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Presenting a Sustainable Tire Closed-Loop Supply Chain Model Using Risk Passive Defense Approach

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Abstract: In this paper, we present and solve an integrated robust closed-loop supply chain model for tire industry with passive defense approach using a "whale optimization algorithm" (WOA) and a "non-dominated sorting genetic algorithm" (NSGA-II).A test problem is solved in three groups of small, medium and large sample sizes using WOA. To prove the performance of this algorithm, the model is also solved with NSGA-II algorithm, and the two solution results are compared based on comparison metrics of quality, diversity, uniformity, and computational time.The results show that in all cases, WOA has a higher ability to achieve higher quality and near-optimal solutions than the NSGA-II algorithm. Also, the diversity metric values show that WOA is more powerful in exploring and exploiting feasible solutions. The results of uniformity metric and computational time also show that NSGA-II algorithm has less computational time than WOA and searches the solution space more uniformly.

Keywords: Green Closed-Loop Supply Chain, Passive Defense Method, Multi-Criteria Decision, Tire Industry

1. Introduction

A supply chain consists of a set of sequential activities, including procurement of raw material, production, inventory management, distribution, and flow of product to the end user in which each specific process is planned and optimized using desirable decision criteria. A closed-loop supply chain consists of a forward supply chain and a reverse supply chain combined[1].

Sustainable supply chain management is defined as the management of materials, information, and investment in coordination between elements of the supply chain, which has been the focus of managers and researchers for several decades [2]. In recent years, sustainability in supply chain management, attention to environmental factors, and social aspects have become important issues [3][4]. Environmental and social sustainability is a relatively complex subject area that affects various parts of the supply chain [5].

On the other hand, due to increasing uncertainty in the supply chain and the presence of some factors such as political issues, demand fluctuations, technological changes, financial instability, natural disasters, etc., organizations are trying to reduce vulnerability and increase their supply chain flexibility and robustness by investing resources in analyzing and forecasting supply, demand and the uncertainty associated with their internal operation. Attention to these uncertainties and risk factors led to the subject of risk management in the supply chain [6]. The existence of risk and failure in the supply chain can have a significant impact on short-term performance and long-term negative impact on the financial performance of the organization. Therefore, supply chain risk management is necessary to reduce failures caused by various risks such as uncertain economic cycles, uncertain customer demand, unpredictable natural disasters, etc. [7]. Risk management requires the identification, evaluation, and ranking of various risks. Risk assessment is one of the pillars of risk management, and its purpose is to measure risk based on various criteria such as the impact and the probability of occurrence. The accurate results of this risk assessment indicate that the risk management process is performed with a higher degree of confidence.

In recent years, many studies have presented models for the closed-loop supply chain by considering sustainability and risk management in the supply chain. However, despite the importance of passive defense in the sustainable closed-loop supply chain, not enough attention has been paid to this subject area. Therefore, this study has been performed with the aim of presenting and solving a sustainable closed-loop supply chain model with passive defense approach. To the best ofauthor's knowledge, no paper has been published using passive defense approach on the design of the environmentally conscious closed-loop supply chain in the tire industry. In order to achieve the research goal, a four-objective mathematical model is presented and solved using the Whale optimization algorithm based on the Pareto archive. To evaluate the performance of the proposed algorithm, the results are compared with the results of NSGA-II algorithm based on comparison metrics of quality, uniformity, and diversity.

2. Literature review

2.1. Closed-loop supply chain and tire supply chain

There have been many researches in the field of closed-loop supply chains. A comprehensive review on environmentally conscious manufacturing and product recovery was provided by Ilgin and Gupta (2010) [8]. Demirel et al. (2014) proposed a multi-period, multi-product mixed-integer linear programming model for a closed-loop supply chain network [9]. Vahdani et al. (2015) presented a multi-product and multi-period model for designing a closed-loop supply chain network under fuzzy uncertainty [10]. In their article, Fallah-Tafti et al. (2014) designed an integrated multi-stage supply chain network that includes assembly centers, collection, disposal centers, and customers [11]. Ma et al. (2016) have proposed a bi-objective model for a robust closed-loop supply chain under uncertainty. They solved the proposed model using Lingo software. Due to the NP-hard nature of the problem and Lingo's inability to solve large size problems, they only solved the model for small size problems [12]. Banasik et al. (2017) have designed a multi-objective linear optimization model of a closed-loop supply chain network for mushroom production[13]. Hassanzadeh and Baki (2017) have presented a multi-objective facility location model for a closed-loop supply chain under fuzzy uncertainty focusing on the location of the reverse logistics facilities [14]. Dulman and Gupta (2018) studied the financial impact of sensors on closed-loop supply chain systems [15].

Lin et al. (2018) proposed a mathematical model for the location-allocation problem in the reverse logistics network for used vehicle collection with the aim of minimizing location and allocation costs[16]. Xiao et al. (2019) investigated the location-allocation problem in the reverse logistics network for the collection of used vehicles by considering greenhouse gas emissions[17]. Zhou and Gupta (2019) provided a pricing strategy for new and remanufactured high-tech products [18]. In another study, they proposed partial least square method to explore the factors that affect value depreciation rate and price differentiation between new and remanufactured iPhone and iPad [19]. Aldoukhi and Gupta (2019) proposed a new model for designing a closed-loop supply chain network by considering a downward product substitution policy under four carbon emission regulation policies[20]. In another study, they proposed a multi-objective model to design a closed-loop supply chain network with the aim of minimizing the total cost, minimizing the carbon emission, and maximizing the service level of the retailers[21]. Fadhel and Gupta (2019) evaluated the food waste valorization alternatives from a sustainability point of view[22]. Safdar et al. (2020) also examined the issue of designing a reverse logistics network for electronic waste management[23]. Kuroki et al. (2020) also studied and modeled the location-routing problem in the recycling system with the aim of improving economic efficiency[24]. Oliveira and Machado (2021) provided a literature review on the application of optimization methods in a closed-loop supply chain [25].

In 1997, Ferrer published a paper and estimated the optimal number of times each tire can be retreaded [26]. Sasikumar et al. (2010) provided an optimization model for a tire remanufacturing case [27]. Amin et al. (2017) examined a case study for the closed-loop supply chain network for tire industry in Toronto, Canada[28]. Subulan et al. (2015) examined tire remanufacturing case study in Turkey using a fuzzy mixed integer programming approach [29]. Derakhshan et al. (2017) presented a technique for recycling and reuse of tire waste [30]. O'Brien and North (2017) investigated the emission of pollutants from tire waste. They studied the types of gases generated from car tire waste [31]. Fathollahi-Fard et al. (2018) designed a closed-loop tire supply chain and used a hybrid optimization approach to solve the model[32]. SahebJamnia et al. (2018) also modeled a robust closed-loop supply chain and used hybrid metaheuristic algorithms to solve the model [33]. Lokesh et al. (2018a) studied tire retreading supply chain network under carbon tax policy. In another study, Lokesh et al. (2018b) used a fuzzy goal programming approach for Brownfield tire retreading case study under carbon tax policy [34][35]. Kumar et al. (2020) designed a sustainable tire supply chain with a fuzzy goal planning approach [36].

2.2. Sustainable supply chain

Some research has been conducted in the field of sustainable supply chain. Teuteberg and Wittstruck (2010) presented a systematic approach to sustainable supply chain management[37]. Devika et al. (2014) designed a sustainable closed-loop supply chain network[38]. Aravendan et al. (2014) have presented a multi-echelon multi-products model for a sustainable closed-loop supply chain[39].Bhattacharjee and Cruz (2015) have examined the issue of economic sustainability in the closed-loop supply chain[40]. Zhalechian et al. (2016) modeled a sustainable closed-loop supply chain by taking into account location, routing, and inventory under uncertainty[41]. Bettini et al. (2016) examined the sustainable closed-loop supply chain in humanitarian operations that provide aids during natural disasters[42]. Rezaei and Kheirkhah (2017) have studied the sustainable closed-loop supply chain and have presented a tri-objective mathematical model with economic, social, and environmental objectives[43]. Das (2018) examines the lean system in designing a sustainable

supply chain network. The purpose of this research is to integrate lean systems applications in design and supply chain planning to improve the overall business performance [44].

2.3. Risk passive defense model in the supply chain

Numerous studies have discussed risk passive defense in the supply chain and some studies have conducted a literature review on supply chain risk management [7]. Tuncel et al. (2010) have studied a two-tier supply chain network design including supply, transportation, and customer nodes by considering the risk of facility disruption such as disruption in the transfer of products [45]. Giannakis and Louis (2011) provide a framework for designing a multi-factor decision support system to manage the risks associated with production supply chain [46]. Azaron et al. (2008) proposed a multi-objective stochastic planning approach to supply chain design under uncertainty by considering risk [47]. In another study by Goh et al. (2007), an algorithm is proposed to deal with the issue of multi-stage global supply chain networks with the goal of maximizing profit and minimizing risk associated with supply, demand, exchange rates, and network failure [48]. Aghaei and Ebadati (2013) designed the supply chain management network by considering the risk of passive defense. They proposed a mathematical model for this problem and solved the model using a heuristic algorithm [49]. Xu et al. (2013) designed a tri-level planning model based on the Conditional Value at Risk (CVAR) approach to managing the risk in a three-stage supply chain [50]. Soleimani and Govindan (2014) also have designed a reverse logistics network using Conditional Value at Risk [51]. Golpira et al. (2017) proposed a robust bi-objective optimization for green supply chain network by considering uncertainty and environmental risk [52].

3. Mathematical modeling

As illustrated in Fig. (1), the proposed robust supply chain network includes suppliers, manufacturers, distribution centers, and customers on forward direction; and collection centers, used product markets, recycling centers, retreading centers, and energy recovery centers in the reverse direction. In this research, customer demand may not be satisfied, and there is a penalty cost for unsatisfied demand, and competition between retreading centers.

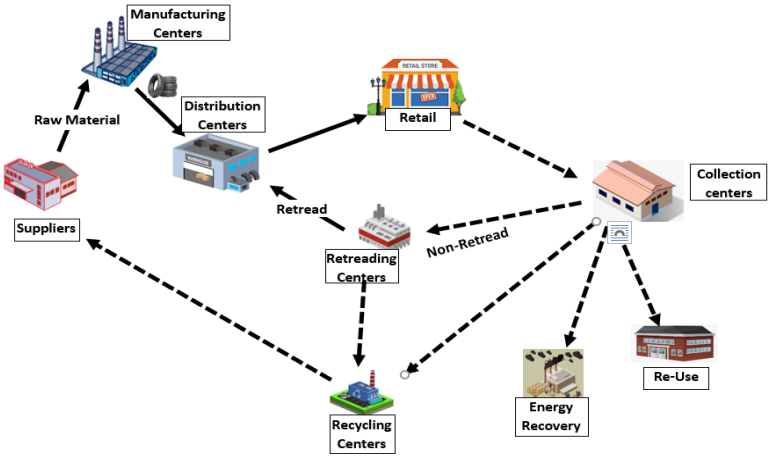

Figure 1- Schematic view of supply chain network under consideration

In the proposed supply chain model, in the forward direction, suppliers are responsible for providing components and raw materials to the manufacturers. New products are shipped from manufacturing centers through distribution centers to the customers to meet their demand. In the reverse direction, returned products are sent to the collection centers where a thorough inspection and evaluation is performed, and based on the result, high-quality tires with good tread depth are transferred to the used tire market, the tires that their casing is in good condition are transferred to retreading centers. The remaining tires are sent to either recycling or energy recovery centers. From the retreading centers, the retread tires are sent to the distribution centers and are placed in the distribution cycle.In this study, in order to increase supply chain resiliency, risk management as one of the capabilities of risk passive defense in the supply chain is utilized. Also, considering diversity as one of the passive defense measures, in the present study, the principle of diversity is used for facility location in the supply chain. On the other hand, in order to use the passive defense approach, supply chain agility and flexibility are also considered, which are applied in the mathematical modeling as the relevant constraints, and in objective functions as minimization of risk, delay costs, and non-compliance with the minimum level of flexibility.

In this research, three dimensions of supply chain sustainability, including economic, social, and environmental impacts, have been considered. Each of these dimensions is considered in the model based on different criteria and related constraints. For environmental aspects, the impact of the supply chain on the amount of waste generated in the supply chain is considered. To evaluate the economic aspect, the impact of the supply chain on investment, revenue from sales of tires, retread and recycling tires are considered. The social aspect focuses on the impact of supply chain on social sustainability, the number of jobs created and workforce injuries in manufacturing centers.In the following, based on the problem description, the mathematical model is designed, and the elements of the proposed model are described.

3.1. Model parameters

Indices:

I: Set of supplier locations $i \in I$

J: Set of manufacturing locations $j \in J$

L: Set of customer locations $l \in L$

R: Set of potential locations for retreading centers, $r \in R$

M: Set of potential locations for collection centers, $m \in M$

N: Set of potential locations for potential energy recovery, $n \in N$

K: Set of potential locations for potential distribution centers, $k \in K$

P: Set of potential locations for recycling centers, $p \in P$

S: Set of types of tires, $s \in S$

S': Set of raw material, $s' \in S'$

T: period Index, $t \in T$

Parameters:

$\tilde{r}_l^{st}$: The return rate of tire s from customer l in period t

$\tilde{d}_l^{st}$: Demand for tire s from customer l in period t

$Price_s$: Price of new tire s sold in the market

$pricem_s$: Price of the returned tire s paid to the customer (upon collection)

$pricer_s$: Selling price of the returned tire s sold in the second-hand market

$costp_s$: The cost of producing a unit of product s

$costrc_s$: Cost of recycling a unit of tire s

$costrt_s$: Cost of retreading a unit of tire s

$costn_s$: Cost of energy recovery per unit of tire s

$valuep_s$: Value added to the system after recycling a unit of tire s

$valuer_s$: Value added to the system after retreading a unit of tire s

pen_{ls}: Penalty costs imposed on the system due to unsatisfied customer demand

$B0_r$: The maximum attraction of the retreading center r. Retreading centers compete with one another

B_r: The attraction coefficient of the retreading center r. $B_r = B0_r e^{-\gamma d^2}$ where d is the Euclidean distance and γ is the attraction coefficient

βr^{St}: Return rate of tire s from the collection center m to the retreading center r in period t

Brk^{st}: Retreading rate of tire s at retreading center k in period t

βn^{St} : Return rate of tire s from the collection center m to energy recovery center n in period t

βk^{St}: Return rate of product s from the collection center m to second-hand market in the period t.

βp^{St}: Return rate of product s from the collection center m to the recycling center p in period t

$rate_{ss'}$: Rate of raw material s' needed to produce one unit of tire s

$ratep_{ss'}$: Recycling rate of raw material s' from one unit of tire s at recycling centers

f_k: Fixed opening cost of a distribution center at location k

f_r : Fixed opening cost of a retreading center at location r

f_m: Fixed opening cost of a collection center at location m

f_p : Fixed opening cost of a recycling center at location p

f_n : Fixed opening cost of an energy recovery center at location n

$c_{ij}^{s'}$: Transportation cost of a unit of raw material s' from supplier i to manufacturing center j

c_{jk}^{s}: Transportation cost of a unit of tire s from manufacturing center j to distribution center k

c_{kl}^{s}: Transportation cost of a unit of tire s from distribution center k to customer l

c_{lm}^{s} : Transportation cost of a unit of used tire s returned from customer l to the collection center m

c_{mp}^{s}: Transportation cost of a unit of used tire s from collection center m to recycling center p

c_{mn}^{s}: Transportation cost of a unit of used tire s from collection center m to energy recovery n

c_{m}^{s}: Transportation cost of a unit of used tire s from collection center m to the second-hand market

c_{mr}^{s}: Transportation cost of a unit of used tire s from collection center m to retreading center r

c_{rk}^{s} : Transportation cost of a unit of used tire s from retreading center r to the distribution center k

c_{pi}^{s} : Transportation cost of a unit of used tire s from recycling center p to supplier center i

c_{rp}^{s}: Transportation cost of a unit of tire from retreading center r to recycling center p

$c_{pi}^{s'}$: Transportation cost of a unit of raw material s' from recycling center p to supplier i

cap_i: The capacity of the supplier at location i

cap_j : Capacity of the manufacturing center at location j

$capj_j$: Capacity of manufacturing center's warehouse at location j

cap_r: Capacity of retreading center at location r

cap_k : Capacity of distribution center at location k

cap_m : Capacity of collection center at location m

cap_p : Capacity of recycling center at location p

cap_n : Capacity of energy recovery center at location n

h_j^s : The cost of storing each unit of product s in the manufacturer's warehouse at location j

α_k: The number of job opportunities created in distribution center k

α_{inv}: Number of job opportunities created in reverse logistics centers

dl_j : Average lost working days due to work injury in production center j per unit of tire produced

θ_l: Weight factor of work injury

sp_{js}: Average waste generated at production center j to produce one unit of tire s

dp_{js}: Average hazardous materials used in production center j to produce one unit of tire s

θ_w: Weight factor of produced waste (weight of waste produced in the objective function)

θ_h: Weight factor of hazardous substances (weight of hazardous substances in the objective function)

$VARD_{is't}$: Risk of delay in delivery of raw material s' from supplier i in period t

$VARD_{kst}$: Risk of delay in delivery of product s by distributor k in period t.

$VARQ_{is't}$: Risk of defective raw material s' received from supplier i in period t

$VARQ_{Kst}$: Risk of defective product s received from distributor k in period t

$VARND_{it}$: Risk of occurrence of natural disasters to the supplier i in period t

$VARF^{sen}{}_{it}$: Liquidity risk of supplier i in period t

$dk_{kk'}$: The distance between distributors k and k', which is calculated as the Euclidean distance

$dk_{rr'}$: Distance between retreading centers r and r' which is calculated as the Euclidean distance

$dn_{nn'}$: Distance between energy recovery centers n and n' which is calculated as the Euclidean distance

$dm_{mm'}$: Distance between collection center m and m' which is calculated as the Euclidean distance

$dp_{pp'}$: Distance between recycling centers p and p' which is calculated as the Euclidean distance

DK: Minimum distance between established distribution centers

DR: Minimum distance between established retreading centers

DM : Minimum distance between established collection centers

DN: Minimum distance between established energy recovery centers

DP: Minimum distance between established recycling centers

$LDC_{is't}$: Delay cost of supplier i to supply raw material s' in period t

$O_{is't}$: Cost of ordering product s to supplier i in period t

$R_{is't}$: Percentage of returned product s from supplier i in period t

R0 : Maximum acceptable percentage of non-conforming material received in planning horizon

Variables:

y_k: If the distribution center is open at location k, its value is 1 and otherwise it is 0

y_m: If the collection center is open at location m, its value is 1 and otherwise it is 0

y_p : If the recycling center is open at location p, its value is 1 and otherwise 0

y_n : If the energy recovery center is open at location n, its value is 1 and otherwise it is 0

y_r : If the reproduction center is open at location r, its value is 1 and otherwise 0

$x_{ij}^{s't}$: Quantity of raw materials s' shipped from supplier i to the production center j in period t

x_{jk}^{st}: Quantity of tire s shipped from manufacturing center j to distribution center k in period t

x_{kl}^{st} : Quantity of tire s shipped from the distribution center k to the customer l in period t

x_{lm}^{st} : Quantity of used tire s shipped from the customer l to the collection center m in period t

x_{m}^{st} : Quantity of used tire s shipped from collection center m to the second-hand market in period t

x_{mp}^{st} : Quantity of used tire s shipped from collection center m to the recycling center p in period t

x_{mn}^{st} : Quantity of used tire s shipped from collection center m to energy recovery center n in period t

x_{mr}^{st} : Quantity of used tire s shipped from collection center m to retreading center r in period t

x_{rp}^{st}: Quantity of used tire s shipped from retreading center r to recycling center p in period t

$x_{pi}^{s't}$: Quantity of recycled raw material s' from recycling center p to the supplier i in period t

U_{j}^{st}: Residual inventory of tire s remains in the manufacturer's warehouse at location j in period t

q_{l}^{st}: Unsatisfied customer demand for tire s in period t

3.2. Mathematical model:

The first objective function is to maximize the total profit of the network. The elements of this objective function includefacilities opening costs, transportation costs, cost of unsatisfied demand,storage costs, buyback cost, production cost,retreading cost,recycling cost, energy recovery cost, ordering and delay cost, revenue from selling new and retread tires, selling used tires and recycled material. The total profit is obtained by subtracting the total cost from revenue:

$$
\begin{aligned}
\max z1 = {} & \sum_t\sum_s\sum_k \mathrm{price}_s\left(\sum_l x_{kl}^{st}\right) + \sum_t\sum_s\sum_m \mathrm{pricem}_s\left(x_m^{st}\right) + \sum_t\sum_s\sum_p \mathrm{valuep}_s\left(\sum_m x_{mp}^{st}\right) \\
& + \sum_t\sum_s\sum_p \mathrm{valuer}_s\left(\sum_r x_{rk}^{st}\right) - [\sum_k f_k y_k + \sum_m f_m y_m + \sum_n f_n y_n + \sum_p f_p y_p + \sum_r f_r y_r \\
& + \sum_t\sum_{s'}\sum_i\sum_j c_{ij}^{s'}\left(x_{ij}^{s't}\right) + \sum_t\sum_s\sum_j\sum_k c_{jk}^{s}\left(x_{jk}^{st}\right) + \sum_t\sum_s\sum_k\sum_l c_{kl}^{s}\left(x_{kl}^{st}\right) \\
& + \sum_t\sum_s\sum_l\sum_m c_{lm}^{s}\left(x_{lm}^{st}\right) + \sum_t\sum_s\sum_m\sum_p c_{mp}^{s}\left(x_{mp}^{st}\right) + \sum_t\sum_s\sum_m\sum_n c_{mn}^{s}\left(x_{mn}^{st}\right) \\
& + \sum_t\sum_s\sum_m\sum_r B_r\, c_{mr}^{s}\left(x_{mr}^{st}\right) + \sum_t\sum_s\sum_m c_{m}^{s}\left(x_{m}^{st}\right) + \sum_t\sum_s\sum_r\sum_k B_r c_{rk}^{s}\left(x_{rk}^{st}\right) \qquad (1) \\
& + \sum_t\sum_s\sum_r\sum_p c_{rp}^{s}\left(x_{rp}^{st}\right) + \sum_t\sum_{s'}\sum_p\sum_i c_{pi}^{s'}\left(x_{pi}^{s't}\right) + \sum_t\sum_j\sum_s h_j^s U_{js}^t + \sum_t\sum_s\sum_l\sum_m \mathrm{pricem}_s\left(x_{lm}^{st}\right) \\
& + \sum_t\sum_s\sum_j \mathrm{cost}_s\left(\sum_k x_{jk}^{st} + U_{js}^t\right) + \sum_t\sum_s\sum_r \mathrm{costr}_s\left(\sum_k x_{rk}^{st}\right) + \sum_t\sum_s\sum_p \mathrm{costp}_s\left(\sum_m x_{mp}^{st}\right) \\
& + \sum_t\sum_s\sum_n \mathrm{costn}_s\left(\sum_m x_{mn}^{st}\right) + \sum_i\sum_t\sum_j\sum_{s'}(O_{is't} + LDC_{is't})x_{ij}^{s't} + \sum_t\sum_s\sum_l \mathrm{pen}_{ls}(q_l^{st})]
\end{aligned}
$$

The second objective function is to maximize social benefits:

$$\max z2 = \sum_{k} \alpha_k y_k + \sum_{m} \alpha_{inv} y_m + \sum_{n} \alpha_{inv} y_n + \sum_{p} \alpha_{inv} y_p + \sum_{r} \alpha_{inv} y_r - \theta_l \sum_{t}\sum_{s}\sum_{j} dl_j \left(\sum_{k} x_{jk}^{st} + U_{js}^{t} \right) \quad (2)$$

The third objective function is to minimize total environmental impacts:

$$\min z3 = \theta_w \sum_{t}\sum_{s} (\sum_{j} sp_{js} (\sum_{k} x_{jk}^{st} + U_{js}^{t})) + \theta_h \sum_{t}\sum_{s} (\sum_{j} sp_{js} (\sum_{k} x_{jk}^{st} + U_{js}^{t}))) \quad (3)$$

The fourth objective function is to minimize risk:

$$\min z4 = \sum_{t}\sum_{s}\sum_{i} VARD_{ist} (\sum_{j} x_{ij}^{st}) + \sum_{t}\sum_{s}\sum_{k} VARD_{kst} (\sum_{l} x_{kl}^{st}) + \sum_{t}\sum_{s}\sum_{i} VARQ_{ist} (\sum_{i} x_{ij}^{st})$$
$$\sum_{t}\sum_{s}\sum_{k} VARQ_{kst} (\sum_{l} x_{kl}^{st}) + \sum_{t}\sum_{s}\sum_{i} VARND_{it} (\sum_{j} x_{ij}^{st}) + \sum_{t}\sum_{s}\sum_{i} VARF_{it} (\sum_{j} x_{ij}^{st}) \quad (4)$$

Constraints:

$$\sum_{k} x_{kl}^{st} + q_l^{st} = \tilde{d}_l^{st} \qquad \forall l, s, t \quad (5)$$

$$\sum_{m} x_{lm}^{st} = \tilde{r}_l^{st} \qquad \forall l, s, t \quad (6)$$

$$\sum_{r} x_{mr}^{st} = Br^{st} \sum_{l} x_{lm}^{st} \qquad \forall m, s, t \quad (7)$$

$$\sum_{p} x_{mp}^{st} = Bp^{st} \sum_{l} x_{lm}^{st} \qquad \forall m, s, t \quad (8)$$

$$\sum_{n} x_{mn}^{st} = Bn^{st} \sum_{l} x_{lm}^{st} \qquad \forall m, s, t \quad (9)$$

$$x_m^{st} = Bk^{st} \sum_{l} x_{lm}^{st} \qquad \forall m, s, t \quad (10)$$

$$\sum_{k} x_{rk}^{st} = Brk^{st} \sum_{m} x_{mr}^{st} \qquad \forall r, s, t \quad (11)$$

$$\sum_{p} x_{rp}^{st} = \sum_{m} x_{mr}^{st} - \sum_{k} x_{rk}^{st} \qquad \forall r, s, t \quad (12)$$

$$\sum_{i}\sum_{s'} rate_{s's} x_{ij}^{s't} = \sum_{k} x_{jk}^{st} + U_{js}^{t} \qquad \forall j, s, t \quad (13)$$

$$\sum_{r} x_{rk}^{st} + \sum_{j} x_{jk}^{st} = \sum_{l} x_{kl}^{st} \qquad \forall k, s, t \quad (14)$$

$$\sum_{m}\sum_{r}\sum_{s} ratep_{s's} (x_{mp}^{st} + x_{rp}^{st}) = \sum_{i} x_{pi}^{s't} \qquad \forall p, s', t \quad (15)$$

$$\sum_{s}\sum_{j} x_{ij}^{st} \le cap_i \qquad \forall i, t \quad (16)$$

$$\sum_{s}\sum_{k} x_{jk}^{st} \le cap_j \qquad \forall j, t \quad (17)$$

$$\sum_{s} U_{js}^{t} \le cap_{jj} \qquad \forall j, t \quad (18)$$

$$\sum_{m}\sum_{s} x_{mr}^{st} \le y_r cap_r \qquad \forall r, t \quad (19)$$

$$\sum_{l}\sum_{s} x_{kl}^{st} \le y_k cap_k \qquad \forall k, t \quad (20)$$

$$Br^{st} + Bk^{st} + Bn^{st} + Bp^{st} + Bm^{st} = 1 \qquad \forall s, t \quad (21)$$

$$dk_{kk'} \ge DK \qquad \forall k, k' \quad (22)$$

$$dr_{rr'} \ge DR \qquad \forall r, r' \quad (23)$$

$$dn_{nn'} \ge DN \qquad \forall n, n' \quad (24)$$

$$dp_{pp'} \ge DP \qquad \forall p, p' \quad (25)$$

$$dm_{mm'} \ge DM \qquad \forall m, m \quad (26)$$

$$\sum_{s'} rate_{s's} \sum_{t}\sum_{i} R_{is't} \sum_{j} x_{ij}^{s't} \le R_0 \sum_{t}\sum_{l} \tilde{d}_{ls}^{t} \qquad \forall s \quad (27)$$

$$y_k, y_r, y_m, y_p, y_n = \{0,1\} \qquad \forall k, r, p, n, m \tag{28}$$

$$x_{ij}^{s't}, x_{jk}^{st}, x_{kl}^{st}, x_{lm}^{st}, x_{m}^{st}, x_{mn}^{st}, x_{mp}^{st}, x_{mr}^{st}, x_{rk}^{st}, x_{rp}^{st}, x_{pi}^{s't}, U_{js}^{t}, q_{l}^{st} \geq 0 \tag{29}$$

Constraint (5) ensures that the market demand for new tires is satisfied. Constraint (6) calculates the total quantity of tires returned to each collection center in the reverse direction. Constraint (7) calculates the total quantity of tires send to retreading centers. Constraint (8) calculates the total quantity of tires send to recycling centers. Constraint (9) calculates the total quantity of tires send to recycling centers. Constraint (10) indicates the total quantity of tires sent to the used tire market. Constraints (11) and (12) are equilibrium constraints at each retreading center. Constraint (13) guarantees that the raw material needed at production centers are satisfied. Constraints (14) and (15) ensures flow balance at retreading and collection centers, respectively. Constraint (16) shows the amount of recycled material transferred from recycling centers to suppliers. Equations (17) to (21) ensure that the capacity of the centers is not violated given the centers are open. Constraints (22) to (26) ensure that at least one of the potential centers is active. Equation (22) ensures that the sum of the coefficients for the returned product is 1. Constraints (23) to (27) relate to the conditions of diversity in the construction of facilities for the consideration of passive defense requirements. Equation (28) ensures that the total number of returned products does not exceed the maximum allowable level. Equation (29) relates to the level of supplier flexibility, which must be higher than the level set by the organization. Ultimately, constraints (30) and (31) enforces the binary and non-negative constraints on the corresponding decision variables.

In order to estimate the value of risk, Value at Risk (VaR) method is utilized. In that respect, the following parameters are introduced:

$D_{is't}$: Distribution function for delay in delivery of raw material s′ from supplier i in period t

D_{kst}: Distribution function for delay in delivery of tire s by distributor k in period t

$Q_{is't}$: Distribution function for defective raw material s′ received from supplier i in period t

Q_{jst}: Distribution function for defective tire s received from the manufacturer j in period t

ND_i : The number of natural disasters that have disrupted the supplier's activity

F_{it}: Fixed purchasing cost from supplier i in period t

$VF_{is't}$: Variable cost of purchasing raw material s′ from supplier i in period t

There are several methods for estimating the VaR, one of which is extreme value theory (EVT) that was introduced by François Longin (2000) [53]. Considering that risk managers tend to focus on the marginal values of the distribution of future and heavy losses, the highest focus should be on accurately estimating the distribution of these losses. Therefore, extreme value theory can be a suitable and valuable method for estimating the VaR. It should be noted that the probability of these types of incidents is low, but they have a significant impact.The general form of the distribution function of the EVT can be displayed as follows:

$$f_{\gamma,\delta,k}(x) = \begin{cases} \exp\left(-\left[1 - k\left(\frac{x-\gamma}{\delta}\right)\right]^{\frac{1}{k}}\right) & 1 - k\left(\frac{x-\gamma}{\delta}\right) \geq 0, k \neq 0 \\ \exp\left(-exp\left(\frac{x-\gamma}{\delta}\right)\right) & -\infty \leq x \leq \infty, k = 0 \end{cases} \tag{30}$$

Where $f_{\gamma,\delta,k}(x)$is the cumulative distribution function of the EVT, γ related to the distribution position; δ is the distribution criteria and k indicates the shape or density of the tale of the distribution.

3.3. Demand uncertainty and Robust optimization

As it was mentioned, the customer demand parameter is fuzzy, which is modeled with triangular fuzzy numbers. In order to convert fuzzy parameters to their equivalent crisp value, the method that was introduced by Jimenez et al. (2007) is utilized [54]. Therefore, the following substitution can be utilized:

$$\tilde{d}_{ls}^{t} = (1-\alpha)\frac{d_{ls}^{t1} + d_{ls}^{t2}}{2} + \alpha\frac{d_{ls}^{t2} + d_{ls}^{t3}}{2} \tag{31}$$

$$\tilde{r}_{ls}^{t} = (1-\alpha 1)\frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha 1\frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \tag{32}$$

The objective function z1 can be expressed as follows:

$$\max z1 = E(z1) + \gamma\left(z_{max} - E(z1)\right) + \varphi 1\left[(1-\alpha)\frac{d_{ls}^{t,1} + d_{ls}^{t,2}}{2} + \alpha\frac{d_{ls}^{t,2} + d_{ls}^{t,3}}{2}\right] + \varphi 2[R_0\sum_t\sum_l(1-\alpha 1)\frac{d_{ls}^{t,1} + d_{ls}^{t,2}}{2} + \alpha 1\frac{d_{ls}^{t,2} + d_{ls}^{t,3}}{2}] \quad (33)$$

Where, γ indicates the weight or importance of deviation from the mean; φi also shows the penalty for deviating from constraints with a fuzzy parameter.

4. Solution method

Most logistics network design models, including the one discussed in this article, are considered Hard problems. Such problems can be reduced to the facility location problem with limited capacity. The facility location problem with limited capacity is in the NP-complete category [55]. Therefore, the problem of logistics network design studied in this research belongs to the NP-hard category. Due to the high computational time, accurate methods cannot be used to solve such problems on a large scale. Therefore, in this research, a whale optimization algorithm based on the Pareto archive has been utilized to solve the proposed model. The results of this algorithm have been compared with the results of the known NSGA-II algorithm.

4.1. Whale optimization algorithm

The whale optimization algorithm (WOA) starts with a set of random solutions. At each iteration, search agents update their positions with respect to either a randomly chosen search agent or the best solution obtained by far. The "a" parameter is introduced, and its value decreases from 2 to 0 in order to provide exploration and exploitation. Two methods are considered to update the position of the search agent. When |A|>1, a random search agent is chosen, and if |A|<1 ,then the best solution is selected. Finally, WOA stops when stopping criteria are met. In the present study, this algorithm is designed in combination with an improvement method based on the variable neighborhood search (VNS) method.

4.1.1. Solution representation

In this research, a matrix is used to represent each solution. Each solution consists of several matrices, which are designed according to the model outputs. For example, for the variable z_m, a linear one-dimensional matrix is defined which number of elements is equal to m (m is the number of collection centers); A one-dimensional matrix is defined for the variable y_k; For the variable x_{ij}^{st}, a 4-dimensional matrix with I * J * S * T elements is defined.

4.1.2.solution initialization method

In this paper, a stochastic approach is used to generate the initial solutions. To generate the initial solutions, first y_k‘y_m‘y_p and $y_n$matrices are randomly generated, and then the rest of the solution matrices (model variables) are quantified according to the model constraints. Assuming that the population size is equal to N,each time that a solution is generated as described, the solution is added to the population given the solution is not repetitive. This procedure will continue until the number of solution population reaches α × N, where α is integer greater than 1.

The process of generating solutions stops after α × N iteration. On the other hand, the number of solutions in each iteration of the algorithm is equal to N. Therefore, out of α × N available solutions, N solutions should be selected as the initial solutions. In this study, the selection of the initial population of solutions is based on the "fast non-dominated sorting approach" proposed by Deb et al. (2002) [55]. This method works in such a way that the α x N existing solutions created by the mentioned algorithm are sorted and ranked based on the nondomination. Each solution is assigned a fitness (or rank) equal to its nondomination level. Level 1 is the best level, 2 is the next-best level, and so on. Then, for the solutions in each level, a criterion called "Crowding Distance" is calculated [55]. The criterion for the solutions in each level indicates the diversity of the solutions in that level. In this paper, C_s is introduced for selecting the initial solutions, which can be expressed as follows:

$$C_s = \frac{rank}{crowding\_dis} \quad (34)$$

Where "rank" indicates the level number where the solution is located and "crowding_dis" is the crowding distance of each solution that is proportionate to the rank of that solution.The above metric is calculated for each of the available solutions and is sorted in ascending order of C_s values. The first N solutions that have lower C_s values are selected as the initial solutions for the algorithm. The use of C_s metric is based on the logic that the solutions with higher quality and good spread are selected as the initial population.The initial

solutions are then improved as much as possible using the improvement method which is described in the next section.

4.1.3.Improvement procedure

In the proposed whale optimization algorithm, an improvement procedure is designed that is applied to the selected solutions in the previous section. The output of this improvement procedure is selected as the population for the next iteration of the algorithm. The improvement procedure in this study is based on variable neighborhood search (VNS). The VNS method uses four neighborhood search structures (NSS) [56]. The neighborhood search operators used in the VNS structure are as follows:

First Neighborhood Search Operator; one of the distribution centers is randomly selected, and its location matrix will change.Second Neighborhood Search Operator; one of the collection centers is randomly selected, and its location matrix will change.Third Neighborhood Search Operator; one of the recycling centers is randomly selected, and its location matrix will change.Fourth neighborhood search operator; one of the retreading centers is randomly selected, and its location matrix will change.

It should be noted that in the above operators, the method of changing the location matrices is such that the index of one of the centers is randomly selected, and if that center is 1 (considering the constraints on the minimum number of open centers) then it becomes 0, and if it is 0, it becomes 1.

4.1.4. Updating solution and search parameters

In the whale optimization algorithm, the search formulas and parameters are updated based on the following formulas:

$$\vec{D} = \left|\vec{C}.\vec{X}^*(t) - \vec{X}(t)\right| \quad (35)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \quad (36)$$

Where $\vec{D}$ is the search space, $\vec{C}$ and $\vec{A}$are coefficient vectors, $\vec{X}^*(t)$the best answer in t^{th} iteration; $\vec{X}(t)$are the solutions of tth iteration and $\vec{X}(t+1)$are the solutions of the (t + 1) iteration. The vectors $\vec{C}$ and $\vec{A}$ are updated per the below formula:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (37)$$

$$\vec{C} = 2\vec{r} \quad (38)$$

where $\vec{a}$starts with initial value of 2 and decreases linearly in each iteration. Also, $\vec{r}$ is a random vector in [0,1].

4.1.5 Selecting next generation of solutions

At each stage of the whale optimization algorithm, among the previous solution and the new solution, N (population size) solutions are chosen according to the degree of fitness, C_s . The method of selection is such that for all the locations, the value of C_s is calculated and are sorted by ascending order of the value of C_s and finally, the first N solutions are selected.

4.1.6 Updating Pareto archive

In multi-objective problems, due to the conflicts between objectives, there is no single solution that optimizes all the objective functions. Therefore, a set of dominant solutions are selected as the optimal or near-optimal solutions. Here, we solve the problem based on Pareto archive, which is updated in each iteration of the algorithm. For updates, all the solutions in the archive and the newly generated solutions are collected into a pool of solutions, and they are sorted. Then all the first level solutions are selected as the solution for the new pareto archive.

5. Computational results

In this paper, in order to check the validity of the model and the algorithm, the model is solved with a small test problem using both GAMS software. After validating the model, in order to test the efficiency of whale and genetic algorithms, the model is solved by both whale and genetic algorithms in MATLAB and the results are compared using comparison metrics of quality, uniformity, diversity and computational time. It should be noted that all calculations were performed using the i7 7500U -12GB -1TB -R5 M335 4GB Core computer.

5.1. Comparison metrics

There are many different metrics for evaluating the performance of the multi-objective meta-heuristic algorithms. In this paper, for comparison, the three metrics of quality, uniformity, and diversity will be considered [56], which are described below:

Quality metric - This metric compares the quality of Pareto solutions obtained by each algorithm. In fact, all the Pareto solutions obtained by both whale and genetic algorithms are sorted in different levels to determine what percentage of solutions belong to each method. The higher this percentage, the higher the quality of the algorithm.

Spacing metric - This metric determines the uniformity of the distribution of Pareto solutions and is defined as follows:

$$s = \frac{\sum_{i=1}^{N-1} |d_{mean} - d_i|}{(N-1) \times d_{mean}} \qquad (39)$$

Where, $d_i$represents the Euclidean distance between two non-dominant adjacent solutions and d_{mean}represents the mean of the d_i.

Diversity metric - This metric is used to determine the number of non-dominant solutions and can be expressed as follows:

$$D = \sqrt{\sum_{i=1}^{N} \max\left(\left\|x_t^i - y_t^i\right\|\right)} \qquad (40)$$

Where $\left\|x_t^i - y_t^i\right\|$ represents the Euclidean distance between two adjacent solutions x_t^i and y_t^ion the optimal boundary.

5.2. Experimental problem

In this paper, several test problems in small, medium, and large size have been designed. The data for the sample problems is collected from literature and some of the parameters that are not covered by previous research have been randomly selected.

5.3. Setting the parameters

The algorithm parameters are set as follows:

- In the whale algorithm, the population size is 150, the number of VNS iterations is 5, and the number of iterations of the algorithm is 300.
- In the genetic algorithm, a rate of 0.8 is considered for the intersection and 0.1 for the mutation, and the population size is 150.
- To generate triangular numbers related to each of the fuzzy parameters (m1, m2, m3), first m2 is generated, then a random number r is generated in the range of (0,1). m1 is generated using "m2*(1-r)"and m3 is generated using the "m2*(r + 1)" equations.
- In each period (t), customer demand L for product S is calculated using triangular fuzzy numbers (m1,100, m3).
- The capacity of each supplier is 6000, the capacity of each production center is 9000, the capacity of each retreading center is 4000, the capacity of each distribution center is 4000, the capacity of the collection center is uniform distribution between [2000,4000], the capacity of recycling center is uniform distribution between [4000,6000], capacity of energy recovery centers in uniform distribution between [2000,4000].
- The cost of opening a new energy recovery center is uniform distribution between [4000,6000], the cost of opening a new collection center is uniform distribution between [8000,10000] and the recycling centers in a uniform distribution between [12000,16000]. Also, the cost of opening a new distribution and retreading centers is uniform distribution between [5000,10000].
- The rate of return of the product from the collection centers is randomly generated in the range of (0,1).
- All transportation costs are randomly generated in a uniform range [1,1000].
- The inventory holding cost is uniform distribution between [400,600].
- The price of second-hand and new tires is produced in uniform intervals [10,30] and [50,100], respectively.
- The value added to the system for each returned product is calculated based on 10% of its average price.
- The cost of recycling and energy recovery of a unit of product is uniform distribution between [5,15].

It should be noted that the above values are only designed for small-scale problems. Since algorithms for solving medium and large size problems with these capacity levels could not find a feasible solution, the values of the parameters for these problems have been determined by trial and error. For both medium and large

groups, the capacity of each center is equal to the values of small-scale problems multiplied by the number of potential centers.

5.4.Model validation results

In order to check the validity of the model, the four-objective model has been transformed into a single-objective model using the LP metric method. First, the individual objective functions are optimized, then the single objective function from LP metric method is minimized. In this method, the value ofP is 1, and the weights of all the objective functions are equal. To solve the model with GAMS, a small-scale problem in which the number of suppliers, manufacturers, and distributors is equal to 2, the number of customer centers is equal to 3, the number of collection centers, retreading centers, energy recovery, and recycling centers is equal to 2. The number of products is equal to 1, the number of time periods is equal to 2. The results are as follows:

Table 1- Values of the location of distribution and collection centers ($\boldsymbol{y_k}$&$\boldsymbol{y_m}$)

y_m	collection centers	y_k	distribution center
0	1	1	1
1	2	0	2

Table 2- Values of location of recycling and energy recovery centers ($\boldsymbol{y_p}$&$\boldsymbol{y_n}$)

y_n	Energy recovery centers	y_p	Recycling centers
0	1	0	1
1	2	1	2

Table 3- Values of location of retreading centers ($\boldsymbol{y_r}$)

y_r	Retreading centers
1	1
0	2

The value of the objective function obtained from solving with GAMS is equal to 4.963. The results of this study indicate the feasibility and validity of the model. On the other hand, the model has been solved with the aim of optimizing the LP metric method by the whale algorithm. The similarity of the results of GAMS and the whale algorithm indicates the convergence of the solution algorithm towards the optimal and near-optimal solution.

5.5. Execution results

In this section, the designed test problems are solved using whale and the NSGA-II algorithms. The results of the implementation of the two algorithms according to the comparison metrics are shown below (Tables4,5,6). It should be noted that the expressionS/I/J/K/L/M/P/N/R has been used to show the sample size where S is the number of products, I number of suppliers, J number of production centers, K number of distribution centers, L number of customerlocations, M represents the number of collection centers, P represents the number of recycling centers, N represents the number of energy recovery centers and R represents the number of retreading centers.For all problems, the number of periods is equal to 4 and the number of retreading centers is 2.

Table 4 - Results of solving with small size problems

Problem	WOA			GA		
	Quality metric	Spacing metric	Diversity metric	Quality metric	Spacing metric	Diversity metric
1/2/2/2/2/2/2/2/2	100	1.1	698.2	0	0.70	445.8
1/2/2/2/2/3/3/3/3	95.05	1.13	605.2	4.95	0.70	356.2
1/2/2/2/2/4/4/4/4	87.9	0.84	717.2	12.1	0.46	287.4
1/2/2/2/2/5/5/5/5	73.1	0.71	732.8	26.9	0.31	557.3

Table 5- Results of solving medium size problems

Problem	WOA			GA		
	Quality metric	Spacing metric	Diversity metric	Quality metric	Spacing metric	Diversity metric
1/3/7/7/7/7/5/4/4	85.2	0.92	985.2	14.8	0.78	740.7
2/3/7/7/7/7/5/4/4	83.5	0.51	1365.9	16.5	0.47	840.9
3/3/7/7/7/7/5/4/4	88.1	0.64	1439.9	11.9	0.56	850.2
1/6/8/10/10/8/6/5/5	100	1.06	1468.3	0	0.71	1130.6
2/6/8/10/10/8/6/5/5	87.7	0.68	1582.2	12.3	0.44	1220.4
3/6/8/10/10/8/6/5/5	87.6	0.91	1702.3	12.4	0.78	1261.3
1/7/9/15/15/9/7/7/5	83.4	0.71	1708.9	16.6	0.47	1349.1
2/7/9/15/15/9/7/7/7	85.8	0.73	1763.2	14.2	0.62	1360.6
3/7/9/15/15/9/7/7/7	88.1	1.01	1930.2	11.9	0.49	1218.4

Table 6- Results of solving large size problems

Problem	WOA			GA		
	Quality metric	Spacing metric	Diversity metric	Quality metric	Spacing metric	Diversity metric
1/10/20/20/30/16/7/6/6	90	0.75	2871.6	10	0.74	1901.6
2/10/20/20/30/16/7/6/6	85.9	1.72	2685.3	14.1	0.64	1954.2
3/10/20/20/30/16/7/6/6	87.6	1.67	3063.5	12.4	0.76	2112.5
1/15/40/40/70/35/12/10/10	70.9	0.73	2636.3	29.1	0.65	1901.9
2/15/40/40/70/35/12/10/10	89.9	0.71	2816.5	10.1	0.70	2265.1
3/15/40/40/70/35/12/10/10	66.8	1.70	3486.3	33.2	0.54	2793.6
1/15/45/45/90/40/15/13/10	87.2	1.17	4121.9	12.8	0.65	3278.6
2/15/45/45/90/40/15/13/10	100	1.13	4565.9	0	0.64	3397.7
3/15/45/45/90/40/15/13/10	88.4	1.04	5054.1	11.6	0.73	4758.7

As can be seen in the tables above, in all small, medium and large size problems, the value of quality and diversity metrics calculated for the whale algorithm is greater than the values calculated for the genetic algorithm, which indicates the higher capability of the whale optimization algorithm compared to the genetic algorithm in achieving the near-optimal solution as well as higher ability to explore and extract the feasible solution space. Also, the value of the uniformity metric indicates that the genetic algorithm searches the solution area with more uniformity. Figure (2) shows that the computational time of whale algorithm in all cases is greater than genetic algorithm and this means that the whale algorithm needs more time than the genetic algorithm to solve these problems. It should be noted that as the size of the problem increases, the computation time of the algorithm increases rapidly, and the time to solve large-scale problems is much higher than solving the small and medium-sized problems, which indicates that the problem is NP-hard.

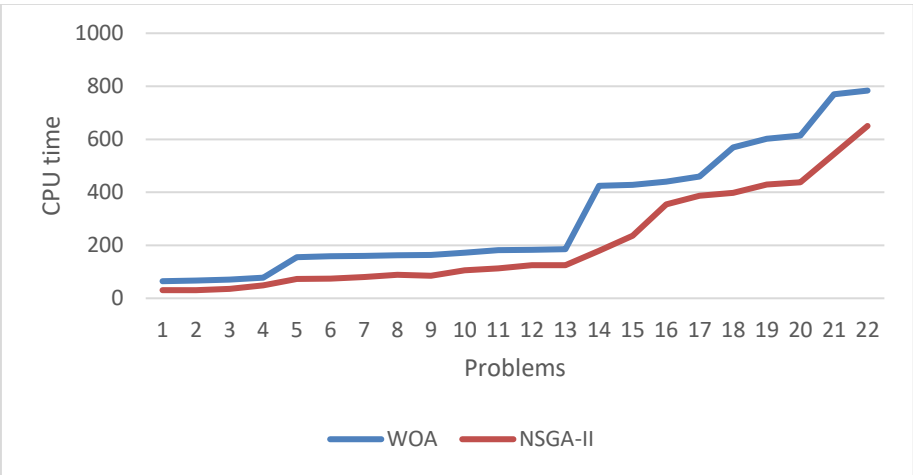

Figure 2. Computational times (seconds)

6. Conclusion

In this paper, a robust optimization model for a sustainable closed-loop supply chain network for tire industry with passive defense was studied. In order to achieve the purpose of the paper, a four-objective optimization model with fuzzy demand was presented, which was solved by whale optimization algorithm and genetic algorithm. To solve the proposed model, an experimental sample problem in three groups of small, medium, and large size were designed, and the results of two whale optimization algorithms and genetic algorithm were compared using comparison metrics of quality, diversity, spacing, and computation time. The results showed that in all cases, the whale algorithm has a higher ability to explore and exploit the feasible space and achieve a near-optimal solution. In terms of uniformity and computational time, the genetic algorithm performed better than the whale algorithm. Also, examining changes in computational time by increasing the size of the problem is confirmation of the NP-hard nature of the problem under this study.For future research, a real case study in the tire industry with actual industry data should be considered.

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