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# A Metaheuristic Algorithm for Optimizing Strategic and Tactical Decisions in a Logistics Network Design Problem

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#### Abstract

Todays, industries are seeking the ways to improve their competitiveness and responsiveness in order to achieve the most share of markets and customer satisfaction. Optimization of strategic and tactical decisions in a logistics network would improve total performance of the supply chain in a long term planning horizon. This paper presents a Mixed-integer linear programming (MILP) model to optimize logistics networks under real limitations such as demand, capacity, and budget constraints. Due to NP-hard nature of the proposed model a Differential Evolutionary (DE) algorithm is proposed to solve the large sizes of the presented model in reasonable time. Finally, the computational results obtained through the DE algorithm are compared with the solutions obtained by GAMS optimization software. The results reveal that the proposed methodology is an efficient tool to optimize large scale logistics networks.

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## INTRODUCTION

One of the vital challenges for organizations in today's competitive markets is the need to respond to customer needs which are very volatile and can be occurred in volume and variety of customer needs (Amir, 2011). Supply chain management integrates interrelationships between various entities through creating alliance, such as information-system integration and process integration between entities to improve response to customers in various aspects such as higher product variety and quality, lower costs and faster responses. Logistics network design decisions, as the most important strategic and tactical decisions in supply chain management, concerned with complex interrelationships between various tiers including suppliers, manufacturers, distribution centers and customer zones as well as determining the number, location and capacity of facilities to meet customer needs, efficiently (Babazadeh et al., 2012).

Regarding the strategic decisions issues, both opening and closing a facility as a strategic decision, is a time-consuming and costly process. Therefore, changing facility location is impossible in the short time. On the other hand, determining the material flow between network nodes as a tactical decision is more flexible to change in short time and usually happen in real world (Pishvaee et al., 2009). Due to impossibility of changing locations of facilities in the short time, the logistics network should be designed in an efficient and optimum way. Mathematical programming approach is one of the well-known approaches recognized to model and optimize different real world problems.

One of the main challenges of this approach is that these models may be not solvable through exact algorithms such as Benders decomposition, Branch and Bound and available optimization software for large cases in the real world (Hosseini Nasab, 2015). Also, finding optimum solution for some NP-hard problems may need several years which make it inapplicable for solving the problems. To deal with the computational complexity of the real world optimization problems, many researchers and practitioners have proposed efficient heuristic and meta-heuristic algorithms to solve the large size problems in reasonable computational time.

The logistics network design problem is computationally complex problem and categorized in NP-hard class (Gen et al., 2006). In the literature, finding optimum solution for this problem through developing heuristic, metaheuristic and exact algorithms has been agenda. Exact algorithms, such as Lagrangian relaxation (Amiri, 2006) and Benders decomposition (Üster and Agrahari, 2011), provide global optimum solutions. Meanwhile, their computational efficiency is significantly reduced in real large-sized problems. Also, implementing exact solution methods in many problems is really a difficult task and their successful implementation needs strong knowledge about mathematics. In contrast, heuristic or meta-heuristic algorithms provide local optimum solutions in very low computational time. Many researchers have reported the efficiency of heuristic based algorithms in achieving good quality solutions in reasonable time.

The efficiency of meta-heuristic algorithms is dependent upon a solution representation method (Lotfi and Tavakkoli-Moghaddam, 2013). A good solution representation method should be feasible and its feasibility is not violated when applying the operators of different meta-heuristic algorithms. The better solution representation approach leads to speedy convergence of the algorithm to optimal or near-optimal solutions and also decreases the used memory. The logistics network design problem is subject to many realistic limitations such as demand satisfaction, material flow balance and capacity. Therefore, emerging infeasible solutions in this problem are inherent when evolutionary algorithms are applied. To deal with the infeasible solutions, three methods including repairing, discard, and penalty approaches are used in the literature (Gen et al., 2006). These methods increase computational time and used memory in solution procedure of the problem.

The best solution representation for different meta-heuristic algorithms is the one considering the problem structure so that infeasibility of the solution is avoided in all iterations when different operators of the algorithm are applied. Considering the structure of the logistics network design problem, five solution representation methods including matrix-based representation (Michalewicz et al., 1991), basic feasible solution representation (Liu et al., 2008), direct transportation tree representation (Eckert and Gottlieb, 2002), spanning tree based representation by a Prüfer number (Gen and Cheng, 2000), and priority-based representation (Gen et al., 2006) have been proposed. Advantageous and disadvantageous of these methods have concisely been discussed by Lotfi and Tavakkoli-Moghaddam (2013). Notably, the superiority of the prioritybased encoding scheme compared to other mentioned methods has been investigated in the literature by researchers and practitioners (Pishvaee et al., 2010). Differential evolutionary (DE) algorithm is one of the well-known heuristic algorithm which have been efficiently applied in various optimization problems (Das et al., 2016).

In this paper, a MILP model is proposed to design the logistics networks under real limitations such as demand satisfaction, capacity and budget. The objective function of the model is to minimize total costs including opening facilities in different tiers, and transportation costs. Since the proposed model is categorized in NP-hard class, an efficient DE algorithm is proposed to deal with the computational challenges of the model. Due to the mentioned constraints of the model, the solution of the DE algorithm may be violated when applying the operators of the algorithm. To confront this problem, we propose a prioritybased encoding scheme for solution representation. By this way, all produced solutions by the algorithm will remain feasible in all iterations of the algorithm. The main contributions of this paper that differentiates it from the available works in the literature include:

• Proposing a DE algorithm to optimize logistics network design problem,

• Using priority-based encoding scheme to avoid infeasible solutions in DE algorithm.

The remainder of this paper is presented as follows. The related works are reviewed in Section 2. Section 3 includes the description and formulation of the proposed model. The proposed DE algorithm and solution representation method are described in Section 4. Section 5 reports the computational experiments. Finally, Section 6 presents some concluding remarks and offers some directions for further research.

### LITERATURE REVIEW

In this section, the related literature of logistics network modelling and its optimization through application of different heuristic or metaheuristic algorithms are reviewed. Although many efficient heuristic and metaheuristic algorithms such as genetic algorithm (Wang and Hsu, 2010), memetic algorithm (Pishvaee et al., 2010), scatter search (Du and Evans, 2008), and simulated annealing (Subramanian et al., 2013) have been proposed in the literature of logistics networks optimization, there is still a need to develop variants of these algorithms to deal with the real and large size problems.

Tiwari et al. (2010) presented a MILP model to optimize strategic and

tactical decisions in a multi-echelon logistics network. They proposed a hybrid Taguchi-immune system metaheuristic approach, in which a chromosome is composed of location and transportation decisions. Venkatadri et al. (2012) demulti-objective veloped a stochastic programming model for supply chain design under uncertainty. They used simulated annealing algorithm to optimize the strategic and tactidecisions of the proposed model. cal Rajabalipour et al. (2013) presented a multi-objective, multi-stage and flexible model to design a logistics network with the aim of minimizing response time and cost criteria. An efficient multi-objective evolutionary algorithm based on genetic algorithm (GA) was proposed. Bing et al. (2014) developed a case-based MILP model for sustainable a reverse logistics network aimed to recycle household plastic waste. The objective is to minimize the overall transportation cost and environmental impact. Govindan et al. (2015) proposed a hybrid multi-objective algorithm based on the adapted multi-objective electromagnetism mechanism algorithm and adapted multiobjective variable neighborhood search to solve a sustainable supply chain network design problem under demand uncertainty. Trivedi et al. (2016) presented a hybrid algorithm based on GA and DE approaches for solving a unit commitment problem which is a nonlinear, high-dimen-

sional, highly constrained, and mixed-integer optimization problem. Lieckens and Vandaele (2016) presented an advanced resource planning model to optimize the lot size decisions in stochastic supply chain systems. They used DE algorithm to solve the proposed non-linear model. Babazadeh et al. (2017) extended a multi-objective MILP model to design the logistics network under uncertainty. Their model minimizes total costs and environmental impacts as objective functions. They proposed a new fuzzy mathematical formulation to deal with the uncertain parameters of the model. Eskandarpour et al. (2017) proposed a neighborhood search algorithm to solve a four-layer single period multi-product supply chain network design problem. Also, they used a greedy algorithm to optimize material flow within the network.

## MATHEMATICAL FORMULATION OF THE PROPOSED MODEL

The proposed model to design logistics networks is a MILP model which integrates strategic facility location decisions with tactical transportation decisions within the structure of the three-layer logistics network. The echelons of the logistics network include: manufacturers, warehouses and customer zones. The echelons are linked together with a forward shipment of products and backward flow of information in a pull system. In the proposed model, as illustrated in Figure 1, the finished goods are produced in the manufacturers and are shipped to the warehouse centres. Then, the products are shipped to the customers according to their demands.

The aim is to determine the optimum number and location of facilities in different echelons among candidate locations and optimum material flow between facilities of the configured logistics network.

The main assumptions used in the problem formulation are as follows:

• Customer zones are known and fixed with deterministic demand.

• Fixed cost of opening facilities and transportation costs are known and deterministic.

• The potential location of facilities (i.e., manufacturers and warehouses) are known, but the best locations for opening facilities should be determined among these potential locations.

• The capacity of each candidate facility is known and fixed.

• The capacities of facilities are limited.

• The number of facilities that can be established in different echelons are restricted due to budget limitation.



Fig.1. The structure of the considered logistics network

The following indices, parameters, and variables are used in formulation of the mathematical model:

Indices

- i Set of manufacturers (i=1,..,I)
- j Set of warehouses (j=1,..,J)
- k Set of customer zones (k=1,..,K)

**Parameters** 

- dk Demand of customer zone k
- Fixed cost of opening plant *i* Ci
- Fixed cost of opening warehouse *j* Qj

Transportation cost of unit product shipyij ment from plant i to warehouse *j* 

Transportation cost of unit product shipδjk ment from warehouse i to customer k

Capacity of plant *i* capi

Capacity of warehouse *j* caj

Maximum number of warehouses which Vcan be opened

U Maximum number of plant which can be opened

## Variables

Amount of products transported from xij plant i to warehouse *j* 

Amount of products transported from vik warehouse i to customer zone k

ui 1 if plant i is opened at potential location *i*: 0 otherwise

1 if warehouse *j* is opened at potential lovi cation *j*; 0 otherwise

According to the above-mentioned descriptions, the mathematical model can be presented as follows:

$$\operatorname{Min} Z = \sum_{i} C_{i} u_{i} + \sum_{j} Q_{j} v_{j} + \sum_{i} \sum_{j} \gamma_{ij} x_{ij} + \sum_{j} \sum_{k} \delta_{jk} y_{jk}$$
(1)

Subject to:

$$\sum_{j} y_{jk} \ge d_k \qquad \forall k \tag{2}$$

$$\sum_{i} x_{ij} = \sum_{k} y_{jk} \qquad \forall j \tag{3}$$

$$\sum_{j} x_{ij} \le cap_i u_i \qquad \forall i \tag{4}$$

$$\sum_{j} y_{jk} \le c a_j v_j \qquad \forall j \tag{5}$$

$$\sum_{j=1}^{k} v_j \leq V$$
(6)

$$\sum_{i=1}^{J} u_i \le U \tag{7}$$

$$u_i, v_j \in \{0, 1\} \tag{9}$$

Objective function (1) minimizes the total costs including opening costs of plants and warehouses and transportation costs from manufacturers plants to warehouses and then from warehouses to customers. Constraint (2) ensures that demand of customers is fulfilled and shortage is not permissible. Constraint (3) is a balance constraint at warehouses. This constraint insures that all products received from manufacturers are shipped to customers. Constraints (4) and (5) consider capacity limitations for manufacturers and warehouses, respectively. If a facility is not opened in a specific location, its related capacity would be zero. Constraints (6) and (7) satisfy that the opened manufacturers and warehouses do not violate their upper bounds. These constraints are considered due to budget limitations. Constraints (8) and (9) consider non-negative and binary restrictions for variables.

## **SOLUTION METHOD: DE ALGORITHM**

The proposed model for optimization of strategic and tactical decisions is a NP-hard problem and therefore developing an efficient solution method which could provide optimal or near optimal solutions in reasonable time is highly interested. In this section, we propose a DE metaheuristic algorithm to solve the proposed model. We use priority based encoding scheme for solution representation to avoid infeasible solutions when initializing and applying the operators of the DE algorithm.

Differential Evolution (DE) is one of the most powerful and efficient evolutionary algorithms for optimizing different optimization problems with discrete and continuous solution spaces (Das et al., 2016). The DE was proposed by Storn and Price (1997) to find the global optimum of non-linear, non-convex, multi-modal and nondifferentiable functions defined in the continuous parameter space. The standard DE algorithm includes four basic steps: initialization, mutation, recombination or crossover, and selection. After initialization of the parameters, the other three steps are repeated till a termination criterion is satisfied. At the following the steps of the algorithm are summarized (Das et al., 2014; 2016).

#### Initialization

The DE starts with a randomly initiated population of Np d-dimensional real-valued decision vectors. Each vector called genome/chromosome, is a solution to the multi-dimensional optimization problem. Assume that each iteration of the algorithm is denoted by  $t=0,1,...,t_{max}$ . Also, each d-dimensional vector i in each iteration is represented as follows:

$$x_{i}^{t} = \left(x_{i,1}^{t}, x_{i,2}^{t}, \cdots, x_{i,d}^{t}\right)$$
(10)

For each decision variable, the random values are generated within their minimum and maximum values as follows:

$$x_{\min} = \left(x_{\min,1}, x_{\min,2}, \cdots, x_{\min,d}\right) \quad (11)$$

$$x_{\max} = \left(x_{\max,1}, x_{\max,2}, \cdots, x_{\max,d}\right) \quad (12)$$

Therefore, the  $j^{th}$  component of the  $i^{th}$  decision vector in initial population (i.e., iteration 0) could be randomly generated within related ranges as follows:

$$x_{i,j}^{(0)} = x_{\min,j} + rand_{i,j}[0,1](x_{\max,j} - x_{\min,j})$$
(13)

Where  $rand_{i,j}[0,1]$  is a uniformly distributed random number lying between 0 and 1. In this paper, we use priority based encoding scheme for initialization population and feasible solution creation.

#### **Mutation operator**

Mutation operator explores among the chromosomes of the created population to create mutants. After creating initial population, randomly, the mutation operator is applied on the target vector  $x_i^{(l)}$  to create corresponding mutant vector  $v_i^{(l)}$ . There are some mutation strategies in the literature (Das et al., 2016). In this paper, we use the following mutation strategy:

$$v_i^{(t)} = x_{best}^{(t)} + F\left(x_{R_1^i}^{(t)} - x_{R_2^i}^{(t)}\right) \quad (14)$$

The indices  $R_1^i$  and  $R_2^i$  are mutually exclusive integers randomly chosen from the population and all are different from the base index *i*. The scaling factor *F* is a positive control parameter for scaling the difference vectors. Its value is between 0 and 1. We consider F=0.8. *xbest*<sup>(t)</sup> is the best individual vector with the best fitness in the population at iteration *t*.

#### **Crossover operator**

Crossover operator exploits solution space i.e. the chromosomes of the population to create new offspring vectors. The crossover operator creates the trial/offspring vector  $u_i^{(t)}$  through mixing the mutant vector  $v_i^{(t)}$  with target vector  $x_i^{(t)}$ . In this paper, binomial crossover is applied on

each of the *d* variables whenever a randomly generated number between 0 and 1 is less than or equal to the crossover rate (*CR*). We consider CR=0.6. The following equation describe the scheme of offspring production.

$$u_{i,j}^{(t)} = \begin{cases} v_{i,j}^{(t)} & if \ j = k \ or \ rand_{i,j}[0,1] \le CR \\ x_{i,j}^{(t)} & Otherwise . \end{cases}$$
(15)

#### Selection

The selection operator determines whether the target vector  $x_i^{(t)}$  or the offspring vector  $u_i^{(t)}$  survives to the next iteration. The following equation describes the selection operation:

$$x_{i}^{(t+1)} = \begin{cases} u^{(t)} & \text{if } f(u^{(t)}) \leq f(x_{i}^{(t)}), \\ x_{i}^{(t)} & Otherwise. \end{cases}$$
(16)

Where f(.) is the objective function to be optimized.

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Fig. 2. The flowchart of the DE algorithm

Fi. 2 shows the flowchart of the DE algorithm used to solve the considered logistics network design problem. The maximum iteration achievement is considered as a stopping criterion.

#### Solution representation method

A good solution representation method has great influence on the performance of the evolutionary algorithm. The solution representation method is different for different problems. A priority-based solution representation method proposed by Gen et al. (2006) is so compatible with the structure of the logistics network design problem. By this method, the produced solutions remain feasible under applying different operators of evolutionary algorithms. Other solution representation methods such as matrix based representation needs repairing mechanism to produce feasible solutions (Pishvaee et al., 2010). In other methods, a lot of time is spent for checking and eliminating infeasible solutions.

In this method, solutions are encoded as arrays of size |I|+|J|, in which the location of each cell within the structure of the solution represents the sources and depots and the value of each cell indicates the priority of the node for making a tree among candidates. In the proposed logistics network design model, assume there are two plants, three distribution centers, and four customer zones (see Fig. 3). The demands of customers, capacity of warehouses and plants have been shown in this figure.



Fig. 3. General structure of the logistics network

The matrices A and B show the transportation costs for the first and second segments, respectively.

$$A_{(2\times3)} = \begin{bmatrix} 7 & 13 & 12 \\ 9 & 11 & 14 \end{bmatrix}, \quad B_{(3\times4)} = \begin{bmatrix} 8 & 16 & 14 & 15 \\ 13 & 11 & 15 & 12 \\ 12 & 13 & 16 & 10 \end{bmatrix}$$

To apply the priority based solution representation method, firstly the second segment is selected. In the second segment, there are three sources (warehouses) and four depots (customer zones). Then, priorities of nodes are defined from 1 to 7. The priorities in a solution are randomly generated. The node with the highest priority is selected and the amount of its link is determined through related transportation costs, demands and capacities. Fig. 4 illustrates how the decision variables related to material flow of the second segment of the logistics network presented in Fig. 3 are calculated through this representation method.

							Depot			
Depot						400	300	250	350	
so	urce	600	400	300	e.	600	400		200	
	700	600		100	nrc	400		300	50	50
- J	600		400	200	So	300				300
First segment						S	Second	l segm	ent	

Fig. 4. Material flow calculation by priority based method

It is worthy to note that if the material flow from/to a node is assigned, the corresponding binary variable of that node would be equal to 1, otherwise its value is set to 0.

## **COMPUTATIONAL EXPERIMENTS**

To evaluate the performance and efficiency of the proposed DE algorithm in solving the logistics network design problem, 10 numerical examples are produced in small, medium, and large sizes. The parameters are deterministic and have been randomly generated from the data available in literature (Pishvaee et al., 2009; 2010). Table 1 shows the size of different test problems generated to evaluate the performance of the proposed DE algorithm.

The proposed DE algorithm is coded in Matlab 2012 optimization software. Also, the proposed model is coded in GAMS 23.5 optimization software and solved by a CPLEX algorithm, which provides a global optimum solution.

Table 2 indicates the best results achieved by the proposed DE algorithm and solutions achieved by GAMS software (exact solution). The number of iterations of each algorithm is considered to be 30, and the best result of all iterations is reported for each algorithm. Also, the number of population in each iteration is as-

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sumed to be 100. The last column of Table 2 shows the gap between the solutions of the proposed DE algorithm and the solutions achieved by exact algorithm. The following relation is used for gap calculation:

$$GAP = \frac{Exact \ solution - DE \ solution}{Exact \ solution}.$$

Problem No.	<b> I</b>	<b>J</b>	<b>K</b>
P1	2	5	12
P2	2	4	10
P3	4	8	20
P4	3	10	18
P5	3	9	22
P6	4	7	15
P7	4	9	26
P8	5	8	28
P9	5	7	25
P10	5	10	30

Table 1: Characteristics of the test problems

Table 2: Comparison of the DE algorithm results with exact solution

Problem No.	Exact Solution	<b>DE Solution</b>	GAP
P1	44215340	44216838	3.39E-05
P2	43863090	43864645	3.55E-05
P3	69585120	69622437	0.000536
P4	60991940	61006422	0.000237
P5	87327850	87474751	0.001682
P6	52585730	52639256	0.001018
P7	96711330	96735903	0.000254
P8	97255040	97268227	0.000136
Р9	88977260	88981096	4.31E-05
P10	103089700	103098444	8.48E-05



Fig. 5 illustrates the convergence of the DE algorithm for solving test problem P9 in 30 iterations.

The results show that the proposed DE algorithm is a suitable optimization tool to find optimum or near optimum solutions in logistics network design problem. The good results for the applied algorithms could be explained due to using priority-based solution representation method which does not need any repairing mechanism when mutation and crossover operators are applied. The computational times for all runs of the DE algorithm are under several minutes. Evidently, several minutes run time for optimizing strategic and tactical decisions in logistics network design problem is negligible.

## **CONCLUDING REMARKS**

Increasing the competitiveness and customer satisfaction importance have put pressure on organizations to design or redesign their logistics networks. Logistics network design is a powerful modelling approach which significantly reduces total costs of the network and improves supply chain responsiveness and competitiveness. In this paper, firstly a MILP model is proposed to optimize strategic and tactical decisions of logistics network design problem. Then, an efficient DE algorithm as a powerful metaheuristic algorithm is proposed to solve the proposed model for real and large sizes. We apply priority based solution representation method to create feasible solutions in the algorithm. By this method, the produced solutions remain feasible under applying all operators of the algorithm. Computational results justify the efficiency and applicability of the proposed approach in optimizing strategic and tactical decisions of logistics network design problem. Also, it could be concluded that priority based method for solution representation has great impact on the performance of the metaheuristic algorithms in optimization of supply chain and logistics problems.

For the future, the following researches may be followed up by researchers and practitioners. The proposed model could be studied under uncertainty of cost parameters and demands. Also, considering environmental impact minimization would lead to a multi-objective logistics network optimization problem and therefore there would be a need for developing multi-objective evolutionary algorithms. The efficiency of prioritybased encoding scheme compared to other solution representation methods could be investigated in the future.

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