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Modeling and Pareto optimization of multi-objective order scheduling problems in production planning ☆

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ABSTRACT

This paper addresses a multi-objective order scheduling problem in production planning under a complicated production environment with the consideration of multiple plants, multiple production departments and multiple production processes. A Pareto optimization model, combining a NSGA-II-based optimization process with an effective production process simulator, is developed to handle this problem. In the NSGA-II-based optimization process, a novel chromosome representation and modified genetic operators are presented while a heuristic pruning and final selection decision-making process is developed to select the final order scheduling solution from a set of Pareto optimal solutions. The production process simulator is developed to simulate the production process in the complicated production environment. Experiments based on industrial data are conducted to validate the proposed optimization model. Results show that the proposed model can effectively solve the order scheduling problem by generating Pareto optimal solutions which are superior to industrial solutions.

1. Introduction

In manufacturing companies, production planning is at the top level of production management and is crucial to successful production management because its performance greatly affects the performance of production control and supply chain management. This paper investigates a decision-making problem in the production planning stage, a multi-objective multi-site order scheduling problem in a medium-term planning horizon, by developing an effective methodology for the problem.

1.1. Multi-site order scheduling in production planning

Consider the real-world production environment of the manufacturing company with multiple plants (sites), multiple production departments and multiple production processes. The manufacturing company receives a large number of production orders from different customers, which need to be assigned to the company's self-owned or collaborative plants for production. The production of a product (or a production order) involves multiple production processes, including ordinary processes and special processes. Each plant can produce all ordinary processes. However, not every plant can produce special processes because some plants do not have the production department required for the corresponding special processes. As a variety of production orders need to be assigned to appropriate plants for production, it is probable that different production processes of an order need to be assigned to different plants. The manufacturer must determine how to assign each production process of this order to an appropriate plant (site) and determine the beginning time of each process in a planning horizon of several months, which is called the multi-site order scheduling (MSOS) problem. This problem is faced by a large number of manufacturing companies from labor-intensive industries such as the apparel industry. The investigation on this problem is very important because its performance greatly affects the performance of downstream production control and the entire supply chain.

The MSOS problem is a complicated combinatorial optimization problem with a huge solution space. Take a simple order scheduling problem considering 10 production orders and 3 factories as an example. There are 3^{10} candidate solutions for this problem even if each order has only one production process. The real-world problems have a much greater solution space because they need to handle the production of a large number of production orders (often more than 100) with multiple production processes in a longer time period and determine the values of a large number of variables. There does not exist an effective methodology for this problem nowadays. The order scheduling process in today's labor-intensive manufacturing mainly rests on the experience and subjective assessment of the production planner.

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1.2. Research issues in production planning decision-making

Production planning decision-making involves a wide variety of research issues, including master production schedule (Sahin, Robinson, & Gao, 2008; Venkataraman & Nathan, 1994), material requirements planning (Dolgui & Prodhon, 2007; Le, Gunn, & Nahavandi, 2004), manufacturing resource planning (MRP II) (Sawyer, 1990; Wazed, Ahmed, & Nukman, 2010), enterprise resource planning (Ehie & Madsen, 2005; Parush, Hod, & Shtub, 2007), and aggregate planning (Jamalnia & Soukhakian, 2009; Lee, Steinberg, & Khumawala, 1983). A great number of papers have been published in this area and some researchers provided comprehensive review papers (Dolgui & Prodhon, 2007; Mula, Peidro, Diaz-Madronero, & Vicens, 2010; Wang, Keshavarzmanesh, Feng, & Buchal, 2009; Wazed et al., 2010).

Some researchers investigated the decision-making problems in production planning from other perspectives. Li, Man, Tang, Kwong, and Ip (2000) addressed the production planning and scheduling problems in a multi-product and multi-process production environment with the lot-size consideration. Jozefwska and Zimniak (2008) presented a decision support system for short-term production planning and scheduling in production plants characterized by a single-operation manufacturing process. Some researchers investigated the multi-site production planning problem (Guinet, 2001; Leung, Tsang, Ng, & Wu, 2007; Timpe & Kallrath, 2000), which consider each site as an independent and parallel production unit and usually belong to aggregate planning problems. However, few studies have focused on release and scheduling of production orders (or processes) among different sites in production planning stage so far.

Ashby and Uzsoy (1995) presented a set of heuristic rules to integrate order release, group scheduling and order sequencing in a single-stage production system. Axsater (2005) addressed the order release problem in a multi-stage assembly system, which focused on determining the starting time of different production operations but did not consider where the process was produced. Chen and Pundoor (2006) addressed order allocation and scheduling at the supply chain level, which focused on assigning orders to different production plants and exploring a schedule for processing the assigned orders in each plant. However, their study has not considered the effects of different production departments and their production capacities on scheduling performance. Each production department indicates a type of shop floor. The order release and scheduling problem in the production planning stage, considering multiple plants and multiple production departments and multiple production processes, has not been investigated.

This paper will investigate the MSOS problem with the consideration of multiple production plants and multiple types of production processes. Due to the complexity of the investigated problem, the values of objective functions of each candidate order scheduling solutions cannot be obtained directly by mathematical formulas, which can only be derived by simulating the production of all production processes in appropriate plants. Unfortunately, no simulation model is available so far.

In this paper, the mathematical model of the investigated MSOS problem in the production planning stage will be established firstly. Based on the mathematical model, an effective optimization model is developed to solve the MSOS problem. In the optimization model, a simulation model, called the production process simulator, is proposed to simulate the production of different production orders in multiple plants.

1.3. Multi-objective optimization techniques in production decision-making

In real-world production decision-making, it is usual that multiple production objectives need to be considered and achieved simultaneously. Some researchers use the weighted sum method to turn the multi-objective problems to single-objective ones (Guo, Wong, Leung, Fan, & Chan, 2008a; Ishibuchi & Murata, 1998). However, it is difficult for some problems to determine the weights of different objectives. It is also impossible to have a single solution which can simultaneously optimize all objectives when multiple objectives are conflicting. To handle this problem, some researchers used the concept of Pareto optimality to provide more feasible solutions (Pareto optimal solutions) to the production decision-maker (Chitra, Rajaram, & Venkatesh, 2011; Ishibashi, Aguirre, Tanaka, & Sugimura, 2000; Jozefwska & Zimniak, 2008; Liu, Yan, & Yu, 2009; Zhang & Gen, 2010).

The GA is the most commonly used meta-heuristic technique for multi-objective optimization problems (Chang & Chen, 2009; Deb, Pratap, Agarwal, & Meyarivan, 2002; Guo, Wong, Leung, & Fan, 2009; Guo et al., 2008a, Guo, Wong, Leung, Fan, & Chan, 2008b; Jones, Mirrazavi, & Tamiz, 2002; Zhang & Gen, 2010). Some researchers focused on developing multi-objective GAs to seek Pareto optimal solutions (Deb et al., 2002; Ishibashi et al., 2000). A significant paper for multi-objective GA was published by Deb et al. (2002), in which a fast elitist non-dominated sorting GA (NSGA-II) was proposed. Since then, the NSGA-II has attracted more and more attention, and was used and modified for various optimization problems. However, the NSGA-II has not been reported to handle the combinatorial optimization problems in production planning. The existing NSGA-II cannot be directly used to handle the MSOS problem because different chromosome representations and genetic operators are required for different optimization problems.

An effective Pareto optimization model, which combines a NSGA-II-based optimization process and a production process simulator, is developed to provide Pareto optimal solutions for the investigated MSOS problem. To construct the NSGA-II-based optimization process, the chromosome representation and genetic operators are modified to handle the MSOS problem.

The rest of this paper is organized as follows. Section 2 presents the mathematical model of the investigated MSOS problem. In Section 3, a Pareto optimization model is developed to solve the problem. In Section 4, experimental results to validate the performance of the proposed model are presented. Finally, this paper is summarized and future research direction is suggested in Section 5.

2. Mathematical model of the order scheduling problem in production planning

This section presents the mathematical model of the MSOS problem in the production planning stage.

2.1. Nomenclature

The notations used in developing the mathematical model of the MSOS problem investigated are classified into 3 categories, including production order-related, production process-related and production department-related notations, which are listed out below.

Production order-related notations

G_h	hth production order group
O_i	ith production order ($1 \leqslant i \leqslant m$)
$\boldsymbol{m}$	the number of production orders (parameter)
D_i	due date of order O_i (parameter)
$\boldsymbol{F_i}$	finishing time of order O_i, the time when order O_i is delivered to central warehouse (intermediate variable)
TD_i	tardiness (tardy days) of order O_i (intermediate variable)
TPT_i	throughput time of order O_i (intermediate variable)

(*continued on next page*)

Production process-related notations

P_{ij} production process of type j of order O_i, ($1 \leqslant j \leqslant N$). P_{ij} exists if O_i includes production process of type j, otherwise P_{ij} does not exist

N the total number of the types of production processes in all plants (parameter)

A_{ij} arrival time of process P_{ij} in the production department processing P_{ij} (intermediate variable)

B_{ij} beginning time for performing process P_{ij} (decision variable)

C_{ij} completion time for performing process P_{ij} (intermediate variable)

T_{ij} processing time of process P_{ij} (intermediate variable)

TTS_{ij} time (days) to transport semi-finished products with finished process P_{ij} between production departments (plants) chosen by the developed optimization model (intermediate variable)

W_{ij} workload of P_{ij} (parameter, unit: standard man days)

WT_{ij} waiting time, time to wait for the arrival of process P_{ij} in the idle production department (intermediate variable)

X_{ij}^k, indicates if process P_{ij} is assigned to production department S_{kj}, X_{ij}^k is equal to 1; otherwise it is equal to 0. (decision variable)

Production department-related notations

S_{kj} production department of type j in the kth plant ($1 \leqslant \boldsymbol{k} \leqslant \boldsymbol{n}$). S_{kj} exists if the kth plant includes shop floors of type j, otherwise S_{kj} does not exist. S_{kj} can only produce P_{ij}

$\boldsymbol{n}$ the number of production plants (parameter)

IS_{kj} indicate if S_{kj} exists, $IS_{kj} = 1$; otherwise $IS_{kj} = 0$ (parameter)

PC_{kj} daily production capacity of S_{kj} (parameter, unit: standard manpower)

SP_{kj} set of production processes assigned to S_{kj} for processing

TIT_{kj} total idle time of production department S_{kj} (intermediate variable)

TT_k time (days) to transport finished products to central warehouse from the kth plant (parameter)

2.2. Problem description

The MSOS problem considers n production plants located in different locations. These plants involve N production departments numbered as 1 to N, which perform, respectively, N types of different production processes denoted as process type 1 to process type N. These production departments can be classified into two categories: ordinary category and special category. Each category involves multiple production departments. Each plant includes all production departments of ordinary category whereas it is possible that a plant only partly includes (or even does not include) production departments of special category. In other words, different plants can have different numbers of production departments. In this research, we use the term "standard manpower" to represent the standard available manpower in each production department. The standard manpower of a production department is equal to the summation of each operator's average efficiency in the department.

In today's labor-intensive industries, a production order usually has a small product quantity and a tight due date. The manufacturer always receives a number of production orders with the same or close due dates from a customer (e.g., the retailer) at a time. We group these orders according to their due dates. Each group of these orders with the same due date is defined as an order group. Each order group usually consists of multiple production orders, each of which consists of a maximum of N production processes. In each order, the production process with larger process type number needs to be performed earlier. Each order involves all production processes performed in the production departments of ordinary category whereas it is possible that the order only partly involves (or even does not involve) processes performed in production departments of special category. Each production process of an order is assigned to only one plant for processing due to the small product quantity. All finished products are delivered to a central warehouse for product delivery and distribution. The transportation time between different production departments in a plant is considered in the processing time of production processes.

2.3. Assumptions

In this research, the addressed MSOS problem is formulated based on the following assumptions.

(1) One production department cannot perform more than one production order at a time.
(2) Once a production process is started, it cannot be interrupted.
(3) There is no shortage of materials in production.

2.4. Constraints

The real-world manufacturing environment is subject to the following constraints.

(1) Process allocation constraint: If production process P_{ij} exists, it must and can only be assigned to one production department for processing, i.e.,

$$\sum_{k=1}^{n} X_{ij}^k = 1 \tag{1}$$

If the first production process P_{i1} of order O_i is assigned to the kth plant, its subsequent processes also need to be assigned to this plant if the plant includes the corresponding production departments performing these processes, i.e.,

$$X_{ij}^k = 1 \ (j > 1) \quad \text{if } X_{i1}^k = 1 \quad \text{and} \quad IS_{kj} = 1 \tag{2}$$

To speed up production and decrease transportation cost, the production processes of the same process type in each production order group must be assigned to the same plant for processing in real-world production, i.e.,

$$X_{i'j}^k = 1 \quad \text{if } X_{ij}^k = 1, \quad O_i \in G_h \quad \text{and} \quad O_{i'} \in G_h \tag{3}$$

(2) Process precedence constraint: For order O_i, the production process with smaller process type number must be performed earlier, i.e.,

$$B_{ij} \leqslant B_{i(j+1)} \tag{4}$$

(3) Beginning time constraint: Production process P_{ij} cannot be processed before the process is transported to the assigned production department, i.e.,

$$A_{ij} \leqslant B_{ij} \tag{5}$$

where

$$A_{ij} = \begin{cases} C_{i(j-1)} + TTS_{i(j-1)} & (j > 1) \\ 0 & (j = 1) \end{cases} \tag{6}$$

If processes P_{ij} and $P_{i(j+1)}$ are produced in two different plants, TTS_{ij} equals the transportation time between the two plants; otherwise TTS_{ij} is equal to 0.

(4) Processing time constraint: Each existing production process must be assigned with the processing time. For production process P_{ij}, there exists

$$C_{ij} = B_{ij} + T_{ij} \tag{7}$$

The processing time $\boldsymbol{T}_{ij}$ of process P_{ij} is equal to this process's workload $\boldsymbol{W}_{ij}$ divided by the daily production capacity of the assigned production department, i.e.,

$$T_{ij} = \sum_{k=1}^{n} \frac{W_{ij} \cdot X_{ij}^{k}}{PC_{kj}} \tag{8}$$

(5) Finishing time constraint: Finishing time $\boldsymbol{F}_i$ of order O_i is equal to the completion time $\boldsymbol{C_{iN}}$ of its last production process plus the transportation time from the assigned production plant to the central warehouse, i.e.,

$$\boldsymbol{F_i} = \boldsymbol{C_{iN}} + \sum_{\boldsymbol{k}=1}^{\boldsymbol{n}} \boldsymbol{X_{iN}^{k}} \cdot \boldsymbol{TT_k} \tag{9}$$

2.5. Objective functions

The investigated MSOS problem aims at minimizing three important and commonly used production objectives in competitive labor-intensive industries by determining the optimal solutions of beginning time $\boldsymbol{B_{ij}}$ and process allocation $\boldsymbol{X_{ij}^{k}}$ of production process P_{ij}. The first objective of the addressed problem is to minimize the total tardiness of all orders, which is expressed as

$$\text{Objective 1}: \ \min Z1\left(B_{ij}, X_{ij}^{k}\right)$$

with

$$Z1\left(B_{ij}, X_{ij}^{k}\right) = \sum_{i=1}^{m} TD_i \tag{10}$$

where $TD_i = \max(0, F_i - D_i)$.

The second objective of the addressed problem is to minimize the total throughput time of all orders, which is expressed as follows:

$$\text{Objective 2}: \ \min Z2\left(B_{ij}, X_{ij}^{k}\right)$$

with

$$Z2\left(B_{ij}, X_{ij}^{k}\right) = \sum_{i=1}^{m} TPT_i = \sum_{i=1}^{m} (C_{iN} - B_{i1}) \tag{11}$$

The third objective of the addressed problem is to minimize the total idle time of all production departments, which is expressed as follows:

$$\text{Objective 3}: \ \min Z3\left(B_{ij}, X_{ij}^{k}\right)$$

with

$$Z3\left(B_{ij}, X_{ij}^{k}\right) = \sum_{k=1}^{n}\sum_{j=1}^{N} TIT_{kj} = \sum_{k=1}^{n}\sum_{j=1}^{N} \sum_{\forall P_{ij} \in SP_{kj}} WT_{ij} \tag{12}$$

where WT_{ij} equals B_{ij} minus the completion time of preceding production process performed in the same production department. The latter is determined by the proposed production process simulator.

The three objectives described above can be conflicting. For example, the solution leading to a less total tardiness $\boldsymbol{Z}1$ can lead to greater total throughput time $\boldsymbol{Z}2$ and greater total idle time $\boldsymbol{Z}3$.

3. Pareto optimization model for multi-objective order scheduling problems

The process of optimization can be divided into two parts: generating candidate solutions and evaluating candidate solutions (Fu, 2002). In this paper, a Pareto optimization model is proposed to implement the optimization process for the MSOS problem investigated, in which a NSGA-II-based optimization process is developed to generate candidate solutions of order assignment to different plants, and a production process simulator is then developed to determine the beginning time of each production process and evaluate the performance of all candidate solutions. The flow chart of the proposed Pareto optimization model is shown in Fig. 1.

3.1. NSGA-II-based optimization process

The NSGA-II (Deb et al., 2002) was modified to handle the MSOS problem investigated. Fig. 2 shows the processes (steps) involved in the NSGA-II. To generate Pareto optimal solutions to the MSOS problem formulated in Section 3, some processes of the NSGA-II are modified. The modified processes are described in detail below.

3.1.1. Representation

The first step of the NSGA-II is to encode possible order scheduling solutions into chromosomes. A chromosome represents a feasible solution. To handle the MSOS problem addressed, a feasible solution needs to be able to determine the assignment of each production process of each order to an appropriate plant. According to formula (3), the solution can be determined by the assignment of each order group's production processes.

In real-world production, the number of plants assigned to process a production order should be as few as possible so as to reduce the transportation time and cost between different plants. According to formula (2) in Section 3, the assignment of production process 1 of each order group will determine the assignments of subsequent processes in this order group. This research constructs the chromosome by using the assignment of production process 1 of each order group to an appropriate plant. The assignment and processing sequence of the subsequent production processes of each order group will be deduced by the process assignment procedure of the production process simulator described in Section 3.2.2.

In this research, each chromosome is a sequence of genes whose length is equal to the number of order groups to be processed. Each gene identifies an order group and the value of each gene indicates the plant assigned to produce production process 1 of the corresponding order group. Fig. 3 shows an example of this representation which considers an order scheduling problem of assigning 10 order groups to 4 plants. Based on this chromosome, only one

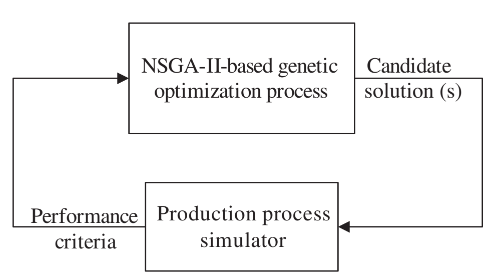

Fig. 1. Flow chart of proposed Pareto optimization model.

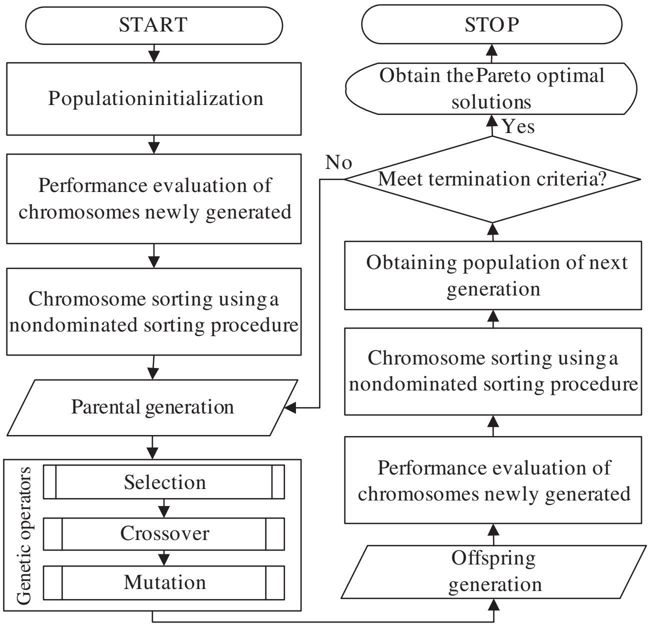

Fig. 2. Flow chart of the NSGA-II.

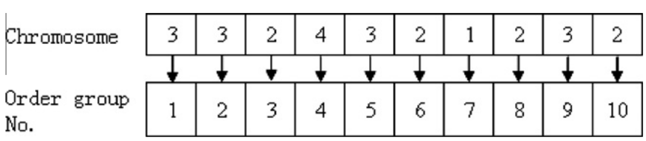

Fig. 3. Example of the chromosome representation.

order group (order group 7) is assigned to plant 1 for the production of its production process 1 while 4 order groups (order groups 1, 2, 5 and 9) are assigned to plant 3.

3.1.2. Population initialization

The initialization process generates the initial population of the genetic optimization process in the NSGA-II-based optimization process, which can be implemented by the following 4 steps:

Step (1) Initialize parameters: index $i = 1$, population size PS, population $POP = \{\phi\}$ and the number NG of order groups.
Step (2) Based on the proposed chromosome representation, randomly generate one chromosome CHR. That is, for each gene, randomly select a plant number as its value.
Step (3) Check if the values of genes in CHR contain all plant numbers. If not, the generated child chromosome is an invalid solution and go to Step 2; otherwise set $POP = POP \cup CHR$ and go to Step 4.
Step (4) Set $i = i + 1$. Stop if $i > PS$, else go to Step 2.

3.1.3. Crossover

To adapt the proposed presentation, a uniform crossover (Goldberg, 1989) – based crossover operator was adopted, which is implemented by using the following steps:

Step (1) Randomize a bit string with the same length as the chromosomes.
Step (2) Find the gene positions where the value is 1 in the bit string.
Step (3) Fill in the same gene positions in Child 1, found in Step 2, by copying the genes from the corresponding positions of Parent 1. (Now in Child 1, the positions are filled in wherever the bit string contains "1" and positions are left blank wherever the bit string contains "0".)
Step (4) Fill in the remaining positions in Child 1 by copying the genes from the corresponding positions of Parent 2 wherever the bit string contains "0".
Step (5) Check if the generated child chromosome is an invalid solution. If so, go to Step 1; otherwise output the generated chromosome.
Step (6) Child 2 is produced using a similar process as above.

Fig. 4 shows an example of the crossover operator described above, in which two child chromosomes are both valid solutions.

3.1.4. Mutation

A modified mutation operator is proposed based on the uniform mutation (Goldberg, 1989) usually used for binary and real-coded representations, which is implemented according to the steps below:

Step (1) Randomly generate a positive integer i, which is less than the half of the length of the chromosome.
Step (2) Randomly select i genes as mutation genes in the original chromosome.
Step (3) For each mutation genes selected, randomly change its value in its value range.
Step (4) Check if the chromosome generated in Step 3 is an invalid solution. If so, go to Step 2; otherwise, output the generated chromosome.

An example of the proposed mutation operator is shown in Fig. 5, in which the 3rd and the 9th genes are selected as mutation genes.

3.1.5. Performance evaluation and termination criterion

This section describes the process to evaluate the newly generated chromosomes and the termination criterion of the NSGA-II process.

(1) Performance evaluation of chromosomes newly generated
For each newly generated chromosome in the initial population and offspring generation, it is necessary to evaluate its performance by calculating the values of objective functions to be optimized. In this research, these values are equal to the outputs of the production process simulator.
(2) Termination criterion
The evolutionary process of NSGA-II in this research is controlled by a specified number of generations. If the maximum number of generations is reached, the genetic evolution process is terminated.

Fig. 4. Example of the crossover operator.

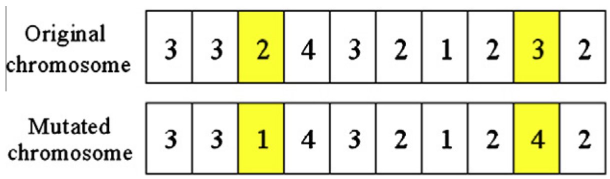

Fig. 5. Example of the mutation operator.

3.1.6. Heuristic pruning and final selection decision-making

The heuristic pruning and final selection decision-making is performed using two processes, including a pruning process and a final selection process. The pruning process is firstly used to prune the Pareto optimal set and obtain a set of preferred optimal solutions (pruned solutions). The final selection process is then used to pick a final solution for real production from these pruned solutions instead of the Pareto optimal set.

The non-numerical objective function ranking preference method, proposed by Taboada and Coit (2008), was adopted to implement the pruning process, which is described as below:

Step 1. Rank objectives according to the preference and importance of each objective. The objective with higher priority and importance has a higher rank.
Step 2. Normalize the values of objective functions based on each objective.
Step 3. Randomly generate a weight set w = ($\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_n$) for objective functions $\boldsymbol{F}_1, \boldsymbol{F}_2, \ldots, \boldsymbol{F}_n$ based on the following rules: (a) The objective function with a higher rank has larger weight and (b) The summation of weights is equal to 1, i.e., $\boldsymbol{w}_1 + \boldsymbol{w}_2 + \cdots + \boldsymbol{w}_n = 1$.
Step 4. Sum up weighted objectives to form a single function $\boldsymbol{F}' = \sum_{i=1}^{n} \boldsymbol{w}_i \boldsymbol{F}_i$.
Step 5. Find the solution that yields the minimal (optimal) value for $\boldsymbol{F}'$ from the Pareto optimal set.
Step 6. Increase the counter corresponding to that solution by a value of one.
Step 7. Repeat Steps 2–6 until no new preferred solution can be found for 100 consecutive iterations.
Step 8. Determine the pruned Pareto optimal set, i.e., the solutions that have non-zero counter values (counter > 0).

The solutions obtained by the above pruning process are then used as the inputs of the final selection process to obtain the final preferred solution for real-world production. The final solution is usually selected based on actual production environment and production requirements. That is, the manufacturing company can adopt different strategies to select the final solution under different production environments and requirements.

Assume that the pruning process generated $\boldsymbol{\rho}$ pruned solutions. We firstly sort the $\boldsymbol{\rho}$ pruned solutions according to the value of objective 1 in an ascending order. The sorted solutions are numbered as pruned solutions 1,2, ..., $\boldsymbol{\rho}$. Let $\boldsymbol{z}_{\boldsymbol{ki}}$ denotes the values of $\boldsymbol{k}(1 \leqslant \boldsymbol{k} \leqslant 3)$ objective functions generated by pruned solution $\boldsymbol{i}$. In this research, we have $\boldsymbol{z}_{11} \leqslant \boldsymbol{z}_{12} \leqslant \cdots \leqslant \boldsymbol{z}_{1\rho}$. $\boldsymbol{z}_{1i}$ is greater than or equal to 0 while $\boldsymbol{z}_{2\boldsymbol{i}}$ and $\boldsymbol{z}_{3\boldsymbol{i}}$ are greater than 0. The procedures of the final selection process to select the preferred one from the $\boldsymbol{\rho}$ pruned solutions are described below.

(1) Set $\boldsymbol{i} = 1$ and $\boldsymbol{j} = 2$.
(2) Calculate the relative percentage difference $\boldsymbol{d}_{\boldsymbol{k}}$ of solutions $\boldsymbol{i}$ and $\boldsymbol{j}$ according to the following rules:
If $\boldsymbol{z}_{\boldsymbol{ki}} \neq 0$, then $\boldsymbol{d}_{\boldsymbol{k}} = \left(1 - \frac{\boldsymbol{z}_{ki}}{\boldsymbol{z}_{kj}}\right) \cdot 100\%$.
If $\boldsymbol{z}_{1\boldsymbol{i}} = 0$, $\boldsymbol{d}_1$ is a step function of the absolute value $\boldsymbol{e}$ of the difference of $\boldsymbol{z}_{1\boldsymbol{i}}$ and $\boldsymbol{z}_{1\boldsymbol{j}}$. That is, $\boldsymbol{d}_1(\boldsymbol{e}) = \sum_{\tau=1}^{s} \boldsymbol{\delta}_\tau \chi_{\boldsymbol{I}_\tau}(\boldsymbol{e})$, where $\boldsymbol{s} \geqslant 1$, $\boldsymbol{\delta}_\tau \in (0, 100\%]$ are real numbers, $\boldsymbol{I}_\tau$ are intervals and $\chi_{\boldsymbol{I}_\tau}$ is the indicator function of $\boldsymbol{I}_\tau$:
$$\chi_{\boldsymbol{I}_\tau}(\boldsymbol{x}) = \begin{cases} 1 & \text{if } \boldsymbol{x} \in \boldsymbol{I}_\tau, \\ 0 & \text{if } \boldsymbol{x} \notin \boldsymbol{I}_\tau \end{cases}$$
(3) Calculate the summation of three relative percentage differences. If $\sum_{k=1}^{3} \boldsymbol{d}_{\boldsymbol{k}} \geqslant \boldsymbol{pct}$, solution $\boldsymbol{i}$ keep unchanged; else use solution $\boldsymbol{j}$ to replace solution $\boldsymbol{i}$. $\boldsymbol{pct}$ is a percentage pre-specified by the production planner.
(4) If $\boldsymbol{j} < \boldsymbol{\rho}$, set $\boldsymbol{j} = \boldsymbol{j} + 1$ and go to Step (3); else stop and return solution $\boldsymbol{i}$ as the final preferred solution.

In practice, the values of $\boldsymbol{s}$, $\boldsymbol{I}_\tau$, $\boldsymbol{\delta}_\tau$ and $\boldsymbol{pct}$ are specified by production planners based on actual production environments and requirements. In this research, we set that $\boldsymbol{s} = 3$, $\boldsymbol{I}_1$ is the interval $(0, 2]$, $\boldsymbol{I}_2$ is the interval $(2, 20]$, $\boldsymbol{I}_3$ is the interval $(20, 366]$, $\boldsymbol{\delta}_1 = 20\%$, $\boldsymbol{\delta}_2 = 50\%$, $\boldsymbol{\delta}_3 = 100\%$, and $\boldsymbol{pct} = 1\%$.

3.2. Production process simulator

The production process simulator is developed to simulate the production capacity of each production department and determine the beginning time of each production process by simulating the production process of each production order in the assigned plants in an aggregate manner. In this manner, each production department in a plant processes the orders assigned in turn, i.e., produces only a maximum of one process at a time.

The simulation flow of the production process simulator is shown in Fig. 6. The input of the simulator is a candidate solution (chromosome), which represents the assignment of the first type of production process of each order group to different plants. The output of the simulator is the values of objective functions (three performance criteria). The simulation process of the simulator consists of 5 procedures, each of which is described below in detail.

3.2.1. Data initialization

The data initialization stage needs to load and initialize all data and variables related to the simulation process, which involves the following four parts:

(1) Load given production data, including due date and workload of each order, production departments included in each plant, daily production capacity of each production department, transportation time of semi-finished products between the current production department and its next one (or central warehouse).
(2) Initialize the variables related, including arrival time, beginning time, processing time, completion time and transportation time of each production process of each order. Set their values to 0.
(3) Assign a sequence number to each order group (order group number) by sorting all order groups in terms of Rule Set One.
(4) Assign a sequence number to each order (order number) by sorting all orders in terms of Rule Set Two.

The examples of order group numbers and order numbers can be found in Appendix Tables A.1–A.3.

Rule Set One:

Rule (1) The order group with an earlier due date needs to be assigned a smaller sequence number.
Rule (2) If multiple order groups have the same due date, the order group with the less workload needs to be assigned a smaller sequence number.

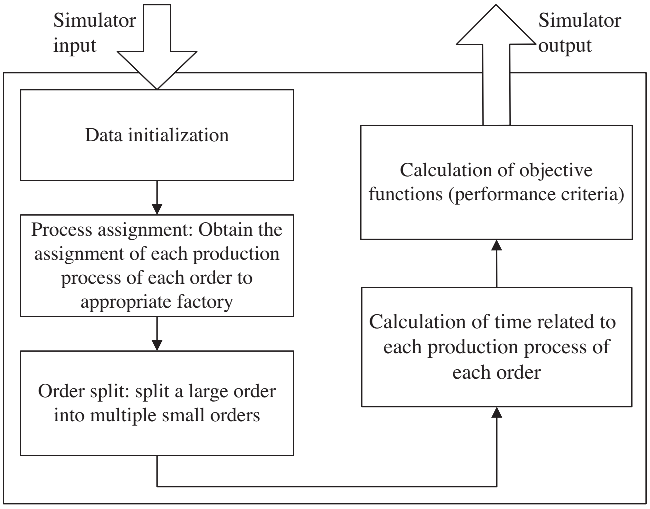

Fig. 6. Simulation flow of the production process simulator.

Rule (3) All order group numbers must be consecutive, which start from number 1.

Rule Set Two:

Rule (1) In an order group, the order with an earlier due date needs to be assigned a smaller order number.
Rule (2) In an order group, if multiple orders have the same due date, the order with larger number of production processes needs to be assigned a smaller order number.
Rule (3) In an order group, if multiple orders have the same due date and the same number of processes, the order with less workload needs to be assigned a smaller order number.
Rule (4) The sequence numbers of all orders must be consecutive, which start from number 1.
Rule (5) Suppose that the sequence number of order group A is smaller than that of order group B. The order numbers of orders in order group A must be smaller than those in order group B.

3.2.2. Process assignment

Based on the simulator input, assign the production processes of each order to appropriate plants in terms of the assignment rules below:

Rule Set Three:

Rule (1) For all orders in each order group, the production processes with the same process number are assigned to the same plant for processing.
Rule (2) For an order, if the plant, which is assigned to processing its first production process, has the production department processing the current production process, the process must be assigned to the same plant for processing. Otherwise, go to rule (3).
Rule (3) For an order, if the plant, which is assigned to processing the last process of the current production process, has the production department processing the current production process, the process must be assigned to the same plant for processing. Otherwise, go to rule (4).
Rule (4) Randomly assign the current production process to another plant capable of processing it.

3.2.3. Order split

If the workload of a production order is too large, it is necessary to split this order to multiple sub-orders so as to eliminate or reduce the waiting time in the downstream production departments.

For an order, if the workload of its sewing production process is greater than a specified order split percentage α ($30\% < \alpha < 60\%$) of the daily production capacity of the assigned plant, this order needs to be divided into two or more sub-orders so that the semi-finished products of this order can be transported timely to the next production departments. The value of α can be determined according to the actual production progress. If an order is divided into q ($q > 1$) sub-orders, the workloads of the first $q - 1$ sub-orders are all equal to the daily production capacity of the assigned plant multiplying the percentage α. The workload of the qth sub-order is equal to the remaining workload of the order.

3.2.4. Calculation of the time related to each production process

For each production process of an order (sub-order), the time for processing, transportation, waiting, arrival, beginning and completion of each production process are calculated according to the methods described below:

Processing and transportation time: For each production process, calculate its processing time and transportation time to its next production department (or central warehouse) based on the process assignment solution.

Arrival time: The arrival time A_{ij} of production process P_{ij} is calculated by Eq. (6).

Beginning and waiting time: At time t, production department S_{kj} completes the production of current order and needs to select a new order for processing. The new order and its beginning time are determined in terms of the rules as follows.

Rule Set Four:

Rule (1) If no order reaches the production department S_{kj} at time t, the production department will wait for the arrival of the next order which will be selected for subsequent processing. Otherwise, go to rule 2. The beginning time of the next order in this department is equal to its arrival time. The time to await the arrival of the next process in this department is equal to the beginning time – t.
Rule (2) If only one order reaches the production department S_{kj} at time t, this order will be selected for subsequent processing. The beginning time of the next order in this department is equal to time t. Otherwise, go to rule 3. The waiting time is 0 in this department.
Rule (3) If more than one order reaches the production department S_{kj} at time t, this order with the smallest order number and smallest order group number will be selected for subsequent processing. The beginning time of the next order in this department is equal to time t. The waiting time is 0 in this department.

Completion time: The completion time C_{ij} of production process P_{ij} is calculated by Eq. (7).

3.2.5. Calculation of objective functions

Based on the beginning and the completion time obtained in 3.2.4, the total tardiness and the total throughput time of all orders are calculated by formulas (10) and (11). Based on the waiting time obtained in 3.2.4, the total idle time of all production departments is calculated by Eq. (12).

In the production process simulator described above, the beginning time of all production processes of each order is determined by the beginning time of its first production process and a series of heuristic rules. These rules not only greatly simplify the optimization-seeking process by effectively reducing the search space, but also effectively simplify the simulation process of all production processes in multiple plants.

4. Experimental results and discussions

To investigate the effectiveness of the proposed optimization model, a series of experiments were conducted based on the real-world production data. Public datasets appropriate for the experiments are not available in this research because the MSOS problem has not been investigated in the literature. This research thus collected the experimental data from an apparel manufacturing company producing outerwear and sportswear in Mainland China. This section highlights three typical experiments to validate the effectiveness of the proposed model. The three experiments present three MSOS tasks with different production workloads and production periods. Similar MSOS tasks widely exist in the labor-intensive manufacturing companies. The three MSOS tasks are described as follows.

(1) Experiment 1: 10 order groups with 50 production orders scheduled.
(2) Experiment 2: 12 order groups with 75 production orders scheduled.
(3) Experiment 3: 15 order groups with 145 production orders scheduled.

Tables A.1–A.3 show workloads of all production processes of each order in these experiments. The values in columns 3–7 of each row show the workloads of five production processes of one order. The workload of a production process is set to 0 if it is not included in an order. The due dates of order groups in each experiment are shown in Table 1; only workdays are counted. For example, the due date of order group 1 in experiment 1 is the 7th workday. The production period of experiment 1 is nearly 2 months because one month includes about 20 workdays, whereas the production period of experiment 2 is about 3 months.

The investigated company comprises four plants located in different locations. Five different production departments are involved, which are cutting, embroidering, printing, sewing and finishing respectively. Table 2 shows the standard manpower of production departments in each plant. The standard manpower of a production department is 0 if the department does not exist in the plant. The transportation time between different locations, including four plants and a central warehouse, is shown in Table 3.

In the three experiments, the production departments discussed are empty initially; in other words, there is no work-in-progress in each department. Each production department is available for production starting from time zero (day 0). The ranking preference of objective functions applied to experiments 1–3 is the case in which objective 1 (total tardiness) is more important than objective 2 (total throughput time) and objective 2 is more important than objective 3 (total idle time). This ranking preference is consistent with the policies and priorities of the investigated company.

Due to the uniqueness and complexity of the MSOS problem investigated, the optimization algorithms in the existing literature cannot be used directly to handle this problem. This research thus compares the performance of production planning results generated by the proposed model with those from industrial practice. The solutions from industrial practice are called industrial solutions in this paper, which are the actual order scheduling solutions in the investigated manufacturing company and generated based on the following decision-making rules:

(1) The schedule only focuses on the objective of minimizing the total tardiness of all orders.
(2) The order group with a larger product quantity needs to be assigned to the plants with more available production capacity;
(3) The order group with an earlier due date needs to be processed firstly.

Due to the complexity of the investigated MSOS problem and the large number of production orders, it is very difficult for the production planner to generate an optimal solution in terms of the above rules.

4.1. Experiment 1

The Pareto optimal solutions generated by the proposed model are shown in two two-dimensional spaces in Fig. 7. There are 62 solutions in total, which is a very large set of solutions and it is thus difficult for the production planner to select an appropriate solution for real production schedule.

Based on the 62 Pareto optimal solutions, the heuristic pruning and final selection decision-making process was utilized to obtain the pruned solutions and the final preferred order scheduling solution. Table 4 shows the seven pruned solutions generated by the pruning process. In Figs. 7–9, the pruned solutions are also marked by '○' points while the Pareto optimal solutions are marked by '●' points.

Table 1
Due dates (days) of order groups in three experiments.

	OG1	OG2	OG3	OG4	OG5	OG6	OG7	OG8	OG9	OG10	OG11	OG12	OG13	OG14	OG15
Experiment 1	7	9	10	15	21	27	28	34	35	38	/	/	/	/	/
Experiment 2	7	8	8	12	16	16	20	21	28	31	49	53	/	/	/
Experiment 3	5	9	11	18	21	24	25	26	27	28	28	29	31	33	36

Table 2
Standard manpower of production departments.

	Production Department 1	Production Department 2	Production Department 3	Production Department 4	Production Department 5
Factory 1	10	66	20	190	26
Factory 2	53	0	30	1265	146
Factory 3	39	0	24	1018	99
Factory 4	14	0	0	320	37

Table 3
Transportation time (days) between different locations.

	Factory 1	Factory 2	Factory 3	Factory 4	Central warehouse
Factory 1	0	1	1	1	0.5
Factory 2	1	0	0.5	0.5	1
Factory 3	1	0.5	0	0.5	1
Factory 4	1	0.5	0.5	0	1
Central warehouse	0.5	1	1	1	0

If we compare the pruned solutions with the solution from industrial practice shown in the first line of Table 5, it is clear that the solution better than the industrial one can be found from the pruned solutions whatever objective preference is used. For example, if objective 1 has a higher priority than the other two objectives (i.e., objectives 2–3 are considered when the values of objective 1 are the same), solutions 1, 2, 14 and 15 are superior to the industrial solution. If objective 3 has higher priority than the other two, solutions 36 and 42 are superior to the industrial solution. In this experiment, the final preferred solution, generated by the final selection process, is solution 2 shown in Table 4.

4.2. Experiment 2

Fig. 8 shows the Pareto optimal solutions generated by the proposed model in two-dimensional spaces. There are a total of 82 Pareto solutions. By using the pruning process, 13 pruned solutions are obtained, which are shown in Table 6 and marked by 'o' points in Fig. 8.

In comparing the pruned solutions with the industrial solution shown in the second line of Table 5, it is clear that, in the pruned solutions, Pareto solutions are superior to the industrial solution whatever objective preference is used. For example, if objective 2 has a higher priority than the other two objectives, all pruned solutions generate better performance than the industrial solution. The final preferred solution, generated by the final selection process, is the solution 1 shown in Table 6.

4.3. Experiment 3

Fig. 9 shows the 278 Pareto optimal solutions generated by the proposed model, which include 19 pruned solutions shown in Table 7. The number of pruned solutions is much smaller than the number of original Pareto solutions so that the production planner can select an appropriate solution more conveniently for real production schedule.

If we compare the pruned solutions with the industrial solution shown in the last line of Table 5, we can come to the same conclusion as drawn in experiments 1–2. The pruned solutions can generate better performance than the industrial solution whatever objective preference is used. Using the final selection process, the final MSOS solution of this experiment was obtained, which is solution 1 shown in Table 7.

4.4. Performance analysis on the proposed model

Considering the values of objective functions shown in Tables 4, 6 and 7, it is clear that the decrease of one objective function value can lead to the increase of another objective function value. For in-

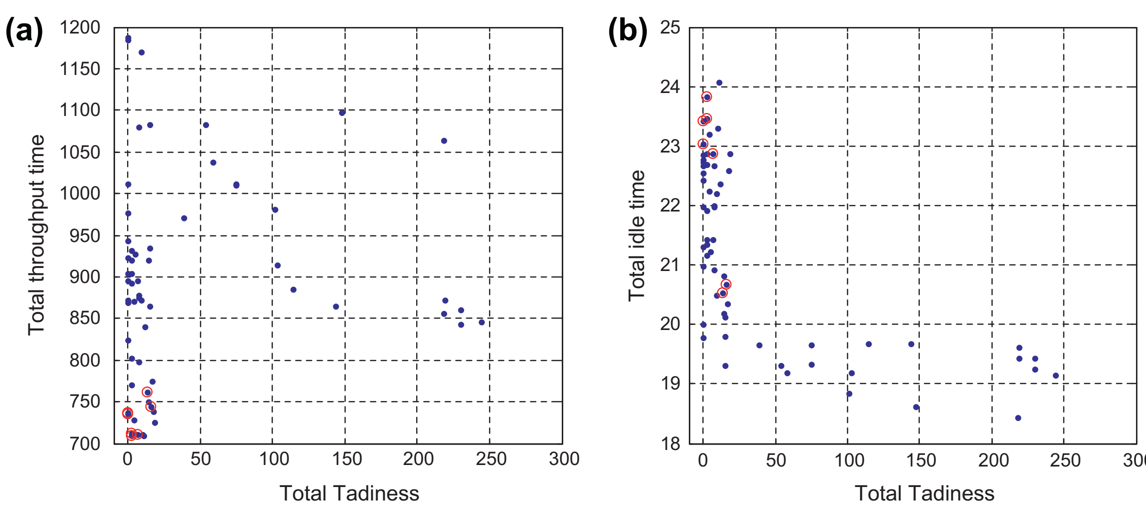

Fig. 7. Pareto optimal set of experiment 1 in two-dimensional spaces. (● – Pareto optimal solutions, ○ – Pruned solutions.)

Table 4
Pruned solutions for experiment 1.

Solution no.	Assignment of production process 1 of each order group (OG)										Values of objective functions		
	OG1	OG2	OG3	OG4	OG5	OG6	OG7	OG8	OG9	OG10	Objective 1	Objective 2	Objective 3
1	3	3	2	4	3	2	1	2	3	2	0	735	23.4
2	3	3	2	1	3	2	4	2	3	2	0	737.4	23
14	3	3	2	4	3	2	1	3	2	2	2.3	709.9	23.8
15	3	3	2	1	3	2	4	3	2	2	2.3	712.3	23.5
25	3	4	2	1	3	2	3	3	2	2	6.0	711.3	22.9
36	1	4	2	4	3	2	3	2	3	2	13.5	761.7	20.5
42	1	4	2	4	3	2	3	3	2	2	15.8	744.3	20.7

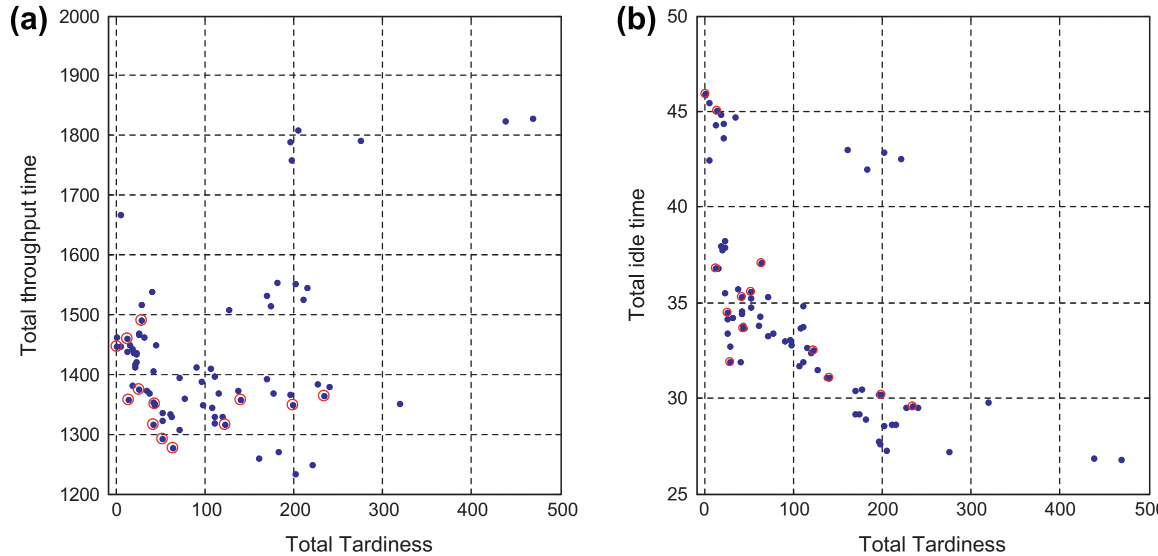

Fig. 8. Pareto optimal set of experiment 2 in two-dimensional spaces (● – Pareto optimal solutions, ○ – Pruned solutions.)

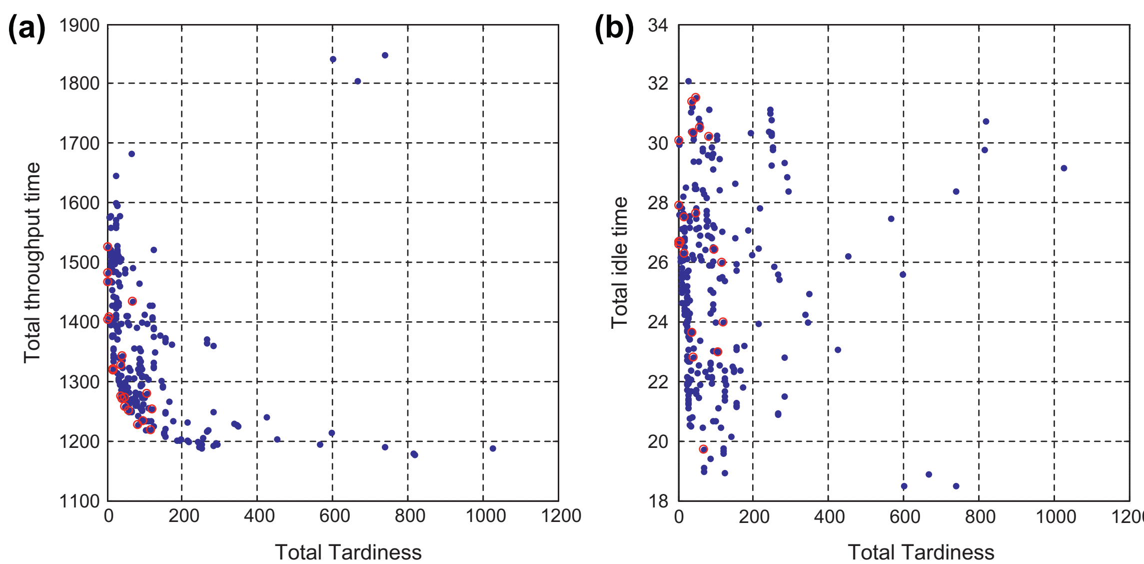

Fig. 9. Pareto optimal set of experiment 3 in two-dimensional spaces (● – Pareto optimal solutions, ○ – Pruned solutions.)

Table 5
Solutions from industrial practice.

Experiment no.	Assignment of production process 1 of each order group (OG)	Objective 1	Objective 2	Objective 3
1	(3, 3, 2, 3, 4, 2, 3, 1, 2, 2)	2.6	903.6	21.4
2	(2, 1, 4, 3, 3, 2, 1, 3, 2, 3, 4, 2)	3.8	1668.2	42.4
3	(3, 1, 2, 4, 1, 3, 2, 2, 3, 1, 4, 2, 2, 4, 3)	7.6	1559.1	26.3

stance, in Table 4, compared with solution 2, solution 14 generated less total tardiness ***Z***1 but more total throughput time ***Z***2. These results provide clear evidences that the investigated three production objectives can be conflicting.

It can be easily found from the results from the above experiments that the performance of the MSOS in production planning is perhaps significantly different if different process assignment solutions are adopted. Thus, it is important to obtain the appropriate solutions according to a specified production objective preference. The proposed methodology can effectively handle the MSOS problem by generating Pareto optimal solutions obviously superior to the results from industrial practice whatever objective function preference is used. Results also show that the proposed chromosome representation and modified genetic operators are effective in seeking optimal solutions. In addition, it was also found that industrial solutions get worse when the problem size and problem complexity increase. This is because the increasing problem complexity increases the difficulty of obtaining good production planning solutions.

This research defines front counter, denoted by $\boldsymbol{FC_s}$, to indicate the number of Pareto optimal front in which the ***s***th candidate solution (***s***th chromosome in GA evolution process) lies. For example, $\boldsymbol{FC_2} = 1$ indicates the 2nd chromosome lies in the 1st Pareto optimal front. Fig. 10 shows, respectively, the evolutionary trajec-

Table 6
Pruned solutions for experiment 2.

Solution no.	Assignment of production process 1 of each order group (OG)												Values of objective functions		
	OG1	OG2	OG3	OG4	OG5	OG6	OG7	OG8	OG9	OG10	OG11	OG12	Objective 1	Objective 2	Objective 3
1	2	4	1	4	3	2	1	3	2	3	3	2	0	1446.7	46
5	2	3	4	1	3	2	1	4	2	3	2	3	11	1460	36.8
7	3	4	1	1	3	2	3	2	2	3	3	2	13.2	1357.6	45
17	3	1	4	4	3	2	1	2	2	3	2	3	23.9	1375.1	34.5
21	3	3	1	3	3	2	1	2	2	4	2	3	27.5	1490	31.9
26	3	4	1	3	3	2	1	2	2	3	2	3	40.5	1317.7	35.3
30	3	4	4	4	3	2	1	2	2	3	2	3	42.4	1350.8	33.7
33	3	4	1	1	3	2	3	2	2	3	2	3	50.5	1292.1	35.6
37	3	4	1	1	3	2	3	2	3	2	3	2	63.4	1277	37.1
51	4	4	1	1	2	2	3	3	2	3	2	3	121.3	1316.5	32.5
54	4	4	1	1	2	2	4	3	2	3	2	3	139.8	1358.1	31.1
65	4	4	1	1	2	2	4	2	2	3	2	3	198	1350	30.2
73	4	4	1	4	2	2	1	2	2	3	2	3	233.6	1363.5	29.6

Table 7
Pruned solutions for experiment 3.

Solution no.	Assignment of production process 1 of each order group (OG)															Objective 1	Objective 2	Objective 3
	OG1	OG2	OG3	OG4	OG5	OG6	OG7	OG8	OG9	OG10	OG11	OG12	OG13	OG14	OG15			
1	2	1	2	4	1	2	1	3	2	3	1	4	2	3	2	0	1525.9	27.9
3	2	3	2	4	1	3	2	2	3	1	1	4	2	3	2	0.9	1403.1	30.1
7	3	1	2	4	1	3	2	2	3	1	4	4	2	3	2	1.2	1467.2	26.7
9	3	1	2	4	1	3	2	2	3	4	1	2	2	3	2	4.6	1407.4	26.7
39	3	4	2	2	4	3	1	2	3	1	1	4	2	3	2	15.1	1318.2	27.5
43	3	1	2	2	4	3	2	2	3	1	1	4	2	3	2	15.5	1322.1	26.3
106	2	3	3	2	2	3	1	2	4	1	1	4	2	3	2	35.8	1275.7	31.4
108	4	1	2	2	3	3	2	2	3	1	1	4	2	3	2	36.8	1327.4	23.6
112	4	1	2	2	4	3	2	2	3	1	1	3	2	3	2	38.2	1342.7	22.8
115	2	3	3	2	4	3	1	2	2	1	1	4	2	3	2	40	1270.1	30.4
121	3	4	3	2	2	3	1	2	4	1	1	2	2	3	2	45.8	1259	31.5
128	2	4	3	2	4	3	1	2	2	1	1	3	2	3	2	48.2	1272.3	27.6
138	3	4	3	2	4	3	1	2	2	1	1	2	2	3	2	56.6	1250.5	30.5
148	4	1	3	3	4	3	1	2	2	1	1	2	2	4	2	66.1	1435.1	19.7
164	3	3	3	2	4	2	1	3	2	1	1	4	2	2	2	81.9	1226.8	30.2
193	2	2	3	3	3	2	1	2	3	1	1	4	3	3	2	95.2	1234.8	26.4
200	4	1	3	3	4	2	3	3	2	1	1	2	2	2	2	107.1	1279.1	23
208	3	4	3	3	4	2	1	3	2	1	1	2	2	2	2	115.7	1219.2	26
209	4	4	3	3	2	3	1	2	2	1	1	2	2	3	2	117.6	1253.1	24

tories of the minimal values of three objectives and the summation $\sum_s \boldsymbol{FC_s}$ of front counters in all candidate solutions of each population over generations in the optimization processes of experiments 1–3. In its subfigures (a)–(d), solid line indicates the results of experiment 1 while dashed line and dash-dotted line indicate the results of experiments 2 and 3 respectively. In each subfigure, the nested graph shows the snapshot of the evolutionary trajectories of the first 50 generations.

It can be clearly found from Fig. 10 that, in each experiment, the 3 objectives got converged after some iterations. Taking subfigure (a) as an example, the minimal value of objective 1 converged to the global minimum after 6, 73 and 523 generations in experiments 1–3 respectively because the value of objective 1 cannot be less than 0. It indicates that the proposed Pareto optimization model has the capacity to find the globally optimal solutions. Experiment 3 took a much more iterations to converge because it handled a MSOS problem with a much larger combinatorial complexity. Subfigure (d) shows that the summations of front counters in each population converged to 500 in experiments 1–2 while it converged to 1000 in experiment 3. It indicates that all individuals (candidate solutions) in the final population lie in the 1st Pareto optimal front because the population sizes in experiments 1–3 are 500, 500 and 1000 respectively. These results show that the proposed model can get converged well and obtain optimal solutions effectively.

The experiments were carried out on a PC with Intel® Core™ i5 Processor 2.5G CPU and 2 GB RAM and using MATLAB version 7.8 (R2009a). The results generated by the proposed model were obtained based on the settings: the population sizes of genetic processes were 500, 500 and 1000 respectively while the maximum numbers of generations were 1000 in experiments 1–3. The crossover probability and the mutation probability are 0.6 and 0.01 respectively. The order split percentage α was 50%. The processing times of each generation in experiments 1–3 are 9.8 s, 12.1 s and 28.6 s, respectively.

5. Conclusion

This paper investigates a multi-objective multi-site order scheduling problem in the production planning stage with the consideration of multiple plants, multiple production departments and multiple production processes. The mathematical model for the investigated problem has been established, which considers three production objectives, including minimizing the total tardiness and throughput time of all orders as well as the total idle time in all production departments. These objectives are particularly useful for manufacturing companies to meet due dates and improve management performance.

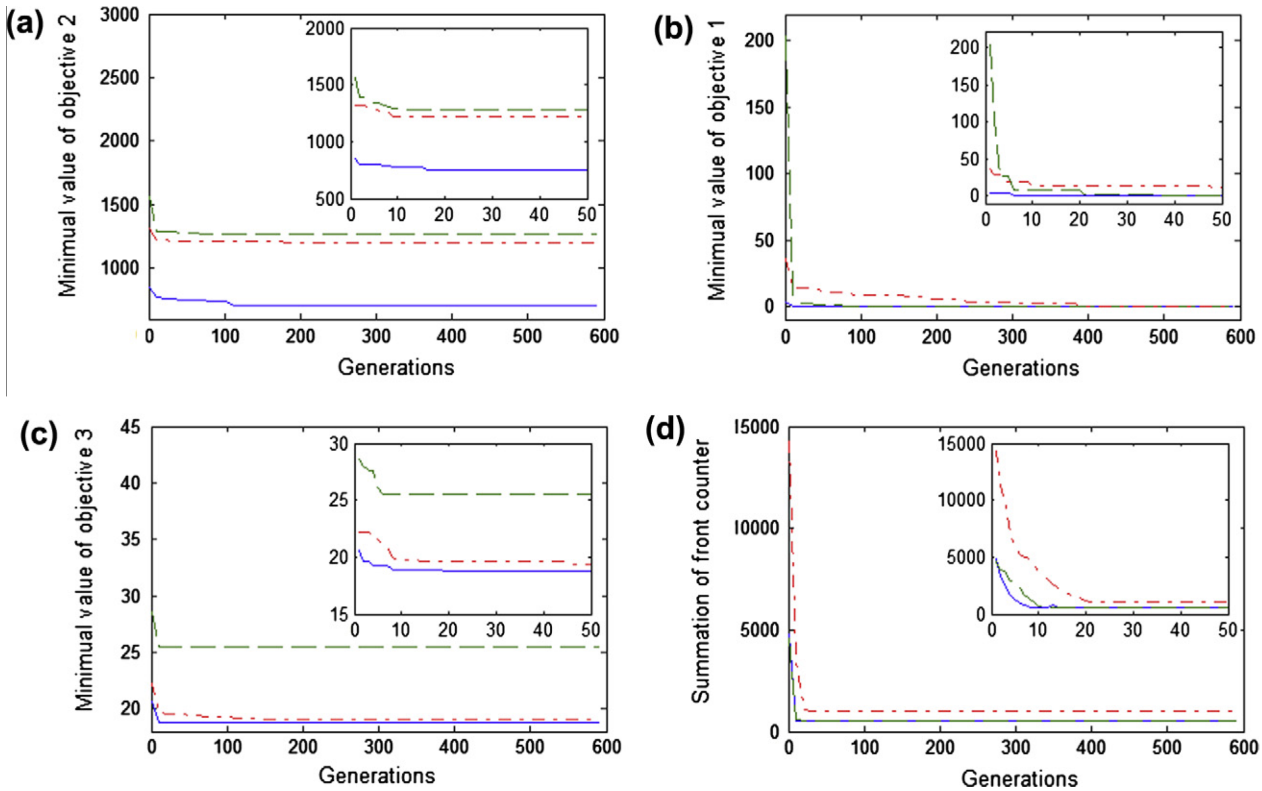

Fig. 10. Change trends of three objectives and front counter in experiments 1–3 (-, experiment 1; –, experiment 2; –., experiment 3).

A Pareto optimization model has been developed to generate the Pareto optimal solutions for the problem investigated, in which a NSGA-II-based optimization process was proposed to seek candidate solutions and an effective production process simulator was developed to evaluate the performance of the candidate solutions. In the NSGA-II-based optimization process, a novel chromosome representation and modified genetic operators were presented to handle the investigated problem while a heuristic pruning and final selection decision-making process was developed to select out the final preferred solution from the set of Pareto optimal solutions. In the simulator, a series of heuristic rules were introduced to effectively simplify the processes of optimization seeking and production simulation of all production processes.

The effectiveness of the proposed optimization model has been validated by using the industrial data from a labor-intensive manufacturing company. The experimental results demonstrate that the proposed model could handle the investigated problem effectively by providing Pareto optimal solutions much superior to the industrial solutions.

The proposed optimization model can be easily extended to handle production outsourcing in labor-intensive industries by considering an outsourcing factory as a production plant. This research is also helpful for manufacturers to make due date negotiations with their customers. Further research will consider the effects of various production uncertainties on production planning, such as uncertain production orders and possible material shortage, and investigate the performances of other pruning methods such as data clustering in final preferred solution and compare its results with those generated by the ranking preference method used in this research. In addition, it is also a desirable direction to develop other intelligent multi-objective optimization models, based on other meta-heuristics such as simulated annealing, evolution strategy, and ant colony algorithm, for the investigated problem and compared the performances of these models with the Pareto optimization model proposed in this research.

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Appendix A

See Tables A.1–A.3.

Table A.1
Workload (standard man days) of each production process of each order (Experiment 1).

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
1	1	14.2	7	9.1	282.4	37
1	2	19.7	10.8	13.4	400.7	46.5
1	3	19.2	9.4	0	400	40
1	4	23.1	12.5	0	489.9	48.6
2	5	8.1	3.6	4.9	161.1	16.2
2	6	6.8	3.8	4.5	164.3	16.5
2	7	7.4	3.9	5.7	176.8	21.9
2	8	8.7	5	5.2	187.5	18.6
2	9	10.9	5	6.8	223.3	27.2
2	10	11.1	6.2	7.6	274.3	32.3
2	11	14.6	7.8	10.3	319	32.7
2	12	15.1	10.1	12.2	366.1	38.8
3	13	57.7	27.7	37.8	1234.5	125.4
3	14	45.1	24.6	33.3	990.8	106.9
3	15	23.6	12.5	0	517.9	53.9
3	16	41.2	0	0	869	108.5
3	17	25	0	0	626.1	77.6
4	18	6.6	3.9	4.7	153.3	17.8
4	19	6.6	4.4	5.2	167.4	21.6

(continued on next page)

Table A.1 (*continued*)

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
4	20	7.5	0	5.1	167.4	16.8
4	21	5	0	0	113.6	13.4
4	22	5.8	0	0	121.1	14.2
5	23	53.3	0	37.8	1088.2	138.2
5	24	104.7	0	71.9	2120	241.7
5	25	71	0	48.3	1450	171.8
6	26	47.3	26.8	25.8	952.4	117.5
6	27	53.7	37.6	48	1333.3	141
6	28	99.2	64	70.2	2232.3	284
6	29	38.7	23.8	25.5	882.4	96.4
6	30	36.4	20.2	24.8	887.8	99.9
6	31	147.5	82.7	104	3767.4	429.7
6	32	210.6	123	0	5109.4	641
6	33	175.9	103.8	0	4000	480.1
7	34	12.2	5.8	8.4	250	27.5
7	35	21	0	13.8	468.8	54
7	36	22	0	0	495	52.9
7	37	12.4	0	0	282.4	30.2
8	38	81.4	51	60.3	1981.4	248.2
8	39	76.5	0	50.5	1575	176.5
8	40	17.9	0	11.7	370.4	46.7
9	41	51.1	25.2	35.2	1055.3	131.1
9	42	51.5	26.7	39	1153.3	149.1
9	43	61.9	0	40.3	1286.7	137
9	44	81.9	0	51	1694.3	193
9	45	84.1	0	63.4	1803.8	232.3
9	46	97.1	0	0	2096.4	250.3
10	47	64.6	0	51.8	1472.2	152.8
10	48	42.6	0	28.2	969.5	119.8
10	49	63.6	0	0	1608	194.5
10	50	114.8	0	0	2762.9	335

Table A.2
Workload (standard man days) of each production process of each order.

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
1	1	6.9	3.1	4.9	140.6	16.6
1	2	7	3.9	5.1	144.8	15.7
1	3	11.7	0	8.7	257.8	32.8
1	4	13.3	0	9.9	282.4	36
1	5	15.8	0	13.5	400	41.1
1	6	18.6	0	11.2	400.7	47.9
1	7	20.1	0	0	456.8	53.8
1	8	22.5	0	0	489.9	60.5
2	9	5.3	2.5	3.9	113.6	11.8
2	10	6.7	4.1	5.3	153.3	18.2
2	11	6.8	0	4.9	163.1	17.5
2	12	7	0	4.6	167.4	17.4
2	13	7.5	0	5.2	167.4	18.3
2	14	5	0	3.7	121.1	14.2
2	15	6.7	0	5	159	18.1
3	16	6.6	0	0	161.1	20.3
3	17	6.7	0	0	164.3	18.3
3	18	8.8	0	0	176.8	22.2
3	19	8.9	0	0	187.5	19.8
3	20	10.9	0	0	223.3	28.3
4	21	11	6.7	8.4	286.8	36
4	22	12.5	7.7	9.8	292	34.6
4	23	15.6	0	0	319	32.3
4	24	15.5	0	0	366.1	37.6
5	25	27.4	0	21.5	661.4	74.8
5	26	76.5	0	47.3	1575	171.1
5	27	72.8	0	53.9	1828.8	183.3
5	28	81.8	0	65	1837.5	238.9
5	29	83.3	0	0	1981.4	251.7
6	30	51.5	24.6	30.4	1055.3	134.8
6	31	82.4	56.7	57.7	2096.4	237.3
6	32	39	26.7	27.6	969.5	107.5
6	33	43.8	32.3	39.6	1153.3	130.4
6	34	52.9	33.6	0	1286.7	168
6	35	59.6	29.6	0	1358.2	174.6
6	36	70.2	38.3	0	1472.2	185.3
7	37	22.4	0	14.8	468.8	46.8

Table A.2 (*continued*)

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
7	38	22.8	0	14.6	495	49.8
7	39	11.5	5.9	0	250	27.2
7	40	13.1	7.9	0	282.4	34.1
7	41	17.9	11.6	0	424.3	47
7	42	24.2	13.3	0	535.7	63
8	43	27.9	18.9	20	725	90.6
8	44	48.9	32.7	40.5	1234.5	157.5
8	45	46.1	21.7	28.7	990.8	101
8	46	41.5	21.7	29.2	869	104.7
8	47	46.9	25.1	0	970.5	114.4
9	48	41.7	23.1	25.8	925	111.2
9	49	41.7	27.3	38	1088.2	125
9	50	66	39.4	56.7	1645.3	191.4
9	51	93.5	43.3	67.8	1950	228.5
9	52	80.8	57.2	65.5	1987.5	257.1
9	53	99.8	45.2	73	2062.5	229.6
9	54	86	55.8	67.5	2200	276.6
10	55	64	38.3	41.6	1494	161.7
10	56	76.3	43.3	53	1608	167.1
10	57	75	40	56.9	1694.3	221.6
10	58	84.7	0	0	1803.8	216.1
10	59	71.5	0	0	1866.3	197.2
11	60	86.4	52.2	0	2000	238.9
11	61	94.4	50.5	0	2155.7	249.6
11	62	104.7	52.5	0	2265.6	298.3
11	63	100	0	76.6	2416.7	252.5
11	64	128.8	0	97.2	2762.9	294.3
12	65	29.5	16.3	21.6	666.7	76.5
12	66	38.9	20.3	26.1	882.4	95.8
12	67	38.1	23.4	29.6	887.8	90.2
12	68	38.4	21.7	30	952.4	116.7
12	69	48	29.5	37.4	1155.3	137.4
12	70	62	35.3	36.3	1333.3	136.2
12	71	95.7	63.3	63.5	2232.3	275.5
12	72	110.1	68	82.8	2373.8	303.7
12	73	155.7	81.6	129.2	3767.4	434.9
12	74	225.1	118.8	158.1	5109.4	556.7
12	75	172	102.5	130.5	4000	424.2

Table A.3
Workload (standard man days) of each production process of each order.

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
1	1	6.5	0	4.1	140	15.5
1	2	9.8	0	6.9	241.2	30.5
1	3	12.3	0	7	257	32.8
1	4	13	0	0	327.5	39.5
1	5	23.7	0	0	495	54.5
2	6	6.1	3.1	4.1	121.7	13.4
2	7	11.2	6	7.1	223.3	27.1
2	8	17.4	0	13.3	400.7	46.2
2	9	23.2	0	15.1	489.9	53.8
3	10	40.9	26	31.4	1022.5	115.3
3	11	34.8	17.8	25.5	727.1	93.7
3	12	31.8	19.7	24.7	760.9	96.5
3	13	42.8	0	25.4	908.9	111
3	14	45	0	30.2	908.9	104.7
4	15	3.1	2.2	2.2	79.5	10.4
4	16	11.3	6.5	8.1	256.5	29.1
4	17	1.3	0.7	1	29.5	2.9
4	18	5.7	3.6	4.3	132.9	14.6
4	19	6	3.3	4	130	14.9
4	20	10.1	6.1	6.1	225	26
4	21	23.9	0	19.5	615.8	66.8
4	22	33	0	24.6	869	91.5
4	23	9.7	0	7.9	253.1	32.7
4	24	8.7	0	5.6	195.2	25.7
4	25	15.2	0	11.5	332.6	43.7
4	26	8.4	4.6	0	167.8	16.9
4	27	6.2	4.2	0	152.2	18.4
4	28	22.1	13	0	556	60
4	29	9.5	4.4	0	193.5	19.5
4	30	5.1	3	0	117.5	12.6

Table A.3 (*continued*)

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
5	31	16.9	10.9	13	429.3	47.1
5	32	9.6	5.2	6.2	211.3	23
5	33	8.4	4.2	5.1	166.9	21.1
5	34	19.7	8.9	14.1	393.3	42.6
5	35	20.4	0	14.3	516.7	63.6
5	36	8.6	0	5.8	170.7	18.3
5	37	0.5	0	0.4	12	1.2
5	38	2.3	0	1.3	45.3	5.4
5	39	19.1	0	13.7	409.5	42.1
5	40	3.1	0	0	63.7	7.6
6	41	23.4	10.8	14	487.1	57.3
6	42	13.1	7.6	10.5	294.3	34.3
6	43	9.4	4.6	7	205.6	25.1
6	44	7.5	4.5	5.2	164.8	16.3
6	45	38	19.9	25	793.6	79.4
6	46	14.3	9.1	10.9	345.7	44.6
6	47	22.6	12.7	17.9	531.4	57.9
6	48	47	24.2	29.6	1055.3	112.3
6	49	50.4	27.4	36.3	1153.3	127.3
6	50	57.5	0	42.7	1286.7	165.9
6	51	37.4	0	29.1	829.3	88
6	52	80.1	0	55.4	1694.3	180.9
6	53	19	0	13.1	390	47.9
6	54	19.2	0	13	416.9	46.7
6	55	17.7	0	12.5	431.9	51.5
6	56	22.6	15.1	0	549.3	67.8
6	57	19.7	9.6	0	406	44
6	58	7.7	4.2	0	190	21.9
6	59	18.3	9.6	0	370.6	47.3
6	60	15.4	0	0	386.1	40.9
6	61	21.5	0	0	473	51
6	62	24	0	0	521.8	55.1
7	63	4.5	0	0	97.6	11.2
7	64	2.5	0	0	65.9	8.2
7	65	10.8	0	0	262.7	30.1
7	66	2.9	0	0	76	9.4
7	67	1.4	0	0	34.2	3.4
7	68	2.1	0	0	45.6	5.3
7	69	5.2	0	0	106.9	12.5
7	70	1.1	0	0	25.6	2.6
8	71	43.6	22.9	32.3	918.6	118.3
8	72	61.9	29.9	37	1267.5	154.6
8	73	76.7	37.4	46.1	1538.9	159.7
8	74	64.1	38	53.9	1543.8	156.8
8	75	70.5	41.3	53.4	1588.6	186.6
8	76	76.7	42	49.1	1791.8	229.1
8	77	78.6	58.8	63.3	2042.1	224.8
8	78	101	0	0	2228.4	266.1
8	79	130.2	0	0	3317.6	379.9
9	80	6.8	0	4.4	151.8	18.5
9	81	14	0	10.9	328.5	42.5
9	82	5.5	0	3.5	123.8	12.9
9	83	7.3	0	5.1	171	22.4
9	84	26.7	0	20.6	638	63.6
9	85	18.8	0	12.3	375	47.7
9	86	15.9	0	9.9	353.5	39.5
9	87	10.1	0	7.5	221.3	25.4
9	88	4.3	0	3.5	101	10.1
9	89	22	0	15.7	476.8	51.8
9	90	8	0	6	192.5	21.8
9	91	2.5	0	1.8	64	6.3
9	92	25.6	0	18.1	548.5	58
10	93	1.7	0.9	1	37.2	3.7
10	94	2.7	1.6	2.1	70.5	7.6
10	95	6.9	0	4.8	150	15.7
10	96	3.2	0	2	72.6	7.8
10	97	2.6	0	1.9	52.6	6.5
10	98	6.6	0	4	142.9	15.3
10	99	2.4	0	1.6	55.8	6.7
10	100	1.9	0	0	46.1	4.7
10	101	3.8	0	0	94.2	10.8
10	102	2.5	0	0	56.3	6.1
10	103	0.9	0	0	21.1	2.7
10	104	0.3	0	0	6.7	0.7
11	105	2.7	1.4	1.8	57.7	5.9

Table A.3 (*continued*)

OG no.	Order no.	Process 1	Process 2	Process 3	Process 4	Process 5
11	106	3.5	2	2	71.2	8.3
11	107	3.1	1.8	2	63.5	6.6
11	108	0.6	0.4	0.5	16.7	2.1
11	109	1.6	0	1.1	31.1	3.6
11	110	2.6	0	2	59.9	6.1
11	111	1.5	0	1.3	39	5.1
12	112	24.3	14.3	20.8	640.7	67.8
12	113	21.1	10.5	14.6	460	57.2
12	114	8.1	4.8	5.5	186.2	20.6
12	115	3.5	2.5	2.6	91	9.3
12	116	16.7	12.1	13.5	423.6	44.7
12	117	4.5	2.6	3.1	96.4	12.7
12	118	8.8	0	6.2	187.9	22.1
12	119	1.8	0	1.3	38.5	4.3
12	120	7.5	0	6.6	194.4	21.5
12	121	33.9	16.6	0	734.3	96
12	122	3.3	1.6	0	70	8.5
13	123	57.6	33.8	0	1336.5	168.9
13	124	13.6	8.9	0	322.4	33
13	125	16.1	0	10.1	332.4	36.2
13	126	23.2	0	15.6	575.4	57.1
13	127	7.4	0	6.9	193.7	22.4
13	128	49.6	0	42.6	1241.3	139.7
13	129	62.1	0	41.4	1241.3	162.2
14	130	29.8	18.9	0	745.9	97.7
14	131	97.1	50.3	0	2301.3	302.5
14	132	17.6	12.9	0	455	51
14	133	9.3	4.7	0	196.3	24.4
14	134	42.9	26.9	0	950.6	109.3
14	135	1.2	0.8	0	30	3.7
15	136	16.7	0	10.7	392.1	41.7
15	137	2.3	0	1.5	53.7	5.7
15	138	36.7	0	26.9	960.6	113.2
15	139	7.8	0	5.5	177.5	18.2
15	140	35.4	0	24	756.7	89.8
15	141	29.9	0	23.4	715.8	79.4
15	142	58.9	0	0	1434.2	171.4
15	143	62.4	0	0	1238.8	134.7
15	144	35.4	0	0	880.5	102.9
15	145	8.1	0	0	186.3	22.8

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