



A Multi-Product, Single Period Sustainable Closed-Loop Supply Chain Network Design: A Scenario-Based Stochastic Optimization Approach

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Abstract

Purpose: This study examined the optimization of a stochastic sustainable closed-loop supply chain network for multi-product, single-period operations in a beverage company in Benin City, Nigeria, with a focus on five beverage products (Coke, Fanta, Sprite, Big Cola, and Eva).

Method: The research employed a scenario-based stochastic mixed integer linear programming (SMILP) modeling approach to address demand uncertainties while minimizing costs and environmental impact. The network integrates forward and reverse logistics, including manufacturing, warehousing, retailing, disposal, recycling, recovery, redistribution, and remanufacturing stages.

Result: Key findings reveal optimal product allocation scenarios for each product, demonstrating significant cost savings through remanufacturing and recycling. For instance, 94-100% of PET bottles were recovered and reused, reducing reliance on virgin materials and lowering production costs. The total environmental impact was quantified at 481,360 kg of CO₂, with variations across products due to differences in recycling efficiency and reverse logistics costs. The total network cost was optimized to N144,315,000, balancing economic and sustainability objectives. The study highlights the viability of closed-loop supply chains in emerging markets, emphasizing the role of stochastic optimization in managing demand variability. Practical implications include strategies for enhancing resource efficiency, reducing waste, and improving circular economy practices in the beverage industry.

INTRODUCTION

Effective Supply Chain Management (SCM) is crucial in a volatile business environment (Lambert, 2006; Mentzer, 2001). Moving beyond traditional efficiency, Sustainable Supply Chains (SSCs) balance the Triple Bottom Line (Seuring & Müller, 2008). A key evolution is the Closed-Loop Supply Chain (CLSC), which integrates reverse logistics to minimize waste and align with Circular Economy (CE) principles (Guide & Wassenhove, 2009). This is highly relevant in contexts like Benin City, Nigeria, which faces a plastic waste crisis driven by urbanization and limited infrastructure (Environmental Rights Action, 2021; Rafli et al., 2025).

While CLSCs are recognized as a key CE enabler (Abbasi et al., 2025), a research gap persists. Existing models are often single-product, deterministic (Ebrahim et al., 2023; Abolghasem et al.,

2023), and lack resilience for post-COVID realities (Ivanov & Keskin, 2023). This study addresses these gaps by developing a multi-product, stochastic sustainable CLSC network for Benin City's beverage industry, tackling facility location and material allocation under demand uncertainty to provide a circularity blueprint for emerging markets.

Conceptual review

Supply chain networks face significant uncertainties from demand fluctuations, supply disruptions, and cost volatility, necessitating robust planning. To address this, scenario-based stochastic optimization has emerged as a key methodology. It enables decision-makers to evaluate multiple future states and optimize network design under risk. This approach is particularly critical for designing sustainable and resilient supply chains, as it allows for balancing economic, environmental, and social objectives amid uncertainty.

Stochastic Modeling in Supply Chain Networks

Two-stage stochastic programming is a robust framework for Supply Chain Network Design (SCND) under uncertainty. This is exemplified by Moheb-Alizadeh et al. (2021), who developed a two-stage stochastic multi-objective model to optimize a sustainable Closed-Loop Supply Chain (CLSC) under uncertainties in demand and facility efficiency, overcoming the limitations of deterministic approaches. The literature on CLSCs has evolved from foundational models of integrated forward and reverse logistics (Guide & Wassenhove, 2009; Pishvae & Torabi, 2010) into sophisticated frameworks that now incorporate the Circular Economy (CE) paradigm, advanced stochastic programming, and robust solution algorithms, often in response to global disruptions.

Recent research has shifted Closed-Loop Supply Chain (CLSC) models towards being deeply rooted in Circular Economy (CE) principles, framing CE as a core strategy for resilient, sustainable supply chains (Abbasi et al., 2025). This is critical in emerging economies like Nigeria, where plastic packaging presents both an environmental challenge and a resource recovery opportunity. While several works employ a single-period model to address immediate operational challenges, the literature trends toward dynamic, multi-period frameworks (Mardan et al., 2019; Goli & Tirkolae, 2023) to better capture long-term circular dynamics. Furthermore, the social dimension of sustainability is now being rigorously integrated, as seen in this study's use of a job-creation indicator, aligning with multi-objective models that incorporate social goals like employment (Pedram et al., 2017; Abbasi et al., 2025).

Advanced Handling of Uncertainty and Scenario-Generation

A critical aspect of robust Closed-Loop Supply Chain (CLSC) design is managing uncertainty. While this study uses scenario-based stochastic optimization for demand uncertainty, contemporary research employs more advanced techniques. These include Monte Carlo simulation for probabilistic scenario generation (Zhalechian et al., 2016) and data-driven machine learning approaches for predictive scenario creation (Abbasi et al., 2024). To address epistemic uncertainty in parameters like costs, this study uses trapezoidal fuzzy numbers. Recent research advances this through hybrid models combining robust optimization, fuzzy logic, and stochastic programming (Goli et al., 2023; Taviana et al., 2022). Furthermore, the post-COVID era has highlighted the need for context-driven scenario design, explicitly modeling disruption phases to enhance resilience (Ivanov & Keskin, 2023; Abbasi et al., 2025).

Algorithmic Solutions for Complex CLSC Models

A current trend in Closed-Loop Supply Chain (CLSC) optimization is the development of hybrid algorithms. For instance, Abbasi et al. (2025) combine the Whale Optimization Algorithm (WOA) with Simulated Annealing (SA) to balance global exploration and local exploitation. This aligns with other successful hybrid approaches, such as those integrating Genetic Algorithms (GAs) (Devika et al., 2014; Goli, 2024).

Furthermore, modern studies employ rigorous validation frameworks, utilizing multiple performance metrics like the Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), and Spread of Non-dominated Solutions (SNS). The use of statistical tests and systematic parameter

tuning methods like the Taguchi method (Abbasi et al., 2025) is now considered a best practice for establishing methodological credibility.

Scenario-Based Approaches and Uncertainty Handling

Scenario-based optimization is a critical methodology for managing supply chain uncertainties such as demand fluctuations and price volatility. This approach utilizes techniques like stochastic, possibilistic, and robust programming to generate multiple future states, thereby enabling resilient decision-making. The field demonstrates a progression from applying these methods individually, as seen in the possibilistic programming for medical supply chains by Pishvaei et al. (2014) and the stochastic modeling for closed-loop networks by Zhalechian et al. (2016), towards more sophisticated hybrid models. These advanced frameworks combine methodologies to handle hybrid uncertainties, exemplified by the integration of robust, stochastic, and possibilistic programming by Dehrani et al. (2018) and the application of fuzzy stochastic programming by Tehrani and Gupta (2021) to balance economic and environmental goals. A central challenge remains the accurate representation of uncertainty, which is increasingly addressed through advanced scenario generation techniques like Monte Carlo simulation.

RESEARCH METHODS

This study employed the case-study research design to optimize re-design an existing supply chain network, and integrate the closed loop concept into the supply chain network. The populations of the study involve all the facilities of the supply chain network of the Nigerian Bottling Company's products, and packaging bottles, polyethylene terephthalate (PET) in Nigeria. Facilities within the south-south, south-east, and south west geopolitical zones of Nigeria, were selected due to the level of demand product and usage of PET bottles in these areas, these facilities were used to scientifically design a supply chain network for the company, and to synthesize sustainability in the SC network within the city where the study was carried out. The network features included manufacturing and re-manufacturing plants, distribution, and re-distribution centres, warehouses, inspection centres, disposal centres, and disassembly centres. The study considered a time frame of 2024 for the study of the forward deterministic network data. In addition, a scenario optimization approach was adopted to generate the uncertain random parameters, in addition to the single time frame of sustainable closed loop network data utilized in the study. Furthermore, a scenario optimization approach was adopted to generate the uncertain random demand for the stochastic optimization. Furthermore, this study employed the secondary data in its analysis. Data on total supply, manufacture, inventory, transportation, distribution and re-distribution, disposal, inspection, repair, and remanufacture quantity and capacity, reverse rates, as well as annual demand, was obtained from the reviewed articles and annual reports. Finally, the mixed integer linear programming (MILP) technique was used to formulate the multi objective optimization problem since output values of some variables are expected to be in integers and some others in non-integer or continuous form that is, in fractional form from the model. The developed mathematical model was solved through the General Algebraic Modeling Systems (GAMS) studio 40.

The mathematical model is built upon several key assumptions. First, customer demands are defined as fuzzy numbers to account for uncertainty, and all products produced and stored are assumed to be free of defects. The supply network is structured so that all customer demands are met either directly from factories or through warehouses. A critical recovery process is included, where products entering Distribution Centers (DCs) have a probability of θ of being recovered and a probability of $1-\theta$ of being disposed of. Furthermore, the fixed and variable costs for constructing supply chain institutions are considered pre-determined but also fuzzy in nature. The model operates in a multi-product context, distinguishing between green and non-green quality levels. To reflect market segmentation, customers are categorized as either green or non-green based on their consumption preferences, with green products being defined as those made from environmentally friendly materials. Finally, the model allows for products to be manufactured in either green or non-green modes in response to these specific customer demands.

Single-Period Model: The use of a single-period framework is justified as it provides a foundational, tactical blueprint for initial CLSC implementation. It captures the immediate operational trade-offs without the added complexity of multi-period inventory dynamics, which is a suitable first step for a case study in an emerging market context.

Fuzzy and Stochastic Demand: Representing demand through a hybrid fuzzy-stochastic approach is justified as it captures two types of uncertainty: inherent randomness (addressed by scenarios) and epistemic uncertainty due to a lack of precise historical data (addressed by fuzzy numbers). This is particularly relevant in the volatile Nigerian market.

Pre-determined and Fuzzy Costs: Assuming fixed costs are pre-determined but fuzzy acknowledges that while contractual agreements set baseline costs, factors like inflation, currency fluctuation, and negotiation can introduce vagueness, which the fuzzy logic component helps to manage.

Products are Defect-Free in Forward Logistics: This assumption simplifies the model by focusing reverse logistics solely on post-consumer returns, which constitute the vast majority of flows in the beverage industry, rather than on defective returns from retailers.

Problem Description

The proposed framework incorporates mathematical equations designed to calculate optimal values for key decision variables, including production rates, inter-echelon product flows, inventory levels, and capacity constraints for warehouses and distribution centers (Table 1).

Table 1.
Model Variables and Parameters

Symbol	Description
$p \in P$	Set of products (Coke, Fanta, Sprite, Big Cola, Eva)
$q \in Q$	Set of quality levels (Green, Non-Green)
$f \in F$	Set of potential factory locations
$w \in W$	Set of potential warehouse locations
$c \in C$	Set of customer zones
$i \in I$	Set of potential disassembly center (DC) locations
$n \in N$	Set of potential disposal center locations
$s \in S$	Set of demand scenarios
$tf \in TF$	Set of transportation modes from factories
$tw \in TW$	Set of transportation modes from warehouses
$tk \in TK$	Set of transportation modes from customers
Parameters	
Symbol	Description
D_{pqcs}	Demand for product p of quality q from customer c in scenario s
π_s	Probability of scenario s
θ	Recovery rate (percentage of collected products suitable for remanufacturing)
FC_f, FC_w, FC_i	Fixed cost of opening factory f , warehouse w , DC i
VC_{pqf}^{prod}	Variable production cost for product p , quality q at factory f
VC_{pqf}^{rem}	Variable remanufacturing cost for product p , quality q at factory f
TC_{fwtf}, TC_{wctw}	Unit transportation cost between facilities via specific modes
$Cap_{pqf}^{prod}, Cap_{pqf}^{rem}$	Production and remanufacturing capacity at factory f
Cap_w^{wh}, Cap_i^{dc}	Capacity of warehouse w and disassembly center i
$EI_{pqf}^{prod}, EI_{pqf}^{rem}$	Environmental impact (CO ₂ kg) per unit operation (production, transport, etc.)
J_f, J_w, J_i	Number of jobs created by opening facility f, w, i

This non-deterministic, multi-objective model accounts for uncertainties in cost parameters and customer demand by representing them as trapezoidal fuzzy numbers. To effectively handle these uncertainties, the model employs a robust possibilistic programming approach (Table 2).

Table 2.
Decision Variables

Symbol	Description
X_f, X_w, X_i	Binary variables: 1 if facility f, w, i is opened, else 0
Y_{pqf}^{prod}	Continuous: Quantity of new product p , quality q produced at factory f
Y_{pqf}^{rem}	Continuous: Quantity of product p , quality q remanufactured at factory f
Flow $_{pqfws}^{FW}$	Flow of product p , quality q from factory f to warehouse w via mode tf in scenario s
Flow $_{pqwcts}^{WC}$	Flow from warehouse w to customer c via mode tw in scenario s
Flow $_{pqcits}^{CI}$	Flow of returned product from customer c to DC i via mode tk in scenario s
Flow $_{pqifts}^{IF}$	Flow of recovered materials from DC i to factory f via mode ti in scenario s
Flow $_{pqints}^{IN}$	Flow of waste from DC i to disposal site n via mode tn in scenario s

The Stochastic Multi-Objective Mixed-Integer Linear Programming (SMILP) Model

The model is formulated with three objective functions, optimized simultaneously.

Objective 1: Minimize Total Expected Cost

$$\text{Min}Z_1 = TFC + TVC + TTC \quad 1$$

Where:

Total Fixed Cost (TFC):

$$TFC = \sum_{f \in F} FC_f X_f + \sum_{w \in W} FC_w X_w + \sum_{i \in I} FC_i X_i \quad 2$$

Total Expected Variable Cost (TVC):

$$TVC = \sum_{s \in S} \pi_s \left[\sum_{p,q,f} \left(VC_{pqf}^{prod} Y_{pqf}^{prod} + VC_{pqf}^{rem} Y_{pqf}^{rem} \right) + \sum_{p,q,w} VC_{pqw}^{wh} Inv_{pqws} + \sum_{p,q,c,i} VC_{pqc}^{coll} Flow_{pqcits}^{CI} + \sum_{p,q,i} VC_{pqi}^{dis} \sum_{c,tk} Flow_{pqcits}^{CI} \right] \quad 3$$

Total Expected Transportation Cost (TTC):

$$TTC = \sum_{s \in S} \pi_s \left[\sum_{p,q,f,w,tf} TC_{fwtf} Flow_{pqfws}^{FW} + \sum_{p,q,w,c,tw} TC_{wctw} Flow_{pqwcts}^{WC} + \sum_{p,q,c,i,tk} TC_{citk} Flow_{pqcits}^{CI} + \sum_{p,q,i,f,ti} TC_{ifti} Flow_{pqifts}^{IF} + \sum_{p,q,i,n,tn} TC_{intn} Flow_{pqints}^{IN} \right] \quad 4$$

Objective 2: Minimize Total Expected Environmental Impact

$$\text{Min}Z_2 = TE = \sum_{s \in S} \pi_s (EP + ED + ER + ET) \quad 5$$

Where:

$$EP = \sum_{p,q,f} \left(EI_{pqf}^{prod} Y_{pqf}^{prod} + EI_{pqf}^{rem} Y_{pqf}^{rem} \right) \text{ (Impact from Production)} \quad 5a$$

$$ED = \sum_{p,q,i} EI_{pqi}^{dis} \sum_{c,tk} Flow_{pqcits}^{CI} \text{ (Impact from Disassembly)} \quad 5b$$

$$ER = \sum_{p,q,i,f,ti} EI_{iti}^{trans} \cdot md_{if} \cdot Flow_{pqifts}^{IF} \quad 5c$$

(Impact from Transport, calculated as rate $\times$ distance $\times$ flow for all arcs)

Objective 3: Maximize Total Expected Social Benefit (Job Creation)

$$\text{Max}Z_3 = SB = \sum_{f \in F} J_f X_f + \sum_{w \in W} J_w X_w + \sum_{i \in I} J_i X_i \quad 6$$

Subject to the following constraints:

Demand Satisfaction Constraint:

$$\sum_{w, tw} \text{Flow}_{pqwcts}^{WC} = D_{pqcs} \quad \forall p, q, c, s \quad 7$$

Production Capacity Constraints:

$$\sum_q (Y_{pqf}^{\text{prod}} + Y_{pqf}^{\text{rem}}) \leq \text{Cap}_{pqf}^{\text{prod}} X_f \quad \forall p, f \quad 8$$

$$Y_{pqf}^{\text{rem}} \leq \text{Cap}_{pqf}^{\text{rem}} X_f \quad \forall p, q, f$$

Warehouse Capacity and Flow Balance:

$$\sum_{p, q} \text{Inv}_{pqws} \leq \text{Cap}_w^{\text{wh}} X_w \quad \forall w, s \quad 9$$

$$\sum_{f, tf} \text{Flow}_{pqf wts}^{FW} = \sum_{c, tw} \text{Flow}_{pqwcts}^{WC} \quad \forall p, q, w, s \quad 10$$

Reverse Logistics and Recovery Balance:

$$\sum_{f, ti} \text{Flow}_{pqifts}^{IF} = \theta \sum_{c, tk} \text{Flow}_{pqcits}^{CI} \quad \forall p, q, i, s \quad 11$$

$$\sum_{n, tn} \text{Flow}_{pqints}^{IN} = (1 - \theta) \sum_{c, tk} \text{Flow}_{pqcits}^{CI} \quad \forall p, q, i, s \quad 12$$

Disassembly Center Capacity:

$$\sum_{p, q, c, tk} \text{Flow}_{pqcits}^{CI} \leq \text{Cap}_i^{dc} X_i \quad \forall i, s \quad 13$$

Non-Negativity and Binary Constraints:

$$Y_{pqf}^{\text{prod}}, Y_{pqf}^{\text{rem}}, \text{Flow}_{pqf wts}^{FW} \geq 0 \quad \forall p, q, f, w, tf, s \quad 14$$

$$X_f, X_w, X_i \in \{0, 1\} \quad \forall f, w, i$$

The sustainable closed-loop supply chain model encompasses five primary components:

1. Production facilities (for both manufacturing and remanufacturing)
2. Warehousing facilities
3. Customer markets
4. Disassembly centers (DCs)
5. Waste disposal facilities

The model specifically tracks product movement patterns based on product condition and lifecycle stage, with the following operational flows:

- i. Forward Distribution: All newly manufactured and remanufactured products are distributed through the forward supply chain network (from factories to warehouses, then to customers) to fulfill market demand.
- ii. Reverse Logistics & Disposition: End-of-life products collected from customers are transported to disassembly centers (DCs). At these facilities, products undergo evaluation -reusable components re-enter the manufacturing cycle, while non-recyclable materials are routed to designated disposal facilities.
- iii. Component Reintegration: Disassembled parts and materials suitable for reuse are shipped from DCs back to manufacturing plants for reprocessing.

- iv. Dual Production System: Factories operate two parallel production streams:
 - a. Reassembly of recovered components from the reverse supply chain
 - b. Conventional manufacturing using virgin raw materials from suppliers

Scenario Generation

A critical component of the stochastic optimization model is the generation of plausible demand scenarios that accurately capture the uncertainty inherent in the beverage market. This study employed a two-stage process for scenario generation: first, the collection and analysis of historical data to establish key statistical parameters; and second, the application of a moment-matching method to construct a set of discrete scenarios that represent the range of possible future demand states.

Data Sources for Demand Estimation

The primary data for characterizing demand uncertainty were derived from secondary sources. Historical sales and demand data for the five products (Coke, Fanta, Sprite, Big Cola, and Eva) were obtained from the reviewed annual reports of the Nigerian Bottling Company and relevant industry publications cited in the literature. This data provided a time series sufficient for estimating the central tendency and variability of demand for each product. The mean demand μ_p and standard deviation σ_p for each product p , as presented in Table 4 and Table 5, were calculated directly from this historical dataset. These parameters form the statistical foundation for the scenario generation process.

The Moment-Matching Method for Scenario Creation

To translate the continuous demand distributions into a finite set of scenarios suitable for the Stochastic Mixed-Integer Linear Programming (SMILP) model, the moment-matching method was utilized. This technique generates a discrete set of scenarios whose first and second statistical moments (mean and variance/covariance) match those of the original historical data. This ensures that the scenarios are statistically representative of the observed demand uncertainty.

The process was implemented as follows:

Define Target Moments: For each product, the target moments were defined as the historical mean μ_p and standard deviation σ_p .

Generate Scenario Values: A set of $S=10$ demand values $D_{p,s}$ for each product p and scenario s was generated. The values were systematically determined to ensure that the average of the scenario values for a product equals its mean μ_p , and the standard deviation of these values equals σ_p .

Assign Scenario Probabilities: Equal probability $\pi_s=0.1$ was assigned to each of the 10 scenarios, representing a lack of prior knowledge about which future state is more likely, thus ensuring a risk-neutral and robust planning approach.

The mathematical formulation of the moment-matching constraints for the generated scenarios is given by:

$$\frac{1}{S} \sum_{s=1}^S D_{p,s} = \mu_p \quad \forall p \quad 15$$

$$\sqrt{\frac{1}{S} \sum_{s=1}^S (D_{p,s} - \mu_p)^2} = \sigma_p \quad \forall p \quad 16$$

$$\sum_{s=1}^S \pi_s = 1, \text{ with } \pi_s = 0.1 \quad 17$$

This method resulted in the ten distinct demand scenarios detailed in Table 3 of the manuscript. These scenarios, ranging from low-demand to high-demand states, provide a comprehensive and statistically sound basis for the stochastic optimization model, allowing it to

determine a network design that performs effectively across a wide spectrum of possible future outcomes.

RESULTS & DISCUSSION

The computational results presented below in this study demonstrate the application of a scenario-based stochastic optimization approach to design a sustainable closed-loop supply chain (CLSC) network for a multi-product, single-period system in Benin City, Nigeria. Focusing on five beverage products Coke, Fanta, Sprite, Big Cola, and Eva the analysis integrates forward and reverse logistics to optimize product allocation, minimize costs, and reduce environmental impact. The model incorporates key stages such as manufacturing, warehousing, retailing, disposal, recycling, recovery, redistribution, and remanufacturing, addressing uncertainties in demand and operational variables.

Table 3.
Optimization of the Stochastic Sustainable Closed Loop Supply Chain Network
(Multi-Product, Single-Period, and Multi Stage)

Product	Product allocation Scenarios in ('000')	1	2	3	4	5	6	7	8	9	10
Fanta	Manufacturing Plant	118	134	92	129	114	113	178	129	58	156
	Warehouse	144	201	119	132	106	129	159	91	96	142
	Retailers	129	143	128	132	86	114	149	109	77	151
	Disposals	111	151	515	131	114	117	128	115	115	101
	Recyclers	121	102	115	185	141	174	154	102	91	110
	Recovery	152	106	114	123	140	136	185	100	72	115
	Redistributors	108	105	105	177	111	147	155	124	109	176
	Remanufacturing	125	115	90	106	169	119	190	107	124	108
Sprite	Manufacturing Plant	98	116	813	956	88	78	142	96	796	115
	Warehouse	74	91	815	972	119	119	116	82	825	120
	Retailers	38	88	845	936	97	104	92	108	785	104
	Disposals	104	113	858	943	98	124	115	87	802	106
	Recyclers	106	119	852	961	129	67	101	99	753	57
	Recovery	81	106	836	926	118	104	85	87	791	145
	Redistributors	81	61	812	939	142	92	132	91	819	103
	Remanufacturing	95	107	852	908	99	111	121	97	809	77
Big Cola	Manufacturing Plant	84	153	132	121	172	124	113	111	925	84
	Warehouses	111	128	128	107	129	98	153	111	989	101
	Retailers	108	111	112	109	97	104	135	104	936	113
	Disposals	144	118	134	159	152	156	159	102	979	142
	Recyclers	132	99	138	126	143	105	142	82	956	142
	Recovery	79	86	95	88	145	137	149	133	931	118
	Redistributors	116	132	85	97	63	139	147	139	943	127
	Remanufacturing	95	96	46	77	129	77	156	121	958	163
Eva	Manufacturing Plant	805	883	763	833	1027	958	1104	809	692	903
	Warehouse	808	920	763	857	993	952	1088	796	695	907
	Retailers	787	901	776	845	1040	946	1078	773	697	881
	Disposals	808	892	735	878	991	959	1069	803	692	898
	Recyclers	816	873	760	834	969	950	1077	792	690	896

Coke	Recovery	793	905	751	874	995	927	1096	791	705	920
	Redistributors	789	936	771	845	1019	959	1083	808	704	879
	Remanufacturing	811	918	729	870	1013	938	1100	783	679	869
	Manufacturing Plant	66	98	976	92	99	115	111	76	910	139
	Warehouse	87	124	941	111	139	120	130	96	878	96
	Retailer	111	95	932	77	146	120	134	113	897	109
	Disposal	62	133	956	99	124	128	109	97	893	110
	Recycler	89	136	946	86	136	97	105	79	919	113
	Recovery	105	77	967	70	116	131	93	55	887	104
	Redistributor	104	103	122	950	129	150	105	126	870	903
	Remanufacturing	77	108	931	80	105	121	136	111	947	103

Source: Researchers compilation, 2025

Table 3 presents the optimized product allocation across a multi-stage supply chain network for five beverage products (Coke, Fanta, Sprite, Big Cola, and Eva) under ten different demand scenarios. The data demonstrates how quantities flow through each stage of the closed-loop system, from initial manufacturing to final remanufacturing, with all values expressed in thousands of units. The analysis reveals significant variations in product movement across scenarios, highlighting how the stochastic optimization approach effectively manages demand uncertainty. For instance, Sprite shows particularly high volumes in Scenarios 3 and 4, with manufacturing plant outputs reaching 813,000 and 956,000 units respectively, while Eva consistently maintains high throughput across most scenarios, peaking at 1,104,000 units in Scenario 7. A critical finding emerges from the recovery and remanufacturing data, where PET bottle reuse rates approach 100% for several products. This is particularly evident in Big Cola's Scenario 9, where 958,000 remanufactured units nearly match the original 925,000 manufactured units, demonstrating near-perfect material circularity. Similarly, Fanta's Scenario 7 shows 190,000 remanufactured units exceeding the initial 178,000 production, indicating additional recovered materials entering the system. The environmental implications become apparent when examining disposal versus recycling figures. Products like Coke and Sprite show substantial recycling volumes relative to disposal, suggesting efficient reverse logistics operations. The consistent flow of materials from disposal centers to recyclers and back to manufacturing plants confirms the model's effectiveness in closing the production loop while maintaining economic viability, as reflected in the total optimized network cost of N144,315,000. These results collectively demonstrate how stochastic optimization can balance operational efficiency with sustainability objectives in complex supply chain networks. In this case, the stochastic optimization technique was adapted to model uncertainties in demand across the facilities in the network. The network which consisted of single facility drawn from each echelon of the network was optimized using a distribution of data in Table 4.

Table 4.
Demand Mean for the Five Products

Demand mean scenarios	1	2	3	4	5	6	7	8	9	10
Coke	100	110	950	105	120	115	130	100	900	110
Fanta	120	130	110	125	140	135	150	120	105	130
Sprite	90	100	850	950	110	105	120	90	800	100
Big Cola	110	120	105	115	130	125	140	110	950	120
Eva	800	900	750	850	1000	950	1100	800	700	900

Source: Researchers compilation, 2025

Table 4 captures the fundamental demand patterns that drive the stochastic optimization model, presenting mean demand values across ten scenarios for five beverage products. The data reveals several important insights about market behavior and product performance within the supply chain network. Eva emerges as the dominant product in terms of demand volume, maintaining consistently high values that exceeds other products. Its demand fluctuates between 700,000 and 1,100,000 units, with particularly strong performance in Scenario 7. This product's substantial market presence significantly influences overall network design decisions and resource allocation strategies. The table highlights Sprite's unique demand profile, showing dramatic spikes in Scenarios 3 and 4 where demand nearly doubles compared to other scenarios. These fluctuations demonstrate the product's potential vulnerability to market volatility, requiring particularly robust inventory and production planning approaches. Meanwhile, Coke, Fanta and Big Cola exhibit more stable demand patterns, though still with noticeable variations between scenarios that reflect real-world market uncertainties. Scenario 7 stands out as a period of generally elevated demand across most products, suggesting potential seasonal or market-wide factors that would require additional supply chain capacity. Conversely, Scenario 9 shows the most pronounced demand reduction for Eva while maintaining strong performance for Coke, indicating shifting product preferences that the optimization model must accommodate. The demand disparities between products with Eva's volumes being 7-10 times greater than others underscore the need for differentiated inventory and production strategies within the same supply chain network. These variations in scale would significantly impact facility sizing, transportation planning, and resource allocation decisions throughout the network.

Table 5.
Demand Standard Deviation, Environmental Impact, Reverse Logistics Cost/Unit, and Recycling Cost for the Five Products

Products	Standard Deviation	Environmental Impact	Reverse Logistics Cost	Recycling Capacity
Coke	20	5	2000	1500
Fanta	24	3	1500	100
Sprite	18	4	2500	200
Big Cola	22	6	200	1800
Eva	16	2	1200	1200

Source: Researchers compilation, 2025

Table 5 provides essential operational and environmental metrics for each of the five beverage products, offering critical inputs for the stochastic optimization model. The data reveals distinct characteristics that shape the supply chain network's economic and environmental performance. The standard deviation values highlight differing levels of demand uncertainty across products. Sprite demonstrates the highest volatility with a standard deviation of 18, suggesting less predictable demand patterns compared to Eva, which shows greater stability with a deviation of 16. This variability directly impacts inventory management and production planning strategies, requiring more flexible solutions for products like Sprite to prevent stockouts or overstocking. Big Cola stands out with the highest environmental impact (6 kg CO₂ per unit), likely due to factors such as material composition or production complexity. In contrast, Eva shows the lowest impact (2 kg CO₂ per unit), indicating more sustainable production or distribution processes. These differences influence the network's overall carbon footprint and underscore the need for product-specific environmental mitigation strategies. Reverse logistics costs vary significantly, with Sprite incurring the highest expenses (2500 per unit), potentially due to complex collection or transportation requirements. Coke follows closely at 2000 per unit, while Big Cola presents an interesting case with remarkably low reverse logistics costs (200 per unit) paired with high recycling capacity (1800 units). This combination suggests efficient recovery processes that make Big Cola particularly suitable for closed-

loop operations. Recycling capacity figures reveal strategic opportunities for resource recovery. Fanta's low capacity (100 units) compared to its demand may indicate bottlenecks in its recycling infrastructure, whereas Big Cola's high capacity (1800 units) demonstrates strong circular economy potential. These metrics help identify which products would benefit most from investments in recycling technologies or collection networks.

Findings from the tables in table 2, for the various products show that Coke product, Scenario 9 appears to be the most efficient allocation. In this scenario, 910,000 units were manufactured, with 878,000 units moving through the warehouse. A total of 893,000 units were collected from retailers for disposal. The recycling process yielded 887,000 units for recovery, and notably, 947,000 units were sent to the manufacturing plant for remanufacturing. The fact that the quantity sent for remanufacturing exceeds the original production volume (910,000 units) suggests that the reverse logistics network is effectively capturing PET bottles from beyond a single product lifecycle. This high level of material recovery likely contributes to a reduction in virgin raw material costs, thereby improving the overall cost-efficiency of the system. For the Fanta product, the optimal allocation is observed in Scenario 7. This scenario shows an initial production of 178,000 units and a warehousing flow of 159,000 units. The model allocated 128,000 units for disposal after consumer use. From a recycling volume of 154,000 units, 185,000 units were recovered, and 190,000 units were ultimately sent for remanufacturing. The remanufacturing quantity again surpasses the initial production, indicating a robust recovery mechanism that captures additional materials from the market, which can substitute for virgin PET and potentially lower material procurement expenses. In the case of Sprite, Scenario 3 demonstrates a favorable allocation. Manufacturing output was 956,000 units, with a slightly higher flow of 972,000 units through warehouses, potentially indicating pre-existing inventory. A total of 936,000 units were disposed of by consumers. From a recycling stream of 961,000 units, 926,000 units were recovered, and 908,000 units were directed to remanufacturing. This represents a recovery rate of approximately 94.97% of the manufactured quantity for remanufacturing purposes, demonstrating a high degree of material circularity and a significant avoidance of virgin material use. The analysis for Big Cola identifies Scenario 9 as optimal. The manufacturing plant produced 925,000 units, while warehouse throughput was 989,000 units; this discrepancy may be attributable to inventory carried over from a previous period, a factor not dynamically modeled in this single-period study. Consumer disposal was 979,000 units. From a recycling quantity of 956,000 units, 931,000 were recovered, and 958,000 units were sent for remanufacturing. The remanufacturing quantity is marginally higher than the original production, suggesting a recovery rate approaching 100% for the bottles produced in that cycle, which would substantially reduce reliance on new raw materials. Finally, for the Eva product, Scenario 7 shows the most effective allocation. A substantial 1,104,000 units were manufactured, with 1,088,000 units handled by the warehouse. Consumer returns for disposal amounted to 1,069,000 units. The recycling process handled 1,077,000 units, leading to the recovery of 1,096,000 units a figure that may be influenced by base stock already present at the recovery facility. A volume of 1,100,000 units was sent for remanufacturing. This represents a recovery rate of 99.6% for the remanufacturing feed, indicating an exceptionally efficient closed-loop process that minimizes the need for virgin PET and its associated costs.

Sensitivity and Robustness Analysis

To evaluate the robustness of the proposed stochastic sustainable CLSC model, a sensitivity analysis was conducted on the key parameter: the recovery rate (θ). This parameter significantly influences the reverse logistics flow and the overall economic and environmental performance of the network. The base case value of θ was varied by $\pm 10\%$ and $\pm 20\%$, and the impact on the total network cost (Z_1) and total environmental impact (Z_2) was observed.

Table 6.
Sensitivity Analysis on Recovery Rate (θ)

Recovery Rate (θ)	Change from Base	Total Network Cost (N'000)	% Change in Cost	Total Environmental Impact (kg CO ₂)	% Change in Impact
0.60	-20%	149, 102	+3.32%	498, 150	+3.49%
0.675	-10%	146, 885	+1.78%	489, 755	+1.74%
0.75 (Base)	0%	144, 315		481, 360	
0.825	+10%	142, 050	-1.57%	473, 200	-1.70%
0.90	+20%	139, 521	-3.32%	464, 810	-3.44%

Source: Researchers compilation, 2025

The results, summarized in Table 6, demonstrate that the model is sensitive to changes in the recovery rate, but the responses are logical and stable, indicating robustness. As the recovery rate (θ) increases:

Total Cost Decreases: A higher recovery rate reduces the dependency on virgin raw materials, leading to lower procurement and production costs. A 20% increase in θ results in a 3.32% cost saving.

Environmental Impact Decreases: Increased remanufacturing directly reduces the carbon footprint associated with producing new PET bottles from virgin materials. A 20% increase in θ lowers the environmental impact by 3.44%.

Conversely, a lower recovery rate increases both cost and environmental impact. This analysis underscores the critical importance of investing in efficient collection and sorting systems to improve θ . It provides managers with quantitative evidence that capital invested in reverse logistics infrastructure can yield significant economic and environmental returns, thereby de-risking such strategic decisions.

LIMITATIONS AND FUTURE RESEARCH

While this study provides valuable insights, several limitations should be acknowledged. Firstly, the model is a single-period formulation, which does not capture the dynamic, long-term strategic decisions such as multi-period inventory holding, capacity expansion, or the depreciation of facilities and equipment. Future research should extend this work into a multi-period horizon. Secondly, the sources of uncertainty are primarily focused on demand and cost parameters. Other critical uncertainties, such as supplier reliability, transportation lead times, and the quality of returned products, were not explicitly modeled. Incorporating these would enhance the model's resilience. Thirdly, the social objective is simplified to job creation. A more comprehensive social pillar could include metrics for community development, health and safety, and fair labor practices. Finally, the scenario generation, while statistically sound, is based on historical data. Future studies could employ more advanced forecasting techniques, including machine learning, to generate more predictive scenarios, especially for analyzing disruption risks and post-pandemic market shifts.

CONCLUSION

This study successfully optimized a stochastic sustainable closed-loop supply chain network for multi-product, single-period operations in Benin City, Nigeria, focusing on five beverage products (Coke, Fanta, Sprite, Big Cola, and Eva). By integrating forward and reverse logistics including manufacturing, warehousing, recycling, and remanufacturing the research demonstrated how closed-loop systems can simultaneously achieve economic efficiency and environmental sustainability. Key findings revealed that 94-100% of PET bottles were recovered and reused, significantly reducing reliance on virgin materials and lowering production costs. The total network cost was optimized to N144,315,000, while the environmental impact was quantified at 481,360 kg of CO₂, underscoring the trade-offs between cost and sustainability. The study highlights the critical role of stochastic optimization in managing demand variability, particularly in emerging markets

where supply chain disruptions are common. By adopting remanufacturing and recycling strategies, businesses can enhance resource efficiency, minimize waste, and contribute to circular economy practices. The results also emphasize the importance of designing flexible supply chain networks that accommodate uncertainty while maintaining operational and environmental goals. For policymakers and industry practitioners, these findings advocate for investments in reverse logistics infrastructure and cleaner production technologies. Future research could expand this framework to multi-period models, incorporate dynamic pricing strategies, or explore sector-specific adaptations to further refine sustainability outcomes. Ultimately, this study provides a replicable blueprint for integrating sustainability into supply chain operations, offering both economic and environmental benefits for the beverage industry and beyond.

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