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Optimizing Agricultural Logistics Networks: Evidence from the Mekong Delta, Vietnam

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ABSTRACT

Agricultural supply chains (ASC) in the Mekong Delta face significant challenges in balancing economic efficiency, social development, and environmental sustainability. This study develops a multi-objective mixed-integer linear programming (MILP) model to optimize the citrus supply chain (CSC) by simultaneously minimizing total costs, maximizing employment, and reducing CO_2 emissions. The augmented ε-constraint method was applied to generate Pareto-optimal solutions and to identify trade-offs among competing objectives. The results indicate that within a predictable range, moderate increases in employment can be achieved with stable marginal costs and emissions. However, beyond a critical knee point, additional social benefits come at disproportionately high economic costs with limited environmental gains. The optimal trade-off solution was identified at v = 4.75, yielding a balanced outcome of 3,304.02 million VND in cost, 718 jobs, and 2,811.87 kg of CO_2 emissions. This research contributes to theory by extending multi-objective optimization in agri-food logistics, provides methodological insights through the use of the augmented ε-constraint approach, and offers practical implications for policymakers and managers in designing sustainable supply chain strategies in the Mekong Delta.

Keywords: *agricultural logistics, supply chain optimization, logistics network, multi-objective optimization, Mekong Delta*

1. INTRODUCTION

Agriculture is one of the key pillars driving Vietnam's economic growth and plays a vital role in ensuring national food security. In 2024, Vietnam's GDP reached 7.09%, with the agriculture, forestry, and fishery sector contributing 5.37% to the country's total value added (NSO, 2024). By the first half of 2025, GDP increased by 7.52% compared to the same period of the previous year. During this period, the agriculture, forestry, and fishery sector grew by 3.84%, contributing 5.59% to the total value added of the economy (NSO, 2025a). Within the agricultural sector, citrus fruits represent one of the most economically valuable groups and are cultivated extensively across various regions. It is estimated that in the first six months of 2025, the export value of fresh and processed vegetables and fruits exceeded USD 6.22 billion (NSO, 2025b). In the current context, consumer demand is steadily increasing, particularly for fruit varieties with high nutritional value and health benefits, which are becoming increasingly preferred. Therefore, the development of citrus fruit supply chains (CFSC) oriented toward efficiency and sustainability has become an urgent requirement.

In 2024, the total fruit cultivation area nationwide reached 1,297.7 thousand hectares, with an output of 8,145 thousand tons (NSO, 2025c). The Mekong Delta (Vietnam) is recognized as the country's largest fruit-producing region. In 2024, the region's fruit cultivation area accounted for 32,000 hectares (out of 276,000 hectares nationwide), yielding 369,000 tons of output (VITIC, 2024). These figures highlight the Mekong Delta's outstanding potential in supplying fruits, particularly citrus varieties. However, the CFSC in this region still faces several limitations, including high logistics costs, inconsistent product quality, considerable post-harvest losses, inadequate preservation and distribution infrastructure, and weak linkages between production, distribution, and consumption (Minh, 2025; Chuyen *et al.,* 2024). These shortcomings not only undermine economic efficiency but also pose significant challenges to the long-term sustainability of the sector in the future.

The analysis of the above challenges indicates that optimizing the CFSC in the Mekong Delta should not only aim at minimizing costs across the entire chain but also ensure social benefits through the creation of stable employment. At the same time, it is crucial to mitigate negative environmental impacts, particularly greenhouse gas emissions arising from logistics activities. Numerous studies worldwide have addressed supply chain (SC) optimization, such as Gholian-Jouybari *et al.* (2024), who investigated the optimization of a closed-loop coconut SC; Roghanian and Cheraghalipour (2019), who examined optimization in a closed-loop CSC; and Pan and Shan (2024), who optimized fruit and vegetable SC. In Vietnam, several authors have also examined SC optimization, such as Wang *et al.* (2021) on the SC of fresh fruits; Wang *et al.* (2024) on the role of rice husk in the rice SC; Kieu *et al.*

(2021), who focused on optimizing distribution center (DC) selection. However, prior studies have primarily concentrated on financial costs, the optimization of individual stages within the SC, or products and SC with different characteristics. Consequently, few studies have integrated economic, social, and environmental objectives into a comprehensive model, nor have there been representative studies addressing the entire fruit SC in Vietnam, particularly in the Mekong Delta.

To address this research gap, the study employs a multi-objective MILP model to optimize the CFSC. The model aims to achieve three primary objectives: (i) minimizing total costs, (ii) maximizing social benefits through employment generation, and (iii) minimizing environmental impacts by reducing CO_2 emissions. In particular, the study employs an augmented ε-constraint approach to derive the Pareto-efficient set of solutions, thereby supporting decision-making under conditions of multiple competing objectives.

To address the identified research gaps, this study aims to answer these key research questions:

1) How can the CSC in the Mekong Delta be optimized simultaneously with respect to economic (cost), social (employment), and environmental (CO_2 emissions) objectives?
2) How does the augmented ε-constraint method support the identification of Pareto-optimal solutions in this multi-objective context?
3) What trade-off scenarios emerge among cost, employment, and emissions, and how can they guide decision-making?
4) What managerial and policy implications can be drawn to foster sustainable CSC in the Mekong Delta?

Through this study, three key contributions are expected in terms of theory, practice, and methodology. From a theoretical perspective, the research extends the application of multi-objective optimization models in the field of agricultural logistics, particularly for CFSC. In terms of practical relevance, the findings provide evidence and policy implications for stakeholders in developing sustainable SC in the Mekong Delta. From a methodological standpoint, the application of the augmented ε-constraint approach enhances computational performance and ensures a balance among objectives, thereby enriching the methodological toolkit for SC optimization research.

The remainder of this article is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the multi-objective optimization model and solution methodology. Section 4 reports the empirical results, while Section 5 discusses the main findings. Section 6 concludes with key implications, followed by the study's constraints and avenues for future investigation.

2. LITERATURE REVIEW

2.1 Logistics Networks and Agricultural Logistics Networks

A logistics network (LN) is a system of nodes and links that connects actors within a SC through the flows of goods, information, and finance. It encompasses producers, collection centers, distribution centers, retailers, and end consumers, along with warehousing infrastructure, transportation facilities, and modern management technologies (Chuyen & Rajagopal, 2025). In ASC, LNs are essential for sustaining the continuity of perishable products while ensuring food security and market stability. According to Orjuela Castro *et al.* (2021), LNs are essential to address seasonal supply–demand imbalances, reduce costs and losses, and improve food accessibility. In Indonesia, Kailaku *et al.* (2022) emphasized that LNs help mitigate high logistics costs and limit mango losses in inter-island transportation. Within cold SC, Shi (2024) highlighted that LN optimization is critical to reducing costs, preserving the quality of frozen products, and enhancing distribution efficiency. At the regional level, Nanthasamroeng *et al.* (2022) confirmed that cross-border LNs in the Mekong Subregion not only maximize profits but also reduce CO_2 emissions.

LNs exhibit complex characteristics that are closely associated with challenges of seasonality, quality, and market uncertainty. According to Abbasian *et al.* (2023), LNs must ensure strict quality control due to the perishable nature of products, while also addressing economic, social, and environmental sustainability factors, as well as resilience to disturbances arising from natural disasters or traffic congestion. Shirzadi *et al.* (2021) emphasized LN innovation through the integration of inventory–routing decisions (IRP) and the application of reverse logistics for recovering and recycling defective products. In the agricultural context, LNs face additional constraints, including seasonal production, fragmented supply sources, weather risks, price fluctuations, and inconsistent quality, which call for effective cold-chain solutions and risk management (Chuyen & Rajagopal, 2025). Hardjomidjojo *et al.* (2022) emphasized that sustainable agro-industry logistics requires spatially informed logistics solutions to reduce supply–demand imbalance and improve regional logistics performance. Furthermore, Li and Shi (2024) noted that multi-channel LNs become even more complex as they must accommodate diverse consumer purchasing behaviors, stringent requirements for freshness and delivery time, and potentially high operating costs if network design is not optimized. Thus, the defining features of agricultural LNs lie in the interplay of perishability, seasonality, high risk, and the pressing need for technological and managerial innovations to ensure efficiency, sustainability, and responsiveness to increasingly demanding market requirements.

The agricultural product logistics network (APLN) is a complex system involving multiple actors across production, collection, sorting, storage, and distribution, aiming to optimize flows of goods, information, and finance. Ghahremani-Nahr *et al.* (2022) identify its distinct challenges, including perishability, demand and cost uncertainties, temperature control, and multimodal transport under budget limits. Perdana *et al.* (2023) note that fresh agricultural product (FAP) supply chains are particularly complex due to short life cycles, special handling, and fragmented smallholder farming, with decentralized governance reducing costs, raising farmer income, and enhancing flexibility. Zhou *et al.* (2024) show that post-harvest losses in China highlight the need for cooperative logistics. Yao *et al.* (2023) and Liao and Chen (2024) further stress APLNs' role in cost reduction, freshness, customer satisfaction, rural revitalization, and sustainability.

2.2 Agricultural Supply Chains (ASC)

The ASC is a complex system encompassing processes ranging from initial material production to the delivery of final products to end consumers, characterized by strong linkages among SC members comprising farmers, processors, traders, retailers, and logistics service providers (Nguyen, 2022; Feng *et al.,* 2023; Sun *et al.,* 2020). According to Azab *et al.* (2023), ASCs generally comprise three main stages: (i) the agricultural stage (including cultivation and harvesting activities); (ii) the connection–transportation stage (covering activities from farms to processing); and (iii) the industrial stage (including processing and storage). In the context of fresh produce, ASCs underscore the symbiotic relationship between farmers, typically small-scale, dispersed and enterprises, usually capital-intensive and concentrated, where appropriate supportive mechanisms are essential for maintaining stability (Sun *et al.,* 2020). To meet increasing demand, modern ASC models have become prevalent, featuring dual-channel integration (traditional and online), cross-border e-commerce, and third-party logistics (3PL) services (Yan *et al.,* 2021; Wang & Gao, 2024; Jin, 2024; Chen & Zhao, 2023).

The salient features of ASC include the perishability and time sensitivity of products, which result in substantial losses, estimated at 25 – 40% in developing countries and exposure to diverse risks such as market, policy, financial, operational, labor, and environmental uncertainties, particularly under the impact of pandemics (Nguyen, 2022; Fan *et al.,* 2021; Chen & Zhao, 2023). Consistent with this view, Gurrala and Hariga (2022) found that food supply chain studies frequently address sustainability, safety, quality, traceability, and transparency challenges, while optimization models remain a dominant analytical approach. ASCs are further complicated by seasonality, price fluctuations, and interdependencies among nodes within the chain (Feng *et al.,* 2023). In addition, the lack of standardized regulations and high logistics costs, especially in cross-border models, heighten vulnerabilities to disruptions and data security risks (Jin, 2024; Zhu, 2024). Meanwhile, emerging technologies like big data, deep learning, and internet-based channels can mitigate information asymmetry, yet they require intensive cooperation and strong collaboration between SC actors (Wang & Gao, 2024; Yan *et al.,* 2021; Sun *et al.,* 2020).

Beyond these challenges, ASCs also contribute to ensuring global food security, fostering rural–urban linkages, promoting the agricultural economy, and supporting sustainable development by reducing waste, ensuring product quality, optimizing profits, and enhancing risk management (Nguyen, 2022; Azab *et al.,* 2023; Fan *et al.,* 2021). They improve production efficiency through technology adoption, enhance the welfare of farmers and consumers, promote exports and agricultural modernization, and simultaneously reduce logistics costs and CO_2 emissions (Feng *et al.,* 2023; Jin, 2024; Zhu, 2024; Chen & Zhao, 2023). Within a symbiotic model, ASCs enhance the value-added of products and strengthen competitiveness (Sun *et al.,* 2020; Yan *et al.,* 2021; Wang & Gao, 2024).

2.3 Citrus Fruit Supply Chain (CFSC)

The CFSC plays a crucial role in global agriculture, as citrus fruits such as oranges, mandarins, grapefruits, and lemons are among the most widely traded fruit crops, cultivated in over 140 countries and contributing significantly to food security and international trade (Rovetto *et al.,* 2024; Vono *et al.,* 2023). Structurally, the CFSC is multi-tiered, comprising smallholder farms, storage facilities, distribution centers, and consumer markets. The CFSC is highly sensitive to time, storage conditions, and inventory levels (Goodarzian *et al.,* 2022). Moreover, it faces challenges related to plant diseases, productivity losses, food safety risks from mycotoxin contamination, agrochemical use, and pesticide resistance (Rovetto *et al.,* 2024; Vono *et al.,* 2023).

Beyond supplying both fresh and processed products to global markets, the CFSC also contributes to quality assurance, food safety, and greenhouse gas reduction through optimized transportation and packaging practices (Goodarzian *et al.,* 2022; Liao *et al.,* 2020). Furthermore, integrated and sustainable SC management is considered essential for improving efficiency, minimizing losses, and fostering environmentally responsible production and consumption (Rovetto *et al.,* 2024; Vono *et al.,* 2023). Current critical challenges include post-harvest losses, high logistics costs, inefficiencies in plastic packaging management, and CO_2 emissions from transportation (Liao *et al.,* 2020; Yue *et al.,* 2025).

In this context, the application of smart sensing technologies, artificial intelligence (AI), the Internet of Things (IoT), and blockchain for quality monitoring, damage detection, traceability, and SC optimization has become widespread across countries (Yue *et al.,* 2025). This indicates that the future development trend of the CFSC will focus on digital technology integration, strengthening reverse logistics, packaging recycling, and advancing closed-loop SC to reduce costs and emissions while fostering a circular economy (Liao *et al.,* 2020; Yue *et al.,* 2025). Accordingly, the CFSC is not only an essential agri-food and trade system but also a network that requires sustainable governance and innovation to meet global market demands for safe, high-quality, and environmentally friendly food.

As shown in Figure 1, the CFSC in Vietnam, and more especially in the Mekong Delta region, travels through a number of steps from input to the end user. In particular, there are six phases in the Mekong Delta region's CFSC (Son et al, 2019; Duc & Yen, 2021). Minh *et al.* (2018), Thu *et al.* (2023), Khong (2022), and Duc & Yen (2021) are some of the elements that make up the CSC.

Input Suppliers: play an important role in the ASC by providing plant varieties and essential inputs such as fertilizers and pesticides. They ensure farmers have access to high-quality seeds that promote healthy crop growth and resistance to pests and diseases, while supplying fertilizers to maintain soil fertility and pesticides to protect crops. Input suppliers also act as advisors, assisting farmers with plant variety selection, fertilization, and pest management. This improves production efficiency, supports sustainable farming practices, and increases the productivity and profitability of agricultural households.

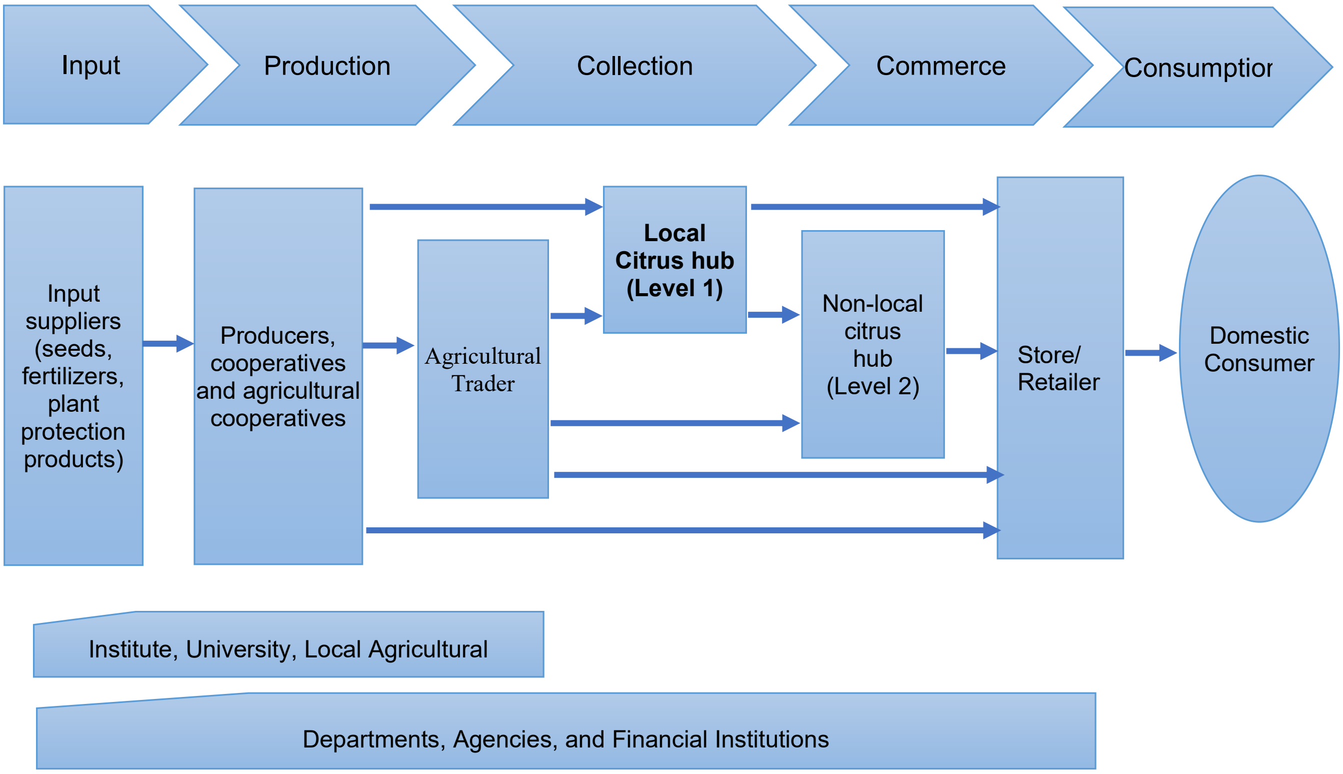

Figure 1 Diagram of the Citrus Fruits Value Chain
Source: Compiled from Minh et al. (2018), Son et al. (2019), Thu et al. (2023), and the authors' survey (2025)

Producers: This group includes individual home-based enterprises (farmers) who produce citrus products. Cooperatives and cooperative organizations also take part. During this phase, partnerships are formed to help one another with every step of the production process, from fertilizers and cultivation methods to locating premium inputs at affordable prices. Notably, these groups (farmers, cooperatives, cooperative groups) also prioritize the product output in order to stabilize the SC, raise economic value, and improve the output product's value.

Agricultural Traders: including local buyers and depot owners, serve as primary agents in the supply chain. They frequently serve as producers' initial point of contact by buying produce straight from farmers and distributing it to bigger markets or processing plants. Depot operators handle both product gathering and commercial dealing, which includes negotiating prices, organizing transportation, and distributing goods to markets. Their involvement guarantees a seamless product flow from farms to markets, improving the efficiency of the supply chain as a whole.

Local and Non-Local Citrus Hubs (Distribution centers): Citrus hubs, managed by local and non-local depot owners, are vital for fruit collection, marketing, and distribution. Acting as key intermediaries between producers and larger markets, they ensure efficient harvesting, initial quality checks, and price negotiations. Non-local hubs, often in urban centers, focus on redistribution to wholesalers and retailers while managing logistics and anticipating demand. Their role streamlines product flow from farms to regional, national, and international markets, ensuring a continuous and organized supply chain.

Store/Retailer: Because they link the supply of citrus with the end users, stores and merchants are essential to the CFSC. They buy from hubs and wholesalers, guaranteeing a variety of products to satisfy demand. Retailers oversee marketing, customer service, and inventory in addition to sales in order to preserve quality and reduce waste. Retailers are essential to the effectiveness and success of the supply chain because they help suppliers modify their offerings by obtaining customer feedback and market trends.

Other Actors: Various institutions, including universities, agricultural extensions, government agencies, and financial bodies, are key players in the CFSC. Universities provide research and technology to improve farming and develop new citrus varieties, while extensions support farmers with training and field assistance. Agencies ensure regulation and planning, and financial institutions supply needed capital. Together, these organizations strengthen efficiency, compliance, and sustainability across the citrus supply chain.

Based on the citrus fruit value chain illustrated in Figure 1, the system encompasses various actors such as input suppliers, farmers, cooperatives, traders, collection centers, retail outlets, and consumers. However, to simplify and facilitate the construction of an optimization model for the logistics network, this value chain can be reformulated into a three-stage SC model as shown in Figure 2: Producers/Farmers, Distribution Centers, and Customers. This three-stage approach enhances the clarity and quantifiability of the analysis, while still capturing the essential characteristics of the citrus fruit value chain. It thereby provides a solid foundation for multi-objective optimization research in the context of the Mekong Delta.

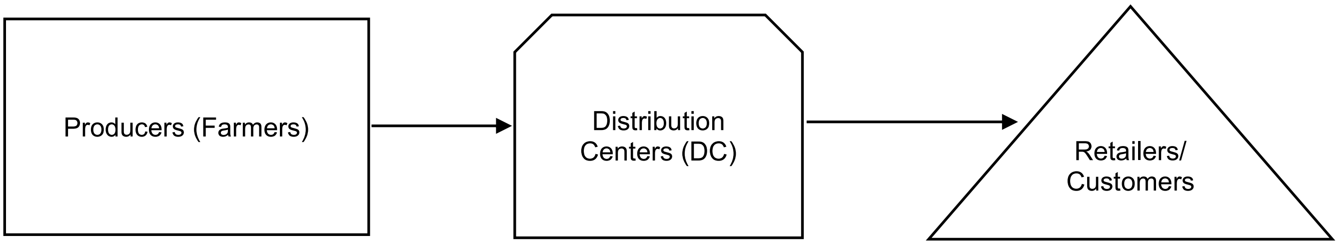

Figure 2 The Proposed Citrus Fruit Supply Chain Model

According to Figure 2, the model consists of the following three primary stages:

Stage 1: The production process where items are made is represented by this stage in citrus fruit plantations. During this stage, farmers are essential to all associated activities. Traders will purchase the goods from the farmers who produce them.

Stage 2: Traders sift and pre-package the items after buying them from the orchards and then deliver them to distribution hubs. When the goods arrive, the DC warehouses them, re-sorts them, finishes the packing, and gets them ready for market distribution.

Stage 3: This phase is essential to getting the goods to the final customer. Following their departure from the distribution hubs, the products are delivered to retail locations like traditional markets, supermarkets, and convenience stores. Retailers receive the products, display them, and sell them directly to customers in their capacity as middlemen between distributors and consumers.

2.4 Multi-Objective Optimization in Logistics Networks

Multi-objective optimization in ASC has been extensively investigated to balance economic, environmental, and social performance. Several scholars have applied MILP and Mixed-Integer Programming (MIP) models to optimize economic objectives in SC of perishable products such as fresh fruit, vegetables, coffee, and flowers (Esteso *et al.,* 2021; Orjuela-Castro *et al.,* 2022; Pitakaso *et al.,* 2022; Chen *et al.,* 2022; Kurniawati & Rochman, 2023; Clavijo-Buritica *et al.,* 2023; Violi *et al.,* 2024; Urra-Calfuñir *et al.,* 2024; Khazaeli *et al.,* 2024; Chen & Chen, 2023). For canned food products, Rahbari *et al.* (2023) conducted an economic optimization of this product line in Iran using an MILP model. Similarly, Yuniarti *et al.* (2023) employed an MILP model to optimize economic objectives for products such as organic vegetables, food waste, and compost in Indonesia.

In addition, the study by Kailaku *et al.* (2022) employed Goal Programming (GP) and the Surplus Model (SM) to maximize the number of customers, minimize post-harvest losses, and reduce transportation costs in the mango SC. Miao and Ni (2023) applied a Simulation (SIM) model to minimize logistics costs and enhance customer satisfaction in agricultural product SC. Biza *et al.* (2024) utilized an MILP model to optimize objectives related to reducing food loss caused by poor management, lowering total costs, and strengthening food security. More recently, Pan *et al.* (2025) addressed the dairy SC in China, aiming to minimize total costs and maximize service levels through an MILP model. Orjuela-Castro *et al.* (2023) applied an MIP model to optimize economic objectives and minimize expected total costs both in pre- and post-disaster phases, while simultaneously improving SC resilience by providing strategic and tactical decision-making under uncertain demand and disruption risks, particularly within worst-case probabilistic distribution scenarios.

Other studies have also employed MIP or MILP models to optimize environmental and economic objectives. Notable examples include research on the SC of milk, fruits, cashew, and apples (Wang *et al.,* 2021; Meidute-Kavaliauskiene *et al.,* 2022; Belamkar *et al.,* 2023; Rajabi-Kafshgar *et al.,* 2023; Flores-Siguenza *et al.,* 2025). Azab *et al.* (2023), in their study on the sugar beet SC, optimized both social and economic objectives.

At the same time, several authors have conducted studies that integrate all three objectives: economic, social, and environmental, across different product categories. A representative example is the study by Drofenik *et al.* (2023), which applied an MILP model to optimize the SC of agricultural products such as fruits, vegetables, and grapes in Slovenia. Similarly, Javanmardan *et al.* (2024) examined the fruit SC in Iran, while Gholian-Jouybari *et al.* (2024) investigated the closed-loop SC of coconuts in the Philippines. More recently, studies by Pan and Shan (2024) and Shekarabi *et al.* (2025) have focused on the milk SC using MILP models.

Overall, research on multi-objective optimization in ASC has largely concentrated on perishable products such as fresh fruits, vegetables, and coffee, primarily employing MILP or MIP models to optimize economic performance, namely, reducing costs, increasing profitability, and minimizing losses (Esteso *et al.,* 2021; Orjuela-Castro *et al.,* 2022; Pitakaso *et al.,* 2022). While some studies have expanded to include environmental or social objectives, most remain limited to addressing two dimensions rather than simultaneously integrating all three (Wang *et al.,* 2021; Azab *et al.,* 2023). Although more comprehensive works have recently emerged, such as those by Drofenik *et al.* (2023) and Javanmardan *et al.* (2024), these studies have been conducted primarily in other regions of the world and do not capture the unique characteristics of tropical production systems. Consequently, a significant research gap lies in the simultaneous optimization of economic, social, and environmental objectives in CFSC in the Mekong Delta, Vietnam. This need is particularly urgent in the context of climate change, growing pressures from export competition, and the heavy reliance of millions of smallholder farmers on this crop.

Table 1 Summary of Related Studies

Sources	Objective Functions				Type of Products	Model	Countries
	Economic	Social	Environment	Others			
Esteso *et al.* (2021)	*				Vegetable, Fresh fruit	MILP	Spain
Wang *et al.* (2021)	*		*	*	Fruit	MIP	Vietnam
Orjuela-Castro *et al.* (2022)	*				Fruit	MILP	Columbia
Meidute-Kavaliauskiene *et al.* (2022)	*		*		Milk	MILP	Turkey
Pitakaso *et al.* (2022)	*				Vegetable	MIP	GMS
Kailaku *et al.* (2022)	*			*	Mango	GP, SM	Indonesia
Chen *et al.* (2022)	*				Vegetable, Fruits	MILP	China
Rahbari *et al.* (2023)	*				Canned food	MILP	Iran
Orjuela-Castro *et al.* (2023)	*			*	Mango, Strawberry, Orange	MIP	Colombia
Drofenik *et al.* (2023)	*	*	*		Vegetable, Fruits, Grapes	MILP	Slovenia
Kurniawati & Rochman (2023)	*				Vegetables, Fruits, Meat, Fish,	MILP	Indonesia
Clavijo-Buritica *et al.* (2023)	*				Coffee	MILP	Colombia
Chen & Chen (2023)	*				Vegetables	MILP	China
Belamkar *et al.* (2023)	*		*		Apple	MILP	India
Yuniarti *et al.* (2023)	*				Organic Vegetables, Food waste and Compost	MILP	Indonesia
Azab *et al.* (2023)	*	*			Sugar beet	MILP	Netherlands
Rajabi-Kafshgar *et al.* (2023)	*		*		Cashew	MILP	Iran
Miao & Ni (2023)				*	Agricultural products	SIM	China
Violi *et al.* (2024)	*				Flowers. Fruits	MILP	Italy
Javanmardan *et al.*(2024)	*	*	*		Fruit	MILP	Iran
Gholian-Jouybari *et al.*(2024)	*	*	*		Coconut	MILP	Philippines
Urra-Calfuñir *et al.* (2024)	*				Olive oil	MILP	Chile
Khazaeli *et al.* (2024)	*				Vegetables	MILP	Iran
Pan & Shan (2024)	*	*	*		Vegetables,Milk, Fruit	MILP	China
Biza *et al.* (2024)	*			*	Tomato	MILP	Ethiopia
Shekarabi *et al.* (2025)	*	*	*		Milk	MILP	Australia
Flores-Siguenza *et al.* (2025)	*		*		Milk	MILP	Ecuador
Pan *et al.* (2025)	*			*	Milk	MILP	China
This study	*	*	*	*	Citrus fruit	MILP	Vietnam

Source: Adapted from Chuyen & Rajagopal (2025), with modifications and additional references

3. OBJECTIVE OPTIMIZATION AND SOLUTION METHOD

3.1 Multi-Objective Optimization

Building on the studies of Javanmardan *et al.* (2024), Gholian-Jouybari *et al.* (2024), Pan & Shan (2024), Shekarabi *et al.* (2025), Chen *et al.* (2023), and Drofenik *et al.* (2023), the optimization objectives are defined as: minimizing costs, maximizing social impact, and minimizing environmental emissions. This section introduces a multi-objective MILP framework designed to optimize these three core objectives within APLN.

$$OBJECTIVES = OBJ_1 + OBJ_2 + OBJ_3 \quad (1)$$

Minimize the Total Cost (OBJ_1)

The cost structure includes a number of elements that are necessary for the SC to run effectively. It comprises shipping costs, which include the costs incurred in transporting goods across locations, and fixed costs, which are the baseline expenses that are unaffected by output levels (Liao et al, 2020; Chen *et al.,* 2023; Drofenik *et al.,* 2023). In order to maintain appropriate stock levels, it also takes into consideration the inventory cost of goods kept at sorting centers, also known as DCs. In order to highlight the costs associated with the production process at the source, the manufacturing cost of gardens is also included. Another crucial element is the cost of sorting and packing at sorting centers, which represents the expenses related to arranging and getting goods ready for distribution (Gholian-Jouybari *et al.,* 2024; Javanmardan *et al.,* 2024; Pan & Shan, 2024; Shekarabi *et al.,* 2025).

$$Min\ OBJ_1 = Z_1 + Z_2 + Z_3 + Z_4 \quad (2)$$

$$Z_1 = \sum_{j=1}^{J} f_j \times D_j + \sum_{k=1}^{K} f_k \times D_k \quad (3)$$

$$Z_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{t'} Tq_{ij} \times Q_{ijt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} Tr_{jk} \times R_{jkt} + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} Tm_{ik} \times M_{ikt} \quad (4)$$

$$Z_3 = \sum_{j=1}^{J}\sum_{t=1}^{t'} Id_{jt} \times Cd_{jt} + \sum_{k=1}^{K}\sum_{t=1}^{T} Id_{kt} \times Cd_{kt} \quad (5)$$

$$Z_4 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{t'} Q_{ijt} \times Cp_{jt} + \sum_{i=1}^{I}\sum_{t=1}^{t'} \alpha_{it} \times Cp' \quad (6)$$

Maximize the Social Benefits (OBJ_2)

Establishing facilities and generating employment opportunities are key components of maximizing social benefits. While variable employment includes seasonal or project-based jobs that adjust to facility needs, fixed employment refers to long-term responsibilities required for continuous operations (Azab *et al.,* 2023; Gholian-Jouybari *et al.,* 2024; Pan & Shan, 2024). For the creation of both fixed and variable jobs, efficient SC management is essential, especially through facility setup and operation. By creating steady jobs, strengthening the local economy, and tackling more general problems like food and economic insecurity, this strategy promotes social sustainability (Javanmardan *et al.,* 2024; Shekarabi *et al.,* 2025; Chen et al 2023; Drofenik *et al.,* 2023).

$$Max\ OBJ_2 = \boldsymbol{Z_{FE}^t} + \boldsymbol{Z_{VE}^t} \quad (7)$$

$$Z_{FE}^t = \sum_{i=1}^{I} FE_i^t \times X_i^t + \sum_{j=1}^{J} FE_j^t \times X_j^t + \sum_{k=1}^{K} FE_k^t \times X_k^t \quad (8)$$

$$Z_{VE}^t = \sum_{i=1}^{I} VE_i^t \times X_i^t + \sum_{j=1}^{J} VE_j^t \times X_j^t + \sum_{k=1}^{K} VE_k^t \times X_k^t \quad (9)$$

Minimizing Environmental Impact (OBJ_3)

In the modern world, cutting emissions is a critical concern. It is clear that the majority of firms prioritize growing their financial advantages. However, by implementing strict environmental rules, environmental managers and organizations have forced businesses and manufacturers to follow sustainability standards. This supports environmental preservation as well as corporate social responsibility (Roghanian & Cheraghalipour, 2019; Liao *et al.,* 2020; Goodarzian *et al.,* 2022). Furthermore, among the most important concerns mentioned in recently published studies are environmental effects including lowering CO2 emissions. These studies highlight how crucial it is to cut emissions in order to safeguard the environment and enhance human well-being (Belamkar *et al.,* 2023; Yuniarti *et al.,* 2023; Javanmardan *et al.,* 2024; Shekarabi *et al.,* 2025).

$$Min\ OBJ_3 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{t'} Dq_{ij} \times \frac{Q_{ijt}}{C_a} x\, \beta_f \times F_{vf} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} Dr_{jk} \times \frac{R_{jkt}}{C_a} \times \beta_f \times F_{vf} + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} Dm_{ik} \times \frac{M_{ikt}}{C_a} \times \beta_f \times F_{vf} \quad (10)$$

Indices

$i = 1, 2,\ldots, I$	The gardens index (the manufacturing locations)
$j_1 = 1, 2,\ldots,J_1$	The distribution sites' fixed points
$j_2 = 1, 2,\ldots,J_2$	The possible sites for the DCs
$j = j_1 + j_2$	Every location of the DCs
$k = 1, 2,\ldots,K$	Customer location index (citrus fruit markets)
$t = 1,2, t',\ldots, T$	The time period index
β_f	The fuel's CO2 emissions factor (f) per kilogram of gasoline used
F_{vf}	Fuel requirement for vehicle v per km of transportation (kg/km)

Parameters

f_j	The initial fixed cost of setting up a DC j
f_k	The initial fixed cost of setting up retail sites k
Tq_{ij}	Cost of shipping each unit of goods from manufacturer i to DC j
Tr_{jk}	The cost of shipping each product from DC j to customer k
Tm_{ik}	Cost of shipping each unit of goods from manufacturer i to buyer k
Cd_{jt}	Cost per unit of inventory held at time t from DC j
Cd_{kt}	Cost of holding inventory per unit from customer k at time t
Cp_{jt}	Expense associated with product preparation and encasement per unit from DC j at time t
Cp'	Cost of production per unit of the producer's goods (gardens)
Dq_{ij}	The transportation distance from producer *i* to DC *j*
Dm_{ik}	The transportation distance from producer i to customer k
Dr_{jk}	Transportation distance from DC j to customer k
FE_i^t	Fixed employment at production site (garden) i
FE_j^t	Quantity of permanent positions employed in DC j
FE_k^t	Quantity of permanent positions employed in retailer k
VE_i^t	Quantity of adaptable employment opportunities produced by production location i at time t
VE_j^t	Number of variable jobs generated by DC j at time t
VE_k^t	Number of variable jobs generated by retailer k at time t
C_a	Capacity of different vehicles
Ω_t	Proportion of harvested products discarded by producers at time t
N	A significantly large positive value
αc_{it}	Maximum output capability of producer i at time t
αh_j	Storage potential of DC j at time t
d_{kt}	Demand product of customer k at time t

Decision Variables:

Q_{ijt}	Volume of goods transported from producer i to DC j at time t
R_{jkt}	Volume of goods dispatched from DC j to customer k at time t
M_{ikt}	Volume of goods transported from producer i to customer k at time t
Id_{jt}	Amount of processed goods held by DC j at time t
Id_{kt}	Quantity of stored processed products by retailer k at time t
D_j	1 If distribution location j is opened at the location, 0 otherwise
D_k	1 If retailer k is opened at the location, 0 otherwise
α_{it}	Volume of output generated by producer i at time t
X_i^t	1 if the potential site for facility i is activated, otherwise 0
X_j^t	1 if the proposed site for facility j is established, otherwise 0
X_k^t	1 if the potential site for facility k is activated, otherwise 0

Different kinds of transportation vehicles are used to accomplish these goals, and each one uses a different kind of fuel *(f)*. The amount of CO2 emissions produced during transportation is directly impacted by the type of fuel used and the vehicle selected. The type of vehicle and the distance traveled, expressed in kilometers, both affect these emissions. The various capacities *(ca)* of the vehicles used to transport agricultural products are important factors in determining how effectively the goods are transported throughout the SC. The number of transportation rounds *nxn* is determined by the number of journeys (for example, *n* trips for the first stage, where ($n = Q_{ijt}/ca$), where Q_{ijt} is the quantity of products) and the amount of items transported at each stage. Furthermore, each transit step entails a particular distance, such as Dq_{ij} kilometers for the initial portion of the trip. It is possible to precisely determine the total CO2 emissions during the transportation process by multiplying the number of commodities and the distance traveled for each stage. This makes it possible to assess the SC logistics' effects on the environment in great detail.

Subject to (st)

$$\alpha_{it} \, x \, (1- \Omega_t) = \sum_{j=1}^{J} Q_{ijt} + \sum_{k=1}^{K} M_{ikt}, \ \forall i \in I, \ \forall t \in T \tag{11}$$

$$\sum_{i=1}^{I} \sum_{t=1}^{t'} Q_{ijt} \leq N \times D_j, \ \forall j \in J \tag{12}$$

$$\alpha_{it} \leq \alpha c_{it}, \ \forall i \in I, \ \forall t \in T \tag{13}$$

$$Id_{j(t-1)} + \sum_{i=1}^{I} Q_{ijt} = Id_{jt} + \sum_{k=1}^{K} R_{jkt}, \ \forall j \in J, \ \forall t \in T \tag{14}$$

$$Id_{jt} \leq \alpha h_j, \ \forall j \in J, \ \forall t \in T \tag{15}$$

$$\sum_{j=1}^{J} R_{jkt} + \sum_{i=1}^{I} M_{ikt} \leq d_{kt}, \ \forall k \in K, \ \forall t \in T \tag{16}$$

$$D_j \in \{0, 1\}, \ \forall j \in J \tag{17}$$

$$Q_{ijt}, R_{jkt}, M_{ikt} \geq 0; \ \forall i \in I, \ \forall j \in J, \ \forall k \in K, \ \forall t \in T \tag{18}$$

$$Id_{jt} \geq 0, \ \alpha_{it} \geq 0, \ \forall i \in I, \ \forall j \in J, \ \forall t \in T \tag{19}$$

Equation (11) shows that the quantity of products distributed from the production site (gardens) to the sorting centers and fruit stores (fruit markets) is balanced with the quantity of the main goods (the number of complete products ready for sale in the market) (fruits produced from orchards minus the damaged, bruised, or rotten fruits). In connection with constraint (11), constraint (12) guarantees that goods are only delivered to a possible site in the event that a DC is established there. According to constraint (13), each producer's output cannot above the anticipated maximum production capability. This clause was put in place to accommodate for the producer's inherent production constraints. Constraint (14) guarantees that the level of inventory at each DC at any given time corresponds to the stock from the preceding period, together with the volume of items purchased from manufacturers and reduced by the quantity of products shipped to consumers. The distribution center's inventory levels at each time period are kept within the facility's maximum holding capacity, as explained by constraint (15). According to constraint (16), each customer's demand during each period must be larger than or equal to the amount of goods received from the manufacturer and the DC. The requirements for binary and non-negativity constraints on the pertinent choice variables are finally outlined in constraints (17), (18), and (19).

3.2 Solution Approach

According to the literature review, a variety of solution techniques have been used to solve multi-objective problems (e.g., Mohebalizadehgashti *et al.,* 2020; Rahbari *et al.,* 2023; Belamkar *et al.,* 2023; Chen & Chen, 2023; Javanmardan *et al.,* 2024; Gholian-Jouybari *et al.,* 2024). The augmented ε-constraint approach, an improved variant of the conventional ε-constraint methodology, has been used in this study based on pertinent research. To make the calculation process easier, this technique is applied to convert the multi-objective model under consideration into an equivalent single-objective formulation.

A single objective function is maximized or minimized using the conventional ε-constraint approach, while the remaining goal functions are treated as constraints with relevant upper and lower thresholds. These bounds represent various amounts of epsilon (ε) and are modified to produce Pareto solutions (Mohebalizadehgashti *et al.,* 2020). However, because of its many advantages, the augmented ε-constraint methodology, which was first put forth by Mavrotas (2009), has garnered a lot of attention from academics lately. The effectiveness of Pareto-optimal solutions can be guaranteed by this methodology. Furthermore, when researchers are requested to solve problems involving more than two objective functions, it may be able to reduce processing time (Mavrotas, 2009). The improved version of the traditional ε-constraint approach has been used in several studies (Mohebalizadehgashti *et al.,* 2020; Roghanian & Cheraghalipour, 2019; Goodarzian *et al.,* 2022; Aghajani *et al.,* 2024). Through the following steps, a multi-objective model is resolved using the augmented ε-constraint methodology (Mavrotas, 2009). The analysis process consists of five steps, which include the following:

Step 1: Choose an objective function to serve as the main objective. Cost minimization was selected as the primary objective of the study.

Step 2: The creation of a reward table is necessary to determine the range of goals that are then converted into limitations. Calculating the highest and lowest numbers related to each goal is essential to achieving this. The objectives of maximizing employment (OBJ2) and lowering CO2 emissions (OBJ3) will be transformed into limitations for the sake of this study. For each objective, the range is then determined through deriving the global optimum solution for that objective and applying the result to the other objective functions. As a result, this procedure will produce three different numbers that make it easier to determine the upper and lower bounds for every goal.

Step 3: To determine the v (|v| = q + 1) grid points corresponding to each optimization objective, partition the span of every objective into q uniform segments. Every grid point represents a unique subproblem that needs to be solved. This means that each sub-problem has a single Pareto-optimal solution.

Step 4: The suggested model's structure has been modified as follows:

$$Min\ OBJ_1$$

$$Subject\ To$$

$$OBJ_2 \geq OBJ_{2\,(min)} + V.\Delta \in OBJ_2 \tag{20}$$

$$OBJ_3 \geq OBJ_{3\,(max)} - V.\Delta \in OBJ_3 \tag{21}$$

$$where\ v = 0, 1, 2, \dots, q$$

$$\Delta \in OBJ_2 = \left(\frac{OBJ_{2(max)} - OBJ_{2(min)}}{q}\right) \tag{22}$$

$$\Delta \in OBJ_3 = \left(\frac{OBJ_{3(max)} - OBJ_{3(min)}}{q}\right) \tag{23}$$

For the environmental objective, the emission constraint is anchored on OBJ3(max). As v increases, the allowable emission ceiling is gradually reduced from OBJ3(max) toward OBJ3(min). This formulation represents a tightening upper bound while remaining feasible within the selected grid range. The reported emission values may still increase across some solutions because the employment lower bound becomes more restrictive and induces higher logistics activity, whereas the emission ceiling remains non-binding in those cases.

Step 5: To ensure the optimality of the generated solutions, the constraints of the objective function in the aforementioned model must be converted into equations by adding suitable slack or surplus variables. Additionally, a critical stage in the process is incorporating these surplus and slack variables into the primary target function. Additionally, this step involves thinking about and adding more restrictions to the model. Consequently, we will have:

$$Min\ OBJ_1 + \varphi\,(L_1 + L_2)$$

$$Subject\ To$$

$$OBJ_2 - L_2 = OBJ_{2\,(min)} + V.\Delta \in OBJ_2 \tag{24}$$

$$OBJ_3 + L_1 = OBJ_{3\,(max)} - V.\Delta \in OBJ_3 \tag{25}$$

$$where\ v = 0, 1, 2, \dots, q$$

$$L_1, L_2 \geq 0$$

Where Ф is an extremely small number, it usually falls between 10^{-3} and 10^{-6}. Nonetheless, it has no effect on the primary objective function's value (Mota *et al.,* 2015). L1 and L2 magnitudes must be exactly zero or extremely near zero in order to get an effective Pareto optimum solution (Felfel *et al.,* 2016). This criterion makes sure that the trade-offs between the conflicting goals are balanced, enabling the best possible solution that successfully meets the model's requirements. The solution can be made more effective and efficient by reducing these magnitudes, underscoring the importance of properly factoring these parameters into the optimization process. For the multi-objective framework to produce positive results, L1 and L2 control is therefore essential.

It is important to understand that no one solution can maximize social benefits, minimize costs, and lessen environmental impact, the three previously mentioned objectives—all at once. Rather, choices frequently necessitate embracing compromises between various goals. By using the augmented ε-constraint technique, a collection of Pareto-optimal solutions is used to evaluate these trade-offs. No solution may enhance one goal without also impairing other goals, according to the Pareto-optimal set. The Pareto approach is thought to be ideal when there isn't a workable way to improve one or more goals without sacrificing the others (Coello and Romero, 2003).

The MILP model was also used in the study to improve the supply chain's efficacy and efficiency. The MILP model was developed and tested using information from both qualitative and quantitative investigations. The optimization challenge was solved using LINGO software, which made it possible to model intricate logistical scenarios and find the best answers. A thorough method for examining and enhancing logistics network governance was made possible by the combination of statistical analysis, thematic analysis, and MILP modeling.

3.3 Model Implementation

To illustrate the implementation of the agricultural logistics network optimization model, this study focuses on the King Orange SC in the Mekong Delta, one of Vietnam's key fruit-growing regions. King Orange is a high-value crop with strong demand in major domestic urban markets and significant export potential (VietNam Economic Times, 2025). However, King Orange SC faces multiple challenges, including high logistics costs, pronounced seasonality, unstable employment opportunities, and mounting pressure to curb greenhouse gas emissions consistent with the green agriculture agenda (LVVN, 2025; MAE, 2025).

According to NSO (2025d), national orange production in 2024 reached approximately 1,915.5 thousand tons, of which the Mekong Delta accounted for 1,353.7 thousand tons, representing over 70% of total national output. Vinh Long stood out as the leading province with 938 thousand tons, followed by Tra Vinh (248.5 thousand tons) and Hau Giang (95.4 thousand tons). This large yet unevenly distributed volume underscores the urgent need for designing an efficient logistics network capable of simultaneously addressing three strategic objectives: (i) minimizing operational costs; (ii) maximizing job creation for local labor; and (iii) reducing CO_2 emissions.

The model is solved using the augmented ε-constraint method (Mavrotas, 2009) to generate a set of Pareto-efficient solutions that capture the trade-offs among the three objectives. To support managerial decision-making, the study adopts a two-stage interactive selection mechanism (Miettinen, 1999; Steuer, 1986). In the first stage, Pareto solutions are generated and visualized to provide an overview of the trade-off relationships between cost, employment, and emissions. In the subsequent stage, a Region of Interest (ROI) is identified, within which potential scenarios are further analyzed to determine the most balanced solution aligned with the sustainable agricultural logistics development agenda (Le & Shin, 2018; Morales-Hernández *et al.,* 2023). In addition, a one-way sensitivity analysis was performed to assess the robustness of the selected knee point. Transportation cost and demand were separately varied by ±10% and ±20%, while the same augmented ε-constraint procedure was repeated for each scenario.

For the empirical data, the study conducted surveys with key actors in the King Orange SC in the Mekong Delta, including: (i) two orange-producing farmers in Vinh Long; (ii) two collectors serving as distribution centers; (iii) four workers at the collection hubs; (iv) two road transport drivers; (v) one retailer in Ho Chi Minh City; and (vi) one retailer in Hanoi. This selection reflects the SC structure spanning production, collection, distribution, and consumption, while highlighting the roles of intermediaries and labor within the system. We acknowledge that the primary survey involved twelve key informants across the King Orange supply chain, including producers, collection hubs, labor at hubs, transport drivers, and retailers in the two major destination markets. This empirical component was designed for model parameterization rather than statistical inference. Therefore, we employed purposive, maximum-variation sampling to ensure coverage of the main decision points that determine cost, capacity, and distance outcomes: (i) production nodes in the dominant cultivation area; (ii) intermediate consolidation and handling at collection hubs; (iii) line-haul transportation; and (iv) retail distribution in metropolitan markets. o reflect regional heterogeneity, key parameters were not treated as single-point estimates. Instead, transportation costs, handling and inventory costs, production costs, capacities, and route distances were represented as ranges derived from (a) multiple quotations and operational records obtained from the interviewed actors and (b) objective route measurements and equipment specifications. These ranges were then used to calibrate the model and to capture variability across short-haul movements within the production area and long-haul movements to metropolitan markets.

The simulation scenario is constructed based on the flow of goods from concentrated production areas (primarily in Vinh Long and Tra Vinh) to distribution centers, followed by transportation to key consumption markets in Ho Chi Minh City and Hanoi. Indicators related to logistics costs, employment generation (including both regular and temporary jobs), and CO_2 emissions from road transport activities are collected and integrated into the model.

The application of the model to the King Orange SC in the Mekong Delta not only enables the identification of an optimal logistics network configuration but also facilitates comparison, trade-off analysis, and the selection of appropriate operational strategies. More importantly, the findings provide empirical evidence to inform policy directions for the sustainable development of agricultural logistics, enhancing economic efficiency, promoting rural livelihoods, and contributing to Vietnam's commitment to reducing greenhouse gas emissions.

Table 2 The Number of Factors in the Supply Chain

Indices	Number of Factors
i	2
j	2
k	2
Workers	4
Driver	2

Table 3 Values of the Parameters

Parameters	Value	Unit of Measurement
f_j	Unit [2,560,000,000; 310,000,000]	VND
f_k	Unit [110,000,000; 127,000,000]	VND
Tq_{ij}	Unit [4,167; 2,274]	VND/Ton/Km
Tr_{jk}	Unit [4,167; 2,274]	VND/Ton/Km
Tm_{ik}	Unit [4,167; 2,274]	VND/Ton/Km
Cd_{jt}	Unit [82,000; 135,000]	VND/Ton/Month
Cd_{kt}	Unit [67,000; 62,500]	VND/Ton/Month
Cp_{jt}	Unit [163,000; 270,000]	VND/Ton/Month
Cp'	Unit [6,263,750; 5,488,636]	VND/Ton
Dq_{ij}	Unit [15; 34]; [11; 29]	Km
Dm_{ik}	Unit [151; 1841]; [150; 1840]	Km
Dr_{jk}	Unit [170; 1860]; [184; 1862]	Km
FE_i^t	Unit [3; 2]	Person
FE_j^t	Unit [10; 10]	Person
FE_k^t	Unit [3; 5]	Person
VE_i^t	Unit [5; 8]	Person
VE_j^t	Unit [90; 18]	Person
VE_k^t	Unit [5; 2]	Person
C_a	Unit [15; 25]	Ton
Ω_t	Unit [5; 5]	Percentage
αc_{it}	Unit [195; 270]	Ton
αh_j	Unit [2100; 1200]	Ton/month
d_{kt}	Unit [150; 240]	Ton/month

4. OBJECTIVE OPTIMIZATION AND SOLUTION METHOD

An analysis of the collected data suggests that, within the scope of this study, the dataset provides adequate coverage of the key variables required for model development and demonstrates acceptable internal consistency and reliability. Specifically, Table 2 provides a complete representation of the stakeholders involved in the SC, while Table 3 details the input parameters, including fixed costs at distribution centers and retail outlets, variable costs per ton/kilometer, transportation distances, as well as socio-economic coefficients and other auxiliary parameters. The use of 15-ton diesel trucks further enhances the practical relevance of the study, as this type of vehicle is widely employed in agricultural logistics operations. Consequently, the dataset not only ensures consistency with real-world conditions but also serves an essential function in generating optimal results with both scientific significance and strong practical applicability.

In the first step, the study divides the range of each objective function into ten discrete points ($v = 10$). Iterative runs conducted from $v = 0$ *to* $v = 5$ yield the results presented in Table 4. Beyond $v = 6$, however, the model fails to generate feasible solutions. The results in Table 4 indicate the presence of a linear trade-off region, which can be identified approximately within the interval from $v = 0$ *to* $v = 4$. Within this region, the incremental changes among the objectives exhibit a relatively stable relationship. Specifically, in order to achieve an increase of approximately 69.05 jobs for objective OBJ2, the OBJ1 consistently rises within the range of 296.81 to 319.00 million VND. Similarly, OBJ3 increase within a predictable margin, ranging from 277.25 to 282.86 kg CO_2. This region represents operational strategies in which the costs associated with achieving social and environmental benefits are both predictable and manageable. Although the upper bound on OBJ3 is tightened as v increases, the realized emission values still rise in the reported solutions because the environmental constraint is not binding in this range. In other words, the increase in OBJ2 induces higher logistics

Table 4 Optimal Results of the Objectives (First step)

v	OBJ 1 (Million VND)	OBJ 2 (Workers)	OBJ 3 (Kg CO2)
0	1,811.46	390.05	1,477.04
1	2,108.27	459.10	1,754.29
2	2,427.15	528.15	2,034.91
3	2,745.98	597.19	2,317.77
4	3,064.85	671.24	2,599.54
5	5,897.55	740.29	2840.49

Table 5 Optimal Results of the Objectives (Second Step)

v	OBJ 1 (Million VND)	OBJ 2 (Workers)	OBJ 3 (Kg CO2)
v = 4.25	3,144.56	683.5	2,670.00
v = 4.50	3,224.32	700.77	2,740.46
v = 4.75	3,304.02	718.03	2,811.87

Table 6 Sensitivity Analysis of Knee Point Robustness

Scenario	Parameter Change	Knee Point (v)	OBJ1	OBJ2	OBJ3
Transportation Cost	-10%	v = 4.75	3,284.91	713.89	2,794.75
	+10%	v = 4.75	3,323.13	718.19	2,812.08
	-20%	v = 4.75	3,265.80	709.75	2,777.63
	+20%	v = 4.75	3,342.24	718.36	2,812.29
Demand	-10%	v = 4.75	3,305.03	718.04	2,811.88
	+10%	v = 4.75	3,303.02	718.04	2,811.88
	-20%	v = 4.75	3,306.03	718.05	2,811.89
	+20%	v = 4.75	3,302.01	717.59	2,810.07

activity, while the imposed emission ceiling remains above the achieved emission level.

In addition, the results indicate the emergence of an inflection point during the transition from v = 4 to v = 5, reflecting a sudden escalation in marginal costs. While the increase in OBJ2 remains stable at 69.05 units of employment, the cost of OBJ1 surged to 2,832.7 million VND, representing an abnormal increment compared to previous steps. Marginal cost analysis reveals that the expense required to generate one additional unit of OBJ2 rose sharply from approximately 4.3 million VND (in the transition v = 3 → v = 4) to 41.0 million VND (in the transition v = 4 → v = 5), equivalent to nearly a 900% increase in cost efficiency. This finding suggests that the system had exhausted all efficient alternatives and was compelled to adopt extreme-cost solutions in order to maximize the social objective. Notably, the increment in OBJ3 during the final step was the lowest (240.95 kg CO_2), indicating a strategic shift towards higher costs but more effective emission reduction.

Based on these quantitative analyses, the application of a more in-depth examination within a ROI is essential. The rationale lies in the sparse distribution of solutions along the Pareto frontier between v = 4 and v = 5. This gap imposes a substantial limitation on policymakers, forcing them to choose between a balanced solution (v = 4) and one with excessively high marginal costs (v = 5), without the availability of intermediate options.

In the second step, the study subdivided the domain of each objective function into three intermediate points within the interval between v = 4 and v = 5 (i.e., v = 4.25, v = 4.50, and v = 4.75). Table 5 demonstrates that within the range of v = 4.0 to v = 4.75, the system exhibits a highly efficient and relatively stable operating region. Specifically, the marginal cost of generating an additional unit of employment (OBJ2) remains low, approximately 4.62 million VND per job. At the same time, the environmental cost displays a predictable pattern, with marginal emissions amounting to 4.07 kg CO_2 per job. This stability indicates that the solutions within this interval (v = 4.25 to v = 4.75) represent a consistent and efficient operational strategy.

However, this analysis precisely identified an inflection point during the transition from v = 4.75 to v = 5.0. At this point, the economic marginal cost surged dramatically from 4.62 million VND to approximately 116.5 million VND per job, a more than 25-fold increase, confirming that any attempt to expand employment beyond this threshold becomes financially infeasible. Interestingly, the behavior of the environmental objective exhibited an inverse pattern: the marginal emission dropped sharply to only 1.29 kg CO_2 per job. This simultaneous yet opposing shift strongly reinforces the hypothesis of a strategic operational transition within the model. To achieve the highest level of employment, the system is forced to abandon cost-efficient options and adopt an extremely expensive configuration that nevertheless yields greater emission efficiency per unit of activity.

Based on a comprehensive analysis of all three objectives, the solution at v = 4.75 (OBJ1 = 3,304.02 million VND; OBJ2 = 718.03 jobs; OBJ3 = 2,811.87 kg CO_2) is identified as the optimal trade-off solution. This point not only represents the maximum achievable threshold of the social objective before economic costs become unsustainable, but also marks the endpoint of a stable environmental trade-off region. While selecting the v = 5.0 solution may appear more favorable in terms of marginal emission reduction at the final step, it comes at an excessively high economic price, and the total emission remains the highest. Therefore, the v = 4.75 solution provides a strong quantitative rationale for policymakers to adopt the most balanced and practical strategy across economic, social, and environmental dimensions.

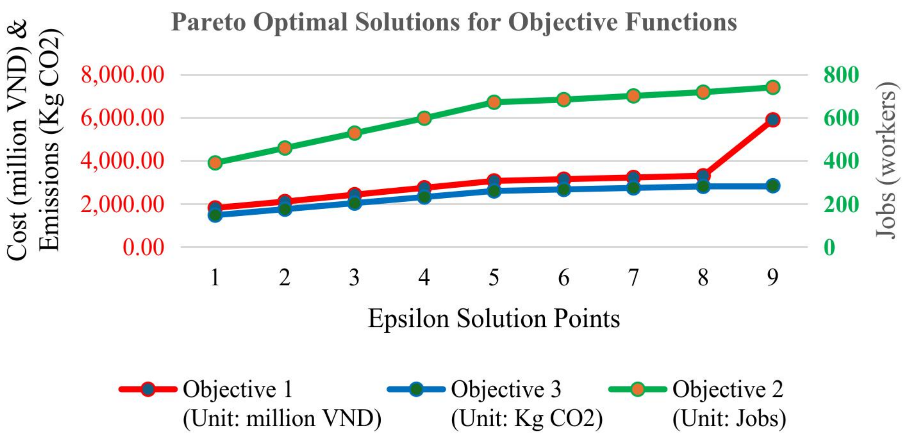

Figure 3 Pareto Solution Set for Multi-Objective Functions

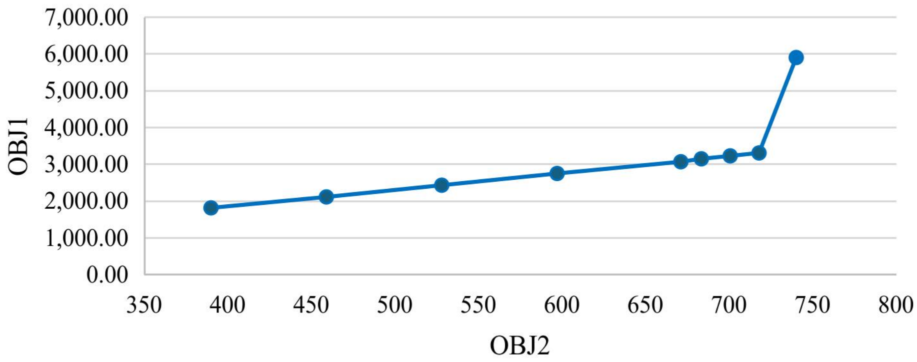

Figure 4 Pareto Chart of Cost and Social Objectives

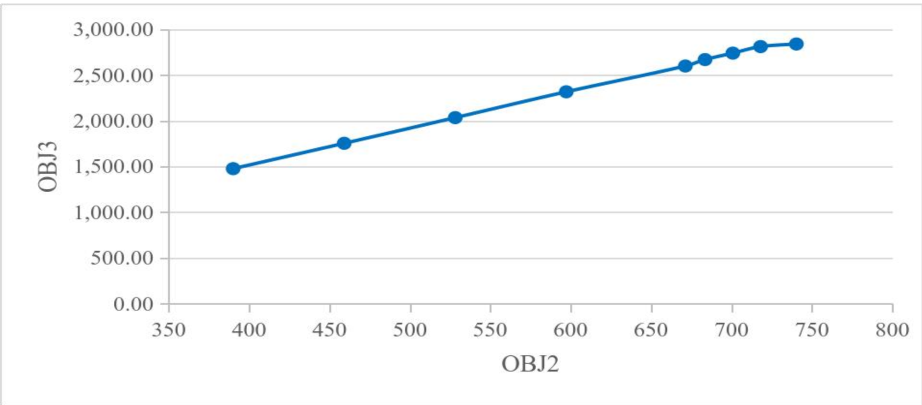

Figure 5 Pareto Chart of Social and Environmental Objectives

To verify the robustness of the identified knee point, a one-way sensitivity analysis was conducted by varying transportation cost and demand by ±10% and ±20%. The results in Table 6 show that the knee point remained unchanged at v = 4.75 across all tested scenarios. Under transportation cost changes, OBJ1 varied within 3,265.80–3,342.24 million VND, while OBJ2 and OBJ3 varied within 709.75 – 718.36 jobs and 2,777.63 – 2,812.29 kg CO_2, respectively. Under demand changes, the variation was even smaller, with OBJ1 ranging from 3,302.01 to 3,306.03 million VND, OBJ2 from 717.59 to 718.05 jobs, and OBJ3 from 2,810.07 to 2,811.89 kg CO_2. These results indicate that the selected trade-off solution at v = 4.75 is robust to moderate changes in transportation cost and demand.

The analysis of the Pareto solution set (Figure 3) highlights the trade-offs among the economic, social, and environmental objectives. Within the range of v = 0 to v = 4.75, the system maintains efficiency, with a stable marginal cost of 4.62 million VND per job and a marginal emission of 4.07 kg CO_2 per job. However, at the transition from v = 4.75 to v = 5.0, the economic marginal cost rises sharply to 116.5 million VND per job (more than 25 times higher), while emissions decline to only 1.29 kg CO_2 per job. Consequently, the solution at v = 4.75 is identified as the optimal trade-off point.

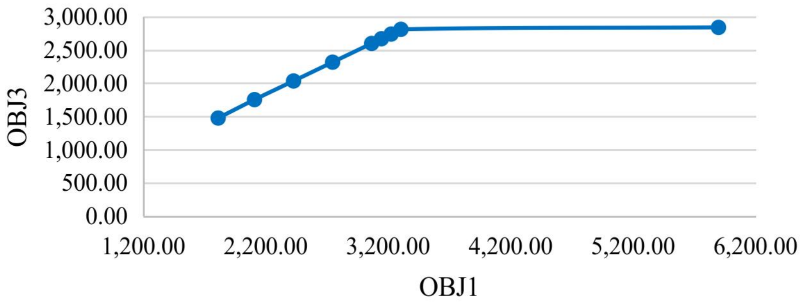

Figure 6 Pareto Chart of Cost and Environmental Objectives

Figure 4 presents the Pareto frontier, visualizing the trade-off between the OBJ1 and OBJ2. The curve illustrates an efficient trade-off region, where increases in employment are accompanied by predictable increases in cost. However, a distinct *knee point* is identified at the solution providing 718.03 jobs at a cost of 3,304.02 million VND. Beyond this threshold, the system becomes economically inefficient, as evidenced by the curve rising almost vertically, indicating that the marginal cost of generating an additional job surges to approximately 116.5 million VND.

Figure 5 presents the Pareto frontier between the OBJ2 and the OBJ3, showing a strong and nearly linear positive correlation. This indicates that increases in employment are associated with predictable rises in CO_2 emissions. Specifically, increasing employment from 390.05 to 740.29 jobs corresponds to a total emission increase from 1,477.04 kg to 2,840.49 kg. This stable relationship suggests the absence of any abrupt environmental impact, reinforcing that the primary determinant for the balanced solution is the economic cost.

Based on the Pareto chart (Figure 6) between the OBJ1 and the OBJ3, the results reveal a nonlinear relationship between these two factors. As costs increase from 1,811.46 million VND to 3,304.02 million VND, CO_2 emissions also rise correspondingly from 1,477.04 kg to 2,811.87 kg. However, beyond the threshold of 3,304.02 million VND, costs escalate sharply to 5,897.55 million VND while CO_2 emissions increase only slightly to 2,840.49 kg, indicating a diminishing return effect. This reflects that, beyond a certain level of investment, the environmental benefits no longer scale proportionally with the costs, thereby helping to identify the optimal point in solution selection.

5. DISCUSSION

The study's conclusions draw attention to the inherent trade-offs involved in minimizing costs, maximizing employment and reducing CO2 emissions while optimizing the CSC network in the Mekong Delta. According to the Pareto frontier analysis, aiming for maximal social benefits results in steeply rising marginal costs, even while modest gains in employment can be attained at comparatively predictable additional costs and emissions. In particular, the existence of an ideal trade-off where the balance between social, economic, and environmental goals is stable is confirmed by the knee point found at solution $v=4.75$. The sensitivity analysis further strengthens the interpretation of the baseline results. Although transportation-cost perturbations slightly changed the objective values, and demand perturbations produced only marginal variations, the knee point remained fixed at $v = 4.75$ in all tested cases. This suggests that the preferred solution is not driven by a single baseline parameter setting. Despite modest gains in marginal environmental performance, the approach becomes economically inefficient beyond this point since more jobs come at disproportionately large prices.

These findings align with recent research that highlights the non-linear link between sustainability and economic goals in ASC (Shekarabi *et al.,* 2025; Javanmardan *et al.,* 2024; Drofenik *et al.,* 2023). This study supports the findings of Pan & Shan (2024) in the context of Chinese milk and fruit chains, which show that at a certain level of investment, more social advantages can only be obtained at much higher prices with declining environmental returns. For example, Pan and Shan (2024) reported that a 40% demand increase leads to an approximately proportional increase in total cost (40%) while the social objective increases less (33%), implying a cost-to-social sensitivity ratio of roughly 1.21, consistent with ‘cost rising faster than social gains’ but substantially milder than the fold-change observed at our knee point. Similarly, Shekarabi *et al.* (2025) quantified cost deterioration under resilience omission, with expected and worst-case costs increasing by 10.21% and 16.54%, respectively. Crucially, the near-linear relationship between employment and CO_2 emissions found here is consistent with Roghanian and Cheraghalipour (2019), who showed that transportation configuration affects both CO_2 emissions and social-performance-related outcomes, with the use of multiple transportation vehicles reducing CO_2 emissions and improving responsiveness by about 14%.

The specific discovery of an inflection point that delineates the distinction between economically viable and non-viable solutions is what sets this study apart. This study incorporates all three objectives and uses the augmented ε-constraint method to produce a robust and interpretable Pareto solution set, whereas the majority of previous works concentrate on two-objective trade-offs (such as cost – environment or cost – social). The findings complement theoretical understandings of multi-objective optimization and offer useful guidance for practitioners and policymakers looking for a well-rounded strategy.

Overall, the conversation emphasizes that attaining sustainability in agricultural logistics involves navigating the practical trade-off space where each stakeholder can align priorities based on economic capacity, social commitments, and environmental obligations rather than minimizing a single goal.

6. CONCLUSION AND IMPLICATIONS

6.1 Conclusion

In order to minimize costs, maximize employment and reduce CO2 emissions in the CFSC in the Mekong Delta, this study created a multi-objective MILP model. The study produced a thorough Pareto set that shows the structure of trade-offs between conflicting aims by using the augmented ε-constraint approach. Although pursuing excessive social goals results in unsustainable financial burdens, the results confirm that moderate gains in employment and environmental outcomes can be accomplished with reasonable cost increases. A balanced approach that generates 718 employment, CO_2 emissions of 2,811.87 kg, and a total cost of 3,304.02 million VND is represented by the optimal trade-off solution found at $v=4.75$. This conclusion is supported by the sensitivity analysis, which confirms that the knee point remains unchanged under ±10% and ±20% changes in transportation cost and demand.

6.2 Implications

Theoretical Implications: By combining economic, social, and environmental goals into a single comprehensive model, this study greatly expands the use of multi-objective optimization in ASC management and provides a comprehensive framework for decision-making. Additionally, it offers empirical support for the augmented ε-constraint strategy, proving its effectiveness in handling practical agricultural logistics problems with several competing objectives. The empirical identification of inflection points along the Pareto frontier, a crucial component that has rarely been quantified in prior research, makes a significant contribution to the sustainability literature by improving our understanding of trade-offs and enabling better operational and policy strategies.

Practical and Policy Implications: This study offers policy and practical implications for stakeholders. By identifying a knee point, the results provide quantitative evidence to support balanced agricultural logistics policies that reduce costs, create jobs, and mitigate emissions. The model offers SC managers a decision-making framework for selecting strategies aligned with cost, employment, and environmental objectives while recognizing trade-offs. The findings also highlight the role of logistics network structure in job creation, social stability, and rural development. Furthermore, integrating CO_2 emissions into logistics planning supports Vietnam's sustainability goals, including green growth and climate change mitigation.

7. LIMITATIONS AND FUTURE RESEARCH

There are various limitations to this study that should be taken into consideration. First, the primary survey was limited in size and geography, which may not fully represent the broader distribution of transport tariffs, vehicle availability and capacity utilization, and route-specific distance and congestion conditions across the Mekong Delta. Future work will expand the sampling frame across additional producing districts and intermediary hubs, and will incorporate a richer set of transport quotations and route observations to better characterize cost, capacity, and distance heterogeneity. Second, the dataset's scope, which depends on a chosen sample of farmers, retailers, and distribution hubs, limits the research. The findings may be more broadly applicable if the dataset is expanded to include a greater range of stakeholders. Third, the results may not be as typical of other fruit SC due to the Mekong Delta's King Orange SC focus, which implies that the insights may not adequately reflect the diversity of the fruit industry as a whole. Fourth, the environmental objective (OBJ3) is limited to transport-related CO_2 emissions, while cold-chain energy use and packaging-related emissions/waste management are not captured due to data constraints. Because cold-chain systems can involve both transport and refrigeration energy burdens, expanding the emission boundary could alter the magnitude and possibly the ranking of Pareto-efficient solutions, and may shift the knee point. Fifth, the study's exclusive focus on the King Orange SC limits the results' generalizability to the broader agriculture industry. To increase the model's resilience and adaptability in various settings, future studies should try to include a wider range of datasets and expand the analysis to include additional fruits and agricultural products.

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CONFLICTS OF INTEREST

No competing interests are required to be declared, according to the authors.

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