



A Robust Stochastic Programming Approach for Blood Collection and Distribution Network Design

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ABSTRACT

Blood supply chain network design is an essential part of the total blood management systems. In this paper, a mixed integer non-linear programming (MINLP) model for the concerned problem is developed. Optimizing the facility location and flows between each echelon of the considered supply chain is our main focus in this study. Also, in order to handle uncertain nature of model parameters, a mixed robust stochastic programming approach is applied to the model. Finally, to test the applicability of the proposed model, a numerical example is proposed using random generated data and then sensitivity analysis is done on a model parameter which plays a role in making trade-off between model robustness and optimality robustness.

1. Introduction

The major role of supply chain management (SCM) and supply chain network design in systems in the recent years has led many researchers to implement its basic rules on wider areas to control the operations in an efficient way [1, 2]. Among the different kinds of facilities, determination of location-allocation of healthcare facilities is very crucial in maximizing the involved people's benefits. In this field, a comprehensive study is done by Papageorgiou [3] and Rais and Viana [4]. But, one of the recent papers which significantly focused on location-allocation of healthcare facilities, are Syam and Côté [5] which proposed location-allocation of specialized healthcare systems. Shariff et al. [6] proposed a Maximal Covering Location Problem in which healthcare facilities of a region in Malaysia has been studied. Also, determining the optimal characteristics (number, size and locations) of regional health facilities has been studied by Dökmeci [7].

Blood supply chain network design, as one of the key subsets of the healthcare systems, is one of the most ready for better management of this life-saving product. Lack of efficient procurement and distribution centers in such supply chains result in imposing risks to lives and properties. According to the American Red Cross (ARC), due to blood inventory shortages in 2007, approximately 28.9% of hospitals reported the cancellation of surgery in the United States on one or more days which affected approximately 412 patients [8].

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Significance and importance of the blood managing system has led researchers to focus particularly on this topic. However, most of the articles related to blood managing system focused on quality aspect of blood products rather than blood collection and distribution planning. To the best of our knowledge, the only similar article to our work is done by Sha and Huang [9] and VafaArani and Bozorgi-Amiri [10, 11].

Sha and Huang [9] focused on determining location-allocation of mobile blood banks in multi-period environment with tactical planning wherein objective functions is to minimize the total costs and the model is tested via a case study in Beijing. VafaArani and Bozorgi-Amiri [10, 11] proposed a bi-objective multi period location-allocation model for blood facilities, considering minimization of the blood shortage and total costs in the proposed network. Then the model has been validated through ϵ -constraint method.

Supply chain of blood products has been widely taken into considerable review by Beliën and Forcé [12]. Comprehensive overview of blood banking supply chain regarding various questions about blood banking functions and locations has been done by Pierskalla and Brailer [13] and Pierskalla [14]. Nagurney and Masoumi [15] addressed a mathematical model for a sustainable network design model for the blood supply chain. Also, location-allocation of blood facilities has been taken into consideration by Jacobs et al. [16] in which facility relocation problem for the mid-Atlantic region of the ARC in Norfolk Virginia has been studied. Şahin et al. [17] developed several mathematical models for solving the location-allocation problems customized in blood services in Turkey. Cetin and Sarul [18] proposed a hybrid set covering model for discrete location approach as well as center of gravity method for continuous location models in order to determine optimum location of blood banks.

Considering the given data as deterministic parameters in the mentioned papers leads to lack of acceptable application of the models in the real world cases. In order to cope with uncertainty, three different methods could be used i.e. fuzzy programming (FP), stochastic programming (SP) and robust programming (RP). In this paper, according to inherent behavior of some parameters, a two-stage stochastic programming is applied to the model.

Stochastic programming in healthcare systems has been considered in Lin et al. [19] which proposed a class of stochastic multi-objective problems with complementarity constraints and applied it to a patient allocation problem in healthcare management. Harper et al. [20] proposed a discrete-event geographical location–allocation simulation model for evaluating different options for the service provisions using stochastic approach. A real case study has also been applied.

Based on the relative gap, we present a location-allocation model for blood collection management under a scenario-based robust stochastic programming approach.

The rest of the paper is organized as follows: In Section 2, problem definition and mathematical formulation are elaborated, In Section 3, application of the model is provided and finally, Section 4 is dedicated to the possible ways for future research.

2. Problem Description and Mathematical Formulation

In this paper, we address a scenario in which donation can take place directly to the MCs or to the TCs, which then will require extra shipment from that TC to the MC at the end of period (see Fig.1).

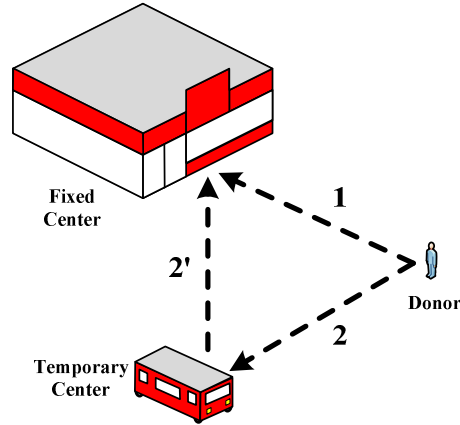


Figure 1. Flow of a single donor.

The indices, parameters and variables used to formulate the problem are as follows:

Indices

I	Set of donators
J	Set of TCs
K	Set of MCs
Ω	Set of scenarios
T	Set of time periods

Parameters

c_{j_1, j_2}	Transportation cost between nodes j_1 and j_2
c_k^n	Establishment cost of MC
$c'_{j,k}$	Transportation cost between nodes j and k
De_θ^t	Total demand for blood in period t under scenario θ ,
π_θ	Probability of scenario θ ,
r_{ij}	Distance between nodes i and j ,
r_0	Coverage radius of TC,
w_{ik}	Distance between nodes i and k ,
w_0	Coverage radius of MC,
q_{jk}	Distance between nodes j and k ,
q_0	Coverage radius of MC, associated to TC,

dd_0	Maximum capacity of TC,
V_k	Maximum capacity of MC,
d_i	Maximum capacity of donation zones,
M	A reasonably large number,
ω	Predefined percentage,
λ	The weight value

Variables

X_{ij}^t	A binary variable that takes 1 if node i is linked to node j ; and 0, otherwise,
X_{ik}^n	A binary variable that takes 1 if node i is linked to node k ; and 0, otherwise,
X_{jk}^m	A binary variable that takes 1 if node j is linked to node k ; and 0, otherwise,
y_{j_1, j_2}^t	A binary variable that takes 1 if a TC goes from j_1 to j_2 ; and 0, otherwise,
z_k'	A binary variable that takes 1 if an MC is established in node k ; and 0, otherwise,
P	Number of TCs,
$s_{ij\theta}^t$	Flow between nodes i and j under scenario θ at period t ,
$s_{ik\theta}^n$	Flow between nodes i and k under scenario θ at period t ,
$s_{jk\theta}^m$	Flow between nodes j and k under scenario θ at period t ,
Z_θ	The objective function value under scenario θ .

The mathematical model of the discussed problem is as follows:

$$\text{Min } Z = \lambda \sum_{\theta=1}^{\Omega} \pi_{\theta} Z_{\theta} + (1-\lambda) \sum_{\theta=1}^{\Omega} \pi_{\theta} |Z_{\theta} - \sum_{\theta'=1}^{\Omega} \pi_{\theta'} Z_{\theta'}| \quad (1)$$

$$Z_{\theta} = \sum_{t=1}^T \sum_{j_1=1}^J \sum_{j_2=1}^J y_{j_1, j_2}^t c_{j_1, j_2} + \sum_{k=1}^K z_k c_k'' + \sum_{t=1}^T \sum_{j=1}^J \sum_{k=1}^K \sum_{i=1}^I s_{jk\theta}^m c'_{j,k} \quad (1')$$

s.t.

$$\sum_{j_1=1}^J y_{j_1, j_2}^t \leq 1, \quad \forall j_2, t, \quad (2)$$

$$\sum_{j_1=1}^J \sum_{j_2=1}^J y_{j_1, j_2}^t = P, \quad \forall t, \quad (3)$$

$$\sum_{j_2=1}^J y_{j_1, j_2}^t \leq \sum_{j=1}^J y_{j, j_1}^{t-1}, \quad \forall j_1, t \geq 2, \quad (4)$$

$$\sum_{k=1}^K X_{ik}'' + \sum_{j=1}^J X_{ij}^t \leq 1, \quad \forall i, t, \quad (5)$$

$$X_{ij}^t r_{ij} \leq r_0 \sum_{j_1=1}^J y_{j_1, j}^t, \quad \forall i, j, t, \quad (6)$$

$$X_{ik}'' w_{ik} \leq w_0 z_k', \quad \forall i, k, t, \quad (7)$$

$$X_{jk}''' q_{jk} \leq q_0 z_k', \quad \forall i, j, k, t, \quad (8)$$

$$s_{ij\theta}^t \leq M X_{ij}^t, \quad \forall i, j, t, \theta, \quad (9)$$

$$s_{ik\theta}'' \leq M X_{ik}'', \quad \forall i, k, t, \theta, \quad (10)$$

$$s_{jk\theta}''' \leq M X_{jk}''', \quad \forall j, k, t, \theta, \quad (11)$$

$$\sum_{j=1}^J s_{jk\theta}''' + \sum_{i=1}^I s_{ik\theta}'' \leq V_k, \quad \forall k, t, \theta, \quad (12)$$

$$\sum_{t=1}^T [\sum_{j=1}^J s_{ij\theta}^t + \sum_{k=1}^K s_{ik\theta}''] \leq d_{i\theta}, \quad \forall i, \theta, \quad (13)$$

$$\sum_{i=1}^I s_{ij\theta}^t \leq d d_0, \quad \forall j, t, \theta, \quad (14)$$

$$X_{jk}''' \leq \sum_{j_1=1}^J y_{j_1, j}^t z_k, \quad \forall j, k, t, \quad (15)$$

$$\sum_{i=1}^I \sum_k s_{ik\theta}'' + \sum_{i=1}^I \sum_{j=1}^J s_{ij\theta}^t \geq \omega D e_\theta^t, \quad \forall t, \theta, \quad (16)$$

$$\sum_{i=1}^I s_{ij\theta}^t = \sum_{k=1}^K s_{jk\theta}''', \quad \forall j, t, \theta, \quad (17)$$

$$X_{ij}^t, X_{ik}'', X_{jk}''', y_{j_1, j_2}^t, z_k \in \{0, 1\}, \quad \forall i, j, k, t, \quad (18)$$

$$s_{ij\theta}^t, s_{ik\theta}^t, P \geq 0, \text{int}, \quad \forall i, j, k, t, \theta. \quad (19)$$

The objective function (1) minimizes the tradeoff between the feasibility robustness (i.e., the first term) and the optimally robustness (i.e., the second one), in which Z_θ can be computed as the equation number (1) that calculates the total costs in the network in each scenario type. Constraint set (2) is related to the TC's movement in the course of time. Constraint set (3) defines the required number of TCs. Constraint (4) assures that only a temporary facility like j_1 can be moved to another location if there exists a temporary facility in previous period located in j_1 . In each period, every group of donators can donate only to a main facility or temporary ones (not both of them) that is assured via constraint (5). Constraint sets (6)-(8) impose the coverage limitations. Constraint sets (9)-(11) link the flow variables to the allocation ones. Constraint sets (12)-(15) impose a capacity limitation on MCs, donation zones, and TCs, respectively. Constraint (16) indicates that at for each scenario, a predefined percentage should be covered. Equation (17) is the balancing of flow constraint. Constraint sets (18) and (19) are the non-negativity constraints. Noteworthy, the probabilities assigned to each scenario indicates the importance of individual scenario under inherent uncertain nature of problem's environment [21].

A. Linearization of the model:

As could be seen, objective function and equation (16) are nonlinear. Hence, in order to introducing linear counterpart of the objective function, using Q_θ^+, Q_θ^- as positive variables we will have:

$$\text{Min } Z = \lambda \sum_{\theta=1}^{\Omega} \pi_\theta Z_\theta + (1-\lambda) \sum_{\theta=1}^{\Omega} \pi_\theta (Q_\theta^+ + Q_\theta^-) \quad (20)$$

$$Q_\theta^+ - Q_\theta^- = Z_\theta - \sum_{\theta'=1}^{\Omega} \pi_{\theta'} Z_{\theta'} \quad \forall \theta, \quad (21)$$

$$Q_\theta^+, Q_\theta^- \geq 0, \quad \forall \theta, \quad (22)$$

Also, for transforming the equation (15) to its linear counterpart, it could be replaced with equations (23)-(26) (see [22]) and the rest of the constraints will remain unchanged:

$$X_{jk}^{mt} \leq \sum_{j_1=1}^J l_{j_1,j,k}^t, \quad \forall j, k, t, \quad (23)$$

$$y_{j_1,j}^t + z_k \geq 2l_{j_1,j,k}^t, \quad \forall j, k, t, \quad (24)$$

$$y_{j_1,j}^t + z_k - 1 \leq l_{j_1,j,k}^t, \quad \forall j, k, t, \quad (25)$$

$$l_{j_1,j,k}^t \in \{0,1\}, \quad \forall j_1, j, k, t. \quad (26)$$

3. Computational Experiments

For evaluation of the applicability of the proposed model, test problems are generated based on Table 1, in which range of the required parameters are defined. Also, Tables 2 represents

different values of demands under 4 different scenarios. Test problems are solved using GAMS 22.9 on a core i5 computer with 4GB RAM.

Table 1. The involved parameters and ranges.

<i>Variables</i>	<i>Ranges</i>	<i>Variables</i>	<i>Ranges</i>
r_{ij}	~U [50, 1000]	v_k	~U [200,400]
w_{ik}	~U [50, 1000]	d_i	~U [300, 2500]
q_{jk}	~U [50, 500]	W	~U [0.7, 0.9]
r_o	~U [100, 150]	c_{j1j2}	~U [50, 100]
w_o	~U [10, 50]	c_k	~U [1500, 3500]
q_o	~U [10, 50]	c_{jk}	~U [0.01, 0.2]
dd_o	~U [200, 500]		

Table 2. The values of demand under scenarios.

<i>Scenarios</i>	<i>Scenario probability</i>	<i>Demands</i>
1	0.4	~U [100, 500]
2	0.2	~U [80, 420]
3	0.3	~U [60, 310]
4	0.1	~U [20, 220]

Here it should be noted that, scenarios could be translated as various probable disasters which its occurrences' probability as well as intensity forms the abovementioned Table. For example when an earthquake occurs, based on its Richter magnitude scale, different level of demands will be realized throughout the given territory.

Using data from the model under each scenario as a nominal data for the deterministic (Det) model, both deterministic and the robust stochastic (RS) objective function values have been evaluated and are computed (see Table 3). As we can see, the objective function value of the stochastic model is higher than the mean values of the deterministic one under each scenario.

Table 3. The objective values of models.

<i>Problem size I×J×K×T</i>	<i>Objective value of objective function under $\lambda = 0.9$</i>	
	<i>Det.</i>	<i>RS.</i>
8×5×3×4	2354.290	2105.415

The difference between the Det and the RS values can be called as *the expected value of perfect information* (EVPI), which represents the loss of profit due to the presence of uncertainty [23].

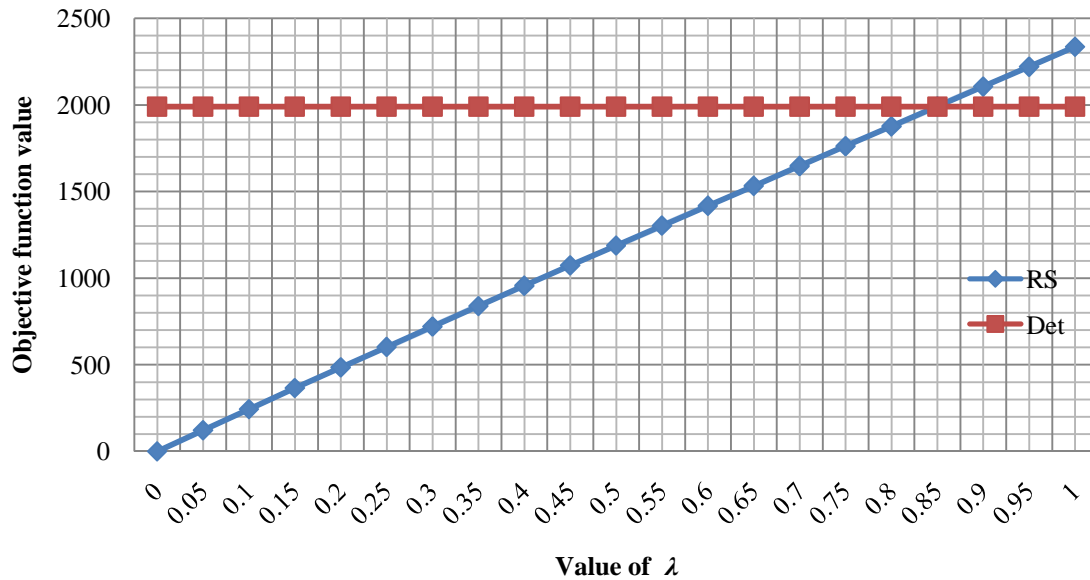
$$EVPI = 2354.290 - 2105.415 = 248.875$$

Table 4 shows the movements of the temporary facilities through the planning horizon. As we can see, in each period, from the five candid locations for temporary centers, only three of them are needed to cover 0.9 of the total demands under Sto model.

Table 4. The movements of the temporary facilities through the planning horizon.

$j_1 \cdot j_2$	t=1	t=2	t=3	t=4
1.1		1	1	
1.5				1
2.2				1
2.5	1	1	1	
5.1	1			
5.2	1	1	1	
5.3				1

A sensitivity analysis on the different values of the λ vs. total costs has been applied and can be seen in Figure 2. As could be seen, with increasing the weight value of λ , the RS model is tend to fulfill its feasibility robustness rather than optimally one; while similarly, we can see with decreasing the value, the RS model reduces the objective function value. The mean values of the objective functions for the Det model under each scenario is also presented in the Figure 2. It can be concluded that with the values of λ lower than 0.85, the RS model should be implemented due it lower costs, while for the values greater than 0.85 which imposes a great impact on the optimally robustness rather than feasibility, applying the RS model does not have any economic justification.

Figure 2. Sensitivity analysis for values of λ

4. Conclusions

To response the demand for blood, this paper with regarding location-allocation of blood facilities (fixed and temporary) addresses better management of such supplies. Because of seasonal changes in demand, multi-period location-allocation of facilities has taken into consideration and for coping uncertainties; two-stage stochastic programming is applied.

With regarding to minimization of total costs in the proposed flow, our model as integrated strategic and tactical planning decisions, determines both optimal numbers of main and temporary facilities, in addition to assigning donators to the facilities and location of blood centers. Solving the larger sizes of problem using heuristic/meta-heuristic methods, applying other novel methods to cope with the parameters uncertainty and applying rolling horizon approach to the model are other research avenues could be explored by interested readers.

References

- [1] Melo, M. T., Nickel, S. and Saldanha-Da-Gama, F. (2009). "Facility location and supply chain management—A review", *European Journal of Operational Research*, Vol. 196, pp. 401-412.
- [2] Pishvaei, M. S. and Razmi, J. (2012). "Environmental supply chain network design using multi-objective fuzzy mathematical programming", *Applied Mathematical Modelling*, Vol. 36, pp. 3433-3446.
- [3] Papageorgiou, J. C. (1978). "Some operations research applications to problems of health care systems (a survey)", *International journal of bio-medical computing*, Vol. 9, pp. 101-114.
- [4] Rais, A. and Viana, A. (2011). "Operations Research in Healthcare: a survey, *International Transactions in Operational Research*", Vol. 18, pp. 1-31.
- [5] Syam, S. S. and Côté, M. J. (2010). "A location–allocation model for service providers with application to not-for-profit health care organizations", *Omega*, Vol. 38, pp. 157-166.
- [6] Shariff, S., Moin, N. H. and Omar, M. (2012). "Location allocation modeling for healthcare facility planning in Malaysia", *Computers and Industrial Engineering*, Vol. 62, pp. 1000-1010.
- [7] Dökmeci, V. F. (1977). "A quantitative model to plan regional health facility systems, *Management Science*", Vol. 24, pp. 411-419.
- [8] Whitaker, B. I., Green, J., King, M. R., Leibeg, L. L., Mathew, S. M., Schlumpf, K. S. and Schreiber, G. B. (2007). "*The 2007 National Blood Collection and Utilization Survey*", The U.S. Department of Health and Human Services.
- [9] Sha, Y. and Huang, J. (2012). "The Multi-period Location-allocation Problem of Engineering Emergency Blood Supply Systems", *Systems Engineering Procedia*, Vol. 5, pp. 21-28.
- [10] Vafa Arani, H. and Bozorgi-Amiri, A. (2013). "*Multi-objective model of location-allocation in emergency response network design for blood supply*", 9th International Industrial Engineering Conference, Tehran, Iran.
- [11] Vafa Arani, H. and Bozorgi-Amiri, A. (2013). "A Dynamic multi-objective model for location-allocation problem in emergency network design for blood supply", *Iran University of Science and Technology Magazine*.
- [12] Beliën, J. and Forcé, H. (2012). "Supply chain management of blood products: A literature review, *European journal of operational research*", Vol. 217, pp. 1-16.
- [13] Pierskalla, W. P. and Brailer, D. J. (1994). "*Applications of operations research in health care delivery*", Handbooks in OR & MS, Vol. 6.
- [14] Pierskalla, W. P. (2005). "Supply chain management of blood banks", *Operations research and health care*, pp. 103-145.
- [15] Nagurney, A. and Masoumi, A. H. (2012). "Supply chain network design of a sustainable blood banking system", *Sustainable Supply Chains*, pp. 49-72.
- [16] Jacobs, D. A., Silan, M. N. and Clemson, B. A. (1996). "An analysis of alternative locations and service areas of American Red Cross blood facilities", *Interfaces*, Vol. 26, pp. 40-50.
- [17] Şahin, G., Süral, H. and Meral, S. (2007). "Locational analysis for regionalization of Turkish Red Crescent blood services", *Computers & Operations Research*, Vol. 34, pp. 692-704.

- [18] Cetin, E. and Sarul, L. S. (2009). "A blood bank location model: A multi-objective approach", *European Journal of Pure and Applied Mathematics*, Vol. 2, pp. 112-124.
- [19] Lin, G. H., Zhang, D. and Liang, Y. C. (2012). "Stochastic multi-objective problems with complementarity constraints and applications in healthcare management", *European journal of operational research*, Vol. 226, pp. 461-470.
- [20] Harper, P., Shahani, A., Gallagher, J. and Bowie, C. (2005). "Planning health services with explicit geographical considerations: a stochastic location–allocation approach", *Omega*, Vol. 33, pp. 141-152.
- [21] Pishvae, M. S., Jolai, F. and Razmi, J. (2009). "A stochastic optimization model for integrated forward/reverse logistics network design", *Journal of Manufacturing Systems*, Vol. 28, pp. 107-114.
- [22] Chang, C. T. and Chang, C. C. (2000). "A linearization method for mixed 0–1 polynomial programs", *Computers & Operations Research*, Vol. 27, pp. 1005-1016.
- [23] Birge, J. R. and Louveaux, F. (2011). *"Introduction to stochastic programming"*, Springer.