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A Robust Multiple Objectives Model to Design a Network of a Closed Loop Supply Chain

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Abstract:
To reduce risks of unpredicted events and increase the efficiency of the supply chain, planning under uncertainties and considering flexibility have become essential steps towards a robust supply chain. In this paper, we propose a model with multiple objectives that considers uncertainties and flexibility for designing a network of closed loop supply chain. The proposed model integrates two approaches that are physical programming and scenario-based robust optimization. This model is considered as the first attempt to solve the problem of a closed loop supply chain network design. To illustrate the usability of the proposed model, we provide a numerical experiment for designing a network of CLSC of the tire industry in Saudi Arabia.
Keywords: *Physical programming, Uncertainties, Product substitution, Closed loop supply chain*

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I. Introduction

The importance of the supply chain lies in the fact that it is widely available in research, case studies and its practical implementation in the majority of industries. However, ignorance of uncertainties that impact the planning of the supply chain leads to reduce in its level of optimality. According to Ivanov (2020) [1], when a network including supply, demand and production is less dynamic, less flexible and ignores uncertainties, it will experience extensive suffering. Imagine for example how the supply chain has suffered from the occurrence of COVID-19. For example, Wuhan city in China has five factories to manufacture LCD panels. They are supposed to satisfy the demand of half of the world's need for LCD panels, which are the main part of TVs, laptops and computer monitors. Experiencing a full shutdown for these factories during the pandemic had its negative effect on satisfying the customer demands and the supply chain generally [2].

Complexity is added to the supply chain once it is extended to a closed loop supply chain (CLSC) which integrates a reverse flow to the supply chain. This complexity arises as a result of unpredicted events, including changes in the demand for products which include new and remanufactured products. In addition, the reverse flow by itself is very complex as uncertainties are involved with the time and quantity of returned products as well as their condition which has a parallel impact on remanufacturing [3]. Thus, the problem of designing the CLSC network becomes extremely challenging.

Despite the fact that the problem of designing the CLSC network has attracted researcher's attention recently, the potential of improving the existing models is still possible [4]–[7]. This is because the available models are either deterministic or considering a single objective. Although there are few models considering uncertainties, they lack flexibility.

In this paper, we present a model for designing the CLSC network that takes a multiplicity of objectives as well as uncertainties into account. In addition, the proposed model considers the flexibility by allowing product substitution. This type of flexibility very important as it enhances satisfying the customer demand and avoids unpredicted events that lead to a shortage.

The rest of this paper is organized as follows: section II. demonstrate the literature review. In section III., we present a description of the problem while section IV. presents the technique used in this paper. A numerical example is shown in section V. and section VI. presents the results. Finally, in section VII., the conclusion and suggested future work are presented.

II. Literature review

We illustrate the major studies discussed designing the network of CLSC under uncertainties using a single objective and multiple objectives.

Design of CLSC network with single objective.

Mohajeri and Fallah (2016) [8] presented a model to plan a CLSC under carbon emission constraints and the objective was to minimize the total cost of the CLSC. It was a single period model where fuzzy programming was adopted to deal with the uncertainties of demand, landfilling rate and recovery rate. Pishvaee, Jolai and Razmi (2009) [9] used a stochastic programming approach to design an integrated forward and reverse supply chain networks and the objective was to minimize the total cost of the CLSC network. In their model, the source of uncertainty considered was from the demand, the number and quality of the returned products and the variable costs associated with the model. Jindal and Sangwan (2014) [10] proposed a single period fuzzy mixed integer programming model to maximize the profit of the CLSC network design. They considered the uncertainty of product demand, cost parameters, recovery options, the fraction of the returned products, quantity, quality and timing of the products returned. Hajipour et al. (2019) [11] proposed a nonlinear stochastic model to design a network of CLSC that uses a radio frequency identification (RFID) system. The proposed model considered the uncertainty of parameters in the objective function, which is about maximization of the profit.

Design of CLSC network with multiple objectives.

Amin and Zhang (2013) [12] considered two objectives in their model: minimizing the total cost and maximizing the utilization of environmentally friendly materials and clean technology in the CLSC network. The source of the uncertainty in their model was the demand and number of the returned products, they implemented weighted sum and the ε-constraints approaches. The planning horizon in their model was over a single period. Paksoy, Pehlivan and Özceylan (2012) [13] proposed a fuzzy programming approach to design the CLSC network under the uncertainty of the aspiration level of the objective function, the product demand, actor and truck capacities. The four objectives in their model included minimizing the carbon emission, the transportation cost of the forward supply chain and the reverse supply chain and maximizing the encouragement to use recyclable products. Özceylan and Paksoy (2014) [14] used a model that integrated fuzzy multiple objectives and mixed integer nonlinear programming to design the CLSC network which included a disassembly line balancing problem. The objective of the proposed model was to minimize the four costs related to designing the CLSC network. The costs to be minimized were the total transportation cost, the total purchasing costs, the total refurbishing costs and the fixed cost of opening a facility in the CLSC network. In addition, the model considered four types of uncertainty including the aspiration level on the objective functions, the capacity of the facilities, the demand and the quantity of the returned products. Another approach of fuzzy multiple objective mixed-integer linear programming optimization was proposed by Jindal & Sangwan's (2017) [15] to consider the uncertainty of different cost parameters in the CLSC network design problem. In their proposed model, maximizing the profit and minimizing the carbon emitted were the goals to achieve. A stochastic programming model was presented by Zhen, Huang and Wang (2019) [16] to consider the uncertainty of the demand and the number of the returned products in designing the CLSC network. The objectives functions in their model were minimizing the operational cost and the carbon emission in the CLSC network. Yu and Solvang (2020) [17] presented a fuzzy-stochastic model that considered two objectives: minimizing the total cost as well as the carbon emission of the CLSC network. All the input parameters in both objective functions are considered uncertain. A study by Tosarkani and Amin (2018) [18] presented a model that integrated the fuzzy analytic network process and ε-constraint approaches to consider the uncertainty of the demand and returned product quantity, selling prices and the cost parameters. Their model aimed to maximize the total profit and green factors of a battery CLSC network. Another fuzzy programming approach was utilized by Jalil et al. (2019) [19] to consider the uncertainty on the aspiration level of the objective functions of designing network the CLSC problem. Minimizing the total cost of the CLSC network, the storage cost of raw materials and the total defects were the objective functions considered.

To the best of our knowledge, the only models considered the flexibility in designing the network of CLSC in terms of product substitution were introduced by Aldoukhi and Gupta (2019 & 2020) [20], [21]. However, in their study in 2019, it only a single objective model while the study in 2020 did not consider uncertainties. This work extends the efforts by Aldoukhi and Gupta, in which we present here a model that considers the multiplicity of objectives and uncertainties.

III. Problem description

The considered CLSC network in this problem involves raw material suppliers, manufacturing centers, distribution centers, collection centers and market locations. At the manufacturing centers, products are produced as new and remanufactured products. The new products are produced using the raw material supplied from the raw material suppliers and the remanufactured products are produced using the returned products. The finished products, including the new and remanufactured products, are then shipped from the manufacturing centers to the market locations through the distribution centers. The returned products, which are collected at the market locations, are shipped to the collection centers. At the collection centers, the returned products are inspected and sorted based on their conditions. Remanufcturable products are shipped to the manufacturing centers for remanufacturing, the rest are disposed of. The outcome of the proposed model is to design a flexible network of the CLSC to achieve multiple objectives under the consideration of uncertainties. Thus, our model finds the optimal values of different variables, including the number of facilities opened, the quantity of products produced, substituted and shipped across the network.

The objectives considered are to minimize the total cost of the network, minimize negatives impacts on the environment and maximize the service level. The total cost includes the fixed cost of opening the facilities, cost of purchasing the raw material, cost of producing the new product, cost of remanufacturing the returned product (according to their quality level), cost of transporting products within the network, cost of sorting and cleaning the returned products (collection cost) and cost to substitute the product. To reduce the negative impact on the environment, we aim to reduce the carbon emission in this objective, which is resulted from production, transportation and disposal activities. For the service level, we aim to maximize the satisfaction of the market locations, which are evaluated using the maximal covering location problem (MCLP). For the same purpose, Selim and Ozkarahan (2008) [22] as well as Zarandi, Sisakht and Davari (2011) [23] used MCLP to maximize the service level.

The uncertainties considered in the proposed model are the demand for the new and remanufactured products and the number of returned products. To make our model more significant from other available models in the same area, we use the concept of product substitution that can be considered as flexibility, in which we use specifically one-way substitution policy. This policy allows the new products to substitute the remanufactured products in case of inability to fulfill the original demand.

IV. Methodology

As the considered problem involves multiple objectives as well as uncertainties, we seek to integrate approaches that are capable of providing a realistic solution. Therefore, we integrate physical programming and robust optimization scenario-based. Also, the MCLP is used to measure the score of the service level and explained in this section.

Linear physical programming (LPP) is an approach that finds a more realistic solution for optimization problems with multiple objectives compared with other techniques. This is because it avoids the traditional way of weighting the objectives. Instead, it gives the decision-maker the freedom by specifying ranges of different preference levels [24]. It provides different class functions, as shown in figure 1, where the decision-maker expresses his preference of each objective function according to different preference levels as shown in table 1 for class-1. We refer the reader to the review paper published by Ilgin and Gupta (2012) [24] to learn more about this approach.

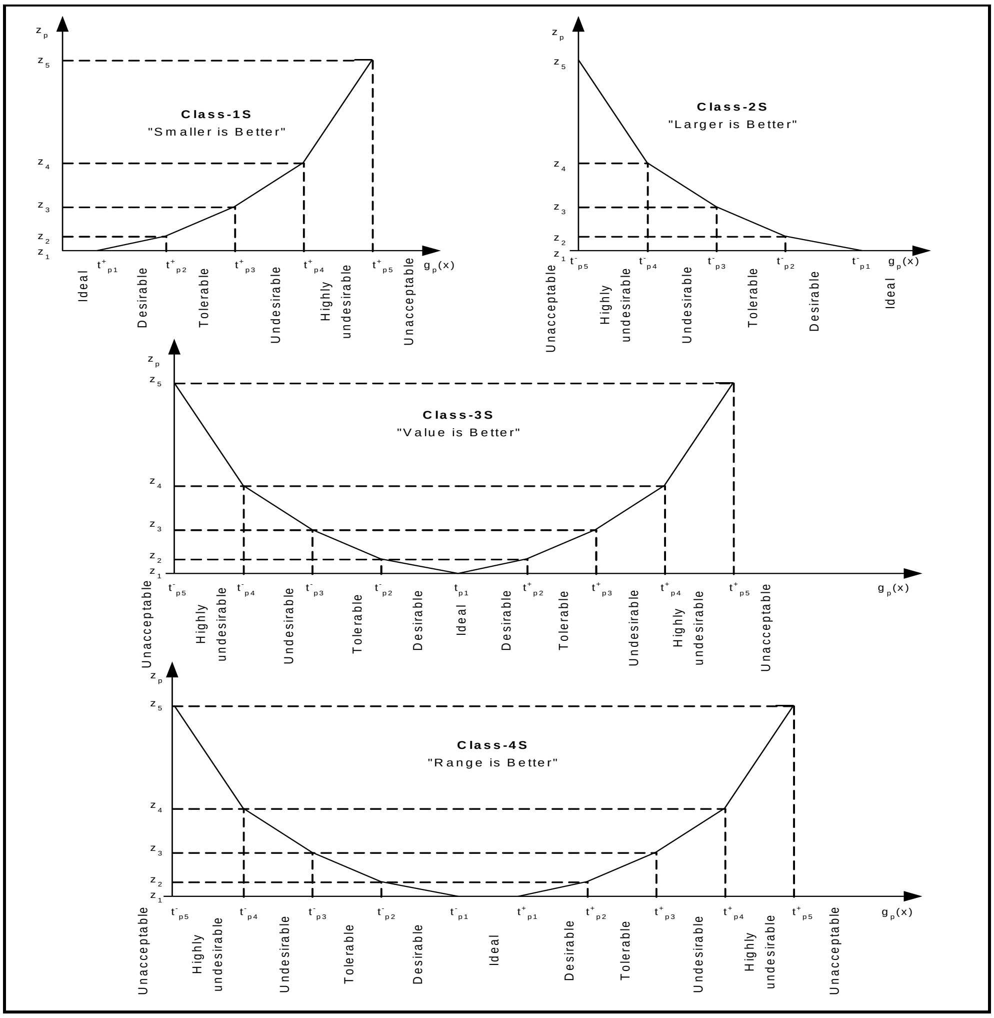

Figure 1: Soft Class Functions for Linear Physical Programming

Table 1: Preference levels and constraints for class-1

Preference levels	Constraints
Ideal	$g_i \leq t_{i,1}^{+}$
Desirable	$t_{i,1}^{+} \leq g_i \leq t_{i,2}^{+}$
Tolerable	$t_{i,2}^{+} \leq g_i \leq t_{i,3}^{+}$
Undersirable	$t_{i,3}^{+} \leq g_i \leq t_{i,4}^{+}$
Highly Undersirable	$t_{i,4}^{+} \leq g_i \leq t_{i,5}^{+}$
Unacceptable	$g_i \geq t_{i,5}^{+}$

The final LPP formulation is as follows:

$$Min\ Z = \sum_i \sum_{ra\geq 2}^{5} (wt_{i,ra}^{+}\, d_{i,ra}^{+} + wt_{i,ra}^{-} d_{i,ra}^{-}) \quad (1)$$

$$g_i - d_{i,ra}^{+} \leq t_{i,ra-1}^{+} \quad (2)$$

$$d_{i,ra}^{+} \geq 0\ and\ g_i \leq t_{i5}^{+} \quad (3)$$

In equation (1), $\boldsymbol{wt_{i,ra}^{+}}$ is a positive weight and $\boldsymbol{wt_{i,ra}^{-}}$is a negative weight for objective i in the desirability range $\boldsymbol{ra^{th}}$. These weights are calculated using linear physical programming weight (LPPW) algorithm as demonstrated in Ilgin and Gupta (2012). The deviations between the value of objective i ($\boldsymbol{g_i}$) and $\mathbf{t_{i,ra}^{+}}$ and $\mathbf{t_{i,ra}^{-}}$, which are the target values, are represented by $\boldsymbol{d_{i,ra}^{+}}$and $\boldsymbol{d_{i,ra}^{-}}$. This approach was implemented in different areas, including disassembly optimization problems [25]–[29], network design problems in reverse supply chain [30]–[33] and product design evaluation problems in reverse logistics [34]–[36].

To solve optimization problems involved with uncertainties, fuzzy programming, as well as stochastic programming, have been used widely in the literature. However, robust optimization scenario-based is another approach that tackles the lack of using an exact probability distribution which is required by the above-listed approaches. Thus, the uncertainty is considered as a set of scenarios where each scenario has an occurrence probability (ρ_{sc}) and ($\sum_{sc} \rho_{sc} = 1$). This approach was firstly introduced by Mulvey, Vanderbei and Zenios

(1995) [37]. It considers two types of robustness: the robustness of the solution and the model. We refer the reader to [37], [38] to learn more details about this approach.
The formulation of robust optimization scenario-based is presented as follows:

MIN Z = $\sum_{sc} \rho_{sc}\ \xi_{sc} + \lambda \sum_{sc} \rho_{sc} [(\xi_{sc} - \sum_{sc'} \rho_{sc'}\ \xi_{sc'}) + 2\theta_{sc}] +\ \omega \sum_{sc} \rho_{sc}\ \delta_{sc}$ (4)

$s.t\ \ Ax = b$ (5)

$B_{sc}x + C_{sc}y_{sc} + \delta_{sc} =\ e_{sc}$ (6)

$\xi_{sc} - \sum_{sc} \rho_{sc}\ \xi_{sc} + \theta_{sc} \geq 0$ (7)

$x, y_{sc}, \delta_{sc} \geq 0$ (8)

Equation (4) is the objective function, which consists of solution robustness, part 1 and part 2, and model robustness, part 3 of the function. λ controls the solution robustness ω controls the model robustness. In the above model, x is the design variable, y_{sc} is the control variable and $\xi_{sc} = x +\ y_{sc}$. Equations (5) and (6) are the design and control constraint, respectively. In equation (6), δ_{sc} is the violation variable that occurs in case of infeasibility of any scenario realization and it is penalized in the objective function to ensure the model robustness (4). Equation (7) is used as auxiliary constraint to linearize the quadratic format of the model proposed by Mulvey et al. (1995). Equation (8) is the non-negativity constraint.
Our integrated approach is as follows:

$Min\ Z =\ \sum_i \sum_{ra\geq 2}^{5} (wt_{i,ra}^{+}\ d_{i,ra}^{+} +\ wt_{i,ra}^{-} d_{i,ra}^{-}\ )$ (9)

$G_i -\ d_{i,ra}^{+} \leq\ \ t_{i,ra-1}^{+}$ (10)

$d_{i,ra}^{+} \geq 0\ and\ G_i \leq\ \ t_{i5}^{+}$ (11)

$G_i = \sum_{sc} \rho_{sc}\ \xi_{sc} + \lambda \sum_{sc} \rho_{sc} [(\xi_{sc} - \sum_{sc'} \rho_{sc'}\ \xi_{sc'}) + 2\theta_{sc}] + \omega \sum_{sc} \rho_{sc}\ \delta_{sc}$ (12)

$Ax = b$ (13)

$B_{sc}x + C_{sc}y_{sc} + \delta_{sc} =\ e_{sc}$ (14)

$\xi_{sc} - \sum_{sc} \rho_{sc}\ \xi_{sc} + \theta_{sc} \geq 0$ (15)

$x, y_{sc}, \delta_{sc} \geq 0$ (16)

As mentioned in the above context, we implement the MCLP to calculate the scores that are used in maximizing the service level of the market locations. The service level score of a market location is expressed as a coverage level of a market location within an upper and lower distance from the service provider (distribution center) using one of the coverage functions shown in figure 2. Here, we use the coverage function (a).

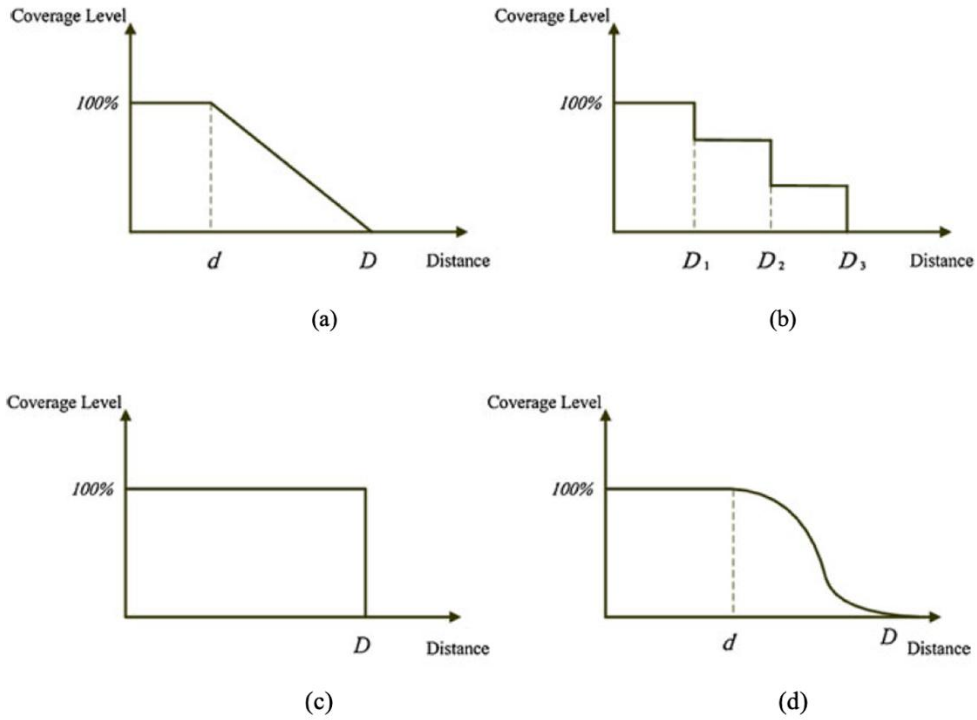

Figure 2: Coverage functions [39]

V. Numerical example

One of the implementations recommended for the proposed model is to use it for businesses willing to start. Thus, we choose a case of designing a network of the CLSC in the tire industry in Saudi Arabia. This is due to the willingness of the government of Saudi Arabia aims to start this business and to be the first one of its kind in that region.

The source of some of the data utilized in this example was collected from National Industrial Clusters Development Program (NICDP) [40], Saudi Authority for Industrial Cities and Technology Zones (MODON) [41] and GCC Automobile Industry Report in 2016 [42]. Other data were assumed and based on similar studies on the tire industry. We show in table 2 the number and location of facilities considered in the CLSC network. We used Google Maps to calculate the required distances. The decision tree which represents the occurrence probability of each scenario is illustrated in figure 3. The probability of occurrence of the 27 scenarios generated is shown in table 3. Table 4 and 5 summarize the durability rages and the calculated LPPW weights, respectively. we The desirability ranges of each objective and It is assumed that the cost of purchasing the raw material includes transporting the raw material to the manufacturing centers.

Table 2: Number of facilities and locations data

Facility	Number	Location
Manufacturing center	1 1 1	Riyadh industrial city 1 Riyadh industrial city 2 Riyadh industrial city 3
Distribution center	1 1 1	Suair industrial city Alkharj industrial city Durma industrial city
Collection center	1 1 1	Alahsa industrial city 2/ Salwa Hail industrial city 2 Madinah industrial city
Market locations	5 1 1 1 1 1	Saudi Arabia { Central region (SACR), Eastern region (SAER), Western region (SAWR), Northern region (SANR), Southern region (SASR) Bahrain- Sitra industrial city (BHR) Oman- Rusayl industrial city (OMN) Qatar- Alrayyan industrial city (QAT) Kuwait – Shuwailkh industrial city. (KT) Alquiz industrial area 4 (UAE)

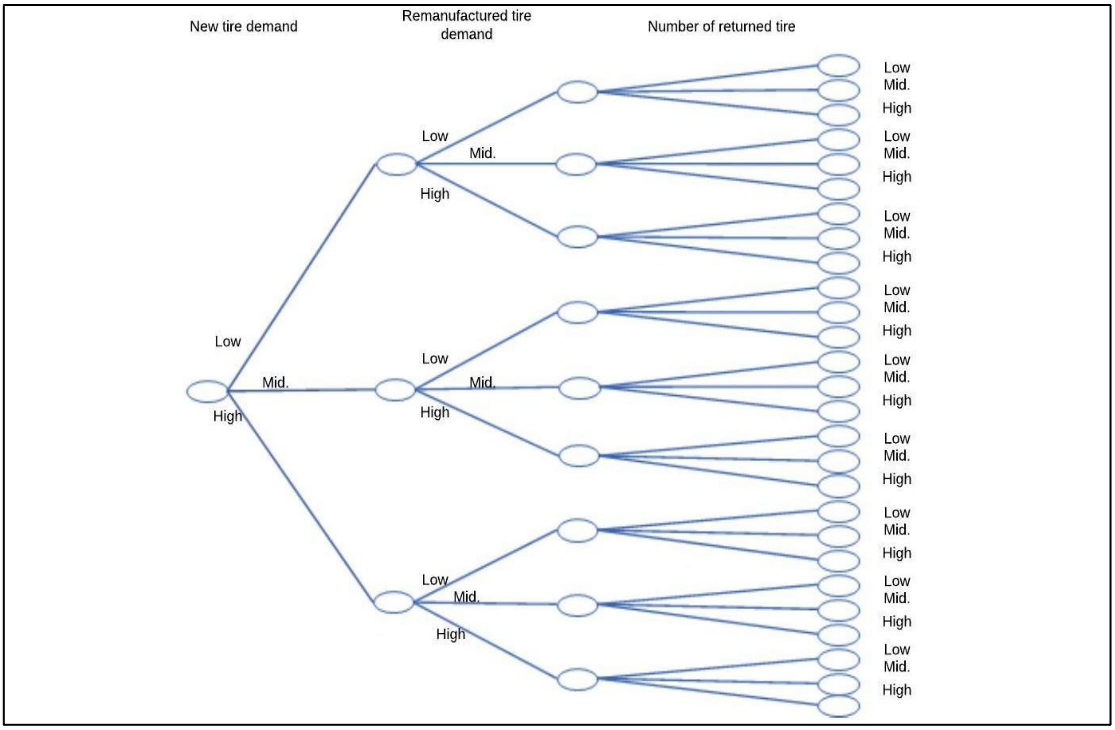

Figure 3: Decision tree analysis

Table 3: Probability of occurrence of each scenario

	Scenario (new tire demand. Reman. tire demand. Returned tire)	Probability of each secnario Low = .2, mid. = .5, high = .3
SC1	low.low.low	0.008
SC2	low.low.mid	0.02
SC3	low.low.high	0.012
SC4	low.mid.low	0.02
SC5	low.mid.mid	0.05
SC6	low.mid.high	0.03
SC7	low.high.low	0.012
SC8	low.high.mid	0.03
SC9	low.high.high	0.018
SC10	mid.low.low	0.02
SC11	mid.low.mid	0.05
SC12	mid.low.high	0.03
SC13	mid.mid.lxow	0.05
SC14	mid.mid.mid	0.125
SC15	mid.mid.high	0.075
SC16	mid.high.low	0.03
SC17	mid.high.mid	0.075
SC18	mid.high.high	0.045
SC19	high.low.low	0.012
SC20	high.low.mid	0.03
SC21	high.low.high	0.018
SC22	high.mid.low	0.03
SC23	high.mid.mid	0.075
SC24	high.mid.high	0.045
SC25	high.high.low	0.018
SC26	high.high.mid	0.045
SC27	high.high.high	0.027
		$\sum$ =1

Table 4: Desirability ranges

	Objective 1	Objective 2	Objective 3
Ideal	≤ 31,028,100	≤ 205,330	18,000 ≥
Desirable	(31,028,100 , 31,032,100]	(205,330 , 209,330]	[17,000 , 18,000)
Tolerable	(31,032,100 , 31,036,100]	(209,330 , 213,330]	[15,500 , 17,000)
Undesirable	(31,036,100 , 31,040,100]	(213,330, 217,330]	[14,000 , 15,500)
Highly Undersirable	(31,040,100 , 31,044,100]	(217,330 , 221,330]	[12,500 , 14,000)
Unacceptable	31,044,100>	221,330>	< 12,500

Table 5: Calculated weights for LPPW

Objective	Weights							
i = 1	$W_{1,2}$	0.015	$W_{1,3}$	0.018	$W_{1,4}$	0.0396	$W_{1,5}$	0.08712
i = 2,	$W_{2,2}$	0.06	$W_{2,3}$	0.072	$W_{2,4}$	0.1584	$W_{2,5}$	0.34848
i = 3	$W_{3,2}$	1.2	$W_{3,3}$	1.44	$W_{3,4}$	3.168	$W_{3,5}$	6.9696

VI. Results

We used the C++ algorithm to calculate the LPPW and Microsoft Windows 7 with Intel® Core™ i5-2430M CPU @ 2.4GHz to conduct the numerical experiment. By setting $\lambda = 1$ and $\omega = 10$, we found that the supplier of raw materials 1 and 3 are selected, Riyadh industrial city 3 manufacturing center is opened, Durma industrial city distribution center is opened and Alahsa industrial city 2 (Salwa) collection center located is opened. The robust solution of the economic objective (G_1) is $ 31,028,100 (the desirability range is ideal), the environmental objective (G_2) is 208,557 kg of CO_2 (the desirability range is desirable) and the service level objective (G_3) is 18,696 unit (the desirability range is ideal).

The quantity of the new tires, the remanufactured tires and the new tires substituting the remanufactured tires in the 27 scenarios are shown in figure 4. Scenario 19 (high demand for the new tires, low demand for the remanufactured tires and a low number of the returned tires) has the largest quantity of new tires shipped to all market locations with 22,198 tires. Scenario 9 (low demand for the new tires, high demand for the remanufactured tires and a high number of the returned tires) has the largest quantity of remanufactured tires shipped to all market locations with 12,435 tires. Scenario 7 (low demand for the new tires, high demand for the remanufactured tires and a low number of the returned tires) has the largest quantity of the new tires substituting remanufactured tires shipped to all market locations with 6,727 tires. In figure 5, we illustrate additional information regarding the quantity of the new tire (circle shape), the remanufactured tires (square shape) and the new tires substituting the remanufactured tires (plus sign) shipped to all the market locations over each objective function. Each color represents a scenario of the 27 scenarios considered.

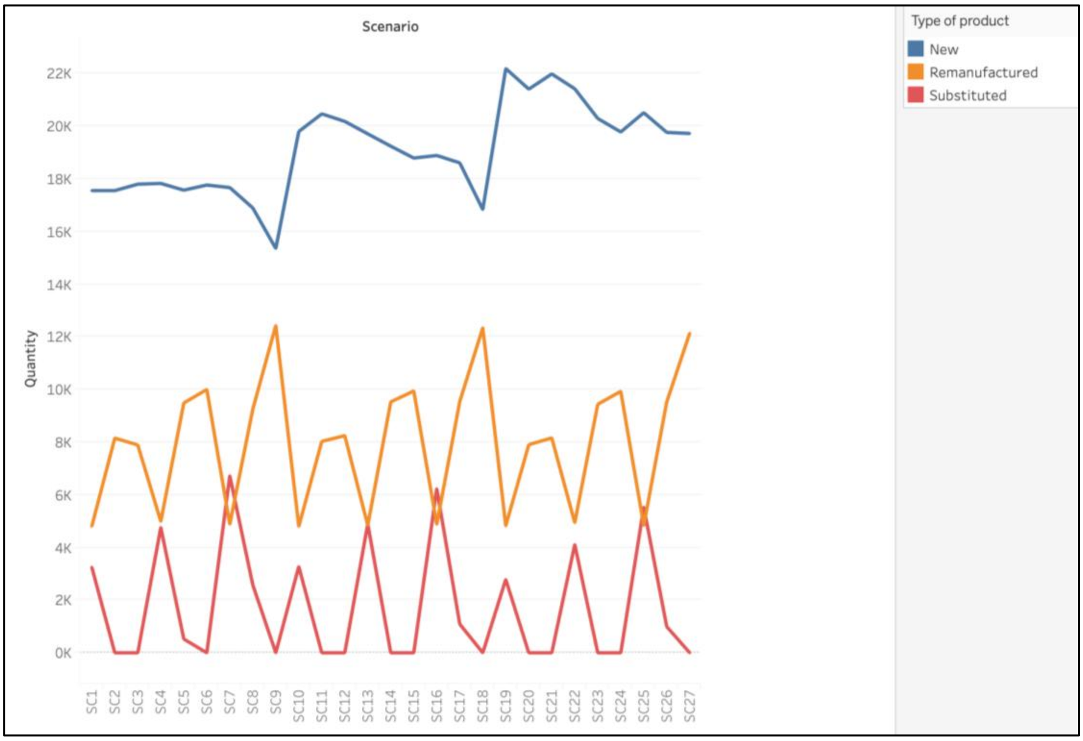

Figure 4: Quantity of tires shipped to all customer of each scenario

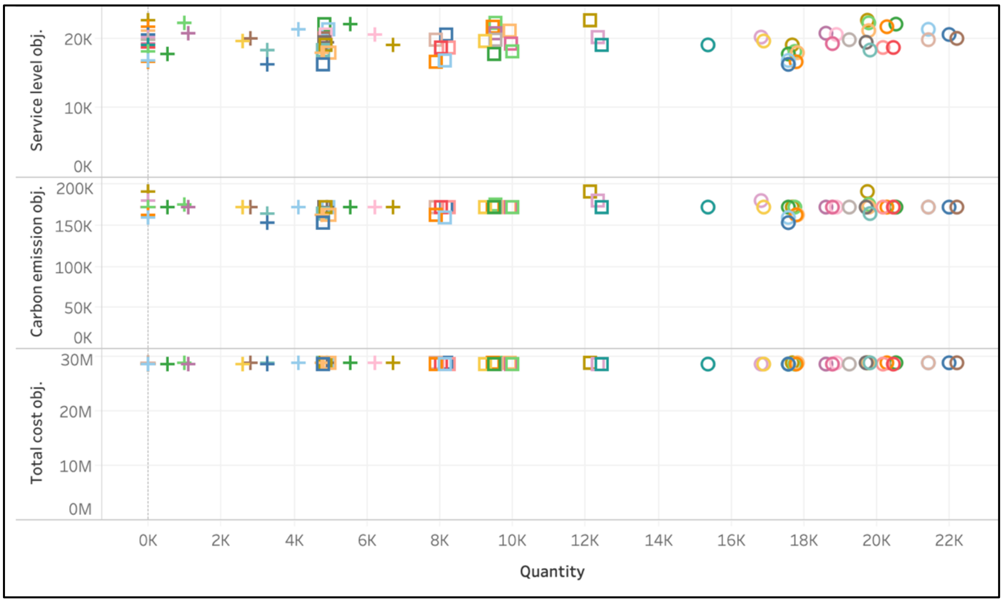

Figure 5: Quantity of tires shipped to all customer in each scenario vs each objective function

As shown in figure 6, scenario 2 (low demand for the new tires, low demand for the remanufactured tires and a medium number of the returned tires) generates the lowest total cost among all scenarios is at $ 28,663,909. On the other hand, scenario 25 (high demand for the new tires, high demand for the remanufactured tires and a low number of the returned tires) generates the largest total cost among all scenarios at $ 28,860,480.

According to figure 7, the lowest quantity of carbon emitted is 153,949 kg allocated in scenario 1 (low demand for the new tires, low demand for the remanufactured tires and a low number of the returned tires). However, the highest quantity of carbon emitted is 191,106 kg allocated in scenario 27 (high demand for the new tires, high demand for the remanufactured tires and a high number of the returned tires).

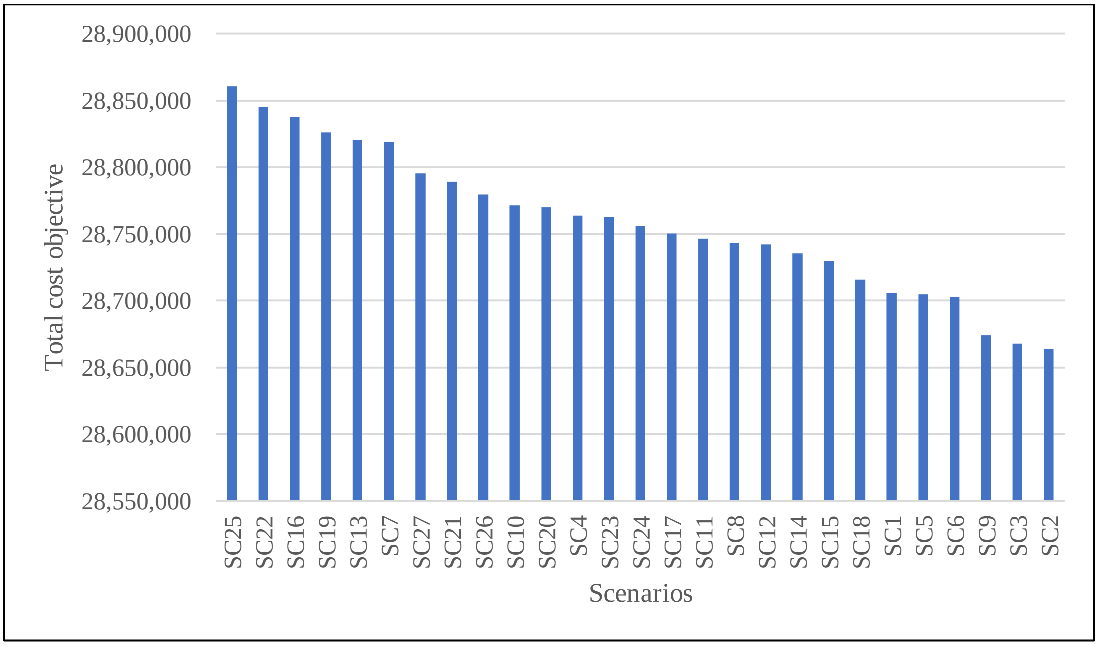

Figure 6: Total cost objective of each scenario

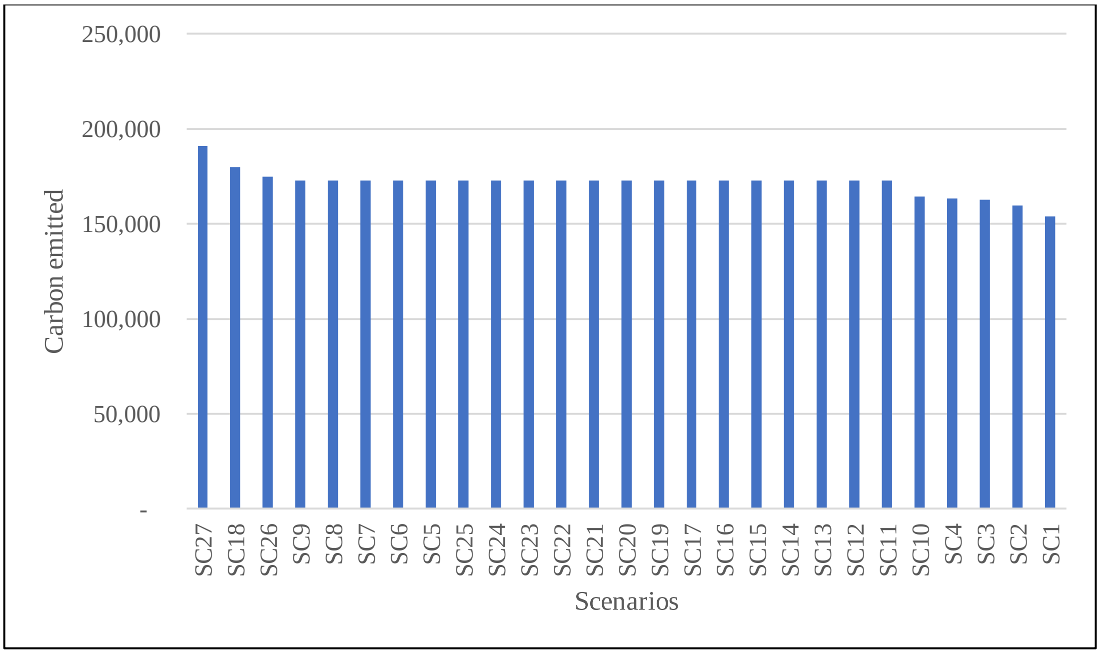

Figure 7: Amount of carbon emitted of each scenario

VII. Conclusion

The topic of CLSC has been trending the past few years. This is due to the undeniable benefits to the economy and environment resulted from practicing the CLSC. Network design is a complex problem in the area of CLSC, especially when it concerns multiple objectives, uncertainties and flexibility. This paper proposed a new model that integrates physical programming and robust optimization scenario-based approaches to design a CLSC network with multiple objectives, considers uncertainties and flexibility. The considered objectives are economic objective, environmental objective and service level objective. The considered uncertainties are the uncertainty of product demand, including the new and the remanufactured products, and the number of returned products. The considered flexibility is associated with allowing the product to substitute. We implemented the proposed model on a numerical experiment that concerns designing a network of CLSC in the tire industry in Saudi Arabia.

It is possible to extend this work by implementing the proposed model in different industries. Also, we considered here a limited size problem. Thus, in case of the problem size increases, using heuristics techniques would be more appropriate.

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