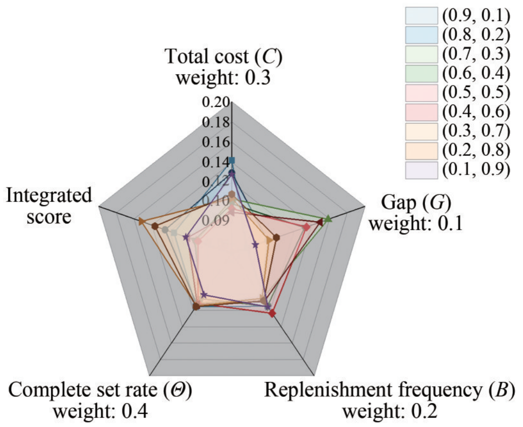

Figure 3 Comparison diagram of scheme operation results

The results show that the best scheme is Scheme 7. The scenario probability ratio between the traditional outfitting equipment production workshop and the laser processing center is 3:7. The numerical performance of the four indicators shows that the operation solution in this scheme can achieve a high complete kit rate of outfitting equipment and low total cost. This result is the best choice among the nine schemes. With this combination, the best result is selected to generate the best scheme of self-made outfitting equipment.

Job scheduling under the best scheme is shown in Table 12 and visually represented by the Gantt chart in Figure 4 (Jia et al., 2007). The production arrangement of outfitting equipment is shown in Table 13 and visually represented by a three-dimensional diagram in Figure 5. The purchasing solution of raw materials is presented in Table 14.

In the case of the shipyard of China Merchants Heavy Industry Co., Ltd., the total cost under the current scheduling scheme, which consists of three parts: job scheduling cost, temporary renewable resource expansion cost, and non-renewable resource (material) supplement cost, is 877 630. Then, the total cost under the optimal scheduling scheme is 622 779 based on the integrated optimization scheduling model of ship outfitting production with endogenous uncertainty. Notably, the total cost under the optimal scheduling scheme has been reduced by approximately 29.05% compared with the total cost under the original scheduling scheme. The value of optimal scheduling models in reducing costs, i. e., practical benefits, such as more efficient production processes, better product quality, and more efficient resource utilization, is achieved. In addition, optimal scheduling can achieve a higher material completion rate and fewer replenishment times while reducing total costs.

4.4 Practical implications

The numerical calculation experiment shows that the production arrangement (the scheme probability ratio between the traditional outfitting equipment production workshop and the laser processing center is 3:7) has the highest comprehensive evaluation value in the schemes with different probabilities. Compared with other scheme settings, this scheme has a high outfitting complete kit rate and fewer temporary replenishment times under the condition of low expected total cost. The generation of the scheme can provide constructive suggestions for production in the shipyards of China Merchants Heavy Industry Co., Ltd.

In addition, the uncertainty of the environmental scene is introduced in the model, which makes it possible to improve the prediction of future trends and make the best production decision on the environmental uncertainty of future shipbuilding outfitting production. In this solution, the smaller the gap value of the scheme, the fewer replenishment times corresponding to it. The higher outfitting complete kit rate is also obtained. Furthermore, according to the replenishment decision of the optimal scheme, the replenishment frequency is an optimization of the inventory, which ensures a high inventory turnover rate, reduces the risk of shortage, avoids the impact of ship manufacturing delivery time, and improves the actual ship manufacturing benefits.

In this research, an integrated optimization model of production scheduling and material ordering of outfitting

Table 12 Optimal job scheduling scheme

Job serial number (j)	Job starting time (t)	Job processing time (pt): ω	Job completion time (pt): ω	Job processing time (pt): ω'	Job completion time (pt): ω'
Job1	10	4	14	3	13
Job2	9	2	11	1	10
Job3	4	3	7	2	6
Job4	8	3	11	2	10
Job5	9	3	12	2	11
Job6	13	3	16	2	15
Job7	10	2	12	1	11
Job8	16	4	20	3	19
Job9	6	3	9	2	8
Job10	9	2	11	1	10
Job11	19	4	23	3	22
Job12	20	4	24	3	23
Job13	23	3	26	2	25
Job14	18	4	22	3	21
Job15	22	4	26	3	25
Job16	9	2	11	1	10
Job17	13	3	16	2	15
Job18	10	2	12	1	11
Job19	4	3	7	2	6
Job20	9	3	12	2	11
Job21	3	4	7	3	6
Job22	16	4	20	3	19
Job23	5	2	7	1	6
Job24	1	3	4	2	3
Job25	20	2	22	1	21
Job26	9	3	12	2	11
Job27	9	2	11	1	10
Job28	9	3	12	2	11
Job29	5	2	7	1	6
Job30	4	3	7	2	6

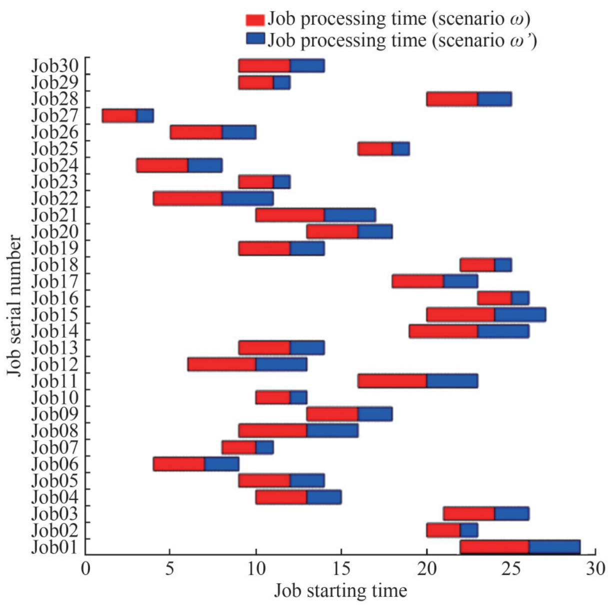

Figure 4 Job scheduling Gantt chart

is proposed for practical application in the shipbuilding industry. For the endogenous uncertainty in the production process of outfitting manufacturing, the corresponding scenario probability variables are set and added to the model, and the results are used to guide the processing of outfitting manufacturing and material purchasing of shipyards.

4.5 Performance of the proposed method

In this section, experiments are conducted to test the performance of the proposed method. To test the performance of the algorithm, this study creates five test instance classes. The instance classes are represented by (A, B), where A is the number of jobs and B is the number of periods (Sha et al., 2021).

In each instance class, 10 test instances are randomly generated. The performance of the proposed branch and bound (B&B) algorithm and heuristic approximate (HA) algorithm is compared with that of Commercial SoPlex (CPLEX). Depending on the characteristics of each solu-

Table 13 Production and processing arrangement of optimal outfitting equipment schemes (except v = 1–4)

Outfitting equipment (v)	Time (t)	Processing batch (q): ω = 1	Processing batch (q): ω = 2	Outfitting equipment (v)	Time (t)	Processing batch (q): ω = 1	Processing batch (q): ω = 2
1	1	11	11	3	1	13	13
1	2	16	6	3	2	5	0
1	3	18	14	3	3	6	2
1	4	20	16	3	4	11	7
1	5	5	1	3	5	17	13
1	6	18	14	3	6	18	14
1	7	16	12	3	7	5	1
1	8	17	10	3	8	16	12
1	9	1	0	3	9	7	3
1	10	9	5	3	10	16	12
1	11	10	6	3	11	9	5
1	12	7	3	3	12	14	10
1	13	19	15	3	13	13	9
1	14	10	6	3	14	13	9
1	15	15	11	3	15	20	16
1	16	19	15	3	16	9	5
1	17	6	2	3	17	5	1
1	18	11	7	3	18	13	9
1	19	11	7	3	19	18	14
2	1	9	9	3	20	5	1
2	2	20	12	3	21	18	14
2	3	6	2	4	2	8	4
2	4	16	12	4	3	6	2
2	5	9	5	4	4	19	15
2	6	15	11	4	5	15	11
2	7	12	8	4	6	9	5
2	8	20	16	4	7	5	1
2	9	8	4	4	8	20	16
2	10	18	14	4	9	5	1
2	11	16	8	4	10	8	4
2	13	11	7	4	11	7	3
2	14	7	3	4	12	13	9
2	15	16	12	4	13	20	16
2	16	10	6	4	14	7	3
2	17	12	8	4	15	14	10
2	18	22	18	4	16	17	13
2	19	4	0	4	17	15	11
2	20	14	10	4	18	11	7
2	21	11	7	4	19	5	1
2	22	12	8	4	20	12	8
2	23	13	9	4	21	19	15

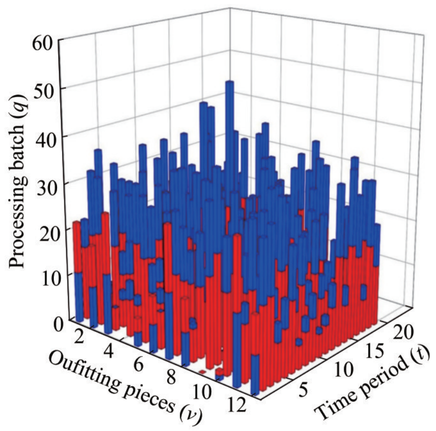

Figure 5 Batch diagram of outfitting equipment processing

Table 14 Purchase of raw materials for the optimal outfitting equipment schemes (except v=0–10)

Raw materials (k)	Time (t)	Order quantity (z): ω	Raw materials (k)	Time (t)	Order quantity (z): ω
3	10	78	13	10	36
4	10	96	14	10	39
5	10	31	15	10	35
7	5	31	16	6	43
7	7	62	16	7	86
14	8	48	17	6	123
15	9	44	18	5	39
47	9	93	18	7	78
48	9	38	28	8	74
48	10	76	29	9	93
49	9	78	30	9	82
49	10	78	58	9	58
51	10	78	59	9	80
52	4	47	60	9	76
52	5	94	62	10	78
62	4	105	63	4	76

tion approach, different criteria are used in the computational experiments. The CPLEX terminates if the running time limit of 7 200 s is exceeded or the optimality gap becomes smaller than 5% (Keller and Bayraksan, 2009). The computational results are reported in Table 15. Each entry in Table 15 is the average of the corresponding results over all 10 test instances in each instance class. B&B provides a higher solution accuracy within a shorter running time. $\mathrm{B\&B_{ojb}}$ is the objective function value obtained by B&B. The last column $\frac{\mathrm{HA_{ojb}} - \mathrm{B\&B_{ojb}}}{\mathrm{B\&B_{ojb}}}$ shows that the optimization approach significantly reduces the total cost compared with the traditional HA approach.

Table 15 Performance of the proposed method

Instance	$\mathrm{Time_{B\&B}}$	$\mathrm{Gap_{B\&B}}$ (%)	$\mathrm{Time_{HA}}$	$\frac{\mathrm{HA_{ojb}} - \mathrm{B\&B_{ojb}}}{\mathrm{B\&B_{ojb}}}$ (%)
(4, 20)	3 867.23	1.98	4 012.80	5.43
(5, 20)	4 613.37	2.45	4 892.19	4.87
(6, 20)	5 542.89	3.01	5 839.21	6.19
(7, 20)	6 652.13	3.92	6 910.58	6.34
(8, 20)	7 109.37	4.86	7 199.99	5.81

5 Conclusions

This study investigated the bidirectional connection between purchase planning and production scheduling of outfitting. The existing shipbuilding production planning process has difficulty in realizing a methodology that connects purchase planning with production scheduling because of the endogenous uncertainty of each planning stage and the lack of an appropriate algorithm. In this study, the authors present a novel two-stage SP model based on the integration optimization of outfitting production scheduling and material ordering with endogenous uncertainty.

The ideal gap generated by the integrated optimization model can be used as the best solution to guide enterprises to generate new outfitting production and procurement plans and solve the material ordering and job scheduling problems with uncertain processing time and resource consumption. The complete kit rate of outfitting equipment and emergency replenishments are improved under the minimum expected total cost. Simultaneously, the generation of the scheme can provide constructive guidance for actual production in the shipyard, considerably improve the production efficiency of the shipbuilding industry, and reduce costs.

The limitations of this study can provide directions for future study. First, additional studies are required for the comprehensive integration and development of shipbuilding production planning. Second, existing optimization algorithms and recent reinforcement learning should be applied. In addition, because of practical limitations, this study could only conduct a case study for a single shipyard. In the future, the methodology verified through this study will be used to conduct a plan integration study of other large shipyards.

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