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Case Report

Optimization of transportation channels in supply chain design Using Genetic Algorithm

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ABSTRACT
A supply chain is a set of facilities, supplies, customers, products and methods of controlling inventory, purchasing, and distribution. Each manufacturer or distributor has some subset of the supply chain that it must manage and run profitably and efficiently to survive and grow. So it is important that goods produced and delivered at the right quantities and at the right time while minimizing costs as well as satisfying customer requirements. According to reasons, optimization of supply chain network involves decisions over several aspects. This paper addresses a problem of designing a multi-echelon supply chain with the single sourcing type and the related inventory systems. In the first echelon the manufacturers transport the product to distribution centers. In the second echelon the distribution centers transport the product to the customers. In this work, the optimal solution of a supply chain networking is obtained by using the non-traditional technique such as genetic algorithm which was performed to solve the problem. Designing the entire supply chain network becomes a key factor for the successful business.

Keywords: minimizing costs, distributers, Supply chain network, and genetic algorithm.

1. INTRODUCTION
Traditionally, marketing, distribution, planning, manufacturing, and purchasing organizations along the supply chain operated independently. These organizations have their own objectives and these are often conflicting. But, there is a need for a mechanism through which these different functions can be integrated together. Supply chain management (SCM) is a strategy through which such integration can be achieved.

Managing a supply chain is very different from managing one site. Activities at the various sites have complex interrelationships. A large amount of literature on Supply Chain Management places great emphasis on integration of different components of the chain. Finding the right strategy that is optimal across the entire supply chain is a huge challenge (Quinn 2000; Simchi-Levi et al. 2001).

Design and optimization of supply chain configuration is a problem at the highest level, the strategic level. Supply chain configuration design consists of deciding on the facility location, stocking location, production policy (make-to-stock or make-to-order), production capacity (quantity and flexibility), assignment of distribution resources and transportation modes while imposing standards on the operational units for performance excellence. Therefore, the aim of supply chain configuration optimization is to find the best or the near best alternative configuration with which the supply chain can achieve a high level of performance (Truong &Azadivar 2003).

One of the important factors of the total productivity and profitability of a supply chain is to consider its distribution network, which can be used to achieve the various supply chain objectives.

In this paper we address a supply chain design problem, based on a two-echelon single-product system. The problem considers the location of facilities, the selection of transportation channels and the calculation of the flows between facilities. Therefore, solving large-sized problems is not possible by linear programming using ordinary operational research software in a reasonable time. A genetic algorithm (GA) has unique characteristics compared to other meta-heuristic methods.

The following advantages have been added in the revised paper (Goldberge, 1989),

- A genetic algorithm (GA) works with the coding of the parameter set, not the parameters themselves.
- It uses probabilistic transition rules, not deterministic rules.
- It trades-off between exploration and exploitation.
- It is capable of working with any kinds of the objective functions and constraints in linear and/or non-linear forms within any solution space (discrete or continuous).

Consequently, it is applied in this paper with respect to the model complexity. It is a bio-inspired algorithm taken from the nature and it is also one of the most popular meta-heuristics, which is applied in many optimization problems with different functions (F Forouzanfar and R Tavakkoli-Moghaddam, 2012)

2. Literature review

Today, integrated planning is finally possible due to advances in information technology, but most companies still have much to learn about implementing new analytical tool needed to achieve it. In order to stay competitive and continue to survive they need to be their competitors. World class organizations now realize that non-integrated manufacturing process, nonintegrated distribution process and poor relationship with suppliers and customers are inadequate for their success (Danalakshmi&Kumar)

The review by Current et al. (1990) makes evident that the balance of these criteria had not been studied extensively. After that, Arntzen et al. (1995) addressed the supply chain design problem for a company that handled the cost-time tradeoff as a weighted combination in the objective function. The decision variable was the quantity of productto be sent through each transportation mode available. Transportation time was variable with respect to the quantity shipped. The problem was solved using elastic penalties for violating constraints, and a row-factorization tech- nique. Zeng (1998) emphasized the importance of the lead time-cost tradeoff, associated to the transportation modes available between pairs of nodes in the network. A mixed-integer program- ming model was proposed to design the supply chain optimizing both objectives. In this work facility location was not addressed. The method proposed was a dynamic programming algorithm to construct the efficient frontier assuming the discretization of time. In the model proposed by Graves and Willems (2005) cost and time were combined in the objective function. The supply chain was configured selecting alternatives at each stage of the production and distribution network. A dynamic programming algorithm was used to solve this problem.

In recent years multiobjective problems in supply chain design have been treated with more emphasis taking advantage of increased computational resources and new methods. Chan et al. (2006) presented a multi-objective model that optimized a combined objective function with weights. Some of the criteria included cost and time functions, and one of the components of time was transportation time. Transportation time varied linearly with the quantity transported. The model included stochastic components, but facility location was not considered. A genetic algorithm was the base of an iterative method where scenarios with changingweights were solved. Altiparmak et al. (2006) proposed a model with three objective functions: to minimize total cost, to maximize total customer demand satisfied, and to minimize the unused capacity of distribution centers. Here, transportation time was handled as a constraint that determined a set of feasible distribution centers able to deliver the product to the customer before a due date. They proposed a procedure based on a genetic algorithm to obtain a set of non-dominated solutions. In the work by ElMaraghy and Majety (2008) a model was proposed to optimize cost, including the cost of late delivery. The model considered the dynamic nature of the decisions. They used commercial optimization software to solve the model, analyzing different scenarios. The review by Farahani et al. (2010) about multi-criteria models for facility location problems describes some works where metrics of cost and service level are considered. The metaheuristic methods mentioned include multi- objective versions ofScatter Search, Tabu Search, Simulated Annealing, Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO). However, some other metaheuristics that were created for multiobjective applications were also mentioned, like Simple Evolutionary Algorithm for Multi- Objective Optimization (SEAMO), Strength Pareto Evolutionary Algorithm version 2 (SPEA2), Pareto Envelop based Selection Algorithm (PESA), Non-dominated Sorting Genetic Algorithm II (NSGA-II), Vector Evaluated Genetic Algorithm (VEGA), and the Multi-Objective Genetic Algorithm (MOGA).

More recently, several works have appeared for multiobjective supply chain design. Pishvaee et al. (2010) studied a model for a forward/reverse logistics network design from a bi-objective optimization perspective. The objectives to optimize were the total cost of the system and the fullfillment of the demand and return rates. Although they considered lead time into their model, similar to Altiparmak et al. (2006) it was considered in the meeting of a due date, and not related to transportation alter- natives. They developed a memetic algorithm to solve this NP- hard problem. Moncayo-Martinez and Zhang (2011) proposed a model similar tothat of Graves and Willems (2005) where activities must be selected to design the supply chain. This was a bi-objective model that optimized cost and lead time in a multi- echelon network. The decision variable is the selection of the resource for a certain activity in the supply chain. They used a Pareto Ant Colony Optimization metaheuristic to obtain the Pareto Optimal Set. Liao et al. (2011) also studied a multiobjective problem for supply chain design. In this case they integrated location and inventory decisions. The objectives were the mini- mization of cost, the maximization of the fill rate, and the maximization of demand fulfilled within a coverage distance. The lead time was implied in the cost of the safety stock, but it was not related to transportation decisions. The method proposed was a hybrid of NSGA-II and an assignment heuristic. Pinto-Varela et al. (2011) presented a bi-objective optimization model for the design of supply chains considering economic and environmental criteria. In their model, time was considered since the point of view of a multi-period approach. Different transportation modes may exist, but they are not associated to the time. They solved three small examples with mathematical programming commercial software. The review by Mansouri et al. (2012) emphasized the importance of multiobjective optimization techniques as decision support tool in supply chain management. Although order promising decisions and network design decisions were identified as important criteria, none of the works reviewed integrated them in a multiobjective approach. Chaabane et al. (2012) presented a multi-period multiobjective optimization problem where cost and environmental objectives were opti- mized. In their mixed-integer programming model, the selection of transportation modes was considered as a decision variable but it was not connected with time. They used mathematical programming commercial software to solve small instances of the problem. Sadjady and Davoudpour (2012) studied a problem for supply chain design where cost and time were tied to transportation alternatives. The approach, however, was to opti- mize a single objective function where lead time from the transportation alternative was transformed into a cost function. The cost objective function is optimized using a Lagrangian relaxation method. As proposed by Olivares-Benitez et al.(2012), the cost and time criteria may not be comparable and should be treated in separate objectives(Sohrabi et al, 2015).

It is important to highlight some works that solve real cases for supply chain design. Altiparmak et al. (2006) applied their genetic algorithm for a supply chain design for plastic products in Turkey. Pati et al. (2008) solved a case for the Indian paper recycling industry. Sousa et al. (2008) applied their models for the design of an agrochemicals supply chain. Gumus et al. (2009) solved the case for a company in the alcohol free beverage sector. Moncayo-Martinez and Zhang (2011) applied a Pareto Ant Colony Optimization metaheuristic to design a supply chain for Bulldozer production. Pinto-Varela et al. (2011) presented a bi-objective model for designing supply chains in Portugal. Chaabane et al. (2012) solved a case for aluminum production. Funaki (2012) proposed a very complete model and a dynamic programming algorithm to design a supply chain for a machinery product. Marvin et al. (2012) formulated a mixed integer linear program- ming problem to design a supply chain for ethanol biorefining. Paksoy et al. (2012) applied fuzzy optimization for the design of a vegetable oil supply chain. These works illustrate an increasing interest in the application of supply chain design models in industry.

Finally, it is interesting to note the review by Griffis et al. (2012) where they presented the use of metaheuristics in logistics and supply chain management from year 1991 to 2012. Near 15% of the applications were in the area of supply chain design. They highlight the use of Simulated Annealing and Tabu Search among local search metaheuristics, with minor attention in the literature to greedy randomized adaptive search procedure (GRASP), vari- able neighborhood search (VNS) and others. In terms of popula- tion search techniques, the most popular have been Genetic Algorithms and Ant Colony Optimization, with fewer mentions for Scatter Search, Particle Swarm Optimization, and others. However in this review it is evident the few applications of multiobjective metaheuristics, especially for supply chain design problems.

The research described above shows that few works consid- ered the cost-time tradeoff derived from the transportation channel selection in the supply chain design. Other differences with the problem addressed in this research are explained in the following lines.

First, in some works the transportation time is a linear function ofthe quantity transported. In the model presented here, a single time is used for each arc between nodes, which represents more real conditions in the operation of transportation. Second, in many studies the time-cost tradeoff has been addressed from a single objective perspective transforming the time in a cost function. Here, the time and cost are treated as separate criteria allowing forthe construction of sets of non-dominated solutions. This approach may be a good choice when the preference of the decisionmaker forone of the objectives is not known, or when the criteria cannot be compared easily. Third, in many multiobjective problems for supply chain design, the cost-time tradeoff was not associated to the selection of the transportation channel. In the problem addressed here, the selection of transportation from several alternatives has a direct impact inthe leadtime objective. The combination of theseelements andtraditional supply chain design decisions makes relevant the problem addressed, and the necessity to solve it.

3. Problem description and mathematical model

The problem introduced by Olivares-Benitez et al. (2012) was a two-echelon distribution system for one product in a single time period. A set of manufacturing plants produce and send the product to distribution centers in the first stage. Later, the distribution centers transport the product to the customers. The number and location of plants and customers, along with demands and capacities respectively, are known. The distribution centers must be selected from a discrete set of potential locations with fixed opening costs and limited capacities. A single sourcing policy was assumed for the transportation from the distribution centers to the customers. Fig. 1 depicts the structure of the supply chain.

The transportation of the product from one facility to the other in each echelon of the network is done selecting one of several alternatives available. Each transportation channel represents a type of service with associated cost and time parameters. These alternatives can be obtained from offers of different companies, the availability of different types of service for each company (e.g. Express and regular), or the use of different modes of transportation (e.g. Truck, rail, airplane, ship or inter-modal). It was assumed that a faster service is usually more expensive. The capacity of the transportation channel was assumed as unlimited, considering that any capacity can be contracted.

A bi-objective mixed-integer programming model was proposed to solve the problem described previously, as follows. Sets:

K : set of plants k

J : set of potential distribution centers j

I : set of customers i

Plants(k) potential customers (i) distribution centers (j)

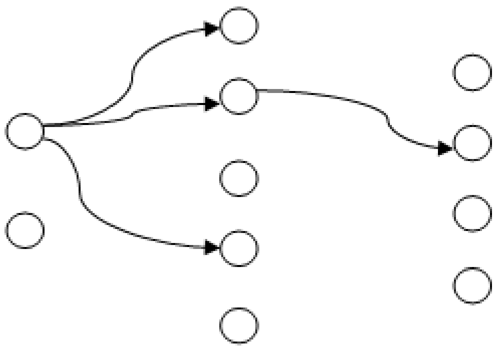


Fig. 1. Single product, single period, and two-echelon distribution system.

Each transportation channel has a unitary cost (a_{ji}, b_{kj}) associated.

Parameters:

b_{kj} : Cost of transporting one unit of product from plant (k) to distribution center (j); $k \in K$, $j \in J$

a_{ji} : Cost of sending one unit of product from distribution center (j) to customer (i); $j \in J$, $i \in I$

P_k : Capacity of plant (k); $k \in K$

D_j :capacity of distribution center (j); $j \in J$

R_i : Demand of customer (k); $k \in K$

Decision variables:

y_{kj} : Quantity transported from plant (k) to distribution center (j); $k \in K$, $j \in J$

x_{ji} : Quantity transported from distribution center (j) to customer (i); $j \in J$, $i \in I$

Model:

Min(f)

$$f = \sum_k \sum_j b_{kj} y_{kj} + \sum_j \sum_i a_{ji} x_{ji} \qquad (1)$$

Subject to:

$$\sum_j x_{ji} \geq R_i \qquad i \in I \qquad (2)$$

$$\sum_i x_{ji} \leq D_j \qquad j \in J \qquad (3)$$

$$\sum_j y_{kj} \leq P_k \qquad k \in K \qquad (4)$$

$$\sum_k y_{kj} = \sum_i x_{ji} \qquad j \in J \qquad (5)$$

$$x_{ji}, y_{kj} \geq 0 \qquad k \in K, j \in J, i \in I \qquad (6)$$

In this model, objective function Eq.(1) minimizes the sum of the transportation cost. Constraints Eq.(2) force the demand satisfaction for each customer. Constraints Eq. (3) the flow going out from a distribution center must not exceed its capacity. Constraints Eq. (4) imply that the capacities of the plants are not exceeded. Constraints Eq. (5) keep the flow balance at each distribution center and Constraints Eqs. (6) are for declaration of variables.

About the computational complexity of the problem, it has been demonstrated that the well-known UFLP (Uncapacitated Fixed-Charge Facility Location Problem) is polynimially reducible to the model described above (Olivares-Benitez et al., 2012). Since the UFLP is NP-hard (Cornuejols et al., 1990), the model above is NP-hard too.

4. Metaheuristic method

The genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness” (i.e., minimizes the cost function). The method was developed by John Holland (1975) over the course of the

1960s and 1970s and finally popularized by one of his students, David Goldberg, who was able to solve a difficult problem involving the control of gas-pipeline transmission for his dissertation (Goldberg, 1989).

4.1 Proposed genetic algorithm

In this work we used roulette wheel as selection mechanism. The basic part of the selection process is to stochastically select from one generation to create the basis of the next generation. The requirement is that the fittest individuals have a greater chance of survival than weaker ones. This replicates nature in that fitter individuals will tend to have a better probability of survival and will go forward to form thémating pool for the next generation. Weaker individuals are not without a chance. In nature such individuals may have genetic coding that may prove useful to future generations.

We also used crossover and mutation as operators. The crossover is done to explore new solution space and crossover operator corresponds to exchanging parts of strings between selected parents. Similar to crossover, mutation is used to prevent the premature convergence and explore new solution space. However, unlike crossover, mutation is usually done by modifying gene within a chromosome. And all the constraints were modeled by penalty function.

beta=10;
FinalCost=TotalCost*(1+beta*Violation);

4.1Performance evaluation of the algorithm

In order to evaluate the performances of the GA on SCN design problem with single objective we considered original problem.The problem and its objective functionis listed below:

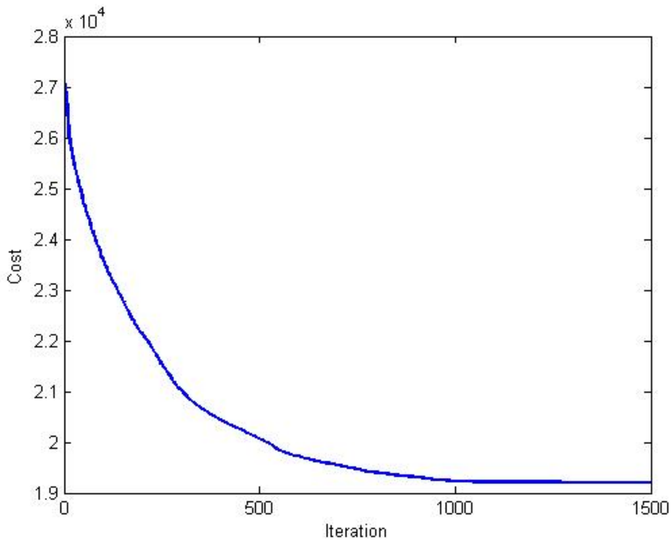
Problem: min*f*

The proposed algorithm was coded with Matlab programming language and run on Pentium 4, 2.8 GHz clock pulse with 512 MB memory. GA runsover 10 times considering following parameters: population size = 500; crossover rate = 0.8 , mutation rate = 0.8and number of generation = 1500.These parameters had been determined after experiments.

Numerical results are summarized in Tables

Table 1. 2 Plants to 5Distributers in problem size 2-5-20

		K1		K2	
capacity		cost per unit	best	cost	best
J1	170	16	0.0000	14	132.3538
J2	151	22	0.0000	16	62.3067
J3	176	24	0.0000	12	175.9999
J4	178	14	0.0000	12	174.3429
J5	171	12	170.9967	23	0.0000



Iteration

Chart 1. Rate of convergence

Table 2. 5Distributers to 20Customers in problem size 2-5-20

		J1		J2		J3		J4		J5	
capacity		cost per unit	best	cost per unit	best	cost per unit	best	cost per unit	best	cost per unit	best
I1	43	22	0.0000	30	0.0000	15	0.0001	31	0.0000	10	42.9999
I2	47	18	0.0003	11	20.2694	13	26.7302	35	0.0000	31	0.0000
I3	15	19	0.0005	39	0.0000	11	14.9976	23	0.0001	21	0.0018
I4	47	33	0.0001	34	0.0001	15	46.9927	25	0.0001	23	0.0071
I5	35	30	0.0000	31	0.0000	33	0.0000	18	34.9999	31	0.0000
I6	13	30	0.0000	15	0.0363	13	12.9636	25	0.0000	39	0.0000
I7	21	20	0.0171	28	0.0001	16	13.3885	33	0.0000	17	7.5942
I8	32	25	18.1916	31	0.0001	37	0.0000	39	0.0001	26	13.8082
I9	49	14	48.9985	14	0.0002	17	0.0000	36	0.0000	17	0.0012
I10	49	35	0.0001	17	0.0001	38	0.0000	20	0.0000	16	48.9998
I11	16	17	15.9984	29	0.0001	24	0.0000	20	0.0015	35	0.0000
I12	49	28	0.0001	27	0.0001	38	0.0000	18	48.9998	33	0.0000
I13	49	33	0.0000	21	0.0000	27	0.0000	12	19.3412	11	29.6587
I14	29	26	0.0000	34	0.0000	38	0.0000	14	28.9999	27	0.0001
I15	42	24	0.0000	10	41.9997	20	0.0001	15	0.0002	34	0.0000
I16	15	19	0.0552	26	0.0001	15	14.0360	28	0.0002	18	0.9085
I17	27	30	0.0000	31	0.0000	33	0.0000	23	0.0001	12	26.9998
I18	47	17	0.1089	38	0.0000	14	46.8909	35	0.0000	26	0.0001
I19	42	40	0.0000	12	0.0003	23	0.0000	13	41.9997	39	0.0000
I20	49	10	48.9829	34	0.0000	35	0.0000	36	0.0000	12	0.0171

K	J	I	Iteration	Optimize cost	Runtime (sec)
2	5	20	1500	19,188.00	456"
2	5	50	1500	45,085.00	529"
5	10	50	3500	37,869.00	1293"
5	10	100	4500	78,890.00	1988"

Table 3. Numerical Results

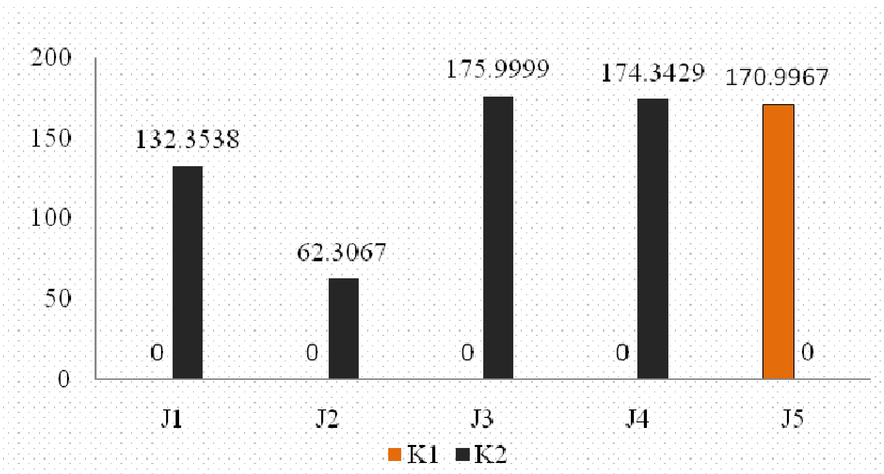


Chart 2. The amount ofincominggoodstodistributorsJ1-J5 fromplant K1,K2

The approach developed here provides companies the opportunity to design their supply chains, not only by optimizing their own internal operations, but also by examining and improving the entire supply chain's performance. The new optimization approach is designed to be robust and general. Thus the supply chain discussed in this section must be a typical one that includes several manufacturing/assembling stages for a product line from very beginning raw materials to finished products. Many suppliers/manufacturers contribute to the production process. At the downstream of the supply chain, the distributor stores finished products at its central warehouses and delivers them to retail stores. The objective of the supply chain configuration design optimization problem is to minimize the overall system widecost whiles the customer service at retailer stores is kept at a pre-specified level. The decision variables of this optimization problem are the two variables mentioned above.

5 CONCLUSIONS

The process of supply chain management involves decisions over several aspects. The most treated decisions in the literature are facility location, transportation flows, production levels, supplier selection, and inventory levels. In the present study, an evolutionary algorithm (GA) is used for optimization of transportation flows in a multilayer supply chain problem. Transportation flows are supposed to be continuous variables in the optimization process. Presented supply chain problem includes two plants, five distribution centers and twenty customers. As shown in column charts, all the arcs between plants and distribution centers are not necessarily used in transportation flow of supply chain. For example, fewer than 50 percent of possible flow arcs in every distribution center are used for complete transportation of products between distribution centers and customers. For plant number one (K_1), just one of the possible flow arcs is used for transportation of products. In other words, selection of plants and distribution centers are dependent to the transportation unit cost of products between plants and distribution centers and also distribution centers and customers. These unit costs are affected by many factors such as location of plants and distribution centers, type of transportation of products between them and etc. The optimization process is well done by genetic algorithm to address the optimum solution of supply chain problem.

6 REFERENCES

1. Altiparmak, F., Gen, M., Lin, L., Paksoy, T., 2006. A genetic algorithm approach for multi-objective optimization of supply chain networks. Computers & Industrial Engineering 51, 196–215.
2. Arntzen, B.C., Brown, G.C., Harrison, T.P., Trafton, L.L., 1995. Global supply chain management at Digital Equipment Corporation. Interfaces 25 (1), 69–93.
3. Chaabane, A., Ramudhin, A., Paquet, M., 2012. Design of sustainable supply chains under the emission trading scheme. International Journal of Production Economics 135 (1), 37–49.
4. Chan, F.T.S., Chung, S.H., Choy, K.L., 2006. Optimization of order fulfillment in distribution network problems. Journal of Intelligent Manufacturing 17 (3), 307–319.
5. Current, J., Min, H., Schilling, D., 1990. Multiobjective analysis of facility location decisions. European Journal of Operational Research 49 (3), 295–307.
6. ElMaraghy, H.A., Majety, R., 2008. Integrated supply chain design using multi-criteria optimization. International Journal of Advanced Manufacturing Technology 37 (3), 371–399.
7. Farahani, R.Z., SteadieSeifi, M., Asgari, N., 2010. Multiple criteria facility location problems: a survey. Applied Mathematical Modelling 34 (7), 1689–1709.
8. Forouzanfar, F., Tavakkoli-Moghaddam, R., 2012. Using a genetic algorithm to optimize the total cost for a location-routing-inventory problem in a supply chain with risk pooling. Journal of Applied Operational Research4(1), 2–13.

9. Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley.
10. Graves, S.C., Willems, S.P., 2005. Optimizing the supply chain configuration for new products. Management Science 51 (8), 1165–1180.
11. Holland, J.H., 1975. Adaptation in Natural and Artificial Systems. Ann Arbor: University of Michigan Press.
12. Liao, S.-H.,Hsieh, C.-L.,Lai,P.-J.,2011.Anevolutionaryapproachfor multiobjective optimizationoftheintegratedlocation-inventorydistribution network problem in vendor-managedinventory.ExpertSystemswithApplications 38(6),6768–6776.
13. Mansouri, S.A., Gallear, D., Askariazad, M.H., 2012. Decision support for build-to-order supply chain management through multi-objective optimization. Inter national Journal of Production Economics 135 (1), 24–36.
14. Moncayo-Martinez, L.A., Zhang, D.Z., 2011. Multi-objective ant colony optimisation: a meta-heuristic approach to supply chain design. International Journal of Production Economics 131 (1), 407–420.
15. Olivares-Benitez, E., Gonzalez-Velarde, J.L., Rios-Mercado, R.Z.,2012.Asupply chain designproblemwithfacilitylocationandbi-objectivetransportation choices. TOP20(3),729–753.
16. Olivares-Benitez, E., Rios-Mercado, R.Z., Gonzalez-Velarde, J.L., 2013. A metaheuristic algorithm to solve the selection of transportation channels in supply chain design. International Journal of Production Economics 145, 161–172.
17. Pishvaee, M.S., Farahani, R.Z., Dullaert, W., 2010. A memetic algorithm for bi-objective integrated forward/reverse logistics network design. Computers and Operations Research 37 (6), 1100–1112.
18. Pinto-Varela, T.,Barbosa-Povoa, A.P.F.D.,Novais,A.Q.,2011.Bi-objectiveoptimization approachtothedesignandplanningofsupplychains:economicversus environmental performances.ComputersandChemicalEngineering35(8), 1454–1468.
19. Quinn, F. J. 2000. The Master of Design: An Interview with David Simchi-Levi. Supply Chain Management Review, 74-80.
20. Sadjady, H., Davoudpour, H., 2012. Two-echelon, multi-commodity supply chain network design with mode selection, lead-times and inventory costs. Computers and Operations Research 39 (7), 1345–1354.
21. Sohrabi. Abolfazl, Pourbijan. Farrokh, Asayesh. Kourosh (2015) Comparison Analysis of Attitude to Change in Knowledge-Based and Non-Knowledge-Based Organization, Bulletin of the Georgian National Academy of Sciences, vol:8, no:2.
22. Truong, T.H., Azadivar, F., 2003. Simulation based optimization for supply chain configuration design. Proceedings of the 2003 Winter Simulation Conference S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.
23. Zeng, D.D., 1998. Multi-issue Decision Making in Supply Chain Management and Electronic Commerce. Ph.D. Dissertation. Graduate School of Industrial Administration and Robotics Institute, Carnegie Mellon University, Pittsburgh, USA, December.