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Designing a Tire Closed-Loop Supply Chain Considering Sensor Embedded Tires

Mohsen Tehrani[1], Surendra M. Gupta[2]
[1,2] *(Mechanical & Industrial Engineering/ Northeastern University, U.S.A)*

Abstract: Environmental concerns, an increase in amount of waste generated and the reduction in natural resources has led governments to impose stricter regulations on manufacturing corporations to hold them responsible for their end of life (EOL) products. This concern is greater for the tire industry due to the large volume of tires produced and their hazardous materials composition. This has led corporations to focus on designing a sustainable and efficient closed-loop supply chain (CLSC) network. One of the biggest challenges facing the CLSC network design is the uncertainty associated with the parameters in the network, including the return rate and the conditions of the EOL tires after being returned for value recovery. Something that has been studied in the past decade is designing smart products that can collect valuable information during the life cycle of the product, which can be used to extend the life span of the product and also improve value recovery of EOL products. This study proposes a sustainable and environmentally cautious closed-loop supply chain network for the tire industry under uncertainty and various recovery options. The study aims to assess the impact of tire pressure monitoring system on the EOL tire recovery and performance of the network. In order to deal with this hybrid uncertainty, a robust fuzzy stochastic programming approach has been proposed, and the proposed mixed-integer programming model is applied to a sample problem to validate the model. The result indicates the applicability of the proposed model and the role of sensor embedded tires on the reduction in negative environmental impact.
Keywords: Closed-loop supply chain, Robust optimization, sensor embedded Tire, Hybrid uncertainty, Vehicle routing

1. Introduction

A great supply chain system is a necessity for any manufacturing organization to gain higher advantage in a competitive market. Closed-loop supply chain, which considers the combination of forward and reverse logistics has received a lot of attention due to government regulation and environmental concerns. Reverse logistics is a network where end of life (EOL) products transfer from the end users for value recovery, which could be repair, remanufacturing, or recycling [1]. In addition to government regulations, consumer's awareness and their responsibility against the environment and potential economic benefits are some of the motives [2][3].

Worldwide, more than a billion tires are manufactured every year of which a significant number are thrown away after being used. In 2019, 267.8 million new passenger tires, 37.9 million new light truck tires, and 25.4 million new medium and heavy truck tires were shipped within the United States. The average commercial semi-truck tire weighs about 110 pounds and contains oil and other combustible carbon compounds, which create a fire hazard. Tire piles, in addition to fire hazard, can create a breeding ground for pests such as rodents and mosquitos that contribute to the spread of diseases [4][5]. Disposing scrap tires in landfills consumes valuable space and can also result in the penetration of pollutants and metal contents into the underground water. Therefore, designing a sustainable and green closed-loop supply chain (CLSC)network for a tire is necessary. There are a few recovery options available for EOL tires which some of them are as follows:

Tires with enough thread depth can be sold in the used tire market. Whole tires can also be used for several applications, including erosion control, playground equipment, crash barriers on the side of the highway, and boat bumpers at the docks.

Retread or recap is a process in which the worn thread of the tire is removed from the tire casing and replaced with new treads.

Waste tires are typically shredded before they are recycled. Recycled tires can be used as crumb rubber in asphalt pavement or as an aggregate in Portland cement concrete. Tires are also cut up and used in garden beds to hold in the water and to prevent weeds from growing [6].

A large percentage of scrap tires are used as fuel. Tire-derived-fuel (TDF) is a fuel derived from scrap tires. Scrap tires, either shredded or whole, are used to supplement coal in power plants, cement kilns, paper mills, etc. Research has shown that atmospheric contamination dramatically increases when tire rubber is used as fuel [7-11].

Amongst available recovery options, retread is the most environmentally friendly option after reuse. With recent research and advancement in the composition of the tire, tires have become even more durable.

When the tire treads are worn out, most of the time the tire casing is still in good condition and can be reused many times. According to EPA, 25 gallons of oil are needed to produce a new truck tire compared to only 7 gallons of oil to retread a used one. That results in a significant reduction in greenhouse gas emission, preserving raw material, and minimizing the amount of waste disposed of in the landfills. With good tire management practices in the fleet and trucking industry, a tire can be retreaded multiple times.

There are some factors that impact the retreadability of the tire. The key to maximizing the life of a new or retread tire is to run the tire at the manufacturer's recommended pressure. Maintaining proper air pressure will help to reduce irregular wear and extend tread life and protect the tire casing, which is essential for getting the maximum number of retreads. Under inflation causes excessive heat build-up and damages the tire casing. According to the Technology & Maintenance Council's S.2 Tire & Wheel Study Group, properly inflated tires can help to increase fuel efficiency by 1 percent, extend tread life by 15 percent and can account for up to 20 percent longer casing life. The tire pressure monitoring system (TPMS) is an electronic monitoring system that keeps track of the vehicle's tire air pressure and temperature and notifies the driver when they drop or exceed the predefined limits.

In recent years, major tire manufacturers such as Continental and Goodyear have focused on designing an intelligent tire that has a intelligent sensor embedded in the tire (Fig. 1). These advanced sensors can collect more data such as tire wear, inflation, and road-surface conditions in real-time and send to cloud storage to be analyzed. Using these systems to adapt a proper tire management can increase the life span and retreadability of the tire.

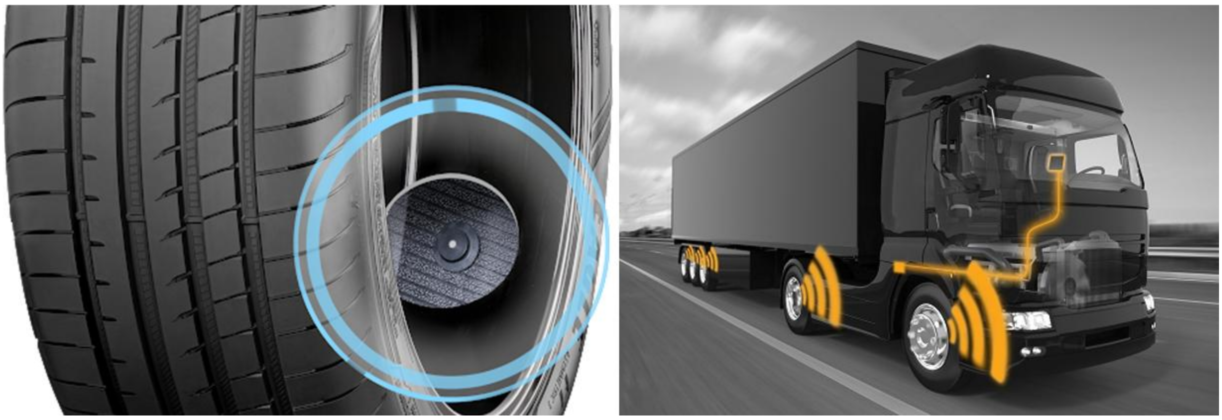

Fig.1. Schematic view of a sensor embedded tire

Uncertainty with the parameters is probably the biggest challenge facing the supply chain network (SCN) design. Random and fuzzy uncertainties are generally the two types of uncertainty in the design of a supply chain network. In this study, robust fuzzy stochastic programming is used to cope with hybrid uncertainties in the mixed-integer linear programming (MILP) model. We are designing a bi-objective, multi-product, multi-capacity, multi-transportation, green closed-loop supply chain network by considering the impact of sensor-embedded tires on the profitability and performance of the network. Our model aims to maximize the total CLSC profit and minimize the total greenhouse gas (GHG) generated along the CLSC.

To the author's best knowledge, no previous study has been conducted on the design of the CLSC for tire industry with a focus on sensor-embedded tires.

The paper is structured as follows. In Section 2, the relevant literature on closed-loop supply chains network design and tire industry is reviewed; some works concerning sensor-embedded products are also analyzed. In Section 3, the main problem characteristics, assumptions, and mathematical formulation are presented. In Section 4, a proposed Robust Fuzzy/Possibilistic Stochastics Programming (RFSP) approach is described. In Section 5, the proposed model is applied to a sample problem. The computational results and the sensitivity analysis are also presented in this section. Finally, in Section 6 some conclusions and future work are discussed.

2. Literature Review

2.1. Closed-Loop Supply Chain

Designing a robust and flexible supply chain network (SCN) that includes optimizing the number, capacity, and location of network facilities has received a lot of attention these days [12]. There have been many papers published in this subject area and especially green closed-loop supply chain network. A comprehensive review on environ-mentally conscious manufacturing and product recovery was provided by Ilgin and Gupta

(2010) [12]. Zhou and Gupta (2019) provided a pricing strategy for new and remanufactured high-tech products [13]. 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 [14]. Aldoukhi and Gupta (2019) proposed a new model for designing a closed-loop supply chain network by considering downward product substitution policy under four carbon emission regulation policies [15]. In another study, they proposed a multi-objective model to design a CLSC network with the aim of minimizing the total cost, minimizing the carbon emission, and maximizing the service level of the retailers [16]. Adel and Gupta (2019) evaluated the food waste valorization alternatives from a sustainability point of view. They estimated energy utilization and GHG emission reduction for each potential food waste processing technique [17]. Zahedi et al. (2021) proposed a closed-loop supply chain network considering multi-task sales agencies and multi-mode transportation [18]. Gupta et al. (2020) presented a compilation of six recent papers on a variety of topics to demonstrate the pioneer research activity within responsible and sustainable manufacturing [19]. Sazvar et al. (2021) designed a sustainable CLSC for pharmaceuticals by considering manufacturer's brand and waste management [20].

2.2. Closed-Loop Supply Chain Network Under Uncertainty

Inconsistent, unreliable, and uncertain data is one of the biggest challenges facing the SCN. Stochastic programming and Possibilistic programming are the most common methods to deal with randomness and Epistemic (fuzzy) uncertainty, respectively [21][22]. A flexible robust optimization approach for scenario-based stochastic programming models was proposed by Mulvey et al. (1995) [23]. Their approach was later developed by Yu and Li, 2000 [24]. Pishvaee et al. (2018) also developed a new approach called robust possibilistic programming [25]. Mousazadeh et al. (2018) used a robust possibilistic approach for health service network design [26]. Tozanli and Gupta et al. (2017) provided a literature review paper for environmentally concerned logistics operation (ECLO) in fuzzy environment. They utilized over 800 papers between 1994 and 2017 and performed a detailed analysis of ECLO with an emphasis on fuzzy application [27]. Yolmeh and Saif (2020) provided a supply chain network design with assembly and disassembly line balancing under uncertainty [28]. Wang et a. (2021) studied various incentive mechanisms in a green supply chain under demand uncertainty [29]. Rafael et al. (2021) provided a review of simulation optimization methods for designing a resilient supply chain under uncertainty [30].

2.3. Closed-Loop Supply Chain for tire

There has been some research on the tire CLSC network [31][32]. Amin et al. (2017) examined a case study for CLSC network for the tire industry in Toronto, Canada using mixed-integer linear programming model under uncertainty [33]. Subulan et al. (2015) examined a tire remanufacturing case study in Turkey using a fuzzy mixed integer programming approach [34]. Derakhshan et al. (2017) presented a technique for recycling tire waste as well as reuse of the waste [35]. O'Brien and North (2017) investigated the emission of pollutants from tire waste. [36]. Fathollahi Fard et al. (2018) proposed a tri-level programming model for tire CLSC to identify the decision variable using real data sets [37]. Pedram et al. (2018) used stochastic programming to design a single objective tire CLSC network [38]. 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 [39][40]. Sahebjamnia et al. (2018) also modeled a robust closed-loop supply chain of the tire industry and used hybrid metaheuristic algorithms to solve the model [41]. Abdolazimi et al. (2019) proposed a multi-objective closed-loop supply chain by integrating on time delivery and the cost [42]. Mehrjerdi at al. (2020) studied sustainability and resiliency of a closed-loop supply chain using multiple sourcing strategy [43]. Lokesh et al. (2020) also designed a sustainable tire supply chain with a fuzzy goal planning approach [44].

2.4. Closed-Loop Supply Chain and sensor-embedded products

There has been some research in the area of sensor-embedded products. Ilgin and Gupta (2009) presents a quantitative assessment of the impact of the sensor-embedded products on the various performance measures of a Kanban-controlled disassembly line [45]. In similar study, they presented a quantitative assessment of the impact of sensor-embedded products (SEPs) on the various performance measures of a Kanban-controlled washing machine disassembly line [46]. They also provided a quantitative evaluation of the impact of sensor-embedded products (SEPs) on the performance of an appliance dis-assembly line [47]. Algahtani and Gupta (2019) proposed a simulation model for remanufactured items sold with one-dimensional non-renewing cost sharing warranty (CSW) and cost limit warranty (CLW) [48]. Dulman and Gupta (2015) investigated the benefits of Sensor embedded cell phones (SECPs) over conventional cell phones (CCPs) in product recovery [49]. In another study, they studied maintenance and EOL operation performance of sensor embedded laptops [50]. Ondemir and Gupta (2012) studied and ad-dressed the order-driven component and product recovery (ODCPR) problem for sensor-embedded products (SEPs) in an reverse supply chain [51]. They also presented a remanufacturing-to-order system for EOL sensor embedded products. They proposed an integer programming (IP) model to determine how to process EOL products on hand to meet the demand and the cost objectives [52]. Aditi et al. (2016) studied an advanced remanufacturing to order disassembly to order system by considering different design alternatives of a sensor-embedded EOL products [53]. Algahtani and Gupta (2018) studied Money-back guarantee warranty policy with preventive maintenance strategy for sensor-embedded remanufactured products [54].

Designing an economically optimized and environmentally friendly CLSC network is a prerequisite for tire manufacturers not only to earn a profit but also to decrease waste, preserve natural resources and save landfills. In this study, we will introduce a robust bi-objective, green closed-loop supply chain network under hybrid uncertainty with a focus on sensor-embedded tires with the aim of maximizing profit and reducing environmental impacts.

3. Problem description and formulation

As shown in Fig.2, we are considering a multi-product and multi-echelon CLSC network consisting of suppliers, production centers, distribution centers, collection centers, retreading centers, recycling, and energy recovery centers. In the forward flow, various raw materials are procured from the available choice of suppliers. Tire are manufactured with and without sensors based on the market demand. After tires are manufactured, they are distributed through the distribution centers and the retailers to the end users. The location of retailers is fixed, and there might be unsatisfied demands due to uncertainty in demand. In the reverse flow, used tires are transferred to collection centers where the initial inspection is performed, and based on the condition of the tires, they are either routed to retreading center or the recycling centers. In this study, the future demand is expressed under few scenarios. The return rates, retreading rates, procurement, and production costs are fuzzy; therefore, possibilistic approach has been utilized to deal with these parameters.

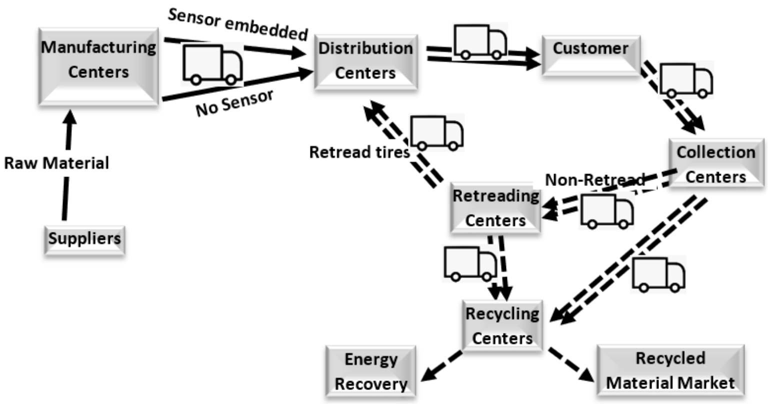

Fig. 2. Schematic view of the proposed CLSC

3.1. Problem assumption and notation

The main characteristics and assumptions are as follows:

- The potential location of new manufacturing centers, distribution centers, retreading centers, and recycling centers are fixed and predefined.
- Production, distribution, retreading, and recycling capacities are limited, and all are subject to capacity level U.
- Each manufacturing facility is capable of manufacturing each type of tire with or without sensors.
- Capacity of the energy recovery centers is unlimited, but it has the most damaging environmental impact.
- The return, recycling, and retreading rate of new and retread tires are fuzzy.
- Raw material procurement costs and production costs are fuzzy, and their fuzzy expected value will be utilized.
- Customer demand is stochastic and is expressed in different scenarios.
- There are different types of ground transportation options available to transport finished products.
- There is a buyback price for used tires paid to the customer.
- The demand for new tires must be satisfied, and there is a penalty for unsatisfied demand.

Indices:

$\xi \in \Xi$	Set of possible scenarios
S	Set of raw material suppliers
M	Set of raw materials
P	Set of types of tires
F^a	Set of existing production centers
F^b	Set of potential production centers
D^a	Set of existing distribution centers
D^b	Set of potential distribution centers
C	Set of customer delivery points
I	Set of collection centers
J	Set of recycling centers
K	Set of retreading centers
W	Set of energy recovery centers
G	Set of tire technologies; 1 if sensor is used in tire; 2 if no sensor is used
V	Set of types of vehicles used for transportation
U	Set of capacity levels

Parameters:

Tilde symbol (~) is to distinguish the uncertain parameters:

$fc^F_{f,u}$	Fixed opening cost of production center at location f at capacity level u
fc^D_{du}	Fixed opening cost of distribution center at location d at capacity level u
fc^I_{iu}	Fixed opening cost of collection center at location i at capacity level u
$fc^J_{j,u}$	Fixed opening cost of recycling center at location j f at capacity level u
$fc^K_{k,u}$	Fixed opening cost of retreading center at location k at capacity level u
fc^S_s	Fixed ordering cost of raw material from supplier s
$\widetilde{mc^S_{m,s}}$	Unit cost of raw material m from supplier s (fuzzy)
$\widetilde{pc^F_{p,g,f}}$	Production cost of a unit of tire p, g at prod. center f (fuzzy)
$ccp_{p,g,c}$	Buyback price of a unit of EOL tire p with g from customer c
$rtc1^k_{p,g,k}$	Retreading cost of a unit of tire p with g at retreading center k
$rc^J_{p,j}$	Recycling cost of a unit of tire p at recycling center j
$ic^W_{p,w}$	Incineration cost of a unit of tire p with g at incineration center w
$tr^{S\to F}_{m,s,f}$	Transportation cost for unit of raw material m from center s to center f
$tr^{F\to D}_{p,f,d,v}$	Transportation cost for a unit of tire p from center f and d using v
$tr^{D\to C}_{p,d,c,v}$	Transportation cost for a unit of tire p from center d and c using v
$tr^{C\to I}_{p,c,i,v}$	Transportation cost for a unit of tire p from center c and I using v
$tr^{I\to J}_{p,i,j,v}$	Transportation cost for a unit of tire p from center i and j using v
$tr^{I\to K}_{p,i,k,v}$	Transportation cost for a unit of tire p from center i and k using v
$tr^{K\to D}_{p,k,d,v}$	Transportation cost for a unit of tire p from center k and d using v
$tr^{K\to J}_{p,k,J,v}$	Transportation cost for a unit of tire p from center k and j using v
$tr^{J\to W}_{p,j,w,v}$	Transportation cost for a unit of tire p from center j and w using v
$cap^S_{m,s}$	Maximum capacity of the supplier s for material m
cap^F_u	Maximum capacity of production center f at capacity level u
$g^F_{f,u}$	Binary parameter defining capacity level of existing center f $\in F^a$
cap^D_u	Maximum capacity of distribution center d at capacity level u
$g^D_{d,u}$	Binary parameter defining capacity level of existing center $d \in D^a$
cap^I_u	Maximum capacity of collection center i at capacity level u
cap^K_u	Maximum capacity of retreading center k at capacity level u
cap^J_u	Maximum capacity of recycling center j at capacity level u
$e^F_{f,p}$	GHG generated at center f for producing a unit of tire p
$e^J_{j,p}$	GHG generated at center j for recycling a unit of tire p

$e^{K}_{k,p}$	GHG generated at center k for retreading a unit of tire p
$e^{W}_{w,p}$	GHG generated at center w for incineration of a unit of tire p
$e^{S\rightarrow F}_{m,s,f}$	GHG generated for transporting a unit of material m from center s to f
$e^{F\rightarrow D}_{f,d,p,v}$	GHG generated for transporting a unit of tire p from center f to d using v
$e^{D\rightarrow C}_{d,c,p,v}$	GHG generated for transporting a unit of tire p from center d to c using v
$e^{C\rightarrow I}_{c,i,p,v}$	GHG generated for transporting a unit of tire p from center c to i using v
$e^{I\rightarrow K}_{i,k,p,v}$	GHG generated for transporting a unit of tire p from center i to k using v
$e^{K\rightarrow J}_{k,j,p,v}$	GHG generated for transporting a unit of tire p from center k to j using v
$e^{K\rightarrow D}_{k,d,p,v}$	GHG generated for transporting a unit of tire p from center k to d using v
$e^{I\rightarrow J}_{i,j,p,v}$	GHG generated for transporting a unit of tire p from center i to j using v
$e^{J\rightarrow W}_{j,W,p,v}$	GHG generated for transporting a unit of tire p from center j to w using v
$r^{F}_{m,p,g}$	Quantity of material m needed to produce one unit of tire p withg
$\widetilde{dem^{C}_{c,p,g,\xi}}$	Market demand for new tires p withg (scenario-based)
$\widetilde{dem1^{C}_{c,p,g,\xi}}$	Market demand for retread tires p withg (scenario-based)
$\widetilde{\alpha_{p,g}}$	Return rate of EOL new tire p withg (fuzzy)
$\widetilde{\alpha1_{p,g}}$	Return rate of EOL retread tire p withg (fuzzy)
$\widetilde{\theta1_{p,g}}$	Retread rate of EOL tire p withg (fuzzy)
β	Recycling rate
$\rho^{0}_{p,g}$	Unit price of the new tire p withg
$\rho^{1}_{p,g}$	Unit price of the retread tire p withg
ρ^{r}_{p}	Value of the recycled material for unit tire p

Variables:

$Y_{m,s,f,\xi}$	Quantity of material m shipped from supplier s to f under scenario ξ
$V_{f,p,g,\xi}$	Total production quantity of tire p withg at the center f under scenario ξ
$Q^{F\rightarrow D}_{f,d,p,g,v,\xi}$	Quantity of new tire p withg shipped from center f to d using vunder scenario ξ
$Q^{D\rightarrow C}_{d,c,p,g,v,\xi}$	Quantity of new tire p withg shipped from center d to c using vunder scenario ξ
$Q1^{D\rightarrow C}_{d,c,p,g,v,\xi}$	Quantity of retread tire withg shipped from center d to c using vunder scenario ξ
$Q^{C\rightarrow I}_{c,i,p,g,v,\xi}$	Quantity of new tire p withg shipped from center c to i using vunder scenario ξ
$Q1^{C\rightarrow I}_{c,i,p,g,v,\xi}$	Quantity of retread tire p withg shipped from center c to i using vunder scenario ξ
$Q^{I\rightarrow K}_{i,k,p,g,v,\xi}$	Quantity of new tire p withg shipped from center i to k using vunder scenario ξ
$Q1^{I\rightarrow J}_{i,j,p,g,v,\xi}$	Quantity of retread tire p withg shipped from center i toj using vunder scenario ξ
$Q1^{K\rightarrow D}_{k,d,p,g,v,\xi}$	Quantity of retread tire p withg shipped from center k to d using vunder scenario ξ
$Q1^{K\rightarrow J}_{k,j,p,g,v,\xi}$	Quantity of retread tire p withg shipped from center k to j using vunder scenario ξ
$Q^{J}_{j,p,g,\xi}$	Total quantity of recycled tire p withg at recycling center j under scenario ξ
$Q^{J\rightarrow W}_{j,W,p,g,v,\xi}$	Quantity of tire p withg shipped from center j to w using vunder scenario ξ
$Q^{W}_{w,p,g,\xi}$	Total quantity of tire p withg incinerated at center w under scenario ξ

Binary Variables:

$x^{F}_{f,u}$	Indicating if center f at capacity level u opened at location $f \in F^{b}$ or not
$x^{D}_{d,u}$	Indicating if center d at capacity level u opened at location $d \in D^{b}$ or not
$x^{I}_{i,u}$	Indicating if center i at capacity level u opened or not
$x^{K}_{k,u}$	Indicating if center k at capacity level u opened or not
$x^{J}_{j,u}$	Indicating if center j at capacity level u opened or not
x^{S}_{s}	Indicating if raw material is purchased from supplier s or not

3.2. Problem formulation

In the following, we will introduce two objective functions z_1 and z_2 under scenario ξ representing the total profit of the network and the total environmental impacts, respectively.

$$
\begin{aligned}
\mathrm{Max} z_1 = {} & \left[\sum_d\sum_c\sum_p\sum_g\sum_v\left(\rho^0_{p,g} Q1^{D\to C}_{d,c.p,g,v,\xi} + \rho^1_{p,g} Q1^{D\to C}_{d,c,p,g,v,\xi}\right) + \sum_j\sum_p\sum_g \rho^r_p Q^J_{jp,g,\xi}\right] \\
& - \left[\sum_{f\in F^b}\sum_u fc^F_{f,u}\,.\,x^F_{f,u} + \sum_{d\in D^b}\sum_u fc^D_{d,u}\,.\,x^D_{d,u} - \sum_i\sum_u fc^I_{i,u}\,.\,x^I_{i.u} + \sum_j\sum_u fc^J_{j,u}\,.\,x^J_{j,u} + \sum_k\sum_u fc^K_{k,u}\,.\,x^K_{k,u}\right] \\
& \left[\sum_s fc^S_s\,.\,x^S_s + \sum_m\sum_s\sum_f \widetilde{mc^S_{m,s,\xi}}\,.\,Y_{m,s,f,\xi}\right] - \left[\sum_f\sum_p\sum_g \widetilde{pc^F_{p,g,f}}\,.\,V_{f,p,g,\xi}\right] \\
& - \left[\sum_c\sum_i\sum_p\sum_g\sum_v cc_{p,g,c}\left(Q^{C\to I}_{c,i,p,g,v,\xi} + Q1^{C\to I}_{c,i,p,g,v,\xi}\right)\right] - \left[\sum_k\sum_d\sum_p\sum_g\sum_v rtc1^k_{p,gk} Q1^{K\to D}_{k,d,p,g,v,\xi}\right] \\
& - \left[\sum_j\sum_p\sum_g rc^J_{pj} Q^J_{j,p,g,\xi}\right] - \left[\sum_w\sum_p\sum_g\sum_v ic^W_{pw} Q^W_{w,p,g,v,\xi}\right] \\
& - \Bigg[\sum_m\sum_s\sum_f tr^{S\to F}_{m,s,f}\,.\,Y_{m,s,f,\xi} - \sum_f\sum_d\sum_p\sum_g\sum_v tr^{F\to D}_{p,f,d,v}.\,Q^{F\to D}_{f,d,p,g,v,\xi} \\
& \qquad - \sum_d\sum_c\sum_p\sum_g\sum_v tr^{D\to C}_{p,d,c,v}.\left(Q^{D\to C}_{d,c,p,g,v,\xi} + Q1^{D\to C}_{d,c,p,g,v,\xi}\right) \\
& \qquad - \sum_c\sum_i\sum_p\sum_g\sum_v tr^{C\to I}_{p,c,i,v}\left(Q^{C\to I}_{c,i,p,g,v,\xi} + Q1^{C\to I}_{c,i,p,g,v,\xi}\right) - \sum_i\sum_k\sum_p\sum_g\sum_v tr^{I\to K}_{p,i,k,v}\left(Q^{I\to K}_{i,k,p,g,v,\xi}\right) \\
& \qquad - \sum_i\sum_j\sum_p\sum_g\sum_v tr^{I\to J}_{p,i,j,v}\left(Q2^{I\to J}_{i,j,p,g,v,\xi}\right) - \sum_k\sum_d\sum_p\sum_g\sum_v tr^{K\to D}_{p,k,d,v}\left(Q1^{K\to D}_{k,d,p,g,v,\xi}\right) \\
& \qquad - \sum_k\sum_j\sum_p\sum_g\sum_v tr^{K\to J}_{p,k,j,v}\left(Q1^{K\to J}_{k,j,p,g,v,\xi}\right) - \sum_j\sum_w\sum_p\sum_g\sum_v tr^{J\to W}_{p,j,w,v}.\,Q^{J\to W}_{j,W,p,g,v,\xi}\Bigg] \quad \forall\, \xi \in \Xi
\end{aligned}
$$

Eq. (1) maximizes the total profit of the network. The components of the Eq. (1) include: The overall cost of opening new centers; Cost of procurement of raw material; Overall manufacturing cost; Overall collection (buyback) cost; Overall retreading cost; Overall recycling cost; Overall energy recovery cost; Total transportation cost; Revenue from sales of new tires; Revenue from sales of retread tires and sales of recycled material.

$$
\begin{aligned}
\mathrm{Min} z_2 = {} & \Bigg[\sum_f e^F_{fp}\,.\,V_{f,p,g,\xi} + \sum_k\sum_d\sum_p\sum_g\sum_v e^K_{kp}\left(Q1^{K\to D}_{k,dp,g,v,\xi}\right) + \sum_j\sum_p\sum_g e^J_{j,p} Q^J_{j,p,g,\xi} \\
& + \sum_w\sum_p\sum_g e^W_{w,p} Q^W_{w,p,g,\xi} + \sum_m\sum_s\sum_f e^{S\to F}_{m,s,f}\,.\,Y_{m,s,f,\xi} + \sum_f\sum_d\sum_p\sum_g\sum_v e^{F\to D}_{p,f,d,v}.\,Q^{F\to D}_{f,d,p,g,v,\xi} \\
& + \sum_d\sum_c\sum_p\sum_g\sum_v e^{D\to C}_{p,d,c,v}.\left(Q^{D\to C}_{d,c,p,g,v,\xi} + Q1^{D\to C}_{d,c,p,g,v,\xi}\right) \\
& + \sum_c\sum_i\sum_p\sum_g\sum_v e^{C\to I}_{p,c,v,i}\left(Q^{C\to I}_{c,i,p,g,v,\xi} + Q1^{C\to I}_{c,i,p,g,v,\xi}\right) + \sum_i\sum_k\sum_p\sum_g\sum_v e^{I\to K}_{p,i,k,v}\left(Q^{I\to K}_{i,k,p,g,v,\xi}\right) \\
& + \sum_i\sum_j\sum_p\sum_g\sum_v e^{I\to J}_{p,i,j,v}\left(Q1^{I\to J}_{i,j,p,g,v,\xi}\right) + \sum_k\sum_d\sum_p\sum_g\sum_v e^{K\to D}_{p,k,d,v}\left(Q1^{K\to D}_{k,d,p,g,v,\xi}\right) \\
& + \sum_k\sum_j\sum_p\sum_g\sum_v e^{K\to J}_{p,k,j,v}\left(Q1^{K\to J}_{k,j,p,g,v,\xi}\right) + \sum_j\sum_W\sum_p\sum_g\sum_v e^{J\to W}_{p,j,k,v}.\,Q^{J\to W}_{j,W,p,g,v,\xi}\Bigg] \quad \forall\, \xi \in \Xi
\end{aligned}
$$

Eq. (2) minimizes the overall environmental impact, which is expressed as the amount of GHG generated at production centers, retreading centers, recycling centers, and energy recovery centers as well as during the transportation of raw material and finished tires between centers.

Constraints:

$$\sum_{f} Y_{m,s,f,\xi} \leq cap^{S}_{m,s} x^{S}_{s} \; ; \forall\, m \in M, s \in S, \xi \in \Xi \tag{3}$$

$$\sum_{p}\sum_{g} V_{f,p,g,\xi} \leq \sum_{u} cap^{F}_{u} . g^{F}_{f,u} \quad ; \forall\, f \in F^{a}, \xi \in \Xi \tag{4}$$

$$\sum_{p}\sum_{g} V_{f,p,g,\xi} \leq \sum_{u} cap^{F}_{u} . x^{F}_{f,u} \quad ; \forall\, f \in F^{b}, \xi \in \Xi \tag{5}$$

$$\sum_{u} x^{F}_{f,u} \leq 1; \; \forall\, f \in F^{b}, \xi \in \Xi \tag{6}$$

$$\sum_{p}\sum_{g} r^{F}_{m} V_{f,p,g,\xi} \leq \sum_{s} Y_{m,s,f,\xi} \quad ; \forall\, m \in M, f \in F, \xi \in \Xi \tag{7}$$

$$V_{f,p,g,\xi} = \sum_{d}\sum_{v} Q^{F\to D}_{f,d,p,g,v,\xi} \; ; \forall\; f \in F, p \in P, g \in G, \xi \in \Xi \tag{8}$$

$$\sum_{f}\sum_{p}\sum_{g}\sum_{v} Q^{F\to D}_{f,d,p,g,v,\xi} + \sum_{k}\sum_{p}\sum_{g}\sum_{v} Q1^{K\to D}_{k,d,p,g,v,\xi} \leq \sum_{u} cap^{D}_{u} . g^{D}_{d,u} \; ; \forall\, d \in D^{a}, \xi \in \Xi \tag{9}$$

$$\sum_{f}\sum_{p}\sum_{g}\sum_{v} Q^{F\to D}_{f,d,p,g,v,\xi} + \sum_{k}\sum_{p}\sum_{g}\sum_{v} Q1^{K\to D}_{k,d,p,g,v,\xi} \leq \sum_{u} cap^{D}_{d} . x^{D}_{d,u} \; ; \forall\, d \in D^{b}, \xi \in \Xi \tag{10}$$

$$\sum_{u} x^{D}_{d,u} \leq 1; \; \forall\, d \in D^{b} \tag{11}$$

$$\sum_{f}\sum_{v} Q^{F\to D}_{f,d,p,g,v,\xi} = \sum_{c}\sum_{v} Q^{D\to C}_{d,c,p,g,v,\xi} ; \; \forall\; d \in D, p \in P, \xi \in \Xi \tag{12}$$

$$\sum_{k}\sum_{v} Q1^{K\to D}_{k,d,p,g,v,\xi} = \sum_{c}\sum_{v} Q1^{D\to C}_{d,c,p,g,v,\xi} ; \; \forall\; d \in D, p \in P, \xi \in \Xi \tag{13}$$

$$\sum_{d}\sum_{v} Q^{D\to C}_{d,c.p,g,v,\xi} = \widetilde{dem^{C}_{c,p,g,\xi}} ; \; \forall\; c \in C, p \in P, g \in G, \xi \in \Xi \tag{14}$$

$$\sum_{d}\sum_{v} Q1^{D\to C}_{d,c,p,g,v,\xi} \leq \widetilde{dem1^{C}_{c,p,g,\xi}} ; \; \forall\; c \in C, p \in P, g \in G, \xi \in \Xi \tag{15}$$

$$\sum_{i}\sum_{v} Q^{C\to I}_{c,i,p,g,v,\xi} = \widetilde{\alpha_{p,g}} \sum_{d}\sum_{v} Q^{D\to C}_{d,c,p,g,v,\xi} ; \; \forall\; c \in C, p \in P, g \in G, \xi \in \Xi \tag{16}$$

$$\sum_{i}\sum_{v} Q1^{C\to I}_{c,i,p,g,v,\xi} = \widetilde{\alpha1_{p,g}} \sum_{d}\sum_{v} Q1^{D\to C}_{d,c,p,g,v,\xi} ; \; \forall\; c \in C, p \in P, g \in G, \xi \in \Xi \tag{17}$$

$$\sum_{i}\sum_{p}\sum_{g}\sum_{v} Q^{C\to I}_{c,i,p,g,v,\xi} + \sum_{i}\sum_{p}\sum_{g}\sum_{v} Q1^{C\to I}_{c,i,p,g,v,\xi} \leq \sum_{u} cap^{I}_{i} . x^{I}_{i,u} ; \forall\; i \in I, \xi \in \Xi \tag{18}$$

$$\sum_{c}\sum_{v} Q^{C\to I}_{c,i,p,g,v,\xi} = \sum_{k}\sum_{v} Q^{I\to K}_{i,k,p,g,v,\xi} ; \; \forall\; i \in I, p \in P, g \in G, \xi \in \Xi \tag{19}$$

$$\sum_{c}\sum_{v} Q1^{C\to I}_{c,i,p,g,v,\xi} = \sum_{k}\sum_{v} Q1^{I\to J}_{i,j,p,g,v,\xi} ; \; \forall\; i \in I, p \in P, g \in G, \xi \in \Xi \tag{20}$$

$$\sum_{i}\sum_{k}\sum_{p}\sum_{g}\sum_{v} Q^{I\to K}_{i,k,p,g,v,\xi} \leq \sum_{u} cap^{K}_{u} . x^{K}_{k,u} ; \; \forall\; k \in K, \xi \in \Xi \tag{21}$$

$$\sum_{d}\sum_{v} Q1^{K\to D}_{k,d,p,g,v,\xi} = \widetilde{\theta1_{p,g}} \sum_{i}\sum_{v} Q^{I\to K}_{i,k,p,g,v,\xi} ; \; \forall\; k \in K, p \in P, g \in G, \xi \in \Xi \tag{22}$$

$$\sum_{j}\sum_{v} Q1^{K\to J}_{k,j,p,g,v,\xi} = \sum_{i}\sum_{v} Q^{I\to K}_{i,k,p,g,v,\xi} - \sum_{d}\sum_{v} Q1^{K\to D}_{k,d,p,g,v,\xi} ; \; \forall\; k \in K, p \in P, g \in G, \xi \in \Xi \tag{23}$$

$$\sum_{k}\sum_{p}\sum_{g}\sum_{v} Q1^{K\to J}_{k,j,p,g,v,\xi} + \sum_{i}\sum_{p}\sum_{g}\sum_{v} Q1^{I\to J}_{i,j,p,g,v,\xi} \leq \sum_{u} cap^{J}_{j} . x^{J}_{j,u} ; \; \forall\; j \in J, \xi \in \Xi \tag{24}$$

$$Q^{J}_{j,p,g,\xi} = \beta\left(\sum_{k}\sum_{v} Q1^{K\to J}_{k,j,p,g,v,\xi} + \sum_{i}\sum_{v} Q1^{I\to J}_{i,j,p,g,v,\xi}\right);\ \forall\ j \in J\,, p \in P, g \in G\,, \xi \in \Xi \tag{25}$$

$$\sum_{w}\sum_{v} Q^{J\to W}_{j,w,p,g,v,\xi} = \sum_{k}\sum_{v} Q1^{K\to J}_{k,j,p,g,v,\xi} + \sum_{i}\sum_{v} Q1^{I\to J}_{i,j,p,g,v,\xi} - Q^{J}_{j,p,g,\xi};\forall\, j \in J\,, p \in P, g \in G\,, \xi \in \Xi \tag{26}$$

$$Q^{W}_{w,p,g,\xi} = \sum_{j}\sum_{v} Q^{J\to W}_{j,w,p,g,v,\xi}\quad \forall\ w \in W\,, p \in P\,, \xi \in \Xi \tag{27}$$

$$\begin{cases} x^{(.)}_{(*,*)}, Y_{m,s,f,\xi} \in \{0,1\} \\ V_{f,p,g,\xi}\,, Q^{\cdot\to\cdot}_{(*,*)} \geq 0 \end{cases} \tag{28}$$

Constraint (3) ensures that the total quantity of raw material sent to tire manufacturing centers is less than or equal to the maximum capacity of each supplier for that raw material. Constraints (4) and (5) ensures that the total quantity of tires produced at each manufacturing center is less than or equal to the maximum capacity of each existing and potential manufacturing center. Constraint (6) ensures that only one production facility at capacity level u can be open at location f. Constraint (7) guarantees that the raw material needed at production centers are satisfied. Constraint (8) is an equilibrium constraint indicating the total quantity of tires transferred from each manufacturing center f to distribution center d is equal to the quantity of tires manufactured at that center. Constraints (9) and (10) ensures that the maximum capacity of the existing and potential distribution centers are not violated. Constraint (11) guarantees that only one distribution center at capacity level u can be open at any potential location d. Constraints (12) and (13), are equilibrium constraints to ensure the total quantity of new and retread (retread) tires transferred out of each distribution center is equal to the total quantity of tires enter that center. Constraint (14) ensure that the market demand for new tires is satisfied. Constraints (15) indicate that the demand for retread tires does not have to be entirely satisfied. It should be noted that the demand parameters are stochastic scenario-based. Constraints (16) and (17) calculate the total quantity of tires returned to each collection center. Constraint (18) controls the maximum capacity of the collection centers. Constraints (19) and (20) are equilibrium constraints that create flow balance at each collection center. Constraint (21) ensures the flow of products into and out of each retreading center does not exceed the capacity of that center. Constraints (22) calculates the quantity of the tires that are being successfully retreaded at each retreading center. Constraints (23) calculates the total quantity of new and retread tires that cannot be retreaded at retreading centers and are being transferred to recycling centers. Constraint (24) controls the capacity of the recycling centers. Constraint (25) calculates the total quantity of products transfers to each recycling center. Constraint (26) creates equilibrium at recycling centers. Constraint (27) calculates the total number of tires being incinerated at each energy recovery center. Ultimately, constraint (35) enforces the binary and non-negative constraints on the corresponding decision variables.

The proposed tire CLSC model is an MILP problem under hybrid uncertainty. Fuzzy uncertainty related to return rate, retreading rate, procurement cost, production cost, and scenario-based uncertainty related to demand parameters. In the following, we will discuss a method that can simultaneously deal with these hybrid uncertainties.

4. The proposed approach

Robust Fuzzy/Possibilistic Stochastics Programming (RFSP) is a novel approach in mathematical programming that deals with hybrid uncertain parameters [55]. It is an expansion of possibilistic Programing [56] in which the possible scenarios of the disturbance in the system are additionally being considered and addressed using stochastic scenario-based programming method.

In general, the scenario-based stochastic programming approach can be described as follows:

$$\begin{cases} \max \sum_{\xi\in\Xi} \pi_{\xi}.\, z_{\xi} \\ z_{\xi} = c^{T}_{\xi}.\, x_{\xi} + d^{T}_{\xi} y\ \forall\ \xi \in \Xi \\ A_{\xi}x_{\xi} + K_{\xi}y \leq b_{\xi} \quad \forall\ \xi \in \Xi \\ Ry = q \\ y \in Y\,, x_{\xi} \geq 0 \end{cases} \tag{29}$$

z_ξ is the objective function under scenario $\xi \in \Xi$, x_ξ are the scenario dependent variables, y are the variables independent of the scenario (i.e. Binary variables), $(c_\xi, d_\xi, A_\xi, K_\xi, b_\xi)$ are the parameters under scenario $\xi \in \Xi$, (R, q) are crisp parameters and π_ξ is the probability of occurrence of scenario $\xi \in \Xi$ [55].

In order to prevent excessive deviation of the of the objective function under different scenarios, the variance of the objective function is also considered. Therefore, the resulting robust stochastic programming model would be as follows:

$$\begin{cases} \max \sum_{\xi \in \Xi} \pi_\xi . z_\xi - \lambda . \sum_{\xi \in \Xi} \pi_\xi \left(2\theta_\xi - \left(z_\xi - \sum_{\xi' \in \Xi} \pi_\xi . z_{\xi'} \right) \right) - \omega \sum_{\xi \in \Xi} \pi_\xi . \Delta_\xi \\ z_\xi = c_\xi^T . x_\xi + d_\xi^T y \ \forall \xi \in \Xi \\ \theta_\xi \geq z_\xi - \sum_{\xi \in S} \pi_\xi . z_\xi \ \forall \xi \in \Xi \\ A_\xi x_\xi + K_\xi y \leq b_\xi + \Delta_\xi \quad \forall \xi \in \Xi \\ Ry = q \\ y \in Y, x_\xi \geq 0 \\ \theta_\xi \geq 0 \end{cases} \tag{30}$$

Where λ denotes the importance or weighing scale to measure the tradeoff between optimality and the cost under different scenarios. θ_ξ denotes the absolute deviation from the mean under each scenario. Δ_ξ represent the deviation for violation of the control constraint, and ω is the robustness coefficient or feasibility robustness multiplier which its value can be equal to the penalty cost of the shortage. The above model is known as the Mulvey Robust stochastic model [23], although the above model is the linear version of the model based on the research of Yu and Li [24].

If some of the data in an optimization problem are imprecise due to insufficient data or unavailability of the information, but their approximate values can be expressed in fuzzy numbers, fuzzy mathematical programming can be used [57]. If fuzzy data in the optimization problem is expressed as Trapezoidal Fuzzy Number (TFN) and the possibility of occurrence of the possibilistic parameters are measured by Pos. and Nec., then possibilistic programming can be used where Pos. is the maximum level of occurrence of parameters and Nec. is the minimum possibility level.

The general form of possibilistic programming can be expressed as follows:

$$\begin{cases} \max Z = E(\tilde{c}x) \\ \text{s.t.} \\ Me\left(Ax \leq \tilde{\mathcal{F}}\right) \geq \mathbb{p} \\ x \in X \end{cases} \tag{31}$$

Where Me(.) is a fuzzy measure, $\tilde{\mathcal{F}} = (f_{(1)}, f_{(2)}, f_{(3)}, f_{(4)})$ and $\tilde{c} = (c_{(1)}, c_{(2)}, c_{(3)}, c_{(4)})$ are the fuzzy parameters in the form of TFN. $\mathbb{p}$ is the minimum confidence level and $E(\tilde{c}x)$ is the fuzzy expected value of the objective function, which can be expressed as:

$$E(\tilde{c}x) = \frac{\left(c_{(1)} + 2c_{(2)} + 2c_{(3)} + c_{(4)}\right)}{6} x$$

In order to control fuzzy constraints, one of the most widely used fuzzy measures is credibility measure (Cr) which is expressed as the average of the optimistic (Pos) and pessimistic (Nec) measures:

$$Cr(.) = \frac{1}{2}(Pos(.) + Nec(.))$$

And the following relationship can exist [58]:

$$\begin{cases} Cr(Ax \geq \tilde{\mathcal{F}}) \geq \mathbb{p} \Leftrightarrow Ax \geq f_{(3)} + (2\alpha - 1)(f_{(4)} - f_{(3)}) & : \mathbb{p} \geq 0.5 \\ Cr(Ax \leq \tilde{\mathcal{F}}) \geq \mathbb{p} \Leftrightarrow Ax \leq f_{(2)} - (2\alpha - 1)(f_{(2)} - f_{(1)}) & : \mathbb{p} \geq 0.5 \end{cases} \tag{32}$$

One of the disadvantages of classical programming is that the $\mathbb{p}$ value is determined subjectively by the decision maker (DM) and is usually set inactively or ultimately interactively and may not be optimal. This issue has been first addressed in the research conducted by Pishvaee (2012)[25].

In their proposed model, taking into account the two concepts of feasibility robustness and optimality robustness, the optimal levels of $\mathbb{p}$ value are obtained proactively and objectively. This approach has been used in several studies [59-61].

The RFSP approach is an extension of the combination of scenario-based stochastic programming and possibilistic programming in which random scenarios and fuzzy data are controlled simultaneously. The RFSP approach can be summarized as follows:

$$\begin{cases} \max \sum_{\xi \in \Xi} \pi_\xi . z_\xi - \lambda . \sum_{\xi \in \Xi} \pi_\xi \left(2\theta_\xi - \left(z_\xi - \sum_{\xi' \in \Xi} \pi_{\xi'} . z_{\xi'} \right) \right) - \omega \sum_{\xi \in \Xi} \pi_\xi . \Delta_\xi - \Psi . \vartheta(\mathbb{p}) \\ z_\xi = E(c_\xi^T . x_\xi + d_\xi^T y) = \frac{(c_{(1)} + 2c_{(2)} + 2c_{(3)} + c_{(4)})}{6} x_\xi + d_\xi^T y \quad \forall \xi \in \Xi \\ A_\xi x_\xi + K_\xi y \leq b_{(2)\xi} - (2\mathbb{p} - 1)(b_{(2)\xi} - b_{(1)\xi}) + \Delta_\xi \quad \forall \xi \in \Xi \\ Ry = q \\ \theta_\xi \geq z_\xi - \sum_{s \in S} \pi_\xi . z_\xi \quad \forall \xi \in \Xi \\ y \in Y, x_\xi \geq 0 \\ \theta_\xi \geq 0 \\ \mathbb{p} \geq 0.5 \end{cases} \tag{33}$$

Where Ψ is the coefficient for estimating fuzzy numbers, $\vartheta(\mathbb{p})$ is a non-negative descending function that calculates the violation of fuzzy constraints with confidence level $\mathbb{p}$. $\vartheta(\mathbb{p})$ can be expressed as the difference between the substituted crisp numbers, $(b_{(2)\xi} - (2\mathbb{p} - 1)(b_{(2)\xi} - b_{(1)\xi}))$, and the worst-case value of the imprecise parameters (TFNs) and can be expressed as follows:

$$\vartheta(\mathbb{p}) = \left(b_{(2)\xi} - (2\mathbb{p} - 1)(b_{(2)\xi} - b_{(1)\xi})\right) - b_{(1)\xi} = (b_{(2)\xi} - b_{(1)\xi}) - (2\mathbb{p} - 1)(b_{(2)\xi} - b_{(1)\xi})$$
$$= (1 - 2\mathbb{p} + 1)(b_{(2)\xi} - b_{(1)\xi}) = 2(1 - \mathbb{p})(b_{(2)\xi} - b_{(1)\xi})$$

Δ_ξ *calculates* shortage under each scenario. It should be noted that λ denotes the weighing scale to measure the tradeoff between optimality and the cost under different scenarios, θ_ξ denotes the absolute deviation from the mean under each scenario. Δ_ξ represent the deviation for violation of the control constraint, and ω is the model robustness coefficient or feasibility robustness multiplier.

4.1. Coping with multi-objective functions

In order to solve multi-objective decision making (MODM) optimization problems, several approaches have been proposed, such as Weighted Sum Method (WSM), Epsilon Constraint (E.C.), Augmented Epsilon Constraint (A.E.C.), Goal Programing (G.P.), Lexicographic (Lex) and so on. The general form of a MODM problem is as follows:

$$\begin{cases} \text{Min } (f_1(x), f_2(x), \dots, f_n(x)) \\ x \in X \end{cases} \tag{34}$$

4.2. Epsilon Constraint

Let's assume the first objective is the main objective, and the remaining objectives will have an upper bound of epsilon and will be presented as constraints of the model. In this case, the E.C. method is being used, and the resulting single objective model can be described as follows:

$$\begin{cases} \text{Min } f_1(x) \\ f_i(x) \leq e_i \ i = 2,3,..,n \\ x \in X \end{cases} \tag{35}$$

In the above model, the first objective is considered as the main objective, and the remaining objectives are considered as constraints and are bound by maximum e_i. By changing the e_i different results can be obtained, which may be weakly efficient or not efficient.

This issue can be resolved with minor modification, which is known as the AEC method [62]. To better implement the AEC method, the appropriate range of epsilons e_i can be obtained using the Lex method [63]. In the AEC method, the appropriate range of e_i is first determined and then the Pareto front obtained for different values of e_i.

4.3. Appropriate interval for e_i with Lex method

In order to find the appropriate interval for e_i related to the objective function f_i (i = 2,…, n), the following optimization problem is first being solved:

$$\mathrm{PayOff_{jj}} = \mathrm{Min}\ \mathrm{f_j(x)} \quad \mathrm{j} = 1,2,\ldots,\mathrm{n}$$
$$\mathrm{x} \in \mathrm{X}$$

where $PayOff_{jj} = f_j(x^{j,*})$ is the optimum value of f_j and $x^{j,*}$ is the vector of decision variables that optimizes f_j.

Then, with the solution that optimizes the objective function f_j, the value of the remaining objective functions is obtained as follows:

$$\mathrm{PayOff_{ij}} = \mathrm{Min}\ \mathrm{f_i(x)}$$
$$\mathrm{f_j(x)} = \mathrm{PayOff_{jj}}$$
$$\mathrm{x} \in \mathrm{X}$$
$$\mathrm{j} = 1,2,\ldots,\mathrm{n}\,;\mathrm{j} \neq \mathrm{i}$$

where $PayOff_{ij} = f_i(x^{i,j,*})$ is the optimum value of f_i and $x^{i,j,*}$ is the vector of decision variables that optimizes f_i. Using the Lex method, the following payoff matrix is obtained:

$$\mathrm{PayOff} = [\mathrm{payOff_{ij}}]$$

After calculating the payoff table for f_ii=1,…..n, the followings can be defined:

$$\mathrm{Min(f_i)} = \mathrm{Min_j}\{\mathrm{payOff_{ij}}\} = \mathrm{payOff_{ii}}$$
$$\mathrm{Max(f_i)} = \mathrm{Max_j}\{\mathrm{payOff_{ij}}\}$$
$$\mathrm{R(f_i)} = \mathrm{Max(f_i)} - \mathrm{Min(f_i)}$$

Using the above definition, appropriate rage for each $\mathrm{e_i}$ can be obtained using the Lex method:

$$\mathrm{e_i} \in [\mathrm{Min(f_i)}, \mathrm{Max(f_i)}]$$

The value $\mathrm{R(f_i)}$ is used to normalize the objectives in the AEC objective functions.

4.4. Augmented Epsilon Constraint

The AEC model can be expressed as follows:

$$\begin{cases} \mathrm{Min}\ \ \mathrm{f_1(x)} - \sum_{i=2}^{n} \phi_i s_i \\ \mathrm{f_i(x)} + \mathrm{s_i} = \mathrm{e_i}\ \ \mathrm{i} = 2,3,\ldots,\mathrm{n} \\ \mathrm{x} \in \mathrm{X} \\ \mathrm{s_i} \geq 0 \end{cases} \tag{36}$$

Where $\mathrm{s_i}$ are non-negative variables for the shortage, ϕ_i is a parameter for normalizing the first objective with respect to $\mathrm{f_i}$ and $\phi_i = \frac{\mathrm{R(f_1)}}{\mathrm{R(f_i)}}$.

In the proposed AEC method in this study, first $\mathrm{e_i} \in [\mathrm{Min(f_i)}, \mathrm{Max(f_i)}]$is obtained using Lex method, then eq. (34) is solved, which provides an optimum solution.

5. Computational Experiment

To check the validity and performance of the model, this model has been applied for the design and optimization of a sample problem. The relevant data presented in Table.1,2,3,4 are collected from literature, field data, interviewing experts in the field, and the organizations involved in this field, including EPA, U.S. Tire Manufacturers Association, Tire Retread & Repair Information Bureau (TRIB), Modern Tire Dealer (MTD), and Institute of Scrap Recycling Industries (ISRI).

We are evaluating the feasibility of expanding an existing forward logistics network by adding additional manufacturing facilities, distribution centers, collection centers, retreading centers, and recycling centers. New potential facilities are selected such that they are within 120 Kilometer of the subsequent facilities in the network. The goal is to optimize the number, location, and capacity of the facilities, increase the efficiency and profitability of the network, reduce the amount of greenhouse gases generated in the network. The return rate and retreading rate of sensor-embedded tires are assumed to be fifteen percent more than the non-sensor tires.

The selling price of sensor-embedded new and retread tires, retreading cost of sensor-embedded tires, and buyback price of sensor-embedded tires are assumed to be ten percent higher than non-sensor tires. There is a single type of vehicle used for transferring the raw material. The cost of transferring raw material is \$0.002 for one unit of raw material. There are two types of transportation vehicles used for transferring finished products, 22-foot, and 16-foot trucks. Assuming a full truckload on each transfer, the cost of transferring one unit of tire per kilometer is \$0.02 for 16-foot truck and \$0.03 for 22-foot truck. The amount of Co2 generated per unit of tire transferred between facilities is 0.002 kg per km for 16-foot truck , 0.003 kg for 22-foot truck and is 0.0004 kilogram per kilometer for one unit of raw material being transferred.

Table 1. Network parameters

F^a	2	C	40	W	3
F^b	3	I	10	G	2
D^a	5	J	5	M	6
D^b	5	K	4	V	2
S	5	P	5		

Table 2. Values of scenario-based parameters (Demands)

Scenarios (ξ)	Recession	Good	Growing
Scenario Probability	0.20	0.50	0.30
$\widetilde{dem^{C}_{c,p,g,\xi}}$	U (4000-4100)	U (4100-4300)	U (4300-4500)
$\widetilde{dem1^{C}_{c,p,g,\xi}}$	U (3000-3100)	U (3100-3300)	U (3300-3500)

Table 3. Values of fuzzy parameters

Parameters	$c_{(1)}$	$c_{(2)}$	$c_{(3)}$	$c_{(4)})$
$\widetilde{\alpha_{p,g}}$	U (0.7- 0.75)	U (0.75-0.8)	U (0.80-0.85)	U (0.85-0.9)
$\widetilde{\alpha1_{p,g}}$	U (0.65-0.7)	U (0.7-0.75)	U (0.75- 0.8)	U (0.8- 0.85)
$\widetilde{\theta1_{p,g}}$	U (0.6- 0.65)	U (0.65-0.7)	U (0.7-0.75)	U (0.75-0.8)
$\widetilde{pc^{F}_{p,g,f}}$	U (\$100- \$110)	U (\$110- \$120)	U (\$120- \$130)	U (\$130- \$140)
$\widetilde{mc^{S}_{m=1,s}}$	U (\$9, \$9.5)	U (\$9.5, \$10)	U (\$10, \$10.5)	U (\$10.5, \$11)
$\widetilde{mc^{S}_{m=2,s}}$	U (\$43, \$44)	U (\$44, \$45)	U (\$45, \$46)	U (\$46, \$47)
$\widetilde{mc^{S}_{m=3,s}}$	U (\$9, \$9.5)	U (\$9.5-\$10)	U (\$10-\$10.5)	U (\$10.5-\$11)
$\widetilde{mc^{S}_{m=4,s}}$	U (\$9, \$9.5)	U (\$9.5-\$10)	U (\$10-\$10.5)	U (\$10.5k-\$11)
$\widetilde{mc^{S}_{m=5,s}}$	U (\$10, \$10.5)	U (\$10.5, \$11)	U (\$11, \$11.5)	U (\$11.5, \$12)
$\widetilde{mc^{S}_{m=6,s}}$	U (\$15, \$20)	U (\$20, \$25)	U (\$25, \$30)	U (\$30, \$35)

Table4. Parameters subject to multi capacity levels

	Capacity level (U)		
	Low	Medium	High
$fc^{F}_{f,u}$	U (\$3M- \$4M)	U (\$4M-\$6M)	U (\$6M- \$10M)
fc^{D}_{du}	U (\$.2M-\$.3M)	U (\$.3M-\$.5M)	U (\$.5M- \$.7M)
fc^{I}_{iu}	U (\$.2M- \$.3M)	U (\$.3M- \$.4M)	U (\$.4M- \$.5M)
$fc^{J}_{j,u}$	U (\$.3M, \$.4M)	U (\$.4M, \$.5M)	U (\$.5M- \$.7M)
$fc^{K}_{k,u}$	U (\$.8M- \$1.5M)	U (\$1.5M- \$2.5M)	U (\$2.5M- \$4M)
cap^{F}_{u}	U(200K-400K)	U (400K-600K)	U (600K-1000K)
cap^{D}_{u}	U (100K-200K)	U (200K-300K)	U (300K-400K)
cap^{I}_{u}	U (200K-400K)	U (400K-600K)	U (600K-800K)
cap^{K}_{u}	U (100K-400K)	U (400K-600K)	U (600K-800K)
cap^{J}_{u}	U (100K-400K)	U (400K-600K)	U (600k-800k)

Table 5. Other parameters

$r^F_{m,p,g}$	m1: U (4-6), m2: U (14-17), m3: 4-6), m4: U (9-12), m5: U (10-12), m6: {0,1}		
fc^S_s	U ($1000-$1200)	$ic^W_{p,w}$	U ($3-$8)
$cc_{p,g,c}$	U ($30-$50)	e^F_f	U (9-10) kg
$rtc^k_{p,g,k}$	U ($40-$50)	e^W_w	U (10-12) kg
$rc^J_{p,j}$	U ($5-$10)	e^K_k	U (6-7) kg
$\rho^0_{p,g}$	U ($450- $550)	e^J_j	U (1-2) kg
$\rho^1_{p,g}$	U ($200- $300)	β	U (0.6-0.7)
ρ^r_p	U ($25- $30)		

5.1. Computational results and Sensitivity analysis

In order to evaluate the performance of the proposed model, it is solved using GAMS software and a P.C. laptop with the following configuration: Intel® Core™ i7-1165G7 Processor (2.80 GHz),16 GB DDR4 3200MHz.Table 6. shows the optimum configuration of the network using the mean approach (λ=0). In this configuration, 3 additional production centers will be open at high and medium capacity, 2 additional distribution centers will be open at low capacity, 6 collection centers will be open at low capacity, 3 retreading centers open at medium capacity, and 3 recycling centers open at low capacity. It can be seen in the optimum configuration of the network that the appropriate capacity levels of the open centers were determined in order to eliminate the shortage. The optimum confidence level of the fuzzy constraints ($\mathbb{p}$) was also determined based on the objective functions and the constraints which resulted in zero violation of fuzzy constraints ($\vartheta(\mathbb{p})$).

Fig. 3shows the quantity of sensor embedded and non-sensor tires shipped using the available vehicle options. Fig. 4 shows the quantity of tires being retreaded. It can be observed that the total quantity of sensor-embedded tires that are retreaded is greater than the non-sensor tires.

Table 6. Summary of optimum result using mean approach

Value of Coefficients	$\lambda = 0$, $\omega = 0$, $\Psi = 1$
Obj 1(Profit- Million Dollar)	1361
Obj.2 (Total GHG)	454,344
Production Centers	2 centers open @High capacity/ 1center open @Medium capacity
Distribution Centers	2 centers open @ Low capacity
Collection Centers	6 centers open @ low capacity
Retreading Centers	3 centers open @ Medium capacity
Recycling Centers	3 centers open @ Low capacity
Suppliers being utilized	2 suppliers
θ_ξ (Scenario variability)	244.414
Δ_ξ (shortage)	0
$\vartheta(\mathbb{p})$	0
$\mathbb{p}$ (confidence level of fuzzy constraints)	$\mathbb{p}_1 = .5/\mathbb{p}_2=0.5\ /\mathbb{p}_3 = 0.5$

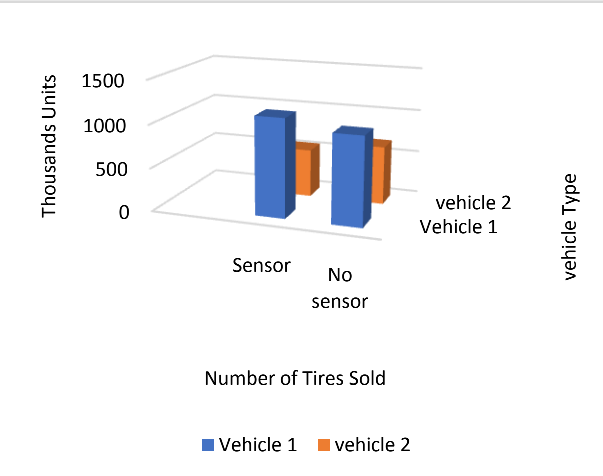

Fig.3. Total number of tires sold

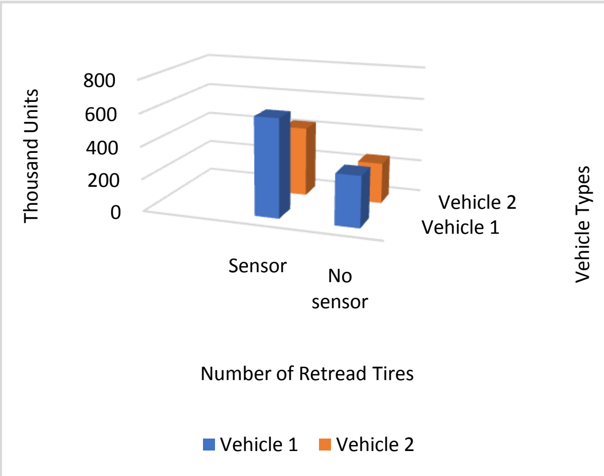

Fig.4. Total number of tires retreaded

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Further sensitivity analysis is performed to evaluate the impact of sensor embedded tires on the optimal configuration of the network and its environmental impacts. In that respect, we evaluate the impact of increasing the production of sensor embedded tires and eliminating the production of non-sensor tires. As illustrated in Table 7.an increase in production of sensor embedded tires has resulted in an increase in the capacity of the distribution centers, an increase in number and capacity of the collection centers and retreading centers.Fig.5 and Fig.6 illustrates the quantity of sensor-embedded tires sold and retreaded considering that only sensor embedded tires are produced. It can be observed that the total quantity of tires that are retreaded has significantly increased which explains the increase in the number and capacity of collection centers, retreading centers and distribution centers.

Table 7. Summary of optimum result (only sensor embedded tires are produced)

Value of Coefficients	$\lambda = 0$, $\omega = 0$, $\Psi = 1$
Obj 1(Profit- Dollar)	1541
Obj.2 (GHG-Kg)	421,324
Production Centers	2 centers open @High capacity/ 1center open @Medium capacity
Distribution Centers	4 centers open @ Medium capacity
Collection Centers	4 centers open @ low capacity& 2 centers open @ Medium capacity
Retreading Centers	2 centers open @ Medium capacity& 2 centers open @ High capacity
Recycling Centers	3 centers open @ Low capacity
Suppliers being utilized	2 suppliers
θ_{ξ} (Scenario variability)	257.414
Δ_{ξ} (shortage)	0
$\vartheta(\mathbb{p})$	0
$\mathbb{p}$ (confidence level of fuzzy constraints)	$\mathbb{p}_1 = .5/\mathbb{p}_2=0.5 /\mathbb{p}_3 = 0.5$

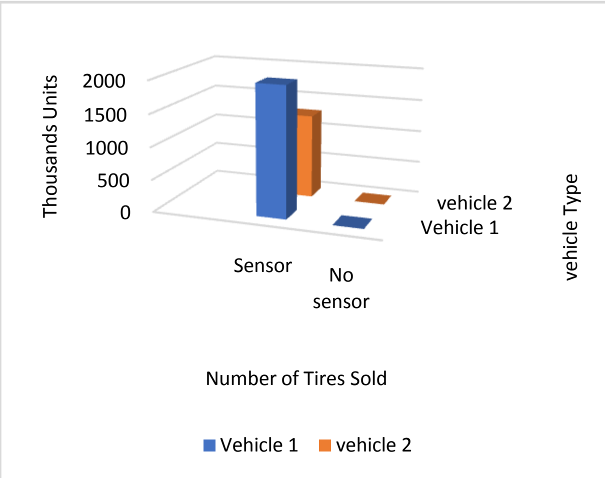

Fig.5. Total number of sensor-embedded tires sold

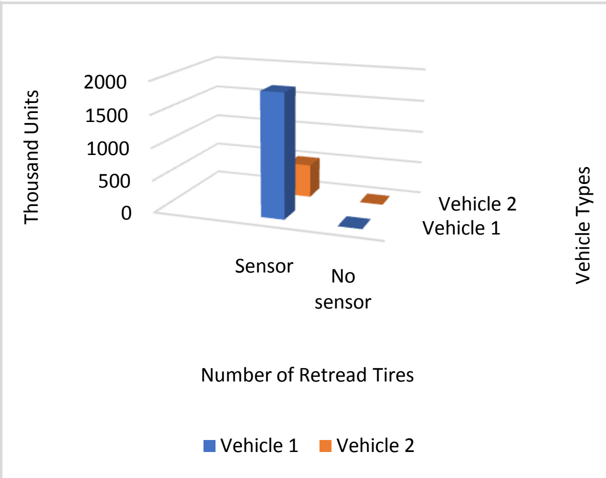

Fig.6. Total number of sensor-embedded tires retreaded

6. Conclusion

Environmental concerns and reduction in natural resources has compelled manufacturers to move toward designing a green sustainable CLSC network. In addition to CLSC network design, manufactures are also focusing on designing smart products that can collect valuable information during the life of product which can help with extending the life span of the product and increasing the efficiency of processing the EOL products. Tire manufacturers have recently been focusing on designing smart sensor embedded tires that can collect and transmit information such as tire temperature, tire air pressure, tire wear, and road-surface conditions in real time and send to the cloud storage to be analyzed. In this study, we designed a green CLSC network by considering impact of sensor embedded and non-sensor tires on the overall performance of the network. The proposed bi-objective MILP model was solved using robust fuzzy stochastic programing method. The result indicates that more sensor embedded tires being routed to retreading centers compared with non-sensor tires which consequently result in an increase in number and capacity of the facilities in the reverse logistics network such as collection centers, retreading centers and distribution centers.

For future study, the impact of different retreading technologies on the overall performance of the network can be considered. Also, the quality and service level provided by retreading centers can be analyzed.

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