Flexible Model to Design Closed Loop Supply Chain Network Under Uncertainties

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Abstract
As there are chances that businesses and supply chains might be easily disturbed due to pandemics, for example, planning under uncertainties becomes an essential step that would mitigate the consequences. In this context, multiple objectives, considering the uncertainties and flexibility model to design a closed loop supply chain is proposed. We use a new approach that integrates linear physical programming and scenario-based robust optimization, which is the first of its kind to solve the problem of designing a closed loop supply chain network. We conclude the paper by presenting a numerical experiment to show the use of our model to design a tire industry CLSC in Saudi Arabia.

Keywords
CLSC network, tire industry, uncertainties, linear physical programming, scenario-based robust optimization.

1. Introduction
It is undeniable that forecasts and estimates fall apart when disasters take place. COVID-19 pandemic is a good example of what the world is going through as the pandemic had a negative impact economically and socially. In terms of the supply chain, when a network including supply, demand and production is less dynamic, less flexible and ignore uncertainties, it will experience an extensive suffer (Ivanov 2020). For example, to clarify how the supply chain was impacted from COVID-19: half of the world's need for LCD panels, which are the main part of TVs, laptops and computer monitors, is manufactured in China. Wuhan city, which is the center of coronavirus spread in china, has five factories to manufacture LCD panels that all experienced a full shut down (McCrea 2020).

Planning a closed loop supply chain (CLSC), which is an extension of the regular supply chain, is more complex than the regular supply chain. The complexity arises from the uncertainties associated with CLSC by itself. In reverse logistics of the CLSC, the number of returned products, their condition and time of their arrival are highly uncertain (Ilgin and Gupta 2013). These are very important factors as they are being considered a source of recycling or remanufacturing, depending on the CLSC type. This is in addition to other uncertainties already existing from the regular supply chain, such as a demand for products. Therefore, designing the CLSC network becomes a more challenging problem from this perspective.

Although there are available papers discussing designing the CLSC network, the majority of their proposed models are deterministic (Gupta and Ilgin 2018; Ilgin and Gupta 2010; Ilgin et al. 2015; Lahane et al. 2020). There is less research about uncertainties in their proposed models. In this paper, we extend the model proposed by Aldoukhi and Gupta (Aldoukhi and Gupta 2020), in which we integrate uncertainties on the product demand and the number of returned products. Our model differs from other available models by allowing the product to substitute, which adds flexibility to our model and using a new approach that integrates linear physical programming (LPP) and scenario-based robust optimization. To the best of our knowledge, this is the first attempt to use this new integrated approach in this area.

2. Problem Description
The problem of our concern is a network of CLSC that consists of raw material suppliers, manufacturing centers, distribution centers, collection centers and market locations. The manufacturing centers are responsible for producing new and remanufactured products and then shipping them to the market locations through the distribution centers. The returned products are shipped from the market locations to the collection centers, where they are inspected and sorted. Products with remaining useful life are shipped to the manufacturing centers for remanufacturing according to their quality level while the remaining products are disposed of. Our goal is to design the CLSC network with an optimal

number of facilities opened and the number of products shipped across the network under multiple objectives, considering uncertainties and flexibility.

The objectives considered are economic objective, which aims to minimize the total cost of the network, environmental objective, which minimizes carbon emission of different activities in the network, and service level objective, which aims to maximize market locations' level of service in terms of products delivered from distribution centers. More details on the service level objective and how to calculate the level of service coefficient of the market location are shown in the maximal covering location problem section.

The uncertainties considered in the proposed model are the demand of new and remanufactured products and the number of returned products. Allowing products to substitute in case of not being able to satisfy the original demand of a product using a one-way substitution policy, is the flexibility considered in our model and this differs our model from other available models.

3. The Maximal covering location problem (MCLP)

To calculate the level of service coefficient of the market locations in the service level objective, we use MCLP which was first introduced by Church and ReVelle (1974). It aims to maximize the service level (coverage level) to a location within a predetermined distance from the service provider according to a coverage function as shown in figure 1. Selim and Ozkarahan (2008) and Zarandi et al. (2011) implemented the same technique to find the service level coefficient. However, the first model was only for a forward supply chain and both models neglected uncertainties, except the second model by Zarandi and Davari which considered fuzziness in the objective functions.

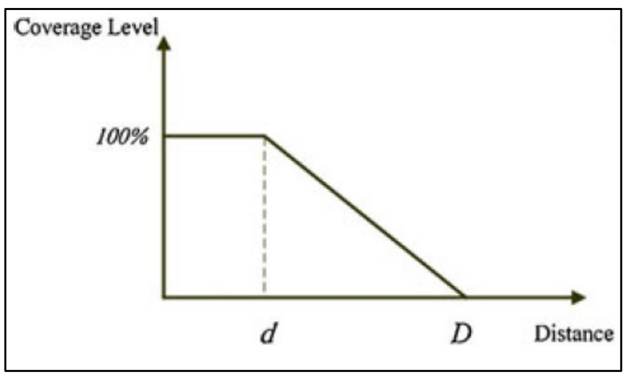

Figure 1. Coverage functions (Eiselt and Marianov 2009)

4. Methodology

For the first time in the literature, we use an approach that integrates LPP and a scenario-based robust optimization. LPP deals with optimization problems consisting of multiple objectives. By using preference functions as shown in figure 2, expressing the preference of each objective function becomes more accurate to the decision-maker. For more information about how LPP is performed, we refer the reader to Ilgin and Gupta (2012). The final LPP formulation is as follow:

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

Subjected to:

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

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

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 $\boldsymbol{ra^{th}}$. To find these weights, we use the linear physical programming weight (LPPW) algorithm as explained 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 $\boldsymbol{d_{i,ra}^{-}}$. A lot of research has been done using this approach where it showed a full capability to handle complex problems in areas like disassembly-to-order problems (Imtanavanich and Gupta 2006a, 2006b; Kinoshita et al. 2018; Kongar and Gupta 2002, 2009), designing reverse supply chain network problems (Alkhayyal 2019; Ijuin et al. 2017; Pochampally and Gupta 2012; Pochampally et al. 2004) and evaluation of the product design in reverse logistics (Joshi and Gupta 2018b, 2018a, 2019).

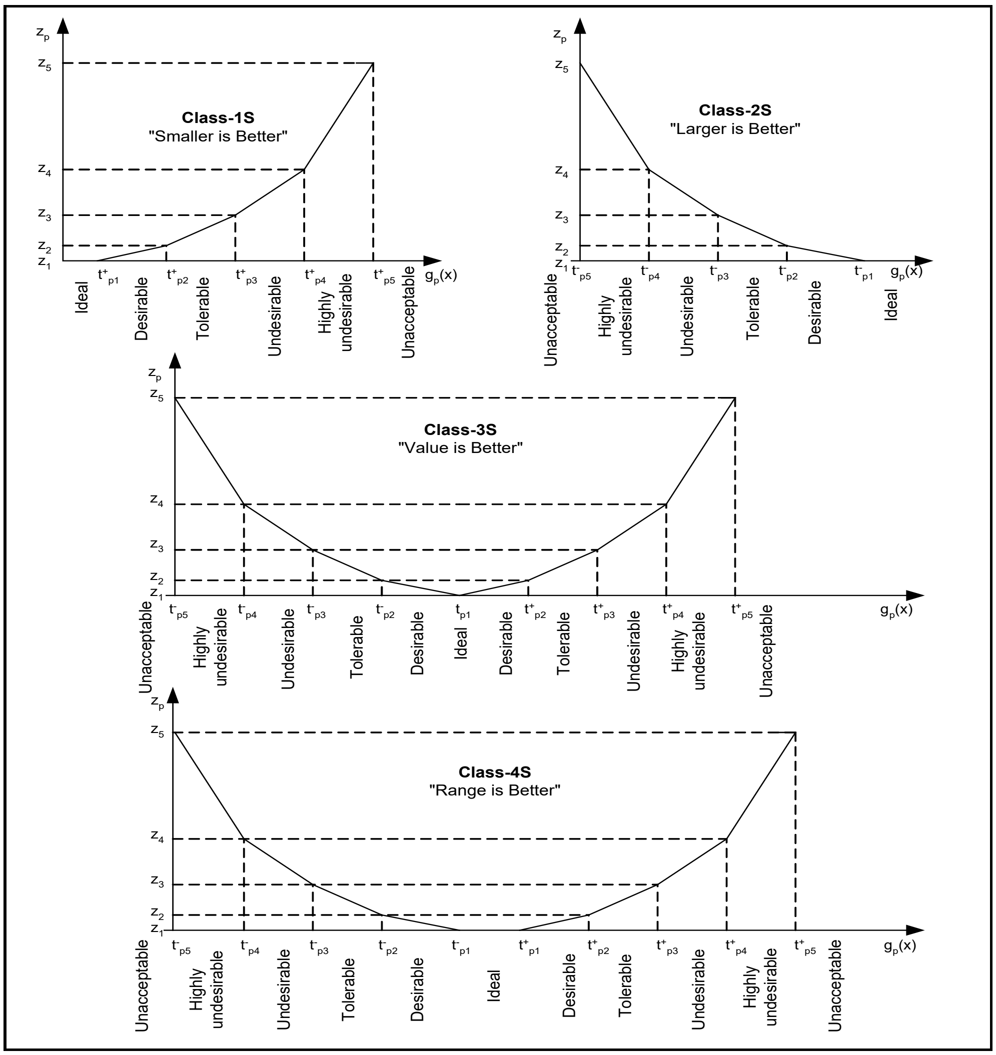

Figure 2. Soft Class Functions for Linear Physical Programming

Scenario-based robust optimization, on the other hand, is an approach that is concerned with uncertainties. In this approach, there are two types of variables that are considered here, design and control variables. The uncertainty is considered as a set of scenarios where each scenario has a probability of occurrence (ρ_{sc}) as shown in the below simple model. To have a better understanding of how this approach has been developed and for space limitation, we refer the reader to (Li HL 1996; Mulvey et al. 1995; Yu and Li 2000).

Our integrated approach is as follow:

$$Min\ Z = \sum_{i} \sum_{ra\geq 2}^{5} (wt^{+}_{i,ra}\, d^{+}_{i,ra} + wt^{-}_{i,ra} d^{-}_{i,ra}) \tag{4}$$

S.T

$$G_i - d^{+}_{i,ra} \leq t^{+}_{i,ra-1} \tag{5}$$

$$d^{+}_{i,ra} \geq 0 \text{ and } G_i \leq t^{+}_{i5} \tag{6}$$

$$G_i = \sum_{sc} \rho_{sc}\ \xi_{sc} + \lambda \sum_{sc} \rho_{sc} [(\xi_{sc} - \sum_{sc'} \rho_{sc'}\ \xi_{sc'}) + 2\theta_{sc}] + \omega \sum_{sc} \rho_{sc}\ \delta_{sc} \tag{7}$$

$$Ax = b \tag{8}$$

$$B_{sc}x + C_{sc}y_{sc} + \delta_{sc} = e_{sc} \tag{9}$$

$$\xi_{sc} - \sum_{sc} \rho_{sc}\ \xi_{sc} + \theta_{sc} \geq 0 \tag{10}$$

$$x, y_{sc}, \delta_{sc} \geq 0 \tag{11}$$

In our integrated approach, G_i in equation (5), (6) and (7) is the robust objective function i where λ and ω are parameters to control the robustness of our solution and model, respectively. x is the design variable, where it represents in our model the decision variable of opening facilities, and y_{sc} is the control variable, which represents the other variable such as the number of products to ship in the network and $\xi_{sc} = x + y_{sc}$. Equation (8) is a constraint that is not associated with uncertainties while equation (9) is associated. δ_{sc} is the violation variable that occurs in case of the infeasibility of any scenario realization and it is penalized to ensure the model robustness. Equation (10) is used as an auxiliary constrain to linearize the problem as its original has a quadratic format. Equation (11) is the non-negativity constraint. We assume the same value of λ and ω for all objective functions. In addition, the time horizon in this model is a single period.

5. Numerical Example

We implemented our model to design the CLSC network in the tire industry, as the government of Saudi Arabia aims to open up this business and to be the first one of its kind. Most of the data used are obtained from National Industrial Clusters Development Program (NICDP), Saudi Authority for Industrial Cities and Technology Zones (MODON) and GCC Automobile Industry Report (GCC Automobile Industry Report 2016; National Industrial Clusters Development Program (NICDP) in Saudi Arabia 2016; Saudi Authority for Industrial Cities and Technology Zones (MODON) 2020). In table 1, we present data regarding the number and location of facilities considered in the CLSC network while the distance data are calculated using google map. We set λ = 1 and ω = 10. Giving that there are 3 scenarios assumed for the new and remanufactured tire demand and the number of returned tires as shown in figure 3, we generate 27 scenarios using the decision tree analysis and the probability of occurrence of each scenario is shown in table 2.

Table 1. Number of facilities and locations data

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

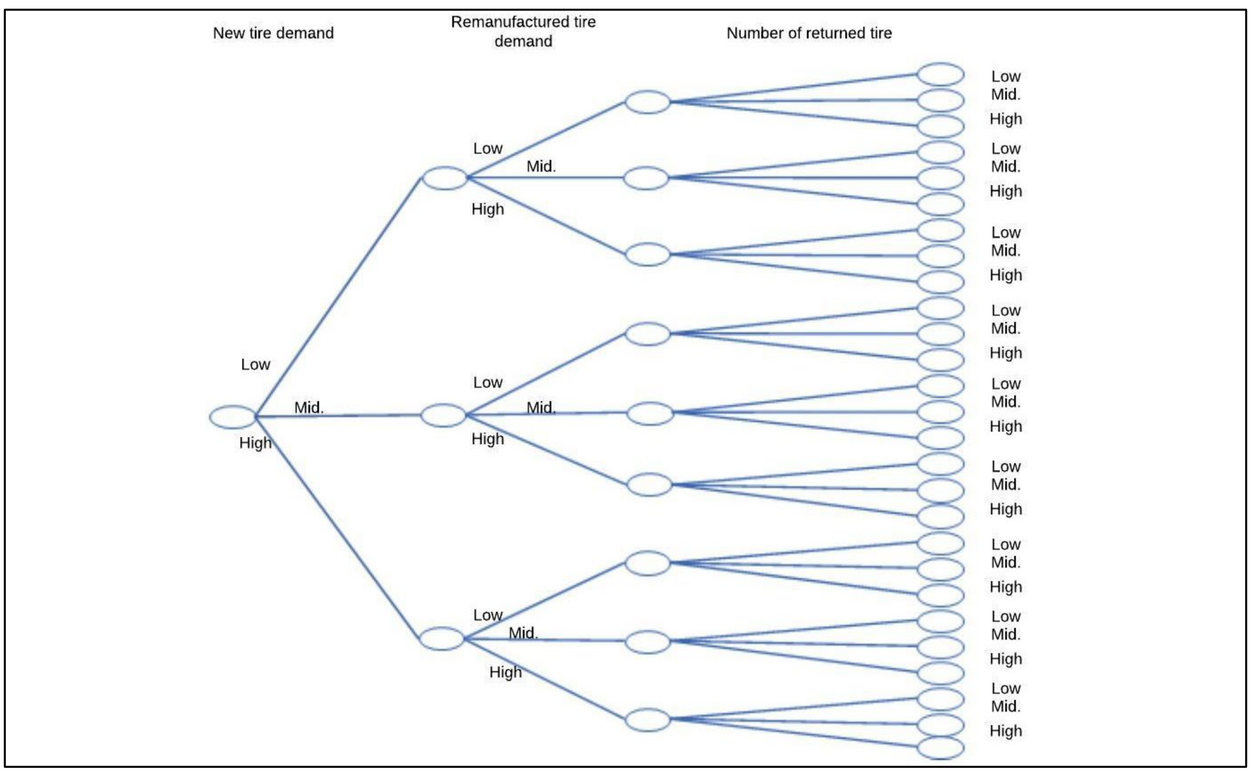

Figure 3. Decision tree analysis

Table 2. 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
		$\sum = 1$

6. Results

The numerical experiment was conducted using Microsoft Windows 7 with Intel® Core™ i5-2430M CPU @ 2.4GHz. Our results recommend selecting raw material suppliers 1 and 3 and opening the manufacturing center located in Riyadh industrial city 3, the distribution center located at Durma industrial city and the collection center located at Alahsa industrial city 2 (Salwa). The robust solution of the economic objective (G_1), the environmental objective (G_2) and the service level objective (G_3) is \$ 31,028,100, 208,557 kg of CO2 and 18,696 unit, respectively. Therefore, the desirability range of G_1 is ideal, G_2 is desirable and G_3 is ideal as shown in figure 4.

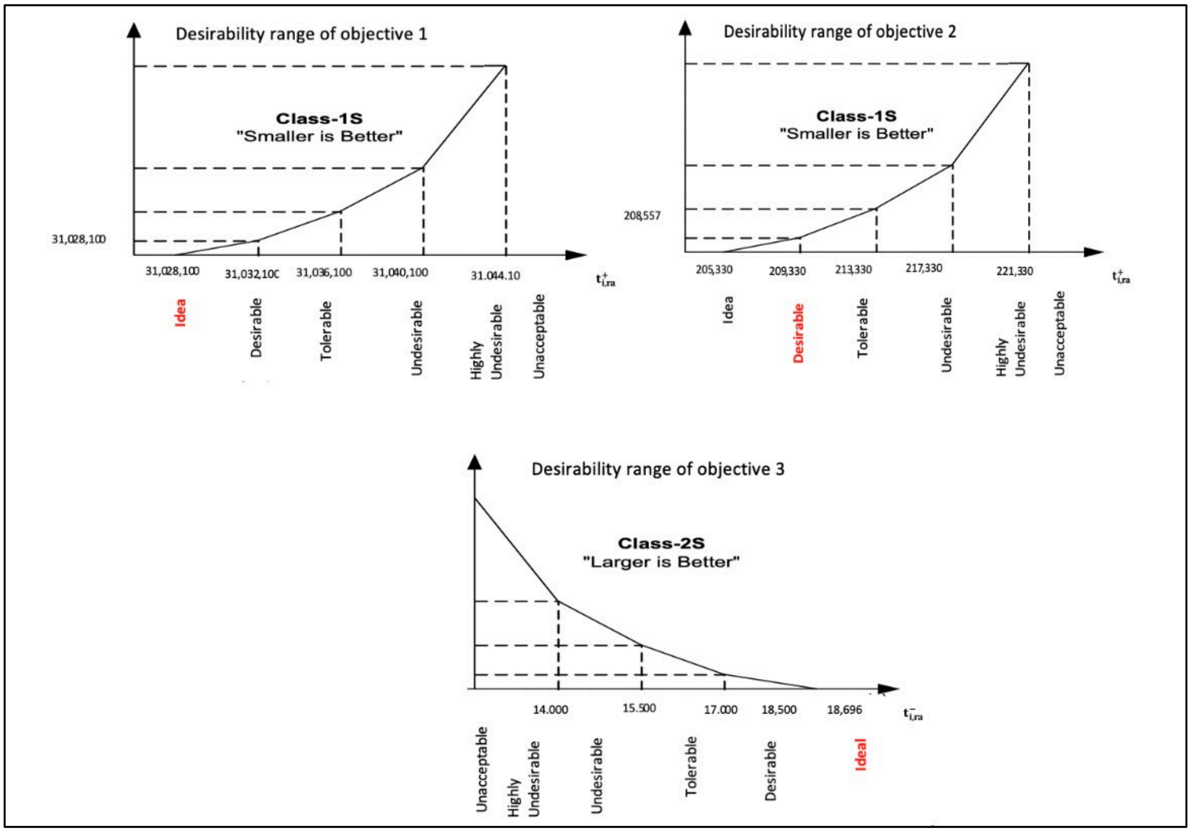

Figure 4. Desirability range results of objective 1, 2 and 3

Figure 5 shows the number of new tires, remanufactured tires and new tires substituting remanufactured tires in the 27 scenarios. The largest quantity of new tires shipped to all market locations is 22,198 tires which is in scenario 19 where the demand of new tires is high and the demand of remanufactured tires and the number of returned tires are low. The highest number of remanufactured tires shipped to all market locations is 12,435. This is in scenario 9 where the new tires demand is low and the remanufactured tires demand and number of returned tires are high. The highest number of the new tires substituting remanufactured tires is 6,727 tires. This is in scenario 7 where the demand of the new tires and the number of returned tires is low while the demand of remanufactured tires is high. More information is shown in figure 6 which demonstrates the quantity of each category of tires shipped to all customers over each objective function where each color represents a scenario, a circle represents new tires, a square represents remanufactured tires, a plus represents substituted tires.

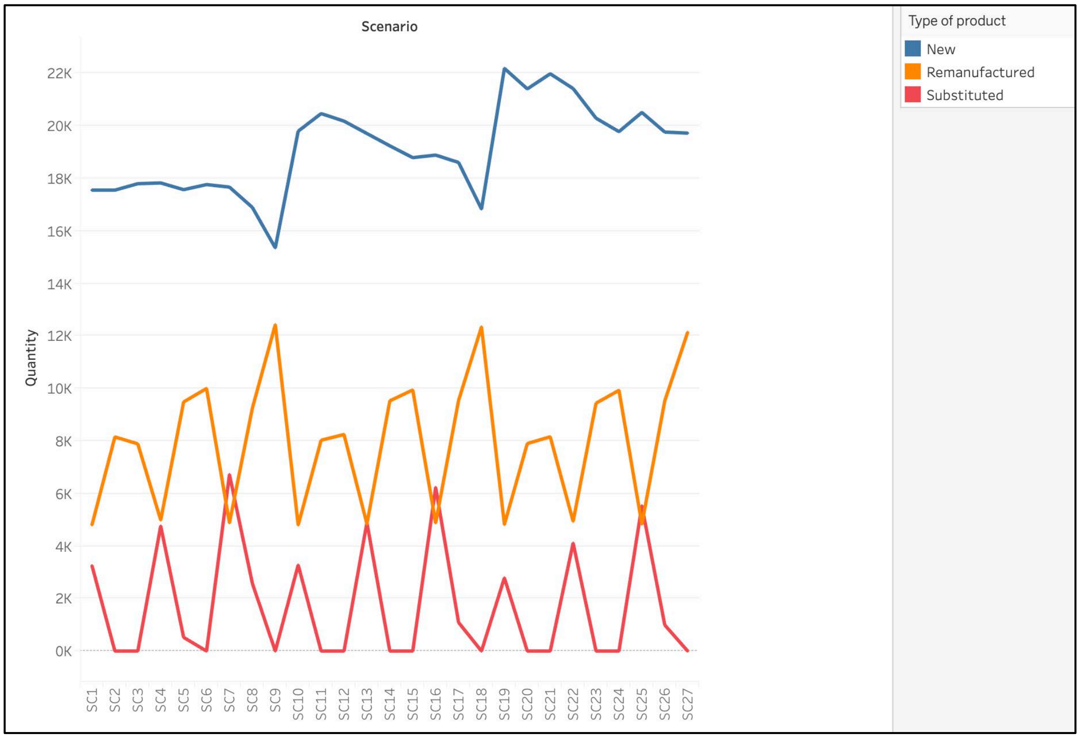

Figure 5. Quantity of tires shipped to all customer of each scenario

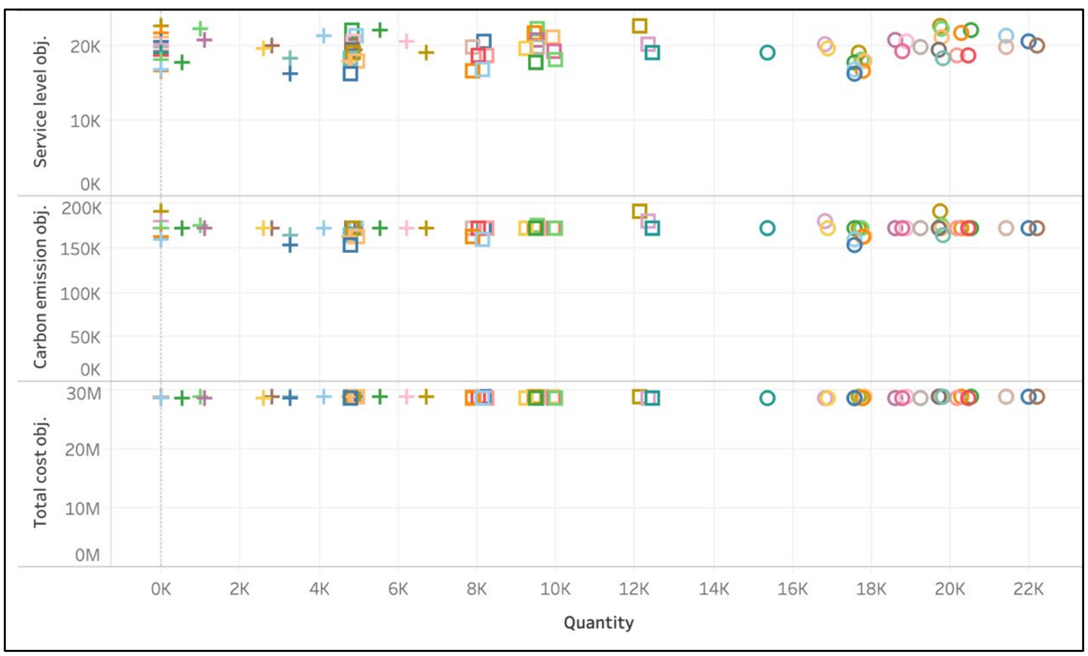

Figure 6. Quantity of tires shipped to all customer in each scenario vs each objective function

In the total cost objective, the largest total cost among all scenarios is scenario 25 at $ 28,860,480. In this scenario, the demand of the new and remanufactured tires is high while the number of returned tires is low. However, scenario 2 is the lowest total cost among all scenarios at $ 28,663,909. In this scenario, the demand for the new and remanufactured tires is low and the number of returned tires is mid as shown in figure 7.

For the carbon emission objective, 191,106 kg is the highest amount of carbon emitted which is associated with scenario 27. This scenario represents the high demand of the new and remanufactured tires as well as the number of returned tires. On the other hand, scenario 1 is the lowest scenario in terms of emitting carbon. The demand on new and remanufactured tires as well as the number of returned tires are low in this scenario as shown in figure 8.

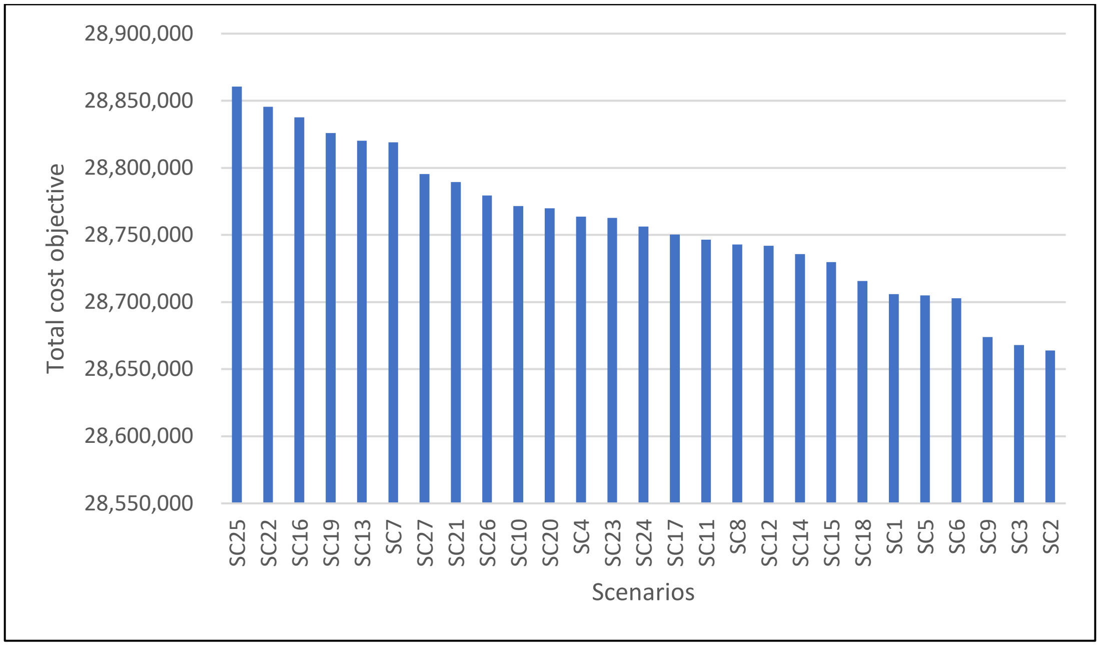

Figure 7. Total cost objective of each scenario

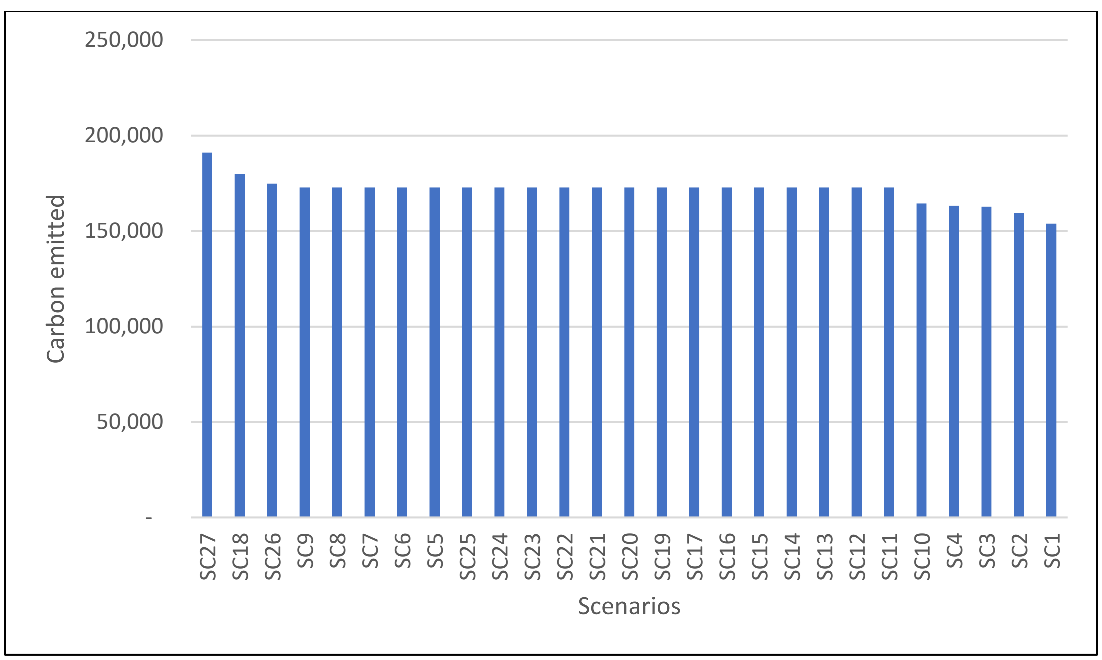

Figure 8. Amount of carbon emitted of each scenario

7. Conclusion

This study presents a new approach to design the CLSC network considering multiple objectives, uncertainties and flexibility. Our proposed approach integrated LPP and a scenario-based robust optimization. The numerical experiment used in this paper is based on designing the CLSC network in Saudi Arabia to start a business of manufacturing tires to satisfy the demand to locate markets and neighbor countries (GCC). Future research is expected to extend our study by using heuristics for a larger size problem, multiple period time horizon and different product substitution policy.

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Biographies

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