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A Collaborative Stochastic Closed-loop Supply Chain Network Design for Tire Industry

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ABSTRACT

Recent papers in the concept of Supply Chain Network Design (SCND) have seen a rapid development in applying the stochastic models to get closer to real-world applications. Regaring the special characteristics of each product, the stracture of SCND varies. In tire industry, the recycling and remanufacturing of scraped tires lead to design a closed-loop supply chain. This paper proposes a two-stage stochastic model for a closed-loop SCND in the application of tire industry. The first stage of model optimizes the expected total cost. Then, financial risk has been considered as the second stage of model to control the uncertainty variables leading to a robust solution. To solve the developed problem, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have been used. To enhace the efficiency of metaheuristic algorithms, Response Surface Method (RSM) has been applied. Finally, the proposed model is evaluated by different test problem with different complexity and a set of metrics in terms of Pareto optimal solutions.

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1. INTRODUCTION

One of the important products for humans is car and its tires. According to the published reports by Amin et al., [1], each family in United States has three cars and each car approximately goes through two or three sets of tires per year. In this regard, perhaps thirty tires are used per each family in three years. Each tire maybe rotated every 10K kilometers (km) then disposed after 40-60K km [2]. By another point of view, recent reports indicate that approximately 290 million scraped tires are disposed of every year and almost 20% of them (about 55 million tires) are illegally dumped. On the other hand, world demand for tires is projected to rise 4.1 percent per year to 3.0 billion units in 2019 [1].

According to the scientific directions in this research zone, Supply Chain (SC) can be defined and illustrated as the activities of facilities to provide the materials, to manufacture the products, to transform between different parties, and to distribute the final products among users [3]. In addition, managers of SC recently focused on consumed products in an attempt to generate more profit by recovering, remanufacturing or recycling products in the backward echelon's levels [4, 5]. In this regard, Supply Chain Management (SCM) guides the proper approach to manage all parts in these business functions [6].

Supply Chain Network Design (SCND) is an important topic in SCM [7]. It deals with designing an efficient and effective network in SC [8]. The literature of SCND is rich [9, 10], however, it is relatively scarce when it comes to the tire industry, especially that the type of the product significantly affects the SC structure and configuration [1]. The tire industry is characterized by the many times the product can be reused for. Chopra and Meindl [11] note that in the United States only three percent of sold tires are reused and retreaded between 2009 and 2011. Ferrer [12] explains the tire SC showing the value-adding operations and the tire retreading process. He also estimates the number of times which a tire can be reused. Sasikumar et al. [13]

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propose an optimization model for truck tire remanufacturing process. Subulan et al. [2] present a case study in Turkey to investigate the tire remanufacturing process. Recently, Amin et al. [1] develop an optimization model for closed-loop tire SC in Toronto, Canada.

Closed-Loop Supply Chain (CLSC) has been appealing for researchers in the last decade [14, 15]. This type of SC network considers the reverse and forward SC in an integrated manner [16]. Furthermore, different configurations and structures of SCs of different products are considered totally distinct SCs (i.e., they are different for different products) [17]. Kannan et al. [18] propose a CLSC for two types of products: Tires and plastics. They used Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to solve them. They only considered the flow of products between different levels of CLSC as well as the location and allocation decisions. Their model also was deterministic and a type of Mixed Integer Linear Programming (MINLP) formulation. In this regard, according to the operational and tactical decisions of CLSC, an efficient solution is so important. Metaheuristics are a type of stochastic optimization in nature which gives an optimal solution in a reasonable time. In this regard, several new and recent meta-heuristics are also used in this area. For instance, Devika et al. [19] propose six hybridized meta-heuristics based on the Imperialist Competitive Algorithm (ICA) to tackle their proposed CLSC problem in glass industry. They also considered the impact of technology selection for the model. Mirakhorli [20] proposes a GA heuristic-based algorithm to optimize bread production. They optimized the transportation time as well as the total cost in their model. In another similar study, Subulan et al. [21] investigate the application of CLSC on battery production using an exact solution algorithm for tactical decisions in the model. They also recommended the use of metaheuristics for large sizes for their developed problem. Additionally, Fathollahi Fard et al. [7] proposed a two-stage stochastic programming model for CLSC in glass industry. To solve their problem, ICA, PSO and GA were used. In a recent study, Fathollahi Fard and Hajiagahei-Keshteli [22] propose a tri-level decision-making model to design a forward/reverse supply chain of glass industry. They use Water Wave Optimization (WWO) and Keshtel Algorithm (KA) in a nested approach.

The proposed optimization model consists of two objective functions: expected total cost and financial risk. In order to address the problem two powerful meta-heuristics are used in this paper: Particle Swarm Optimization (PSO) [23] and Genetic Algorithm (GA) [24]. The parameters used in PSO and GA are tuned by Response Surface Method (RSM). While Fathollahi Fard et al. [7] proposed a two-stage stochastic programming model for glass industry. In this research, a new two-stage stochastic model is developed for the tire industry closed-loop supply chain network design problem.

The rest of the paper is organized as follows: In Section 2, the problem is described and formulated in a two-stage stochastic programming model. In Section 3, the encoding scheme is introduced. Computational results are investigated in Section 4. Finally, discussion and suggestions for the future works are discussed in Section 5.

2. PROBLEM DESCRIPTION

Usually, the recovery activities in tires consist of reusing, remanufacturing and recycling. As shown in Figure 1, the proposed Closed-Loop Supply Chain (CLSC) network for tire manufacturing and remanufacturing is presented. In a nutshell, suppliers provide raw materials for manufacturers. The manufacturers sell the tires to the retailers in large quantities. Then, customers purchase their demands from retailers. Only a fraction of used tires from customers will be collected by drop-off depots. The collected tires are divided into two categories. Some of them needs to retreading or remanufacturing return to manufacturers. It should be noted, the collected tires have a lower price than raw materials from suppliers as well as they need some minor process to produce as a new product from manufacturers. Consequently, the rest of collected tiers should be recycled and be sell to suppliers with lower prices.

The proposed optimization model is based on the following assumptions:

✓ The demand of each customer must be met.

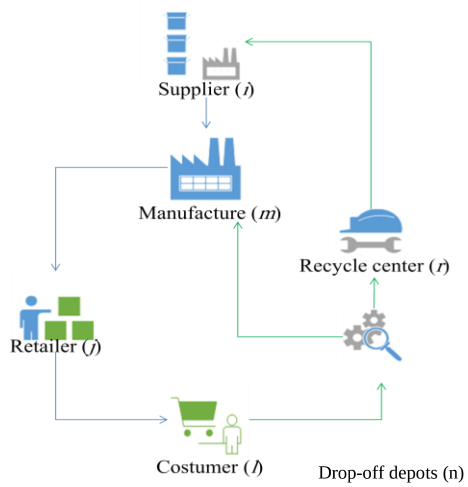

Figure 1. The graphical structure of proposed tire CLSC [1]

- ✓ Each customer can be assigned to only one of retailers in the forward flows and drop-off depots in the reverse flows.
- ✓ The number of facilities in echelons is predefined.
- ✓ No flow exists between the same facilities.
- ✓ The transportation and fixed costs are known and fixed. The other parameters such as demand and the rate of returned tires are under uncertainty and defined by a set of scenarios.
- ✓ All members of the SC have capacity constraints.
- ✓ The number of returned tires of a certain tire type to drop-off depots is considered by a fraction of the customer's demand of that respective tire type as originally proposed in literature [1].

We define the indexes, parameters and decision variables in Tables 1, 2 and 3, respectively.

TABLE 1. List of Indexes

Indexes	Description
i	Index of suppliers: i∈{1, 2,…, I}
m	Index of potential manufactures: $m \in \{1, 2, \ldots, M\}$
j	Index of potential retailers: j ∈{1, 2,…, J}
l	Index of customer zones: l ∈{1, 2,…, L}
n	Index of potential drop-off depots: n ∈{1, 2,…, N}
r	Index of potential recycling centers: r ∈{1, 2,…, R}
p	Index of tire's type: p ∈{1, 2,…, P}
s	Index of scenarios: s ∈{1, 2,…, S}

TABLE 2. The sets of parameters

Parameters	Description
fc_f	The fixed opening cost for facility f $\forall f \in \{m, j, n, r\}$
$tc_{ff'}^{p}$	The transportation cost for facility *f* to facility *f'* for type of tire p $\forall f \in \{i, m, j, l, n, r\}$
pc_f^{ps}	The rate of purchasing tire p from facility *f* over scenario s $\forall f \in \{i, m, j\}$
mc_m^{ps}	The manufacturing cost for type of tire *p* at manufacture *m* over scenario s
ac_{jl}	The per unit cost of assigning customer *l* to retailer *j* for type of tire *p*
d_l^{ps}	The demand of costumer *l* for tire *p over scenario s*
$\propto_l^p$	The fraction of returned tires from costumer *l* for type of tire *p*
hc_{ln}^{p}	The handling cost of costumer *l* to drop-off depot *n* for type of tire *p*
cp_f^p	The capacity of facility *f* for type of tire *p* $\forall f \in \{i, m, j, l, n, r\}$
pr_m	The per unit monetary resulted from the drop-off depots for remanufacturing
max_f	The predefined number of each facility *f* ,$\forall f \in \{m, j, n, r\}$
pr_r	The per unit monetary resulted from the drop-off depots for recycling
γ_n	The fraction of used tires shipped to recycle centers.
pb_s	The probability for each scenario.

TABLE 3. The sets of variables

Variables	Description
$X_{ff'}^{ps}$	Number of products that flow from facility *f* to facility *f'* for type of tire *p* over scenario s $\forall f \in \{i, m, j, l, n, r\}$
$Z_{ff'}^{ps}$	1 if facility *f* is assigned to facility *f'* over the type of tire *p* over scenario *s*, 0 otherwise $\forall f \in \{i, m, j, l, n, r\}$
Y_f	1 if facility f is to be established, 0 otherwise
$V_{s\varphi}$	The amount of expected financial risk for each scenario

$$E(Cost) = \sum_f fc_f Y_f + \sum_s pb_s \Big(\sum_f \sum_{f'} \sum_p tc_{ff'}^{p} X_{ff'}^{ps} + \sum_i \sum_m \sum_p \big(pc_i^{ps} + mc_m^{ps}\big) X_{im}^{ps} + \sum_j \sum_l \sum_p (pc_j^{ps} + ac_{jl}) d_l^{ps} Z_{jl}^{ps} + \sum_l \sum_n \sum_p hc_{ln}^{p} \propto_l^{ps} d_l^{ps} Z_{ln}^{ps} - pr_m \big(\sum_c \sum_d \sum_p (1-\gamma_n) X_{ln}^{ps}\big) - pr_r \big(\sum_u \sum_m \sum_p \gamma_n X_{ln}^{ps}\big)\Big) \tag{1}$$

In the objective function, the first term is the fixed cost of opening facilities. The remaining is multiplied by the corresponding probability of its scenario. The second represents the transportation cost between facilities. The third term represents the purchasing and manufacturing costs for the manufacturers. The fourth term represents the purchasing cost from retailers and the costs associated with assigning a retailer to a costumer. The fifth term is the cost associated with assigning costumers to drop-off depots to collect used tires in the Reverse Logistic (RL) represented as handling cost multiplied by the fraction of demand that is going to be reused. The sixth and seventh terms represent the saving resulting from the remanufacturing and recycling of used tires. These terms specify the profit of RL network in our model.

$$Min\ DRisk_{\varphi} = \sum_s pb_s V_{s\varphi} \tag{2}$$

Risk management is needed to be considered as an important issue when proposing a scenario-based stochastic programming model to control and to manage the risk associated with unfavourable scenarios. In this regard, the second objective function is to minimize the downside risk of the model by considering the probability of scenario s and its profitability according to the following constraint:

$$V_{s\varphi} \geq Cost^s - \varphi, \forall s \tag{3}$$

The above equation lets decision maker evaluate each scenario to consider its efficiency to find a robust solution. In addition, the following constraints specify tire flow between different facilities and costumers as shown in Figure 1.

$$\sum_i X_{im}^{ps} = \sum_m X_{mj}^{ps} \quad \forall p, m, j, s, l \tag{4}$$

$$\sum_l X_{ln}^{ps} = \sum_n X_{nr}^{ps} + \sum_n X_{nm}^{ps} \ \forall n, r, s, m \tag{5}$$

$$\sum_j X_{jl}^{ps} = \sum_j d_l^p Z_{jl}^{ps} \quad \forall p, l, s \tag{6}$$

$$\sum_n X_{ln}^{ps} = \sum_l \propto_l^p d_l^p Z_n^{ls} \quad \forall\ l, n, p, s \tag{7}$$

$$\sum_r X_{nm}^{ps} = (1-\gamma_n) \sum_n X_{ln}^{ps} \quad \forall\ n, l, p, s \tag{8}$$

In addition, each costumer should be assigned to only one retailer as well as one drop-off depots in the RL as a real assumption considered in the related studies e.g. [1]; [19] as follows:

$$\sum_j Z_{jl}^{ps} = \sum_n Z_{ln}^{ps} = 1\ \forall\ \text{l, p} \quad f \in \{j, m, s\} \tag{9}$$

The predefined amount of suppliers as illustrated in Equation (10) limits the capacity of facilities. In addition, the flow of products through a facility is only allowed if the respective facility is open and has enough capacity as formulated by Equations (11)-(14) for manufacturers, retailers, drop-off depots and recycling centers, respectively:

$$\sum_m X_{im}^{ps} \le cp_i^p \quad \forall\ i, p, s \tag{10}$$

$$\sum_j X_{mj}^{ps} \le cp_m^p Y_m \quad \forall\ m, p, s \tag{11}$$

$$\sum_l X_{jl}^{ps} \le cp_j^p Y_j \quad \forall\ j, p, s \tag{12}$$

$$\sum_l X_{ln}^{P} \le cp_n^p Y_n \quad \forall\ n, p, s \tag{13}$$

$$\sum_n X_{nr}^{P} \le cp_r^p Y_r \quad \forall\ r, p, s \tag{14}$$

Furthermore, the number of facilities in each echelon is limited by a predefined maximum budget.

$$\sum_f Y_f \le max_f \quad f \in \{m, j, n, r\} \tag{15}$$

The binary and continuous variables for the first stage of model are as follows.

$$Y_f, Z_{ff'}^{ps},\ \in \{0,1\} \tag{16}$$

$$X_{ff'}^{ps} \ge 0,\ V_{s\varphi} \ge 0 \tag{17}$$

3. SOLUTION APPROACH

This study uses two famous metaheuristics to solve the proposed *NP-hard* two-stage stochastic model. Since the algoritms are well-known and only adopted by this study, we refer the readers to go through literature [25-27]. In the following subsection, the encoding scheme used in the proposed solution procedures is detailed.

3.1. Encoding Scheme Whenever a metaheuristic procedure is used, coding and decoding the solution of mathematical problem is required [26]. This paper utilizes a two-stage technique called Random-Key (*RK*) to solve the developed discrete problem. Researchers have used this technique repeatedly during last two decades [28, 29]. This technique helps the users to use any continuous and binary metaheuristics to solve a mathematical formulation model with various variables and constraints [22]. The illustration of encoding sub-solutions is shown in Table 4. First, a matrix with size $|q|$ elements that are uniformly distributed over 0 to 1 is constructed (Table 4 (a)). This sub-solution is transformed into binary variables indexation the selection of manufacturers and retailers (Q2, Q4, and Q5 in the given example). Eventually after the algorithm runs, Table 4 (b) determines the flow of products. In the other words, a random matrix is formed with number of rows equals the number of non zero element obtained (3 in the given example) and number of columns equal to destination facilities (4 in the given example). The columns of the second matrix are then normalized to specify how retailers and other facilities distribute their supply.

4. COMPUTATIONAL EXPERIMENTS

In this section, the test problems are first introduced followed by tuning the algorithms' parameters using the Response Surface Method (*RSM*). Then, the evaluation metrics are investigated. Finally, the performance of both of the proposed algorithms is evaluated.

4. 1. Instances In this section, 18 random test problems divided into three levels (*i.e.,* small, medium and large sizes) were examined as shown in Table 5. It should be noted that the number of scenario in all test problems is equal to 10. The computational time is limited for both algorithms according to the size of problems.

4. 2. Parameter Setting To evaluate the performance of any metaheuristic, the model parameters should be optimized [28]. It is necessary to tune the parameters to balance between the two phases of metaheuristics. In this paper, *RSM* introduced by Box and Wilson is utilized [19]. The factors, their levels, and the number of experiments are shown in Table 6.

TABLE 4. The proposed encoding plan

	Q_1	Q_2	Q_3	Q_4	Q_5
1	0.34	0.57	0.25	0.68	0.92
			$P_{Max} = 3$		
2	0	1	0	1	1

(a) Facilities selection sub-solution

	d_1	d_2	d_3	d_4
Q_2	0.65	0.12	0.45	0.33
Q_4	0.49	0.08	0.38	0.17
Q_5	0.68	0.38	0.52	0.82

	d_1	d_2	d_3	d_4
Q_2	0.36	0.21	0.33	0.25
Q_4	0.27	0.14	0.28	0.13
Q_5	0.37	0.66	0.39	0.62

(b) Shipment from plants to retailers

TABLE 5. Design of test problem size

The levels of problem	Problem number (T_i)	Computational time (Second)	Size of problems (I, M, J, L, N, R, P)
Small	T1	20	(7, 5, 10, 9, 4, 3, 22)
	T2	30	(11, 8, 12, 13, 5, 4, 22)
	T3	40	(14, 12, 16, 15, 8, 7, 22)
	T4	50	(17, 16, 15, 16, 11, 10, 22)
	T5	60	(19, 14, 17, 19, 14, 12, 22)
	T6	70	(23, 16, 21, 20, 15, 13, 22)
Medium	T7	80	(25, 29, 30, 31, 19, 18, 22)
	T8	100	(29, 31, 32, 33, 21, 19, 22)
	T9	120	(34, 32, 33, 35, 23, 20, 22)
	T10	140	(37, 35, 34, 37, 25, 21, 22)
	T11	160	(41, 37, 36, 39, 27, 22, 22)
	T12	180	(45, 39, 38, 41, 29, 24, 22)
Large	T13	260	(67, 55, 59, 111, 36, 31, 22)
	T14	300	(71, 57, 61, 115, 37, 32, 22)
	T15	340	(75, 59 , 63, 119, 39, 33, 22)
	T16	380	(79, 61, 65, 123, 40, 34, 22)
	T17	420	(83, 63 , 67, 127, 42, 35, 22)
	T18	460	(87, 65, 69, 131, 43, 36, 22)

TABLE 6. Factors, levels, and number of experiments of the two proposed algorithms

Algorithm	Factors and their levels				N. of experiments; Total Number= (n_f, n_{ax}, n_{cp})
PSO	nPop	W	C1	C2	30=(2^4, 8, 6)
	(100, 200)	(0.65, 0.9)	(1.2, 2)	(1.2, 2)	
GA	nPop	P_C	P_M		20=(2^3, 6, 6)
	(100, 200)	(0.5, 0.8)	(0.02, 0.1)		

nPop=number of population, W=inertia weight, C1=acceleration coefficient of local optimum, C2=acceleration coefficient of global optimum , P_C=probability of crossover, P_M=probability of mutation

Consequently, the tuned values for parameters, *R*-squared (R^2) and desirability (*D*), are approximated as displayed in Table 7.

4. 3. Evaluation Metrics In order to solve the proposed problem, four metrics are presented. These metrics aim to assess the quality of the Pareto optimal solutions (Diversification Metric (DM), Spread of Non-dominance Solution (SNS), Data Envelopment Analysis (DEA) and Percentage of Domination (POD)) [7]. The higher value of these metrics the better the solution quality. The characteristics of these metrics are outlined in Table 8. These parameters are presented in recent researches [7, 19, 27, 28].

4. 4. Comparison of Metaheuristics This sub-section aims to discuss the effectiveness and efficiency of the proposed solution approaches. Each algorithm is applied on all test problems for 30 times, and the best solution is saved. Then, the proposed evaluation metrics are calculated as shown in Table 9. Furthermore, to check statistically the validation of the results, an analysis of variance (ANOVA) is performed to analyze and to evaluate the obtained results. At the first glance, the results reveal that there is a mixed statistical difference between the performance and efficiency of the both algorithms. The means plot and LSD intervals (at the 95% confidence level) for all methods are shown in Figure 2. It should be noted that for both algorithms, the results of the metrics are analyzed by Relative Percentage Deviation (*RPD*). Lower RPD values mean better capability.

According to Figure 2, based on DM metric, GA has a slightly better performance, in comparison of PSO. In SNS metric, the behaviour both algorithms are analogous.

TABLE 7. Optimized values of algorithms parameters and Desirability (D)

Algorithm	Tuned parameters	D
PSO	nPop=133, W=0.73, C1=1.46, C2=1.46	0.6823
GA	nPop=168; P_C=0.75; P_M=0.05	0.6523

TABLE 8. Metrics used to measure the quality of Pareto front

Metrics	Definition
Diversification Metric (DM)	Measures the spread of non-dominated solution set.
Spread of Non-dominated Solution (SNS)	Measures the diversity of solutions.
Percentage of Domination (POD)	Measures the ability of an algorithm to dominate the solutions of other algorithms
Data Envelopment Analysis (DEA)	Determines the efficiency of solutions.

TABLE 9. The evaluation metrics to algorithms performance (DM, SNS, DEA and POD) for test problems

No. of problems	DM		SNS		DEA		POD	
	PSO	GA	PSO	GA	PSO	GA	PSO	GA
T1	14389	16452	2267	1748	0.16	0.12	0.22	0.14
T2	15842	14753	3351	3274	0.74	0.65	0.33	0.41
T3	14632	15742	5574	6632	0.21	0.63	0.33	0.36
T4	12669	13745	1422	1544	0.44	0.15	0.24	0.32
T5	17275	19743	7210	5426	0.12	0.18	0.18	0.19
T6	6833	7491	7296	6948	0.22	0.26	0.20	0.10
T7	29164	34112	3105	2915	0.14	0.22	0.14	0.11
T8	12742	13671	1834	751	0.26	0.18	0.18	0.16
T9	25199	23749	1282	675	0.12	0.12	0.14	0.12
T10	22102	25761	4912	4466	0.14	0.20	0.16	0.14
T11	31054	32144	5187	5514	0.18	0.14	0.18	0.14
T12	7401	6195	5853	6432	0.22	0.20	0.16	0.08
T13	8132	8512	4831	3957	0.18	0.12	0.14	0.16
T14	55261	54771	2745	5544	0.74	0.41	0.32	0.41
T15	23614	22516	3514	3422	0.36	0.21	0.23	0.31
T16	31474	23964	2988	6211	0.41	0.33	0.41	0.44
T17	44752	41636	3425	2855	0.33	0.21	0.33	0.22
T18	41957	38456	2671	3166	0.52	0.12	0.24	0.17

However, PSO is better than GA. Additionally, for both DEA and POD metrics, PSO is strongly better than GA and shows a mixed performance.

5. CONCLUSION AND FUTURE STUDIES

In this paper, a new two-stage stochastic programming for the tire industry closed-loop supply chain model is developed. The model is different from other similar papers in the literature by considering the financial risks. In the proposed model, a special network for tire production is proposed. Two metaheuristics *i.e.* GA and PSO are utilized to address the problem. Four assessment metrics are proposed to evaluate the performance of the algorithms under different criteria to study the structure of the Pareto optimal solutions. Finally, results showed that PSO is slightly better than GA in comparisons. Also, the present model shows the importance of collecting and recycling of scraped tires to consider a performance decisions for consumers and manufacturers.

For the future works, more comprehensive analyses on the proposed model can be suggested. In addition, other assessment parameters could be implemented to analyze the performance of algorithms. Moreover, some real cases may be used to present the model more efficiently. Regarding the application side, more real life constraint should be added on the proposed model increasing the complexity of the problem, such as: vehicle routing operations to reduce the transportation cost or sustainable considerations.

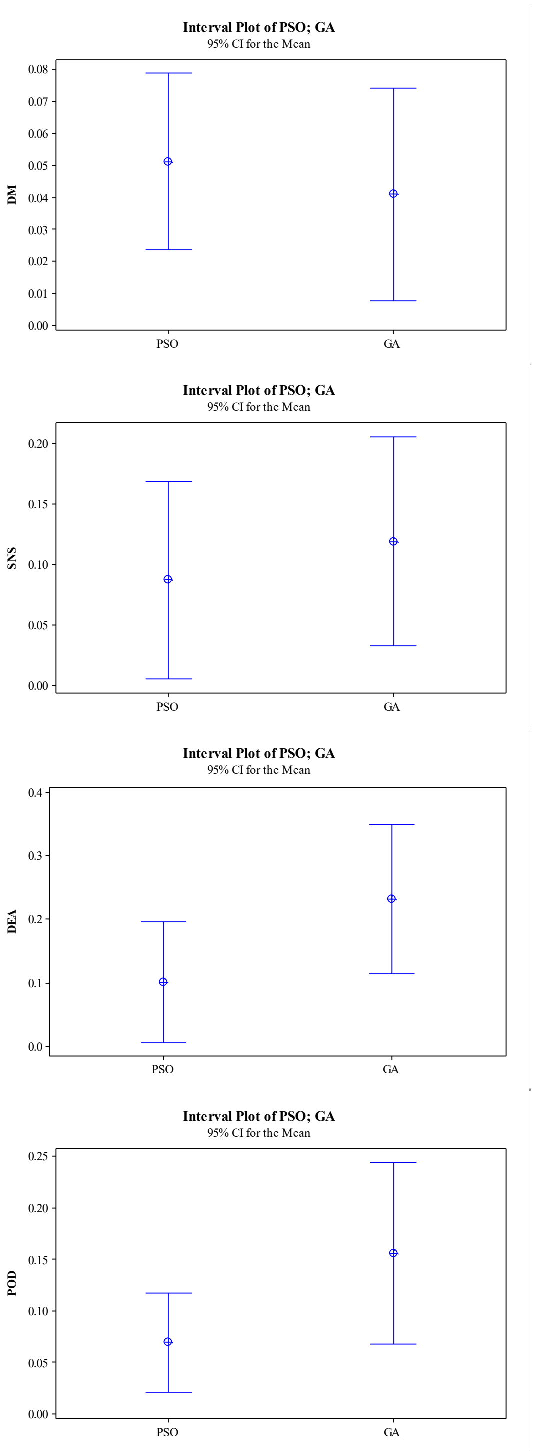

Figure 2. The interval plot for four proposed metrics

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A Collaborative Stochastic Closed-loop Supply Chain Network Design for Tire Industry

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چکیده

مقاله های اخیر در مورد طراحی شبکه زنجیره تامین به سرعت در حال توسعه با استفاده از مدل های تحت عدم قطعیت برای نزدیک شدن به کاربردهای دنیای واقعی است. با توجه به نوع محصولات مانند چرخ خودرو، ساختار زنجیره تامین تغییر می کند. در صنعت تایر، سختی ها و باز استفاده تایرهای کهنه و همه این سختی ها در بازسازی انرژی و هزینه های اضافه منجر به بازیافت چرخ های خودرو استفاده شده در میان یک طراحی شبکه زنجیره تامین حلقه بسته می شود. این مقاله، یک مدل دو مرحله ای تصادفی را برای زنجیره تامین حلقه بسته تایر طراحی می کند. در مرحله اول، مدل هزینه انتظاری را بهینه سازی می‌کند. سپس، ریسک مالی در یک تابع هدف مجزا در مرحله دوم مدل اقدام به کنترل عدم قطعیت متغیرهای تصمیم گیری برای رسیدن به یک جواب پایدار می کند. برای حل این مساله، الگوریتم بهینه سازی ازدحام ذرات و الگوریتم ژنتیک به کار گرفته شده اند. برای افزایش اثربخشی الگوریتم ها، روش سطح پاسخ به کار گرفته شده است. مدل پیشنهاد شده با مسائل مختلف با سطح های دشواری متفاوت و پارامترهای ارزیاب مختلف برای جواب های بهینه پارتو با یکدیگر مقایسه شده اند.

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