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LOCATION ALLOCATION PLANNING OF LOGISTICS DEPOTS USING GENETIC ALGORITHM

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Abstract Location planning of logistics depots and customer allocation are important decisions in supply chain network design. A carefully planned network design positively impacts the economics of business organizations and their competitivity in national and international markets. In this paper, we present a genetic algorithm based approach for solving location allocation planning problem of logistics depots. The problem is solved considering multiple criteria such as minimal distance, travel cost, travel time etc. A numerical application is provided to demonstrate the proposed approach.

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1. INTRODUCTION

Location planning of logistics depots and customer allocation are important decisions in supply chain network design. A carefully planned network design positively impacts the economics of business organizations and their competitivity in national and international markets. Improper planning can lead to poor service quality towards customers, long delivery times, and high investment and maintenance costs for the logistics operators, which is detrimental to their business operations and profitability.

In this paper, we address the problem of location allocation planning of logistics depots. The *Location-allocation* (LA) problem involves locating an optimal set of facilities to satisfy customer demand at minimal transportation cost from facilities to customers (Love et al, 1988). Numerous approaches have been developed over years to solve the location allocation problem which can be mainly classified into a) Exact approaches, b) Data analysis, c) Simulation, d) Muticriteria decision analysis, e) Heuristics, f) Metaheuristics, g) Hybrid approaches or combinations of the above.

The exact approaches or the mathematical programming approaches involve the use of techniques such as linear programming, integer programming, multiobjective optimization etc. to arrive at optimal solutions. Exact solution methods for LA have been investigated by Drezner (1984), Brimberg and Revelle (1998), Arora et al (1998), and Fazel-Zarendi and Beck (2009).

The data analysis techniques perform inspecting, cleaning, transforming, and modeling data with the goal of highlighting useful information, suggesting conclusions, and supporting decision making. Data analysis techniques for LA problem have been studied by Hsieh and Tien (2004), and Barreto et al (2007). Simulation techniques are used for describing the behavior, constructing theories or hypotheses, and applying these theories to predict future behavior of systems (Banks, 1998). Simulation for LA problem has been investigated by Armour and Buffa (1965), and Canbolat and van Massow (2011). The multicriteria decision making involves evaluation of a set of alternatives using a pre-defined set of criteria by a committee of decision makers or experts. Examples of MCDA techniques are AHP, ANP, TOPSIS, SAW etc. MCDA techniques for LA problem have been studied in Freek (1999), Fortenberry and Mitra (1986) , and Doerner et al (2009).

Heuristics methods yield good solutions at reasonable cost and can be used for providing good initial solutions in other optimizing methods (Anand and Knott, 1986). Heuristics approach for the location allocation problem have been studied by Cooper (1964), and Gamal and Salhi (2001). A metaheuristic is an approach used for optimization by iteration in the neighborhood of solution space. Examples of metaheuristics are simulated annealing, tabu search, genetic algorithms etc. Zhou et al. (2003) use genetic algorithm approach for allocation of logistics depots to customers. Murray and Church (1996) apply simulated annealing for location allocation problem. Tabu search for location allocation problems was investigated by Ohlemüller (1997). Chan and Kumar (2009) apply multi ant colony optimization approach for customers allocation.

Some hybrid algorithms have been also suggested, such as the one based on simulated annealing and random descent method (Ernst and Krishnamoorthy 1999) and the one utilizing the Lagrange relaxation method and genetic algorithm (Gong et al. 1997). Abdinnour-Helm (1998) developed a hybrid heuristic based on *Genetic Algorithms* (GAs) and *Tabu Search* (TS) for the uncapacitated hub location problem. Chen (2007) proposes hybrid heuristics based on simulated annealing, tabu list, and improvement procedures for the uncapacitated single allocation hub location problem. Location-allocation problem is a NP-hard problem (Azarmand & Neishabouri, 2009). In literature, metaheuristics have shown to perform better than exact programming approaches to tackle larger NP-hard problems. Therefore, we pro-pose to use *Genetic Algorithms* (GA) to solve the location allocation problem. The rest of the paper is organized as follows. In section 2, we present the problem definition. The solution approach is presented in Section 3 followed by a numerical example in section 4. The model verification and validation are presented in sections 5 and 6 respectively. Finally, we conclude in section 7.

2. PROBLEM DEFINITION

Let us consider a logistics network comprising of i, (i=1,2,..,m) facilities/depots and j (j=1,2,..,n) customers. The maximum number of depots is denoted by m and the maximum number of customers is denoted by n. The cost of opening a facility i is denoted by c_i and its capacity by b_i. The demand for customer j is given by d_j. The distance between depot i and customer j is given by d_{ij}, travel cost by c_{ij}, and travel time by t_{ij}. The binary variable y_i is 1 if facility i is opened, otherwise it is set equal to 0. Similarly, binary variable x_{ij} is equal to 1 if customer j is allocated to depot i and is set equal to 0 in the contrary case. The quantity of goods transported between i and j (if they are connected) is given by q_{ij}. The goal is to minimize the total costs, that is, opening costs of facilities and delivery costs of goods to customers from logistics depots. The delivery cost for customers is a weighted function of travel distance (d_{ij}), travel cost (c_{ij}) and travel time (t_{ij}) where the weights of travel distance, travel cost and travel time are represented by w_1, w_2 and w_3 respectively. Since, the facility opening costs, travel distance, travel time, travel costs etc. are in different units, they are normalized before being used in the objective function. Let us denote the normalized values of c_i, d_{ij}, c_{ij} and t_{ij} by $c_i^{'}, d_{ij}^{'}, t_{ij}^{'}, c_{ij}^{'}$ where $c_i^{'} = c_i / \sum c_i, d_{ij}^{'} = d_{ij} / \sum d_{ij}, t_{ij}^{'} = t_{ij} / \sum t_{ij}, c_{ij}^{'} = c_{ij} / \sum c_{ij}$. Using the normalized values $c_i^{'}, d_{ij}^{'}, t_{ij}^{'}, c_{ij}^{'}$, the mathematical formulation of the problem is presented as follows:

Objective:
Minimize

$$\sum_{j=1}^{n} y_i * c_i^{'} + \sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij} * (w_1 * d_{ij}^{'} + w_2 * t_{ij}^{'} + (1 - w_1 - w_2) * c_{ij}^{'}) \quad (1)$$

s.t

$$\sum_{i=1}^{m} x_{ij} = 1, \forall j \in 1,2,..,n \quad (2)$$

$$\sum_{i=1}^{m} q_{ij} x_{ij} = d_j, \forall j \in 1,2,..,n \quad (3)$$

$$\sum_{j=1}^{n} q_{ij} x_{ij} \le b_i y_i, \forall i \in 1,2,..,m \quad (4)$$

$$x_{ij} \in \{0,1\}$$

$$y_i \in \{0,1\}$$

$$q_{ij} \ge 0$$

It can be seen from (1) that the objective function comprises of multiple factors such as facility opening costs ($c_i^{'}$), travel distance ($d_{ij}^{'}$), travel cost ($c_{ij}^{'}$) and travel time ($t_{ij}^{'}$). Equation (2) ensures that each client is served by exactly one facility. Equation (3) shows the demand satisfaction constraint of the customers. Equation (4) shows the capacity restriction constraints for the logistics depots. The facility location selection variable x_{ij} and the customer allocation variable to logistics facilities y_i are binary. The quantity allocations q_{ij} are non-negative real numbers.

3.SOLUTION APPROACH

The capacitated location allocation problem treated in this paper is multiobjective in nature. Since all the functions are of minimization type in the objective function (1),we have used the weighted sum method (Marler & Arora, 2009). The weights of the objective functions can be obtained using multicriteria decision making approaches such as AHP. Before applying the weighted sum method, we normalize all the factors used in the model to bring them to a common unit to avoid discrepancies of scale. If s_{ij} represents an element of matrix $S_{m \times n}$ where i=1,2,..,m and j=1,…,n, then the normalized values a_{ij} is obtained using $aij = s_{ij}/\sum(s_{ij})$.

Our solution approach is based on Genetic Algorithms, a kind of stochastic search and optimization technique based on principles from evolution theory.

Goldberg (1989) defines genetic algorithm as a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions, search and optimize better solution from neighborhood of solution space. The various steps of the genetic algorithm as applied for location allocation problem are presented as follows:

Representation Scheme

The representation scheme for the chromosome is a *n*-bit string where *n* represents the number of customers. A non-zero value for the i^{th} bit implies that a depot is allocated to that customer. If a depot is not present in the string, it implies that this depot was not opened or closed for non-feasibility reasons (allocation of zero customers). Let us consider a network comprising of 21 customers and 7 logistics depots. The representation of an individual chromosome (solution) is illustrated as follows:

Case (a)

Customers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Logistics depots	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	7	7	7

Case (b)

Customers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Logistics depots	1	6	2	3	5	3	1	4	2	2	2	2	6	4	3	3	3	4	2	1	3

Using case (a), we can say that logistics depot 1 is allocated to customers (1,2,3), logistics depot 2 to customers (4,5,6), etc. On analyzing results for case (b), we see that logistics depot 1 is allocated to customers (1,7,20), logistics depot 3 to (4,6,15,16,17,21). However, in case (b) the logistics depot 7 is absent which means it was not opened for the reasons of zero allocation of customers.

Fitness Function

The fitness function is same as eqn (1) for multifactor subject to constraints (2-4).

Parents Selection Procedure

To select the parents for crossover, we have chosen the ranking method, that is, picking the best individuals every time.

Crossover Operator

We chose the one-point cross-over in our approach which involves randomly generating one cross-over point and then swapping segments of the two parent chromosomes to generate two child chromosomes.

Mutation Operator

Mutation is applied to each child after crossover by selecting randomly one of the customers in the child chromosome and allocating to another logistics facility picked at random.

Replacement population method

The incremental replacement method is used for population replacement. In this method, the newly generated child solutions are put back into the original population to replace the “less fit” members. The average fitness of the population increases as child solutions with better fitnesses replace the less fit solutions ("incremental replacement"). Note that when replacing a solution, care must be taken to avoid duplicate solutions from entering the population as it will severely limit the GAs ability to generate new solutions.

Population size

The performance of GA is influenced by the population size. Small populations run the risk of seriously under-covering the solution space, while large populations are computationally intensive (Jaramillo et al, 2002). Alander (1992) suggests that a value between *n* and 2*n* is optimal for the problem type considered, where *n* is the length of a chromosome. In our case, we chose a population size equal to *n* which is equal to the number of customers in the LA problem.

3.1. High level pseudocode for GA

1. Set iteration counter $t = 0$.
2. Generate the initial population, *P(t),* randomly.
3. Evaluate fitness of the population *P(t)* using the objective function.
4. While (number if iterations t <= Maximum value) or (improvement in objective function value <= 10^{-5}) do

4.1. Set $t= t+ 1$

4.2. Select two solutions P1 and P2 from the population using the ranking method.

4.3. Apply genetic operators to P1 and P2

4.3.1. If crossover, then combine P1 and P2 using single point crossover to generate offspring O1.

4.3.2. If O1 is identical to any of its parents, then apply mutation operator to the parent with the best fitness to form a offspring O1.

4.3.3. Evaluate the fitness of the new child set using the objective function

4.3.4. If fitness of chromosome is improved or objective value is reduced (in case of minimization) then utilize the incremental replacement method to create P(t) and update population size.

5. Stop. Print final results.

4. NUMERICAL APPLICATION

Let us consider the input data for location allocation problem using multiple factors "distance", "time" and "cost" for a logistics network comprising of 7 logistics depots (D1, D2… D7) and 21 customers (C1, C2 … C21). The distance and time matrix, customer demands, depot opening costs and depot capacities are presented in Table 1.

Table 1 Time and Cost matrix

Cus	Depots					(T,C)		Dem
	D1	D2	D3	D4	D5	D6	D7	
C1	1.0,2.9	4.83,3.2	3.00,3.5	2.7,3.14	5.0,3.15	3.0,3.0	2.1,2.1	120
C2	3.0,3.9	2.88,4.0	2.86,4.3	3.3,3.62	4.9,3.60	4.1,4.1	5.8,5.8	200
C3	4.6,3.5	3.76,3.6	3.74,3.5	4.2,3.14	6.1,3.12	3.6,3.6	4.8,4.8	80
C4	3.4,3.5	3.10,3.6	3.28,3.6	3.3,3.19	4.4,3.17	2.6,3.6	4.9,4.9	110
C5	4.0,3.3	3.38,3.4	3.24,3.0	4.2,2.99	6.0,3.07	3.4,3.4	4.6,4.6	130
C6	13.3,3.3	3.4,3.4	3.1,3.1	3.04,3.04	3.63,3.13	8.5,3.5	4.0,4.7	90
C7	3.1,3.1	3.3,3.3	3.8,3.8	3.31,3.31	3.28,3.28	3.9,3.2	1.8,1.8	140
C8	7.2,2.5	3.3,2.9	2.8,3.0	2.88,2.83	2.97,3.00	3.3,2.7	9.4,3.0	170
C9	2.7,3.2	3.0,3.3	7.1,3.0	2.92,2.88	3.0,2.86	2.8,3.3	2.7,4.1	90
C10	2.9,4.0	4.0,4.1	8.4,4.6	2.47,3.76	2.65,3.74	2.9,4.2	3.5,6.1	115
C11	1.5,3.1	2.6,3.3	3.5,3.4	6.30,3.10	3.38,3.28	3.7,3.3	5.2,4.4	100
C12	2.7,3.1	3.0,3.4	3.0,4.0	2.6,3.38	3.1,3.24	3.2,3.2	2.6,2.0	125
C13	3.6,2.8	9.7,3.0	5.8,3.2	3.28,2.95	3.2,3.04	4.3,2.8	6.8,2.5	85
C14	3.0,3.0	3.2,3.2	8.6,3.6	3.18,3.18	2.7,3.03	3.0,3.0	8.1,2.3	180
C15	3.1,3.1	3.2,3.2	3.4,2.6	3.1,2.74	3.04,2.82	3.13,3.2	3.5,4.1	130
C16	3.2,3.2	13.3,3.3	1.3,2.8	13.8,2.88	13.31,2.97	3.28,3.3	3.2,4.4	95
C17	6.7,2.7	13.0,3.0	0.3,3.1	6.8,2.92	2.88,3.05	2.97,2.8	7.3,2.7	175
C18	2.92,2.9	3.05,3.0	23.0,2.4	3.1,2.47	2.92,2.65	3.05,2.9	2.8,3.5	150
C19	8.47,3.5	2.65,3.6	3.0,3.5	12.4,3.30	12.47,3.38	2.65,3.7	2.9,5.2	190
C20	3.30,2.7	3.38,3.0	3.6,3.2	3.5,2.96	3.30,3.14	3.38,3.0	3.7,3.5	95
C21	9.96,3.6	8.14,3.7	3.0,3.8	3.2,3.28	2.96,3.27	23.1,3.7	3.2,5.1	160
Cap	800	800	1100	1000	700	1100	900	
OC	14	21	17	15	25	13	22	

T: Time, C: Cost, Cap: Capacity, Dem: Demand, Cus; Customer, OC: Opening Cost

Using $w_1=0.2$, $w_2=0.3$, and $w_3=1-w_1-w_2$, the total objective function values obtained are presented in Table 2.

Figure 1 presents the results obtained from the proposed Genetic algorithm.The blue color dots (middle curve) shows the normalized facility opening cost values and the green colored dots (lower curve) show the normalized multifactors used for customer allocation to logistics facilities. The red colored dots (upper curve) represent the total value of the objective function. It can be seen that the results for costs and distance stabilize over time (4854673 iterations) after which the best values of objective function (1.1182) for opening logistics depots and customer allocations are said to have been obtained.

Table 2 Normalized objective function values

Customers	Depots						
	D1	D2	D3	D4	D5	D6	D7
C1	0.0052	0.0068	0.0068	0.0058	0.0066	0.0067	0.0039
C2	0.0066	0.0068	0.0071	0.0062	0.0074	0.0071	0.0109
C3	0.0071	0.0067	0.0065	0.0061	0.0067	0.0061	0.0090
C4	0.0066	0.0066	0.0066	0.0070	0.0066	0.0059	0.0092
C5	0.0066	0.0062	0.0058	0.0069	0.0060	0.0063	0.0086
C6	0.0094	0.0066	0.0061	0.0066	0.0064	0.0082	0.0086
C7	0.0057	0.0060	0.0091	0.0062	0.0063	0.0065	0.0049
C8	0.0061	0.0056	0.0056	0.0053	0.0055	0.0054	0.0077
C9	0.0055	0.0058	0.0079	0.0056	0.0058	0.0063	0.0111
C10	0.0082	0.0069	0.0090	0.0075	0.0073	0.0075	0.0107
C11	0.0054	0.0058	0.0083	0.0067	0.0062	0.0063	0.0085
C12	0.0053	0.0059	0.0066	0.0070	0.0060	0.0079	0.0039
C13	0.0059	0.0078	0.0070	0.0060	0.0091	0.0057	0.0071
C14	0.0063	0.0059	0.0078	0.0048	0.0056	0.0056	0.0061
C15	0.0058	0.0060	0.0051	0.0053	0.0054	0.0063	0.0075
C16	0.0060	0.0098	0.0048	0.0087	0.0088	0.0062	0.0070
C17	0.0063	0.0098	0.0050	0.0066	0.0072	0.0071	0.0067
C18	0.0071	0.0057	0.0107	0.0048	0.0052	0.0056	0.0058
C19	0.0081	0.0054	0.0064	0.0078	0.0091	0.0066	0.0104
C20	0.0053	0.0058	0.0073	0.0057	0.0057	0.0058	0.0053
C21	0.0081	0.0083	0.0075	0.0061	0.0062	0.0144	0.0083

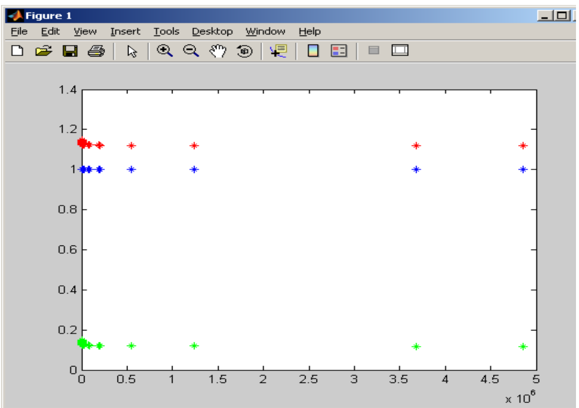

Fig. 1 Convergence of GA result

Figure 2 provides the difference between the initial and final solution obtained using GA for the multifactor case. It can be seen that all logistics depots are opened and allocated to customers using the proposed GA.

Fig. 2 GA model results

Customers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Depots (Initial solution)	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	7	7	7
Depots (final result)	7	4	4	6	2	3	7	5	5	6	5	7	1	2	5	3	1	4	2	7	5

5.CONCLUSIONS

In this paper, we address the problem of location allocation planning of logistics depots. A genetic algorithm based approach is proposed. The advantage of the proposed approach is that it supports multi-objective optimization, can be applied to new problems with exploratory type of solutions, always improves solutions over time, and can be easily parallelized or distributed. The limitations include careful selection of chromosomes, cross-over and mutation operators to generate better results over time. If they are not carefully planned, there is risk of getting trapped into local optima and the algorithm may involve high computational times for generating final results. The next step of our work involves testing of proposed approach on real life problem instances and solving capacitated location allocation under stochastic demand.

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