Journal of Optimization in Industrial Engineering
Vol.14, Issue 2, Summer & Autumn 2021, 129-135
DOI: 10.22094/JOIE.2020.1866273.1648

Research Article

Solving a Multi-Item Supply Chain Network Problem by Three Meta-heuristic Algorithms

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Received 04 April 2019; Revised 03 March 2020; Accepted 06 June 2020

Abstract

The supply chain network design not only assists organizations production process (e.g., plan, control and execute a product's flow) but also ensure what is the growing need for companies in a long term. This paper develops a three-echelon supply chain network problem including multiple plants, multiple distributors, and multiple retailers with a multi-mode demand satisfaction policy inside of production planning and maintenance. The problem is formulated as a mixed-integer linear programming model. Because of its NP-hardness, three meta-heuristic algorithms (i.e., tabu search, harmony search and genetic algorithm) are used to solve the given problem. Also, the Taguchi method is used to choose the best levels of the parameters of the proposed meta-heuristic algorithms. The results show that HS has a better solution quality than two other algorithms.

Keywords: Supply chain network design; Multi-mode demand; Tabu search; Harmony search; Genetic algorithm.

1. Introduction

A network is a series of equipment or subsystems that play key roles in supply chain development. In the supply chain network, there are producers of raw materials and product-making factories, distributing centers and customers. Costs in the network include two types. The first type of costs includes the costs of building factories and distribution centers and the second type includes the costs of producing, distributing and maintenance the goods in each phase of the supply chain network. Chandra and Fisher (1994) considered a plant that produces several products over time and maintains an inventory of finished goods at the plant. Flipo (2000) presented a hierarchical scheme, which decomposes a global industrial problem into several sub-problems. A model for these sub-problems was developed based on an analogy to the vehicle routing problem (VRP). To solve the single-product multi-stage supply chain network design (SCND) problem, Altiparmak et al (2006) proposed a multi-objective mixed-integer non-linear programming (MINLP) model.

Lun and Vairaktarakis (2007) considered an integrated scheduling and distribution model to minimize the sum of the delivery cost and customers' waiting costs. Manzini and Bindi (2009) proposed a mixed-integer linear programming (MILP) model with a multi-echelon and multi-level production/distribution system with a cluster analysis. Longinidis and Georgiadis (2011) proposed an MILP problem that enchases a financial statement analysis through financial ratios and demand uncertainty through a scenario analysis. Amorim et al. (2012) formulated two intertwined planning problems at an operational level through a multi-objective framework, in which perishable goods have a fixed and a loose shelf-life. Ruimin et al (2015) investigated the forward and reverse supply chains model with multi-plants, collection centers and demand zones. Fattahi et al (2015) illustrated a multi-product supply chain network, in which customer zones have price-sensitive demands.

Bahrampouret al (2016) presented a three-phase multi-product supply chain model. Ardalan et al (2016) presented the SCND model with a multi-mode demand satisfaction policy, in which some modes were defined by customers. Pawar and Nandurkar (2018) addressed a procedure for finding the optimum combination of a reorder point of each product for each buyer, number of shipments of each product to each buyer for a single-vendor multi-buyer inventory model. Badri et al (2017) developed a two-stage stochastic programming model for the value-based SCND. Parkinson and Thompson (2003) defined maintenance as a series of actions taken during the use of a product to enable it to the function at predetermined levels during its economic lifetime. A supply chain system has rapidly been developing during these decades. Within this advancement, maintenance becomes an important supporting factor. Preventive maintenance (PM) is one of the maintenance strategies to prevent incipient failures.

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Yeh et al (2011) developed two periodical PM policies to decrease the high failure rate of the second-hand products. PM has many different variations and is the subject of various researches to determine the best and most efficient way to maintain equipment. It has the following meanings: (1) the care and servicing by personnel to maintain equipment and facilities in a satisfactory operating condition by providing for systematic inspection, detection, and correction of incipient failures either before they occur or before they develop into major defects; (2) maintenance, including tests, measurements, adjustments, and parts replacement, performed specifically to prevent faults from occurring (Mehdizadeh and AtashiAbkenar, 2014). Eduardo et al (2017) proposed a method, which aims to integrate information provided by intelligent maintenance systems into the operational planning of a spare parts supply chain. Sasitharanand Lazim (2018) studied the effect of PM practices and supply chain management (SCM) in improving manufacturing performance. In overall, this study finds that the PM is greater than SCM in traditional manufacturing in optimizing their end-to-end operations to achieve greater cost savings and product delivery.

Kalinowski et al (2019) considered the annual planning of maintenance for Australia's largest coal rail network. The current planning approach used the concept of a maintenance access window (MAW), which provides a train-free time windows across geographically contiguous track locations that define a maintenance zone. They introduced a mixed-integer programming (MIP) model, which facilitates the planning of different maintenance resources across this network to schedule MAWs. Tirkolaee et al (2019) addressed a multi-echelon capacitated location-allocation-inventory problem under uncertainty by providing a robust MILP model considering production plants at level one, central warehouses at level two, and the retailers at a level three to design an optimal supply chain network. Zhen et al (2019) presented an integration perspective for developing a green and sustainable closed-loop supply chain (CLSC) network under uncertain demand. A bi-objective optimization model was proposed with two objectives for $Co2$ emissions and total operating cost.

The multi-stage logistic network considered in this paper consists of three stages: plants, distribution centers and retailer locations. The problem deals with determining the optimal transportation network with PM to satisfy the retailer multi-mode demands of several products. Thus, this paper addresses a three-echelon supply chain structure including multiple plants, multiple distributors, and multiple retailers with a multi-mode demand satisfaction policy inside of production planning and maintenance.

The remaining of this paper is organized as follows: Section 2 describes a production and supply chain network model with PM. Explanation of the solution approach presented in Section 3. Tuning the parameters and computational results are shown in Section 4. Section 5 provides concluding remarks and some future directions.

2. Mathematical Model

The logistics network discussed in this paper is a three-echelon supply chain structure including multiple plants, multiple distributors, and multiple retailers. In the network shown in Fig. 1, new products are shipped from the plants to the distribution centers through direct (i.e., shipped from plants to distribution centers and then to retailers) routes to meet the demand of each retailer.

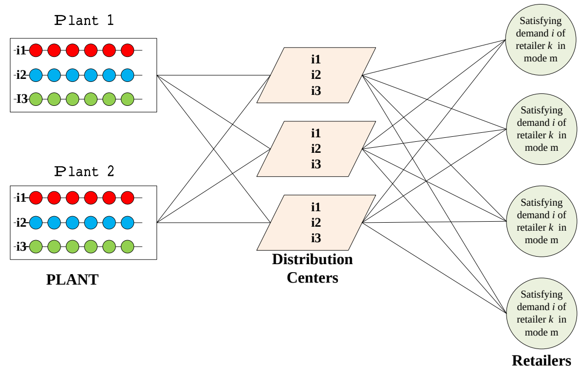

Fig. 1. Structure of the logistics network

The process or control of the equipment failure can have adverse results in both human and economic terms. Therefore, PM is a very important ongoing accident prevention activity, which you should integrate into operations/ product manufacturing process. In this section, we present an MILP model for the multi-product, multi-stage supply chain network with the maintenance with a multi-mode demand satisfaction policy.

2.1. Assumptions

The assumptions of the proposed model are as follows:

- ✓ The demand modes and location of retailers are known in advance.
- ✓ For each retailer, only one demand mode can be satisfied by distribution centers.
- ✓ Locations of plants and distribution centers are a selection from candidate options.
- ✓ Plants and distribution centers are capacitated.
- ✓ If maintenance is not performed in period t, the time and cost of maintenance will not apply to the model, the failure costs will be considered in period $t+1$ instead, and downtime will be deducted from the available machine capacity.

2.2. Indices

i	Index of product, $i= \{1, 2,\ldots,I\}$.
j	Index of distribution centers, $j= \{1, 2,\ldots, J\}$.
k	Index of retailers, $k= \{1, 2,\ldots,K\}$.
m	Index of mode satisfaction, $m= \{1, 2,\ldots,M\}$

t Index of periods, $t = \{1,2,\ldots,T\}$
n Index of machines, $n = \{1,2,\ldots,N\}$
f Index of plants, $f = \{1,2,\ldots,F\}$.

2.3. Parameters

Prc_{it}	Sale price of each unit of product i in period t.
Vcp_{int}	Variable production cost of product i on machine n in period t
D^m_{ikt}	amount demand of product i from retailer k in mode m in period t
CCP_{ft}	Fixed costs of establishing plant f in period t
$CCDC_{jt}$	Fixed cost of establishing distribution center j in period t
CPW_{ifjt}	Shipping cost of one unit product i between plant f to distribution center j in period t
CWR_{ijkt}	Shipping cost of one unit product i between distribution center j to retailer k in period t
CP_{fit}	Capacity of plant f to the production of product i in period t
CW_{ijt}	Capacity of distribution center j of product i in period t
CB_{nt}	Failure cost of machine n in period t
CM_{nt}	Cost of service to maintenance of machine n in period t
M	A large number
MT_{nt}	Time of maintenance on machine n in period t
K_{nt}	Percentage of the capacity of machine n, lost during period t (due to lack of maintenance in the previous period) due to failure
E_{in}	Time required for the machine n to produce a unit of product i

2.4. Decision variables

X_{ifjt}	Total products i transported from plant f to distribution center j in period t
Y_{ijkt}	Total products i transported from distribution center j to retailer k in period t
R^m_{ikt}	1 if demand i of retailer k is satisfied in mode m in period t; 0, otherwise
W_{jt}	1 if distribution center j is established in period t; 0, otherwise
PM_{nt}	PM decision variable on machine n in period t, a binary variable.
P_{ft}	1 if plant f is established; 0, otherwise

2.5. Proposed model

The objective of this problem is to maximize the profit, which is mathematically written by:

$$\text{Max } Z = \sum_i \sum_t \sum_k \sum_m \left(\left(Prc_{it} - \sum_n Vcp_{int} \right) D^m_{ikt} R^m_{ikt} \right) - \left[\begin{array}{l} \sum_f \sum_t CCP_{ft} P_{ft} + \sum_j \sum_t CCDC_{jt} W_{jt} \\ + \sum_i \sum_f \sum_j \sum_t CPW_{ifjt} X_{ifjt} \\ + \sum_i \sum_j \sum_k \sum_t CWR_{ijkt} Y_{ijkt} \\ + \left(\sum_n \sum_{t=2} CB_{nt} (1 - PM_{n,t-1}) \right) \\ + \left(\sum_n \sum_t^{T-1} CM_{nt} . PM_{nt} \right) \end{array} \right] \tag{1}$$

s.t.

$$\sum_m R^m_{ikt} = 1 \qquad \forall i,k,t \tag{2}$$

$$\sum_j Y_{ijkt} = \sum_m R^m_{ikt} D^m_{ikt} \qquad \forall i,k,t \tag{3}$$

$$\sum_f X_{ifjt} \geq \sum_k Y_{ijkt} \qquad \forall i,j,t \tag{4}$$

$$\sum_k Y_{ijkt} \leq CW_{ijt} . W_{jt} \qquad \forall j,i,t \tag{5}$$

$$\sum_j X_{ifjt} \leq CP_{fit} . P_{ft} \qquad \forall i,t,f \tag{6}$$

$$\begin{array}{l} (\sum_i E_{in} \sum_f \sum_j X_{ifjt}) + PM_{nt} MT_{nt} \\ + (1 - PM_{n,t-1}) K_n M_{nt} \leq M_{nt} \\ \quad ; \quad t = 1, \ldots, T \qquad n = 1, \ldots, N \end{array} \tag{7}$$

$$X_{ifjt}, Y_{ijkt} \geq 0 \qquad \forall i,j,k,t,f \tag{8}$$

$$R^m_{ikt}, W_{jt}, PM_{nt}, P_{ft} \in \{0,1\} \qquad \forall i,j,m,k,t,n,f \tag{9}$$

Objective function (1) maximizes the total profit of the network. The first term is the total income of satisfying demands. The two subsequent terms are the fixed cost of opening plants and distribution centers, respectively. The third term is transportation costs from plants to distribution centers and then to retailers. The fourth term is failure and maintenance costs of machines. Constraint set (2) guarantees that only one mode of demand satisfaction is available for each retailer. Constraint set (3) represents that transported each product from distribution centers to each retailer is equal to satisfying mode of the retailer's demand. Constraint set (4) enforces that the total inputs of each distribution center is bigger than its total outputs. Constraint sets (5) and (6) Indicate capacity limitations for plants and distribution centers. Constraint set (7) shows the total amount of time needed to produce the product in the machine, maintenance time in the system and the reduced time of capacity due to the system failure should be less than the available capacity of the machine during the course.

The non-negativity restrictions on the corresponding decision variables are enforced by Constraint sets (8) and (9).

3. Solution Approaches

The SCND problem belongs to the notably difficult NP-hard class of problems (Gourdin, 2000). Three algorithms are applied to solve each instance. Table 1 shows the three algorithms and their components and characters. The basic idea of tabu search (TS) is to introduce the notion of memory in the policy of solutions' exploration. TS is an efficient local search integrating a learning mechanism. This algorithm was proposed by Glover (1986).
Harmony search (HS) proposed by Geem, et al (2001) is a heuristic method that mimics the improvisation of music players. The genetic algorithm (GA) is a powerful method for combinatorial optimization problems. It was proposed by Holland (1975). Yao and Hsu (2009) proposed a new spanning tree-based GA for the design of multi-stage supply chain networks with nonlinear transportation costs. Kannan et al. (2010) proposed a GA applied as a solution methodology to solve the MILP model.
In this paper, the general structure of the solution representation performed for two products, two retailers, and two modes is shown in Fig. 2. All algorithms are compiled in Visual Basic programming language. All computational tests are performed on a Dell not book at Intel Core2 Duo Processor 2 GHz and 2 GB of RAM.

R_{ikt}^{m}	T1				T2			
	i=1		*i*=2		*i*=1		*i*=2	
	m=1	*m*=2	*m*=1	*m*=2	*m*=1	*m*=2	*m*=1	*m*=2
K=1	0	1	1	0	1	0	0	1
K=2	0	1	1	0	1	0	0	1

Fig. 2. Solution representation

4. Computational Results

4.1. Parameter calibration

The suitable design of parameters has an important effect on the productivity of meta-heuristics. In this paper, to calibrate the parameters of the HS, TS and GA, we use the Taguchi method developed by Taguchi and Chowdhury (2000). In this paper, the Taguchi method with L27 for HS, GA and TS is used for the adjustment of the parameters for the algorithms, respectively. Table 2 shows the factors of and levels of parameters. Figs. 3 to 5 show the S/N ratios. According to these figures, 12, 50, 0.4, 0.2, 30, 110, 300, 0.8, 0.1, 0.75, 150 are the optimal level of the factors TL, NS, PAR, HMCR, HMS, STOP, Npop, P_m, P_C, Sm and Iteration.

Table 1

Three algorithms and their components

Algorithm	Algorithm components and characters
GA	Five phases are considered in a GA. The process begins with a set of individuals, which is called a population. The fitness function determines how fit an individual is (i.e., the ability of an individual to compete with other individuals). The idea of the selection phase is to select the fittest individuals and let them pass their genes to the next generation. Crossover is the most significant phase in a GA. In certain new offspring formed, some of their genes can be subjected to a mutation with a low random probability. The algorithm terminates if the population has converged (i.e., does not produce offspring that are significantly different from the previous generation).
HS	Initialize the optimization problem and algorithm parameters memory size (HMS); harmony memory consideration rate (HMCR); pitch adjusting rate (PAR) to apply HS. Improvise a new harmony from the HM After defining the HM. Update the HM. the evolution process stops if the best solutions do not be improved in 30 generations.
TS	Solution representation and evaluation. Neighborhood structure/Move mechanism. Move Attribute (used for tabu classification). Tabu status and duration (tenure). Aspiration criteria. Stopping criteria. Initial Solution (systematically obtained, randomly generated, number of restarts)

Table 2
Factors and their levels

Factor	Algorithm	Notation	Level	Value
Size of the tabu list	Tabu	*TL*	3	6, 12, 18
Neighborhood size		*NS*	3	40, 50, 60
Pitch adjustment rate	HS	*PAR*	3	0.2, 0.4, 0.7
Harmony memory consideration rate		*HMCR*	3	0.1, 0.5, 0.9
Harmony memory size		*HMS*	3	10, 30, 50
Stopping criteria		*STOP*	3	60, 110, 160
Number of populations	GA	*Npop*	3	150, 300, 460
Probability of mutation		P_m	3	0.1, 0.8, 0.95
Probability of crossover		P_c	3	0.04, 0.085, 0.1
Strongly mutation		S_m	3	0.45, 0.75, 0.95
Stopping criteria		*Iteration*	3	50, 150, 250

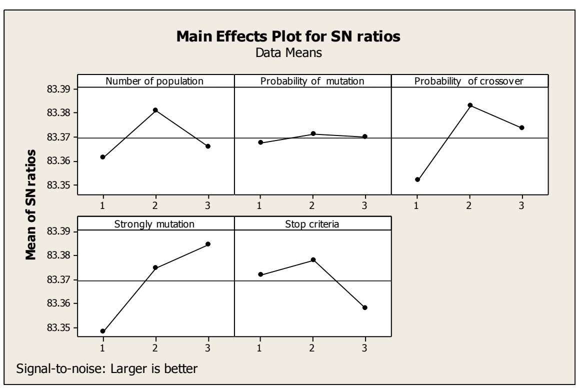

Fig. 3. S/N ratios for the GA

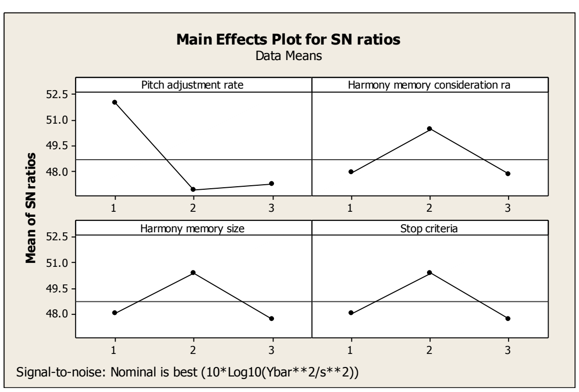

Fig. 4. S/N ratios for the HS algorithm

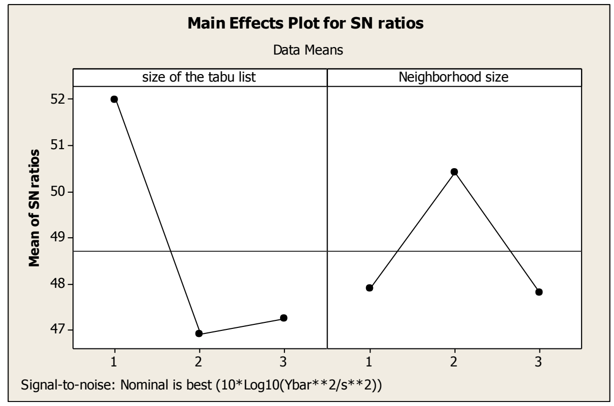

Fig. 5. S/N ratios for the TS algorithm

4.2. Computational results

We define 15 instances that can be characterized by the number of products (n_i) that are between 2 and 10, plants (n_f) that are between 3 and 8, distribution centers (n_j) that are between 2 and 8, retailers (n_k) that are between 2 and 9, satisfactions mode (n_m) that are between 2 and 9, periods (n_t) that are between 2 and 14, machines (n_n) that are between 2 and 11. Details of computational results for all test problems and the objective function values are shown in Table 3.

Table 3
Solution qualities of the Lingo, GA, HS and TS

Problem	Objective function values			
	(n_i, n_f, n_j, n_k, n_m, n_t, n_n)	HS	TS	GA
1	(2,3,2,3,2,3,2)	3207.6	3207.6	3207.6
2	(2,3,4,4,3,3,3)	6458.4	6458.4	6458.4
3	(3,3,4,4,3,4,3)	120667.3	120667.3	120667.3
4	(3,4,4,5,3,4,3)	55064.5	46176.3	55064.5
5	(3,4,4,5,4,5,4)	37651.7	36223.6	35473.4
6	(4,4,5,5,4,5,3)	17498.66	17488.51	17488.51
7	(4,4,5,6,5,6,3)	24270.7	22804.58	21634.88
8	(4,4,5,6,5,7,4)	29301.97	26411.45	25530.52
9	(5,4,4,5,4,8,5)	34788.15	32830.12	29896.16
10	(6,5,5,6,6,9,6)	44479.1	38815.7	33226.46
11	(7,5,5,6,5,10,7)	51237.21	44980.91	37219.48
12	(7,6,6,7,6,11,8)	58278.44	52459.44	41394.47
13	(8,7,7,7,7,12,9)	69140.58	59975.15	44593
14	(9,7,8,8,8,13,10)	79333.97	65668.58	50718.19
15	(10,8,8,9,9,14,11)	81684.406	75453.24	66243.57

It can be seen that the HS algorithm has a better solution quality in each instance between the three algorithms. To clarify the matter, confidence distances for different sizes are illustrated in Table 5 and Fig. 4. The objective function value obtained by HS is bigger than the other two algorithms in each instance. TS and GA are the second and third best algorithms based on solution quality, respectively.

Table 4 shows the CPU time of the three algorithms in each instance. Confidence distances for different sizes are illustrated in Table 6 and Fig. 7. For the remaining algorithms, the incremental sequence is HS, TS and GA according to the computational time.

Table 4
CPU time of GA, HS andTS for each instance

Problem	CPU time			
	(n_i, n_f, n_j, n_k, n_m, n_t, n_n)	HS	GA	TS
1	(2,3,2,3,2,3,2)	4	2	3.2
2	(2,3,4,4,3,3,3)	11.8	20	17.6
3	(3,3,4,4,3,4,3)	16.1	80	65.6
4	(3,4,4,5,3,4,3)	50.9	260	209.6
5	(3,4,4,5,4,5,4)	106.8	376	302.4
6	(4,4,5,5,4,5,3)	144.5	870	697.6
7	(4,4,5,6,5,6,3)	190.4	923	740
8	(4,4,5,6,5,5,4)	271.2	1650	1321.6
9	(5,4,4,5,4,3,5)	355.9	2302	1843.2
10	(6,5,5,6,6,3,6)	404	3290	2633.6
11	(7,5,5,6,5,3,7)	692.5	3396	2718.4
12	(7,6,6,7,6,3,8)	753.8	4123	3300
13	(8,7,7,7,7,3,9)	925.2	5427	4343.2
14	(9,7,8,8,8,3,10)	1359	5787	4631.2
15	(10,8,8,9,9,3,11)	2070.5	5907	4727.2

Table 5
ANOVA for objective values of test problems

Source	DF	SS	MS	F	P
Result	2	792498864	396249432	0.47	0.631
Error	42	35763970010	851523095		
Total	44	36556468874			

Table 6. Analysis of variance for CPU time of test problems

Source	DF	SS	MS	F	P
Result	2	26378673	13189337	4.75	0.014
Error	42	116526317	2774436		
Total	44	142904990			

5. Conclusions

In this paper, we developed a three-echelon supply chain structure including multiple plants, multiple distributors, multiple retailers and multiple customers with production planning and maintenance. We formulated the problem as a mixed-integer linear programming (MILP) model to maximize the total profit. While formulating the profit-maximizing objective, we evaluate several costs such as processing costs, transportation costs, preventive maintenance (PM) costs, failure costs, fixed cost of establishing distribution centers and plants. Since the problem was NP-hardness, it was solved by using harmony search (HS), tabu search (TS) and genetic algorithm (GA). Also, a widespread parameter calibrating with performing the Taguchi method was done for choosing the optimal levels of the factors that affected on the algorithm's performance. The results showed that the solution qualities obtained by HS were better than TS and GA. Determining the optimal routes and vehicles when there is a limited budget for hiring vehicles in a supply chain network problem with a multi-mode demand satisfaction policy can be considered for the future study.

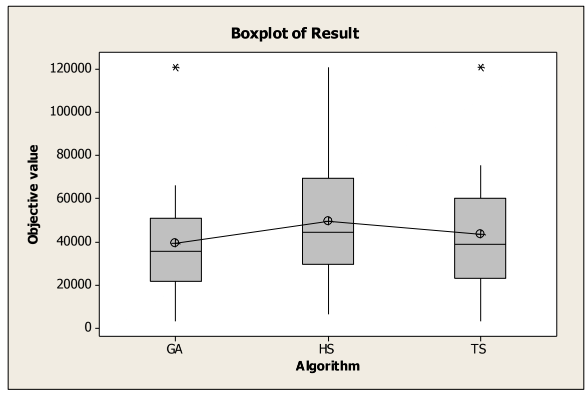

Fig. 6. Individual value plot of objective values

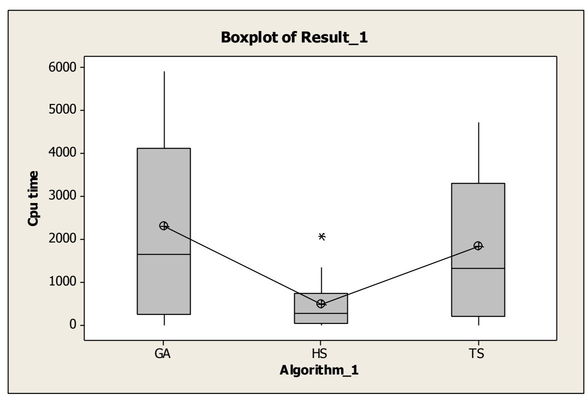

Fig. 7. Individual value plot of the CPU time

References

Amorim. P., Gunther, H O., Almada-Lobo. B., (2012). Multi-objective integrated production and distribution planning of perishable products. *International Journal of Production Economics*, 138, 89–101.

Ardalan. Z., Karimi. S., Naderi. B., ArshadiKhamseh, A., (2016). Supply chain networks design with multi-mode demand satisfaction policy. *Computers and Industrial Engineering*, 96, 108-117.

Badri. H., Ghomi. F., Hejazi. T., (2017). A two-stage stochastic programming approach for value-based closed-loop supply chain network design. *Transportation Research Part E: Logistics and Transportation Review*, 105, 1-17.

Bahrampour. P., Safari. M., Taraghdari. M,B., (2016). Modeling multi-product multi-stage supply chain network design. *Procedia Economics and Finance*, 36, 70 – 80.

Chandra. P., Fisher. M. L., (1994). Coordination of production and distribution planning. *European Journal of Operational Research*, *72*(3), 503–517.

Dhaenens-Flipo. C., (2000). Spatial decomposition for a multi-facility production and distribution problem, *International Journal of Production Economics*, 64, 177–186.

Eduardo. F., Andre. A., Enzo. F., Bernd. H., (2017). Operational supply chain planning method for integrating spare parts supply chains and intelligent maintenance systems. *IFAC-PapersOnLine*, 50(1), 12428-12433.

Fattahi. M., Mahootchi. M., Kannan. G., Husseini. M., (2015). Dynamic supply chain network design with capacity planning and multi-period pricing. *Transportation Research Part E: Logistics and Transportation Review*, 81,169-202.

Taguchi. G., S. Chowdhury., (2000). *Taguchi: Robust Engineering*, McGraw-Hill, New York.

Geem. Z., Kim. J., Loganathan. G., (2001). A new heuristic optimization algorithm: Harmony search. *Simulation*, 76(2), 60–8.

Gen. F., Lin. M., Paksoy. T., (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers & Industrial Engineering*, 51, 196–215.

Glover. F., (1986). Future paths for integer programming and links to artificial intelligence. *Computer& Operation Research*, 13, 533-549.

Gourdin. E., Labbe. M., Laporte. G., (2000). The uncapacitated facility location problem with client matching. *Operations Research*, 48(5), 671–85.

Holland. J.H., (1975). *Adaptation in natural and artificial systems*, Ann Arbor: The University of Michigan Press.

Kalinowski, T., Matthews, J., Waterer. H., (2020). Scheduling of maintenance windows in a mining supply chain rail network. *Computers & Operations Research*. 115,

Kannan. G., Sasikumar. P., Devika. K., (2010). A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling. *Applied Mathematical Modelling*, 34, 655-670.

Kostis. T., Chrissoleon. P., (2016). A design model and a production–distribution and inventory planning model in multi-product supply chain networks. *International Journal of Production Research*, 54, 6436-6457.

Longinidis. P., Georgiadis. M.C., (2011). Integration of financial statement analysis in the optimal design of supply chain networks under demand uncertainty, *International Journal of Production Economics*, 129, 262–276.

LunLi. C., Vairaktarakis. G., (2007). Coordinating production and distribution of jobs with bundling operations, *IIE Transactions*, 39, 203–215.

Manzini. R., Bindi. F., (2009). Strategic design and operational management optimization of a multi stage physical distribution system. *Transportation Research* Part E: Logistics and Transportation Review, 45(6), 915-936.

Mehdizadeh. E., Atashi Abkenar. A., (2014). An integrated aggregate production planning model with two-phase production system and maintenance costs.*International Journal of Applied Operational Research*, 4, 87-106.

Parkinson. H., Thompson. G., (2003). Analysis and taxonomy of remanufacturing industry practice. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, 217(3), 243–256.

Pawar. P.J., Nundurkar. K.N., (2018). Optimization of single supplier multi buyer multi product supply chain system, *Procedia Manufacturing*, 26, 21–28.

Ruimin. M., Lifei. Y., Maozhu. J., Peiyu. R., (2015). Robust environmental closed-loop supply chain design under uncertainty, *Chaos Solitons& Fractals*, 89, 195-202.

Sasitharan. D., Lazim. D.M., (2018). Effect of Preventive Maintenance Practices and Supply Chain Management in Improving Manufacturing Performance. *International Journal of Innovative Research & Development*. 7 (9), 223-226.

Tirkolaee. E.B., Mahmud khani. J., Bourani. M. R., Tavakkoli-Moghaddam. R., (2019). A Self-Learning Particle Swarm Optimization for Robust Multi-Echelon Capacitated Location-Allocation-Inventory Problem. *Journal of Advanced Manufacturing Systems*, 18, 677-694.

Yao. M.J., Hsu. H.W., (2009). A new spanning tree-based genetic algorithm for the design of multi-stage supply chain networks with nonlinear transportation costs. *Optimization and Engineering*, 10(2), 219-237.

Yeh. R.H., Lo. H.C., Yu. R.Y., (2011). A study of maintenance policies for second-hand products. *Computers and Industrial Engineering*, 60(3), 438–444.

Zhen. L., Huang. L., Wang. W., (2019). Green and Sustainable Closed-Loop Supply Chain Network Design under Uncertainty. *Journal of Cleaner Production*. 227, 1195-1209.

Fatehi Kivi, A., Mehdizadeh, E., Tavakkoli-Moghaddam, R., Najafi, S. (2021). Solving a Multi-Item Supply Chain Network Problem by Three Meta-heuristic Algorithms.
Journal of Optimization in Industrial Engineering, 14(2), 129-135.

http://www.qjie.ir/article_677652.html
DOI: 10.22094/JOIE.2020.1866273.1648