

A robust approach to multi period covering location-allocation problem in pharmaceutical supply chain

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Abstract

This paper proposes a discrete capacitated covering location-allocation model for pharmaceutical centers. In the presented model, two objectives are considered; the first one is the minimization of costs and the second one tries to maximize customer satisfaction by definition of social justice. Social justice in the model means that we consider customers satisfaction by using distance. The introduced model is an extension of the maximum covering model by adding zone constraint. Actually, the distance between facility and customer zone is used to define the possible and not possible location. The model tries to locate facilities in a best and possible location. In addition, number of missed customers is important and the model considers this issue. Since the nature of the demand is uncertain, a robust approach is proposed. The proposed model is suitable for perishable products. A numerical example presents the performance of the proposed model. **Keywords:** Pharmaceutical centers, covering location-allocation problem, robust approach

1- Introduction

The main objective of a location-allocation (LA) problem is to locate a set of new facilities such that to minimize the transportation cost from these facilities to customers. An optimal number of facilities are placed in an area of interest in order to satisfy the customer demand. The covering problem locates a set of new facilities such that the customers can receive the suitable service from facilities that their distance to the customer is equal or less than a predefined number.

The global presence of the pharmaceutical industry is evident with the roll out of continent specific R&D programs and drugs, which help companies, maximize penetration of markets and garner increased revenues with intercontinental treatment demand of patients receiving services from often one or two mega research centers in the continent. Led by these markets, the total world consumption of pharmaceutical products has displayed strong growth and is expected to grow further with expanding populations in emerging markets. Aging populations, chronic/lifestyle diseases, emerging-market expansion, treatment and technology advances spur life sciences sector growth in 2015. However, efforts by governments, health care providers, and health plans to reduce costs, improve outcomes, and demonstrate value is dramatically altering the health care demand and delivery landscape. It is becoming increasingly evident that the global life sciences sector is operating in an era of significant transformation.

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A dynamically changing clinical, regulatory, and business landscape require that pharmaceutical, biotechnology, and medical technology companies adapt traditional research and development (R&D), pricing, supply chain, and commercial models to:

- Support value-based payments many countries public and private health care systems are moving from volume-based to value-based payment models.
- Contain costs Governments and other payers are instituting price controls and increasing their use of generics and bio-similar to contain drug and device costs.
- Maintain regulatory compliance a growing list of regulatory requirements and expectations are imposing new challenges on the sector.
- Focus on emerging markets slowing revenue growth in developed countries is prompting entry and expansion in new, up-and-coming markets.

Perishable products are another critical issue in pharmaceutical and drug supply chains. In 2003, the estimated in curried costs due to the expiration of branded products in supermarkets and drugstores was over 500 million dollar

The pharmaceutical industry is a complex of processes, operations and organizations involved in the research, development and manufacturing of drugs and medications. The World Health Organization (WHO) defines a drug or pharmaceutical preparation as:

"Any substance or mixture of substances manufactured, sold, offered for sale or represented for use in the diagnosis, Treatment, mitigation or prevention of disease, abnormal physical state or the symptoms thereof in man or animal; [and for use in] restoring, correcting or modifying organic functions in man or animal."

Many papers and researches aimed pharmaceutical industry and pharmaceutical supply chains. Most of the existing papers are on the subject of drug supply chain. Subjects like location of drugstores and allocation of customers to drugstores have not attracted high attentions, since subject of location and allocation of pharmaceutical centers have a high impact on quality of life, considering this issue can be very impressive.

Pitta and Laric (2004) presented a model of the health care value and supply chain. This supply chain is not linear or sequential in nature. It closely extends the follow of information through the system. Fleischhacker and zhao (2011) examined the optimal decision of production lot size for clinical trial supply chain. They generalized the Wagner-Witten model (W-W model) to incorporate the risk of failure. Jetly et al. (2012) developed a multi-agent simulation model for pharmaceutical supply chains. Masoumi et al.(2012) construct a generalized network oligopoly model with arc multipliers for supply chain of pharmaceutical products using inequality variation theory. The numerical examples demonstrate that a brand pharmaceutical product may lose its dominate market share as a consequence of patent rights expiration and because of generic competition. Chen et al. (2012) improved management of clinical supply chain. A simulation-optimization approach is presented including patient demand simulation and demand scenario forecast. Kelle et al. (2012) focused on pharmacy supply chain and current managerial practices in a case of hospital, examined the often-conflicting goals in decision making amongst the various stakeholders and explore the managerial tradeoffs presents at the operational, tactical and strategic level of decision-making. Costanio et al. (2013) addressed the optimal design of the last supply chain branch i.e. the distribution network, starting from manufactures to the retailers and to show the effectiveness of method, the optimization model is applied to a case study describing an Italian regional health care drug distribution network. Alnaji and Ridha (2013) focused on the performance of supply chain management in pharmaceutical industry. Ceselli et al.(2013) presented a model for optimization of logistics' operation in emergency health care systems. They focused on efficient distribution of vaccines or drugs through the simultaneous and coordinated use of distribution center and vehicles. Spiliotopoulou et al. (2013) studied the tradeoff between risk of drug resistance and operational costs when using multiple drugs for specifics diseases. Uthayakumar and Priyan (2013) studied on understanding the current operations of health care industries and in offering decision support tools that improve health

policy, public health, patient safety and strategic decision-making in pharmaceutical supply chain and inventory management. Reinholdt *et al.*(2014) developed a two stage stochastic model to support decision of market launch preparation. It trades off the costs of accepting these risks, for example the risk of packing before authorization, against the lost revenue caused by risk-averse operations. Mousazadeh *et al.*(2015) developed a bi-objective mixed integer linear programming for pharmaceutical network. The model helps to make several decisions about the strategic issues such as opening of pharmaceutical manufacturing centers and main/local distribution centers along with optimal material flows over a midterm planning horizon as the tactical decisions.

Table1. Comparison between other works and this research

author	App	oroach		Ol	ojective					
			Supply chain	cost	Satisfa	ction	profit	Missed customer	uncertain	certain
	covering	Location allocation	ply		demand	social justice	_			
Fleischhacker and Zhao(2011)			√	√					√	
Kelle(2012)			✓	✓					✓	
Masoumi(2012)			✓				✓			✓
Chen et al(2012)			✓	✓					✓	
Uthayakumar and Priyan(2013)			√	✓						√
Spiliotopoulou(201 3)			√						√	
Costantino et al(2013)			√	√						√
Ceselli et al(2014)		√			✓					✓
Hansen and Grunow(2014)			√	√					√	
Mousazadeh et al(2015)			√	✓	√				√	
This paper	√	√		✓		√		√	✓	

According to Table 1, the main differences between the present research compared with other works is using covering location model on pharmaceutical centers, considering missed customers and the new definition of social justice as the objective function. Social justice in the model means that we consider customers satisfaction by using distance. The less distance between facility and customer causes a high degree of customer's satisfaction. In addition, the model can be used in hospital drugstores and centers that present perishable goods with limited shelf life.

The reminder of the paper is organized as follows; problem definition and mathematical formulation followed by linearization of developed model and robust probabilistic approach are presented in section 2. In addition,, $\varepsilon - constraint$ method is utilized in section 2. Validation of the proposed model with a numerical example and sensitivity analysis are showed in section 3. Finally, Section 4draws the conclusions and future works.

2- Problem definition and Mathematical models

The concerned model is a multi-product, multi-period one and includes distribution centers and several facility center (pharmacies) and customer zone. Therefore, we have main DCs that are located in a fixed

location. For the location of the facility, many potential locations are available. The model must define the best location for each facility to ensure demands' satisfaction. The model has two main objective functions, first one try to minimize the costs. Costs consist of fixed cost, transportation cost, inventory-holding cost and cost of losing customers. Fixed costs include investments on facilities construction's and changing the place of facilities.

For second objective function, the model tries to maximize customer's satisfaction. The distance between facility and customer zone is categorized as best, possible and not possible location as shown in Figure 1. If the distance between customer and facility is smaller than r_{jk}^1 , relative distance is set to 1, if it is greater than r_{jk}^2 , relative distance is set to 0 and so if it is between r_{jk}^1 and r_{jk}^2 , relative distance is set between 0 and 1. Therefore, the model tries to locate facilities in the best and possible location to maximize customer's satisfaction. According to the definition of covering problem and according to our definition of two-critic numbers r_{jk}^1 and r_{jk}^2 , if the distance between facilities and customer zone is less than r_{ik}^2 , it is possible to locate the facility.

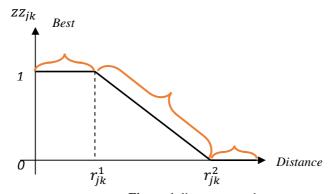


Figure 1.distance covering

One of the decision variables of the model is the amount of drugs transported from DCs to facilities and from facilities to customer zone. In addition, the location of facilities are another decision variable. The missed customers are the customers with unfulfilled demand. We consider a penalty cost for missed customer and try to minimize the number of missed customers.

Drugs have two types: specific type and common type. Specific drugs are drugs that their maintenance requirements' are different from common one and their round up cost is higher than common drugs.

2-1- Model formulation

Consider the following notations:

indices

i Index of distribution centers

j Index of candidatefacility location

k Index of customer zone

t Index of periods

c Index of drugs' type

parameters

 f_j Fixed costs of opening facility in candidate location j

 $co_{i,j,t}$ Unit transportation cost of drugs from DC i to facility j at period t

 $a_{j,k,t}$ Unit transportation cost of drugs from facility j to customer zone k at period t

 H_{iktc} Unit storage cost in facility j at period t for type c

 w_{jtc} Unit waste cost in facility j at period t for type c m_{jt} Percentage of drugs expired in facility j at period t e_{jc} Storage capacity of inventory at facility j for type c e_{ic} Storage capacity of inventory at DC ifor type c

 d_{jk} Distance between facility at location j and customer zone k

 dem_{kc} Demand of customer zone k for type c

 $pcost_{kc}$ Cost of losing customers for facility j and customer zone k

 r_{jk}^1 Best distance for facility j and customer zone k r_{jk}^2 Possible distance for facility j and customer zone k

P Number of facilities

variables

 x_{jktc} Quantity of drugs transferred from facility j to customer zone kat period t for type c

 x_{ijtc} Quantity of drugs transferred from DC i to facility j at period t for type c

 $missed_{kc}$ Number of missed customer at customer zone k for type c and by division of $risk_{kc}$ on dem_{kc}

 $risk_{kc}$ Number of unsatisfied demands for customer zone kand drug type c

 z_j 1 if facility at candidate location j is open and 0 other wise inv_{itc} Inventory level of drugs for facility j at period tfor type c

 zz_{jk} 1 if relative distance is best, between 0 and 1 if relative distance is possible and 0 otherwise.

 u_{ik} 1 if distance utility is best, between 0 and 1 if distance utility is possible and 0 otherwise.

 y_{jk}^1 1 If distance between facility j and customer k is less than $r1_{jk}$ and 0 otherwise.

 y_{jk}^2 1 If distance between facility j and customer k is between $r1_{jk}$ and $r2_{jk}$ and 0 otherwise.

 y_{jk}^3 1 If distance between facility j and customer k is greater than $r2_{jk}$ and 0 otherwise.

The proposed model is as follows:

$$\min z_1 = \sum_j f_j \times z_j + \sum_{i,j,t,c} x_{ijtc} \times co_{ijt} + \sum_{j,k,t,c} a_{jktc} \times d_{jk} \times x_{jktc} + \sum_{jt} w_j \times m_{jt}$$
 (1)

$$\times (\sum_{c=1} inv_{jtc}) + \sum_{jtc} h_{jtc} \times inv_{jtc} + \sum_{kc} (\frac{risk_{kc}}{dem_{kc}}) \times pcost_{kc}$$

$$\max \sum_{j,k,c} u_{jk} \times dem_{kc} \tag{2}$$

$$\sum_{j} Z_{j} = P \tag{3}$$

$$\sum_{k} x_{jktc} \le e_{jc} \times Z_j \quad \forall j, t, c \tag{4}$$

$$\sum_{j} x_{jktc} + risk_{kc} = dem_{kc} \quad \forall k, t, c$$
 (5)

$$\sum_{i} X_{ijtc} \le e_{ic} \quad \forall i, t, c \tag{6}$$

$$X_{ijtc} \le Z_j \times e_{ic} \quad \forall i, j, t, c$$
 (7)

$$inv_{j,t-1,c} + \sum_{i} X_{ijtc} \le Z_j \times e_{j,c} \quad \forall j,t,c$$
 (8)

$$inv_{jtc} = \left[\left(1 - m_{j,t-1} \right) \times inv_{j,t-1,c} + \sum_{i} X_{ijtc} - \sum_{k} X 1_{jktc} \right]$$

$$(9)$$

$$d_{jk} - r_{jk}^1 - M \times (1 - y_{jk}^1) \le 0 \tag{10}$$

$$d_{ik} - (r_{ik}^1 + 0.01) \times (1 - y_{ik}^1) \ge 0 \tag{11}$$

$$d_{ik} + (M - r_{ik}^2)(1 - y_{ik}^3) \le M \tag{12}$$

$$d_{ik} - (r_{ik}^2 + 0.01) \times (1 - y_{ik}^3) \ge r_{ik}^2 + 0.01 \tag{13}$$

$$y_{ik}^1 + y_{ik}^2 + y_{ik}^3 = 1 (14)$$

$$ZZ_{jk} \times (r_{jk}^2 - r_{jk}^1) = (r_{jk}^2 - d_{jk}) \times y_{jk}^2 + y_{jk}^1 \times (r_{jk}^2 - r_{jk}^1)$$
(15)

$$U_{ik} = ZZ_{ik} \times Z_i \tag{16}$$

$$y_{jk}^1, y_{jk}^2, y_{jk}^3, z_j \in \{0,1\}$$

$$\tag{17}$$

$$U_{jk}, ZZ_{jk} \in [0,1] \tag{18}$$

$$x_{iktc}, x_{ijtc}, missed_{kc}, risk_{kc}, moj_{itc} \ge 0$$
 (19)

Objective function (1) consists of fixed costs, transportation costs, inventory-holding costs and risk cost based on missed customer. The second objective function (2) tries to maximize customer's satisfaction by choosing the best facility for each customer zone, to spend less time and distance to receive services.

Constraint (3) guarantees that there are always *P* facilities at work. Constraint (4) ensures that quantity of drugs that customers can receive from every facility is less than the capacity of that facility if facility is open. Constraint (5) shows that the demand of customer zone must be satisfied. Constraints (6) and (7) ensure that the storage capacity in every distribution center must be satisfied. It means that the quantity of drugs transported from distribution center to facility is less than storage capacity of that distribution center. Constraint (8) guarantees that the total number of drugs transported to each facility is less than the capacity of the facility. Constraint (9) is the inventory balance equation for each type of drugs at each period.

Constraints (10) and (11) ensure that if the distance between facility and customer zone is less than r_{jk}^1 then y_{jk}^1 is equal to 1 and 0 otherwise. Constraints (12) and (13) ensure that if the distance between facility and customer zone is greater than r_{jk}^2 then y_{jk}^3 is equal to 1 and 0 otherwise. Constraint (14) guarantees that only one of y_{jk}^1 , y_{jk}^2 or y_{jk}^3 is equal to 1. Constraints (15), (16) show the definition of U_{jk} , ZZ_{jk} . Constraints (17),(18),(19) are about the decision variables.

2-2- Linearization of the proposed model

Since the constraint (16) is non-linear, the linear counterpart of the proposed model is as follows (H. Paul Williams, 2014).

$$U_{ik} \le M \times Z_i \tag{20}$$

$$U_{ik} \le ZZ_{ik} \tag{21}$$

$$ZZ_{ik} - U_{ik} \le M(1 - Z_i) \tag{22}$$

2-3- Robust approach

Mathematical programming models with noisy, erroneous or incomplete data are common in operation research applications. Difficulties with such type of data are typically dealt by sensitivity analysis through stochastic programming. Since finding real parameters in pharmaceuticals industry is very difficult, using stochastic programming is hard. Therefore, this paper uses robust optimization method.

Robust optimization, first introduced by Mulvey et al. (1995), is an effective tool for optimal design and management of supply chains in uncertain environments. Robust optimization tackles the preferred risk aversion or service-level function through expressing the values of critical input data in a set of scenarios. The approach would then result in a series of solutions that are progressively less sensitive to realizations of data from a scenario set.

According to nature of some critical parameters (demand), we formulate these parameters as probabilistic data in form of Mulvey approach as follows:

Parameters

Demand of customer zone (k) for drug type c by scenario (s) dem_{kcs} probability of scenario (s) Variability weight

Risk aversion weight (penalty weight)

Variables

Quantity of drug that facility j at period t for drug type c provide for scenario s x_{iktc} Control variable Error vector for the allowed infeasibility in the control constraints under scenario s Value of first objective under scenario s Number of unsatisfied demands for customer zone kand drug type c under scenario s Value of second objective under scenario s

Number of missed customers in customer zone k for type c under scenario s $missed_{ksc}$ By using notations, the robust model is as follows.

$$\min \sum_{s} p_s \times z_s^1 + \lambda \times \sum_{s} p_s \times \left[z_s^1 - \sum_{s} p_s \times z_s^1 + 2\theta_s \right] + \omega \times \sum_{s} p_s \times \delta_s$$
 (23)

$$\max \sum_{s} p_{s} \times z_{s}^{2} - \lambda \times \sum_{s} p_{s} \times \left[z_{s}^{2} - \sum_{s} p_{s} \times z_{s}^{2} + 2\theta_{s} \right] - \omega \times \sum_{s} p_{s} \times \delta_{s}$$
 (24)

$$\sum X_{jktcs} \le e_{jc} \times Z_j \quad \forall j, t, c$$
 (25)

$$\sum_{j} X_{jktcs} \le e_{jc} \times Z_{j} \quad \forall j, t, c$$

$$\sum_{j} X_{jktcs} + risk_{kcs} + \delta_{s} = dem_{kcs} \quad \forall k, t, c$$
(25)

$$z_{1s} = \sum_{i,j,t,c} x_{ijtc} \times co_{ijt} + \sum_{j,k,t,c} a_{jktc} \times d_{jk} \times x_{jktcs} + \sum_{jt} w_j \times m_{jt}$$

$$\times (\sum_{c=1} inv_{jtc}) + \sum_{jtc} h_{jtc} \times inv_{jtc} + \sum_{kc} risk_{kcs} \times pcost_{kc} \quad \forall s$$

$$(27)$$

$$z_{2s} = \sum_{i} u_{jk} \times dem_{kcS} \quad \forall s$$
 (28)

$$z_{1s} - \sum_{s}^{j,\kappa,c} p_s \times z_s^1 + \theta_s \ge 0 \qquad \forall s$$
 (29)

$$z_{2s} = \sum_{j,k,c} u_{jk} \times dem_{kcs} \quad \forall s$$

$$z_{1s} - \sum_{s} p_{s} \times z_{s}^{1} + \theta_{s} \ge 0 \quad \forall s$$

$$z_{2s} - \sum_{s} p_{s} \times z_{s}^{2} + \theta_{s} \ge 0 \quad \forall s$$

$$(29)$$

$$\theta_s, \delta_s, x_{iktcs}, risk_{kcs} \ge 0$$
 (31)

In the above-mentioned model, the first and second term of objective function (23) are mean value and variance of the total cost, respectively, and aim to measure solution robustness. The third term in (23) measures the model's robustness with respect to infeasibility of the control constraint. Second objective function (24) also changes to robust form and try to maximize customer satisfaction with scenario based. Constraints (3), (6)-(8), (10)-(15), (17), (19) and (20)-(22) are same. Constraints (27), (28), (29) and (30) define the variables. Constraints (27) and (28) explain objective functions of first model with scenario based.

2-4- " ε – constraint" method

The proposed model has two objectives and is a multi-objective one. One method to solve this is ε - constraint method. As indicated by the most widely accepted classification, the Multi-Objective Mathematical Programming (MOMP) methods can be classified as a priori, interactive and a posteriori, according to the decision stage in which the decision maker expresses her/his preferences. Although the a priori methods are the most popular, the interactive and the a posteriori methods convey much more information to the decision maker. Especially, posteriori (or generation) methods give the whole picture (i.e. the Pareto set) to the decision maker, before her/his final choice, reinforcing thus, her/his confidence to the final decision.

This multi-objective method is a posteriori or generation method (Ehrgott, 2005). By using this method, a good approximation of the Pareto optimal solutions could be achieved, which facilitates the process of decision making when facing multi-objective problems. For this purpose, the model optimizes each objective function separately to find two extreme efficient points of the Pareto frontier. Then, by shifting one of the objective functions to the constraint set and relaxing the value of right hand side (ε parameter) step-by-step, the method obtains other Pareto optimal solutions. It is clear that by implying small changes on the right hand side value; much more Pareto optimal solutions is obtained while the required computational time will increase.

3- Implementation and evaluation

In this section, performance and usefulness of the proposed model is presented via numerical examples.

3-1- numerical examples

In this section, a numerical example shows the introduced model. Suppose we want to locate 7 facilities like drugstores in a region including 12 zones (customers). Demand of each customer zone is shown in Table 2, distance between facilities and customer zone and capacity of each facility are shown in Table 3. We consider 3scenarios with their occurrence probabilities in Table 4.

Table 2.demand of each customer zone

	Scen	ario 1	Scen	ario 2	Scen	ario 3
customer	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
1	45	22	26	13	10	8
2	10	37	16	21	6	25
3	38	17	42	16	27	19
4	23	21	24	11	18	34
5	30	45	14	22	16	28
6	25	34	15	34	18	21
7	15	36	29	33	4	17
8	28	42	22	16	6	38
9	16	21	14	23	26	19
10	32	10	31	22	21	11
11	24	28	40	19	23	38
12	41	16	26	19	32	24

Table 3. Distance between facilities and customer zone and capacity of facilities

	Distance to Customer							capa	acity					
facility	1	2	3	4	5	6	7	8	9	10	11	12	Type 1	Type 2
1	11	11	15	19	25	22	37	29	40	33	51	65	95	78
2	30	21	19	37	10	21	22	41	47	43	14	25	94	127
3	7	14	22	35	7	39	29	17	10	43	15	43	181	141
4	57	54	41	40	25	38	25	21	18	59	20	9	141	268
5	33	20	38	47	12	55	29	16	31	42	21	14	126	116
6	19	30	16	12	27	31	45	28	39	41	50	24	127	121
7	8	11	25	16	34	48	20	39	13	6	36	22	63	195

Table 4.probabilities of scenarios

scenario	probabilities
1	0.25
2	0.25
3	0.5

Following the procedure of ε – *constraint* method, the proposed model is solved separately for each objective function, which gives two extreme points i.e. (367.1791, 2162711.167), and (388.15833, 2162502.167)

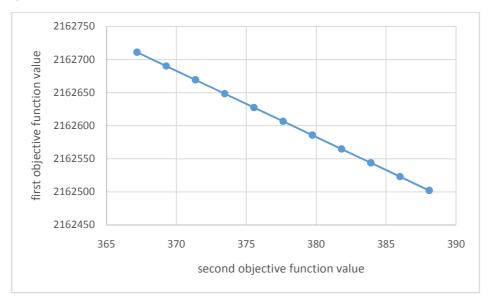


Figure 2.pareto front found by ε – constraint method

By transforming the second objective function to a constraint, the model is solved as regarding the first objective function as the single objective. Figure 2 shows the pareto front found by ε – constraint method. Finally, the model is solved and 3 facilities are selected to locate. $z_1 = z_2 = z_3 = 1.00$. Table 5, shows risk variable value and Table 6 shows u_{jk} values.

Table 5. Risk_{kcs} Values

S		1	2		3		
K	C=1	C=2	C=1	C=2	C=1	C=2	
1	6.000	_	-	_	-	_	
2		_	ı	_	ı	_	
3	_	_	_	_	_	_	
4		_	10.000	_	-	_	
5		_		_		_	
6	23.000	11.000	15.000	_	_	_	
7		_	18.000	_	ı	_	
8	28.000	32.000	4.000	_	_	8.000	
9	16.000	21.000		_	-	_	
10	32.000	10.000	31.000	_	_	11.000	
11	_	_		_		_	
12	41.000	16.000	26.000	_	26.000	24.000	

Table 6.U_{jk}Values

J	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000	1.000	1.000	1.000	1.000	1.000	0.200	0.733	-	0.467	_	_
2	0.667	1.000	1.000	0.200	1.000	1.000	1.000	_	_	_	1.000	1.000
3	1.000	_	1.000	0.333	1.000	0.067	0.733	1.000	1.000	_	1.000	_
4	_	1	-	1	-	1	-	_	_	1	-	_
5	1	ı	1	1	1	1	1	_	_	1	1	_
6	_			_		_		_	_			_
7	_	_	_	_	_	_	_	_	_	_	_	_

According to Table 6, facilities opened at candidate location j = 1,2,3 so u_{jk} at j = 4,5,6,7 are not covered.

3-2- Sensitivity analysis

In this section, to validate the proposed model by conducting sensitivity analysis on some critical parameters like probability of scenarios is shown in Table 7, best and possible distance between facilities and customer zone is shown in Table 8 and Figure 3, change in capacity of facilities are reported in Figure 4.

Table 7. Sensitivity analysis on probability of scenarios

	p_s		
s = 1	s = 2	s = 3	ZF
0.15	0.15	0.7	1649897.821
0.25	0.25	0.5	2162502.167
0.35	0.35	0.3	2347844

According to Table 7, under constant value of the ε – constraint method, any decrease in scenario 3 will incur more costs in the model.

Table 8. Effect of distance between facilities and customers zone on objective function

r_{jk}^1	r_{jk}^2	ZF
15	50	2162331.227
20	45	2162685.234
25	40	2162502.167
30	40	2164098.209
35	45	2168488.709

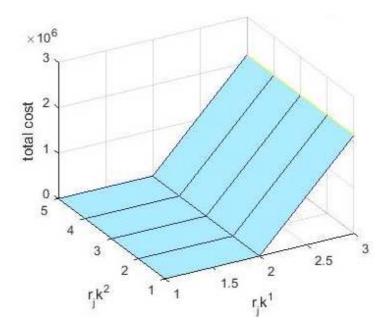


Figure 3. Effect of distance between facilities and customers zone on objective function(total cost)

Considering reported results in Table 8 and Figure 3, any increase in constant value of best distant and possible distant, will decrease our objective function. The reason for this fact is that the number of facilities that can be in the best and possible distant increase and so the model can easily chose the facilities that have fewer costs and less total costs. Therefore, the objective function will decrease. In other way, any decrease in interval between r_{jk}^1 and r_{jk}^2 will increase our costs because the selected number of facilities decreases and facilities with higher costs must be selected. Figure 4 shows the sensitivity analysis results on change of capacity. By increasing the capacity of each facility, the total costs as the main objective reduces. Increasing the capacity may result more demand, so the risk of missing customer reduces. By decreasing the number of missing customers, we will have fewer costs.

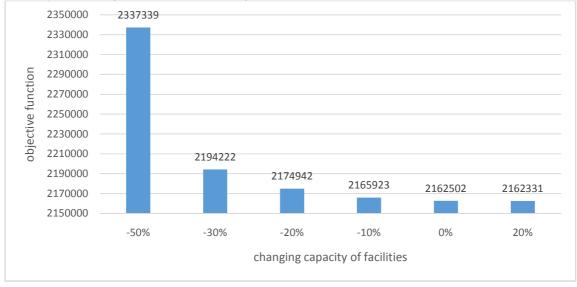


Figure 4. Change in capacity of facilities vs. costs as objective

4- Conclusion

This paper proposes a multi-objective multi period mixed integer covering location-allocation model for pharmaceutical centers. The model helps to make several decisions about strategic issues such as opening drugstore (called facility) to optimize the flow of material and make it easy the accessibility of customers to facilities. In addition, the model can solve the problems of other industries that have limitation about their products (such as perishable foods or other perishable products). The presented model's advantage over the traditional covering location problems is the maximization of social justice and minimization of missed customers. Since the problem deal with the uncertainty in demands, a robust approach is applied. In addition, the performance of the proposed model some numerical examples are considered. Finally, a multi-objective decision making (MODM) techniques, the ε -constraint method, is applied to find pareto solution and help us to sensitivity analysis of the model. As a result, the model shows that any increase in constant value of the best distant and possible distant, will decrease our objective function or by increasing the capacity of each facility, the total costs is reduced. Providing a heuristic method for large-scale instances and using the model in other uncertainty programming methods like fuzzy, stochastic programming and other robust approach can make the model more complex. Furthermore, for more future research issues, using the definition of social justice in other location problems, considering competition for pharmaceutical centers and using dynamic competition, static competition or competition with foresight and extending the model to address the location of distribution centers are researches that may need future investigations.

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