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Facility Location Decisions Within Integrated Forward/Reverse Logistics under Uncertainty

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Abstract

In this paper, a stochastic mixed integer linear programming (SMILP) model is proposed to optimize the location and size of facilities and service centres in integrated forward and reverse streams under uncertainty. The objective of the model is to minimize establishment, transportation and inventory management costs and simultaneously maximize customer satisfaction with sustainable perspective. The model incorporates different elements and features of distribution networks including inventory management, transportation and establishment of new facilities as well as existing centres. The presented model is the streamlined approach for multi-objective, multi-period, multi-commodity distribution system, and it is supported by a real case study in automobile after sales network. Genetic algorithm is implemented to solve the model in reasonable time. The performance of the model and the effects of uncertainty on provided solution are studied under different cases. Competitive result of the stochastic model compared to deterministic model ensures that the proposed approach is valid to be applied for decision making under uncertainty.

Keyword: Facility location; Closed-loop supply chain; uncertainty; Genetic Algorithm; Distribution-service network;

1. Introduction

Successful implementation of a closed-loop supply chain (CLSC) needs dealing with challenges in collocation and integration of forward/reverse flows as well as required resources [1, 2]. Although recycling products decreases negative effects on the environment and provides benefits in terms of recovered raw material and reused components, uncertainties which exist in the supply chains threat their performance. There are two major sources of uncertainty including variation in customers demand and return rate of used products. The second source significantly affects the configuration of the CLSC. Sub-optimal configurations may show a poor operational performance of supply chain and lead the managers to hesitate in implementing such solutions. Hence, it is essential developing practical managerial tools that support forward and reverse flow integration. These tools help to correctly implement reverse logistics, avoid poor operational performance, and encourage supply chain managers in adopting CLSC models [3].

2. Literature review

Recently, supply chain design regarding facility location has attracted increasing attention [4]. Researchers have proposed different models to handle classical facility location decisions problem including supplier selection, inventory management, distribution, routing and other logistics activities [5]. New researches support complex structure of supply chains by using dynamic, multi-objective, multi-echelon models. We divide related literature into deterministic and stochastic models. In deterministic models data about all

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parameters of the model are available and known. Krikke et al. [6] proposed a mixed integer linear programing (MILP) model to cover economic and ecologic features of closed-loop supply chain. The bi-objective mixed integer model proposed by Pishvaee et al. [7] provided solution to minimize total cost and maximize the responsiveness of closed-loop network. To solve the model, a multi-objective memetic algorithm (MOMA) with dynamic local search is developed which showed more options in setting capacity options and competitive results with exact method. Gupta and Evans [1] presented a goal programing model for the operations in supply chain. The purpose of the model is to maximize the profit through different operation of the supply chain for multiple product and multiple periods. Real cases in supply chain witness uncertainty in at least one of the parameters. In such cases, models that deal with uncertainty are proposed. Salema et al. [8] presented a general model to overcome uncertainties in product demands and returns through multi-scenario method. The expanded formulation allows for any number of products, establishing a network for each product while guaranteeing total capacities for each facility at a minimum cost. The mixed integer model of this paper was solved using standard branch and bound technique. Francas and Minner [9] developed two alternative manufacturing network configurations when demand and return flows are both uncertain. Pishvaee et al. [10] performed a stochastic mixed integer model to deal with uncertain demand, quantity and quality of returns, and variable costs in supply chain. Lee and Dong [11] considered forward and reverse demand as stochastic parameters. A two-stage stochastic programing model based on dynamic deterministic model for multi-period reverse logistic network was proposed.

In summary, in the most of the reviewed papers, demand and return rate are considered as uncertainties sources in designing and planning the closed-loop supply chains. The deterministic and stochastic mixed integer linear programing models are solved by application of different approaches. In spite of validation of these models by numerical experiments, most of used approach lack practical application. The complexity of the methods and their solutions made it hard for practitioners to adopt these methods for other general cases.

In this paper, a stochastic mixed integer linear programming (SMILP) model is constructed to identify the optimal location and size of facilities in a CLSC. The model includes inventory management, transportation and establishment of new facilities as well as existing centres. A genetic algorithm is performed to return the optimal solution of the facility location decisions within CLSC since it is a complex and NP-hard problems [10, 12, and 13]. The model is utilized in a real case study to redesign the current network. Finally, two scenarios named the best case and worst-case is considered to study the performance of the model and the impact of uncertainty on provided solution.

3. Model description

The considered integrated logistics network in this paper is shown in Fig.1. It is a multi-layer network including central manufacturing/distribution facilities, regional warehouses, customers, collection/inspection sites, and central remanufacturing facilities. The main goal of the model is to determine the optimal capacity and inventory level of each facility.

In forward logistic network, regional warehouses receive new brand products from central warehouse for seasonal demand in each region. After that, the distribution of these products will be carried out between customers based on their demands. In most supply chains, particular regulations are used to reuse/recycle used products. It happens when customers return used part or managers are asked for pick up those parts. The collection/inspection sites are assigned to gather reusable parts which are returned, and disposal collection sites are devoted to others. In collection/ inspection sites, reusable parts are disassembled to disposals and sent to disposal collection sites where possible parts are transported to central remanufacturing facilities to be rebuilt. In this process, the main decision variables are optimal location, the number and the capacity of central and regional facilities to serve the demand of customers.

Nomenclature

L	Set of central warehouses
M	Set of regional warehouses
N	Set of customers
O	Set of good types
F	Set of periods
a_{pit}	Demand of customer *i* for commodity *t* in period *p*
b_{pjt}	Demand (capacity) of regional warehouse *j* for commodity *t* in period *p*
C	Cost of transportation per unit
d_{ij}	Distance between regional warehouse *j* and customer *i*
d'_{jk}	Distance between regional warehouse *j* and central warehouse *k*,
e_{pkt}	Capacity of central warehouse *k* for commodity *t* in period *p*
α	Weight of first objective function
β	Minimum level of customer satisfaction for commodity *t*
q	Cost of installation central warehouse
w	Cost of installation regional warehouse
h_w	Warehousing cost per unit goods in warehouses
h_s	Warehousing cost per unit goods in stocks
π	Back ordered cost per unit goods
W'_j	Cost of establishing of recovery sites
g'	Percentage of parts which can be sent for recycling
x_{pjit}	Percentage of demand of customer *i* for commodity *t* that is supplied by central warehouse *j* in period *p*
y_{pkjt}	Percentage of demand of regional warehouse *j* for commodity *t* that is supplied by central warehouse *k* in period *p*
U_j	A binary variable which is equal to 1 if a regional warehouse is located in the potential point *j*
V_k	A binary variable which is equal to 1 if a central warehouse is located in the potential point *k*

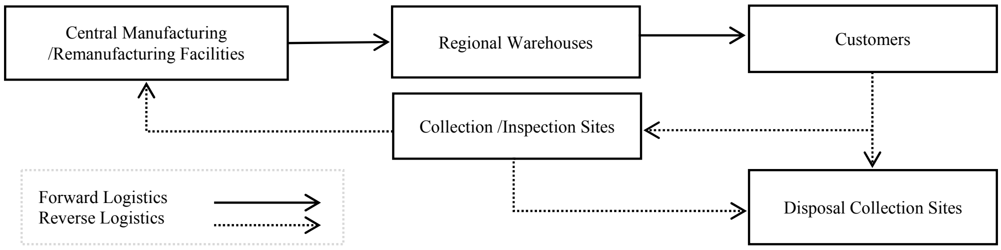

Fig. 1. Material Flow for the proposed model in closed-loop supply

The total costs and customer satisfaction are two main and conflictive objectives in design of closed-loop logistics networks. Hence, identifying the optimal capacity and location of facilities whereas both objectives are fulfilled is a challenge for decision makers. A stochastic multi-objective mixed integer linear programing model is proposed for the defined problem. The following assumptions are made in the model:

- Customer demand has stochastic nature which can vary over time horizon (in each period).
- The recovery rate is stochastic for each good type, customer and period.
- The capacity of each regional warehouse and central warehouse is flexible.

According to the structure of the logistics network, mathematical model is formulated as follows:

$$Min(Z_1) = \sum_{p,j,i,t} c \times d_{ij} \times a_{pit} \times x_{pjit} \tag{1}$$

$$+ \sum_{p,k,j,t} c \times d'_{jk} \times b_{pjt} \times y_{pkjt} + \sum_{p,j,i,t} c \times d_{jk} \times g' \times a_{pit} \times x_{pjit}$$

$$+ \sum_{p,j} h_w \times \Big(\sum_{k,t} b_{pjt} \times y_{pkjt} - \sum_{i,t} x_{pjit} \times a_{pit}\Big)$$

$$+ \sum_{p} h_s \times \Big(\sum_{k,t} e_{pkt} - \sum_{k,j,t} y_{pkjt} \times b_{pjt}\Big)$$

$$+ \sum_{p,t} \pi \times \Big(\sum_{i} a_{pit} - \sum_{i,j} a_{pit} \times x_{pjit}\Big)$$

$$+ \sum_{j} (w_j + w'_j) \times u_j + \sum_{k} q_k \times v_k$$

$$Max(Z_2) = \sum_{p,j,i,t} (x_{pjit})/(n.o.f) \tag{2}$$

Subject to:

$$\sum_{j} x_{pjit} \le 1 \quad \text{for p, i, t} \tag{3}$$

$$\sum_{k,t} b_{pjt} \ge \sum_{i,t} a_{pit} \times x_{pjit} \quad \text{for p=1, j} \tag{4.1}$$

$$\sum_{k,t,i} b_{pjt} + (b_{p-1,jt} - (a_{p-1,it} \times x_{p-1,jit})) \tag{4.2}$$

$$\ge \sum_{i,t} a_{pit} \times x_{pjit} + a_{p-1,it} \times (1 - x_{p-1,jit}) \quad \text{for p>1, j}$$

$$\sum_{k,t} b_{pjt} \times y_{pkjt} - \sum_{i,t} a_{pit} \times x_{pjit}) \le \sum_{t} b_{pjt} \quad \text{for p=1, j} \tag{5.1}$$

$$\sum_{k,i,t} b_{pjt} \times y_{pkjt} + b_{p-1,jt} \times y_{p-1,kjt} - \tag{5.2}$$

$$\sum_{i,t} (a_{pit} \times x_{pjit} + a_{p-1,it} \times x_{p-1,jit}) -$$

$$(a_{p-1,it} \times (1 - x_{p-1,jit})) \le \sum_{t} b_{pjt} \quad \text{for p>1, j}$$

$$\sum_{i,t} x_{pjit} \le n \cdot o \cdot u_j \quad \text{for p, j} \tag{6}$$

$$\sum_{j} x_{pjit} \ge \beta \quad \text{for p, i, t} \tag{7}$$

$$\sum_{k} y_{pkjt} \le 2 \quad \text{for p, i, t} \tag{8}$$

$$\sum_{j,t} y_{pkjt} \le m \cdot o \cdot v_k \quad \text{for p, k} \tag{9}$$

$$\sum_{j,t} b_{pjt} \times y_{pkjt} \le \sum_{t} e_{pkt} \quad \text{for p=1, k} \tag{10.1}$$

$$\sum_{j,t} b_{pjt} \times y_{pkjt} - \Big(\sum_{t} e_{p-1,kt} - \sum_{j,t} b_{p-1,jt} \times y_{p-1,kjt}\Big) \tag{10.2}$$

$$\le \sum_{t} e_{pkt} \quad \text{for p>1, k}$$

$$e_{pkt} \times v_k \ge \sum_{j} b_{pjt} \times y_{pkjt} \quad \text{for p, k, t} \tag{11}$$

$$\sum_{t} b_{pjt} \times u_j - \sum_{i,t} a_{pit} \times x_{pjit} \ge 0 \quad \text{for p, k} \tag{12}$$

$$x_{pjit} \ge 0 \tag{13}$$

$$y_{pkjt} \ge 0 \tag{14}$$

$$u_j \in \{0,1\} \tag{15}$$

$$v_k \in \{0,1\} \tag{16}$$

Where, the first objective function (Z_1) is to minimize the total cost including transportation, establishment, and inventory management cost. α is the weight factor of objective function. Maximization of customer satisfaction is constructed the second objective function (Z_2). Constraint (3) represents that the total percentage of supplied products (*t*) from different regional warehouses (j) for each customer (k) in period (p) must be less than or equal to the demand. In constraints (4), (5), and (12) the capacity of each regional warehouse is defined such that guaranty meeting the demand of customers. Constraint (6) and (9) binds to supply demands from the open regional warehouse and central warehouses, respectively. The desirable level of customer satisfaction is specified by constraint (7). Constraint (8) is similar to constraint (3) but its application is for central warehouse. The right hand side value is set as 2 to allow the capacity of each regional warehouse (j) to be as much as required for supplying customers. Constraints (10) and (11) are related to the capacity of central warehouses. Constraints (13) to (16) define non-negative variable as well as integer variables.

4. The solution approach

In this study, the stochastic multi-objective problem is solved by application of weighted sum method in a multi-objective genetic algorithm. The genetic algorithm (GA) is a meta-heuristic approach that its general idea is taken from biological evolution. As a process of genetic algorithm, a set of chromosomes are randomly generated and evaluated. During the GA procedure, the chromosomes are gradually evolved by using different operator including fitness function, selection, crossover, and mutation. The good chromosomes are preserved through the recombination operator. The search process continues until it finally converges to an optimal or near optimal solution. In developing a genetic algorithm, it is always necessary to select an appropriate representation, selection, crossover, and mutation scheme [14].

4. Result and discussion

The mentioned SMILP model is implemented in automobile part distribution chain to redesign its current network. The focal company is in charge of spare parts distribution after sales network. The main aim is to locate new regional and central distribution facilities to meet customers demand. The size of the considered case study is presented in Tab. 1. In the reviewed supply chain, the management process of forward and reverse logistics networks are completely separated in terms of facilities, material and information. In this study, by using historical data of demand for 5 years a uniform probability distribution function is estimated to generate demand at customer nodes. Moreover, a uniform distribution function is applied to provide a random number in range [0.1, 0.4] for estimation of return rate.

Tab. 1. The case study sets, indices, and parameters

Set, Indices, and Parameter	Symbol	Value
Number. of customers	*i*	31
Number of candidate regional warehouses	*j*	8
Number of candidate central warehouses	*k*	2
Number of commodities	*o*	5
Number of periods	*p*	4

The GA concept is implemented to handle the formulated case study based on the proposed method. In the purpose of validation behaviour of the model, some analysis is performed under different parameters values. In this context, the impact of stochastic demand and return rate on the model result is studied by considering stochastic and deterministic cases; in the first case the demand and return rate are modelled stochastically while in the second case they are assumed as deterministic parameters. Certainly, a post-analysis is developed in order to help decision maker in selection of one solution between many solutions.

The proposed model is solved through the stochastic solution method and by the deterministic approach to study the effect of stochastic demand and return rate on result of the model. Result of the deterministic approach is compared with proposed method when β is set as a specific level. The stochastic model is run for 10 replications then worst case (WC) and best case (BC) regarding weighted combination objective functions (Z) are selected and shown in Fig. 2 and Fig. 3. It means, the best case has the minimum Z and the worst case has the maximum one.

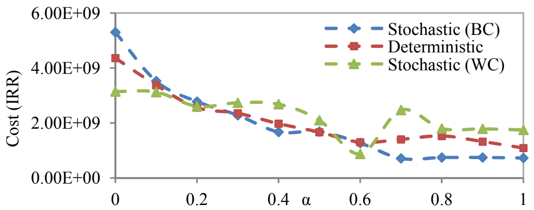

Fig. 2. Cost objective functions versus different α values for deterministic and stochastic cases

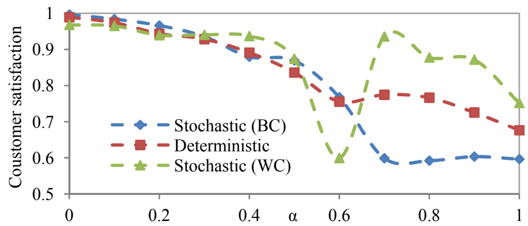

Fig. 3. Customer satisfaction versus different α values for deterministic and stochastic cases

An innovative post analysis approach is followed to help managers through difficulties in selecting one optimum solution. In the first step, a desirable customer satisfaction (β) value should be set by managers. It is minimum value that they expect to obtain from CLSC. In other word, it reflects the risk that they are able to consider in the desired network. A new function which is the summation of normalized cost function (Z_1) and customer dissatisfaction ($1\text{-}Z_2$) is defined as the main goal to be minimized, Eq. (17). Desired level of α is identified by minimum value of new function in desirable β level. It means that the model will be solved by selected α and β. The new objective function for different α and β is depicted in Fig. 4. For instant, consider the customer is interested in customer satisfaction of 0.8 (β=0.8), hence, the minimum value of Z' occurred in α=0.2, see Fig. 4. Thus, in this case the best choice is setting α at 0.2 and β at 0.8. For this point, the value of decision variable is presented in Tab.2 and Tab. 3 since the ultimate aim of the proposed model is to define optimum set of regional and central warehouses.

$$\text{Min } (Z' = Z_1 + 1 - Z_2) \tag{17}$$

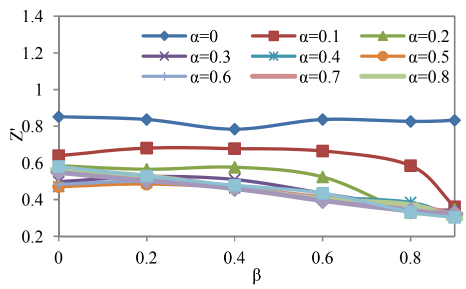

Fig. 4. The value of Z' for different α and β values

After initializing α and β values at 0.2 and 0.8, the model is run for 10 replications as the stochastic parameters are applied in the model. In this experiment, the solutions are sorted based on the Z values to select the best case and the worst case. It is worth mentioning that the supply chain managers have to select one of the alternatives based on different criteria (cost, customer satisfaction or the revenue of the supply chain).

Tab. 2. Optimal solution obtained for α =0.2 and β =0.8

	Cost (IRR)	Customer Satisfaction	Z	Profit (IRR)
Best Case	1.22E+09	0.92	-0.69	3.98E+11
Worst Case	1.53E+09	0.91	-0.67	3.94E+11

Tab. 3. Optimal decision variables obtained for α =0.2 and β =0.8

	U(1, 2, 3, 4, 5, 6, 7, 8)	V(1,2)
Best Case	(0, 0, 0, 1, 0, 1, 0, 0)	(1, 1)
Worst Case	(0, 0, 1, 0, 0, 0, 0, 1)	(1, 1)

5. Conclusion

In this study, a stochastic multi-objective genetic algorithm (SMOGA) is proposed for the new facility location decisions problem in closed-loop supply chain under uncertainty. The novelty of the paper is that integrated forward and reverse streams are designed to simultaneously minimize supply chain total cost and maximize customer's satisfaction. The total cost includes transportation cost, installation cost of regional, central and collection/inspection facilities, inventory and backorder cost. In order to increase the dynamism and responsibility of supply chain, the model takes seasonal fluctuations into consideration for multiple products. The solution approach applies the weighted sum method to handle the complex multi objective optimization problem.

Ambitious results of the stochastic model establish that the proposed approach is valid to be applied for decision making under uncertainty. It is resulted that although the variations of data in forward and reverse network significantly affects the quality of solutions, the stochastic model can guarantee the optimal or near optimal solution under these variations.

As future work, it is recommended to implement a new heuristics approach which provides more efficient and effective solutions for the mentioned problem. Another research can be considering production operations and design decisions in facility location process. Incorporating supply chain configuration decisions in early product design phase provides optimal operation management such as optimal modular design, material selection and manufacturing process.

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