Chapter 12
Three Short Time-Space Network Models for Medicine Management

Generally, medicine order and delivery are operated based on the previous experiences. First of all, estimating the average annual demands of hospital storage center. Second, planning a medical goods order and delivery schedule based on the annual average demands as well as establishing the period of ordering and delivering. Third, in the process of operating, medical system supplies goods according to the re-order point and safe stock. In this chapter, we propose three time-space network models for medicine order and shipment, which may help improve the effectiveness when managing the medicine in hospitals.

12.1 Model I: A Basic Time-Space Network Model

12.1.1 Introduction

To minimize the operation cost, Wei [1] applied the concept of JIT and stockless in hospital materials management system. Breen and Crawford [2] pointed out that the use of electronic commerce technology can improve the internal pharmaceutical supply chain. Danas et al. [3] proposed virtual hospital pharmacy (VHP) information system to meet the demands and calculate minimum stock level and reorder point of hospital departments. Zhu et al. [4] designed an improved randomized algorithm for the vehicle routing problem of medical goods for large-scale emergency scenario.

The time-space network approach has been popularly employed to solve medical material transit scheduling problems, because it is natural and efficient to represent conveyance routings in the dimensions of time and space. Liao [5] and Cao [6] employed time-space network techniques with the system optimization perspective to construct a deterministic real-time and stochastic real-time medical goods scheduling model and adopted integer programming method to minimize the total cost of medical system. Yan and his colleagues [7, 8] developed a novel time-space network model with the objective of minimizing the length of time needed for emergency repair.

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Steinzen et al. [9] presented a new modeling approach that is based on a time-space network representation of the underlying vehicle-scheduling problem. Yan et al. [10, 11] applied time-space network to present a logistical support scheduling model for the given emergency repair work schedule to minimize the total operating cost.

This study presents a logistics support model for medical goods scheduling to address the uncertain demand in the hospital nodes. The model is a stochastic order and delivery scheduling model, which systematically considers the demand of medical goods for every time slot in different hospital nodes, the storage capacity and other constraints, as well as the integrated delivery plan of medical goods in the dimensions of time and space. The problem is formulated as a mixed 0–1 integer programming model and a heuristic algorithm is proposed to solve it. The test results show the good performance of the proposed model. Hence, it is expected to be a useful planning tool for decision-maker to get effective medical goods supply order and delivery schedules.

12.1.2 The Time-Space Network Model

In this section, we will first introduce the dynamic decision-making structure and the time-space network structure which can help us to understand the logistics support process. After that, we will give the mathematical formulation of the problem.

(1) **The dynamic decision-making structure**

As Fig. 12.1 shows, we make a dynamic decision-making framework for the whole planning cycle. We operate the model once a week and it will present the scheduling result for the whole remainder planning cycle. For example, in the first week, the optimal result will show the schedules for the whole 26 weeks. However, only the

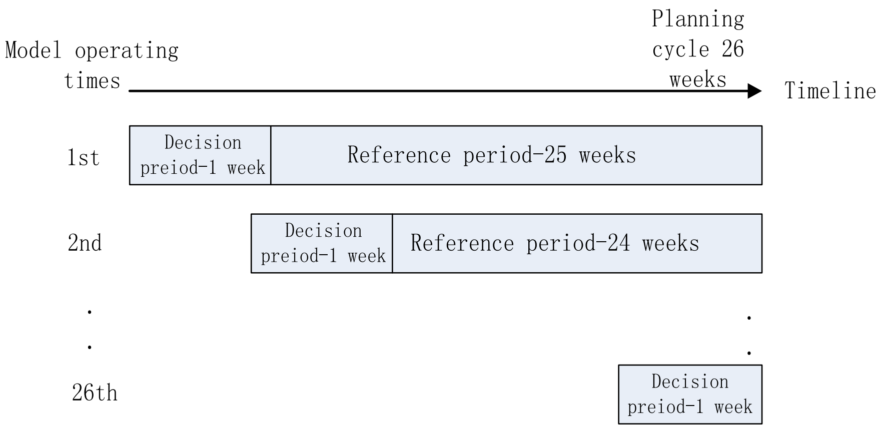

Fig. 12.1 Dynamic decision-making framework

result for the first week will be adopted while the results in the other 25 weeks are used as reference. We do this because the demand information in the recent week is more deterministic and the demand information in further is inaccurate. After that, we will update the demand information in the following weeks and then repeat the above work until the end of the planning cycle.

(2) **Time-space network structure**

As Fig. 12.2 shows, a time-space network is built for supply routing and inventory state at one planning cycle. The horizontal axis represents the manufacturer, the supplier and the hospitals in medical system; the vertical axis stands for the time duration. "Nodes" and "arcs" are the two major components in the network. The nodes include the manufacturer, the supplier, the hospitals and the collection points. The supplier node provides medical goods to hospitals. The hospitals nodes order medical goods from suppliers. The collection node is used to ensure flow conservation. One time point represents one week. The arc flows express the flow of medical goods in the network. The arc flow's lower and upper bounds are defined as the minimum and

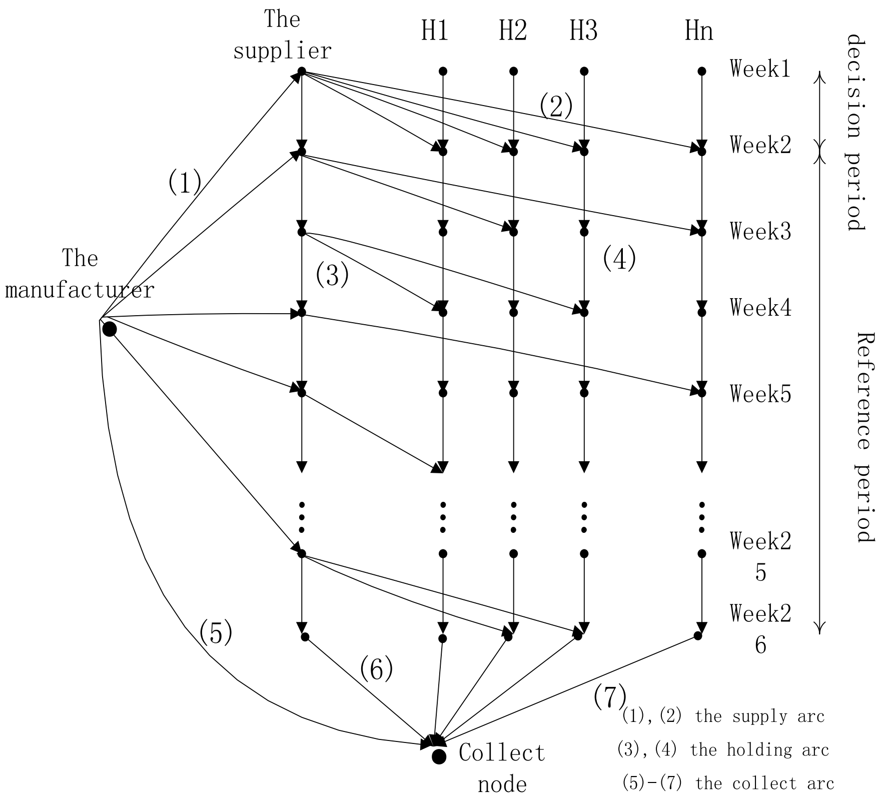

Fig. 12.2 The time-space network

maximum number of flow units allowable on the arc. Three types of arcs are defined as below.

(i) Supply arc. A supply arc (see (1–2) in Fig. 12.2) represents the medical goods are delivered from the manufacturer to the supplier, or from the supplier to the hospital. The arc's cost for (1–2) is the purchase cost of the medical goods plus the fixed ordering cost. The arc flow's upper bound for (1–2) is the inventory capacity of the supplier or the hospital. The arc flow's lower bound is zero.

(ii) Holding arc. A holding arc (see (3–4) in Fig. 12.2) represents the holding of medical goods in the supplier or in the hospital. The arc flow denotes the number of medical goods held in the supplier or the hospital in a moment. The arc's cost is the inventory cost. The arc flow's upper bound is the inventory capacity of the supplier or the hospital. The arc flow's lower bound is safe stock of the supplier or the hospital.

(iii) Collection arc. A collection arc (see (5–7) in Fig. 12.2) connects the last node associated with a supplier, the last node associated with a hospital and the manufacturer node to the collection node. It is used to ensure flow conservation at the last time associated with each supplier and hospital point. The arc flow's upper bound is infinity and the arc flow's lower bound is zero. The arc's cost is zero.

(3) **Mathematical formulation**

The assumptions for the mathematical formulation are listed below:

1. Demand for each hospital node at every time point is uncertain and obey random distribution. When the model is operated, the demand information will be updated in each decision period.
2. The manufacturer can provide enough medical goods, thus out-of-stock will not take place.
3. Lead time of the order is one week. However, when to order and the order quantity is uncertain, they are the decision variables.
4. For simplicity, only one manufacturer, one supplier and one kind of medical good are considered in the supply network.
5. The initial inventory of every hospital in the first week is the safe inventory plus the maximum demand.

Before introducing the model's formulation, the notations and symbols are listed below:

Parameters:

cb_{ij}	Supply arc (i, j) cost.
cs_{ij}	Holding arc (i, j) cost.
co_{ij}	Fixed ordering cost for the supply arc (i, j).
l_{ij}	Arc (i, j) flow's lower bound.
u_{ij}	Arc (i, j) flow's upper bound.
S, W, H	The set of all manufacturer, supplier and hospital nodes, respectively.

NM Set of all nodes in the network.
AB, AS Set of all supply arcs and holding arcs, respectively.
$a_i(w)$ The ith node's supply or demand in the *wth* random event (if $a_i \geq 0$, supply; else demand).

Decision variables:

$x_{ij}(w)$ The supply arc (i, j) flow in the *wth* random event.
$y_{ij}(w)$ The holding arc (i, j) flow in the *wth* random event.
$\delta_{ij}(w)$ A binary variable in the *wth* random event which indicates whether supply arc (i, j) in the network has flows. If $\delta_{ij}(w) = 1$, then $x_{ij}(w) > 0$; else, $x_{ij}(w) = 0$

Based on the notations, the proposed problem can be formulated as follows:

$$\text{Min } z = \sum_{\forall ij \in AB} cb_{ij} x_{ij}(w) + \sum_{\forall ij \in AS} cs_{ij} y_{ij}(w) + \sum_{\forall ij \in AB} co_{ij} \delta_{ij}(w) \tag{12.1}$$

$$\text{s.t.: } \sum_{j \in W \cup H} x_{ij}(w) + \sum_{r \in W \cup H} y_{ir}(w) - \sum_{p \in S \cup W} x_{pi}(w) - \sum_{c \in W \cup H} y_{ci}(w) = a_i(w), \quad \forall i \in NM \tag{12.2}$$

$$x_{ij}(w) \leq M \delta_{ij}(w), \quad \forall ij \in AB \tag{12.3}$$

$$l_{ij} \leq x_{ij}(w) \leq u_{ij}, \quad \forall ij \in AB \tag{12.4}$$

$$l_{ij} \leq y_{ij}(w) \leq u_{ij}, \quad \forall j \in AS \tag{12.5}$$

$$x_{ij}(w),\ y_{ij}(w) \in I, \quad \forall j \in AS \tag{12.6}$$

$$\delta_{ij}(w) = 0, 1, \quad \forall ij \in AB \tag{12.7}$$

The objective function (12.1) minimizes the total cost of the medical system. The first item of objective function represents all supply costs; the second item stands for all inventory costs; the third item expresses all order costs. Constraint (12.2) denotes the flow conservation constraint at every node in the network. Constraint (12.3) denotes whether the node orders medical goods or not. Constraint (12.4) and (12.5) holds all the arc flows within their bounds. Constraint (12.6) ensures the integrality of the supply flows and holding flows, and constraint (12.7) denotes all the decision variables are either 0 or 1.

12.1.3 Solution Algorithm

The model is formulated as a mixed 0–1 integer network flow problem that is characterized as NP-hard problem. To efficiently solve this problem we develop a heuristic algorithm, with the assistance of the mathematical programming solver, CPLEX. The procedure is described as follows:

Step 1. Initialization, generate a sequential data follows uniform distribution, which includes 26 data stand for the demand at 26 time points.
Step 2. Set $f = 1$ as the decision period.
Step 3. With the target of minimizing the total cost of the medical system, we solve the medical goods order and delivery schedules for the remainder weeks by CPLEX.
Step 4. Take the schedules of decision period (f) as a certain result. Then we execute it and put the holding situation and the ordering situation in the decision period as the initial conditions of the next decision period.
Step 5. If $f = 26$, then go to Step 6; otherwise, $f = f + 1$, and return to Step 3.
Step 6. Record the optimal schedules and the operations cost.

12.1.4 Numerical Tests

To test how well the proposed model may be applied in the real world, we perform some numerical tests using data in Ref. [5]. The matlab computer language, coupled with the CPLEX 12.4 mathematical programming solver, is used to develop all the necessary programs for building and solving the proposed model. Assume there are five hospitals and thus the model contains 156 nodes, 468 variables and 778 constraints.

(1) **The initial data setting**

We generate the demands for the hospitals by using unidrnd() function in the matlab tool. The average of each hospital demand is 450, 550, 600, 450 and 450, respectively. The variance of each hospital demand is 300, 833, 133, 208 and 300, respectively. The unit procurement price for the supplier is 20 yuan, and it is 22 yuan for the hospital. The unit inventory cost for the supplier and the hospital is 0.3 yuan and 0.5 yuan per week, respectively. The fixed ordering cost for the supplier and the hospital is 3000 and 600 yuan, respectively. Safe stock in each hospital is set as 450, 550, 600, 450 and 500, respectively. The safe stock of the supplier is 3 times of the sum of all hospital's average demand. The inventory capacity of the supplier and the hospital is 5 times of their safe stock, respectively. In practice, relevant data can be set according to the actual situation.

(2) **The test results**

As shown in Fig. 12.3, the objective value decrease as the dynamic decision-making

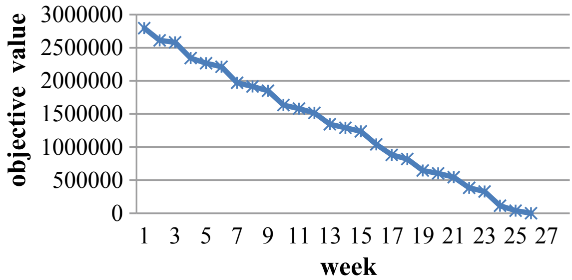

Fig. 12.3 Objective value variation with the solution procedure continuous implement

procedure continuous implement. In the first week, the optimal result will give out the schedules for the whole 26 weeks. Thus the total cost is 2,796,137.7 yuan. As the reference period goes down, the number of decision variables reduce, then the objective values decrease.

To test the stability of the solution result, we adjust the inventory capacity as 2, 3, 4, 5 and 6 times of the safe stock, and then we solve the model respectively. The results are shown in Fig. 12.4. As inventory capacity increases, the total costs reduce. For the frequency of ordering decrease, but the order quantity increases. When the fixed ordering cost and the inventory cost balanced, the inventory capacity will not affect the final result.

We change the variances of the demands to observe the influence on the objective values. When the variances are changed to 1, 4 and 9 times of the original variances, their squared correlation coefficient (R^2s) are 0.9917, 0.992 and 0.9921 in scatter diagrams, as shown in Fig. 12.5. The results show that variances of demands can only bring slight changes on the objective values.

Furthermore, we evaluate our model with a certain order time model which may always adopted in an actual operation. The order time of the certain order time model is one week. Other parameters are set as the same to proposed model. We adjust the ordering cost for the two models. The comparison results are shown in Fig. 12.6.

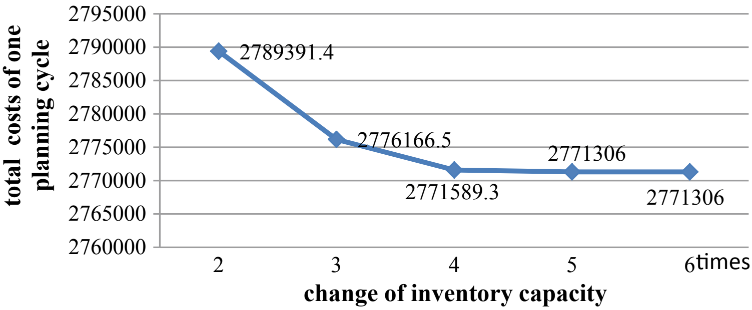

Fig. 12.4 Sensitivity analysis of inventory capacity

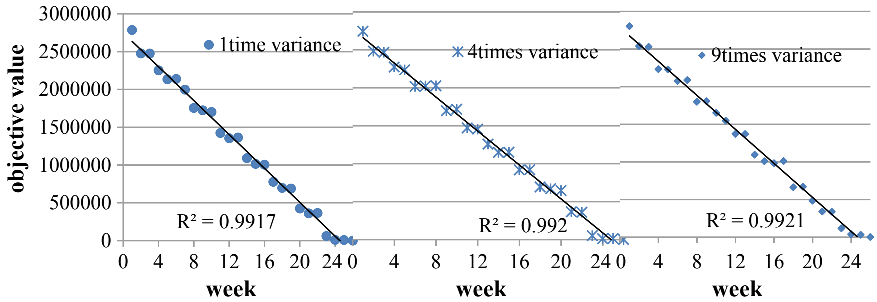

Fig. 12.5 The variance of demands is 1, 4 and 9 times of the original variance

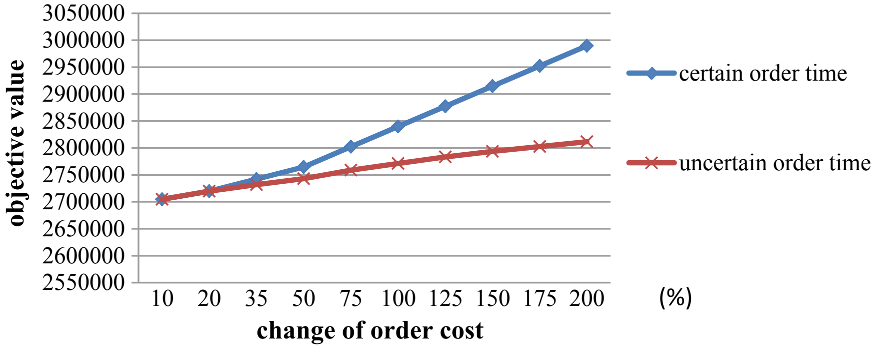

Fig. 12.6 Comparison of certain order time model and uncertain order time model

When the ordering cost is set as no more than 50% of the original costs setting, the two results are similar. However, when the ordering cost is greater than 50% of the original costs setting, the objective values of the proposed model in this work is more optimal.

12.1.5 Conclusions

In this study, the time-space network technique is applied to develop a model to find optimal medical goods order and delivery schedules. The model is a stochastic order and delivery scheduling model, which systematically considers the demand of medical goods for every time slot in different hospital nodes, the storage capacity and other constraints, as well as the integrated delivery plan of medical goods in the dimensions of time and space. The problem is formulated as a mixed 0–1 integer programming model and a heuristic algorithm is proposed to solve it. In an actual practice, the medical goods could be multi-commodities, and lead time of the order would be influenced by many factors and therefore be stochastic. Hence, how to incorporate a multiple commodity flow and stochastic lead time of the order into the model, to make the schedule more reliable, are our research directions in the future.

12.2 Model II: An Improved Time-Space Network Model

12.2.1 Introduction

Nowadays, most domestic hospitals still make medical resource order plans by experience or according to historical data. In actual operations, this subjective and unscientific method could not only increase inventory level, but also lead to stock-outs sometimes. Hence, how to plan the order and distribution of medical resource, and how to improve hospitals' service quality has become a hot issue in recent years.

To the best of our knowledge, several past studies have focused on the medical resource order and distribution scheduling problem. For example, Shi [12] developed a two stage supply chain inventory or supplier-hospital model with Vender Managed Inventory (VMI), which could effectively reduce the overall inventory cost of the hospitals and the supply chain. Rachaniotis et al. [13] established a deterministic model to schedule limited available resource under the situation of an epidemic infection with the concept of deteriorating jobs. Zhou et al. [14] built a stochastic dynamic programming model for ordering a perishable medical product, and concluded that the total expected cost was sensitive to changes in the expected demand as well as the regular policy. Nagurney [15] developed a tractable network model and computational approach for the design of medical nuclear supply chains to minimize the total operational cost, the cost associated with nuclear waste discarding, and capacity investment costs. Chen et al. [16] proposed a model based on a relational view, delineating the factors that influence hospital supply chain performance: trust, knowledge exchange, IT integration between hospital and its suppliers, and hospital-supplier integration. Uthayakumar and Priyan [17] presented an inventory model that integrated continuous review with production and distribution for a supply chain to achieve hospital customer service level (CSL) targets with a minimum total cost.

As the time-space network can visually and effectively show the movement both in the dimensions of time and space, this approach has been widely used to solve scheduling problems in many fields. Zhang and Li [18] applied time-space network to establish a dynamic pricing model to maximize manufacturers' profits. To help airport authorities with flight-to-gate reassignments following temporary airport closures, Yan et al. [19] developed a reassignment network model with the objective to minimize the number of gate changes. Steinzen et al. [9] developed a time-space network model to solve the integrated vehicle- and crew-scheduling problem in public transit with multiple depots, and numerical results showed that this approach could perform well. Buhrkal et al. [20] used the time-space concept to develop three main models of the discrete dynamic berth allocation problem, and the results indicate that a generalized set-partitioning model outperforms all other existing models. Yan et al. [10] developed a logistical support scheduling model for the emergency roadway repair work schedule to minimize the short-term operating cost subject to time constraints and other related operating constraints. Lin et al. [21] developed a planning model and a real-time adjustment model based on a time-space network to plan courier routes and schedules and adjust the planned routes in actual operations for an international express company facing uncertain demands.

But as for medical resource order and distribution scheduling, the time-space network concept has seldom been applied to this problem. Liao [5] and Cao [6] established a deterministic real-time and stochastic real-time medical resource order and transit scheduling model based on the time-space network with the objective of minimizing the total operation costs. However, they did not consider the constant ordering cost (related to ordering frequency), which is not practical. In this work, the ordering cost is taken into consideration, and we employ the time-space network flow technique to develop a model designed to help a hospital to plan the order and distribution of medical resource.

12.2.2 Model Formulation

This section presents the formulation of medical resource order and distribution model. In practice, hospital staff would periodically review the current standards of purchasing plans (e.g. safety inventory, ordering frequency), and adjust the plans to new demands. Therefore, the 'dynamic decision-making framework' is introduced into the time axis of the scheduling model to correspond with real-world operations. The time axis is divided into 2 parts: 'decision period' and 'reference period'. To make the scheduling results more consistent with reality, after every decision period, the order and distribution will be rescheduled according to new demands. This operation would be repeated until the end of the scheduling cycle. Besides, the scheduling results during decision period are deterministic scheduling, and results during reference period can be used as a reference for the current scheduling.

For example, if we implement the model every week, the duration of every scheduling is from the time where the implementation starts to the end of scheduling cycle, as shown in Fig. 12.7. The duration of implementation for the first time is 26 weeks. After that, 25 weeks is remained for the second time, and 24 weeks for the third time. It's worth mentioning that only the scheduling results during the decision period (the first week) would be put to actual use.

(1) **Basic assumptions**

Only one kind of medical resource is considered in this work. To facilitate the model formulation, we set some assumptions as follows:

1. Demands for medical resource at each time interval can be set to obey a normal distribution according to history data.
2. The scheduling cycle is half a year (26 weeks); both of the order lead time and the distribution lead time are one week.

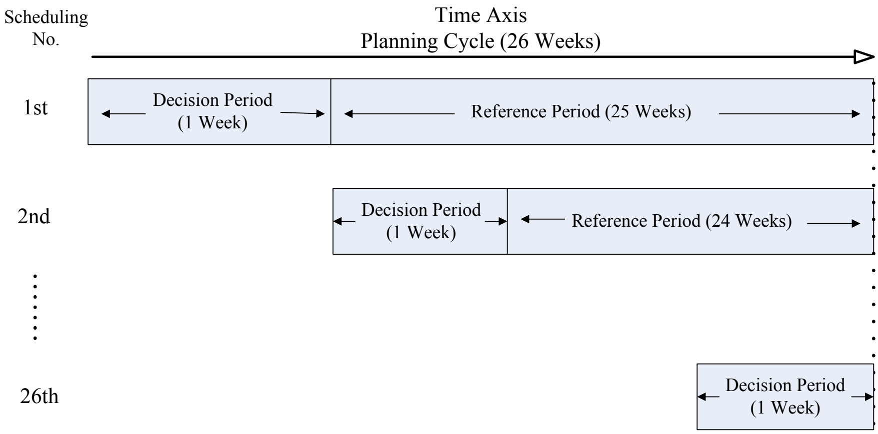

Fig. 12.7 Dynamic decision framework of the scheduling model

3. Medical resource is supplied by one supplier; there is only one warehouse in the hospital.
4. The supplier can meet the market demand completely, and transit medical resources to the hospital warehouse in time and in the right quantity.
5. The storage capacity of the hospital warehouse and departments are known and fixed.

(2) **Time-space network of medical resource order and distribution**

A time-space network is established to describe the supply of medical resource in the dimensions of time and space, as shown in Fig. 12.8. The horizontal axis represents the supplier, the hospital warehouse and departments. The vertical axis stands for the duration of scheduling. The time interval is one week.

The time-space network contains two basic elements: node and arc. Next, we will introduce them in detail respectively as follows.

1. Node

A node represents the supplier, the hospital warehouse or a department at a specific time. There are 4 types of nodes in this time-space network: the supplier node, the hospital warehouse node, the hospital department node and the collection node. The supplier must convey the medical resource to the warehouse first, and then the resource will be distributed to each department after arrangement. The department nodes will place an order to the warehouse when their inventory cannot afford their demands. The warehouse and each department have an initial amount of medical resource at the beginning of the scheduling cycle, which is the remaining inventory of the previous scheduling cycle. The collection node maintains the flow conservation of the network. All unused medical resource on the nodes will assemble at the collection node at the last week of the scheduling cycle.

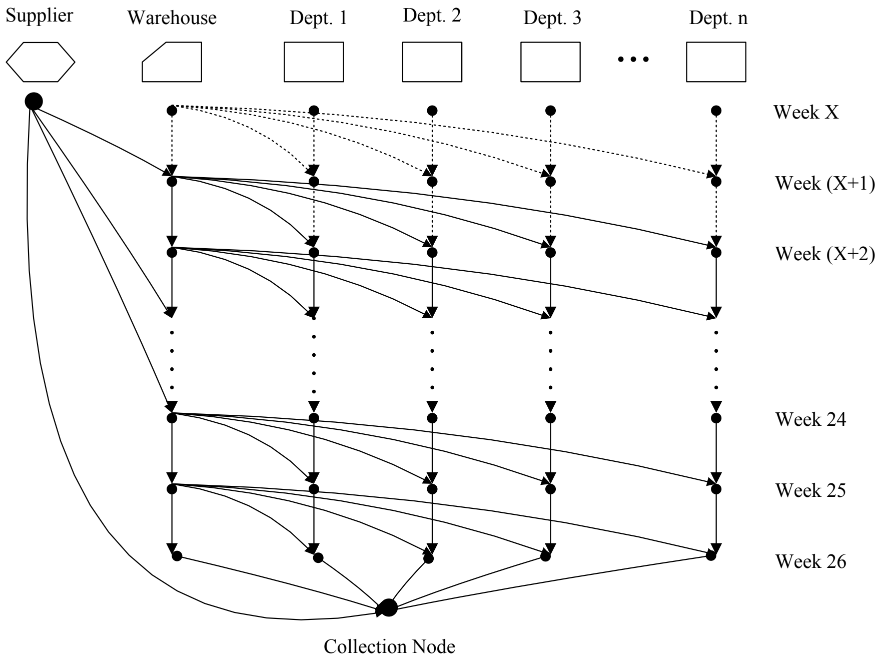

Fig. 12.8 Time-space network of medical resource scheduling

2. Arc

An arc denotes the activity of medical resource distribution in different time and space. The arc flows express the flow of medical resource in the network. There are 4 types of arcs: supply arc, distribution arc, holding arc and collection arc.

(i) Supply arc: It represents that the supplier delivers medical resource to the hospital. The arc cost is the unit price of medical resource plus a fixed ordering cost. The arc flow's upper bound is the warehouse's storage capacity, and the lower bound is zero.
(ii) Distribution arc: It represents that the warehouse delivers medical resource to the departments. The arc cost is the unit distribution cost plus a fixed labor cost. The arc flow's upper bound is each department's storage capacity, and the lower bound is zero.
(iii) Holding arc: It represents the holding of medical resource at the warehouse or departments. The arc cost is the unit inventory-holding cost. The arc flow's upper bound is the storage capacity of the warehouse/departments, and the lower bound is the safety stock of the warehouse/departments.
(iv) Collection arc: It connects the supplier node, the warehouse node and department nodes to the collection node, and ensures the flow conservation of this network. The arc cost is zero. The supplier collection arc flow's upper bound

is infinity, and the lower bound is zero. The warehouse/departments collection arc flow's upper bound is the storage capacity of the warehouse/departments, and the lower bound is the safety inventory of the warehouse/departments.

(3) **Notations used in the model formulation**

Parameters:

Z The total costs of the order and distribution of medical resource;
a_{jt} The demand for medical resource of the jth department at the time interval of t;
p_{SW} Unit purchasing cost from the supplier;
s_{WD} Unit distribution cost from the warehouse to departments;
f_1 Constant fixed ordering cost from the supplier to the warehouse;
f_2 Constant fixed labor cost from the warehouse to departments;
h_w Unit inventory-holding cost of medical resource in the warehouse;
h_d Unit inventory-holding cost of medical resource in each department;
T The set of time interval;
SW The set of arcs between the supplier and the warehouse;
WD The set of arcs between the warehouse and the departments;
D The set of all departments in the hospital;
LW Minimum inventory level of the warehouse;
UW Maximum inventory level of the warehouse;
LD_j Minimum inventory level of the jth department;
UD_j Maximum inventory level of the jth department.

Decision variables:

x_{ij} Supply arc (i, j) flow from the supplier to warehouse;
y_{jk} Distribution arc (j, k) flow from the warehouse to departments;
z_{wt} Holding flow in the warehouse at the time interval of t; when $t = 0$, z_{wt} represents the initial inventory of medical resource in the warehouse;
z_{jt} Holding flow in the jth department at the time interval of t; when $t = 0$, z_{jt} represents the initial inventory of medical resource in the jth department;
δ_{ij} A binary variable that indicates whether the hospital warehouse sends an order to the supplier. If $\delta_{ij} = 1$, then $x_{ij} \geq 0$; if $\delta_{ij} = 0$, then $x_{ij} = 0$;
ξ_{jk} A binary variable that indicates whether the departments send an order to the warehouse. If $\xi_{jk} = 1$, then $y_{jk} \geq 0$; if $\xi_{jk} = 0$, then $y_{jk} = 0$.

(4) **The mathematic model**

Based on the notations, the scheduling model can be formulated as follows:

$$Min\ Z = \sum_{ij \in SW} (p_{SW} x_{ij} + f_1)\delta_{ij} + \sum_{jk \in WD} (s_{WD} y_{jk} + f_2)\xi_{jk} + h_w z_{wt} + \sum_{j \in D} h_d z_{jt} \tag{12.8}$$

Subject to:

$$x_{ij}\delta_{ij} + z_{wt-1} - \sum_{j \in D} y_{jk} = z_{wt}, \quad \forall ij \in SW, \; jk \in WD, \; t \in T \tag{12.9}$$

$$y_{jk}\xi_{jk} + z_{jt-1} - z_{jt} = a_{jt}, \quad \forall jk \in WD, \; j \in D, \; t \in T \tag{12.10}$$

$$0 \le x_{ij} \le UW, \quad \forall ij \in SW \tag{12.11}$$

$$0 \le y_{jk} \le UD, \quad \forall jk \in WD \tag{12.12}$$

$$LW \le z_{wt} \le UW, \quad \forall t \in T \tag{12.13}$$

$$LD_j \le z_{jt} \le UD_j, \quad \forall j \in D, \; t \in T \tag{12.14}$$

$$x_{ij} \in I, \quad \forall ij \in SW \tag{12.15}$$

$$y_{jk} \in I, \quad \forall jk \in WD \tag{12.16}$$

$$z_{wt} \in I, \quad \forall t \in T \tag{12.17}$$

$$z_{jt} \in I, \quad \forall j \in D, \; t \in T \tag{12.18}$$

$$\delta_{ij} = 0 \; or \; 1, \quad \forall ij \in SW \tag{12.19}$$

$$\xi_{jk} = 0 \; or \; 1, \quad \forall jk \in WD \tag{12.20}$$

The objective function (12.8) denotes the minimization of total costs of medical resource order and distribution, including purchasing cost, distribution cost in hospital and holding cost. Constraints (12.9) and (12.10) indicate the flow conservation in this network. Constraints (12.11) to (12.14) ensure that all arc flows are within their bounds. Constraints (12.15) to (12.20) ensure that all variables are binary number or integers.

12.2.3 The Solution Procedure

In this section, we discuss how to solve the proposed model. The model is formulated as a mixed 0–1 integer network flow problem with NP-hard complexity. Considering the long scheduling cycle and the number of departments in practice, it is almost impossible to optimally solve this large problem within a limited time. Thus the solution effectiveness and efficiency need to be traded off. To efficiently solve this problem, we develop a heuristic algorithm, with the assistance of the mathematical programming solver, CPLEX. The procedure is described as follows:

Step 1: Initialization. Set parameters of the model, including simulation rounds, the storage capacity, the safety inventory, the initial inventory, cost data and other related data.
Step 2: Set $t = 1$. Solve the model for the first round.
Step 3: Use MATLAB function normrnd() to generate N groups of demands for medical resource at each time interval.
Step 4: Call function cplexmilp() to solve the model and obtain the scheduling results of the whole scheduling cycle. The results from the previous decision period will be taken as the input data for the current decision period.
Step 5: Continue generating demands of the remaining time intervals. Solve and get the rest of scheduling results.
Step 6: Repeat step 4 and 5, until obtaining the scheduling results at the last time interval of the scheduling cycle. If $t = 26$, then go to Step 7; otherwise, $t = t + 1$, and return to Step 4.
Step 7: Record the optimal schedules and the total operation costs.

12.2.4 Numerical Tests

To test how well the proposed model may be applied in the real world, we perform several numerical tests using historical operating data of a certain kind of medical resource from a hospital in Nanjing, China, with reasonable simplifications. The tests were performed on a personal computer equipped with a Intel (R) Core (TM) 2.13 GHz CPU and 2.00 GB of RAM in the environment of Microsoft Window 7.

(1) **Case data**

This kind of medical resource has only one supplier. There is one warehouse and five departments in the hospital. The scheduling cycle is 26 weeks. The time interval is one week. We set the demands to obey a normal distribution, and use MATLAB to generate the demands of 26 weeks. The averages of each department's demand are 10, 11, 12, 8 and 13 respectively, and the standard deviations are 2, 2, 2, 1 and 1, respectively. According to the hospital's practical operations in Nanjing, the related cost data and inventory bounds are set as in Tables 12.1 and 12.2.

Table 12.1 Parameter settings

p_{SW}	s_{WD}	f_1	f_2	h_w	h_d
20	8	50	15	0.7	1.4

Table 12.2 Inventory bounds settings

	Warehouse	Dept. 1	Dept. 2	Dept. 3	Dept. 4	Dept. 5
LD	250	12	13	15	10	15
UD	750	36	40	50	30	45

(2) **Test results**

As shown in Fig. 12.9, we get the total operation costs from one scheduling cycle. The horizontal axis represents the week that is scheduled; the vertical axis represents the objective value at each week. In different rounds of programming, the objective value decreases weekly until it equals zero as the dynamic decision-making procedure continuously proceeds. The objective values are the results during decision period and reference period. In the early decision period, most of supply and distribution arcs are idle, the number of variables in the model is large, and the scope of scheduling is the whole scheduling cycle (26 weeks), so the objective value is high. As time advances, the reference period of dynamic decision framework gets shorter, and the number of variables declines, so the objective value reduces.

Besides, we test the scheduling model for five times and get five groups of objective value data, from whom we select five sets of results of the 1st, 6th, 12th, 18th, 24th week to compare the changes of objective values at the same scheduling interval. As shown in Fig. 12.10, in the vertical direction, the 5 sets of objective values all decrease as the model continues to be implemented, which is in line with the characteristic of the objective value's changes in each scheduling cycle shown in Fig. 12.9. On the other hand, horizontally, the objective value at the same week is fluctuant for the reason that the demands data are generated randomly by MATLAB function normrnd(). But the amplitude of fluctuation is small (the largest rate of change from the 5 sets of results above is 10.70%), which reveals that the randomly generated demands would not influence the objective value, and then proves the stability of the model.

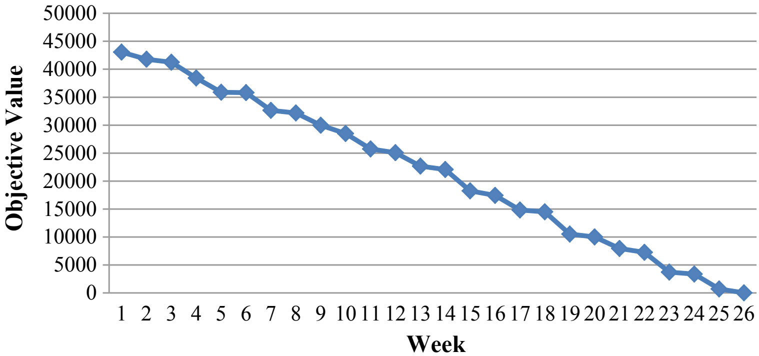

Fig. 12.9 Changes of objective value in one scheduling cycle

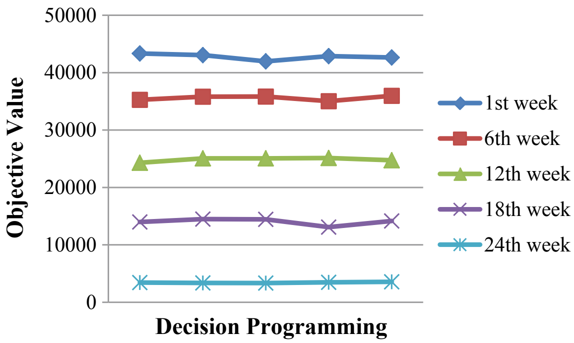

Fig. 12.10 Comparison of objective values at the same scheduling interval in different scheduling cycles

(3) **Sensitivity analysis**

To understand the influence of the related parameters on the proposed model, several sensitivity analyses are performed here, which could be taken as references for warehouse managers. In consideration of emergencies (e.g., number of patients increases, or overdue supplying), safety inventory is necessary to be set accurately. So we performed the sensitivity analysis on safety inventory of the warehouse to understand its influence on the total operating costs. We tested five situations, 60, 80, 100, 120 and 140% of the original safety inventory. The results are shown in Fig. 12.11. The results show that the objective value grows with the increase of safety inventory. When the safety inventory rises from 60 to 140% of the original, the growth rates of objective value are 4.6, 4.5, 4.4 and 4.3% respectively, from which we can see that the growth is trending down. When the warehouse's safety inventory increases, the hospital manager would order more medical resource for each time, so the inventory cost increases. But the ordering frequency declines, so the ordering cost declines. The inventory cost and ordering cost would finally achieve a balance and then the objective value would level off and approach a certain constant value. However, in

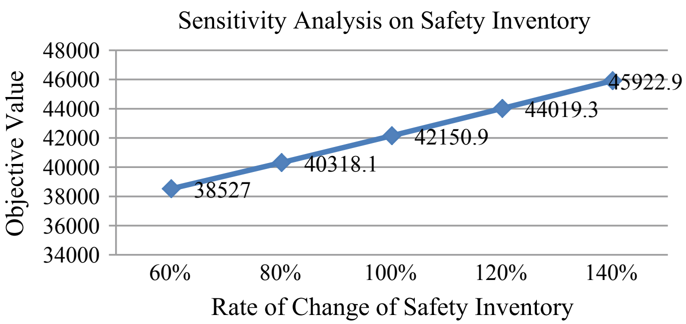

Fig. 12.11 Sensitivity analysis on safety inventory

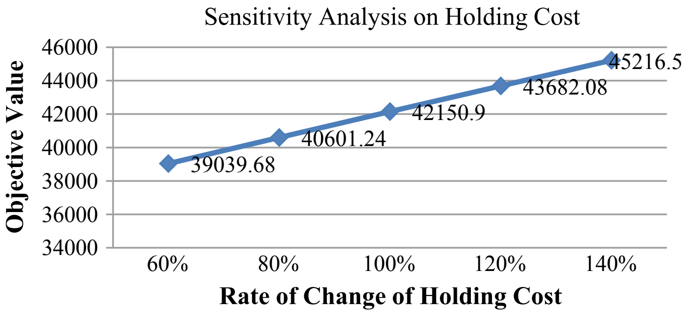

Fig. 12.12 Sensitivity analysis on unit holding cost

actual operations, managers should not reduce safety inventory level without limit to obtain less operation costs. An adequate safety inventory level is indispensable to mitigate risk of stock-outs due to uncertainties in supply and demand, and permit operational activities to proceed according to their plans.

In order to test whether the holding cost is properly set, we performed the sensitivity analysis on it. We tested five situations, 60, 80, 100, 120 and 140% of the original safety inventory. The results are shown in Fig. 12.12. The results show that the objective value grows with the increase of unit holding cost. When the holding cost rises from 60 to 140% of the original, the growth rates of objective value are 4.0, 3.8, 3.6 and 3.5% respectively. So we can conjecture that the objective value would reach to a certain constant value if the unit holding cost keeps increasing. As the unit holding cost increases, the manager would order less medical resource for each time to reduce the total holding cost, but the frequency of ordering gets relatively high, and which increases the ordering cost. When the unit holding cost continues increasing, the ordering cost and total holding cost would be balanced until the objective value reaches to a certain fixed value.

In general, every supplier has different ordering fees and price standards, and the hospital should make a trade-off among them and select a supplier modestly. So there is a need to perform a sensitivity analysis on the shipment cost to understand the influence of different ordering costs on total costs. We tested five situations, 60, 80, 100, 120 and 140% of the original ordering cost. As we can see on Fig. 12.13, the objective value increases as the ordering cost increases. When the constant ordering cost rises from 60 to 140% of the original, the growth rates of objective value are 0.2863, 0.2855, 0.2738 and 0.2603% respectively. With the increasing of the constant ordering cost, the hospital manager would order more medical resource for each time to reduce the ordering frequency, and then to reduce the ordering cost. When the ordering cost keeps rising, it would finally balance with the ordering cost until the objective value reaches to a certain fixed value. Hence, the hospital should select a right supplier for a right ordering fee.

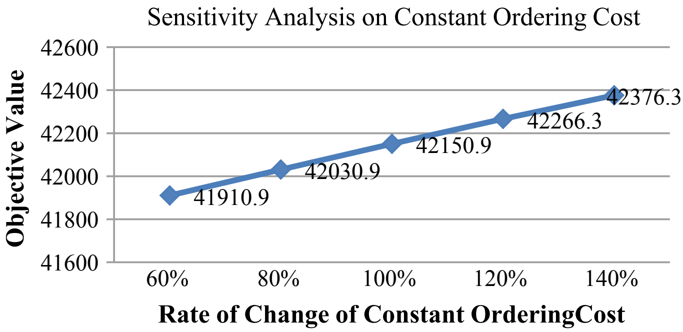

Fig. 12.13 Sensitivity analysis on constant ordering cost

12.2.5 Conclusion

In this work, we creatively take the ordering cost into consideration, and employ the ideas of time-space network and dynamic decision framework to describe the order and distribution of medical resource in a hospital. The problem is formulated as a mixed 0–1 integer programming model. Then a heuristic algorithm is developed to solve it. The test results show the good performance and practicability of the model.

Future research would be useful in at least the following directions. First, since we assume the demands are known and the lead time is certain, the problem to be solved is how to optimize the total cost of medical resource order and distribution under stochastic conditions. Second, only one kind of medical resource is considered in the model, hence it would be more practical and useful to consider multi-variety problem.

12.3 Model III: A Chance-Constrained Programming Model Based on Time-Space Network

12.3.1 Introduction

High operating cost has been a thorny problem for most hospitals in China all the time. Aside of institutional reasons, management method in purchase and inventory should also be responsible for it. Although most major hospitals have adopted electric purchasing management information systems, parameters inside them are often set according to staff's experience. This could give rise to inaccurate decisions due to lack of systematic analysis and overdependence on staff's subjective judgments.

To the best of our knowledge, many studies have focused on the hospital medical resources order and distribution scheduling problem. Lapierre and Ruiz presented an inventory cost oriented model and a balanced schedule model, and used a tabu search metaheuristic to solve them. The supply schedules generated by this method were efficient and well balanced [22]. Chang et al. [23] established an optimal purchase model to minimize a hospital's drug inventory management cost, and obtained the optimal quantity and frequency to order medicine. Liao and Chang [24] established a simulation model for the supply chain of the hospital logistics system based on the dynamic Taguchi method, and proposed an optimal approach to obtain an optimal robust design in achieving optimal multi-performance. Uthayakumar and Priyan [25] presented an inventory model that considers multiple pharmaceutical products, variable lead time, permissible payment delays, constraints on space availability, and the customer service level (CSL) designed to achieve hospital CSL targets with a minimum total cost for the supply chain. Then they put this problem in a fuzzy-stochastic environment and extended the model [26].

Particularly, Liao [5] and Cao [6] applied the time-space network concept to medical resources order and distribution scheduling, and constructed a deterministic model and a stochastic model respectively. Zhang and Liu [27] developed a mixed 0–1 integer programming model based on time-space network with the assumptions that the demand is known and the supplier can completely meet the market demand.

In this study, we discuss the order and distribution under uncertainty, where the departments' demands are stochastic, and cannot be completely met by the supplier, which may cause a penalty cost due to stock shortage. With time-space network and stochastic programming, a chance-constrained programming model is constructed with the objective to help a hospital to plan the order and distribution of one certain kind of medical resources. Generic algorithm is applied to solve the proposed model.

12.3.2 Model Formulation

(1) **Basic assumptions**

To facilitate the model formulation, some assumptions are set as follows:

1. Demand for medical resources of every week is stochastic, and obeys a Gaussian distribution.
2. The weekly supply quantity of the supplier is a known value, and the supplier might not completely meet the hospital's demand.
3. The whole scheduling cycle is 52 weeks; the lead time of order and distribution are both one week.
4. The safety stock and stock capacity of the warehouse and departments are known and fixed.
5. There is a certain known amount of initial stock in the warehouse and departments at the beginning of the scheduling cycle.

(2) **Time-space network**

A time-space network is established to describe the supply of medical resources as shown in Fig. 12.14. The horizontal axis represents the supplier, the hospital

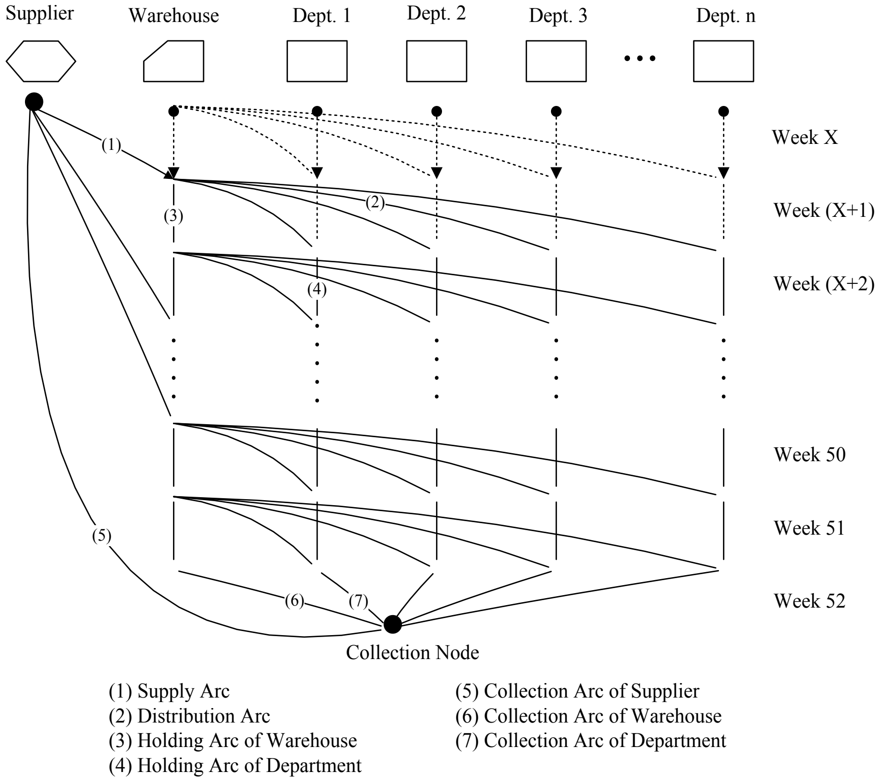

Fig. 12.14 Time-space network for medical resources ordering and distribution

warehouse and departments. The vertical axis stands for the duration of scheduling. The time interval is one week. The time-space network contains two basic elements: node and arc.

1. Node

A node represents the supplier, the hospital warehouse or a department at a specific time. There are 4 types of nodes in this network: (1) Supplier node: It supplies medical resources to the hospital. (2) Warehouse node: It delivers the resources to departments. (3) Department node: They receive the resources from the warehouse node. (4) Collection node: It maintains the flow conservation of the network. All unused medical resources would assemble at this node at the end of the scheduling cycle.

2. Arc

An arc denotes the activity of medical resources distribution in different time and space. The arc flows express the flow of medical resources in the network. There are 4 types of arcs: (1) Supply arc: It represents that the supplier delivers medical resources to the hospital. The arc cost is the unit purchase price of medical resources plus a fixed ordering cost. The arc flow's upper bound is the warehouse's stock capacity, and the lower bound is zero. (2) Distribution arc: It represents that the warehouse delivers medical resources to the departments. The arc cost is the unit distribution cost. The arc flow's upper bound is each department's stock capacity, and the lower bound is zero. (3) Holding arc: It represents the holding of medical resources in the warehouse or departments. The arc cost is the unit stock holding cost. The arc flow's upper bound is their stock capacity, and the lower bound is their safety stock. (4) Collection arc: It connects the supplier node, the warehouse node and department nodes to the collection node, and ensures the flow conservation of this network. The arc cost is zero. The supplier collection arc flow's upper bound is infinity, and the lower bound is zero. The warehouse and departments collection arc flow's upper bound is their stock capacity, and the lower bound is their safety stock.

(3) **Notations used in the model formulation**

Parameters:

$AM,\ NM$	The set of all arcs and nodes respectively;
SW	The set of all arcs between the supplier and hospital warehouses;
WD	The set of all arcs between the hospital warehouses and departments;
HA	The set of all holding arcs in the network;
RM	The set of all arcs except HA;
D	The set of all department nodes;
p	Unit purchase price;
d	Unit distribution cost from the warehouse to departments;
h	Unit stock holding cost in the warehouse and departments;
c	Fixed cost incurred by every ordering;
t	Unit shortage cost;
l_{ij}/u_{ij}	The lower/upper bound of the arc $(i,\ j)$'s flow;
a_{ij}	The demand quantity of the node i;
α, β, λ	The confidence levels of the corresponding chance constraints.

Decision variables:

x_{ij} The flow of arc $(i,\ j)$;

y_i The shortage quantity of node i, and $y_i = \max\left\{a_i - \sum_{j \in NM} x_{ji}, 0\right\}, i \in NM.$

δ_{ij} A binary variable that indicates whether the hospital places an order to the supplier. When $\delta_{ij} = 1, x_{ij} > 0$; when $\delta_{ij} = 0, x_{ij} = 0$.

(4) **The mathematic model**

Based on the notations, the scheduling model can be formulated as follows:

$$\text{Min } \overline{f} \tag{12.21}$$

$$\Pr\left\{\sum_{ij\in SW}(px_{ij}+c)\delta_{ij}+\sum_{ij\in WD}dx_{ij}+\sum_{ij\in HA}hx_{ij}+\sum_{i\in D}y_i t\le \overline{f}\right\}\ge\alpha \quad (12.22)$$

$$\Pr\left\{\sum_{j\in NM}x_{ij}\delta_{ij}-\sum_{k\in NM}x_{ki}\delta_{ki}=a_i\right\}\ge\beta,\quad \forall i\in NM \quad (12.23)$$

$$\Pr\left\{l_{ij}\le x_{ij}\right\}\ge\lambda,\quad \forall ij\in HA \quad (12.24)$$

$$x_{ij}\le u_{ij},\quad \forall ij\in HA \quad (12.25)$$

$$l_{ij}\le x_{ij}\le u_{ij},\quad \forall ij\in RM \quad (12.26)$$

$$x_{ij}\in I,\quad \forall ij\in AM \quad (12.27)$$

$$\delta_{ij}\in 0,1\quad \forall ij\in AM \quad (12.28)$$

The objective function (12.21) denotes the minimization of total costs of medical resources order and distribution. Constraint (12.22) means the model obtains the optimal solution under the confidence level α. Constraint (12.23) indicates the flow conservation in this network under the confidence level β. Constraint (12.24) ensures all holding arc flows exceed the corresponding safety stock under the confidence level λ. Constraints (12.25) and (12.26) set bounds for all arc flows. Constraints (12.27) and (12.28) guarantee all variables are binary numbers or integers.

12.3.3 The Solution Procedure

The model is formulated as a chance-constrained stochastic programming problem with NP-hard complexity. Considering the scale of the problem, it is almost impossible to solve it with general enumeration method. Practices have proven that genetic algorithm can solve NP-hard problems effectively by virtue of its superior global optimization search strategy, and is regarded as one of the best tools to find the satisfactory solution. Therefore, genetic algorithm is applied to solve the mathematic model.

12.3.4 Numerical Tests

To test how well the model may be applied in the real world, we performed numerical tests based on operating data of a certain kind of medical resources from a major hospital in Nanjing, China, with reasonable simplifications. We used MATLAB R2012a to build the model and to solve the problems. The tests were performed on a PC equipped with an Intel (R) Core (TM) 2.13 GHz CPU and 2.00 GB of RAM in the environment of Microsoft Windows 7.

(1) **Input data**

We consider 1 supplier, 1 hospital warehouse and 3 departments in the test case. The input data of the computer program conclude: demand of each department, unit purchase price, fixed ordering cost, unit distribution cost (in hospital), unit stock holding cost, unit shortage cost, safety stock and stock capacity of the warehouse and each departments, and the three confidence levels α, β, λ. As for genetic algorithm parameters, we set population size = 50, maximum evolutional generations = 200, crossover probability = 60%, and mutation probability = 30%.

(2) **Test results**

After running the program in the MATLAB environment, we get the scheduling results. As shown in Fig. 12.15, with genetic algorithm "selecting the superior and eliminating the inferior" generation by generation, the objective value decreases until it becomes a fixed value at about 120th generation, which is the model's optimal value.

Also, we get the order and distribution scheduling results of 52 weeks, including warehouse order quantity and distribution quantity of every department, as shown in Fig. 12.16. We can find that there are some weeks when the hospital doesn't order medical resources. Because of the fixed ordering cost for every purchase order, the hospital can neither place an order every week, nor order all the needed medical

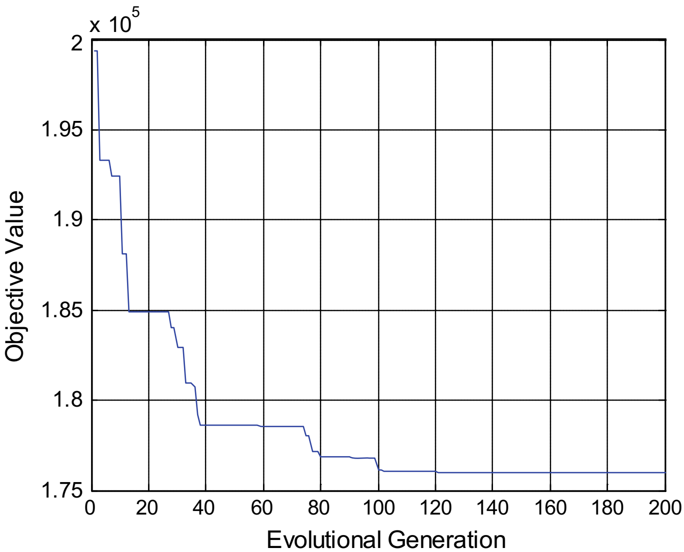

Fig. 12.15 The objective value for every evolutional generation

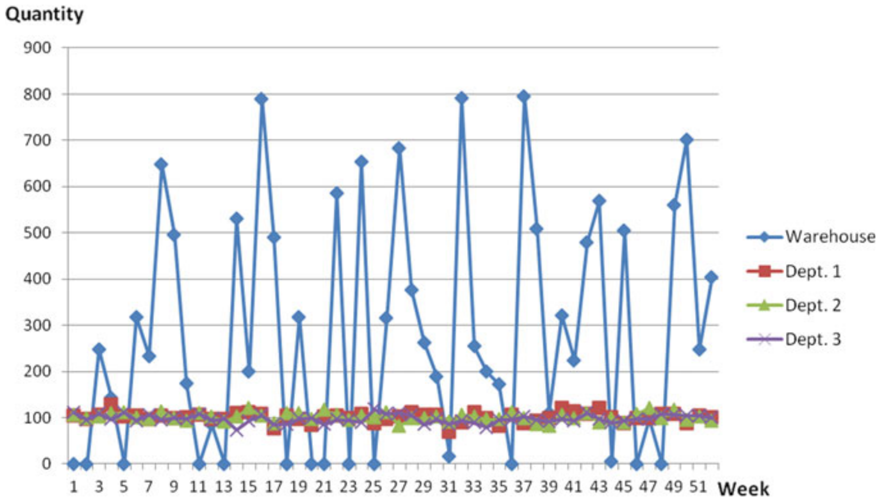

Fig. 12.16 Scheduling results of weekly order and distribution quantity

resources for the whole year at the first week, which could result in huge stock holding cost. The model keeps a good balance between fixed ordering cost and stock holding cost, and obtains the minimum total operating cost.

(3) **Sensitivity analyses**

With different parameter settings, the scheduling model may get different scheduling results and performance. In order to understand the parameters' influence on the proposed model, several sensitivity analyses are performed in this section. For each rate of change, we run the program 20 times, and take the mean of these 20 objective values as the observation value.

1. Sensitivity analysis on average demand

With other parameters being constant, we change the average of the demand from 80 to 120%. The planning results are shown in Fig. 12.17. As the rate increases, the mean objective value goes up. The reason could be that when the demand rises, the hospital must purchase more medicaL resources as inventory reserves in response to random disturbances in actual operations.

2. Sensitivity analysis on standard deviation

We change the standard deviation from 80 to 120%. As we can see in Fig. 12.18, the mean objective value grows up as the rate increases. That the RATE of change for standard deviation rises suggests the stochastic disturbances increase. So when the variation range of the demand for every week increases, it leads to the advance of the objective value. Therefore, the more the demand is disturbed in real operations, the more operating cost the hospital will pay.

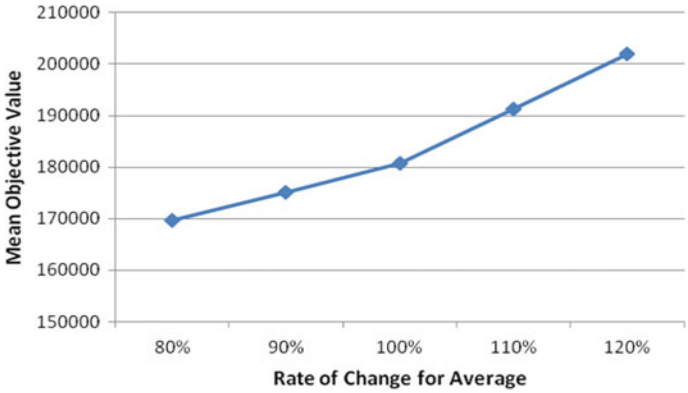

Fig. 12.17 Sensitivity analysis on average demand

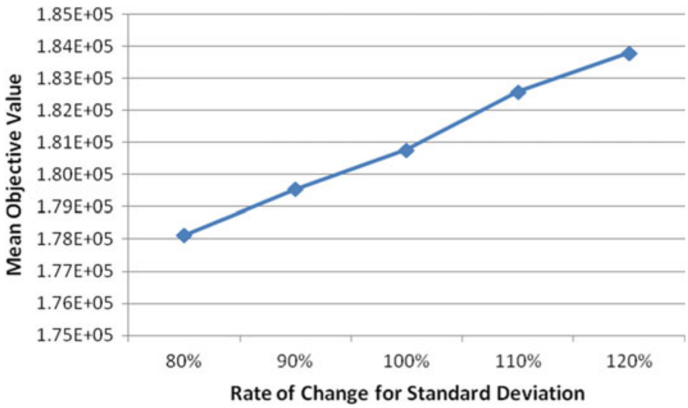

Fig. 12.18 Sensitivity analysis on standard deviation

3. Sensitivity analysis on fixed ordering cost

We change the fixed ordering cost from 50 to 150%. The test results are shown in Fig. 12.19. With the rate increasing, the mean objective value descends until 100% at first, and then goes up. So we can get the optimal objective value with the original fixed ordering cost, which demonstrates the importance of a proper fixed ordering cost.

12.3.5 Conclusions

In this work, we study the order and distribution of medical resources in an environment characterized by stochastic demand and limited supply. A chance-constrained

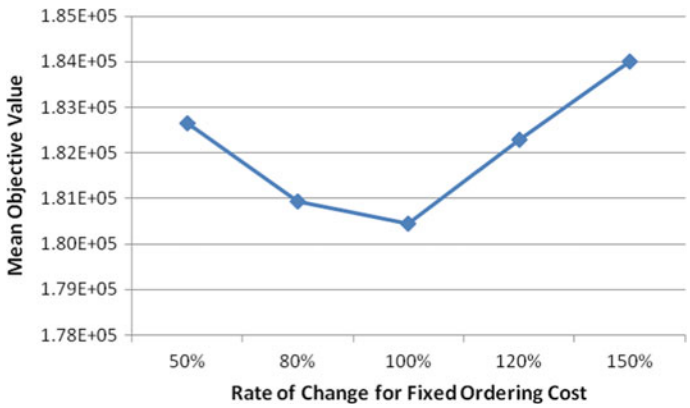

Fig. 12.19 Sensitivity analysis on fixed ordering cost

programming model is constructed based on time-space network. Generic algorithm is applied to solve the model. The test results show the good performance of the proposed model.

Future research would be useful in at least the following directions. First, since we discuss only one kind of medical resources, future work could study multiple kinds of medical resources. Second, the lead time in this model is certain, so it would be more practical and useful to consider an uncertain lead time.

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