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Two-way scheduling optimization of the supply chain in one-of-a-kind production based on dynamic production capacity restrictions

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ABSTRACT

One-of-a-kind production (OKP) is the extreme mode of mass customization. An OKP supply chain is studied as a pull-based production model with time-variant nature and lean manufacturing feature in this paper; meanwhile, its characteristics and a systematic analysis of a core idea in OKP supply chains are demonstrated. Supply chain scheduling optimization in OKP requires a dynamic optimization involving stochastic demand and time-variable resource restrictions. To resolve this problem, the dynamic production capacity restriction, which is the dominant restriction mechanism in an OKP supply chain, is investigated based on a process-driven service performance analytical computation from the perspective of dominant members (i.e. core OKP enterprises) in an OKP supply chain. To address the contradiction triggered by the dynamic production capacity restriction relation, an integrated stochastic dynamic optimization model based on a dynamic pricing mechanismn is proposed for two-way scheduling optimization in an OKP supply chain. The two-way supply chain scheduling optimization, on one hand, coordinates every member's remaining production capacity and, on the other hand, schedules key orders and general orders from customers to reduce the total production cost and time.

1. Introduction

As a typical manufacturing paradigm, one-of-a-kind production (OKP) presents various production management challenges and is controlled differently than is mass production. An OKP industry can be characterized by the following: (1) The industry's product designs essentially change with every new order (Madsen et al. [13]). (2) Most of their customers' orders contain one and only one product type (Madsen et al. [13]). (3) Most OKP products are produced only once, and although certain OKP products may be repeatedly produced, there is no fixed repetition period (Mei et al. [14]). In this non-repetitive manufacturing mode that produces various customized products with unique components, "productivity improvements do not reproduce like in mass production" (Tietze et al., pp. 21 [25]). (4) Production stability is poor, and the production and process specialization degree are low owing to "varying production requirements, inadequate operation experience, the unique components and related operations in OKP" (Wang et al., pp. 20 [26]); most of the work requires multiple processes. Finally, (5) the production automation level is low compared to non-OKP industries (Mei et al. [14]). OKP is generally complex and flexible manufacturing that is time-variant because dynamics of production state should be "timely detected and controlled, otherwise serious order delays and work-in-progress redundancies would occur" (Wang et al. [26]). The traditional production management and control system, theory, and methods for mass production do not handle this situation well because these technologies are developed with a view to time-invariant or static production state in large batch scale "push-type" manufacturing based on demand forecast (make-to-stock) instead of actual demand.

Physical examples of OKP industries can be easily found in heavy-equipment-type industries, e.g., shipbuilding, large electrical equipment building, heavy machinery building, steel structure building, special equipment manufacturing. These large-scale OKP represent the extreme mode of mass customization, and thus is just-in-time (JIT) production which is based on the demand side and attempts to operate with zero inventory. Generally, JIT production in OKP is a "pull" and "one piece flow" type of production, which combines "dashboard management" and the core technology of JIT control to achieve lean production in all production links. A pull production system in OKP means make-to-order, in which one-of-a-kind products are produced based on actual demand from customers; in addition, one piece flow implies an ideal state of efficient operations, where parts are manufactured one at a time, and flow throughout the manufacturing and supply chain as single unit, transferred as customer's order. OKP enterprises represent the core of OKP supply chains, so OKP supply chains

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are typically modelled as pull-based lean production models that are time-variant.

From the aspect of supply chain at a macro level, scheduling optimization of an OKP supply chain is a typical dynamic optimization problem: the production resource utilization in an OKP supply chain should be maximized, which determines multiple aspects (e.g., minimize cost or production time) for evaluating the supply chain performance. From the aspect of OKP manufacturing at a micro level, the time-varying stochastic demand, which results from the arrival uncertainty of discrete customer orders and non-substitutability of time-varying production resources (are collectively called the time-varying stochastic demand), strongly influences the production system transient performance of OKP manufacturing and therefore necessitates the dynamic scheduling optimization based on dynamic production capacity restrictions in an OKP supply chain.

In this paper, OKP supply chain scheduling mechanism will be studied based on an analysis of the dynamic production capacity of the supply chain's dominant members, i.e. core OKP enterprises. The dominant members, known as chain leaders, have a strong direct or indirect influence on supply chain resource allocation and application. Furthermore, "two-way" scheduling optimization based on a dynamic pricing mechanism for an OKP supply chain will be discussed. The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 describes the characteristics of the production pattern and dominant restrictive factors in OKP supply chain. Section 4 introduces an OKP dynamic production capacity analysis based on a process-driven service performance analytical computation of a case study in a shipbuilding block production yard. Section 5 presents an integrated stochastic dynamic optimization model for scheduling optimization in an OKP supply chain and discusses the performance of this dynamic optimization scheduling. Finally, Section 6 draws conclusions and proposes future research.

2. Literature review

Research on the scheduling optimization of supply chains and enterprise production planning has been performed for many decades, and the literature and research reports concerned with production operation management in manufacturing are extensive. However, to the best of our knowledge, there are only a relatively small number of references that discuss, to a meaningful extent, the relationship between a manufacturing enterprise's dynamic production capacity constraint and the scheduling optimization of an OKP supply chain. In this section, several representative papers are briefly reviewed and then the requirements for the substantial characterization of the dynamic production capacity of an OKP are discussed.

2.1. Literature review on make-to-order system or mass customization

Johansen et al. [11] discussed a decision structure model for OKP decision process. Xiao et al. [27] developed game-theoretic models to explore the interactions between channel structure decision and the price-leadtime decisions for a make-to-order duopoly system under three game scenarios. Thürer et al. [24] outlined a planning and control concept known as workload control (WLC) that integrates customer enquiry management, including a due-date setting rule, with order release control. Feng et al. [9] studied the coordinated contract selection and capacity allocation problem, in a three-tier manufacturing supply chain, with the objective to maximize the manufacturer's profitability. Sawik [22] analyzed the selection of a dynamic supply portfolio in make-to-order environment with risks. Gunasekaran et al. [10] provided a review of the literature available on the modeling and analysis of BTO-SC or MTO-SCM (the build-to-order supply chain or make-to-order supply chain management) that may be useful for developing a unified framework based on configuration and coordination level issues for the modeling and analysis of BTO-SC; and suggested some important problems in BTO-SC. Rubino et al. [21] considered a dynamic control problem for a make-to-order, parallel-server queuing system; and proposed a nongreedy outsourcing and resource allocation policy. Chen et al. [8] considered an integrated production-distribution scheduling model in a make-to-order supply chain consisting of one supplier and one customer; and found a schedule for order processing and a way of packing completed orders to form delivery batches such that the total distribution cost is minimized subject to the constraint that a given customer service level is guaranteed. Celik et al. [7] presented a method of dynamic pricing and lead-time quotation for a multiclass make-to-order queue. Yao et al. [29,28] discussed supply chain planning and scheduling optimization in mass customization. Ata [3] considered an admission control problem for a multiclass, single-server queue and proposed a nested threshold policy. Bish et al. [5] showed that the performance of the system depends heavily on the allocation mechanism used to assign products to the available capacity through a stylized two-plant, two-product capacitated manufacturing setting.

2.2. Literature review on production planning with stochastic customer orders

Pazour et al. [18] studied rental vehicle threshold policies that considered expected waiting times for two customer classes. Souza et al. [23] analyzed incorporating priorities for waiting customers in a hypercube queuing model in an application of an emergency medical service system in Brazil. Roy et al. [20] presented queuing models to analyze dwell-point and cross-aisle locations in autonomous vehicle-based warehouse systems. Altendorfer et al. [2] discussed the influence of order acceptance policies on optimal capacity investment with stochastic customer required lead times. Renna et al. [19] proposed an approach to deal with the multiple suppliers-manufactures problem within dynamic industry cluster. Altendorfer et al. [1] compared made-to-stock and made-to-order processes in multi-product manufacturing systems with variable due dates. Morabito et al. [16] examined approximate decomposition methods for the analysis of multicommodity flow routing in generalized queuing networks; their focus was on steady-state performance measures such as average delays and waiting times in the queue.

Some relevant contributions dealing with the multi-objective optimization of supply chains are as follows. Musavi et al. [17] presented a multi-objective sustainable hub location-scheduling model for perishable food supply chain; however, the parameters of the model like demand and travel times in this research are assumed as deterministic, which shows some limitations in tackling uncertain environments. Bortolini et al. [6] also proposed a tri-objective linear programming model for the design of multi-modal fresh food distribution networks.

From the aspect of production approach, OKP is the extreme mode for highly customized and low volume products, which is make-to-order; while from the aspect of production object, OKP is the production of one product type, rather than the production of large amounts of standardized products. "Make-to-order" is only considered as one attribute of OKP. Because of OKP's particularity and its characteristics, its production time-variant nature should be considered. Most researches on BTO-SC or MTO system lay stress on the conversion of stochastic problems which are caused by uncertainty of customer orders; however, do not focus on the time-variant nature of the system itself (especially OKP system) that results from the pull-based production which is based on actual demand. Methods generated from traditional push-type production or mass production, which is based on demand forecast and make-to-stock, are still widely used in the research of the above production pattern. These methods, in different extent, show limitations in the study of OKP system. In this paper, we reckon that time-variant nature of OKP system gives rise to time-variable resource restrictions; what's more, triggers the principle contradiction of system resource allocation.

For most of the OKP enterprises, although the average service time and production capacity already satisfied the needs of customer order arrival, the manufacturing enterprises continued to experience the problem that certain orders could not be produced or served in time. Considering the production cost-benefit, the primary problem of the current production capacity analysis is to determine how to judge the existing production capacity to describe the real process of current production busyness situation, which should identify the variability of the related production performance measures that greatly fluctuate around the mean. However, many of the most popular studies in production planning with stochastic customer orders only consider the time-invariant or static production state, and continue to use queuing systems as their core, which always focus on steady-state performance measures such as average values and expectations and thus cannot provide the specific variability identification of performance measures.

Production process in OKP is a discrete event stochastic dynamic system and its system state is time-variable. Therefore, based on queuing system theory, in Section 4, the process-driven model, which is similar to the entity flow process, is utilized to simulate the production capacity; and the dynamic production capacity is clarified as the main factor that influences OKP supply chain scheduling mechanism based on the simulation study and analytical computation. Furthermore, to address the contradiction triggered by the dynamic production capacity restriction relationship, an integrated stochastic dynamic optimization model based on a dynamic pricing mechanism for two-way scheduling optimization in an OKP supply chain is provided; meanwhile, the dynamic model simulation solution and analysis are carried out.

3. Production core features in an OKP supply chain

An OKP supply chain model is considered as a pull-based lean production model which has a time-variant nature. A further elaboration of core production features in an OKP supply chain is conducted in the following:

3.1. Discrete events: random orders

From the perspective of supply chain individual members' production process, the arrival of random customer order is a discrete event occurred with time, which indicates the production system of customer orders is a discrete event system. This system can also be called a dynamic production system, in which production state changes are driven by discrete arrival of random customer orders. Discrete event system model cannot be described in the form of equation.

The occurrence of discrete events is usually random. Random customer orders produce variation in demand over time; the bullwhip effect takes place in a "pull-based" supply chain: for example, ship orders are random at shipyards, and this demand signal becomes more chaotic and unpredictable as one moves up the supply chain from ship-owners to raw material & equipment suppliers. For dominant enterprises in an OKP supply chain, it is indispensable to dissect the time-varying demands to further analyze dynamic available production capacity.

3.2. Dynamic production capacity based on discrete events

In the long run, the daily operations and production of various enterprises in an OKP supply chain exhibits certain capacity constraints. For example, in the block yard of a shipbuilding enterprise, the average monthly output of the block production process is constant. Due to the irregular arrival of consumer orders, the quantity of products that enter into the production area does not follow a uniform distribution. The supply chain individual members' production process is a stochastic discrete event dynamic system (DEDS). "DEDS is a dynamic, asynchronous system, where the state transitions are initiated by events that occur at discrete instants of time" (Ben-Naoum et al., pp. 3 [4]). The variation of available production capacity, i.e. dynamic production capacity, is because of irregular arrival of random demands; thus the production system state varies with time. This dynamic production capacity constraint in an OKP supply chain determines that OKP enterprises in cooperative relationships should show concern for the detailed production system transient performance evaluation.

In this paper, a process-driven service performance analog simulation is carried out to analyze the stochastic dynamic production capacity restriction from the perspective of dominant members in an OKP supply chain. Based on the analog simulation, a time variability analysis of existing production capacity used to describe the real process of current production busyness situation, which should identify the variability of the related production performance measures, has practical significance.

4. Analysis of dynamic production capacity restriction based on discrete events

In this section, the production capacity constraint in discrete event stochastic dynamic production system of OKP supply chain dominant enterprises is analyzed.

4.1. Problem description of the SYPC

The manufacturing process of a large-scale OKP primarily includes two types of production areas: a block workshop and an external field (block yard). Shipbuilding is a typical OKP; and shipyard is the dominant manufacturing member (or chain leader) in OKP supply chain, where major shipbuilding takes place. Since block yard production capacity constraint is the key consideration of OKP manufacturing cost-benefit, simulating the dynamic production capacity in block yard has practical significance. The problem is described as an analog simulation of yard production capacity (SYPC). In this paper, analytical computation for the construction capacity of the panel block yard in a shipyard is carried out to indicate the production capacity constraint in a discrete event stochastic dynamic production system.

OKP interim product manufacturing is a continuous process, so a Discrete Event Simulation (DES) will be utilized in this paper. The DES can clearly express the time and sequence of events and can indicate the type of entity stream that flows through the system. Here, the entity includes not only tangible objects but also the information or works awaiting processing. The DES Model can be generated using several different methods such as Activity-oriented Simulation, Process-driven Simulation and Event-driven Simulation. The investigation of the block yard's current production situation in a shipyard shows the production process is a "queuing system" that is an effective model for discrete event systems; therefore a Process-driven Simulation is selected for the modeling of the SYPC.

Based on queuing theory, the production capacity of the block yard is simulated according to the operation situation of the OKP enterprise; and the busy and idle times in an annual production process are obtained through a process-driven model that was developed to produce feasibility decision data for production planning. The statistical data for each service performance measure of the block yard, such as average value, median, standard deviation, coefficient of variation, skewness, kurtosis, minimum and maximum, are obtained by the analytical computation of DES.

4.1.1. Description of the queuing system in a block yard

Most OKP companies divide the production of orders into various types of block manufacturing, which means that different types of blocks, such as panel blocks and curved surface blocks, are professionally produced in the corresponding series of servers. Moreover, the production process of block manufacturing is a multi-operation process (e.g., panel block production process includes board jointing of inner bottom plates, automatic welding, assembly of inner bottom longitudinal, floor hanging, longitudinal bone & inner bottom welding, floor & inner bottom welding, floor & longitudinal welding, turning-over of frame, turning outer bottom plate upside down and outer bottom & frame welding). To enhance generality of simulation results for distinct shipyards, the multi-operation production process of the same type of block is regarded as one server, which simplifies the sequence servers used in actual block building into a single server. Then, the total service time of a single server and service resource occupation through the simulation are analyzed.

4.1.2. Queuing theory and the $M/M/1$ model

According to the actual building process of the large-scale OKP block production in the yard, the basic elements of the queuing model are described and the process-driven simulation model is built for the actual block building process.

According to three basic elements of this queuing system, the analysis is as follows: (1) The arrival process. For a given block production yard, assume that the block construction task arrivals follow a standard Poisson distribution, and the interarrival times are exponentially distributed. (2) The queue. When an entity arrives, if the service is busy, the entity will wait in the waiting line or the queue. The service discipline determines the rule regarding when the next entity is selected. The most commonly used laws are First Come First Served (FCFS), Last Come First Served (LCFS), Random Service (RS), and the Priority Decision Rule (PDR). According to the actual situation of the investigated OKP enterprise (for example, a shipyard), most production tasks in the waiting line are served in accordance with the FCFS discipline. The PDR is selected in a few cases. For convenience of analysis, our simulation follows the FCFS rule. (3) The structure of service. The structure of service indicates the features of servers. According to the various characteristics of the service, there are single-server systems, multi-server systems and sequence-server systems. Because the customer orders in an OKP process arrive in an irregular manner, and as a result of the production task distribution for the specific production process, the service rate of multi-servers in the block production yard varies according to a probability distribution. As indicated above, since distinct shipyards have different block manufacturing methods, the generality of simulation results for distinct shipyards will be reduced if taking into account each sub-link of multi-server systems or sequence-server systems. Here, the multi-operation production process of the same type of block is regarded as one server. With this simplification for various types of block yards, the simulation does not aim at analyzing distinct constructions of various kinds of blocks. The simulation principal object, which is determined according to the need of analog simulation, can not only be a specific block yard (e.g. panel block yard) but also be the block yard of an entire shipyard.

As discussed above, the following assumptions can be summarized for a block queuing model: (1) Poisson arrival; (2) exponential service time; (3) single server; and (4) FCFS service discipline. With regard to performance indices of the construction process in the block yard, the following mathematical description is used.

Assume an arrival intensity λ, which is the reciprocal of the mean interarrival time, and denote the mean service time as $1/\mu$. Obviously, the number of blocks that have arrived in unit time λ must be less than the number of blocks that can get service in unit time μ ($\lambda < \mu$). Otherwise, the number of blocks in the waiting line will continue to increase and form a queue based on queuing theory. According to the above assumptions, the following main operating characteristics of the single-server queuing system of the block yard are obtained:

(1) Average Waiting Time: $W_a = \frac{\lambda}{\mu(\mu-\lambda)}$.
(2) Average Number in Queue: $L_q = \frac{\lambda^2}{\mu(\mu-\lambda)}$
(3) Average Time in System: $W = \frac{1}{\mu-\lambda}$
(4) Average Number in System: $L = \frac{\lambda}{\mu-\lambda}$
(5) Idle Probability of Servers: $P_0 = 1 - \frac{\lambda}{\mu} > 0$
(6) Percentage of Busy Time: $\rho = \frac{\lambda}{\mu}$

Based on queuing system theory, a process-driven model in Section 4.2 is established to simulate the time-variable construction capacity of block yard. For convenience of analysis, the panel block yard of a shipyard is used as an example. As discussed in Section 2, the simulation aims at providing the specific variability identification of production capacity performance measures instead of focusing on steady-state performance measures such as average values and expectations, i.e. in actual block building process, the above production performance measures greatly fluctuate around the mean.

4.2. Process-driven service performance analytical computation of the block yard

The panel block yard of a shipyard is operated in a mode where task scheduling and production are arranged according to shipbuilding tasks such as the design department's annual construction plan and time requirements. The basic construction data of a certain year in the block yard are currently known.

According to the historical data provided by the shipyard, the blocks arrive in the yard at a random rate of 8 blocks per month, i.e., 1 block every 4 days ($1/\lambda = 4$). The average service time is 3 days for 1 block ($1/\mu = 1/3$). Although the average service time and capacity already satisfy the needs of block arrival, the block yard must address the issue whereby some blocks cannot be produced or served in time, which results in work delays and idle time in relevant departments. Currently, only the block yard offers production services; therefore, the analog simulation needs to obtain the performance measures of the actual service process in this block yard to provide a reasonable analysis for block yard stochastic dynamic production capacity constraint.

The construction processes for the panel blocks in the yard are as follows. First, a panel block arrives; if the panel block yard is idle, then the construction process is started; if the block yard is busy, this arrival block waits in the line for service until the blocks that previously arrived are served. The end time of the service is equal to the start time of the service plus the actual service time. After a panel block is serviced, the block leaves the yard and continues to the next production link (in shipbuilding, for example, this process consists of total assembly and the closing of blocks on the building berth).

4.2.1. Establishment of the process-driven model

4.2.1.1. Parameter setting. The fixed parameters and variable parameters are illustrated in the following tables (Tables 1 and 2):

4.2.1.2. The graphic description and mathematical description of block yard service. The objective of the simulation is to analyze the block yard busy degree in the actual operation process, which attempts to determine the block yard's current basic operation conditions, e.g., $\lambda_0 = 1/4 = 0.25$, $\mu_0 = 1/3 = 0.333$. Therefore, based on the above parameter descriptions, further graphic description and mathematical description of block yard servicing are needed.

A graphical description of the block yard service is described is presented below (Fig. 1):

A mathematical description of block yard service is described in the following:

Because a certain number of blocks are served by the yard in a certain amount of time, the simulation objectives (i.e. service performance measures) include first determining the average waiting time of arriving blocks, namely, $AVE(TimeWaiting(i))$. Then, the idle

Table 1
The fixed parameters.

The fixed parameters	
$\lambda_0 = 1/4 = 0.250$	the average arrival rate of the panel blocks ($/day$)
$\mu_0 = 1/3 = 0.33$	the service speed of the panel blocks ($/day$)

Table 2
The variable parameters.

The variable parameters	
$NumberBlock(i)i = 1, 2\cdots\cdots$	the number of panel blocks that are in the block yard (according to the FCFS sequence)
$TimeSpace(i)i = 1, 2\cdots\cdots$	the interarrival time of two adjacent blocks
$TimeArriving(i)i = 1, 2\cdots\cdots$	the actual arrival time of blocks
$TimeStart(i)i = 1, 2\cdots\cdots$	the service start time of blocks
$TimeDuration(i)i = 1, 2\cdots\cdots$	the service duration time of blocks
$TimeEnd(i)i = 1, 2\cdots\cdots$	the service end time of blocks
$TimeWaiting(i)i = 1, 2\cdots\cdots$	the waiting time parameter, in the case that an arrival block has to wait until its precursor block is served in the block yard
$TimeFree(i)i = 1, 2\cdots\cdots$	the idle time parameter, which indicates the time between completion of the service on the precursor and the service on the following block in the yard, in the case that the arrival block can be immediately served because there is no precursor block in the yard
$InlineBlock(i)i = 1, 2\cdots\cdots$	the waiting block number in line when a block arrives

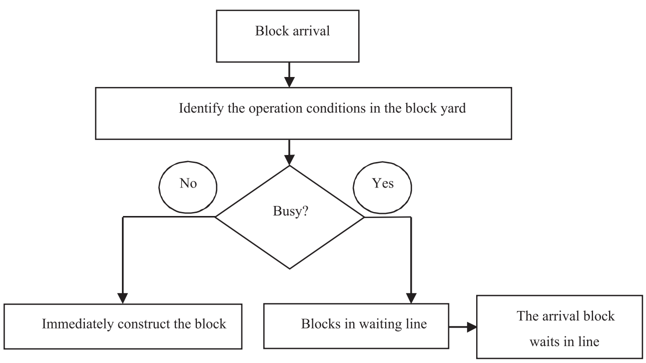

Fig. 1. The flow-process diagram of block yard service.

percentage of the yard, which is the percentage of idle time of the entire operation time, namely, $Per(TimeFree(i))$, is determined. Finally, according to the current status of the yard's operations, the maximum number of blocks waiting in line that are likely to appear in the yard, $Max(InlineBlock(i))$, is determined.

Assume that a block $NumberBlock(i)$ arrives at the yard after the precursor block $NumberBlock(i-1)$ and waits for servicing in the yard. The arrival time of a block is calculated as follows: $TimeArriving(i) = TimeArriving(i-1) + TimeSpace(i)$. If the yard is idle when the block arrives, this block can be immediately served. The service start time is then $TimeStart(i) = TimeArriving(i)$. When a block arrives, if the yard is busy, the block needs to wait in line until all blocks ahead of it in line are served, which means that when multiple blocks are waiting in line, the service principle is FCFS.

The subprogram loop process is described by the following diagram (Fig. 2):

The above calculation can achieve the first two objectives of the simulation; however, the number of blocks waiting in line must still be further analyzed. When the ith block arrives, $TimeArriving(i)$ is compared to $\min[TimeEnd(k)]$, $(k = 1, 2, \cdots, i-1)$; for the k'-th block ($k' \in [1, 2, \cdots, i-1]$), if $TimeEnd(k') < Timearriving(i)$ and $TimeEnd(k'+1) > Timearriving(i)$, then there are $(i - k')$ blocks waiting in line.

4.2.2. Implementation of the model

FORTRAN 90 is utilized to construct the corresponding simulation for the above model and obtained the following results. The single-replication simulation results are described by the following data (Table 3):

The multiple-replication simulation results are described by the following data (Table 4):

The statistical data obtained by the analytical computation in this paper are described in the following (Table 5):

The space-time variations of the queuing system in the block yard are shown in the following diagram (Fig. 3), which indicates the number of blocks waiting in line over time (365 days/year).

4.3. Analysis of analog simulation results

The analytical computation of the SYPC demonstrate the following: The average waiting time calculated using the queuing system is $\frac{0.25}{0.333 \times (0.333 - 0.25)} = 9\,days$, and the idle percentage of the yard is $1-\frac{0.250}{0.333} = 0.25$. After the SYPC was performed 100 times, as illustrated above in Table 5 and Fig. 3, the average waiting time of arriving blocks was found to be 7.47 days, which is considerably less than 9 days, and the yard idle percentage from the simulation was 0.267, which is slightly higher than 0.25. The average value of the maximum number of blocks waiting in line was 9.68. The above three simulation results were obtained for a block production yard with long-term stable operation. Although there was an idle probability of 26.7% in the block production yard, because the average value of the maximum number of blocks waiting in line per day was 9.68 and the standard deviation was 3.44, which is higher than the average block yard daily production capacity, the existence of partial time's busy states is inevitable in the block yard.

The block yard production capacity is the key consideration of OKP enterprises, e.g., a shipyard, for production planning and decision making from the perspective of costs and benefits. Effectively analyzing the current production capacity of a block yard through a simulation using three indicators, including the block waiting time, block yard idle time and maximum number of blocks waiting in line, provides decision support for OKP enterprises. As a typical dominant manufacturing node in OKP supply chain, shipyard is chosen for case study. Based on the simulation result analysis of a real block yard's stochastic dynamic production capacity constraint, the relevant elaboration is presented as follows:

First, as illustrated in Table 5 and Fig. 3, production process of OKPs is a discrete event stochastic dynamic production system that is time-variable; moreover, production system performance of dominant manufacturing enterprises fluctuates with time due to irregular arrival of random demands, which causes available production capacity wide variations of other cooperative enterprises in OKP supply chain as a result of bullwhip effect. Although the specific performance measures of the production capacity for raw material suppliers, manufacturers and logistics etc. are different, the essence is consistent. These dynamic production capacity constraints trigger the principal contradiction in OKP supply chain.

Second, time-dependent fluctuations of production system performance measures, which demonstrate dynamic production capacity, also reflect the non-substitutability of limited production resources of OKPs. In order to illustrate this dynamic process, Yao et al. [28] provided a diagram to show the relationships among the available production capacity, production time and production cost of the same product in the same manufacturing enterprise by dynamic data sampling, and indicated variations in the production cost and production time when the same product is produced at different times.

Third, large-scale OKP are the complex flexible manufacturing, which implies customized product production time is determined by multiple factors' interaction. Production time of various customized

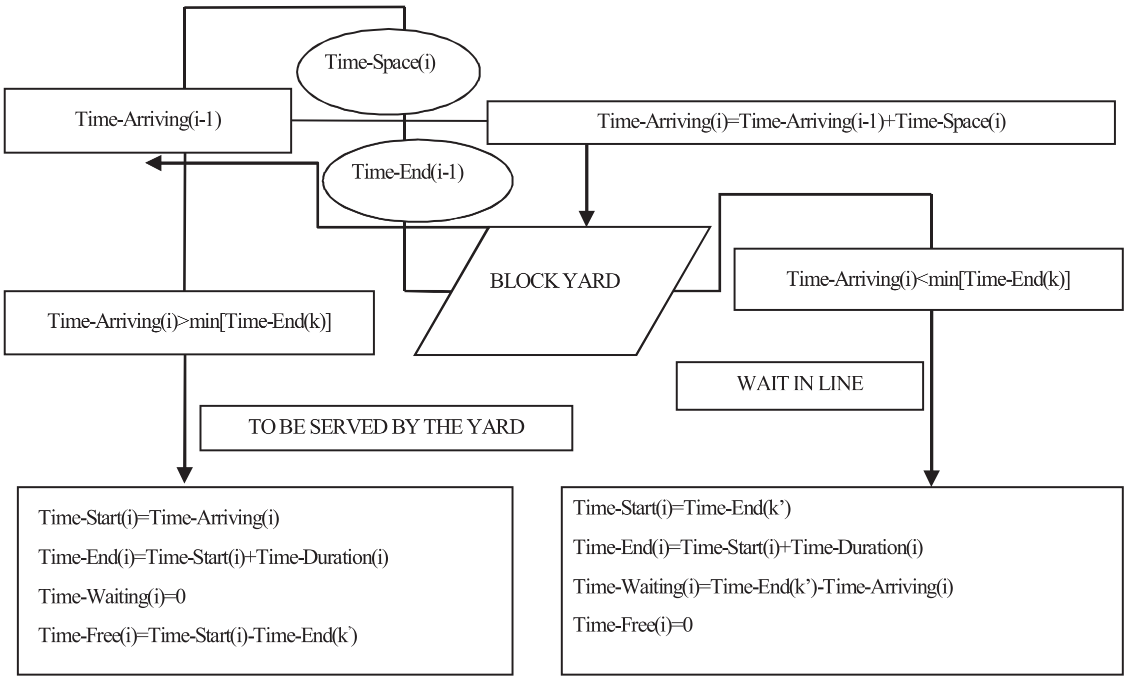

Fig. 2. The subprogram loop body.

products is "not only related to product composition parameters such as production schemes, workers of various sorts and different types of manufacture equipment, but also to a great extent affected by production process parameters" (Mei et al., pp. 864 [15]), e.g., flexible production line structural relationships and manufacturing or assembly sequences (Liu et al. [12]). Consequently, the production time of customized products is distinct; besides, customized product production time (or man hour) in OKP is the unit of cost measurement. This characteristic also directly leads to the time-dependent fluctuation of production cost, and further influences available production capacity in OKP as well.

In order to further analyze the block yard production capacity of shipyard indirectly, based on a current situation investigation, the analog simulation of block yard production schedule (SYPS) is made by the activity-oriented paradigm. This analytical computation is according to the annual block manufacturing tasks of a shipyard and part of the historical data is as follows (Table 6):

This simulation intends to schedule weekly block production rationally for each manufacturing year so as to satisfy JIT block supply for next production link. The input variables for the simulation system are: number of batches at the begin of each week, stochastic demand batches, number of completed batches, number of batches at the end of each week, overtime work identification and work completion identification. The total number of work weeks in one year is 48. The current rated block production capacity in the block yard is 25 batches/week. The maximum overtime work capacity is 20 batches/week. Here, "batch" is used as a unit in the simulation, which considers block manufacturing as an invisible product in simulating remaining block manufacturing when satisfying block production demand at a certain time. Since block manufacturing in a block yard usually spans a period of time, "batch" represents the simplification of block construction period, which already takes various construction complexities of different types of blocks into consideration. Therefore, the superposition

Table 4
The multiple-replication simulation data.

Number of simulations	AVE (Time-Waiting (i))	PER (Time-Free (i))	Max (Inline-Block (i))
1	0.176	0.176	0.176
2	1.067	1.243	2.481
3	6.684	7.928	7.928
4	0.613	8.541	12.294
……	……	……	……
96	0.319	375.353	387.866
97	4.342	379.695	395.059
98	6.202	385.897	397.445
99	0.588	386.485	399.188
100	0.996	387.481	408.505

Table 3
The single-replication simulation data.

Number-Block (i)	Time-Space (i)	Time-Arriving (i)	Time-Start (i)	Time-Duration (i)	Time-End (i)	Time-Waiting (i)	Time-Free (i)	Inline-Block (i)
0	0	0	0	0	0	0	0	0
1	0 . 176	0 . 176	0 . 176	2 . 305	2 . 481	0	0 . 176	1
2	1 . 067	1 . 243	2 . 481	0 . 351	2 . 383	1 . 238	0	2
3	6 . 684	7 . 928	7 . 928	4 . 367	12 . 294	0	5 . 095	1
4	0 . 613	8 . 541	12 . 294	2 . 976	15 . 270	3 . 753	0	2
……	……	……	……	……	……	……	……	……
96	0 . 319	375 . 353	387 . 866	3 . 883	391 . 750	12 . 831	0	7
97	4 . 342	379 . 695	395 . 059	2 . 387	397 . 445	15 . 363	0	6
98	6 . 202	385 . 897	397 . 445	1 . 743	399 . 188	11 . 549	0	5
99	0 . 588	386 . 485	399 . 188	9 . 317	408 . 505	12 . 703	0	6
100	0 . 996	387 . 481	408 . 505	3 . 239	411 . 744	21 . 025	0	7

Table 5
The statistical data of the service performance in the block yard.

	AVE (Time-Waiting (i))	PER (Time-Free (i))	Max (Inline-Block (i))
Number of simulations	100	100	100
Average value	7 . 47	26.7%	9.68
Median	6.006	27.05%	9.00
Standard deviation	4.88	0.088	3.44
Coefficient of variation	0.650	0.329	0.354
Skewness	1.903	−0.125	1.192
Kurtosis	5.385	−0.236	2.319
Minimum	1.223	0.048	4
Maximum	31.292	0.485	24

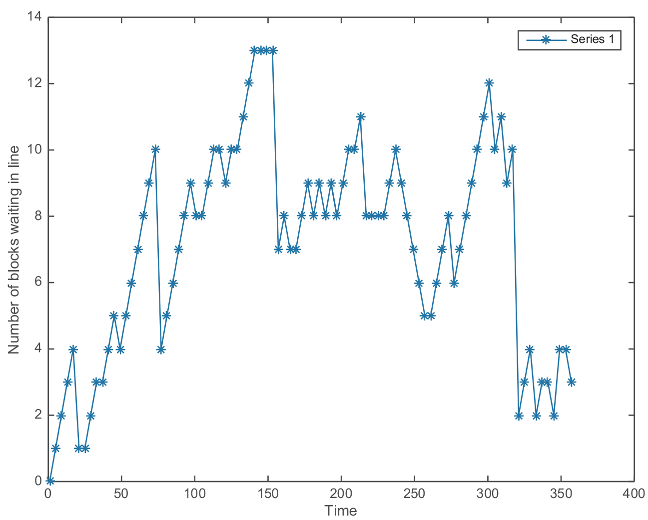

Fig. 3. The space-time diagram of the queuing system in a block yard.

Table 6
The annual completed blocks in a panel block yard.

Block Name	Port & Starboard	Block Length	Block Width	Block Weight	Welding Seam Length	Building Start Time	Finish Time
BN14	P	17.910	11.8	105.9	890	Jan-1	Jan-16
BN14	S	17.910	10.5	88.4	715	Jan-3	Jan-8
BN15	P	17.910	11.8	105.3	947	Jan-4	Jan-16
BN15	S	17.910	10.5	89.6	756	Jan-5	Jan-9
BN16	P	17.910	11.8	99.9	909	Jan-5	Jan-9
BN16	S	17.910	10.5	85.8	727	Jan-7	Jan-11
BN17	P	17.910	11.8	107.1	927	Jan-6	Jan-23
BN17	S	17.910	10.5	92	750	Jan-10	Jan-17
N16	P	17.910	11.6	253	967	Jan-5	Jan-9
N16	S	17.910	10.5	200.2	874	Jan-7	Jan-11
……	……	……	……	……	……	……	……
N17	S	17.910	10.5	230.1	880	Nov-20	Dec-7
N18	P	17.020	11.6	232.8	882	Nov-5	Dec-9
N18	S	17.020	10.5	255.9	785	Nov-27	Dec-21

of the number of units (batch) can be applied to analyze actual block construction situation in a block yard. To determine the stochastic demand batches, the lower and upper limits of stochastic demand are estimated as [20, 30] batches/week according to historical experience; and a random function generates random demand values. According to Table 6, the following analysis results can be obtained:

Number of overtime work: $Sumovertimework = 14$; number of times when the block batches aren't completed: $SumIFremainingbatches = 6$, JIT factor $JIT = \frac{48 - Sum\ IF\ remaining\ batches}{48} = 87.5\%$.

Since the influence of independent variable parameters on overtime work and JIT factor is very complex, based on the principle and method

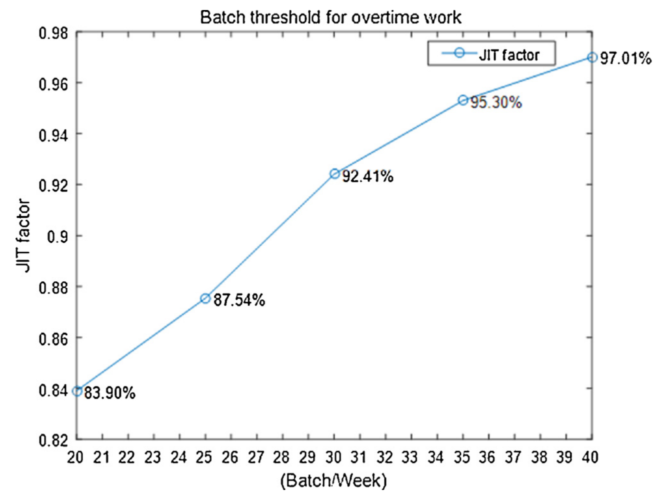

Fig. 4. JIT efficiency chart of production capacity threshold.

of Monte Carlo simulation, the obtained simulation results are further statistically analyzed after multiple-replications (150 large sample simulation tests) in the simulation system. The assumed block production capacity means the threshold value for overtime work. The corresponding efficiency chart of production capacity threshold is illustrated as follows (Fig. 4):

As indicated in Fig. 4, when the assumed block production capacity in the block yard is 40 batches/week, $JIT = 97\%$, i.e. the production capacity can meet JIT block supply. When the input variable is changed in the simulation system and "production capacity threshold" is replaced with "number of overtime work", the values are 13.127, 13.213, 13.133, 12.747, and 12.533, i.e. these values of "number of overtime work" do not change significantly so that the main parameters and results can be obtained from the above simulation. The current rated block production capacity in the block yard is 25 batches/week, which cannot guarantee JIT block supply ($JIT = 87.5\%$) for the next production link and annually requires additional 14 overtime work to make satisfied JIT supply. This SYPS illustrates that the actual block manufacturing fluctuates with time in the block yard and the demand for production capacity of block yard is also time-variable. Consequently, the corresponding occurred production cost changes over time.

This study attempts to explore the interactive relationships between OKP manufacturing at a micro level and its supply chain at a macro level in this research. Dynamic available production capacity, which is provided by the "stochastic discrete event dynamic" production system and determined by irregular arrival of discrete customer orders and non-substitutability of time-varying production resources, fluctuates with time and therefore influences the corresponding production cost and time. Since both production cost and production time have the time-varying feature in OKP, dynamic pricing based on costs and production time (delivery date), which are influenced by the dynamic available production capacity, can implement two-way scheduling optimization in an OKP supply chain. Furthermore, an integrated stochastic dynamic optimization model based on a dynamic pricing mechanism for two-way scheduling optimization in an OKP supply chain is proposed in Section 5 to address the principal contradiction triggered by the dynamic production capacity restriction relation.

5. Scheduling optimization model for an OKP supply chain

The dynamic production capacity restriction is the dominant restriction mechanism in an OKP supply chain. Based on the above analysis, an integrated stochastic dynamic optimization model for OKP supply chains is proposed. Yao et al. [28,29] presented a scheduling optimization model of supply chains based on time threshold value for mass customization that regards the total production cost and production time as the multiple objectives. However, like the push-type method of supply chain management that is represented by "make to stock", "time threshold value" theory is also based on demand forecast (not actual demand) and comparatively laid on "static" production state, which to some extent cannot be adopted one-to-one on mass customization (especially on OKP) pull-based lean manufacturing; besides, the production cost cannot indicate the dynamic constraint relationship between the suppliers and customers in the OKP supply chain, nor it can reflect the interactions between micro-level OKP manufacturing and its macro-level supply chain.

To address the contradiction generated by the dynamic production capacity restriction relationship which is analyzed in Section 4, a dynamic pricing mechanism for two-way scheduling optimization in an OKP supply chain is presented. Two-way scheduling optimization in an OKP supply chain coordinates every member's remaining production capacity and schedules key orders and general orders from customers by macro market dynamic guidance prices to reduce the total production costs and time in an OKP supply chain.

5.1. Problem description and notation

In this section, based on the model description of Yao et al. [28], the problem settings and notation are described as follows.

S denotes the number of production stages for OKP products in a supply chain production system, and s denotes each production stage, $s = 1, 2, \cdots, S$. For example, in a shipbuilding supply chain, the basic echelons are raw material & equipment suppliers, shipyards and shipowners.

N_s denotes the number of independent production members in each production stage s.

In this study, an OKP supply chain accepts two types of orders: general orders and key orders. Price mechanism shows two-way adjustment effects in macro level supply chain scheduling, so the concept of macro market dynamic guidance prices is introduced in the proposed scheduling optimization model. At a certain moment of supply chain scheduling, key orders represent orders that need to enter the supply chain system right away and are not influenced by the present market guidance price according to customers' inclinations; orders that don't have to enter the supply chain system at once and are influenced by market dynamic guidance prices are general orders. As a threshold in a macro supply chain environment, market guidance prices change over time and differentiate orders that intend to enter the supply chain system, which guarantees supply chain scheduling efficiency, i.e. the current available production capacity in the supply chain preferentially satisfies the demands of key orders.

O_T denotes the number of customer orders that dominant members receive during time T. Here, dominant members in OKP supply chain, i.e. core OKP enterprises, are chain leaders who have strong direct or indirect influence on supply chain resource allocation and application; or who force change to occur across the supply chain, e.g. shipyards in a shipbuilding supply chain. $O_K.T$ denotes the number of key orders (K-orders) that have a strict time of delivery requirement. $O_G.T$ denotes the number of general orders (G-orders). $f_G(P_T)$ denotes the number of G-orders as a function of price at time T. $O_{G.T} = f_G(P_T)$; $O_T = O_{K.T} + O_{G.T}$.

T_i' denotes the time of delivery for each order. $i = 1, 2, \cdots, O_T$.

$A^s_{Dem.i}(t)$ denotes the demand of each customer order on the available production capacity in production stage s at time t. $A^s_{Supp.j}(t)$ denotes each production cooperator's available production capacity of production stage s at time t. Under the macroscopic and microscopic price mechanism, the total available production capacity in each production stage of supply chain should satisfy the total production capacity requirement of customer orders in each production stage.

$P^{sj}_i(t)$ denotes the price at time t that each production cooperator in production stage s quotes for each customer order according to the cost, which is influenced by the available production capacity and the time of delivery requirement; $j = 1, 2, \cdots, N_s$. For OKP supply chain scheduling, to reduce the total price of supply chain is obviously one of the optimization goals. $T^{sj}_i(t)$ denotes the production time at t. In OKP supply chain, the more available production capacity of enterprises, the greater the production competitiveness of these enterprises. As discussed in Section 4.3, production time (or man hour) optimization of OKPs, not only concerns production cost optimization but also improves available production capacity of enterprises. Therefore, production time is considered as another optimization objective of OKP supply chain scheduling.

To reduce production time could bring about the relevant inventory cost. $T^{sj}_{Inve.i}(t)$ denotes the extra inventory time, which is "generated by compressing production timetables to improve the available production capacity of each production cooperator in the production process" (Yao et al., pp. 61 [28]). $C^{sj}_{Inve.i}(t)$ denotes the extra incurred inventory cost. φ^{sj} denotes the coefficient, and $C^{sj}_{Inve.i}(t) = \varphi^{sj} \cdot T^{sj}_{Inve.i}(t)$.

The variable $\sigma^{sj}_i(t) = \{0, 1\}$, and $\sigma^{sj}_i(t) = 1$ denotes that the ith order is produced by the jth production cooperator in production stage s at a certain time t. $\sigma^{sj}_i(t) = 0$ denotes other situations.

ξ denotes the tolerance coefficient of the delivery date delay.

5.2. Scheduling optimization model

The scheduling optimization model for an OKP supply chain is developed as follows:

$$\min z = \sum_{s=1}^{S}\sum_{j=1}^{N_s}\sum_{i=1}^{O_T} [(P^{sj}_i(t) + C^{sj}_{Inve.i}(t) + T^{sj}_i(t)) \cdot \sigma^{sj}_i(t)] \tag{1}$$

$$\text{s.t.}\ \ O_T = O_{K.T} + f_G(P_T) \tag{2}$$

$$\sum_{j=1}^{N_s} A^s_{Supp.j}(t) \geq \sum_{i=1}^{O_T} A^s_{Dem.i}(t) \tag{3}$$

$$T_i' \leq \sum_{s=1}^{S}\sum_{j=1}^{N_s} (T^{sj}_i(t) + T^{sj}_{Inve.i}(t)) \cdot \sigma^{sj}_i(t) \leq T_i'(1+\xi) \tag{4}$$

$$\sum_{j=1}^{N_s} \sigma^{sj}_i(t) = 1 \tag{5}$$

Here, $\sigma^{sj}_i(t) = \{0, 1\}$; $C^{sj}_{Inve.i}(t) = \varphi^{sj} \cdot T^{sj}_{Inve.i}(t)$; $s = 1, 2, \cdots, S$; $j = 1, 2, \cdots, N_s$; and $i = 1, 2, \cdots, O_T$. In this model, Eq. (1) is the objective function, which indicates multiple aspects (i.e., to minimize cost and production time) for evaluating the supply chain performance. Here, production price (according to the cost) and production time are two basic performance measures with equal weight for supply chain scheduling, which are treated as the same through a unified measurement scale in this paper. A single output generated from Eq. (1) helps to comprehensively consider the general benefit level and operational efficiency of a supply chain system. Eq. (2) is the customer order constraint; Eq. (3) indicates the relationship between total available production capacity and total production capacity requirement in the supply chain under the macroscopic and microscopic price mechanism; Eq. (4) shows the production time or delivery date constraint for each customer order; and Eq. (5) indicates each customer order production in production stage s only can be completed by one production member.

5.3. Model solution and analysis

At a given time t, the variables associated with t in the above model change to known quantities, which indicates the model is transformed into a linear model. The performance of OKP supply chain optimization scheduling can be analyzed by sampling at a certain moment when market dynamic guidance price is adjusted. Market guidance prices in a macro environment are determined by $P^{sj}_i(t)$ in a micro environment.

At a certain moment, multiple customer orders enter the supply

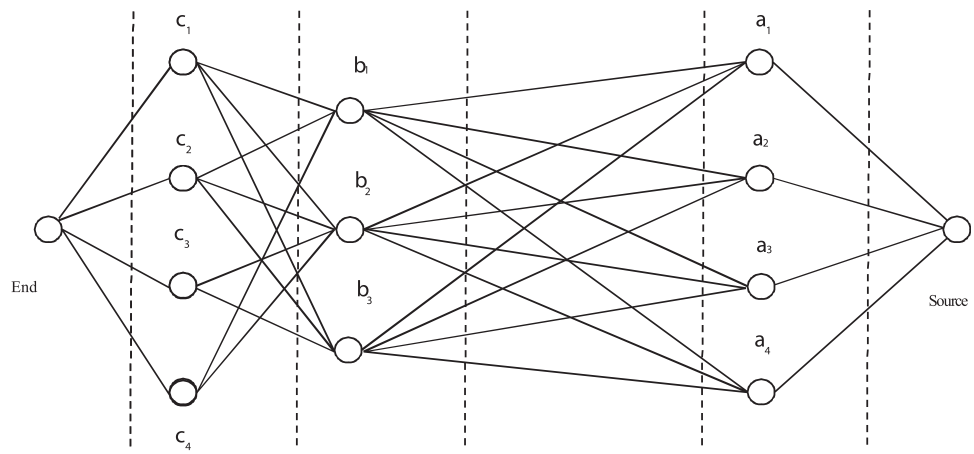

Fig. 5. Network structure of OKP supply chain scheduling algorithm operation.

Table 7
Data of the nodes.

	Customer Order 1 (quoted price, production time)	Customer Order 2 (quoted price, production time)	Customer Order 3 (quoted price, production time)
a_1	(4, 3)	(5, 7)	(9, 2)
a_2	(2, 1)	(12, 4)	(11, 7)
a_3	(3, 7)	(10, 7)	(18, 1)
a_4	(6, 6)	(12, 8)	(20, 3)
b_1	(13, 8)	(3, 1)	(14, 4)
b_2	(11, 8)	(12, 10)	(13, 5)
b_3	(1, 9)	(4, 4)	(17, 5)
c_1	(1,4)	(20, 4)	(5, 7)
c_2	(10, 3)	(6, 1)	(1, 7)
c_3	(1, 2)	(11, 9)	(1, 7)
c_4	(9, 1)	(1, 9)	(19, 8)

chain production system; meanwhile, both the price and production time that each production cooperator quotes for each customer order are different; besides, the repelling interaction among orders should be considered in order to avoid low efficiency of supply chain scheduling when customer orders congregate around a few members of the supply chain in a micro environment. A multi-type ant colony algorithm (MTACA) is presented based on the improvement of basic ant colony algorithm for simulation optimization. The algorithm parameter settings are as follows.

Relevant parameter settings: the quantity of customer orders is 3; the number of ants for each order in this simulation is 20; iteration number is 100; pheromone attenuation factor is 0.1; enhancement factor is 10; node number is 13 (including the source point and the destination point, as shown in Fig. 5).

Algorithm steps are described as the following:

Step 1, ants of various customer orders start from the source point.

Step 2, m ants select the production cooperator of next stage according to probability function, and complete their travelling in the network respectively. Here, path selection probability $P_{i.sj} = 0.7P_A - 0.15P_{R'} - 0.15P_{R''}$, $i = 1, 2, 3$; P_A denotes the attracting probability; $P_{R'}$ and $P_{R''}$ are exclusion probabilities of the other orders in supply chain. Attracting probability factor is 0.7; exclusion probability factor is 0.15.

Step 3, record the best route for this iteration and the number of ants in each cooperative node.

Step 4, update pheromones (the enhancement factor is 10).

Step 5, if the iteration number achieves the specified number of times, then program stop; otherwise, return Step 1.

In simulation analysis, the supply chain network shown in Fig. 5 is

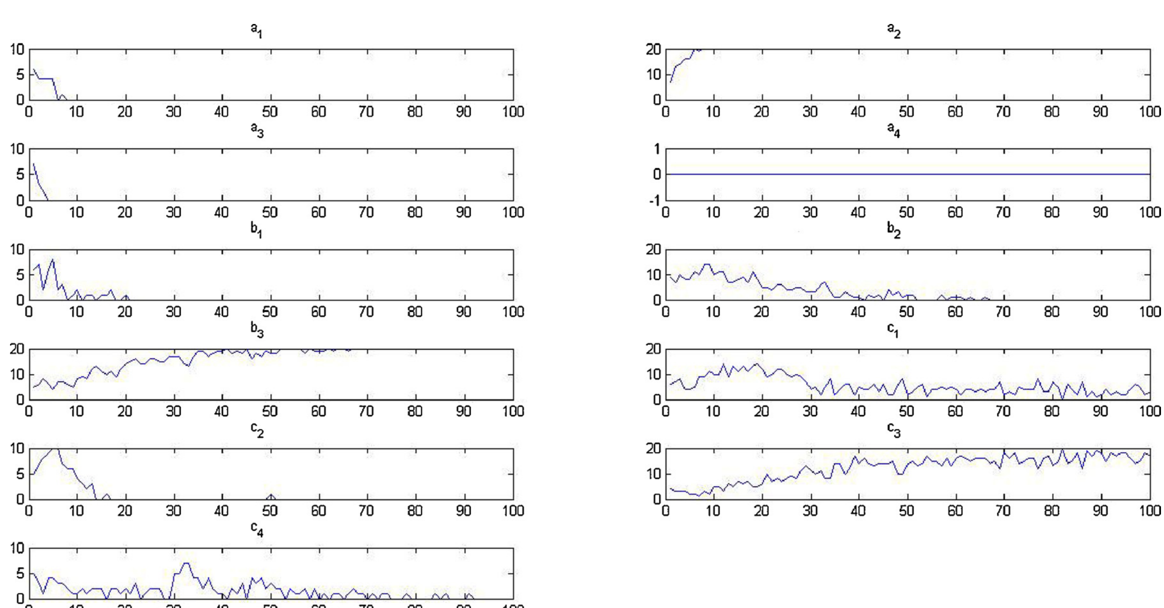

Fig. 6. Convergence charts of customer order 1 on each node.

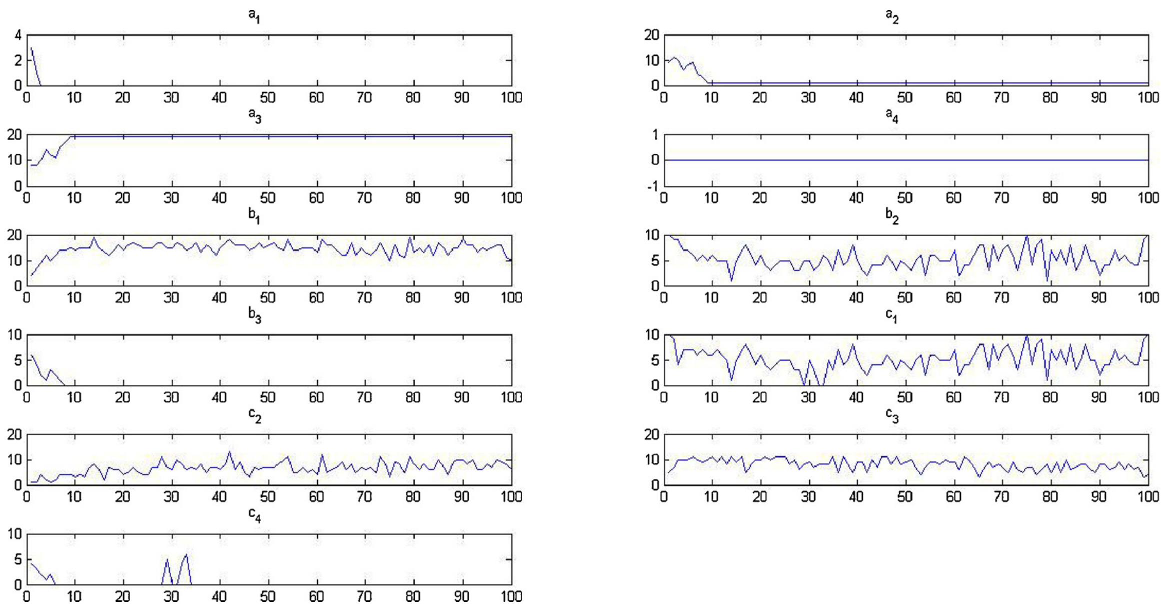

Fig. 7. Convergence charts of customer order 2 on each node.

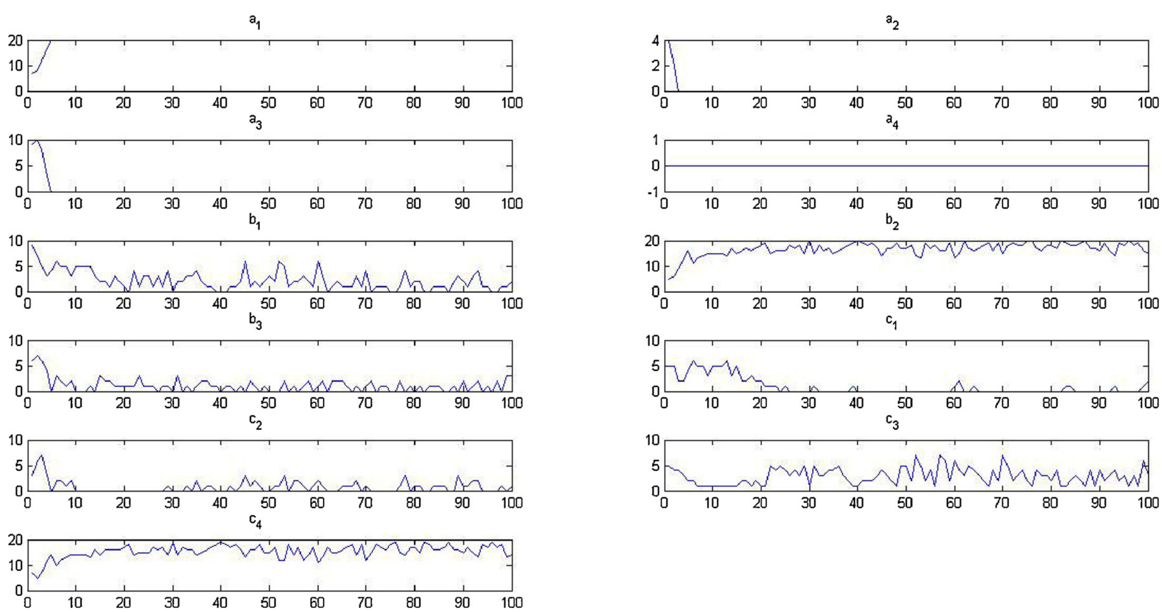

Fig. 8. Convergence charts of customer order 3 on each node.

used to describe OKP supply chain scheduling algorithm operation; besides, considering the general applicability, numerical examples are generated randomly in the program.

One of the numerical examples is provided in this paper. The randomly selected parameters are shown in Table 7. The convergence trend charts of simulation results are illustrated in Figs. 6–8. The simulation software is MATLAB R2015b. Here, quoted prices of each node are the sum of dynamic production prices and inventory costs.

Case studies reflect multiple optimization objectives of OKP supply chain scheduling, i.e. total quoted prices and total production time of customer orders. According to dynamic pricing mechanism and delivery time constraints, in the above case study, when computing comes to a steady state, customer order 1 chooses route (a_2, b_3, c_3) for production; customer order 2 chooses route (a_3, b_1, c_2) for production; customer order 3 chooses route (a_1, b_2, c_4) for production.

In an OKP supply chain, a "two-way" stochastic dynamic scheduling optimization, in a sense, reflects the adjustment of a market economy. The dynamic pricing mechanism based on the dynamic production capability and delivery time embodies the complicated real-world co-operation and competition relationships of supply chain members. In the context of global production, any irregular acts by members can reduce the efficiency of the supply chain. According to the restriction of production resources, "to timely give up" orders implies that the partial process is "unable to have", "should not have", or "does not need to have" these orders "to get" or achieve the goal of the whole process; moreover, achieving the whole process will promote achievement of the partial process. In this research, OKP supply chain scheduling optimization is discussed from the aspect of the interactions between OKP manufacturing at a micro level and its macro-level supply chain.

6. Conclusion

In this paper, OKP supply chain is studied as a pull-based lean production model with time-variant nature, in which the production is based on actual demand. Supply chain scheduling optimization in an OKP is a typical dynamic optimization problem of stochastic demand and time-variable resource restriction. Based on the substantial description of the characteristics and the core idea of the OKP supply chain, the dynamic production capacity restriction, which is the dominant restriction mechanism in the OKP supply chain and the main factor that influences the supply chain scheduling, is analyzed using a process-driven service performance analog simulation from the perspective of dominant members in the OKP supply chain. Based on this simulation study and analytical computation, furthermore, an integrated stochastic dynamic optimization model based on a dynamic pricing mechanism for two-way scheduling optimization in an OKP supply chain is proposed from the aspect of supply chain at a macro level.

As future work, the proposed model can be examined using an example of an OKP supply chain to analyze the optimization objective maturity and verify the feasibility of the model.

Based on some achieved useful research results, the proposed research, from the perspective of OKP manufacturing at a micro level, e.g. block construction in shipbuilding, indirectly provides a basis for further analysis of the yard production capacity and supplies decision support for the yard scheduling and production control. To eliminate bottlenecks caused by dynamic production capacity restriction and achieve balanced production in OKP industrial enterprises, more research on the “optimal” admission of pre-scheduled OKP interim products from the waiting line to the production yard is needed. Moreover, to maximize the production resource utilization in an OKP supply chain, dynamic pricing principles based on enterprises’ dynamic production capability are worth further investigation.

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