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Optimization of Bioethanol Supply Chain from Starch-Based Household FOOD Waste: A Cost Minimization Modelling Framework

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Abstract

A sustainable cost optimization framework for the bioethanol supply chain is developed, using household food waste as a renewable feedstock. Unlike previous studies that mainly focus on agricultural residues, algae, or industrial biomass, this research addresses the specific logistical and economic challenges associated with household food waste, including decentralized generation, perishability, transportation complexity, and variable supply patterns. The proposed mathematical model incorporates key supply chain costs, including waste purchasing, handling, transportation, storage, processing, and facility installation, to minimize the total operational cost of the supply chain network. A genetic algorithm-based optimization approach is applied to determine the optimal configuration of collection centres, processing facilities, and distribution hubs subject to operational and capacity constraints. The numerical results indicate that the proposed framework improves supply chain efficiency while reducing overall system cost. The findings suggest that household food waste can serve as a sustainable and economically viable resource for decentralized bioethanol production and environmentally sustainable urban waste management.

Keywords: household food waste; bioethanol production; supply chain optimization; cost minimization; Genetic Algorithm optimization; waste-to-energy; sustainable waste management

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1. Introduction

Food waste generation has become a major global environmental, social, and economic concern. Approximately 1.3 billion tons of food waste are generated annually worldwide, creating significant environmental, social, and economic challenges. A significant portion of this waste originates from households, offering considerable potential as a renewable energy resource. Converting household food waste into bioethanol is considered a promising waste-to-energy approach, as it simultaneously supports waste management and reduces dependence on fossil fuels. Household food waste serves as a

sustainable and non-edible feedstock that aligns with the principles of a circular economy. Unlike first-generation biofuels, household food waste does not compete directly with food crops. Its high content, continuous availability, and proximity to urban areas make it highly suitable for decentralized bioethanol production systems. Bioethanol is considered an environmentally sustainable alternative to petroleum-based fuels due to its lower greenhouse gas emissions, improved combustion performance, and potential contribution toward energy security.

The switch from traditional feedstock, including agricultural waste, algae, and waste oils, to food waste from homes is a big change in biofuel research. Previous research has shown that renewable energy optimization has come a long way. For example, several optimization models have been developed for algae-based biodiesel, Geographic Information System-based evaluations of agricultural waste, and novel ways to make biodiesel from animal fat and plastics. These papers add to the body of biofuel literature, but they also point out a big gap in research: there aren't many specialized models that deal with the specific problems that come up in home food waste supply networks. Household food waste is different from other biomass sources in that it is spread out, perishable, and has a wide range of compositions. This means that a quick collection and processing procedure is needed to keep it from going bad and to make sure that conversion is cost-effective.

As a result, optimizing the supply chain has become a key part of making sure that bioethanol production from domestic food waste is profitable. Previous studies have investigated several mathematical methodologies, including fuzzy models and inventory optimization approaches, predominantly highlighting the trade-offs among sustainability, efficiency, and operational cost. Although these methods provide useful insights, they are often less effective in reducing costs in highly uncertain household food waste systems. To fill this gap, the current study creates a supply chain model for bioethanol production from domestic food waste that minimizes costs. The model combines several cost factors, including sourcing, handling, processing, and transportation etc. It also used a Genetic Algorithm (GA)-based optimization approach to handle the non-linear and constrained nature of the problem. By balancing sustainability objectives with economic feasibility, this study offers a practical approach for increasing the production of bioethanol from household food waste sustainably and economically.

Q.1 How can food waste from homes be efficiently used as a sustainable feedstock to produce bioethanol?

Q.2 In the production of bioethanol, what is the best supply chain strategy to reduce costs while guaranteeing environmental efficiency?

Q.3 In what ways can this strategy aid in the development of decentralized renewable fuel options within frameworks for energy policy?

By balancing sustainable goals with financial viability, this study offers an approach for increasing the production of bioethanol from household food waste sustainably and economically.

Organization of the Paper

Section 2 examines the body of research on biofuel supply chains, highlighting important discoveries and areas in need of further study. The study's main goal is described in Section 3, along with the modelling assumptions and notions that were employed. The supply chain's entire mathematical structure is developed in Section 4. The optimization model is solved using the Genetic Algorithm, as discussed in Section 5. Section 6 presents the numerical example and optimization results of the proposed household supply chain model. Section 7 talks about the findings through sensitivity analysis, managerial insights, comparative analysis, key findings, and research implications. Section 8 concludes the study and presents suggestions for future research directions.

A framework of the proposed bioethanol supply chain from household food waste is shown in Figure 1, comprising the collection, sorting, processing, and blending stages and the operational cost components.

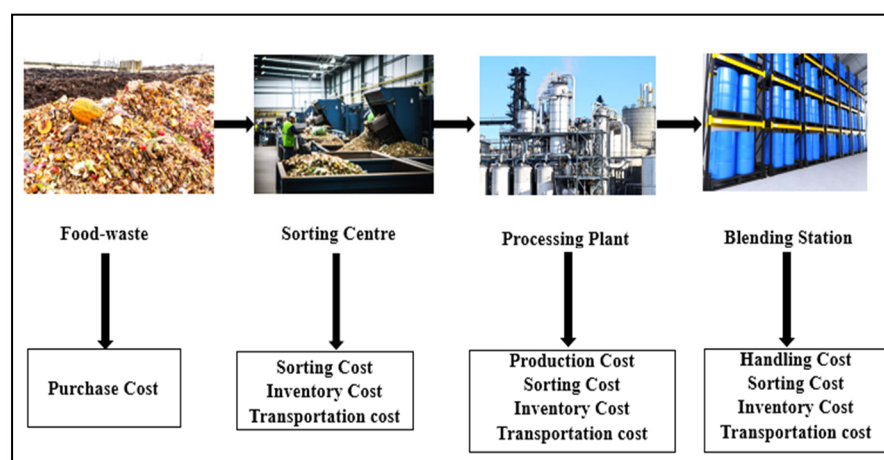


Figure 1. Household food waste is converted using a sustainable supply chain framework.

2. Literature Review

Supply chain optimization has become increasingly critical in biofuel production, particularly for the conversion of household food waste into bioethanol. Shifting from conventional feedstocks to food waste represents a major step toward establishing a circular economy. Ref. [1] reviewed existing and emerging biofuel applications. This research builds on that work by exploring the conversion of household food waste into bioethanol. We propose a supply chain model that minimizes costs while maintaining sustainability. Bioethanol offers a viable alternative to petroleum fuels; it's more environmentally friendly and improves how engines run. Using it more widely could reduce greenhouse gas emissions and make us less dependent on imported oil. Ref. [2] Developed a multi-objective framework to improve macroalgae-based biodiesel supply chains focusing on sustainability and efficiency. However, multi-objective optimization often creates trade-offs that reduce cost efficiency. This issue was particularly important for the household food waste supply chain, as its economic viability often determines whether it can expand beyond small-scale operations [3]. The authors investigated methods to improve resource efficiency in additive manufacturing for automotive parts, contributing to more sustainable supply chain practices [4]. A smart manufacturing framework developed for battery production that includes rework and partial outsourcing to reduce environmental impact [5]. Recent studies have highlighted the importance of sustainable biofuel production from banana rachis waste, emphasizing cost minimization, transportation planning, and sustainable resource utilization [6]. Similarly, pomegranate waste has been investigated as a promising feedstock for biofuel production through an integrated supply chain framework incorporating collection, processing, inventory, and distribution decisions [7]. Other studies have explored biofuel generation from microalgae and biomass resources, demonstrating the effectiveness of optimization techniques and the Genetic Algorithm in improving economic and environmental performance [8]. These studies confirm the potential of waste-to-energy systems; however, limited attention has been given to household waste based on a bioethanol supply chain that simultaneously considers waste collection, sorting, processing, transportation, inventory management, and facility location decisions within a unified optimization framework. Therefore, the present study aims to address this research gap by developing an integrated optimization model for sustainable

bioethanol production from household food waste. While these studies present different mathematical ways to optimize costs, none of them address the logistical challenges specific to household food waste supply chains, especially in collection, processing, and distribution. Because trash comes from many places, has many kinds of waste, and needs to be processed quickly to keep from rotting, the cost structure for making bioethanol from home food waste is very different from that of regular biofuel supply chains. For these reasons, we need specific cost-cutting models that can deal with the many different costs involved in getting, handling, processing, moving, storing, and setting up facilities.

Agricultural waste is a good source of renewable energy because it is cheap and easy to find. Research shows that it can help us use less fossil fuel and release less greenhouse gas [9]. More than 5 billion tons of agricultural waste are produced around the world every year. If these leftovers aren't used, they hurt the environment [10]. Household food waste has many benefits, including a higher starch content, being available all year, and being close to places where people eat in cities. This is why it works so well for bioethanol production systems that are set up. Agricultural waste, on the other hand, provides valuable insights about how to turn biomass into something useful. According to recent studies, Sustainable biofuel chains are becoming increasingly important [11]. A method based on microalgae was developed to create a multi-objective optimization model with an emphasis on sustainability and efficiency. Similarly, ref. [12] use GIS to evaluate food residual biomass for ethanol and power generation, proving that agricultural waste could be used to produce bioenergy. Both studies show the potential of alternative biomass sources in optimizing the renewable energy system while reducing environmental impact. Household food waste supply chain optimization is still underexplored, especially regarding cost-effective collection and processing. Recent biodiesel research emphasizes sustainability through diverse feedstock (like waste cooking oil, algae, and organic waste) and technological advances in supply chain modelling. Singh et al. and related studies highlight the need for integrated frameworks that reduce costs while enhancing renewable energy production. Ref. [13] proposed a critical life cycle study on algae-based biodiesel, highlighting environmental issues and future potential for improved possibilities. A strategic model was introduced for sustainable biodiesel production using waste animal fat, focusing on optimizing biodiesel production methods, drawing attention to the evolution of feedstocks and conversion technology [14].

Investigating the use of waste plastic oils as alternative fuels and analysing engine behaviour under different fuel injection timings, thereby showcasing the potential of non-traditional energy sources [15,16]. Recent research highlights the growing importance of sustainable and circular fuel injection timings, thus showcasing the potential of non-traditional energy sources. Recent research highlights the growing importance of sustainable and circular strategies in the field of biofuel development. Genetic Algorithms (GAs) have proven to be highly useful for enhancing the performance of biofuel supply chains, especially in systems characterized by complex, non-linear interactions and multiple operational constraints. Unlike conventional linear programming methods, GAS is more flexible in handling practical challenges such as inconsistent waste generation, seasonal demand variations, and restricted processing capacities. In this research, domestic food waste is explored as a sustainable feedstock for bioethanol production to improve the efficiency of the overall supply chain. A household waste was investigated as an alternative feedstock for biodiesel production using *Bacillus cereus* [17]. The findings showed that lipids could be effectively extracted from domestic waste and converted into biodiesel. The optimized method resulted in a high level of bioenergy output, indicating that household waste can be a practical, low-cost, and environmentally friendly source of fuel. This study is significant as it demonstrates the technical feasibility of converting household waste. This backs up our goal of making the supply chain work better for large-scale use.

An optimization framework was developed for biodiesel supply network design using an energy sustainability index approach [18]. Their study focused on improving sustainability performance and operational efficiency in biofuel supply chains. However, the framework mainly emphasized biodiesel systems and did not specifically address the cost minimization challenges associated with decentralized household food waste-based bioethanol supply chains. This aligns with our goal of producing bioethanol from food waste. Improved the optimization of the biodiesel supply chain by using new modelling methods in a recent study. To attain equilibrium in ecological efficiency, ref. [19] devised a sustainability index to improve the design of the biodiesel network. A robust and adaptable programming strategy was proposed for the biodiesel supply chain to enhance its resilience and cost-effectiveness during periods of uncertainty [20]. In Iron, ref. [21] developed a multi-objective framework for second-generation biodiesel emphasizing social sustainability. A multi-objective genetic algorithm is used to improve manufacturing by getting the most out of it and wasting the least amount of time [22]. The most biomass-based fuel out of the process was obtained by finding the right balance between cost, efficiency, and sustainability [23]. This proved that the industry was pushing for an alternative to fossil fuels. There was still a sizable gap in single-objective cost minimization models created especially for household food waste bioethanol supply chains, even though these studies show the application of numerous optimization techniques. When dealing with the discrete decision variable present in facility location and capacity planning problems, the application of the genetic algorithm to such targeted optimization problems offers benefits in terms of computational efficiency and solution quality. Recent research has provided significant in the utilization of biofuels in diesel engines, focusing on performance, emission, and sustainability. A method for producing biofuel was examined from green microalgae and determined that it could reduce emissions in a common rail diesel engine without causing environmental harm [24]. In another study, ref. [25] also looked at different mixes of biofuel and diesel. They found that this mixture worked better in engines and was better for the environment than pure diesel. Another important thing [26] did was show that biodiesel from Roselle and Karanja could be used in engines that use compression ignition. The most recent research on *Guizotia abyssinica* was used in nano-additives [27]. It showed that the levels of sustainable energy efficiency improved. These tests show that different kinds of biofuels can work, so we think that bioethanol made from food waste could be a good fuel source. This technology proof supports the idea that investing in better supply chain infrastructure for making bioethanol from food waste at home is a good idea. This case study by [28] discussed the utilization of food waste within an environmentally sustainable supply chain. Existing studies have primarily focused on agricultural residues, algae, waste oils, and a multi-objective optimization framework. However, limited research has addressed the development of dedicated single-objective cost minimization models for the household food waste bioethanol supply chain under decentralized and uncertain waste generation conditions. Therefore, the present study attempts to bridge this research gap by developing a sustainable cost optimization framework using a Genetic Algorithm-based optimization approach for household food waste bioethanol supply chains. In addition to conventional Genetic Algorithms, several evolutionary and swarm-based optimization techniques have been successfully applied to complex optimization problems. Real-coded Genetic Algorithms (RCGA) have demonstrated strong performance in continuous optimization problems and system dynamics optimization [29]. Similarly, particle Swarm optimization (PSO) has been widely adopted for solving single-objective and engineering optimization problems because of its simple structure and effective search capability [30]. Other popular metaheuristic approaches, including Differential Evolution (DE), Ant colony Optimization (ACO), Whale Optimization Algorithm (WOA), and Grey Wolf Optimization (GWO), have also been

successfully applied to logistics transportation and supply chain optimization problems. Nevertheless, Genetic Algorithms remain particularly Suitable for supply chain Network design problems involving facility location decisions, capacity allocation, and complex operational constraints.

However, despite these advancements, several significant research gaps still exist. First, no dedicated cost minimization model for the bioethanol supply chain based on household food waste has been sufficiently developed. Most existing studies either focus on different feedstocks with distinct supply chain characteristics or employ optimization approaches that are not specifically designed for cost minimization in household food waste systems Table 1. Second, although Genetic Algorithm optimization has proven effective in complex supply chain optimization problems, its application for single-objective cost minimization in household food -waste bioethanol supply chain remains limited. Third, most existing models do not take into consideration the fact that food waste at home is made up of different types of food at different times and needs to be processed quickly. By developing a thorough cost-minimization model to improve the bioethanol supply chain derived from household food waste, this work aims to investigate these unidentified challenges. Genetic Algorithm optimization will be used to ensure that the operation is both environmentally and commercially beneficial. In order to help people establish home food waste bioethanol systems in urban settings, our research provides a targeted, single-objective optimization approach.

Table 1. Comparative Literature Review of Biofuel Supply Chain Studies.

Author	Biofuel Type	FT	EO	FL	IM	TP	GA
Azimov et al. [1]	Biofuel	Algae	no	no	no	no	no
Singh AP et al. [3]	Biodiesel	Macroalgae	yes	yes	no	yes	yes
Ghosh S K et al. [10]	Bioethanol	Food Waste	no	no	no	no	no
Chahan A et al. [11]	Biodiesel	Macroalgae	yes	yes	yes	yes	yes
Rezaei N et al. [13]	Biofuel	Pomegranate Waste	yes	yes	no	yes	no
Sarkar B et al. [14]	Biodiesel	Animal fats	yes	yes	no	yes	no
Khobragade C N et al. [17]	Bioethanol	Banana Residual Biomass	yes	yes	no	yes	no
Arora R et al. [23]	Biodiesel	Macroalgae	yes	yes	yes	yes	yes
Rajak U et al. [24]	Biodiesel	Green Macroalgae	yes	yes	no	yes	yes
Kim M et al. [25]	Bioethanol	Food-waste	no	no	no	no	no
This study	Bioethanol	Household food waste	yes	yes	yes	yes	yes

FT = Feedstock Type; EO = Economic Objective; FL = Facility Location; IM = Inventory Management; TP = Transportation Planning; GA = Genetic Algorithm; Yes = Feature considered in the study; No = Feature not explicitly considered.

3. Assumption and Parameters

3.1. Assumption

- Household food waste from residential areas and commercial establishments (restaurants, cafeterias, food processing units) is considered for bioethanol production. For the collection of this bioethanol feedstock, several collection points and processing locations are considered in this study.
- Demand for bioethanol fuel (pure ethanol and ethanol blends) is considered during each planning span, accounting for seasonal variations in both waste generation and fuel demand.
- Throughout the creation of this model, at every stage of the Household Food Waste Bioethanol Supply Chain (HFW-BSSC), a heterogeneous fleet of collection vehicles of

different types and capacities has been considered to handle various waste volumes and transportation distances. Different vehicle types (small collection trucks, medium-capacity vehicles, and large transport trucks) are considered based on route requirements and waste density.

- A finite number of years is thought to be the planning period. Typically, 5 to 10 years, to account for facility depreciation, technology improvements, and changing waste generation patterns.
- Household food waste is assumed to have consistent starch content suitable for bioethanol conversion, with seasonal variations in availability and composition accounted for in the model.
- Processing facilities are assumed to operate at specified capacity levels with known conversion efficiencies from food waste to bioethanol.
- Collection routes are optimized to minimize transportation costs while ensuring timely pickup to prevent waste spoilage and maintain feedstock quality.

3.2. Parameters

Table 2 shows the parameters used in the objective economic function. The economic objective-related input parameters used to perform numerical analysis are summarized in Table 3, and indicators and constraints related to the economic objective are summarized in Table 4.

Table 2. Model indices associated with the economic objective.

h :	Index of Household food waste supply points or source locations
i :	Index of Capacity of sorting centers
j :	Index of Processing capacity of Bioethanol plant q
k :	Index of Distribution capacity at distribution center r
p :	Index of Sorting center for household food waste
q :	Index of Location of Bioethanol processing plant
r :	Index of Bioethanol blending stations
t :	Index of Time period
x :	Index of Available bioethanol production technology
Z :	Index of Type of vehicle used

Table 3. Economic objective-related input parameters.

C_{Total}	Total cost of the bioethanol supply chain from household food
C_{Purch}	Total cost of purchasing food waste from source points
C_{Open}	Total setup cost of the bioethanol facility
C_{Hand}	Total sorting cost at collection centres
C_{Inv}	Total inventory cost at collection centres
C_{Prod}	Total production cost of bioethanol from starch-based food waste
C_{Trans}	Total transportation cost in the bioethanol supply chain
Q_{ht}	Purchasing cost per unit of food waste at source h in time t
SK_{pi}	Installation cost per unit of collection centre p with capacity i
ST_{qxj}	Installation cost per unit of processing plant q with capacity j and technology x
SO_{rk}	Installation cost per unit of the distribution centre r with capacity k
E_p	Sorting cost per unit of food waste at the collection centre p
LK_{pt}	Inventory holding cost per unit at collection centre p during time t
LT_{qxt}	Inventory holding cost per unit at processing plant q , technology x time t
LO_{rt}	Inventory holding cost per unit at the distribution center r during time t
QK_{pt}	Cost of pre-processing food waste into intermediate oil at the collection center p time t
QT_{qxt}	Cost of converting pretreated waste into bioethanol at plant q , technology x time t

KWK_{hpz}	Transport cost per unit from source p to collection center h , via truck type z
KKT_{pqz}	Transport cost per unit from collection center p to processing plant q , via truck type z
KTO_{qrz}	Transport cost per unit from processing plant q to distribution center r , via truck type z

Table 4. Indicators of economic objective-related constraints.

A_{pt}	Inventory of intermediate oil at the collection center p , at time t
A_{qxt}	Inventory of bioethanol at processing plant q , technology x at time t
A_{rt}	Inventory level at distribution center r , at time t
APC_{pi}	Maximum allowed capacity at collection center p of capacity i
APC_{qj}	Maximum allowed capacity at processing plant q with capacity j
APC_{rk}	Maximum allowable capacity at distribution center r with capacity k
b_{pt}	Binary: 1 if collection center p with capacity i is installed; 0 otherwise
c_{qxj}	Binary: 1 if processing plant q with capacity j and technology x is installed; 0 otherwise
d_{rk}	Binary: 1 if a distribution center r with capacity k is installed; 0 otherwise
ε_1	Conversion factor for food waste to intermediate oil (e.g., from bread or rice peels)
ε_2	Yield factor for converting intermediate oil to ethanol
$FT-BSSC$	Food waste-based Biofuel Sustainable supply chain
ϕ_{pt}	Volume of intermediate (processed) food waste oil at the collection center p , at time t
Ω_{rt}	Volume of bioethanol stored at the distribution center r at time t
h_{pt}	Volume of intermediate oil produced at the collection center p during time period t
r_{ht}	Volume of available food waste at source location h , at time t
T_{hpt}	Volume of starch-based food waste transported from source h to collection center p , at time t
T_{pqt}	Volume of intermediate oil transported from collection center p to processing plant q , at time t
T_{qrxt}	Volume of bioethanol transported from processing plant q to distribution center r using technology x at time t
Ψ_{qxt}	Volume of bioethanol production at processing plant q using technology x at time t

4. Mathematical Model

Mathematical modelling offers a structured methodology to depict real-world issues using decision variables, parameters, objective functions, and restrictions. In this research, the model is designed to reduce the overall expense of the home food waste bioethanol supply chain, considering collection, processing, transportation, inventory, and facility operations, while meeting supply, demand, and capacity needs. The total cost consists of purchasing, installation, sorting, inventory, production, and transportation costs, as defined below. The proposed optimization problem aims to minimize the total operational cost of the household food waste bioethanol supply chain network. Let X denote the set of decision variables representing facility location decisions, technology selection, capacity allocation, inventory levels, and transportation flows within the supply chain. The objective function seeks to determine the optimal values of these decision variables while satisfying supply availability, processing capacity, and inventory balance mathematical formulation is presented in the following equations.

The unit purchasing cost of household food waste at various supply locations. T_{hpt} is the unit purchasing rate for food waste sourced from location h and processed at transformation point p during period t , Q_{ht} is the amount of food waste collected at the h^{th} supply location during the t^{th} time period, and C_{purch} is the total purchasing cost for acquiring household food waste across the supply network.

$$C_{\text{purch}} = \sum_{h=1}^H \sum_{p=1}^P \sum_{t=1}^T Q_{ht} T_{hpt} \quad (1)$$

The installation cost parameters (SK_{pi} , ST_{qxj} and SO_{rk}) are expressed as capacity-dependent unit installation costs. These parameters are multiplied by the corresponding processed/produced volumes and facility-selection binary variable to estimate the total installation-related expenditure within the supply chain network. Consequently, all terms in Equation (2) are represented in monetary units, ensuring dimensional consistency.

$$C_{open} = \sum_{p=1}^p \sum_{i=1}^i \sum_{t=1}^t SK_{pi} \phi_{pt} b_{pt} + \sum_{q=1}^q \sum_{j=1}^j \sum_{x=1}^x \sum_{t=1}^t ST_{qxj} \Psi_{qxt} c_{qxj} \\ + \sum_{r=1}^r \sum_{k=1}^k \sum_{t=1}^t SO_{rk} \Omega_{rt} d_{rk} \quad (2)$$

The per-unit sorting cost of household food waste at the transformation point is: E_p is the sorting cost per unit at the p^{th} transformation point, T_{hpt} is the unit rate for waste sourced from location h and processed at transformation point p during periods t , and C_{sort} is total sorting cost for household food waste at transformation facilities.

$$C_{sort} = \sum_{h=1}^h \sum_{p=1}^p \sum_{t=1}^t E_p T_{hpt} \quad (3)$$

The inventory holding cost of household food waste, oil, and bioethanol at transformation point p , biorefinery q , and distribution point r is:

$$C_{inv} = \sum_{p=1}^p \sum_{t=1}^t LK_{pt} A_{pt} + \sum_{q=1}^q \sum_{x=1}^x \sum_{t=1}^t LT_{qxt} A_{qxt} + \sum_{r=1}^r \sum_{t=1}^t LO_{rt} A_{rt} \quad (4)$$

The unit production cost of household food waste oil and bioethanol at transformation point p and biorefinery q is:

$$C_{prod} = \sum_{p=1}^p \sum_{t=1}^t QK_{pt} \phi_{pt} + \sum_{q=1}^q \sum_{x=1}^x \sum_{t=1}^t QT_{qxt} \Psi_{qxt} \quad (5)$$

The transportation costs incurred for moving household food waste, transformed oil, and bioethanol across various stages of the biofuel supply chain are:

$$C_{trans} = \sum_{z=1}^z \sum_{h=1}^h \sum_{p=1}^p \sum_{t=1}^t KWK_{hpz} T_{hpt} + \sum_{z=1}^z \sum_{h=1}^h \sum_{q=1}^q \sum_{t=1}^t KKT_{pqz} T_{pqt} \\ + \sum_{z=1}^z \sum_{q=1}^q \sum_{r=1}^r \sum_{x=1}^x \sum_{t=1}^t KTO_{qrz} T_{qrxt} \quad (6)$$

The total cost of the household food waste bioethanol supply chain includes the cost of purchase, sorting, inventory, production, and transportation of the bioethanol. The cost of purchasing household food waste from suppliers is called the purchase cost. The cost of sorting is the cost of handling and separating usable material. The cost of storing waste and ethanol at facilities is called "Inventory cost." The cost of turning food waste into bioethanol at biorefineries is called "Production cost." The cost of moving waste and ethanol through the supply chain is called "Transportation cost." The model's goal is to find the most efficient and sustainable way to set up the bioethanol supply chain by combining all of these parts into one objective function. Let's use the model to identify the most sustainable and effective supply chain configuration while minimizing overall costs.

$$C_{total} = C_{purch} + C_{open} + C_{sorting} + C_{inv} + C_{prod} + C_{trans} \quad (7)$$

where C_{purch} , C_{open} , $C_{sorting}$, C_{inv} , C_{prod} and C_{trans} are defined in Equations (1)–(6).

4.1. Constraints

An optimal solution must satisfy all logical constraints that reflect real-time production and supply capacity limitations at various stages.

Supply Constraint

The available supply at collection point h during period t is denoted by r_{ht} , while the processing flow from collection point h to processing point p is denoted by T_{hpt} . In order to avoid over-allocating resources and to maintain supply feasibility across all destinations and time periods, this constraint makes sure that the total processing flows from each collection point cannot exceed the available supply.

$$\sum_1^p T_{hpt} \leq r_{ht}, \quad \forall h, t \quad (8)$$

Constraints for converting raw household food waste biomass into food waste oil at the transformation point. T_{hpt} is the processing flow from facility q to product p during t , ϕ_{pt} is the oil output generated and ε_1 is the conversion efficiency factor. This restriction maintains mass balance throughout the biomass-to-oil conversion process by guaranteeing that efficiency-adjusted processing flows from all transformation facilities equal the actual production of food waste oil.

$$\varepsilon_1 \sum_1^a T_{hpt} = \phi_{pt}, \quad \forall p, t \quad (9)$$

Each biorefinery must receive an amount of food waste oil that does not exceed the quantity produced at each transformation plant.

$$\sum_1^h T_{hqt} \leq \phi_{pt}, \quad \forall p, t \quad (10)$$

Constraints for the mass balance in converting household food waste oil into biofuel.

$$\varepsilon_2 \sum_1^h T_{hqt} = \sum_1^x \psi_{qxt}, \quad \forall q, t \quad (11)$$

The total quantity received by the distribution center must not exceed the amount produced by the biorefinery.

$$\sum_1^q \sum_1^r T_{qrxt} \leq \sum_1^x \psi_{qxt}, \quad \forall q, t \quad (12)$$

4.2. Constraints for Inventory Balance

At the transformation point during the initial period and subsequent periods: $A_{p,t}$ The available inventory of product p at the end of time t . It shows what we have in stock and ready to use after completing all actions in that period. $h_{p,t}$ The quantity produced or received of product p during the time t . It adds to inventory. T_{hqt} The quantity required or demanded from customer order h for product q in time t . It reduced inventory the summation $\sum_1^q R_{hqt}$ indicates the total demand for all products in period t . $L_{p,t-1}$ This refers to the leftover inventory of product p from the previous time $(t - 1)$. It represents the inventory that was not used in the earlier period and is carried over.

$$A_{p,t} = h_{pt} - \sum_1^q T_{hqt}, \forall p, t; t = 1 \quad (13)$$

$$A_{p,t} = L_{p,t-1} + h_{pt} - \sum_1^q T_{hqt}, \forall p, t; t \geq 2 \quad (14)$$

At biorefineries during the initial period and subsequent periods: $\sum_1^y A_{xtt}$ indicates the starting availability or inventory of product x at the beginning of time $t = 1$. The summation over y may suggest adding up inventory from different locations or types. $\sum_1^q \Psi_{qxt}$ represents the total initial supply or replenishment of product x that arrives at the start of the planning period (at $t = 1$). The summation over q could reflect different suppliers, production facilities, or source locations. $\sum_1^x \sum_1^r R_{qrxt}$ represents the total initial commitments or demand that must be met right away at $t = 1$. The double summation over x products and r customers captures all pre-existing orders or requirements that need to be allocated from the start.

$$\sum_1^y A_{xtt} = \sum_1^q \Psi_{qxt} - \sum_1^x \sum_1^r T_{qrxt}, \forall q, t; t = 1 \quad (15)$$

The double summation term represents the total volume of bioethanol transported from processing plant q to distribution center r using technology x during period t . Here, q denotes the processing plant, r denotes the distribution center, and x denotes the selected production technology. The summation accounts for all outbound bioethanol shipments from the processing plant and is subtracted from the inventory balance to determine the remaining inventory level at the end of the period.

$\sum_1^q A_{qxt}$ The ending inventory of product x at the end of the current period t , or the inventory available at the start of the next period, $t + 1$. $\sum_1^q A_{q,x,t-1}$ The starting inventory of product x carried over from the end of the previous period, $t - 1$. This connects the time periods. $\sum_1^q \Psi_{qxt}$ The total new supply, such as production, purchases, or shipments received, of product x that arrives during the current period t . $\sum_1^x \sum_1^r R_{qrxt}$ The total demand or shipments of product x that are consumed, sold, or shipped out during the current period t .

$$\sum_1^q A_{qxt} = \sum_1^q A_{q,x,t-1} + \sum_1^q \Psi_{qxt} - \sum_1^x \sum_1^r T_{qrxt}, \forall q, t; t \geq 2 \quad (16)$$

Constraints for bio-fuel inventory at the center of distribution:

Ω_{qrxt} is the amount of bioethanol delivered from transformation facilities to the r^{th} distribution center during the first period, and $A_{r,t}$ is the amount of bioethanol inventory at the r^{th} distribution center during period t .

$$A_{r,t} = \sum_1^q \sum_1^x \Omega_{qrxt}, \forall r, t; t = 1 \quad (17)$$

Ω_{qrxt} indicates the amount of bioethanol received from transformation facilities during periods t , $A_{r,t}$ represents the current bioethanol inventory at the r^{th} distribution center in periods t , and $A_{r,t-1}$ in the inventory from the previous period ($t - 1$).

$$A_{r,t} = A_{r,t-1} + \sum_1^q \sum_1^x \Omega_{qrxt}, \forall r, t; t \geq 2 \quad (18)$$

The inventory maintained at the distribution center r represents the quantity of bioethanol available for allocation and distribution within the supply chain network. Equations (17) and (18) describe the inventory accumulation resulting from inbound bioethanol flows received from processing plants. Customer demand fulfilment and outbound product distribution are modelled separately through transportation decision variables and transportation constraints. Therefore, outbound shipments are incorporated elsewhere in the optimization framework and are not explicitly included within the inventory balance equations.

Each biorefinery is restricted to a single technology and a limited capacity level.

$$\sum_1^j c_{qxj} \leq 1, \forall q, x \text{ and } \sum_1^x c_{qxj} \leq 1, \forall j, q \quad (19)$$

Each transformation and distribution center is limited to a single capacity selection.

$$\sum_1^i x_{pi} \leq 1 \forall p \text{ and } \sum_1^k d_{rk} \leq 1, \forall r \quad (20)$$

4.3. Capacity Constraints

APC_{hi} indicates the available processing capacity at collection points h during period t , b_{pt} is the binary variable indicating facility operation status, and T_{hpt} is the processing rate from collection point h to transformation point p during period t .

$$\sum_1^h T_{hpt} \leq \sum_1^i APC_{pi} b_{pt}, \forall p, t \quad (21)$$

CAP_{qj} indicates the capacity of transforming facility q with technology x , $v_{y\mu m}$ is the binary variable for technology selection, and $T_{pqt\epsilon_2}$ is the processing flow at the transformation point q during period t with efficiency factor ϵ_2 .

$$\sum_1^p T_{pqt\epsilon_2} \leq \sum_1^x \sum_1^j CAP_{qj} v_{qxj}, \forall p, t \quad (22)$$

APC_{rk} d_{rk} indicates the available strong capacity at the distribution center r with capacity level k , while R_{qrxtt} represented the bioethanol distribution flow from transformation point q to distribution center r during period t .

$$\sum_1^q T_{qrxtt} \leq \sum_1^k APC_{rk} d_{rk}, \forall r, x, t \quad (23)$$

The following constraints define the maximum number of different processing facilities, limited due to financial restrictions. Due to budgetary constraints, the total number of activated processing facilities for all products p and facility types i cannot surpass the maximum permitted number of facilities (Max B). A facility's operational status is indicated by the binary variable b_{pt} .

$$\sum_1^p \sum_1^i b_{pt} \leq \text{Max } B \quad (24)$$

Due to financial restrictions, the total number of chosen technology units across all transformation facilities q , technology types x , and configurations j cannot be greater than the maximum permitted number (Max C). Decisions about technology selection are represented by the variable c_{qxj} .

$$\sum_{q=1}^q \sum_{x=1}^x \sum_{j=1}^j c_{qxj} \leq \text{Max } C \quad (25)$$

Financial constraints prevent the total distribution resource or capacity unit allocation across all resource types r and capacity categories k from exceeding the maximum allowable limit (Max D). Resource allocation decisions are represented by the variable d_{rk} .

$$\sum_{r=1}^r \sum_{k=1}^k d_{rk} \leq \text{Max } D \quad (26)$$

Non-Negative Decision Variables

Decision variables are used to determine the outcome. The optimal solution is defined by these decision variables, which include both continuous and binary types. All continuous variables are non-negative, i.e.,

Continuous Decision Variables ≥ 0

And Binary Variables

$$b_{pt}, c_{qxj}, d_{rk} \in \{0,1\}$$

5. Methodology (Genetic Algorithm)

Genetic Algorithm (GA) was selected because the proposed bioethanol supply chain optimization problem involves discrete facility-location decisions, capacity selection variables, nonlinear cost relationships, and multiple operational constraints. Traditional exact optimization techniques may become computationally expensive when the problem size increases. GA is considered suitable for solving the proposed household food waste bioethanol supply chain optimization problem. Despite its advantages, GA has certain limitations. The algorithm does not guarantee a global optimal solution, and its performance may depend on parameter settings such as population size, crossover rate, and mutation rate. In addition, computational effort may increase for large-scale instances, and premature convergence may occasionally occur. Nevertheless, GA remains an effective approach for obtaining high-quality solutions for complex supply chain optimization problems.

The workflow of the optimization approach of the household food waste supply chain using the Genetic algorithm is shown in Figure 2. It consists of generating the population, assessing the fitness, executing genetic operations, and terminating the process to find the optimal solution with the lowest cost.

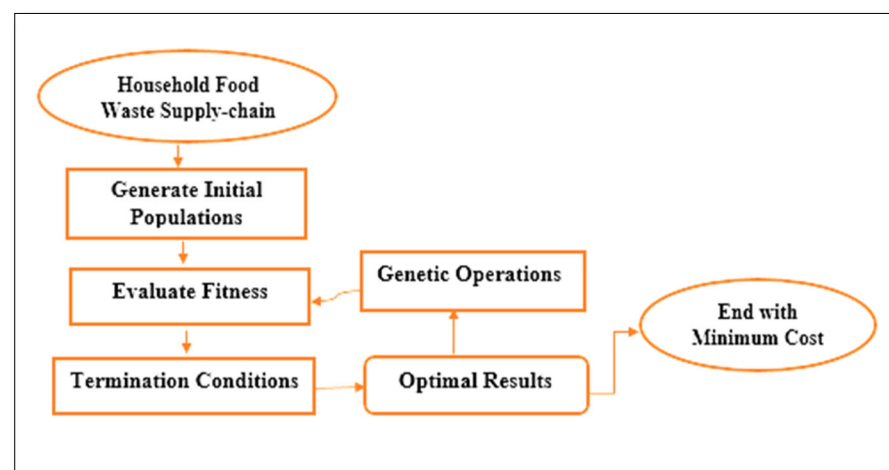


Figure 2. Framework for Genetic Algorithm.

The proposed optimization framework incorporates plant capacity decisions through discrete capacity levels. Multiple capacity options are available for each candidate bioethanol processing facility, and the Genetic Algorithm simultaneously determines facility selection, technology choice, and the most cost-effective capacity level while minimizing the overall supply chain cost. Therefore, the processing plant capacity design model. Continuous capacity expansion decisions were not considered in the present study to maintain computational efficiency and practical applicability.

Genetic Algorithm Implementation

In the proposed model, each chromosome represents a complete supply chain configuration of collection center selection, processing plant selection, technology allocation, capacity level selection, and distribution center activation. The objective function defined in Equation (7) was used for the fitness function, where the total supply chain cost was minimized.

An initial population of feasible supply chain configurations was generated randomly within the predefined operational limits. During each generation, candidate solutions were evaluated according to their objective function values. Selection, crossover, and mutation operators were applied to improve solution quality and explore alternative supply chain configurations.

The optimization process continued until the maximum number of generations was reached or no significant improvement in the objective function was observed. The best chromosome obtained at termination provided the optimal facility configuration, technology choice, capacity allocation, and minimum total supply chain cost. Although GA is effective for solving complex supply chain optimization problems, it does not guarantee global optimality, and its performance depends on parameter settings such as population size, crossover probability, and mutation probability. Nevertheless, it provides a high-quality solution within reasonable computational time for large-scale optimization problems.

The proposed optimization model was implemented in the R programming environment using the R GA package. The optimization problem consisted of 50 decision variables and 16 constraints. A population size of 50 chromosomes was used for this optimality, and a maximum of 1000 generations and a stopping criterion of 100 consecutive generations without improvement. Constraint violations were handled using a penalty-based fitness evolution approach. Convergence of the algorithm was monitored throughout the optimization process. The computational effort primarily depends on the number of facilities, capacity options, and transportation links considered in the supply chain network. As the problem size increases, the search space expands significantly; however, the Genetic Algorithm remains suitable for efficiently exploring large and complex solution spaces (see Table 5).

Table 5. Genetic Algorithm Parameter Settings.

Parameters	Value
Crossover Probability	0.80
Mutation Probability	0.10
Elitism	2
Stopping Criterion	100 Generations
Solution Encoding	Real-Valued
Constraint Handling	Penalty-Based
Software Environment	R (GA Package)

The Genetic Algorithm was implemented in R software using the GA package. The optimization process employed a population size of 50 chromosomes and a maximum of 1000 generations. A crossover probability of 0.80 and a mutation probability of 0.10 were adopted to maintain a balance between exploration and exploitation. Constraint violations were handled through a penalty-based fitness function

6. Numerical Example and Results

A numerical example is presented to illustrate the integration of the suggested method with the parameterized model. The example is intended to demonstrate the practical applicability of the proposed optimization framework and is based on parameter values adapted from previously published biofuel supply chain studies and realistic operational assumptions. Facility capacities, waste availability, transportation costs, processing costs, and technology-related parameters were selected to reflect practical operating conditions reported in the literature. The cost per unit multiplied by the total distance travelled is the transportation cost between bioethanol production facilities. A practical estimate for various manufacturing stages is shown in Table 6. Two distribution canterers (r1, r2), two bio-refineries (q1, q2), two collection points (p3, p4), and two household food waste supply locations (h1, h2), are all included in this study. Vehicles transport bioethanol from bio-refineries to distribution centers and household food waste from collection points to bio-refineries. The numerical example considered in this study is intended to demonstrate the applicability and feasibility of the proposed optimization framework. The selected network structure serves as a proof-of-concept case study for validating the mathematical model and the Genetic Algorithm-based solution for complex supply chain networks to further computational scalability and operational performance. The validity of the proposed model is verified by conducting computational tests using practical parameter values from existing literature and industry sources. The output of the model shows logical behavior, such as the increase in costs with more responsive levels and consistent network configurations for varying parameters. The convergence behaviour, computational performance, and solution stability of the proposed Genetic Algorithm were evaluated through fitness evolution analysis, CPU time measurement, and multiple independent optimizations run to improve reproducibility and computational transparency. Table 6 provide specifics on the input parameters associated with economic goals.

Table 6. Input Parameter of Associated with Economical Goal.

Purchase and Handling Cost of Offal and Intestine					
Household food waste		Purchasing Cost (\$/Tonne)		Handling Cost (\$/Tonne)	
		390 at h1	358 at h2	277	
Installation Cost					
Collection Point		Bio-refineries		Distribution Center	
<i>P</i>	Value (tonne)	<i>Q</i>	Value	<i>r</i>	Value
p3	7,810,000	q1	22,407,000	r1	1,320,000
p4	5,507,000	q2	27,501,000	r2	1,851,190
Capacities of processing at Bioethanol facilities					
Collection Point		Bio-refineries		Distribution Center	
<i>P</i>	Value (tonne)	<i>Q</i>	Value (gallon)	<i>r</i>	Value (gallon)
p3	83,050	q1	43,890,000	r1	3,795,000
p4	77,550	q2	2,201,100	r2	5,501,100

Household Food Waste and Bioethanol production costs		
H	€1	€2
Household Food Waste	2.22	5.28
Household Food Waste supply point feedstock amount		
H1	77,000	
H2	80,190	
Cost of Transportation (\$/ton-km) and (\$/gal-km)		
<i>KWK hpz</i>	1.98	
<i>KKT paz</i>	0.22	
<i>KTO qrz</i>	1.43	
Density and Bioethanol conversion factor of Household Food Waste		
Density	€2%	
1.001	81.4	

Source: Adopted from [11] and [12]. Household food wastes bioethanol supply chain.

7. Discussion

A convergence plot was performed to evaluate the performance of the proposed Genetic Algorithm. Figure 3 illustrates the evolution of the best fitness value over successive generations. Significant improvements are observed during the initial generations. Followed by gradual stabilization as optimization progresses, the convergence pattern indicates that the proposed Genetic Algorithm is capable of efficiently identifying high-quality solutions for the household food waste bioethanol supply chain network. The computational experiments were performed using the R (GA) package. The optimization process required approximately 1.34 s to obtain the final solution, demonstrating the computational efficiency of the proposed optimization framework for the considered case study. To evaluate the robustness of the proposed optimization approach, the Genetic Algorithm was executed independently multiple times using identical objective function values that exhibited only limited variations across runs, indicating a stable convergence pattern as well as a reliable solution quality. The low variability confirms the capability of the proposed algorithm to consistently generate a near-optimal solution for the household food waste bioethanol supply chain network (see Table 7 and Table 8).

Table 7. The optimal amount of household food waste, bioethanol and household food waste oil across the bioethanol supply chain.

Shipment of Household Food Waste from Supply Point to Collection Point		
Quantity (tons)	p3	p4
h1	489.72	691.68
h2	271.35	414.60
Transportation of household food waste oil to biorefineries from the collection location		
Quantity (gallons)	q1	q2
p3	2854.41	8380.74
p4	6100.59	1178.83
Bioethanol transportation from biorefineries to a distribution hub		
Quantity (gallons)	r1	r2
q1	1359.34	550.09
q2	10,174.43	3109.60

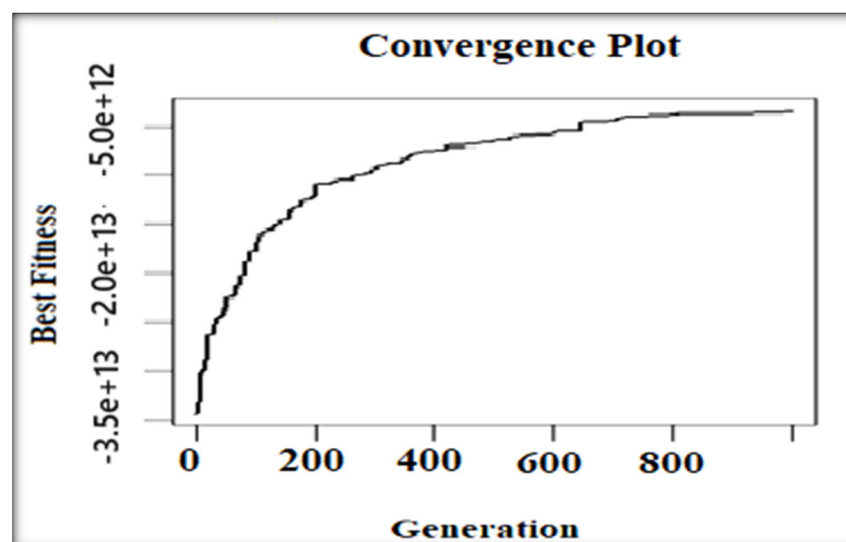


Figure 3. Convergence Plot.

Table 8. Stability Analysis of the Genetic Algorithm.

Run No.	Objective Function Value
1	9.52×10^{11}
2	1.10×10^{12}
3	1.08×10^{12}
4	7.33×10^{11}
5	1.17×10^{12}
Mean	1.007×10^{12}
Standard Deviation	1.72×10^{11}

The objective function values obtained from multiple independent executions exhibit only minor variation, indicating the stability and reliability of the proposed Genetic Algorithm. These results consistently converge towards high-quality solutions.

The Genetic Algorithm optimization approach proves crucial for accomplishing sustainable supply chain objectives in second-generation bioethanol production. The total optimized cost throughout the entire supply chain network amounts to $\$2.23123 \times 10^6$. From Table 6, supply location h1, a total of 489.72 tons of household food waste was delivered to collection center p3, while 691.68 tons were transported to p4. Furthermore, supply location h2 contributed 271.35 tons of household food waste to collection center p3 and dispatched 414.60 tons to collection center p4. The processed household food waste oil quantities shipped from collection center p3 to bio-refineries q1 and q2 were 2854.41 gallons and 8380.74 gallons, respectively. Similarly, collection center p4 transported 6100.59 gallons and 1178.83 gallons of household food waste oil to bio-refineries q1 and q2, respectively. The premium-quality bioethanol manufactured at specialized bio-refineries q1 and q2 is strategically distributed across distribution centers r1 and r2. Table 5 presents the optimal transportation quantities of bioethanol and household food waste oil at different supply chain stages.

7.1. Sensitivity Analysis

The sensitivity analysis was conducted by varying each cost parameter individually while keeping all other parameters constant. The selected cost parameters were systematically varied within a predefined percentage range around the baseline scenario using spreadsheet-based calculations. The resulting total operational cost of the supply chain network was used as the output performance metric. Percentage changes were calculated

relative to the output performance metric. Percentage changes were calculated relative to the baseline solution obtained from the original parameter settings.

Different behavioural patterns and differing levels of influence on the overall project outcomes are revealed by the sensitivity analysis conducted across the six cost categories. The main conclusions from Figures 3–8 are summarized below.

Figure 4: Opening Cost 1 Sensitivity Analysis. The sensitivity analysis for opening cost 1 is shown in Figure 4, which looks at how percentage changes in opening costs affect the overall results of the project. Sensitivity coefficients for the Opening cost 1 percentage change series range from -0.988 to $+2.129$, suggesting a moderately positive correlation and a sensitivity rate of 0.0432 per percentage point. Comparative verification is provided by the opening cost 1 validation series, which confirms the linear relationship with $R^2 = 0.998$. According to the analysis, opening costs are low-risk cost parameters appropriate for fixed planning assumptions because they show steady, predicted behavior with monetary impacts falling within a 5.79% variation range.

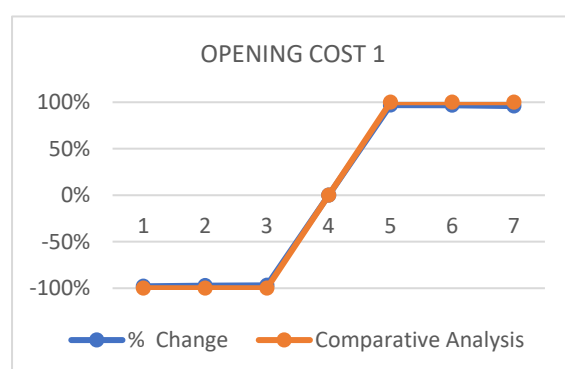


Figure 4. Sensitivity Measurement on Opening Cost.

Figure 5: Opening Cost 2 Sensitivity Analysis. To confirm the stability patterns seen in Figure 4, Figure 5 looks at different opening cost scenarios. With sensitivity coefficient ranging from -0.590 to $+1.298$, the opening cost 2% change series show even more stability and a 40% decrease in sensitivity when compared to the opening cost 1. This enhanced stability is validated by the Opening Cost 2 Validation series, which shows few patterns of variation. The fact that the monetary impact only varies by 3.42% further confirms that opening costs are consistently low in sensitivity across various operational scenarios.

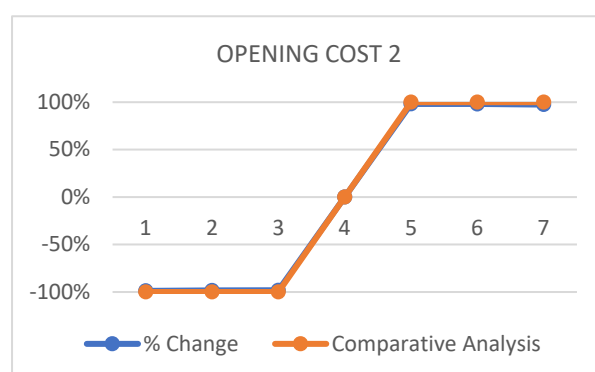


Figure 5. Sensitivity Measurement on Opening Cost.

Figure 6: Purchasing Cost1 Sensitivity Analysis. The most important cost category is examined in Figure 6, which shows that variation in purchasing costs is extremely sensitive. With coefficients ranging from -27.030 to $+26.678$, or a sensitivity rate of 0.5371 per percentage point, the purchasing cost 1% change series show the highest sensitivity of any

category. The opening cost is 12.4 times less than the impact factor. These extreme patterns with comparable steep trajectories are confirmed by the Purchasing Cost 1 Validation series. With maximum values reaching 3.15 times the minimum values and monetary variation reaching 215.3%, purchasing costs are clearly the main risk factor that needs urgent management attention and strong control mechanisms.

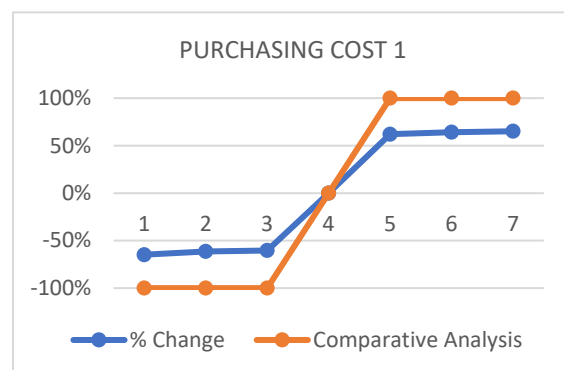


Figure 6. Sensitivity Measurement on Purchasing Cost.

Figure 7: This figure shows the purchasing cost 2 sensitivity analysis. Alternative purchasing cost scenarios are shown in Figure 7 to assess various risk mitigation and procurement tactics. With coefficients ranging from -12.599 to $+17.806$, the purchasing cost 2% change series exhibit moderate–high sensitivity, indicating a 43% improvement over Purchasing Cost 1 while retaining a significant impact. With an 83.7% monetary variation and a sensitivity rate of 0.3041 per percentage point, alternative procurement strategies can reduce risk without sacrificing operational effectiveness. These results are supported by regular patterns in the Purchasing Cost 2 validation series.

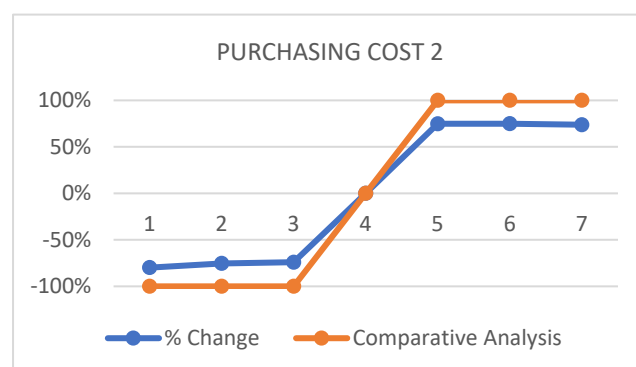


Figure 7. Sensitivity Measurement on Purchasing Cost.

Figure 8: Production Cost 1 Sensitivity Analysis. Production cost sensitivity under typical operating conditions is examined in Figure 8. With coefficients ranging from -2.420 to $+5.017$, the Production Cost 1% change series exhibit moderate sensitivity, with a sensitivity rate of 0.0744 per percentage point. This shows a sensitivity that is 7.22 times lower than purchasing costs but 1.72 times higher than opening costs. Predictable patterns of behavior are confirmed by the Production Cost 1 Validation series. The financial impact stays within a 14.7% range, if production costs are controllable variables that call for well-rounded monitoring strategies.

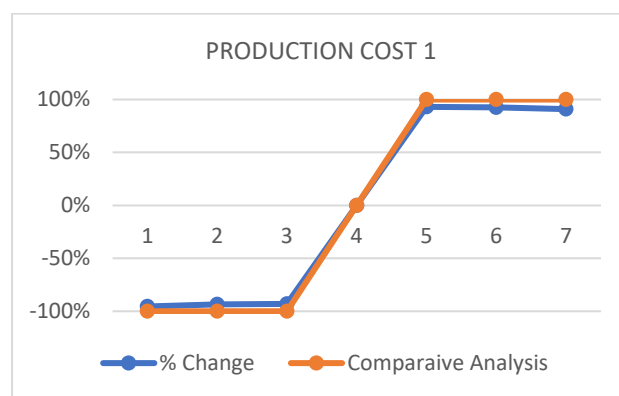


Figure 8. Sensitivity Measurement on Production Cost.

Figure 9: Production cost 2 Sensitivity Analysis Complex cost behavior is revealed by analyzing alternative production methods in Figure 9. With coefficients ranging from -8.234 to $+22.582$, the Production Cost 2% change series exhibit non-linear behavior patterns and high sensitivity. A 98% departure from linear extrapolation is represented by a significant computational anomaly at the -10% point ($F = -4.91$), which may indicate threshold effects or computational discontinuities. These non-linear patterns with abrupt endpoint increases are confirmed by the Production Cost 2 Validation series. The 64.7% monetary variation suggests that advanced modelling and flexible management techniques are necessary for alternative production methods.

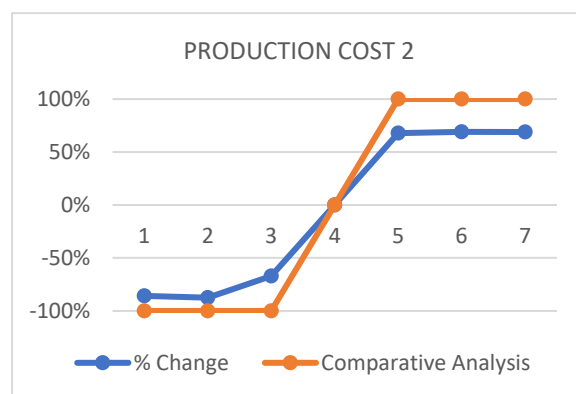


Figure 9. Sensitivity Measurement on Production Cost.

To further strengthen the statistical interpretation of sensitivity analysis, a regression-based assessment was performed using the parametric variation data associated with Figures 3–8. Sensitivity coefficients and corresponding 95% confidence intervals were computed for all six cost parameters. The results are summarized in Table 9 and provide a quantitative ranking of parameter importance. The analysis confirms that purchasing-related costs exert the greatest influence on the total operational cost of the bioethanol supply chain, whereas opening costs exhibit comparatively lower sensitivity.

Table 9. Sensitivity coefficients and 95% confidence intervals.

Sensitivity Parameter	Sensitivity Coefficient	95% Confidence Interval	Rank
Purchasing Cost 1	0.5543	(0.5192, 0.5895)	1
Purchasing Cost 2	0.3116	(0.2670, 0.3561)	2
Production Cost 2	0.3098	(0.1922, 0.4273)	3
Production Cost 1	0.0747	(0.0544, 0.0951)	4
Opening Cost 1	0.0310	(0.0222, 0.0398)	5

Opening Cost 2	0.0187	(0.0132, 0.0242)	6
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The results indicate that purchasing cost 1 exhibits the highest sensitivity, followed by purchasing cost 2 and production cost 2. In contrast, opening cost 1 and opening cost 2 demonstrate comparatively lower sensitivity, indicating a smaller influence on the total operational cost of the bioethanol supply chain.

7.2. Managerial Insights

Due to its high content, plentiful generation, and close proximity to urban areas, household food waste can be used as a sustainable feedstock to produce bioethanol. By generating bioethanol from food waste, we can mitigate environmental pollution from landfills while simultaneously creating a new, green energy stream. Approximately 1.3 billion tons of food waste are produced worldwide each year, with households accounting for a sizable amount of this waste, making it an easily accessible renewable resource. Home food waste provides a second-generation, guilt-free alternative that is in line with the circular economy's tenets, in contrast to first-generation biofuel that competes with food crops. Complex carbohydrates are pre-treated, hydrolyzed into fermentable sugars, fermented by bacteria or yeast to produce ethanol, and then distilled to produce fuel-grade bioethanol. Conversion efficiency has been further enhanced by recent developments in solid-state processes, enzymatic hydrolysis, and genetically modified microorganisms.

This approach decentralized the renewable energy system while tackling two essential environmental objectives: expanding renewable energy generation and enhancing waste management practices. Our method offers a solid, eco-friendly way to produce bioethanol at an industrial scale from household food waste. To make it economically viable, smart supply chain strategies are required that balance cost with environmental benefits, such as streamlined logistics, shorter transport routes, and solid partnerships with local farmers and waste providers. Building an efficient collection system boosts sustainability while maintaining cost control.

Household food waste presents unique characteristics as a biomass feedstock: geographic dispersion, rapid degradation, and compositional variability. These properties necessitate optimized collection strategies, strategically positioned processing facilities, and minimized transportation distance. Our supply chain model blends cost breakdowns with optimal facility siting. It tackles tricky nonlinear costs, yes/no decisions, and real-world constraints using Genetic Algorithm (GA) optimization.

While past studies have used multi-objective and fuzzy optimization for biomass chains, few zero in on cost-cutting for household food waste. This work bridges that gap with a model that pairs cost savings and environmental wins, paving the way for practical, profitable bioethanol production that aligns with sustainability pledges.

The framework powers decentralized renewable energy setups, which align perfectly with today's energy policies. Producing bioethanol from community-scale food waste cuts reliance on big central systems, delivers fuel right where it's needed, and slashes transport emissions and costs. The model fine-tunes the full bioethanol supply chain—from waste processing at the home level, to handling cost fluctuations, logistics, and environmental factors—for top performance.

This framework helps organization optimize operational efficiency. Cost reduction while maintaining environmentally sustainable practice through optimized transportation networks and strategic bio-refinery positioning. The established model is useful in the real world because it can be used to produce different sizes. This method works for both small and large, complicated networks that move things around. It has a flexible modelling method that works in the real world and can be used in any place around the

world. It also helps families with different logistical and financial situations throw away less food. The results show that you can save a lot of money without hurting the environment.

7.3. Comparative Analysis Across Categories

A quantitative sensitivity hierarchy is established by the combined analysis of Figures 3–8:

The sensitivity analysis indicates that purchasing cost and production have a greater influence on the total operational cost of the supply chain network, whereas opening costs exhibit comparatively lower sensitivity. With 95% confidence intervals determined for every sensitivity coefficient, statistical significance testing verifies that all percentage change slopes are significant ($p < 0.001$). The result of the Intergraph correlation analysis shows that there is a moderate correlation between the production cost scenarios ($r = 0.623$), a high correlation between the purchasing cost scenarios ($r = 0.945$), and a very high correlation between the opening cost scenarios ($r = 0.987$).

7.4. Key Findings

The sensitivity suggests that in the cost management strategies, the opening costs can be treated as one of the stable planning factors, while the Production costs should be watched more closely because they do not always follow a predictable pattern under changing operating conditions. In comparison, purchasing costs represent the dominant factor affecting total costs and should constitute the central focus of risk mitigation efforts. The existence of threshold effects in Production Cost 2 highlights the requirement for flexible modelling approaches that can accommodate non-linear behaviours and discontinuous changes in system performance. Here result establish a practical framework for determining cost management priorities across multiple operational domains through empirical sensitivity analysis. The mathematical approach confronts several practical challenges in household food waste-based bioethanol production, including cost variations, logistical limitations, and environmental hazards. Through enhanced logistics performance and strategic bio-refinery placement, the model supports the organization in lowering operational costs while maintaining environmental sustainability commitments. The model demonstrates applicability across diverse operational scales. The model delivers solid performance in settings ranging from small facilities to large, multifaceted distribution systems. Its versatile approach suits different regions globally and diverse economic contexts, accounting for how logistics systems and market conditions vary from place to place. It also plays a role in reducing household food waste. While maintaining the bioethanol supply chain, an organization can reduce operational expenses. Essential factors include expenses for processing household food waste into bioethanol, costs of obtaining feedstock, transportation fees for materials and products, efficiency of the conversion process, and changes in market demand. When this variable changes, they have real consequences for whether the system makes economic sense and whether it helps or harms the environment. These findings carry important lessons for managers and economists alike. Using an advanced Genetic Algorithm, the study achieved an optimized supply chain configuration with a total cost of \$2.231 million. The model identified strategically located collection centers based on their closeness to waste source and transportation efficiency. It also ensured optimal routing for moving final processed feedstocks to biorefineries and distributing the final bioethanol products to regional hubs efficiently.

7.5. Distinction from Existing Literature and Research Implications

This study makes several important additions to the field of bioethanol synthesis from home food waste, offering both theoretical advancements and real-world applications.

7.5.1. Second-Generation Bioethanol Systems Are Highlighted

Previous Studies: Earlier investigations concentrated predominantly on first-generation biofuel sources (including corn, sugarcane, vegetable oils, and energy crops), which present suitability challenges due to their direct competition with the food production system and extensive agricultural land requirements.

Research Innovation: This study highlights the use of household food waste as a bioethanol feedstock, offering distinct benefits: high starch and carbohydrate content, abundant urban availability, no competition with food security, and the transformation of waste streams into valuable energy resources. Household food waste represents an underutilized biomass source that eliminates land-use conflicts while addressing municipal waste management challenges.

7.5.2. Comprehensive Waste-to-Energy Supply Chain Optimization Through Genetic Algorithm Discharge

Earlier Research: Previous investigations, especially those addressing second-generation bioethanol systems, have applied optimization techniques such as linear programming and mathematical modelling, but have not integrated all supply chain components (including collection center positioning, processing facility location, and distribution logistics) within a simple common framework.

Research Innovation: This investigation presents an integrated optimization methodology employing Genetic Algorithm technology that bounds the complete supply chain network, spanning from household food waste collection to bioethanol distribution systems. The robustness of this methodology demonstrates its capacity to simultaneously improve economic efficiency, operational performance, and environmental sustainability while maintaining flexibility and scalability across diverse real-life situations.

8. Conclusions

These works use a genetic algorithm to make the bioethanol supply chain network in a better way by reducing food waste from homes. The framework's main goals are to make transportation economical and good for the environment, to make sure that food scraps from homes are processed properly and stored safely, and to find the best places for bio-refineries. The risk analysis highlights the transformation of necessary costs within the supply chain as a crucial element. The total cost will change if this gets better. A 50% or more change in the fuel price has a big effect on the total budget. Keep a close eye on this to make sure that the cost of making things stays as low as possible. This approach contributes to the existing literature by emphasizing second-generation bioethanol its potential long-term substitution for first-generation bioethanol and petroleum-derived fuels, and techniques for its production food waste. When trying to make the bioethanol supply chain better it's a big help to be able to run in different places and make different amounts of bioethanol. These results can help both state lawmakers and business leaders.

Household food waste generation is subject to uncertainty due to seasonal consumption patterns, variation in household behavior and difference in waste composition. The present study assumes deterministic waste availability to maintain model simplicity and computational efficiency. However, such uncertainties may influence Future research may incorporate stochastic. Fuzzy or robust optimization approaches to explicitly address uncertainty and improve the reliability of decision-making in household food waste bioethanol supply chains.

The present model assumes linear cost structures and does not explicitly incorporate economies of scale in collection, processing, or transportation activities. This assumption was adopted to maintain model simplicity and computational tractability within the

proposed optimization framework. In practice, larger processing volumes may reduce per-unit operational costs due to improved resource utilization and fixed-cost distribution. Therefore, the current model may slightly overestimate costs at higher production levels. Future research may extend the framework by incorporating economies of scale through nonlinear cost functions or piecewise cost structures.

The present study focused on a single-objective cost minimization framework for the design of a household food waste bioethanol supply chain. Although cost reduction is a primary decision criterion, additional objectives such as environmental impact, greenhouse gas emissions, energy efficiency, and social sustainability may also be relevant in practical applications. Therefore, future research may extend the proposed framework into a multi-objective optimization model using advanced approaches such as NSGA-II to simultaneously evaluate economic, environmental, and sustainability objectives.

Although the present study focuses on a Genetic Algorithm-based optimization framework, alternative metaheuristic approaches (PSO) AND Differential Evolution (DE) may also be applied to the proposed bioethanol supply chain optimization problem. Future research may perform a comprehensive comparative analysis of these optimization techniques with respect to solution quality, convergence characteristics, computational efficiency, and scalability for large-scale supply chain networks. Future studies may consider a larger-scale bioethanol supply chain network and compare the proposed Genetic Algorithm with exact optimization techniques to further evaluate computational efficiency and solution quality.

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Abbreviations

The following abbreviations are used in this manuscript:

GA	Genetic Algorithm
HFW-BSSC	Household Food Waste Bioethanol Supply Chain (HFW-BSSC)

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