

A Fuzzy Scheduling Approach for Medicine Supply in Hospital Management Information System with Uncertain Demand

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To cite this article:

Ping Hu, Yufang Li, Ximin Zhou, Zhengying Cai. A Fuzzy Scheduling Approach for Medicine Supply in Hospital Management Information System with Uncertain Demand. *International Journal of Intelligent Information Systems*. Vol. 5, No. 6, 2016, pp. 94-103.

doi: 10.11648/j.ijis.20160506.13

Received: October 23, 2016; **Accepted:** November 7, 2016; **Published:** December 29, 2016

Abstract: Generally, it is very difficult to determine the medicine supply in hospital under uncertain environment. Here, the medical supply decision problem in uncertain environment is modeled as a fuzzy multi-objective linear programming model. First, the medicine supply in hospital management system is analyzed and the uncertainties in medicine supply are modeled as fuzzy numbers. Second, a fuzzy medicine scheduling is built to fit the uncertain demand and the solving steps are illustrated too. Third, a numerical example is presented to demonstrate the proposed model, and the compared results verify its effectiveness. Last, some important conclusions and future work are sum up at the end of the paper.

Keywords: Fuzzy Scheduling, Medicine Supply, Hospital Decision, Uncertain Demand

1. Introduction

Today hospital management information system gained more and more popularity. Syrowatka (2016) introduced features of decision aids in features of computer-based decision aids from systematic review, thematic synthesis, and meta-analyses [1]. Hsiao (2014) introduced a new model in critical factors influencing physicians' intention to computerized clinical practice guidelines with an integrative model of activity theory and the technology acceptance model [2]. This kind of management information system can help us manage medicine supply and intensive care. Hung (2014) discussed an integrated intuitionistic fuzzy similarity measures for medical problems [3]. Ofstad (2014) made a research on temporal characteristics of decisions in hospital encounters and a threshold for shared decision making for a qualitative study [4]. Barasa (2015) extended English, mike, setting healthcare priorities in hospitals from a review of empirical studies [5]. Ahmadi (2015) considered organizational decision to adopt hospital information system

by an empirical investigation in the case of Malaysian public hospitals [6]. Joseph (2016) developed a rules based algorithm to generate problem lists using emergency department medication reconciliation [7]. Rosales (2015) offered the 2Bin system for controlling medical supplies at point-of-use [8]. Santucci (2016) presented evaluation of hospital-wide computerized decision support in an intensive care unit by an observational study [9]. Mijderwijk (2016) indicated clinical prediction model to identify vulnerable patients in ambulatory surgery towards optimal medical decision-making [10]. Gulbrandsen (2014) described confusion in and about shared decision making in hospital outpatient encounters [11]. Sheppard (2015) put forward the association between prehospital care and in-hospital treatment decisions in acute stroke by a cohort study [12].

However, the medicine supply involved a great number of uncertain factors, which made it very difficult to optimize the operational cost. Rachiotis (2014) modelled the medical supplies shortages and burnout among Greek health care workers during economic crisis in a pilot study [13]. Ruan

(2014) talked about a two-stage approach for medical supplies intermodal transportation in large-scale disaster responses [14]. Wang (2016) built an optimizing method for the intermodal transportation of emergency medical supplies using balanced fuzzy clustering [15]. Pishvae (2014) concerned an accelerated Benders decomposition algorithm for sustainable supply chain network design under uncertainty with a case study of medical needle and syringe supply chain [16]. Some researchers applied decision making technology into medicine supply. Cresswell (2014) proposed an evaluation of medium-term consequences of implementing commercial computerized physician order entry and clinical decision support prescribing systems in two 'early adopter' hospitals [17]. Huh (2016) made a model that impact of monitoring surgical prophylactic antibiotics and a computerized decision support system on antimicrobial use and antimicrobial resistance [18]. Baysari (2016) researched that the effectiveness of information technology to improve antimicrobial prescribing in hospitals from a systematic review and meta-analysis [19]. Arboe (2014) evaluated evaluation of the decision support system for antimicrobial treatment, TREAT, in an acute medical ward of a university hospital [20]. Chow (2016) modelled the implementation hurdles of an interactive, integrated, point-of-care computerised decision support system for hospital antibiotic prescription [21].

In this uncertain environment, fuzzy mathematics provides us a good tool to manage different uncertain variables. Barboni (2015) reviewed computer-aided diagnosis system based on fuzzy logic for breast cancer categorization [22]. Zaky (2015) studied multidisciplinary decision making in the management of hepatocellular carcinoma with a hospital-based study [23]. Germini (2015) illustrated Padua prediction score or clinical judgment for decision making on

antithrombotic prophylaxis in a quasi-randomized controlled trial [24]. Field (2014) gave use of an electronic decision support tool improves management of simulated in-hospital cardiac arrest [25]. Sorokin (2016) introduced a rationale and study protocol for the Nursing Home Compare Plus (NHCPlus) randomized controlled trial and provided a personalized decision aid for patients transitioning from the hospital to a skilled-nursing facility [26].

But the researches above didn't solve the uncertain demand problem in hospital medicine supply. Here, the medical supply decision problem in fuzzy environment is modeled as a fuzzy multi-objective linear programming model. First, the uncertainties in medicine supply are analyzed and are modeled as fuzzy numbers. Second, a fuzzy medicine scheduling is built to fit the uncertain demand and the solving steps are illustrated too. Third, a numerical example is presented to demonstrate the proposed model, and the compared results verify its effectiveness. Last, some important conclusions and future work are sum up at the end of the paper.

2. Medicine Supply in Hospital Management System

2.1. Objective Function of Medicine Supply

Medicine supply in hospital management system is multi-product and multi-period involving uncertain demand. Supposing a medicine supply planning is to meet the hospital demand with multi product types, and the problem involves meeting forecast demand, determining inventory levels, adjusting the output rate, subcontracting, etc. A medicine supply in hospital management information system with uncertain demand is shown in figure 1.

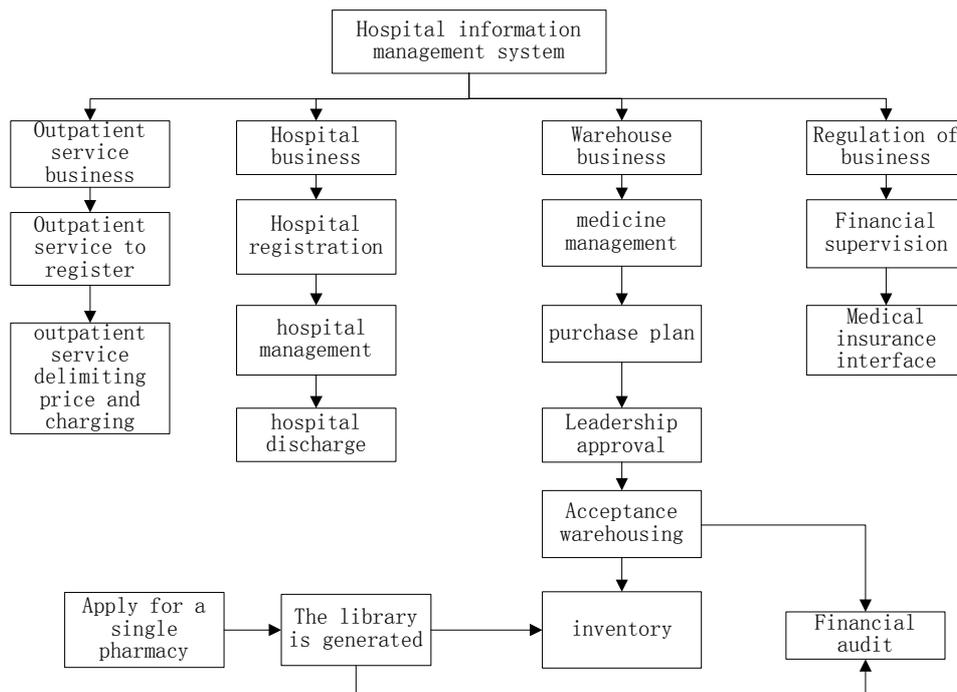


Fig. 1. Medicine supply in hospital management information system.

Fig. 1 gives the specific hospital information management system, including Outpatient service business, Hospital business, Warehouse business and Regulation of business. Outpatient service including the outpatient registration and outpatient fees, hospital business need for hospital registration and management in hospital, and recovered after discharge formalities. Warehouse business is mainly for drugs, the first is the daily management of drugs, and then develop a drug procurement plan, after the approval of the leadership, the drug procurement and acceptance. As for the day-to-day supervision of the business, it is mainly financial supervision and medical insurance interface business. It can be found that the medical supplies play an important role in the hospital information management system from the Fig.1. In order to meet patients' need for medicine and avoid hospital purchasing medicine blindly, the FMOLP model is proposed here.

The objective function of the uncertain variables make it difficult for the application of the decision problem to optimize the supply cost, inventory cost, and shortage cost, as well as demand portability, the changes in reference inventory level, labor rate, logistics capacity, warehouse space, management cost, capital flow.

Based on the characteristics of the application of the above considerations, the following assumptions of the mathematical model developed in this paper are given.

- (1) All relevant fuzzy sets of piecewise linear membership functions are specific.
- (2) Minimal operator is for aggregating fuzzy set.
- (3) The values of all parameters are determined on the next planning horizon T.
- (4) The factors that are constantly upgrading for each cost category in the next T planning horizon are certain
- (5) Each period of the actual level of labor, machine capacity and warehouse space can not exceed the maximum level.
- (6) The predicted demand can be met or out of stock at a given time, but the shortage must be filled in the next period.

Assumptions (1) and (2) are transforming the original fuzzy multi-objective linear programming problem into an equivalent linear programming problem, which can be effectively solved by the standard simplex method.

$$\text{Min } Y_1 \cong \sum_{n=1}^N \sum_{t=1}^T \left[b_n R_{nt} (1+i_b)^t + c_n S_{nt} (1+i_c)^t + d_n T_{nt} (1+i_d)^t + e_n L_{nt} (1+i_e)^t + f_n N_{nt} (1+i_f)^t \right] + \sum_{t=1}^T (u_t P_t + v_t Q_t) (1+i_g)^t$$

where the terms of

$$\sum_{n=1}^N \sum_{t=1}^T \left[b_n R_{nt} (1+i_b)^t + c_n S_{nt} (1+i_c)^t + d_n T_{nt} (1+i_d)^t + e_n L_{nt} (1+i_e)^t + f_n N_{nt} (1+i_f)^t \right]$$

are used to figure up the cost of production. Production costs consist of five parts in time production, overtime,

Assumption (1) according to data mining can specify the fact that the membership degree of each objective function is different, so the piecewise linear function can be used to clarify the fuzzy set. Assumption (2) implies that the minimum operator is able to aggregate fuzzy sets. Assumption (3) and (4) mean that the deterministic attributes must be technically satisfied on behalf of an optimization problem as a linear programming problem. Assumption (5) represents the maximum available labor, machine, and warehouse capacity constraints in normal business operations. Assumption (6) concerns in any period it is important to meet the needs of the market, while the rest of the market demand can be postponed delivery. However, out of stock in the actual situation should not be more than a period of time.

In the following formulas:

b_n is the regular time production cost per unit for n th product in period t , c_n is the overtime production cost per unit for n th product in period t , d_n is the subcontracting cost per unit of n th product in period t , e_n is the inventory carrying cost per unit of n th product in period t , f_n is the backorder cost per unit of n th product in period t .

R_{nt} represents the regular time production for n th product in period t (units), S_{nt} represents the overtime production for n th product in period t (units), T_{nt} represents subcontracting volume for n th product in period t (units), L_{nt} represents inventory level in period t for n th product (units), N_{nt} represents backorder level for n th product in period t (unit).

i_b is an escalating factor for regular time production cost (%), i_c is an escalating factor for overtime production cost (%), i_d is escalating factor for subcontract cost (%), i_e is an escalating factor for inventory carrying cost (%), i_f is an escalating factor for backorder cost (%). i_g is an escalating factor for hire and layoff cost (%).

u_t is the cost to hire one worker in period t (/man-hour), P_t is the worker hired in period t (man-hour), v_t is the cost to layoff one worker in period t (/man-hour), Q_t is the workers laid off in period t (man-hour).

- Minimize total production costs

subcontracting, inventory and shortage;

$\sum_{t=1}^T (u_t P_t + v_t Q_t) (1+i_g)^t$ illustrates the cost of changing the level of labor, including the cost of hiring and firing workers. Factors that are constantly upgrading are included in each cost category.

- Minimize the cost of transportation and shortage

$$\text{Min } Y_2 \cong \sum_{n=1}^N \sum_{t=1}^T \left[e_{nt} L_{nt} (1+i_e)^t + f_{nt} N_{nt} (1+i_f)^t \right]$$

- Minimize the rate of change in the level of labor

$$\text{Min } Y_3 \cong \sum_{t=1}^T (P_t - Q_t)$$

In real-world applications of decision making problems, environmental parameters and operating parameters are usually uncertain, and some information on the time range of the medium is incomplete or unavailable.

2.2. Uncertain Demand and Uncertain Factors

As a result, the medical supply problem is fuzzy with imprecise desire levels, and the solution of the fuzzy multi-objective optimization problem is incorporated into decision makers(DM)'s judgment.

However, for each objective function of the proposed multi-objective linear programming model, they may be different. For simplifying analysis, this paper assumes that DM has such an imprecise goal, that is, the objective function is essentially equal to a certain value. The goal of these conflicts is to optimize the total object in the framework of the fuzzy expectation level.

- Inventory constraints

$$\begin{aligned} L_{nt} - N_{nt} &= L_{nt-1} - N_{nt-1} + R_{nt} + S_{nt} + T_{nt} - F_{nt} \quad \forall n, \forall t \\ L_{nt} &\geq L_{nt\min} \quad \forall n, \forall t \\ N_{nt} &\leq L_{nt\max} \quad \forall n, \forall t \end{aligned}$$

- Restricting the level of labor force

$$\begin{aligned} \sum_{n=1}^N n_{nt-1} (R_{nt-1} + S_{nt-1}) + P_t - Q_t &= \sum_{n=1}^N n_n (R_{nt} + S_{nt}) \quad \forall t \\ \sum_{n=1}^N n_{nt} (R_{nt} + S_{nt}) &\leq W_{t\max} \quad \forall t \end{aligned}$$

- Constraint machine capacity and storage space

$$\begin{aligned} T_{nt} &\leq T_{nt\max} \quad \forall n, \forall t \\ \sum_{n=1}^N r_{nt} (R_{nt} + S_{nt}) &\leq M_{t\max} \quad \forall t \\ \sum_{n=1}^N v_{nt} L_{nt} &\leq V_{t\max} \quad \forall t \end{aligned}$$

- Non negative constraints of decision variables

$$R_{nt}, S_{nt}, T_{nt}, L_{nt}, N_{nt}, P_t, Q_t \geq 0 \quad \forall n, \forall t$$

In order to solve the problem of multi objective application with fuzzy coefficients, a dynamic market demand forecasting should be accurately obtained from the hospital operation. In addition, the maximum available labor level in the formula is not accurate, due to the uncertainty of the labor market supply and demand as well as the capacity of the machine. Thus, constraints (5) are fuzzy in nature. On the other hand, constraints (6), which represent the minimum inventory level constraints, the maximum inventory and sub package level, and the actual warehouse space are usually certain. A fuzzy goal programming model is introduced to solve the decision problem of multi product application. Thus, the constraints (1) - (6) of the proposed multi model are considered to be brittle.

3. Fuzzy Medicine Supply with Uncertain Demand

3.1. Fuzzy Algorithm for Medicine Scheduling

In general, linear membership functions and fuzzy decision making (1970) of Zadeh can be employed by solving the problem into an ordinary linear programming problem.

First this paper has to establish the MOLP model, and to determine the degree of membership, and then give the model matching appropriate to linear equations, to solve the problem by solving the maximum L , solve the multi-objective linear programming model and algorithm to get the answer. If the answer can be accepted, then the test is over, otherwise it will alter the model.

Minimum Selecting Items could be denoted as {NB, NM, NS, Z, PS, PM, PB}, where 7 fuzzy linguistics valuables are involved, and the fuzzy language membership functions are shown in Fig 2 and 3.

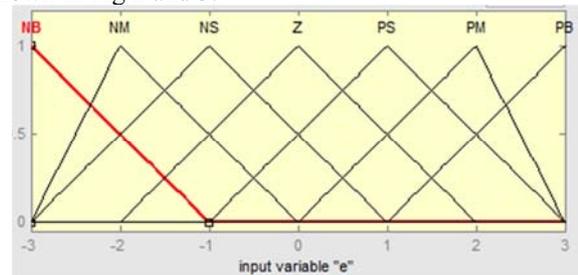


Fig. 2. Fuzzy languages of input.

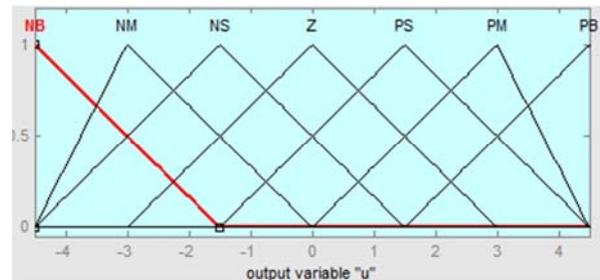


Fig. 3. Fuzzy languages of output.

These fuzzy membership functions are all triangle shape, the fuzzy system can calculate the output by fuzzy reasoning

rule.

According to the medical supply problem, the following is

$$\text{Max } L = \sum_{n=1}^N \sum_{t=1}^T \left[b_{nt} R_{nt} (1+i_b)^t + c_{nt} S_{nt} (1+i_c)^t + d_{nt} T_{nt} (1+i_d)^t + e_{nt} L_{nt} (1+i_e)^t + f_{nt} N_{nt} (1+i_f)^t \right] + \sum_{t=1}^T (u_t P_t + v_t Q_t) (1+i_g)^t + d_{1j}^- - d_{1j}^+ = X_{1j} \quad j=1,2,\dots,P$$

s.t.

$$L \leq \left(\frac{t_{1,P+1} + t_{11}}{2} \right) \left\{ \sum_{n=1}^N \sum_{t=1}^T \left[b_{nt} R_{nt} (1+i_b)^t + c_{nt} S_{nt} (1+i_c)^t + d_{nt} T_{nt} (1+i_d)^t + e_{nt} L_{nt} (1+i_e)^t + f_{nt} N_{nt} (1+i_f)^t \right] + \sum_{t=1}^T (u_t P_t + v_t Q_t) (1+i_g)^t \right\} + \frac{T_{1,P+1} + T_{11}}{2} + \left(\frac{t_{12} - t_{11}}{2} \right) (d_{11}^- - d_{11}^+) + \left(\frac{t_{13} - t_{12}}{2} \right) (d_{12}^- - d_{12}^+) + \dots + \left(\frac{t_{1,P+1} - t_{1P}}{2} \right) (d_{1P}^- - d_{1P}^+)$$

$$L \leq \left(\frac{t_{2,P+1} - t_{21}}{2} \right) \left\{ \sum_{n=1}^N \sum_{t=1}^T \left[e_{nt} L_{nt} (1+i_e)^t + f_{nt} N_{nt} (1+i_f)^t \right] + \frac{T_{2,P+1} - T_{21}}{2} \right\} + \left(\frac{t_{22} - t_{21}}{2} \right) (d_{21}^- - d_{21}^+) + \left(\frac{t_{23} - t_{22}}{2} \right) (d_{22}^- - d_{22}^+) + \dots + \left(\frac{t_{2,P+1} - t_{2P}}{2} \right) (d_{2P}^- - d_{2P}^+)$$

$$L \leq \left(\frac{t_{3,P+1} - t_{31}}{2} \right) \left\{ \sum_{t=1}^T (P_t - Q_t) \right\} + \frac{T_{3,P+1} - T_{31}}{2} + \left(\frac{t_{32} - t_{31}}{2} \right) (d_{31}^- - d_{31}^+) + \left(\frac{t_{33} - t_{32}}{2} \right) (d_{32}^- - d_{32}^+) + \dots + \left(\frac{t_{3,P+1} - t_{3P}}{2} \right) (d_{3P}^- - d_{3P}^+)$$

$$\sum_{n=1}^N \sum_{t=1}^T \left[e_{nt} L_{nt} (1+i_e)^t + f_{nt} N_{nt} (1+i_f)^t \right] + d_{2j}^- - d_{2j}^+ = X_{2j} \quad j=1,2,\dots,P$$

$$\sum_{t=1}^T (P_t - Q_t) + d_{3j}^- - d_{3j}^+ = X_{3j} \quad j=1,2,\dots,P$$

$$L_{nt} - N_{nt} = L_{n,t-1} - N_{n,t-1} + R_{nt} + S_{nt} + T_{nt} - F_{nt} \quad \forall n, \forall t$$

$$L_{nt} \geq L_{nt \min} \quad \forall n, \forall t$$

$$N_{nt} \leq N_{nt \max} \quad \forall n, \forall t$$

$$\sum_{n=1}^N n_{nt-1} (R_{nt-1} + S_{nt-1}) + P_t - Q_t = \sum_{n=1}^N n_{nt} (R_{nt} + S_{nt}) \quad \forall t$$

$$\sum_{n=1}^N n_{nt} (R_{nt} + S_{nt}) \leq W_{t \max} \quad \forall t$$

$$T_{nt} \leq T_{nt \max} \quad \forall n, \forall t$$

$$\sum_{n=1}^N r_{nt} (R_{nt} S_{nt}) \leq M_{t \max} \quad \forall t$$

$$\sum_{n=1}^N v_{nt} L_{nt} \leq V_{t \max} \quad \forall t$$

$$L, d_{1j}^-, d_{1j}^+, d_{2j}^-, d_{2j}^+, d_{3j}^-, d_{3j}^+, R_{nt}, S_{nt}, T_{nt}, L_{nt}, N_{nt}, P_t, Q_t \geq 0 \quad \forall j, \forall n, \forall t$$

the complete FMOLP model:

In the above formulas: $W_{t \max}$ is maximum machine capacity available in period t (machine-hour),

$M_{t \max}$ is the maximum labor level available in period t (man-hour), $V_{t \max}$ is the maximum warehouse space available in period t , $T_{nt \max}$ is the maximum subcontracted volume available for n th product in period t (units), $L_{nt \min}$ is the minimum inventory level available of n th product in period t (units), $N_{nt \max}$ is the maximum backorder level available of n th product in period t (units), r_{nt} is the hours of machine usage per unit of n th product in period t (machine-hour/unit), v_{nt} is the warehouse spaces per unit of n th product in period t (ft²/unit)

3.2. Solving Step

The derivation procedure of FMOLP model is as follows:

Step 1: Specifies the membership of several values for each objective function $Y_i (i=1,2,3,\dots,k)$

Step 2: Piecewise linear membership function.

Step 3: Formulation of linear equations for each piecewise linear membership function $f_i(Y_i) (i=1,2,3,\dots,k)$.

Step 4: The introduction of auxiliary variable L , the problem is transformed into an equivalent of the traditional linear programming problems. Variable L can be interpreted as representing an overall satisfaction with multiple fuzzy goals of data mining.

Step 5: If the data mining is not satisfied with the initial, implementation and modification of the interactive decision-making process.

The whole solving steps is shown in Fig. 4.

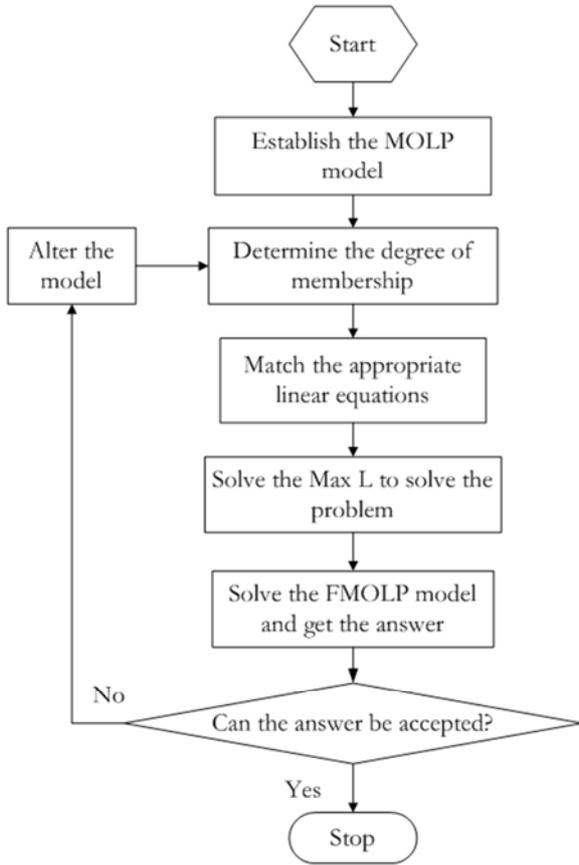


Fig. 4. The block diagram of the interactive FMOLP model development.

Details of the derivation of Fig. 4 give the interactive FMOLP model development block diagram, as follows.

In Step 1, specified membership degree $f_i(Y_i)(i=1,2,3)$ for several values for each of the objective function $Y_i(i=1,2,3)$. Table 1 presents the piecewise linear membership functions, $f_1(Y_1), f_2(Y_2)$ and $f_3(Y_3)$. The specified degree of membership $f_i(Y_i)(i=1,2,3)$ provides several values for each objective function $Y_i(i=1,2,3)$, and piecewise linear membership functions, $f_1(Y_1), f_2(Y_2)$, and

$f_3(Y_3)$, as shown in table 1.

Table 1. Membership function $f_i(z_i)$ is as follows.

Y_k	$> X_{k0}$	X_{k0}	X_{k1}	X_{k2}	...	X_{kP}	$X_{k,P+1}$
$f_k(Y_k)$	0	0	q_{k1}	q_{k2}	...	q_{kP}	1.0

In Step 2, protract the graph of piecewise linear membership function.

The membership function $f_i(Y_i)(i=1,2,3)$ is converted to a form

$$f_i(Y_i) = \sum_{j=1}^P \alpha_{ij} |Y_i - X_{ij}| + \beta_{ij} z_i + \gamma_{ij} \quad \forall i$$

where

$$\alpha_{ij} = \frac{t_{i,j+1} - t_{ij}}{2}, \quad \beta_{ij} = \frac{t_{i,P+1} - t_{i1}}{2}, \quad \gamma_{ij} = \frac{T_{i,P+1} - T_{i1}}{2}$$

Assuming that $f_i(Y_i) = t_{ir}Y_i + T_{ir}$ is always right for every $X_{i,r-1} \leq Y_i \leq X_{ir}$. For anywhere on the line, t_{ir} is the slope and S_{ir} is the intercept on the Y axis, starting from the $X_{i,r-1}$ point and terminating at X_{ir} point.

Thus,

$$f_i(Y_i) = \left(\frac{t_{i2} - t_{i1}}{2}\right) |Y_i - X_{i1}| + \left(\frac{t_{i3} - t_{i2}}{2}\right) |Y_i - X_{i2}| + \dots + \left(\frac{t_{i,P+1} - t_{iP}}{2}\right) |Y_i - X_{iP}| + \left(\frac{t_{i,P+1} + t_{i1}}{2}\right) Y_i + \frac{T_{i,P+1} + T_{i1}}{2} \quad \left(\frac{t_{i,j+1} + t_{ij}}{2}\right) \neq 0 \quad j=1,2,\dots,P$$

There are

$$0 \leq q_{ij} \leq 1.0, q_{ij} \leq q_{i,j+1} \quad i=1,2,3 \quad j=1,2,\dots,P \quad k=1,2,3.$$

The part of the line from X_{1P} point to $X_{1,P+1}$ point,

$$t_{i1} = \left(\frac{q_{i1} - 0}{X_{i1} - X_{i0}}\right), t_{i2} = \left(\frac{q_{i2} - q_{i1}}{X_{i2} - X_{i1}}\right), \dots, t_{i,P+1} = \left(\frac{1.0 - q_{iP}}{X_{i,P+1} - X_{iP}}\right),$$

and $S_{1,P+1}$ is the y-intercept and this can be derived from $f_1(Y_1) = t_{1r}Y_1 + T_{1r}$

$$f_2(Y_2) = \left(\frac{t_{22} - t_{21}}{2}\right) |Y_2 - X_{21}| + \left(\frac{t_{23} - t_{22}}{2}\right) |Y_2 - X_{22}| + \dots + \left(\frac{t_{2,P+1} - t_{2P}}{2}\right) |Y_2 - X_{2P}| + \left(\frac{t_{2,P+1} + t_{21}}{2}\right) Y_2 + \frac{T_{2,P+1} + T_{21}}{2} \quad \left(\frac{t_{2,j+1} + t_{2j}}{2}\right) \neq 0 \quad j=1,2,\dots,P$$

The part of the line from X_{2P} to $X_{2,P+1}$,

$$t_{21} = \left(\frac{q_{21} - 0}{X_{21} - X_{20}}\right), t_{22} = \left(\frac{q_{22} - q_{21}}{X_{22} - X_{21}}\right), \dots, t_{2,P+1} = \left(\frac{1.0 - q_{2P}}{X_{2,P+1} - X_{2P}}\right)$$

And $S_{2,p+1}$ is the y-intercept and this can be derived from

$$f_2(Y_2) = t_{2r} Y_2 + T_{2r}$$

$$f_3(Y_3) = \left(\frac{t_{32} - t_{31}}{2}\right) |Y_3 - X_{31}| + \left(\frac{t_{33} - t_{32}}{2}\right) |Y_3 - X_{33}| + \dots + \left(\frac{t_{3,p+1} - t_{3p}}{2}\right) |Y_3 - X_{3p}| + \left(\frac{t_{3,p+1} + t_{31}}{2}\right) Y_2 + \frac{T_{3,p+1} + T_{31}}{2} \left(\frac{t_{3,j+1} + t_{3j}}{2}\right) \neq 0 \quad j=1,2,\dots,P$$

The part of the line from X_{3p} to $X_{3,p+1}$ is

$$t_{31} = \left(\frac{q_{31} - 0}{X_{31} - X_{30}}\right), t_{32} = \left(\frac{q_{32} - q_{31}}{X_{32} - X_{31}}\right), \dots, t_{3,p+1} = \left(\frac{1.0 - q_{3p}}{X_{3,p+1} - X_{3p}}\right)$$

and $S_{3,p+1}$ is the y-intercept and this can be derived from

$$f_3(Y_3) = t_{3r} Y_3 + T_{3r}$$

s.t.

$$L_{nt} - N_{nt} = L_{nt-1} - N_{nt-1} + R_{nt} + S_{nt} + T_{nt} - F_{nt} \quad \forall n, \forall t$$

$$L_{nt} \geq L_{nt \min} \quad \forall n, \forall t$$

$$N_{nt} \leq N_{nt \max} \quad \forall n, \forall t$$

$$\sum_{n=1}^N n_{nt-1} (R_{nt-1} + S_{nt-1}) + P_t - Q_t = \sum_{n=1}^N n_{nt} (R_{nt} + S_{nt}) \quad \forall t$$

$$\sum_{n=1}^N n_{nt} (R_{nt} + S_{nt}) \leq W_{t \max} \quad \forall t$$

$$T_{nt} \leq T_{nt \max} \quad \forall n, \forall t$$

$$\sum_{n=1}^N r_{nt} (R_{nt} S_{nt}) \leq M_{t \max} \quad \forall t$$

$$\sum_{n=1}^N v_{nt} L_{nt} \leq V_{t \max} \quad \forall t$$

$$L, d_{1j}^-, d_{1j}^+, d_{2j}^-, d_{2j}^+, d_{3j}^-, d_{3j}^+, R_{nt}, S_{nt}, T_{nt}, L_{nt}, N_{nt}, P_t, Q_t \geq 0 \quad \forall j, \forall n, \forall t$$

4. Numerical Example

4.1. Problem Description

To facilitate the analysis, a Chinese hospital was simplified as a numerical example to illustrate the proposed model. Table 2 gives the initial data of the numerical example and the description of other relevant data, as follows (in units of RMB yuan).

- (1) 1500 units of medicine 1 and medicine 2 are the initial inventory in period 1.
- (2) 500 units of medicine 1 and 300 units of medicine 2 are the end inventory in period 3.
- (3) The expected upgrade factor for each cost category is 2%.
- (4) 15 per worker per hour is the hiring costs, 3 per worker per hour is the costs associated with layoff.
- (5) 300 man-hours is the initial labor level.

The problem model of numerical example is as follows.

Table 2. Summarized data in the numerical example (in units of yuan RMB).

Period: 1										
Product	F_{nt} (units)	b_{nt} (/unit)	c_{nt} (/unit)	d_{nt} (/unit)	e_{nt} (/unit)	f_{nt} (/unit)	n_{nt} (h/unit)	r_{nt} (h/unit)	v_{nt} (ft/unit)	$M_{t \max}$ (machine-hours)
1	1500									500
2	3000	30	40	32	0.4	50	0.06	0.12	3	600
3	4000									700
Period: 2										
Product	F_{nt} (units)	b_{nt} (/unit)	c_{nt} (/unit)	d_{nt} (/unit)	e_{nt} (/unit)	f_{nt} (/unit)	n_{nt} (h/unit)	r_{nt} (h/unit)	v_{nt} (ft/unit)	$M_{t \max}$ (machine-hours)
1	1500									500
2	2000	15	20	16	0.2	25	0.09	0.06	4	600
3	4000									700

4.2. Experimental Results

First of all, using the conventional LP model there are $Y_1 = 12374$, $Y_2 = 466$ and $Y_3 = 37.3$ man-hours. Then, using the initial solutions and the MOLP model presented in Section 2 formulate the FMOLP model.

Through reviewing the literature and taking into account the actual situation, this paper chooses the multiple objective function to solve the problem of the application. Figs.5–7 describe the shapes of the corresponding piecewise linear membership functions.

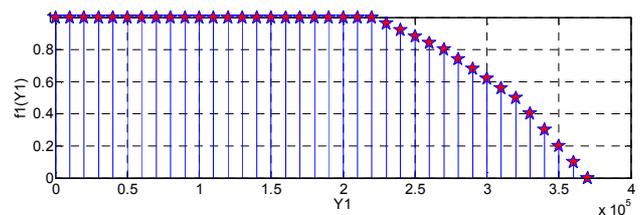


Fig. 5. Shape of membership function $(Y_1, f_1(Y_1))$.

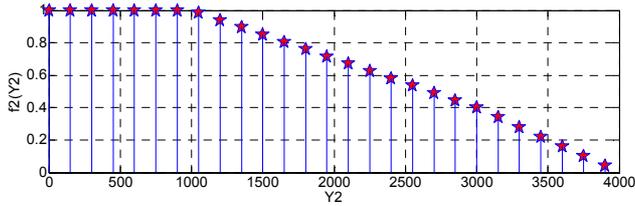


Fig. 6. Shape of membership function $(Y_2, f_2(Y_2))$.

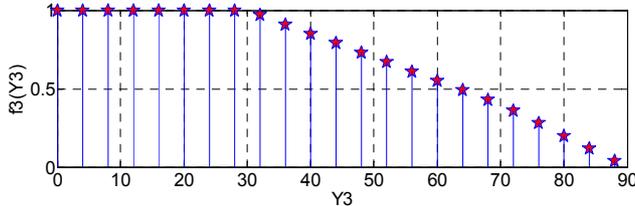


Fig. 7. Shape of membership function $(Y_3, f_3(Y_3))$.

Therefore, the following results are obtained. $Y_1 = 10167$, $Y_2 = 597$, $Y_3 = 42$ man-hours, the overall satisfaction of the DM's multiple fuzzy goals was 0.973. However, the actual problem involves making business applications must consider the cost of production, the skills of workers, the product life cycle, employment law and other factors, in order to minimize the change of total production cost and labor rate. Therefore, three objective functions are considered in the following analysis and discussion.

4.3. Further Discussion

The implementation is suitable for the following seven kinds of cases.

- Case 1: Considering only Y_1 (total production costs) and Y_2 (carrying and backordering costs) in reference [16] at the same time, removing Y_3 (rate of change in labor levels) in reference [22]. The membership function of Case 1 is presented in Fig.8-9.

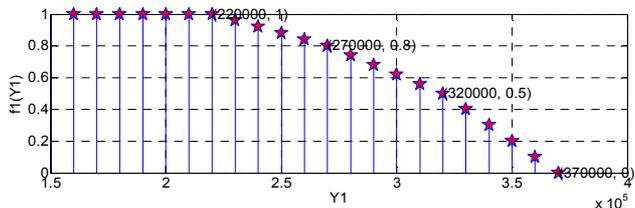


Fig. 8. Membership function of Case 1 $(Y_1, f_1(Y_1))$.

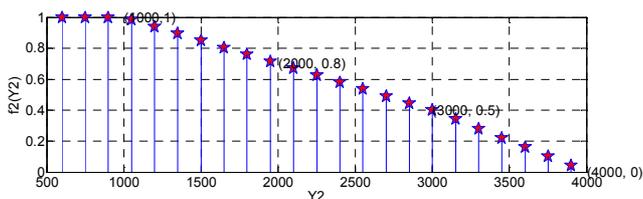


Fig. 9. Membership function of Case 1 $(Y_2, f_2(Y_2))$.

- Case 2: Considering only Y_1 (total production costs) and Y_3 (rate of change in labor levels) at the same time, removing Y_2 (carrying and backordering costs). The membership function of Case 2 is presented in Fig. 10-11.

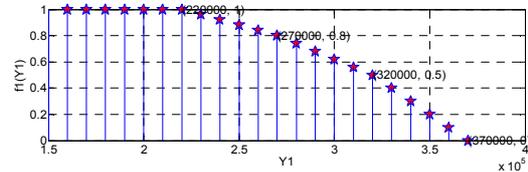


Fig. 10. Membership function of Case 2 $(Y_1, f_1(Y_1))$.

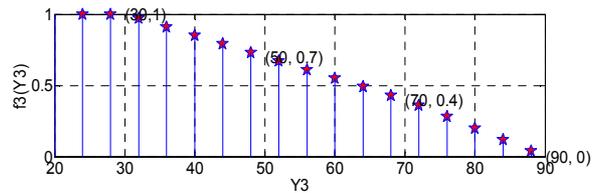


Fig. 11. Membership function of Case 2 $(Y_3, f_3(Y_3))$.

- Case 3: Varying only $(Y_1, f_1(Y_1))$ and setting $(Y_2, f_2(Y_2))$ and $(Y_3, f_3(Y_3))$ to their original values in the numerical example.

Through these solved fuzzy multi-objective values, the proposed model takes advantage over the model in reference [16] and [22], and gets a compromise solution and the DM's overall levels of satisfaction. Furthermore, the proposed model provides a systematic framework that promotes the decision-making process, continuously making a DM interactively to modify the membership functions of the targets until a satisfactory solution is obtained. As a result, the proposed model is actually the most suitable applicable to make APP decisions.

In practical application, several significant instructions are as follows.

- (1) Comparing Case 1 and Case 2 with the numerical example, the trade-offs and conflicts among dependent objective functions are revealed. Therefore, the model can meet the needs of practical applications, as its goal is to minimize total costs.
- (2) The results of Case 3 show that the degree of membership for each objective function strongly affects the output solution for each decision variable. This fact has two important effects. Firstly, the DM's most important task is to specify the rational membership for each objective function; secondly, the DM may flexibly revise the extent of the membership of the degree of membership to yield a satisfactory solution. The changes in the target and the L value of the Case 3 are described in Fig. 8.
- (3) The data of Case 4 shows that the objective and L values are influenced by the uncertain factors. And the backordering costs L sharply decreases. This finding means that the DM must account the time value of

money in a practical application problem. In addition, the DM must also improve the efficiency to reduce the escalating factor. The changes for the objective and L values of Case 4 are described in Fig. 9.

- (4) The sensitivity analysis of unit production cost, carrying cost per unit and hiring and layoff costs of Case 5–7 reveals that the change in the objective functions, L and other output solutions, implying that the production, material, and human resources should be improved by DM to effectively reduce the costs. The changes of the objective and L values of Case 5–7 are described in Figs. 10–11, respectively.

5. Conclusions

By fuzzy numbers, the proposed model can handle uncertain supply and demand of medicine consumption. The goal of fuzzy medicine supply is to decide the medicine supply in hospital management information system with uncertain demand. In addition to this, the proposed model can also help hospital managers to decide the resources which are appropriate to be used. The proposed model aims to lower the total costs, and optimize the labor levels, capacity, warehouse space and the time value of money, the rates of changes in labor levels with reference to inventory level minimum.

Additionally, some assumptions are made to simplify the analysis, such as production capacity, logistics resources, warehouse space available which may be different in practical application. Therefore, in future work, it is important to make the proposed model better suited to the practical application, including the exploration of fuzzy properties of different decision parameters in medicine supply problems. And the averaging or other operators will be applied to solve medicine supply problems in a more complex environment.

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