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Integrated Competitive Pricing and Transshipment Problem for Short Life Cycle Products' Supply Chain

A. Taheri-Moghadam*, J. Razmi, F. Jolai, A. A. Taleizadeh

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

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ABSTRACT

This paper integrates competitive pricing and network design problems for the short life cycle products. The pricing problem determines selling prices of the products for different life cycle phases in a competitive market, as well as acquisition management of returned products. Besides, the selling and acquisition prices are related to the distance between distribution centers and customers. The network design problem aims to determine network flow and fleet assignment in each route. The proposed model is solved by various methods including exact and meta-heuristic approaches. The model and solving approaches have been validated and verified by several simulated examples and sensitivity analyses. Considering life cycle phases, competitive pricing, and transshipment problems as an integrated model, provides a new approach for the optimum solutions, which makes it more practical for application of real cases of short life cycle products. The results showed how the competition and fleet assignment influenced the optimum solution.

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NOMENCLATURE

n	Index of products ($n\in${1-newly developed, 2-brand-new, 3-remanufactured, 4-replaceable newly developed, 5-replaceable brand-new}).	pc_{mn}	Production cost of a unit of product n, which is produced by plant m ($n\in\{1,2,3\}$).
m	Index of plants ($m\in\{1,2,\ldots,M\}$).	vf^{I}_{miv} vf^{II}_{ijv}	Fixed cost of using a vehicle type v for transportation between: I- plant m and distribution center (DC) i; II- DC i and CZ j.
i	Index of distribution centers (DC) ($i\in\{1,2,\ldots,I\}$).	tc_{ij}	Average transportation cost for transferring a unit of product from DC i to CZ j.
j	Index of customer zones (CZ) ($j\in\{1,2,\ldots,J\}$).	MS_{nj}	Market size of CZ j for product n while selling prices of all other products are equal to zero.
v	Index of vehicle types ($v\in\{1,2,\ldots,V\}$).	mr_j	Minimum number of retuned products from CZ j.
S_m	Available resources of plant m.	α_{nj} α'_{nj}	Coefficient of demand sensitivity of CZ j for product n to the selling price of the newly developed products.
s_{mn}	Resources consumed for producing a unit of product n, by plant m ($n\in\{1,2,3\}$).	β_{nj} β'_{nj}	Coefficient of demand sensitivity of CZ j for product n to the selling price of the brand-new products.
RC_j	Maximum available products that can be returned from customer zone (CZ) j.	γ_{nj}	Coefficient of demand sensitivity of CZ j for product n to the selling price of the remanufactured products $n\in\{1,2,3\}$.
ld_v	Maximum loading capacity of vehicle type v.	δ_j	Coefficient of return sensitivity of CZ j to the acquisition price.
xp_n xp'_n	Per unit selling price of product n (if the distance to CZ is zero). 1- $n\in\{1,2,3\}$; 2- $n\in\{4,5\}$;	xv^{I}_{miv} xv^{II}_{imv}	Number of vehicles type v, that are being hired for transportation between plant m, and DC i: I- forward flow; II- backward flow.

*Corresponding Author Email: *taherimoghadam@ut.ac.ir* (A. Taheri-Moghadam)

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xr	Per unit acquisition price for returning used products from CZs (if the distance to CZ is zero).	xv^{III}_{ijv} xv^{IV}_{jiv}	Number of vehicles type v, that are being hired for transportation between DC i, and CZ j: III- forward flow; IV- backward flow.
xf^{I}_{mivn} xf^{II}_{ijvn}	Flow of product n, shipped by vehicle type v, between: I- plant m, and DC i; II- DC i, and CZ j ($n \in \{1,2,3\}$).	D^{I}_{nj} D^{II}_{nj}	Demand of CZ j, for product n: I- $n \in \{1,2,3\}$; II- $n \in \{4,5\}$.
xfr^{I}_{miv} xfr^{II}_{ijv}	Flow of returned product shipped by vehicle type v, between: I- plant m, and DC i; II- DC i, and CZ j.	R_j	Number of used products that are returned from CZ j.

1. INTRODUCTION

Life cycle of products includes development, introduction, growth, maturity, and decline phases. For short life cycle products (SLC), usually the time between developments to decline phases is less than a year. Hence, newly developed SLC products are being introduced to the market while the prior products are not obsolete yet [1].

The pricing problem has been widely investigated by researchers [2]. Most of the studies use game theory approaches in order to determine optimal price of different supply channels. Some of the studies considered remanufactured products as well as brand-new products, and they have rarely investigated acquisition management pricing.

In this paper we tried to investigate price competition in closed-loop supply chain network design (CLSCND) problem of short life cycle products. This article intends to discuss the answers to the following questions:

1. How does the market response to a manufacturer's selling price?
2. What is the impact of the market response to CLSCND?
3. How to adopt a CLSCND problem to fit the condition of SLC products?
4. How do the vehicle types affect the closed-loop supply chain (CLSC) network?

2. LITERATURE REVIEW

Table 1 represents a brief review of the most related papers in the research field of CLSCND and pricing problem in order to clarify research gaps and differentiate our work from the previous studies.

TABLE 1. Brief review of the most related researches

Year	Article	Pricing: Newly developed	Brand-new	Remanufactured	Returned	Rival	Distance dependent	Fleet assignment	Solving approach*	The main advantage over the literature.
2018	[3]		●			●			MINLP, KKT, EC, GT	Consider competition and disruption risks simultaneously.
2018	[4]		●		●				MIP, MH	Dynamic design of a SSC network with a price dependent demand and return.
2018	[5]		●			●			MINLP, KKT, MH, GT	Designing a supply chain network by considering competition between an existing network.
2019	[6]		●		●				MIP	Comprehensive model of CLSC under quality dependent acquisition management with social and environmental objectives.
2019	[7]		●	●					GT	Study the remanufacturing decision for SLC products. Investigate pricing and production for brand-new and remanufactured products considering interactive demand cannibalization.
2019	[8]		●	●					GT	Investigate retailer's fairness concerns and its impacts on the other players' pricing decisions as well as profit allocation.
This paper		●	●	●	●	●	●	●	MINLP, MH, GT	Utilizing market best response into demand function. Considering all of the life cycle phases. Distance dependent price. Fleet assignment.

* Stochastic Dynamic Programing (SDP); Derivate profit function (D); Mixed Integer Non-Linear Programing (MINLP); Mixed Integer Programing (MIP); Karush-Kuhn-Tucker (KKT); Epsilon Constraint (EC); Game Theory (GT); Meta-Heuristic (MH)

2. 1. Contributions Using market response function in modeling the CLSCND problems is the main contribution of this paper. The response function determines the best response of the competitor in order to calculate the demand function and pricing decisions.

Developing a mathematical model that fits the condition of SLC products, by considering all of the life cycle phases in CLSCND, is the second contribution of our work.

Assuming vehicle types (fixed cost and capacity) in CLSCND is another important novelty of our work. As mentioned before, such assumption is a vital assumption for expanding the application of the model in real environment.

Another innovation of our study is the distance dependent prices. Moreover, a hybrid genetic algorithm is developed in order to solve the proposed MINLP model.

3. STRUCTURE OF MATHEMATICAL MODELS

This section presents assumptions and notations of the mathematical models as follows:

Each manufacturer can produce three product types: 1. Newly developed; 2. Brand-new; 3. Remanufactured. However, there is no competition for returned and remanufactured products, because it is assumed that each manufacturer can only repair his own products. ($n_1 \in \{1,2,3\}$, and $n_2 \in \{4,5\}$)

Demand of remanufactured products does not exceed the quantity of returned products, and selling price of remanufactured products is always less than the brand-new products. The revenue functions are assumed to be concave.

4. MODELING

The propose model consists of two stages; the first stage deals with the price competition in order to determine the best response of the market, and the second stage determines the supply chain network design.

4. 1. Price Competition As it is mentioned before, there is a price competition between newly developed and brand-new products of the manufacturers in the market. The best response function of the competitor is calculated in this stage in order to determine competitive demand function, and the network design and pricing decisions are determined by the second stage.

Demand and revenue functions of the competitor have been defined by Equations (1) and (2).

The demand functions contain demand sensitivity coefficients that determine impact of the price variations on demand quantity. The coefficients can be determined by regression method and market research. Please refer to literature [9] for more explanations about the linear demand function.

As the revenue functions are concave, the maximum revenue can be calculated by the first order derivatives, and the best response of the competitor is determined by Equation (3), in which, K_n and K' are presented by Equations (4) and (5); that are defined in order to simplify the Equations.

$$D_{nj}^{II} = MS_{nj} + \sum_{i=1}^{I} \begin{pmatrix} \alpha_{nj}\left(xp_1 + tc_{ij}\right) + \beta_{nj}\left(xp_2 + tc_{ij}\right) + \\ \alpha'_{nj}\left(xp'_4 + tc_{ij}\right) + \beta'_{nj}\left(xp'_5 + tc_{ij}\right) \end{pmatrix} \tag{1}$$

$$\mathrm{Rev}^{II}(xp'_4, xp'_5) = \sum_{n=4}^{5} \left(xp'_n \sum_{j=1}^{J} D_{nj}^{II} \right) \tag{2}$$

$$\begin{cases} xp'^{*}_4 = \dfrac{K_5 \sum_{j=1}^{J}\left(\alpha'_{5j} + \beta'_{4j}\right) - 2K_4 \sum_{j=1}^{J} \beta'_{5j}}{K'} \\ xp'^{*}_5 = \dfrac{K_4 \sum_{j=1}^{J}\left(\alpha'_{5j} + \beta'_{4j}\right) - 2K_5 \sum_{j=1}^{J} \alpha'_{4j}}{K'} \end{cases} \tag{3}$$

$$K_n\left(xp_1, xp_2\right) = \sum_{j=1}^{J} \left(MS_{nj} + \sum_{i=1}^{I} \begin{pmatrix} \alpha_{nj}\left(xp_1 + tc_{ij}\right) \\ + \beta_{nj}\left(xp_2 + tc_{ij}\right) \\ + \left(\alpha'_{nj} + \beta'_{nj}\right) tc_{ij} \end{pmatrix} \right) \tag{4}$$

$$K' = 4I \sum_{j=1}^{J} \alpha'_{4j} \sum_{j=1}^{J} \beta'_{5j} - I \left(\sum_{j=1}^{J} \left(\alpha'_{5j} + \beta'_{4j}\right) \right)^2 \tag{5}$$

Please note that the best response of the competitor is a function of xp_1 and xp_2, and the manufacturer can determine his optimal selling prices by calculating the best response function of the competitor. The demand function of the manufacturer is defined by Equation (6).

$$D_{nj}^{I} = MS_{nj} + \sum_{i=1}^{I} \begin{pmatrix} \alpha_{nj}\left(xp_1 + tc_{ij}\right) + \beta_{nj}\left(xp_2 + tc_{ij}\right) + \\ \gamma_{nj}\left(xp_3 + tc_{ij}\right) + \alpha'_{nj}\left(xp'^{*}_4 + tc_{ij}\right) \\ + \beta'_{nj}\left(xp'^{*}_5 + tc_{ij}\right) \end{pmatrix} \tag{6}$$

4. 2. Network Design The network design problem is defined as follows:

The objective function is maximizing total profit of the manufacturer that is presented by Equation (7), in which the first term is total revenue, the second term calculates acquisition costs, the third term computes production cost and the fourth and fifth terms determine transportation cost.

$$
\begin{aligned}
Max\ Z = & \sum_{n,j,i}\left(\left(xp_n + tc_{ij}\right)\sum_{v} xf^{II}_{ijvn}\right) \\
& - \sum_{j,i}\left(\left(xr - tc_{ij}\right)\sum_{v} xfr^{II}_{ijv}\right) \\
& - \sum_{m,n}\left(pc_{mn}\sum_{i,v} xf^{I}_{mivn}\right) \\
& - \sum_{m,i,v} vf^{I}_{miv}\left(xv^{I}_{miv} + xv^{II}_{imv}\right) \\
& - \sum_{i,j,v} vf^{II}_{ijv}\left(xv^{III}_{ijv} + xv^{IV}_{jiv}\right)
\end{aligned} \tag{7}
$$

Subject to:

$$\sum_{n}\left(s_{mn}\sum_{i,v} xf^{I}_{mivn}\right) \le S_m \quad \forall m \tag{8}$$

$$\sum_{i,v} xf^{I}_{miv3} \le \sum_{i,v} xf^{I}_{miv4} \quad \forall m \tag{9}$$

$$\sum_{i,v} xfr^{II}_{ijv} \le R_j \quad \forall j \tag{10}$$

$$R_j \le RC_j \quad \forall j \tag{11}$$

$$\sum_{m,v} xf^{I}_{mivn} \ge \sum_{j,v} xf^{II}_{ijvn} \quad \forall i, n \tag{12}$$

$$\sum_{m,v} xfr^{I}_{miv} \le \sum_{j,v} xfr^{II}_{ijv} \quad \forall i \tag{13}$$

$$\sum_{i,v} xf^{II}_{ijvn} \le D^{I}_{nj} \quad \forall j, n \tag{14}$$

$$\sum_{n} xf^{II}_{ijvn} \le ld_v\, xv^{III}_{ijv} \quad \forall i, j, v \tag{15}$$

$$xfr^{II}_{ijv} \le ld_v\, xv^{IV}_{jiv} \quad \forall i, j, v \tag{16}$$

$$\sum_{n} xf^{I}_{mivn} \le ld_v\, xv^{I}_{miv} \quad \forall m, i, v \tag{17}$$

$$xfr^{I}_{miv} \le ld_v\, xv^{II}_{imv} \quad \forall m, i, v \tag{18}$$

$$
\begin{aligned}
D^{I}_{nj} = & \qquad\qquad \forall n, j \\
MS_{nj} + \sum_{i=1}^{I} & \begin{pmatrix} \alpha_{nj}\left(xp_1 + tc_{ij}\right) + \beta_{nj}\left(xp_2 + tc_{ij}\right) + \\ \gamma_{nj}\left(xp_3 + tc_{ij}\right) + \alpha'_{nj}\left(xp'^{*}_{4} + tc_{ij}\right) \\ + \beta'_{nj}\left(xp'^{*}_{5} + tc_{ij}\right) \end{pmatrix}
\end{aligned} \tag{19}
$$

$$R_j = mr_j + \delta_j xr \quad \forall j \tag{20}$$

$$
\begin{aligned}
& \left.\begin{matrix} xf^{I}_{mivn},\ xf^{II}_{ijvn},\ xfr^{I}_{miv},\ xfr^{II}_{ijv},\ xv^{I}_{miv}, \\ xv^{II}_{imv},\ xv^{III}_{ijv},\ xv^{IV}_{jiv} \end{matrix}\right\} \in Z^{+} \\
& xp_n,\ xp'_n,\ xr,\ D^{I}_{nj},\ R_j \in R^{+}
\end{aligned} \tag{21}
$$

Equation (8) is the capacity constraint of manufacturers. Equations (9) and (10) ensure that the quantity of remanufactured products and the backward flow do not exceed the quantity of returned products. Equation (11) checks the return capacity of each customer zone. Equations (12) and (13) balance the flow of forward and backward routes respectively. Equation (14) makes sure that the input flow to each CZ does not exceed the demand of that CZ. Equations (15) to (18) check the capacity of hired vehicles in each route. The demand and return quantity of each CZ is determined by Equations (19) and (20). Finally, types of the decision variables are defined by Equation (21).

5. SOLVING APPROACH

Four different solution methods have been utilized in this study. The first method determines global optimum solution by GAMS software that is unable to solve large size problems. The other two methods are meta-heuristic algorithms, which can provide nearly optimum solutions for large size problems in a reasonable computational time. All of the parameters of the proposed meta-heuristic algorithms are set by the Taguchi method [10].

A personal computer with Intel® Core2™ Dou E4600 @2.4GHz processor, 2 GB of RAM, and the Windows 10 operating system is utilized as a platform for solving the test problems. MATLAB R2014b is used for coding the meta-heuristic algorithms, and the BONMINH solver in GAMS 25.0.2 is used for solving the small size examples.

5. 1. Whale Optimization Algorithm (WOA)

The Whale optimization algorithm (WOA) is a very effective novel meta-heuristic algorithm that is proposed by Mirjalili and Lewis (2016) [11]. It is inspired by humpback whales' hunting strategy (known as bubble net strategy) in order to determine optimum solutions.

Such as all of the meta-heuristic algorithms, the WOA considers both exploitation and exploration of the solution space. The exploitation phase consists of two kinds of movements, i.e. spiral and circular movements, while the exploration phase handles only circular movement. Equations (22) and (23) determine position of each whale in next iteration (t+1) by the circular movement. In which, X_t , and X^*_t determine current position of the whale, and the best position obtained by all of the population respectively. V is velocity vector that is determined by the position of the whale and the best position. C and A are coefficient vectors that are calculated by Equations (24) and (25). a is a number between [0, 2] that linearly decreases over the iterations. r is a uniform random parameter in the range of [0, 1] (updates in each iteration).

$$\vec{V} = \left| \vec{C}.\vec{X}_t^* - \vec{X}_t \right| \tag{22}$$

$$\overrightarrow{X_{t+1}} = \vec{X}_t^* - \vec{A}\vec{V} \tag{23}$$

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{24}$$

$$\vec{C} = 2.\vec{r} \tag{25}$$

The spiral movement is simulated by Equations (26) and (27), in which l is uniform random parameter in the range of [-1, 1] (updates in each iteration), and b is a parameter that determines the spiral shape.

$$\vec{V}' = \left| \vec{X}_t^* - \vec{X}_t \right| \tag{26}$$

$$\overrightarrow{X_{t+1}} = \vec{V}' e^{bl}.\cos(2\pi l) + \vec{X}_t^* \tag{27}$$

The exploration phase aims to explore the solution area in order to determine the global optimum solution. Equations (28) and (29) simulate the circular movement around a random solution in order to explore the feasible area, where, X_{random} denotes position of a randomly selected whale in current iteration (t).

$$\vec{V} = \left| \vec{C}.\vec{X}_{Random} - \vec{X}_t \right| \tag{28}$$

$$\overrightarrow{X_{t+1}} = \vec{X}_{Random} - \vec{A}\vec{V} \tag{29}$$

Pseudo code of the utilized WOA is provided as follows:

1. Create initial random solutions (X) that represents the initial position of the whales' population, set t=1, determine value of fitness functions for each whale, determine the best position (X^*);
2. For each whale (search agent) of the current population do steps 3 to 6
3. Determine, p=*rand(*0, 1*)*, a, A, C, l
4. If ($p<pm$ & $-1<A<1$), update position of the search agent using Equation (23) (circular movement)
5. If $p>pm$, update position of the search agent using Equation (27) (spiral movement).
6. If ($p<pm$ & $|A|\geq 1$), choose a random position (X_{random}) and update position of the search agent using Equation (29) (exploration)
7. Update fitness functions for each whale, update X^*, set t=t+1;
8. If maximum number of iterations is reached, stop, else, go to step 2.

Parameters of the proposed WOA are defined by Table 2. Please note that the parameters a, r, and l are explained before and they are not presented by Table 2.

5. 2. Genetic Algorithm (GA) As the GA is one of the most common approaches for solving similar problems [12], we have not provided pseudo code for this algorithm. The utilized GA is similar to the algorithm that is provided by Guo et al. [12]. Table 3 presents the GA parameters.

TABLE 2. Input parameters of the proposed WOA

Parameter	Maximum Iteration	Number of whales	*pm*	*b*
Value	3000	200	0.5	1

5. 3. Hybrid Genetic Algorithm (HGA) Our analyses show that, for solving the proposed model, the WOA exploits the search space properly, but the exploration should be improved. On the other side, the GA explores the search space properly by crossover operator, while the mutation operator can be enhanced in order to improve the exploitation of the GA.

Hence, we tried to utilize the exploitation step of the WOA as an extra step in the GA. That improves the performance of the proposed GA.

The proposed HGA is based on GA, but the spiral movement similar to WOA is utilized in order to search the best solutions' neighborhood. In other words, the proposed HGA has an extra step in which it uses Equations (26) and (27) in order to improve local search of the elite population in each iteration.

Please note that elites of the population are the top ten solutions, that have the best fitness function values. Parameters of the HGA are similar to GA and the spiral movement's parameters (l and b) are set as follows. l is a random number between 0 and 1, and b=1. The results show that the spiral movement improves local search of the GA and makes it more appropriate.

5. 4. Feasible Solution Creation Solution representation and feasibility check is the same for all of the meta-heuristic algorithms. Values of the decision variables are stored in different matrixes. For example values of the selling prices are stored in a matrix named xp, product flows between manufacturers and DCs are stored in a different matrix named xfI, and etc. This approach helps the exploration and exploitation operators to create more feasible solutions. As an instance, the selling prices are crossed with each other, and the network flow variables are crossed with each other. Clearly, if a value of selling price is exchanged with a value of product flow, the solution will be infeasible and the utilized approach avoids such exchange.

TABLE 3. Input parameters of the proposed GA

Parameter	Maximum Iteration	Population size
Value	2000	300
Parameter	Crossover rate	Mutation rate
Value	0.4	0.2

However, utilizing the above approach does not always guarantee the feasibility of the solutions. Hence, a repair algorithm is used in order to fix the infeasible solutions. The repair algorithm checks all of the constraints. Please assume that the repair algorithm distinguished that the demand is less than the input flow to a CZ. It will decrease the input flow. There are some especial solutions that cannot be repaired. The solutions that are unable to be repaired, will suffer a penalty in order to make sure that they will be eliminated in the next generation.

6. NUMERICAL EXPERIMENTS

This section provides numerical examples in order to validate the mathematical model and verify solution approaches. Sensitivity analyses are applied in order to investigate impact of demand and return functions' parameters on the CLSC network.

The test problems (TP) simulate real environment. Random distributions that are applied for generating the parameters are presented by Table 4.

As Table 5 shows, the TPs cover small and large scale problems. The replication of each test problem is presented by Table 5 as well. Please note that as the GAMS results are constant in each replication. The replication of solving the TPs with GAMS are equal to one.

6. 1. Numerical Simulated Example TP1 is solved by GAMS software in order to clarify solution and rationality of the results.

TABLE 4. Random distributions applied for generating TPs

Parameter	S_m	s_{mn}
Distribution	U(1E+5 , 2E+5)	U(10 , 20)
Parameter	ld_v	pc_{mn}
Distribution	U(100 , 1000)	U(2 , 7)
Parameter	vf^{f}_{miv} and vf^{fl}_{ijv}	tc_{ij}
Distribution	U(200, 1000)	mean(vf^{fl}_{ijv} / ld_v)
Parameter	MS_{nj}	mr_j
Distribution	U(1000 , 2000)	U(100 , 200)
Parameter	α_{nj}	α'_{nj}
Distribution	U(-0.05 , 0.02)	U(-0.05 , 0.02)
Parameter	β_{nj}	β'_{nj}
Distribution	U(-0.05 , 0.02)	U(-0.05 , 0.02)
Parameter	γ_{nj}	δ_j
Distribution	U(-0.05 , 0.02)	U(0 , 0.1)
Parameter	RC_j	
Distribution	U(1500 , 3000)	

TABLE 5. Sizes of the test problems

TP	Replication	Size (|*m*| × |*i*| × |*j*| × |*v*|)
TP1	8	2 × 2 × 2 × 2
TP2	8	2 × 2 × 4 × 2
TP3	6	2 × 2 × 4 × 4
TP4	6	2 × 4 × 8 × 4
TP5	4	2 × 4 × 8 × 5
TP6	4	3 × 5 × 10 × 5
TP7	2	4 × 5 × 10 × 6
TP8	2	5 × 6 × 12 × 6
TP9	2	6 × 6 × 12 × 7
TP10	2	7× 7 × 15 × 7

Figure 1 presents the optimal solution of TP1. As Figure 1 shows, all of the decision variables are determined properly. The forward and backward flows are balanced and the vehicles are hired according to their load capacity and rent cost.

6. 2. Comparison of the Solution Approaches The generated TPs are solved by each solving algorithm several times and the results are compared with each other. Two indexes are applied for the comparison: 1. Relative gap; 2. Computational time. The average relative gap (ARG) is determined by Equation (30). In which OF^* is the best solution that is found by all of the algorithms in all iterations, and AR_a is the average results determined by algorithm a in all of the iterations. Table 6 presents the ARG values for all of the solution methods and test problems.

$$ARG_a = \frac{OF^* - AR_a}{OF^*} \times 100\% \qquad (30)$$

The computational time is the other important index for comparing solution methods. Figure 2 shows the average computational time of the solving algorithms for solving different test problems.

As it is mentioned previously, GAMS software determines nearly the optimal solutions, but it is unable to solve test problems larger than TP5, while the other meta-heuristic algorithms are able to solve the test problems in a reasonable time.

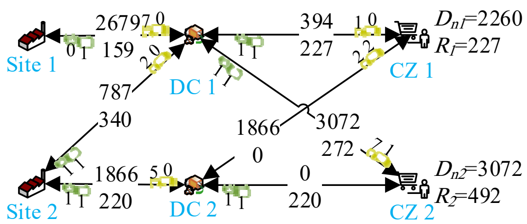

Figure 1. Optimal product flow of TP1

TABLE 6. The average relative gaps of the solution methods

TP	GAMS	GA	WOA	HGA
1	**0%**	2.1%	3.2%	0.9%
2	**0%**	3.9%	2.0%	2.3%
3	**0%**	2.8%	4.7%	0.8%
4	**0%**	2.0%	4.3%	3.7%
5	**0%**	0.5%	3.9%	0.1%
6	-	**0.5%**	3.7%	2.4%
7	-	1.6%	3.7%	**0.4%**
8	-	2.0%	3.8%	**0.5%**
9	-	1.8%	3.7%	**0.6%**
10	-	1.0%	1.9%	**0.5%**

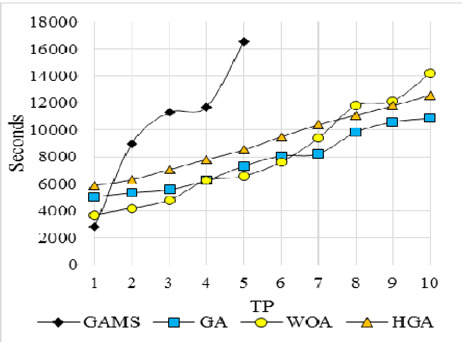

Figure 2. Average computational time

The maximum relative gap between the meta-heuristic algorithms and GAMS is almost 5% which indicates that the performances of the proposed algorithms are appropriate.

The results confirm that the exploitation phase of the proposed HGA is improved in comparison with GA and it provides better solutions in a reasonable time.

6. 3. Sensitivity Analysis Impact of the demand and return functions' parameters (α, β, γ, and δ) on optimal solution is analyzed by this subsection.

Test problem 2 is assumed as the basic model, and in each round one of the mentioned parameters is multiplied by 0.6 to 1.6 in order to determine the impact of such parameter on the optimal solution. Figure 3 and Figure 4 show sensitivity of total profit and total demand to the parameters respectively.

As Figure 3 shows, by increasing the self-price coefficients (α, β, and γ), total profit decreases, because the manufacturer needs to reduce selling price of his products in order to keep the demand of customer zones. In this case the brand-new products provide the most profit share. If the sensitivity to brand-new product (β) is increased, the manufacturer should decrease selling price of the brand-new product in order to avoid

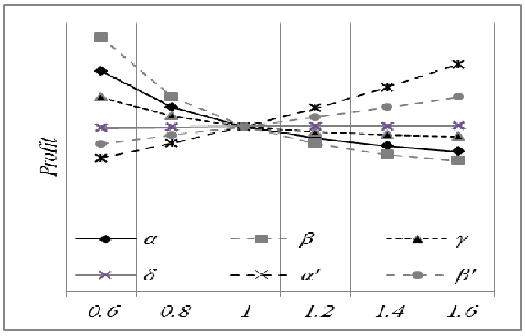

Figure 3. Profit sensitivity

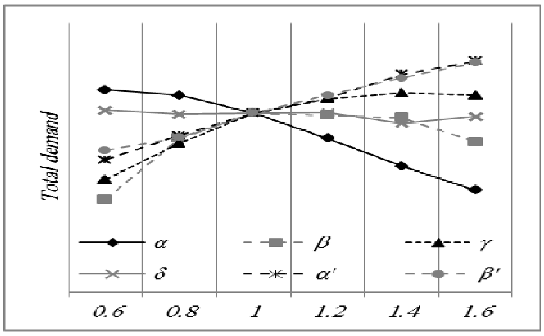

Figure 4. Demand sensitivity

demand reduction. Hence, his profit will be decreased. Similar explanation is true for other products' coefficients (β, γ, and δ). Please note that the remanufactured products provide the least profit share and the sensitivity to (γ, and δ) is less than the other coefficients.

On the other hand, by increasing the competitor's coefficients (α', and β') the profit increases. Because the impact of the competitor on the first manufacturer's demand is decreased.

Besides, Figure 4 shows that the demand functions' parameters impact the demand and selling prices significantly. Hence, solving the pricing and the network design problems simultaneously, can improve rationality of the solutions and gives important insights for the closed-loop supply chain network design problem.

7. CONCLUSIONS AND FUTURE STUDIES

This study investigates integration of competitive pricing and CLSCND problems that is designed to fit the conditions of SLC products.

Considering life cycle phases leads to product cannibalization, which is almost an internal competition between products of a manufacturer. Besides, there is an external competition between manufacturers, similar to other researches.

The proposed model has some limitations that can draw up guidelines to expand its applications. Using dynamic approaches in order to investigate the model through several periods is an attractive topic for future studies. Impact of advertisement and brand investment are another research topics that can be considered in new product development process. The proposed model considers selling prices as the only incentive of the customers, while there are other important motivations such as quality level, service level, guarantee and etc. that are critical issues need to be investigated. Besides, considering other sustainable aspects is another area of future researches.

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Integrated Competitive Pricing and Transshipment Problem for Short Life Cycle Products' Supply Chain

A. Taheri-Moghadam, J. Razmi, F. Jolai, A. A. Taleizadeh

School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

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چکیده

در این تحقیق به مسائل قیمت گذاری در شرایط رقابتی و طراحی شبکه زنجیره تأمین محصولات با چرخه عمر کوتاه به صورت یکپارچه پرداخته شده‌است. در بخش قیمت گذاری، مدل پیشنهادی قادر است قیمت فروش محصولات را در فازهای مختلف چرخه عمرشان به کمک محاسبه تابع پاسخ منطقی بازار تحت شرایط رقابتی تعیین کند. در بخش طراحی شبکه، میزان مراودات بین تسهیلات مختلف زنجیره رفت و برگشت و همچنین تخصیص ناوگان حمل و نقل به هر مسیر بهینه سازی می‌گردد. تخصیص ناوگان بهینه تأثیر به سزایی در بهینه سازی و نزدیک نمودن مدل به واقعیت خواهد داشت. مدل پیشنهادی با استفاده از روشهای مختلفی شامل روشهای دقیق و فرا ابتکاری حل شده‌است. روش‌های فرا ابتکاری مورد استفاده شامل یک الگوریتم کلاسیک (الگوریتم ژنتیک)، یک الگوریتم جدید (الگوریتم بهینه سازی نهنگ) و همچنین ارائه یک الگوریتم ترکیبی جدید است.

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