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Incorporating Vehicle-Routing Problems into a Closed-Loop Supply Chain Network Using a Mixed-Integer Linear-Programming Model

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Abstract: In recent years, there has been a tremendous increase in environmental awareness, due to concerns about sustainability. Designing an efficient supply chain network that fulfills the expectation of both business owners and customers and, at the same time, pays attention to environmental protection is becoming a trend in the commercial world. This study proposes a theoretical model incorporating vehicle routing problems (VRPs) into the typical CLSC (closed-loop supply chain) network architecture. This combination assists all operators to act more efficiently in terms of environmental protection and profitability. A mixed-integer-linear-programming model for CLSC network design with fuzzy and random uncertain data is developed to achieve the goals. The parameters of the CLSC network are also programmed using hybrid fuzzy-stochastic mathematical programming. The model is for a single product and a single timeframe. Several numerical examples are provided to demonstrate the validity of the proposed mixed-integer-linear-programming (MILP) model. This study also investigated probabilistic possibilities for recourse variables with a trapezoidal fuzzy number using a problem size of four cases. The result indicates that the model performed well in the numerical test, suggesting it can help the operation to be more profitable if this model is implemented in their daily routines.

Keywords: closed-loop supply chain; remanufacturing; fuzzy optimization; stochastic programming; circular economy; decision making; combinational optimization

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1. Introduction

The Paris Agreement has highlighted the significance of preserving natural resources and reducing fossil fuel consumption [1]. Although the forum's main objective was reducing global warming, global warming is the direct product of excessive consumption of fossil fuel, which is caused by the unnecessary presence of vehicles in the supply chain network. Another side of the inattentive consumption of fossil fuels that accompanies the destruction of forests and wildlife is transmitting viruses hidden in the natural environment to our living places, which may cause several pandemics with shorter time spans in the future [2]. Moreover, destroying biodiversity can put human health at risk and even put our food security in danger [3], and consequently, the human race is on the precipice of extinction. The global economy is also facing many challenges, such as global imbalances, economic exclusion, prospects for growth, deregulated markets, inflation, energy and the environment, inequality, labor issues, emerging markets, and the impact of new technologies. Policymakers set common sustainability goals, which explain what should be developed and what is to be sustained, for how long, and for the benefit of whom [4].

However, implementing sustainability concepts in the global society is challenging, since it will confront man's current lifestyle, which has been exercised for centuries [5]. With all the challenges, sustainability has been institutionalized to develop rules and regulations to re-structure social intervention, create awareness, and shape behaviors globally. One of the main challenges of sustained economic growth is using a linear production model [6].

In the linear production model, resources are fed to the production line and transported to manufacturers to be processed into some parts and products. After some time, the finalized products will be discarded. This routine will be repeated frequently, increasing resource prices because of resource depletion. Therefore, the goal of sustainable development goal is the long-term stability of natural resources, the environment, societal concerns, and the economy, acknowledging sustainable development through the decision-making process of policymakers. In this regard, the key policy adopted by companies is to take more responsibility in collecting used products at the end of their life cycle and provide recovery alternatives such as remanufacturing, recycling, and the disposal of used products in an environmentally friendly manner. Switching from the linear model, which mainly focuses on the concept of take-make-use-and-dispose, to a circular economy necessitates changes in which companies generate value, understand, and do business. This transformation requires a new business model for sustainability and circularity. Moreover, these changes may lead managers to ambiguous situations in designing and managing the distribution and collection channels for new and used products. Therefore, developing an efficient network that supports the management of both forward and reverse flows is a challenge. In this situation, a closed-loop supply chain network is a sustainable approach.

A closed-loop supply chain is the integration of a forward supply chain (the processes of converting raw material to finished product) and a reverse supply chain (the collection and recovery of the products returned in the supply chain). Due to interdependent decisions in forward and reverse supply chain networks, considering the networks separately could lead to sub-optimal results [7], and therefore it is important to take into account both forward and reverse networks simultaneously or to create a network configuration in the decision-making process.

In designing a CLSC, it is crucial to integrate the operational, strategic, and tactical decisions, ensuring a better business perspective concerning reducing costs and improving customer service levels [8]. A recent literature review by Oliveira and Machado [9] showed that 48% of studies are involved in strategic decision making. Moreover, the research focusing on the tactical decision amounted to 72 papers, representing 23.5% of the reviewed papers. Only three studies have considered strategic, tactical, and operational decision making in their model. One of the critical operational decisions is vehicle-routing management, which finds an efficient route for transferring products through the network [8]. Although identifying an optimal vehicle route has the potential to reduce costs and improve customer-service levels significantly, research studies in the field of CLSC have mostly overlooked the importance of this operational decision [10]. Another limitation of the CLSC model that has yet to be addressed in the literature of CLSC is the simultaneous delivery of products and pick-up of end-of-life products; almost all operators plan and perform different fleets for picking up malfunctioned or end-of-life products. Moreover, some manufacturers prefer to outsource their reverse supply chain or assign them to retailers or third parties [11–13], since they think recycling the used products is costly and is not profitable for their firms. This study develops a new CLSC model with simultaneous delivery and pick-up integrated with location-allocation decisions implying uncertainty. Different types of vehicles, such as trucks, planes, and ships, typically carry out the movement of materials through the supply chain network. They all operate based on precise and empirical programs, which are typically costly for operators and business owners. With this consideration, logistics planning comes forward to facilitate the management of the operation. Vehicle routing programs (VRPs) are part of these procedures that assign each vehicle to each customer on the nodes on the graphs usually designed for logistics planning [14].

Moreover, uncertainties such as the growth in the complexity of structures, market fluctuation, and service facilities make the planning more intricate. Several approaches have been suggested, for instance, stochastic programming [15], robust optimization [16], and fuzzy programming [17]. Researchers have attempted to combine these methods to address uncertainties more efficiently [18]. In order to align this study with the above research stream, this paper proposes a fuzzy-stochastic programming approach to overcome the uncertainties associated with the problem. The general form of an optimization problem is to find the maximum (or minimum) of a particular "objective function" under some "constraints"; the solution to this problem is known as the optimization method. In classical optimizations, the objective function and constraints are deterministic (i.e., not fuzzy). Nevertheless, in the real world, the values are hardly found in deterministic form and typically fluctuate; it needs to be decided which criteria should be implemented in a system or eliminated, so solving uncertain optimization problems is essential for both theory and application. Fuzzy mathematical programming is considered, based on the concept of a fuzzy variable that is one of the complete patterns of fuzziness. This study proposes a new mixed-integer linear mathematical-programming model to minimize the total costs, including transportation, investment, and operational costs.

2. Literature Review

The concept of CLSC has emerged to reconcile the environmental and economic objectives of the supply chain. As a result, many studies can be found in the literature that have attempted to integrate these two aspects into a research frame [19]. In this regard, Govindan and Soleimani [20,21], as well as Govindan, Soleimani [8] conducted a literature review that summarized the growing interest in the closed-loop supply chain and also analyzed the environmental, legal and social, as well as the economic factors involved in CLSC. Quattrociocchi et al. [22] provided a comprehensive overview of the tourism supply chain, which is multi-billion-dollar business; any flaw in this era brings about dire consequences for business owners, consumers, and the environment. Moreover, identifying risk and calculating its effects in an operation can be very helpful for mitigating the side effects of any business practices. Mital et al. [23] formulated a model by implementing the analytic hierarchy process for risk identification and assessing the impacts on business performance. Since this research paper focuses on the latest modeling of CLSC, and the integration of CLSC with the vehicle routing problem, the literature related to this area is briefly reviewed in two streams, namely the CLSC network and VRP, in order to make a comparison with the earlier research works in this field.

CLSC mainly addresses economic-performance improvement through value recovery from end-of-life products [24]. Ghomi-Avili et al. [25] formulated a closed-loop supply chain recruiting a fuzzy bi-objective bi-level function to maintain the supply network at an optimum level in times of disruption when the whole network comes to arbitrary stagnation. Jabbarzadeh et al. [26] fashioned a model utilizing stochastic-robust-optimization methods to guarantee the resiliency and performance of a closed-loop supply chain when an interruption occurs. Their model was mainly focused on locating the facilities and enhancing transportation to minimize the cost of the supply network. Wu and Zhou [27] developed a modeled underlying game theory that analyzed the renewal of manufacturing equipment, conducted by third-party manufacturers, and its economic effects on different players throughout the supply chain. Zheng et al. [12] developed game models and numerical studies analyzing how to share profits among players in CLSC equally and fairly, and maintain their overall satisfaction. Zhen et al. [28] proposed a green closed-loop supply chain with a balance between the normal operations of the supply chain and the operation of environmentally friendly procedures. The authors recruited the Lagrangean relaxation method to solve the problems. Wang et al. [11] formulated a scenario-based model to scrutinize different problems in a CLSC environment where competition among players, from manufacturers to retailers, prevailed in an uncontrolled manner. The authors provided mathematical models to examine different scenarios between manufacturers and recycling firms, to study what happens if a company totally or partially outsources its recycling operations. Liu et al. [29] examined the impact of product design on the profitability of companies. The model revealed that performing CLSC was not profitable for a corporation, but redesigning the products intensified and guaranteed a firm's profitability. Mohtashami et al. [30] presented a comprehensive CLSC model focusing on the logistic portion of the supply network to analyze how fleet-network optimization could provide golden opportunities to minimize the negative environmental impacts typically created by vehicles. The authors provided numerical examples using a queuing system to solve the problems. Govindan et al. [31] provided a model to inspect supply networks from various dimensions, from supplier selection to routing problems. They utilized many mathematical methods for solving problems, such as the fuzzy-analytic-network process, fuzzy-decision-making trial and evaluation laboratory, and multi-objective mixed-integer linear programming. Yavari and Zaker [32] formulated a green closed-loop supply chain mainly focusing on perishable products and the disruption of the supply network, probably instigated by the power outage. The authors also offered several strategies for eliminating the impacts of the problems. Fathollahi-Fard et al. [33] provided a multi-objective stochastic optimization model to tackle the problem of potable water supply and sewerage collection within an uncertain environment. The authors utilized a multi-objective stochastic optimization model to solve the problems. The chief goals of the research were to offer a methodology to curb water-wastage problems, save valuable material as much as possible, and offer some solutions for implementing the strategy in the real world. Chen et al. [13] developed a model to facilitate and rationalize the procedures of selecting providers who conduct reverse supply chains for manufacturers. The critical point for conducting this research was assisting people willing to outsource their circular-economy agenda. Szmelter-Jarosz et al. [34] formulated a convenient model using the neutrosophic-fuzzy method to handle the supply chain in the era of the COVID-19 pandemic, in order to eliminate vehicle congestion and deliver cargo to consumers in an efficient manner. The research aimed to maintain the service level and follow the environmentally friendly operating principles in an era when the public stress level was soaring. Shabbir et al. [35] integrated resiliency, sustainability, and reliability into the supply chain network, following CLSC principles. The authors employed the Lp-metric and Lagrangian relaxation methods to solve the problems. Liao et al. [36] focused on agricultural products, considered to be among those perishable materials, to develop an appropriate supply chain with regard to environmentally friendly principles. Harvesting fresh products is a business that produces excessive pollution if business owners do not follow agricultural laws and regulations. This study provided a comprehensive study on organizing and operating in this era. The researchers utilized the genetic algorithm and simulated annealing to solve the problems.

Amin and Zhang [37] developed a single-product, single-period model for a CLSC network that helps remanufactured products to be sent to a secondary market. Shi, Nie [38] studied a CLSC which utilized third-party-logistics service providers for the forward supply chain. Along the same line of thought, Sasikumar and Haq [39] developed a CLSC network in which a third-party reverse logistics provider (3PRLP) was responsible for the reverse supply chain. Das and Rao Posinasetti [40] addressed environmental concerns arising from harmful emissions and energy consumption in the CLSC-network design. In addition to the economic objective, several researchers incorporate social and environmental objectives, as interest in environmental protection, customer satisfaction, and sustainable development is increasing [24]. Garg, Kannan [41] developed a bi-objective mixed-integer linear-programming model for CLSC-network design to maximize total profits and minimize the number of hired vehicles in the forward supply chain. Taleizadeh, Haghighi [42] developed a multi-objective CLSC to maximize profits, minimize environmental effects, and minimize social objectives. Hasanov, Jaber [43] addressed the effects of inventory policy on CLSC costs by considering emissions from production and transportation. The results showed a higher rate for the collection of used items, improving the environmental performance and reducing its cost. Mawandiya, Jha [44] developed a two-echelon closed-loop supply chain to find the optimal-lot sizing and shipment policies. Giri and Masanta [45] developed a closed-loop supply chain model where the production process is subject to learning and forgetting.

In CLSS-network development, many parameters must be defined precisely, due to the associated uncertainties [46]. In the literature, different approaches have been specified by researchers in handling uncertainty, namely fuzzy optimization [47], stochastic optimization [48], and robust optimization [49]. Soleimani, Seyyed-Esfahani [50] studied a location-allocation problem in a CLSC-network design. They integrated three types of risk measures: mean absolute deviation, value at risk, and conditional value at risk (CVaR) into the two-stage stochastic- programming model. Their profit-oriented model revealed that risk-neutral approaches are not efficient. Later, Subulan, Baykasoğlu [51] developed a mixed-integer linear-programming model by assuming financial and collection risk with almost identical risk measurements as that of Soleimani, Seyyed-Esfahani [50]. Next, Dai and Zheng [52] developed a multi-period, multi-product CLSC-network design addressing uncertainties in the disposing of rates, demand, and capacities. They used a Monte Carlo simulation along with hybrid GA/fuzzy programming and chance-constrained programming. Khatami, Mahootchi [53] developed a mixed-integer linear-programming model for CLSC. The main concerns of their model were the uncertainties about product demand and return. Bender's decomposition was applied to overcome uncertainties. Accordingly, Radhi and Zhang [54] developed a mixed-integer non-linear-programming model by taking into account the uncertainty of quality and demand. Keyvanshokooh, Ryan [55] proposed a hybrid robust-stochastic programming method to address uncertainties about the demand, return, and transportation cost. In another study, Ma, Yao [48] developed a robust multi-objective mixed-integer nonlinear-programming model for the CLSC-network design. This model focused on the environmental impact of the network as well as its cost. Saedinia, Vahdani [56] developed a bi-objective in the oil and gas industry. Jeihoonian, Kazemi Zanjani [57] developed a two-stage stochastic for the CLSC model, where the quality of return products was uncertain. The authors of [58] developed a two-stage stochastic non-linear programming model to minimize total costs. The model was solved by a heuristic-tabu search algorithm.

Physical distribution is one of the most prominent and costly functions of any logistics system, and requires the transportation of products from the manufacturer through the distribution center to the customers. The vehicle routing problem (VRP) is a generic name that refers to optimization problems, in that customers are served using a number of vehicles [59]. Nagy and Salhi [60] extended the basic VRP model by including customers who may receive and send goods. Ahmadi Javid and Azad [61] developed a stochastic supply chain model with location-allocation, an optimum amount of capacity and inventory, and an optimum decision for selecting the best route. Nekooghadirli, Tavakkoli-Moghaddam [62] established a bi-objective location-routing-inventory (LRI) model that considered a multi-period and multi-product system which is used to make strategic and tactical decisions for location and inventory-routing. Bae and Moon [63] developed a multi-depot vehicle-routing problem with time windows to study the delivery and installation of electronic products. They showed the possibility for cost minimization of the depot, delivery, and installation of the vehicle, as well as travel distance and labor. Archetti, Desaulniers [64] developed an inventory-routing problem that minimizes a logistic ratio, which is the ratio of the total routing cost to the total quantity distributed. Iassinovskaia, Limbourg [65] developed an inventory-routing problem where the returnable transport items can be collected at the customer's location. Wang, Shao [66] developed a two-echelon capacitated-vehicle-routing problem with environmental considerations. Ahmadi-Javid, Amiri [67] developed a model for location-routing pricing problems, which considers profit maximization. Madankumar and Rajendran [68] considered a special case of VRP that addresses the routing problem in a semiconductor supply chain. They developed an MILP (mixed-integer linear-programming) model for solving the green VRP with pickup and deliveries in a semiconductor supply chain. Abu Al Hla, Othman [69] solved a VRP model that improves driver satisfaction, customers' perceived quality, and the company's financial objective. They considered three levels of strategic, tactical, and operational decisions. The result shows that giving autonomy to drivers will not involve a significant cost, and the model can be optimum. Madankumar and Rajendran [70] developed an MILP model for VRP with simultaneously delivery and pickup, and considered time windows to improve the performance and responsiveness of the model. Similarly, Zhou, Qin [71] developed VRP with time windows and simultaneous pickup and delivery. Their network consisted of two echelons. They formulated the model and solved it with a neighborhood tabu-search algorithm. The result shows that the algorithm that they used can save 19% computational time, on average.

To better recognize the novelty of the current article compared with the previously published papers, a summary of the previous works is illustrated in Table 1.

Table 1. Literature comparison.

Model Characteristics	**Özceylan, Demirel [72]**	**Farrokh, Azar [73]**	**Jabbarzadeh, Haughton [26]**	**Jerbia, Kchaou Boujelben [74]**	**Almaraj and Trafalis [75]**	**Zhou, Xia [76]**	**Diabat and Jebali [77]**	**Chouhan, Khan [78]**	**Chiu, Cheng [79]**	**This Paper**
Product										
Single				X		X		X	X	X
Multiple	X	X	X		X		X			
Period										
Single				X		X				X
Multiple	X	X	X		X		X	X	X	
Modeling Approach										
Deterministic							X	X	X	
Stochastic-robust optimization										
Fuzzy programming	X					X				
Scenario-based robust optimization			X							
Mixed-integer linear programming	X		X	X	X	X	X	X		X
Two-stage stochastic program				X						
Robust optimization					X					
Fuzzy-stochastic programming		X								X
Solution approach										
Optimization software package	X	X		X	X		X		X	X
Lagrangian relaxation			X							
Metaheuristics algorithms								X		
Decomposition method			X							

Table 1. *Cont.*

Model Characteristics	Özceylan, Demirel [72]	Farrokh, Azar [73]	Jabbarzadeh, Haughton [26]	Jerbia, Kchaou Boujelben [74]	Almaraj and Trafalis [75]	Zhou, Xia [76]	Diabat and Jebali [77]	Chouhan, Khan [78]	Chiu, Cheng [79]	This Paper
Uncertain parameters										
Demand	X	X			X	X				X
Capacity	X	X				X				X
Cost		X		X	X	X				X
Return				X	X					X
Recovery rate				X						
Revenue				X		X				
Error type					X					
Delivery time						X				
Disposal and repair						X				
Objective-function components										
Transportation cost (min)	X	X	X	X		X	X	X	X	X
Inventory cost (min)		X	X			X	X	X	X	
Facility fixed-cost opening (min)	X	X		X			X	X		X
Penalty cost (min)				X	X					
Disposal (min)			X			X			X	
Purchasing (min)	X	X					X		X	X
Collection (min)	X	X	X		X	X				
Manufacturing (min)		X	X	X	X	X			X	X
Disassembling (min)	X									
Recycling cost (min)		X			X				X	
Lost cost (min)			X							
Profit (max)				X					X	
Remanufacturing cost (min)				X		X				
Repair cost (min)						X				
Distribution cost (min)					X					
Procurement cost (min)					X					
Labor cost (min)									X	
Allocation cost (min)									X	
Processing cost (min)							X	X		X

The discussion mentioned above highlighted the research gaps which lack CLSC and VRP integration and are inadequate in addressing uncertainty in the CLSC and the simultaneous delivery and taking of end-of-life materials from customers, which has already been discussed in the introduction. Two researchers, Garg, Kannan [41] and Zhalechian, Tavakkoli-Moghaddam [10] tried to integrate CLSC and VRP; however, Garg, Kannan [41] developed a CLSC model that optimized total profit and the number of hired vehicles in a forward supply chain only, and did not include the reverse supply chain. Zhalechian, Tavakkoli-Moghaddam [10] developed a model to optimize the inventory model of CLSC. None addressed the CLSC-network design and VRP concurrently, a research gap that this paper attempts to cover. Integration of CLSC-network development with VRP supports the company's decision-making by encompassing all three types of strategic, tactical, and operational decisions in parallel. The strategic decision is addressed in selecting the location, the tactical decision is applied by determining the flow of materials and products among the facilities, and the operational decision is conveyed by defining a route to distribute products to the customers.

To address the gaps mentioned above, adopting an integrated fuzzy-mathematical and stochastic-programming approach, such as a hybrid fuzzy-stochastic one, is a suitable choice for addressing uncertainties in CLSC-network design. Therefore, this study developed a mixed-integer linear-programming model for CLSC-network design with routing decisions under fuzzy and random uncertain data.

3. Model Description and Formulation

As stated previously, CLSC is complex by nature, and thus our proposed network provides hybrid facilities to reduce the total costs and complexity of the network. The hybrid facility (HF) at the proposed CLSC network (Figure 1) coordinates a distribution and collection center. The application of HF is of economic benefit to the network because, in general, the co-location of facilities reduces considerable investment in human resources, equipment, and infrastructure [80].

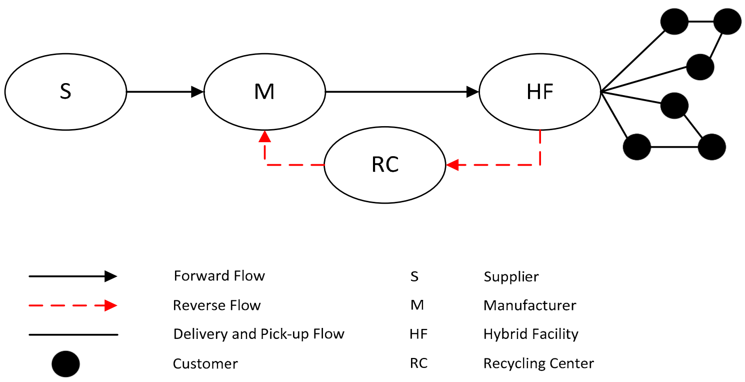

Figure 1. A proposed closed-loop supply chain network.

As shown in Figure 1, OEMs and customers are the existing sites in the network, while HFs are potential new facilities. The OEMs purchase raw materials and components from suppliers (S) and recycling centers (RC). The OEM has special vehicles assigned to deliver products to HFs. These vehicles are used to distribute and collect end-of-life products returned from customers within assigned routes. The challenge in this phase is selecting a route that minimizes total costs while ensuring that each customer receives his demand. Each HF, in addition to its collection activity, is responsible for inspecting, testing, and sorting the used products. For simplicity, inspection, testing, and sorting will be subsequently referred to as sorting. The end-of-life products collected from the HF are sent to the recycling centers to be recycled and reused as materials for production. Customers are grouped in zones called aggregate delivery points [81].

There are two main goals for developing a CLSC model:

1. To select the optimum CLSC-network configuration.
2. Finding the routes for the limited number of vehicles to serve a group of customers with their demand.

Every customer has an uncertain delivery demand, $\widetilde{D}_r$, and a pick-up, $\widetilde{P}_r$, for new and end-of-life products simultaneously. Moreover, the following assumptions are postulated:

1. Facility locations are known beforehand.
2. The following of products between HFs is not allowed.
3. The set-up cost of facilities is considered as fixed and predefined.

3.1. Objective Function

The proposed mixed-integer linear-programming model aims to minimize the total cost, including the establishment cost of HF, purchasing cost from the supplier, production cost, purchasing cost from the recycling center, and transportation costs.

The fixed opening cost includes a decision on the establishment of HFs that can be written as:

$$\sum_{h\in H} F_{1_h} U_{1_h} \tag{1}$$

The processing cost involves both purchasing and production costs. The purchasing cost includes costs related to the purchasing cost of raw materials from recycling centers and suppliers, and the production cost includes the sum of setup cost, labor, and all costs of production, which can be written as follows:

$$\sum_{s\in S}\sum_{i\in I}\sum_{m\in M} PS_{si} X_{0_{sim}} \tag{2}$$

$$\sum_{m\in M}\sum_{h\in H}\sum_{vi\in VI} PM_m X_{1_{mhvi}} \tag{3}$$

$$\sum_{c\in C}\sum_{i\in I}\sum_{m\in M} PC_{ci} X_{4_{cim}} \tag{4}$$

The transportation cost includes the traveling of a vehicle along its defined route between each node. It involves traveling from HSP to HF, from HF to customers, and from HF to the recycling center, which can be written as:

$$\sum_{m\in M}\sum_{h\in H}\sum_{vi\in VI} d_{1_{mh}} TC_{1_{mhvi}} X_{1_{mhvi}} \tag{5}$$

$$\sum_{j\in b}\sum_{j'\in b}\sum_{k\in K} d_{2_{j_{j'}}} TC_{2_{jj'k}} X_{2_{jj'k}} \tag{6}$$

$$\sum_{h\in H}\sum_{c\in C}\sum_{vj\in VJ} d_{3_{hc}} TC_{3_{hcvj}} X_{3_{hcvj}} \tag{7}$$

Although the main objective is to minimize cost, revenue could be achieved from selling the end-of-life products to the recycling center, which can be written as:

$$\sum_{h\in H}\sum_{c\in C}\sum_{vj\in VJ} SPX_{3_{hcvj}} \tag{8}$$

Therefore:

$$\begin{aligned} MinZ =\ & \\ & \sum_{h\in H} F_{1_h} U_{1_h} + \sum_{s\in S}\sum_{i\in I}\sum_{m\in M} PS_{si} X_{0_{sim}} + \sum_{m\in M}\sum_{h\in H}\sum_{vi\in VI} PM_m X_{1_{mhvi}} - \\ & \sum_{h\in H}\sum_{c\in C}\sum_{vj\in VJ} SPX_{3_{hcvj}} + \sum_{c\in C}\sum_{i\in I}\sum_{m\in M} PC_{ci} X_{4_{cim}} + \sum_{m\in M}\sum_{h\in H}\sum_{vi\in VI} d_{1_{mh}} TC_{1_{mhvi}} X_{1_{mhvi}} + \\ & \sum_{j\in b}\sum_{j'\in b}\sum_{k\in K} d_{2_{j_{j'}}} TC_{2_{jj'k}} X_{2_{jj'k}} + \sum_{h\in H}\sum_{c\in C}\sum_{vj\in VJ} d_{3_{hc}} TC_{3_{hcvj}} X_{3_{hcvj}} \end{aligned} \tag{9}$$

3.2. Constraints

The constraints of the model are structured as follows:

$$\sum_{h\in H}\sum_{vi\in VI} X1_{mhvi} \le CM_m \qquad \forall m \in M \tag{10}$$

$$R2_h \le CD_h U1_h \qquad \forall h \in H \tag{11}$$

$$\sum_{h\in H}\sum_{vj\in VJ} X3_{hcvj} \le CC_c \qquad \forall c \in C \tag{12}$$

$$\sum_{m\in M} X4_{cim} \le CC_c U_i \qquad \forall c \in C; \forall i \in I \tag{13}$$

$$\sum_{m\in M}\sum_{h\in H} X1_{mhvi} \le C1_{vi} \qquad \forall vi \in VI \tag{14}$$

$$L2_k \le C2_k \qquad \forall k \in K \tag{15}$$

$$Lt_{jj'k} \le C2_k \qquad \forall j, j' \in b; \forall k \in K \tag{16}$$

$$Lt'_{jj'k} \le C2_k \qquad \forall j, j' \in b; \forall k \in K \tag{17}$$

$$\sum_{h\in H}\sum_{c\in C} X3_{hcvj} \le C3_{vj} \qquad \forall vj \in VJ \tag{18}$$

$$\sum_{h\in H} X4_{cim} + \sum_{s\in S} X0_{sim} = \sum_{h\in H}\sum_{vi\in VI} U_i X1_{mhvi} \qquad \forall m \in M; \forall i \in I \tag{19}$$

$$\sum_{h\in H}\sum_{vi\in VI} U_i X3_{hcvj} = \sum_{m\in M} X4_{cim} \qquad \forall c \in C; \forall i \in I \tag{20}$$

$$\sum_{h\in H}\sum_{vj\in VJ} X3_{hcvj} = R'2_h \qquad \forall h \in h \tag{21}$$

$$\sum_{k\in K}\sum_{j\in b} X2_{jj'k} = 1 \qquad \forall j' \in R \tag{22}$$

$$\sum_{j'\in b} X2_{j'jk} = \sum_{j'\in b} X2_{jj'k} \qquad \forall j \in R; \forall k \in K \tag{23}$$

$$\sum_{j'\in R} X2_{jj'k} = \sum_{j'\in R} X2_{j'jk} \qquad \forall k \in K; \forall j \in H \tag{24}$$

$$\sum_{j\in H}\sum_{j'\in R} X2j_{j'k} \le 1 \qquad \forall k \in K \tag{25}$$

$$\sum_{r\in R} Y2_{hr} \ge U1_h \qquad \forall h \in H \tag{26}$$

$$M2_{rk} - M2_{r'k} + \left(B2 X2_{jj'k}\right) \le B2 - 1 \qquad \forall r, r' \in R; \forall k \in K \tag{27}$$

$$X2_{jj'k} = 0 \qquad \forall k \in K; \forall j, j' \in H \tag{28}$$

$$\sum_{j\in b}\sum_{j'\in b} d2_{jj'} X2_{j_{j'k}} \le MD2_k \qquad \forall k \in K \tag{29}$$

$$\sum_{j'\in b} X2_{jj'k} + \sum_{j'\in b} X2_{ij'k} - Y2_{hr} \le 1 \qquad \forall j \in R; \forall i \in H; \forall k \in K \tag{30}$$

$$\sum_{h\in H} Y2_{hr} = 1 \qquad \forall r \in R \tag{31}$$

$$\sum_{m\in M}\sum_{vi\in VI} X1_{mhvi} \ge R2_h \qquad \forall h \in H \tag{32}$$

$$L2_k \ge \sum_{j\in b}\sum_{j'\in R} \widetilde{D}_r X2_{jj'k} \qquad \forall k \in K \tag{33}$$

$$R2_h \ge \sum_{r\in R} \widetilde{D}_r y2_{hr} \qquad \forall h \in H \tag{34}$$

$$Lt_{jj'k} \le X2_{jj'k} \sum_{r\in R} D_r \qquad \forall j, j' \in b; \forall k \in K \tag{35}$$

$$\sum_{k\in K}\sum_{b\in B} Lt_{brk} \le \sum_{k\in K}\sum_{b\in B} Lt_{rbk} + D_r \qquad \forall r \in R \tag{36}$$

$$L2'_k \ge \sum_{j\in b}\sum_{j'\in R} \widetilde{P}_r X2_{jj'k} \qquad \forall k \in K \tag{37}$$

$$R2'_h \ge \sum_{r\in R} \widetilde{P}_r Y2_{hr} \qquad \forall j \in H \tag{38}$$

$$Lt'_{jj'k} \le X2_{jj'k} \sum_{r\in R} P_r \qquad \forall j, j' \in b; \forall k \in K \tag{39}$$

$$\sum_{k\in K}\sum_{b\in B} Lt'_{brk} \le \sum_{k\in K}\sum_{b\in B} Lt'_{rbk} - P_r \qquad \forall r \in R \tag{40}$$

Constraints (10)–(18) are capacity constraints that ensure the vehicle and facilities meet their capacities. Constraints (10)–(13) ensure production centers, hybrid facilities, and recycling centers cannot exceed their capacity. Constraint (14) is capacity requirements for a vehicle that guarantee the number of products carried with vehicle vj meets the capacity. Constraints (15)–(17) are related to capacity vehicle k, and guarantee that vehicle k cannot load more than its capacity. Constraint (18) is associated with vehicle vj, and ensures vehicle vj meets its capacity. Constraints (19)–(21) are flow-balance constraints at production centers, hybrid facilities, and recycling centers, which specify the relationship between input and output at respective facilities. Constraints (22)–(31) are associated with routing. Constraint (22) ensures every customer belongs to one, and only one, route. Constraint (23) ensures every customer belongs to one, and only one, HF. Constraint (24) indicates that each customer arrives and leaves with the same vehicle. Constraints (25) and (26) secure one HF in each route. Constraint (27) is a sub-tour elimination. Constraint (28) guarantees that there is no route between HFs. Constraint (29) limits the maximum distance of vehicle type k. Constraint (30) is the linkage and allocation constraints that ensure that if vehicle k starts its trip from HF j and serves customer r during its trip, then customer r should be assigned to HF. Constraint (31) assures each customer is assigned to one HF. Constraint (32) assures vehicle load after visiting all HFs. Constraint (33) indicates vehicle load for customers' demand. Constraint (34) satisfies the vehicle load after visiting all customers. Constraints (35) and (36) ensure that the vehicle load is not exceeding the demand quantity. Constraint (37) indicates expected return products for HFs. Constraint (38) assures the vehicle load for the pick-up product after visiting all HFs. Constraints (39) and (40) ensure that the vehicle pick-up load does not exceed the pick-up quantity.

3.3. Proposed Solution

In the stochastic-programming model, uncertainty is characterized by the random nature of the parameters. The objective function and the constraints are developed using fuzzy numbers: this transforms the problem from deterministic to stochastic. The fuzzy-stochastic type of uncertainty can be formulated using two-stage stochastic programming (TSP) with a recourse model. In this method, the decisions are made in two phases:

1. Parameters need to be determined before the value of a random variable.
2. Parameters need to be determined after the random event has happened.

The second-stage decision can be made for the minimization of the penalty that occurs because of infeasibility [82]. Therefore, the TSP model can be formulated as follows:

$$Max \quad f = cx - E[Q(x,\omega)] \tag{41}$$

$$\text{s.t.} \quad Ax \leq b \tag{42}$$

$$x \geq 0 \tag{43}$$

where x is the first-stage anticipated decisions made before random variables are observed and $Q(x,\xi)$ is the optimum value, for any given Ω, of the following nonlinear program:

$$min \qquad q(y,\omega) \tag{44}$$

$$\text{s.t.} \quad W(\omega)y = h(\omega) - T(\omega)x \tag{45}$$

$$y \geq 0 \tag{46}$$

where y is the second-stage decision variable that depends on the realization of the first-stage random vector; $q(y,\omega)$ denotes the second-stage cost functions; $\{T(\omega), W(\omega), h(\omega)|\omega \in \Omega\}$ are model parameters with reasonable dimensions, and are a function of the random vector, (ω). For given values of the first-stage variables, (x), the second-stage problem can be decomposed into independent, linear sub-problems, with one sub-problem for each realization of the uncertain parameters. Then, model (41)–(43) can be reformulated as:

$$Max \quad f = cs - E[\min_{y \geq 0} q(y,\omega)|T(\omega)x + W(\omega)y = h(\omega)] \tag{47}$$

$$\text{s.t. } Ax \leq b \tag{48}$$

$$x \geq 0 \tag{49}$$

The above TSP problem is nonlinear [83]; however, the problem can be converted to a linear form by assuming discrete distributions for the uncertain parameters. Thus, the expected value of the nonlinear term $E[Q(x,\omega)]$ can be linearized as follows [83]:

$$E[Q(x,\omega)] = \sum_{h=1}^{s} p_h Q(x,\omega_h) \tag{50}$$

where ω possesses a discrete and finite distribution, with support $\Omega = \{\omega_1, \omega_2, \ldots, \omega_s\}$; p_h represents the probability of realization of scenario ω_h, with $p_h \geq 0$ and $\sum_{h=1}^{s} p_h = 1$.

Therefore, the model (41)–(43) can be converted to a linear form as in the following:

$$Max\ f = cx - \sum_{h=1}^{s} p_h q(y_h, \omega_h) \tag{51}$$

$$\text{s.t. } Ax \leq b \tag{52}$$

$$T(\omega_h)x + W(\omega_h)y_{\omega_h} = h(\omega_h),\ \omega_h \in \Omega \tag{53}$$

$$x \geq 0 \tag{54}$$

$$y_h \geq 0 \tag{55}$$

The model (51)–(55) can be formulated with chance-constrained programming (CCP), as follows:

$$Max\ f = \sum_{j=1}^{n_1} c_j x_j - \sum_{j=1}^{n_2} \sum_{h=1}^{s} p_h d_j y_{jh} \tag{56}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} a_{rj} x_j \leq b_r \qquad r = 1,2,\ldots,m_1 \tag{57}$$

$$\Pr\left\{\sum_{j=1}^{n_1} a_{ij} x_j + \sum_{j=1}^{n_2} a_{ij} y_{jh} \leq w_{ih}\right\} \geq \gamma_i \qquad \begin{array}{c} i = 1,2,\ldots,m_2 \\ h = 1,2,\ldots,s \end{array} \tag{58}$$

$$x_j \geq 0 \qquad j = 1,2,\ldots,n_1 \tag{59}$$

$$y_{jh} \geq 0 \qquad \begin{array}{c} j = 1,2,\ldots,n_2 \\ h = 1,2,\ldots,s \end{array} \tag{60}$$

where $\gamma_i (\gamma_i \in [0,1])$ is the probability level that constraint i should be satisfied with at least.

In addition to the lack of historical data or the high cost of data acquisition, errors in obtained information, variations in a spatial and temporal unit, and incomplete or imprecise observed information [84,85], make it challenging to determine the probability distribution of uncertain parameters. Fuzzy mathematical programming provides a tool to describe uncertain parameters mathematically. Fuzzy possibilistic programming (FPP), among others, is a suitable method that enables decision-makers to model uncertainty, particularly in cases where the uncertainty lies either in the coefficients of the left-hand side and right-hand side of constraints or coefficients of the objective function [83]. The FPP represents the parameter in a fuzzy form that contains possibility distributions. Therefore, a hybrid fuzzy-stochastic programming model can be formulated as follows [83]:

$$Max\ f = \sum_{j=1}^{n_1} \widetilde{c}_j x_j - \sum_{j=1}^{n_2} \sum_{h=1}^{s} p_h \widetilde{d}_j y_{jh} \tag{61}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} \widetilde{a}_{rj} x_j \leq \widetilde{b}_r \qquad r = 1, 2, \ldots, n_1 \tag{62}$$

$$\sum_{j=1}^{n_1} \widetilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \widetilde{a}_{ij} y_{jh} \leq \widetilde{w}_{ih} \qquad \begin{array}{c} i = 1, 2, \ldots, m_2 \\ h = 1, 2, \ldots, s \end{array} \tag{63}$$

$$x_j \geq 0 \qquad j = 1, 2, \ldots, n_1 \tag{64}$$

$$y_{jh} \geq 0 \qquad \begin{array}{c} j = 1, 2, \ldots, n_2 \\ h = 1, 2, \ldots, s \end{array} \tag{65}$$

where x_j and y_{jh} are first and second-stage decision variables, respectively; c_j and d_j are fuzzy coefficients in the objective function; $\widetilde{a}_{ij}$ and $\widetilde{a}_{rj}$ are fuzzy left-hand side coefficients, and $\widetilde{w}_{ih}$ is the independent random variables with a known probability distribution.

This hybrid fuzzy-stochastic model can be solved by using chance constraint programming (CCP). CCP can be applied when some right-hand-side parameters are uncertain, with a known probability distribution. The CCP approach converts the model to a deterministic form by applying a fixed, certain level of probability, $\widetilde{q}_i \in [0, 1]$ for every uncertain constraint, i, and imposing the condition that the constraint is satisfied with at least a probability level of $\widetilde{\gamma}_i = 1 - \widetilde{q}_i$ with $\widetilde{\gamma}_i \in [0, 1]$. Thus, the fuzzy-stochastic constraint can be described as [83]:

$$\Pr\left\{ \sum_{j=1}^{n_1} \widetilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \widetilde{a}_{ij} y_{jh} \leq \widetilde{w}_{ih} \right\} \geq \widetilde{\gamma}_i \qquad \begin{array}{c} i = 1, 2, \ldots, m_2 \\ h = 1, 2, \ldots, s \end{array} \tag{66}$$

Generally, constraint (66) is nonlinear, and the set of feasible constraints is convex only for some particular distribution and certain level of $\widetilde{q}_i$. Therefore, this constraint can be formulated as the equivalent fuzzy deterministic form [86], as follows:

$$\sum_{j=1}^{n_1} \widetilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \widetilde{a}_{ij} y_{jh} \leq \widetilde{w}_{ih}^{\widetilde{q}_i} \qquad \begin{array}{c} i = 1, 2, \ldots, m_2 \\ h = 1, 2, \ldots, s \end{array} \tag{67}$$

where $\widetilde{w}_{\widetilde{q}_i}^{ih} = F_i^{-1}(\widetilde{q}_i)$, given the cumulative distribution function of $\widetilde{w}_{ih}$ and the probability of violating constraint $i(\widetilde{q}_i)$. Therefore, the model can be written as follows:

$$Max\ f = \sum_{j=1}^{n_1} \widetilde{c}_j x_j - \sum_{j=1}^{n_2} \sum_{h=1}^{s} p_h \widetilde{d}_j y_{jh} \tag{68}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} \widetilde{a}_{rj} x_j \leq \widetilde{b}_r \qquad r = 1, 2, \ldots, m_1 \tag{69}$$

$$\sum_{j=1}^{n_1} \widetilde{a}_{ij} x_j + \sum_{j=1}^{n_2} \widetilde{a}'_{ij} y_{jh} \leq \widetilde{w}_{ih}^{\widetilde{q}_i} \qquad \begin{array}{c} i = 1, 2, \ldots, m_2 \\ h = 1, 2, \ldots, s \end{array} \tag{70}$$

$$x_j \geq 0 \qquad j = 1, 2, \ldots, n_1 \tag{71}$$

$$y_{jh} \geq 0 \qquad \begin{array}{c} j = 1, 2, \ldots, n_2 \\ h = 1, 2, \ldots, s \end{array} \tag{72}$$

The model can be solved with the help of a fuzzy set and $\alpha - cut$ approaches. The possibility distribution of fuzzy parameters $\tilde{b}_r = \left(\underline{b}_r, b_{r1}, b_{r2}, \overline{b}_r\right)$ can be characterized as a trapezoidal fuzzy set when $b_{r_1} \leq b_{r_2}$, and can be specified as a triangular fuzzy set when $b_{r_1} = b_{r_2}$. Parameter $\widetilde{a}_{ij}$ under each $\alpha - cut$ level can be formulated as a closed crisp interval: $[(1-\alpha)\underline{b}_r + \alpha b_{r_1}, (1-\alpha)b_{r_2} + \alpha\overline{b})]$. Kaufmann, Gil Aluja [87] established 11 levels for feasibility degree starting from an unacceptable solution (α = 0) up to a completely acceptable solution (α = 1). The model can be written as a form of two deterministic forms with the range of lower and upper bounds of the objective-function value.

The lower bound is as follows:

$$f^l = \sum_{j=1}^{n_1} [(1-\alpha)\underline{c}_j + \alpha c_{j1}]x_j - \sum_{j=1}^{n_2}\sum_{h=1}^{s} p_h[(1-\alpha)\overline{d}_j + \alpha d_{j_2}]y_{jh} \tag{73}$$

$$\text{s.t.} \quad \sum_{j=1}^{n_1} [(1-\alpha)\overline{a}_{rj} + \alpha a_{rj_2}]x_j \leq [(1-\alpha)\underline{b}_r + \alpha b_{r1}] \qquad r = 1,2,\ldots,m_1 \tag{74}$$

$$\sum_{j=1}^{n_1} [(1-\alpha)\overline{a}_{ij} + \alpha a_{ij_2}]x_j + \sum_{j=1}^{n_2} [(1-\alpha)\underline{a'}_{ij} + \alpha a'_{ij1}]y_{jh} \leq w_{ih}^{[(1-\alpha)\underline{q}_i + \alpha q_{i1}]} \qquad \begin{array}{c} i = 1,2,\ldots,m_2 \\ h = 1,2,\ldots,s \end{array} \tag{75}$$

$$x_j \geq 0 \qquad j = 1,2,\ldots,n_1 \tag{76}$$

$$y_{jh} \geq 0 \qquad \begin{array}{c} j = 1,2,\ldots,n_2 \\ h = 1,2,\ldots,s \end{array} \tag{77}$$

The upper bound is as follows:

$$f^u = \sum_{j=1}^{n_1} [(1-\alpha)\overline{c}_j + \alpha c_{j_2}]x_j - \sum_{j=1}^{n_2}\sum_{h=1}^{s} p_h[(1-\alpha)\underline{d}_j + \alpha d_{j_1}]y_{jh} \tag{78}$$

$$\sum_{j=1}^{n_1} [(1-\alpha)\underline{a}_{rj} + \alpha a_{rj_1}]x_j \leq [(1-\alpha)\overline{b}\ _r + \alpha b_{r_2}] \qquad r = 1,2,\ldots,m_1 \tag{79}$$

$$\sum_{j=1}^{n_1} [(1-\alpha)\underline{a}_{ij} + \alpha a_{ij_1}]x_j + \sum_{j=1}^{n_2} [(1-\alpha)\overline{a}'_{ij} + \alpha a'_{ij_2}]y_{jh} \leq w_{ih}^{[(1-\alpha)\overline{q}_i + \alpha q_{i_2}]} \qquad \begin{array}{c} i = 1,2,\ldots,m_2 \\ h = 1,2,\ldots,s \end{array} \tag{80}$$

$$x_j \geq 0 \qquad j = 1,2,\ldots,n_1 \tag{81}$$

$$y_{jh} \geq 0 \qquad \begin{array}{c} j = 1,2,\ldots,n_2 \\ h = 1,2,\ldots,s \end{array} \tag{82}$$

Then, after solving the lower and upper form of the model with various $\alpha - cut$, a set of optimum solutions related to the hybrid fuzzy-stochastic model can be obtained as the following:

$$x_{jopt} = [x_{jopt}^l, x_{jopt}^u] \qquad \forall j \tag{83}$$

$$y_{jhopt} = [y_{jhopt}^l, y_{jhopt}^u] \qquad \forall j, h \tag{84}$$

$$f_{opt} = [f_{opt}^l, f_{opt}^u] \tag{85}$$

3.4. Numerical Study

Solving the model with the proposed method requires identifying first-stage and second-stage variables. First-stage variables related to the opening of the facilities are the first step, and variables related to allocation are recourse decision variables. In addition, it requires identifying fuzzy parameters and writing models according to their relevant sub-models' lower-bound model (63)–(67) and upper-bound model (68)–(72). To illustrate the validity of the proposed model and the usefulness of the proposed solution approach, several numerical experiments are implemented. This also includes numerical examples that demonstrate how an increase in the size of the problem, which results in model complexity, affects the model and solving time. Table 2 shows the size of the examples with four different problem sizes. In this paper, we considered two scenarios for recourse variables with probability. A value of parameters of the model is assumed to have a trapezoid fuzzy number, and is shown in Table 3. The distance between the manufacturer and the hybrid facility is a uniform distribution between 60 and 450. The distance between hybrid facilities and demand zones and between demand zones and hybrid facilities are uniform distributions between 60 and 500. The utilization value is a uniform distribution between 1 and 4. Six α-cut levels (0, 0.2, 0.4, 0.6, 0.8, 1) were examined for the objective function. The MILP model was written in GAMS optimization software and solved with ILOG CPLEX 15.5.1 It was discovered that the size of the model has a direct relationship with its running time; as the size of the model increases, so does the time required to solve the mode. For example, problem number 2 for α = 0.4 took 0.42 s (CPU time) to solve and problem number 1 for α = 0.4 took 0.25 s (CPU time) to solve. The value of the objective functions for all the problem numbers are presented in Table 4.

Table 2. The size of numerical examples.

Problem No.	No. of Potential Suppliers	No. of Potential Manufacturers	No. of Hybrid Facilities	No. of Existing Customers	No. of Potential Recycling Centers
1	4	2	6	8	3
2	6	4	11	17	4
3	5	3	10	15	6
4	5	5	15	20	5

Table 3. Trapezoidal fuzzy number for parameters.

Parameter	Value			
$\widetilde{D}_r$	~Unif (20,000, 30,000)	~Unif (30,000, 40,000)	~Unif (40,000, 50,000)	~Unif (50,000, 60,000)
$\widetilde{P}_r$	~Unif (5000, 10,000)	~Unif (10,000,15,000)	~Unif (15,000,20,000)	~Unif (20,000, 25,000)
$\widetilde{C}1_{vi}$	~Unif (3,000,000, 4,000,000)	~Unif (4,000,000, 5,000,000)	~Unif (5,000,000, 6,000,000)	~Unif (6,000,000, 7,000,000)
$\widetilde{C}2_k$	~Unif (3,000,000, 4,000,000)	~Unif (4,000,000, 5,000,000)	~Unif (5,000,000, 6,000,000)	~Unif (6,000,000, 7,000,000)
$\widetilde{C}_{3vj}$	~Unif (3,000,000, 4,000,000)	~Unif (4,000,000, 5,000,000)	~Unif (5,000,000, 6,000,000)	~Unif (6,000,000, 7,000,000)
$\widetilde{C}S_{si}$	~Unif (2,000,000, 3,000,000)	~Unif (3,000,000, 4,000,000)	~Unif (4,000,000, 5,000,000)	~Unif (5,000,000, 6,000,000)
$\widetilde{C}M_m$	~Unif (2,000,000, 2,500,000)	~Unif (2,500,000, 3,500,000)	~Unif (3,500,000, 4,500,000)	~Unif (4,500,000, 5,500,000)
$\widetilde{C}D_h$	~Unif (900,000, 1,000,000)	~Unif (1,000,000, 1,500,000)	~Unif (1,500,000, 2,000,000)	~Unif (2,000,000, 2,500,000)
$\widetilde{C}C_c$	~Unif (900,000, 1,000,000)	~Unif (1,000,000, 1,500,000)	~Unif (1,500,000, 2,000,000)	~Unif (2,000,000, 2,500,000)
$\widetilde{F}1_h$	~Unif (200,000, 250,000)	~Unif (250,000, 300,000)	~Unif (300,000, 350,000)	~Unif (350,000, 400,000)
$\widetilde{P}S_{si}$	~Unif (1, 3)	~Unif (3, 6)	~Unif (6, 9)	~Unif (9, 12)
$\widetilde{P}M_m$	~Unif (2, 4)	~Unif (4, 6)	~Unif (6, 8)	~Unif (8, 10)
$\widetilde{P}R_c$	~Unif (2, 4)	~Unif (4, 6)	~Unif (6, 8)	~Unif (8, 10)
$\widetilde{P}C_{ci}$	~Unif (2, 4)	~Unif (4, 6)	~Unif (6, 8)	~Unif (8, 10)
$\widetilde{T}C1_{mhvi}$	~Unif (10, 12)	~Unif (12, 14)	~Unif (14, 16)	~Unif (14, 18)
$\widetilde{T}C2_{jj'k}$	~Unif (10, 12)	~Unif (12, 14)	~Unif (14, 16)	~Unif (14, 18)
$\widetilde{T}C3_{hcvj}$	~Unif (10, 12)	~Unif (12, 14)	~Unif (14, 16)	~Unif (14, 18)
SP	20	30	40	50

Table 4. Optimum value for different sample problems for different levels.

	Problem No.			
$\alpha - cut\ level$	**1**	**2**	**3**	**4**
$\alpha = 0$	[190,528,300, 773,505,400]	[474,328,100, 1,719,479,000]	[590,739,600, 2,150,690,000]	[306,343,100, 1,191,767,000]
$\alpha = 0.2$	[217,807,900, 726,333,400]	[527,852,300, 1,663,605,000]	[662,951,500, 2,150,690,000]	[342,264,400, 1,138,206,000]
$\alpha = 0.4$	[246,618,800, 680,223,700]	[584,420,000, 1,494,726,000]	[727,251,800, 2,032,501,000]	[421,803,700, 1,076,690,000]
$\alpha = 0.6$	[276,812,200, 6,302,216,00]	[631,762,400, 1,387,619,000]	[775,098,100, 1,748,506,000]	[464,338,500, 995,462,700]
$\alpha = 0.8$	[308,375,900, 577,293,400]	[679,946,900, 128,397,3000]	[845,901,700, 1,599,929,000]	[500,146,300, 912,892,800]
$\alpha = 1$	[341,418,500, 526,630,300]	[748,914,300, 1,183,985,000]	[986,029,000, 1,457,822,000]	[554,242,300, 833,767,800]

Figure 2 shows the network structure of the model when α- cut is 0.4 for the lower bound for problem number one, and the model took 0.25 s (CPU time) to be solved. It shows that the model selected suppliers 2 and 3 to send raw materials to the manufacturer. It also shows that hybrid facilities 1, 5, and 6 were selected to support the demand zones. As it can be seen, hybrid facilities 1 supports demand zone 6, 4, and 8, consecutively.

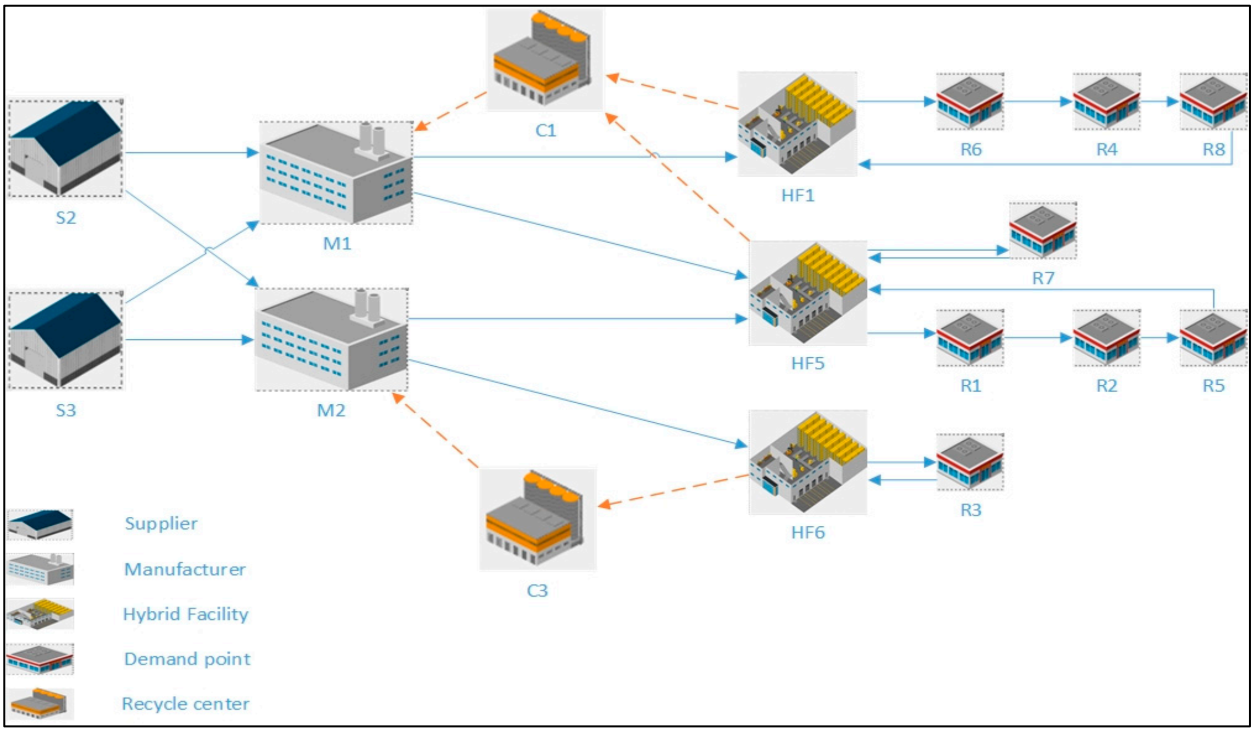

Figure 2. Network configuration when α-cut level is 0.4 for the lower bound for problem number one.

Figure 3 depicts the model's network structure when the cut is set to 0.6 for the lower bound on problem number one. Figures 2 and 3 show that retailer number 5 is assigned to hybrid facility number 6, and each supplier is dedicated to only one manufacturer. Furthermore, retailer 7 has been added to the route of retailers 1 and 2 for hybrid facility 5. When these two figures are compared, the number of arrows decreases, indicating that the model is attempting to optimize routes and assign hybrid functions to retailers as efficiently as possible.

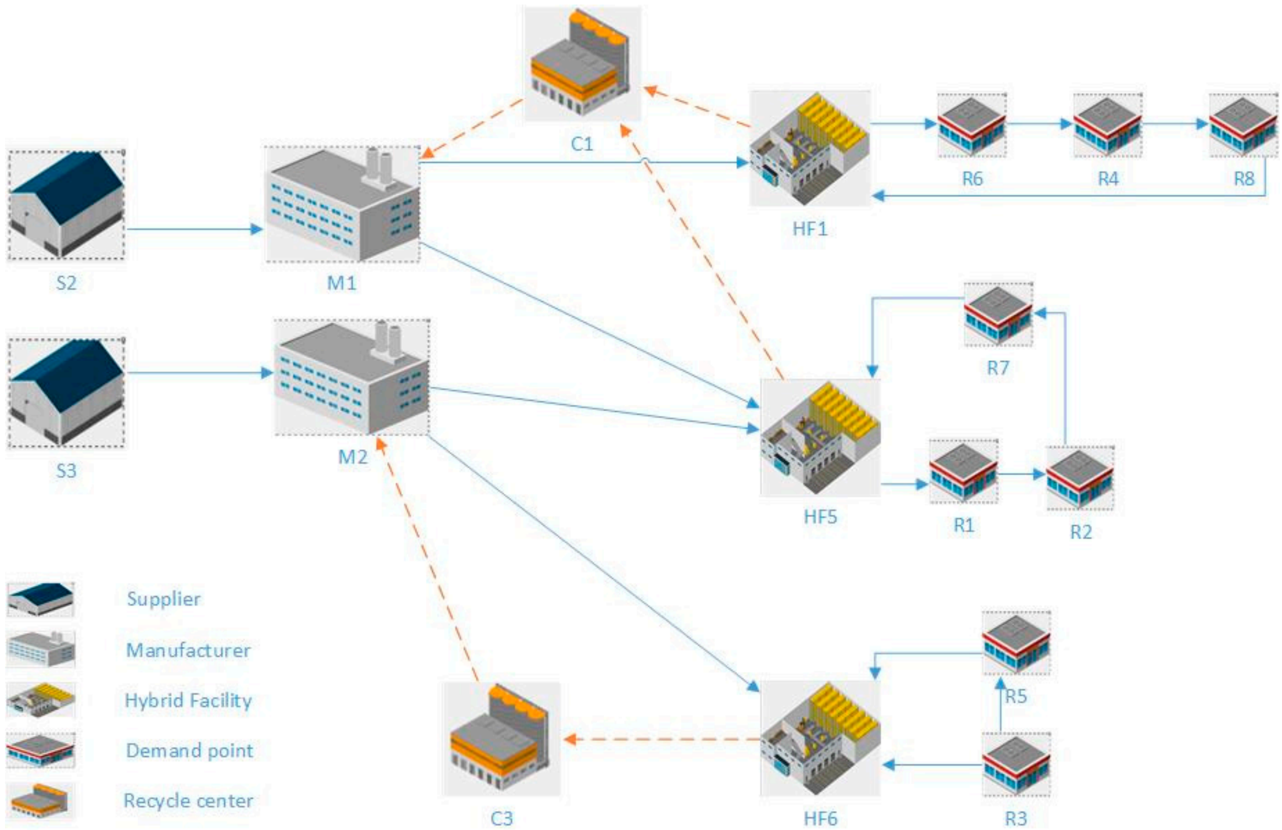

Figure 3. Network configuration when α-cut level is 0.6 for the lower bound for problem number one.

Figure 4 depicts a network structure of the model when the α- cut is 0.4 for the lower bound for problem number two and the model took 0.42 s (CPU time) to be solved. It shows suppliers 2,3 and 5 were selected from among five suppliers. It also shows that hybrid facilities 1, 4, 7, 9, and 11 were selected to support demand zones. Figures 3 and 4 also demonstrate how changes in the size of the model will affect the complexity of the model and the network.

Figure 5 shows the value of the objective function for problem number 2 for the upper and lower bounds. As can be seen, the objective-function value changes with the change in α-cut levels. It shows that with the increase in α-cut levels, the value of the objective function decreases for the upper bound. On the other hand, with the increase in α-cut levels, the value of the objective function increases for the lower bound of the objective function. Moreover, it shows that the acceptable range of the objective function has a reverse relationship with the α-cut levels: an increase in the α-cut-level objective value has a narrower range, and vice versa. This can be explained with the Kaufmann, Gil Aluja [87] rules of feasibility degree. As previously stated, they established 11 levels of feasibility degree, ranging from completely unacceptable (=0) to completely acceptable (=1). When $\alpha = 0.1$ the level of confidence is very low; therefore, the model generates a high range of value for the objective function. As the level of confidence grows, the model becomes more certain, and the objective function value has a narrower range.

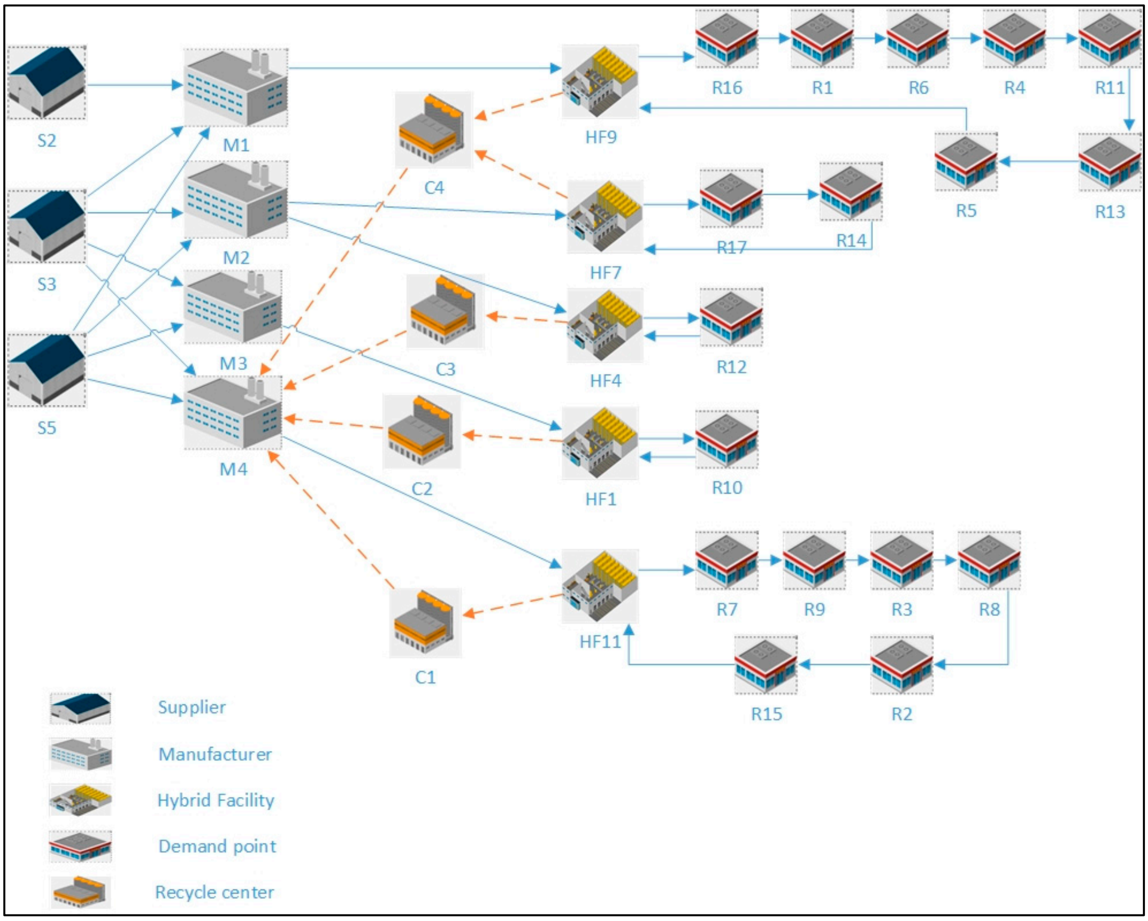

Figure 4. Network configuration when α- cut level is 0.4 for the lower bound for problem number two.

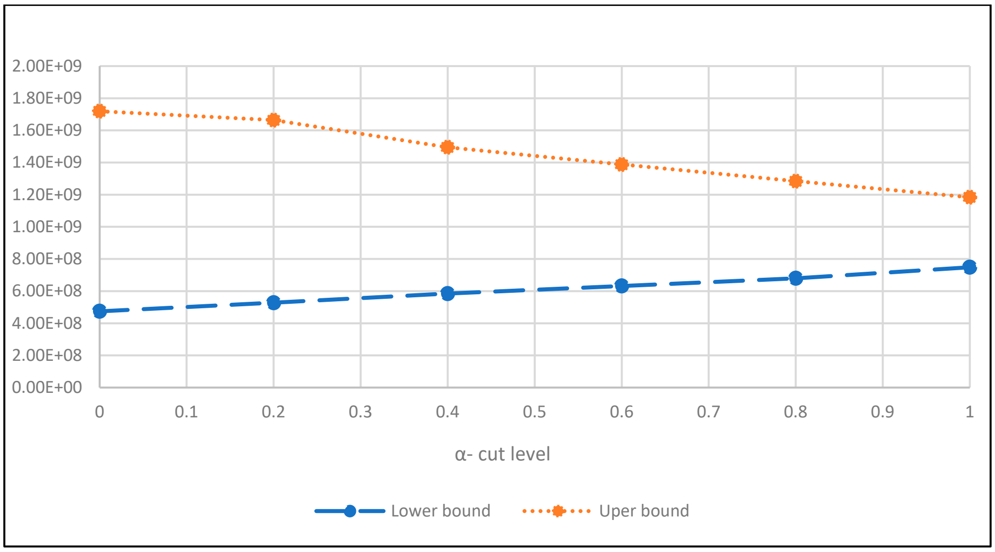

Figure 5. Acceptable level of the objective function.

Figure 6 shows the value of objective functions when the number of return products increased by 20%. It shows that with the increase in α- cut levels, the range of acceptable objective-function values decreases.

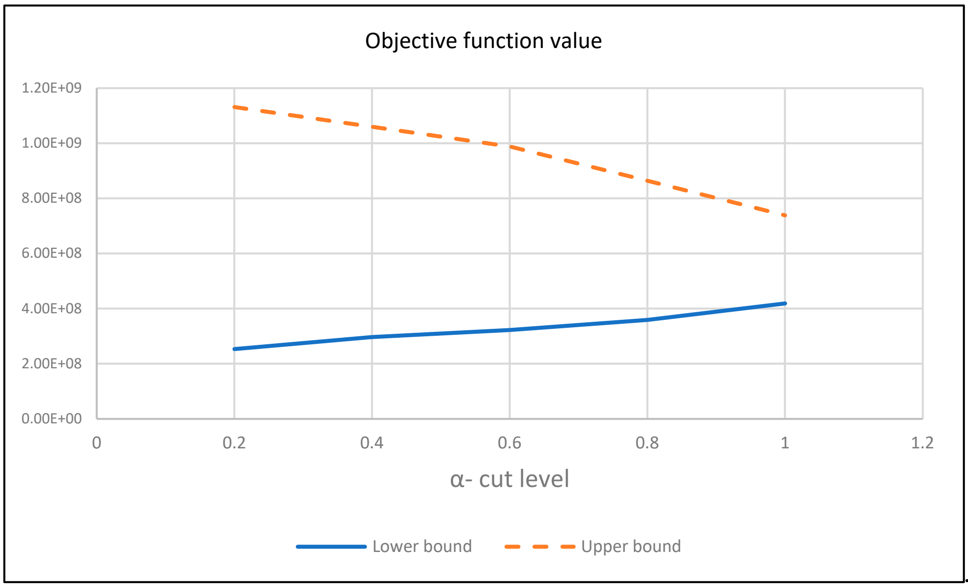

Figure 6. Acceptable level of the objective function with a 20% increase in return products.

4. Conclusions

Because of the growing concern about sustainability and the future, there has been a rise in recent years in the industry-wide awareness of environmental protection [88–90]; despite its price, CLSC is a solution for sustainability [91]. This paper explained that it is possible to achieve significant cost savings and revenue growth while also protecting the environment by designing an efficient supply chain network that considers both forward and reverse networks during the planning process. Moreover, to accomplish this, the authors developed a model that incorporates the vehicle-routing problem into the conventional CLSC-network design and a strategy for dealing with uncertain parameters that arise during the development of the CLSC network. In order to achieve the objectives, a mixed-integer linear-programming model for CLSC-network design with routing decisions under fuzzy and random uncertain data was developed. A hybrid fuzzy-stochastic mathematical-programming approach was employed to overcome the complexity and uncertainty in the parameters of the CLSC network.

Nevertheless, Kabak and D. Ruan [92] proposed a mathematical model with resource allocation and outsourcing decisions. They were only two decision variables in fuzzy form; in this study, all the variables are in fuzzy numbers to assist decision makers to make accurate decisions regarding cost reduction, increasing the revenue of a company as well as environmental protection. The objective function and the constraints are developed using fuzzy numbers, which transforms the problem from deterministic to stochastic. The fuzzy-stochastic type of uncertainty can be formulated using two-stage stochastic programming (TSP) with a recourse model. In this method, the decisions are made in two phases; phase 1 parameters need to be determined before the value of a random variable, and phase 2 parameters need to be determined after the random event has happened. The second-stage decision can be made for the minimization of penalties that occur because of infeasibility. Fallahpour et al. [93] proposed a hybrid fuzzy-programming approach for the modeling of a sustainable, resilient supply chain network. A case study of the palm oil industry in Malaysia was proposed. Their study focuses on the forward supply chain only. The advantage of this current research is that in this research the authors developed a CLSC-network design by integrating VRP. Integrating CLSC with VRP furnishes companies with a useful decision-support system encompassing all three types of strategic, tactical, and operational decisions in parallel. The strategic decision is addressed in selecting the location, the tactical decision is applied by determining the flow of materials and products among the facilities, and the operational decision is conveyed by defining a route to distribute products to the customers.

A series of different examples were formed to demonstrate the validity of the proposed MILP model. In this paper, we considered a variety of scenarios. The model performed well, and it can be used with a single product and for a single period of time, which shows great promise for contributing to the advancement of both knowledge and practice. Every study has limits, regardless of how carefully it is performed, and this study is no exception. When developing the models, there were several limitations, most of which were connected to the models' assumptions. As with most mathematical models which contribute to basic research outcomes, the results of this study are highly dependent on the assumptions that were made in formulating the problem. Future studies can broaden the scope of the study to include a broader range of products and time periods; another area of investigation in the near term is the recognition of a model using real-world data.

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Nomenclature

The following notations have been used in this paper:

s	set of suppliers $s \in S$
i	set of raw materials $i \in I$
m	set of plants $m \in M$
h	set of hybrid facilities (HF_s) $h \in H$
$r\&j$	set of customers
b	aggregate set of hybrid facilities and customers $(h \cup r)$
c	set of recycling centers $c \in C$
vi	set of vehicles $vi \in VI$ at node M
k	set of vehicles $k \in K$
vj	set of vehicles $vj \in VJ$ at node RC
Parameters:	
d_{1mh}	distance between plants $m \in M$ and hybrid facility $h \in H$
$d_{2jj'}$	distance between customer in node $j \in J$ and $j' \in J$
$d_{3_{hc}}$	distance between hybrid facility $h \in H$ and recycling center $c \in C$
$\widetilde{D}_r$	demand of customer $r \in R$
$\widetilde{P}_r$	pickup customer $r \in R$
MD_{2_k}	maximum distance which vehicle $k \in K$ covers in a tour
$C_{1_{vi}}$	capacity of vehicle $vi \in VI$
C_{2_k}	capacity of vehicle $k \in K$
$C_{3_{vj}}$	capacity of vehicle $vj \in VJ$
CS_{si}	capacity of supplier $s \in S$ to supply raw material $i \in I$
CM_m	production capacity of plant $m \in M$
CD_h	distribution capacity of hybrid facility $h \in H$
CC_c	recycling capacity of recycling center $c \in C$
PS_{si}	purchasing cost per unit of material $i \in I$ from supplier $s \in S$

PM_m	production cost per unit of product at plant $m \in M$
PR_c	recycling cost per unit of product at recycling center $c \in C$
PC_{ci}	purchasing cost of unit of material $i \in I$ from recycling center $c \in C$
B_2	total number of customers
F_{1_h}	fixed opening cost of hybrid facility $h \in H$
$TC_{1_{mhvi}}$	transportation cost per unit of product of vehicle $vi \in VI$ between plant $m \in M$ and hybrid facility $h \in H$
$TC_{2_{jj'k}}$	transportation cost per unit of product of vehicle $k \in K$ between customer $j \in J$ and customer $j' \in J$
$TC_{3_{hcvj}}$	transportation cost per unit of product of vehicle $vj \in VJ$ between hybrid facility $h \in H$ and recycling center $c \in C$
u_i	utilization rate of material $i \in I$
SP	selling price of end-of-life product
Decision variables:	
$X_{2_{jj'k}}$	binary variable indicating whether vehicle $k \in K$ travels directly from node $j \in J$ to node $j' \in J$
$Y_{2_{hr}}$	binary variable if hybrid facility $h \in H$ is assigned to customer $r \in R$
U_{1_h}	binary variable if hybrid facility $h \in H$ is open
L_{2_k}	load of vehicle $k \in K$ when leaving hybrid facility
$L_{2'_k}$	load of vehicle $k \in K$ after having serviced all assigned customers
$M_{2_{rk}}$	sub-tour elimination variable for customer $r \in R$ in $k \in K$
R_{2_h}	distribution quantity of hybrid facility $h \in H$
$R_{2'_h}$	pick-up quantity for return product of hybrid facility $h \in H$
$X_{0_{sim}}$	shipment quantity of raw material $i \in I$ between supplier $s \in S$ and plant $m \in M$
$X_{1_{mhvi}}$	shipment quantity between plant $m \in M$ and hybrid facility $h \in H$ with vehicle $vi \in VI$
$X_{3_{hcvj}}$	shipment quantity between hybrid facility $h \in H$ and recycling center $c \in C$ with vehicle $vj \in VJ$
$X_{4_{cim}}$	shipment quantity of raw material $i \in I$ between recycling center $c \in C$ and plant $m \in M$
$Lt_{jj'k}$	unload of demand for vehicle $k \in K$ from node $j \in J$ to node $j' \in J$
$Lt'_{jj'k}$	load of vehicle $k \in K$ from node $j \in J$ to node $j' \in J$

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