



A Mixed-Integer Linear Programming Model for Multi-Echelon Facility Location and Allocation in Agro-Food Logistics Networks

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ABSTRACT

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Agro-food distribution networks often involve dispersed suppliers, uneven demand, capacity-limited facilities, and heterogeneous vehicle fleets. These features make facility-location and allocation decisions difficult, especially when products must move through several distribution echelons over multiple planning periods. This study formulates a mixed-integer linear programming (MILP) model for facility location and product allocation in a three-echelon agro-food supply chain (AFSC). The model jointly considers retailer-opening decisions, product flows, vehicle assignment, facility capacity, customer segmentation, trip limits, and multi-period demand. It is applied to the Banten agro-hub case in Indonesia to examine how the proposed formulation can support case-based distribution planning under deterministic input conditions. The MILP solution selected seven of the eight candidate retailer locations, namely Locations 1, 2, 3, 4, 5, 7, and 8, while Location 6 was excluded. The total operational cost was Indonesian rupiah (IDR) 221,650,020. A 50% increase in vehicle capacity reduced the total cost to IDR 151,963,620 and lowered the required number of trips from 1,113 to 899, whereas a 50% reduction in vehicle capacity and a 50% increase in demand led to infeasible solutions. To provide a computational comparison, a linear programming (LP)-relaxation-based rounding heuristic was also tested and produced a feasible solution costing IDR 225,586,700, which is 1.78% higher than the MILP solution. The results show that the proposed model can organize facility-location, allocation, and fleet-use decisions in a case-specific agro-food logistics network. The findings remain limited by deterministic assumptions regarding demand, travel time, and transportation cost.

1. INTRODUCTION

The global population is projected to exceed 9 billion by 2050, increasing pressure on food systems to produce, process, and distribute safe and nutritious food efficiently [1]. It will become a challenge in the process of providing, processing, and distributing agro-food products from the producer to the end customer while still paying attention to product quality, price, and speed of delivery [2]. Increasing demand must be addressed through enhanced production and distribution capacities to ensure consumption needs are met. Improvements on both fronts are essential, as insufficient output can lead to food shortages and rising prices. Given the fluctuations in both demand and supply, the supply chain must be dynamically adapted to maintain stability [3, 4]. Therefore, a dependable and well-structured supply chain is required to support product availability, reasonable prices, and timely delivery [5, 6].

Agro-food supply chains (AFSCs) often involve perishable products, inventory fluctuations, and time-sensitive delivery

processes, which make distribution planning more complex [7-10]. As a result, AFSCs in developing and emerging economies face increasing pressure to improve operational and distribution efficiency in response to changing market conditions and performance demands [11]. These factors significantly affect transportation planning, processing capabilities, and inventory management. Consequently, effective facility location decisions in determining the optimal number, type, and placement of facilities are vital to achieving efficiency and sustainability across the supply chain [12]. In particular, the design of food supply chain networks has become a critical research focus to support scalability, reduce waste, increase sustainability, and enhance responsiveness [13-17]. However, many AFSC network models still simplify transportation-related assumptions, particularly by using homogeneous or unlimited vehicle capacity. Such assumptions may limit the ability of the model to represent practical distribution settings, where vehicle types differ in capacity, operating cost, and availability [18-21].

A well-designed agro-hub system can improve coordination

between upstream and downstream actors, especially in decentralized agricultural contexts where stronger supply chain integration is needed [22]. Distribution centers designed for AFSCs, often referred to as agro-hubs, function not only as storage facilities but also as consolidation and distribution points for perishable products [23-26]. Their role is particularly relevant in regions with dispersed suppliers and demand points because agro-hubs can support supply aggregation, quality control, product traceability, and more reliable distribution. For this reason, agro-hub placement and its connection with supporting facilities should be considered in facility location models for AFSCs [27-30].

In designing an AFSC network, two interdependent decisions are central: location and allocation. Location decisions involve selecting the best sites for facilities, while allocation decisions determine how products flow from one echelon to another, such as from suppliers to hubs, retailers, and customer zones. Both problems are nondeterministic polynomial-time hard (NP-hard) due to the combinatorial structure of discrete facility choices and continuous product flows [31-36]. The modelling challenge becomes more complex when facility capacity, perishability, multi-echelon structures, and multi-period planning are considered simultaneously. Previous AFSC models have incorporated storage or facility-capacity decisions across multi-echelon procurement, storage, and distribution networks [37], while other studies have considered multi-period and multi-product structures for AFSC design [38]. In most optimization models, the main objective is to reduce total operating costs, including transportation, facility setup, and distribution-related costs [39]. For agro-food products, this cost objective also needs to be considered together with service coverage, product availability, and delivery reliability, since food distribution systems must balance cost efficiency with customer access and timely delivery [40].

Although previous studies have examined facility location, product allocation, vehicle-related constraints, and multi-period planning in AFSCs, these elements are often treated separately or under simplified assumptions. Some studies focus mainly on facility location without explicitly modelling heterogeneous vehicle availability, while others include transportation decisions but provide limited attention to customer segmentation, agro-hub structure, or case-based regional implementation. Therefore, the novelty of this study does not lie in claiming that each modelling component is

entirely new. Rather, it lies in integrating facility location, product allocation, heterogeneous vehicle types, facility capacity constraints, customer segmentation, and multi-period planning within a three-echelon mixed-integer linear programming (MILP) model applied to the Banten agro-hub case in Indonesia.

Therefore, this study develops a multi-echelon MILP model for facility location and product allocation in an AFSC. The model considers a three-echelon structure involving suppliers, an agro-hub, candidate retailer locations, and customer zones. It incorporates heterogeneous vehicle types, facility capacity constraints, customer segmentation, and multi-period planning. The proposed model is applied to the Banten agro-hub case in Indonesia, a regional food distribution setting characterized by dispersed production areas, infrastructure limitations, and varied transport availability. In addition, this study uses a simple linear programming (LP)-relaxation-based rounding heuristic solution procedure and compares its result with the feasible optimization output. The main contributions of this study are as follows:

- This study formulates an integrated multi-echelon MILP model for facility location and product allocation in an AFSC.
- The model incorporates heterogeneous vehicle types, facility capacity constraints, customer segmentation, and multi-period planning in a single decision framework.
- The model is applied to the Banten agro-hub case in Indonesia to evaluate retailer opening decisions, product flows, and vehicle-use decisions in a regional agro-food distribution system.
- A simple LP-relaxation-based rounding heuristic was also tested and compared with the feasible MILP solution to examine the trade-off between computational simplicity and solution quality.

2. MATERIALS AND METHODS

2.1 The structure in the proposed facility location model

The proposed facility location model is formulated as a three-echelon supply chain structure consisting of an agro-hub as the distribution center, retailers, and customers. The customer set is divided into three categories to reflect different demand locations and distribution characteristics in the Banten agro-food logistics system.

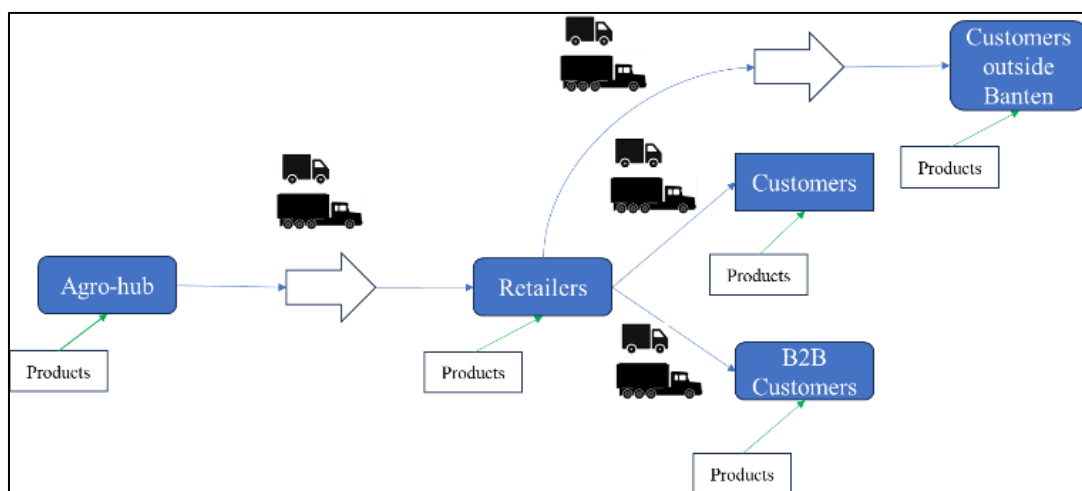


Figure 1. The framework of the agro-hub supply chain

Direct customers represent customers located within the Banten region, while business-to-business (B2B) customers represent business buyers with larger purchase volumes. Customers outside Banten represent external demand points located beyond the regional boundary. This classification is used to distinguish downstream product flows and their related transportation-cost components. In the objective function, transportation cost is separately calculated for the agro-hub-to-retailer flow, retailer-to-direct-customer flow, retailer-to-B2B-customer flow, and retailer-to-customers-outside-Banten flow.

The model is designed to support strategic and tactical decisions in configuring the downstream network of the AFSC in Banten Province, Indonesia. The model is used to determine the number and locations of retailer facilities that should be established across the province to support product distribution from the agro-hub to consumers. In addition to facility placement, the model identifies which products should be delivered, in what quantities, and which vehicle types should be used to support transportation between the agro-hub, retailers, and customers. By optimizing these interconnected decisions simultaneously, the model aims to minimize total supply chain cost subject to demand fulfillment, facility capacity, vehicle availability, and service-related requirements across Banten's eight administrative regions. The model therefore provides a decision-support framework for evaluating retailer location, product allocation, and vehicle-use decisions under regional distribution and infrastructure constraints. The structure and logic of this model are illustrated in Figure 1.

2.2 Limitations and assumptions in the facility location model

In this model, the agro-hub is defined as a single central distribution point that consolidates, temporarily handles, and dispatches agro-food products to selected retailer locations. Products are assumed to be available at the agro-hub before distribution decisions are made. The capacity of the agro-hub is not modeled as a binding constraint, since the focus of this study is on downstream facility-location and allocation decisions.

The facility location model proposed in this study is based on several simplifying assumptions that help structure the model and make it computationally tractable. However, these assumptions also introduce certain limitations that may affect the model's ability to fully reflect real-world complexities. The main assumptions used in this model are as follows:

- Deterministic input data. All demand, supply, and cost parameters are assumed to be known with certainty and remain constant over the planning horizon.
- Linear transportation costs. Transportation costs are calculated as a linear function of distance (per kilometer).
- Distance-based cost aggregation. The per-kilometer transportation cost is treated as a composite metric that reflects fuel consumption, driver wages, vehicle maintenance, and environmental impact (e.g., emissions).
- The model assumes commodities are treated as final products without undergoing additional processing or transformation at the agro-hub. This simplification allows the model to focus on the distribution structure and logistical decisions rather than production activities.
- Predefined retailer location options. The model assumes

that all possible retailer facility locations are known in advance. It does not generate new location options but rather selects the best combination from a set of predefined candidates.

- All customer demand must be fulfilled. The model assumes that the demand of all customers must be fully met.

2.3 Mathematical equations of the facility location model

This subsection presents the mathematical formulation of the facility location model, which serves as a key component in optimizing the distribution network of the AFSC. The model focuses on determining the most cost-efficient configuration for locating retailer facilities that connect the agro-hub to end consumers across the Banten region.

Objective function:

$$\text{Min } Z = Z_1 + Z_2 + Z_3 + Z_4 + Z_5 \quad (1)$$

where,

$$Z_1 = \sum_{v=1}^V \sum_{i=1}^I \sum_{a=1}^A \sum_{r=1}^R \sum_{t=1}^T TC_{vlar}^t \cdot NT_{vlar}^t \cdot DS_{ar} \quad (2)$$

$$Z_2 = \sum_{v=1}^V \sum_{i=1}^I \sum_{r=1}^R \sum_{c=1}^C \sum_{t=1}^T TC_{virc}^t \cdot NT_{virc}^t \cdot DS_{rc} \quad (3)$$

$$Z_3 = \sum_{v=1}^V \sum_{i=1}^I \sum_{r=1}^R \sum_{b=1}^B \sum_{t=1}^T TC_{virb}^t \cdot NT_{virb}^t \cdot DS_{rb} \quad (4)$$

$$Z_4 = \sum_{v=1}^V \sum_{i=1}^I \sum_{r=1}^R \sum_{o=1}^O \sum_{t=1}^T TC_{viro}^t \cdot NT_{viro}^t \cdot DS_{ro} \quad (5)$$

$$Z_5 = \sum_{r=1}^R y_r \cdot \text{Opening_Cost} \quad (6)$$

Eq. (1) represents the objective function of the facility location model. The primary goal of this function is to minimize the total cost associated with the downstream distribution activities in the AFSC network. The total cost is formulated as the sum of five distinct cost components, denoted as Z_1 through Z_5 , where each component reflects a specific operational cost category within the system:

- Z_1 in Eq. (2) accounts for the transportation cost from the agro-hub to retailers,
- Z_2 in Eq. (3) accounts for the transportation cost from retailers to end-customers,
- Z_3 in Eq. (4) reflects the transportation cost from retailers to B2B-customers,
- Z_4 in Eq. (5) reflects the transportation cost from retailers to outside Banten customers, and
- Z_5 in Eq. (6) represents the fixed cost of opening or operating retailer facilities.

By minimizing the total of these five components, the model ensures that the selected facility locations and corresponding product flows are not only feasible but also economically optimal. This objective function serves as the foundation for

evaluating alternative distribution configurations within the Banten agro-food network.

Constraints:

$$NT_{viar}^t \geq Q_{viar}^t / Cap_v, \forall v, \forall i, \forall a, \forall r, \forall t \quad (7)$$

Constraint (7) defines the number of trips required from the agro-hub to each retailer, based on the total quantity of products delivered and the carrying capacity of the assigned vehicle. Specifically, the constraint states that the number of trips is calculated by dividing the total quantity of products transported by a vehicle's maximum load capacity.

$$q_{iar}^t = \sum_{v=1}^V Q_{viar}^t, \forall i, \forall a, \forall r, \forall t \quad (8)$$

Constraint (8) ensures that the total quantity of products delivered from the agro-hub to each retailer is accurately captured. It states that the total amount received by a retailer is calculated as the sum of all quantities transported by each vehicle from the agro-hub to that retailer.

$$\sum_{i=1}^I \sum_{a=1}^a q_{iar}^t \leq y_r V_r, \forall r, \forall t \quad (9)$$

Constraint (9) ensures that the total quantity of products delivered from the agro-hub to each retailer does not exceed the retailer's storage capacity. It links the retailer-opening decision with the inbound product flow from the agro-hub to each retailer. If retailer r is not selected, the right-hand side becomes zero, and no product can be assigned to that retailer. If retailer r is selected, the inbound quantity is allowed but cannot exceed the storage or handling capacity of that retailer.

$$NT_{virc}^t \geq Q_{virc}^t / Cap_v, \forall v, \forall i, \forall r, \forall c, \forall t \quad (10)$$

Constraint (10) defines the number of trips required between each retailer and end-customers, based on the total quantity of products to be delivered and the carrying capacity of the vehicles used.

$$q_{irc}^t = \sum_{v=1}^V Q_{virc}^t, \forall i, \forall r, \forall c, \forall t \quad (11)$$

Constraint (11) ensures that the total quantity of products delivered to each end-customer is determined by summing all deliveries made by vehicles from the assigned retailers.

$$NT_{virb}^t \geq Q_{virb}^t / Cap_v, \forall v, \forall i, \forall r, \forall b, \forall t \quad (12)$$

Constraint (12) defines the number of trips required to deliver products from retailers to B2B customers, based on the total quantity of products transported and the capacity of the delivery vehicles. The number of trips is calculated by dividing the total volume of products delivered to each B2B customer by the vehicle's load capacity.

$$q_{irb}^t = \sum_{v=1}^V Q_{virb}^t, \forall i, \forall r, \forall b, \forall t \quad (13)$$

Constraint (13) ensures that the total quantity of products delivered to each B2B customer is calculated as the sum of all deliveries made by vehicles from the assigned retailers.

$$NT_{viro}^t \geq Q_{viro}^t / Cap_v, \forall v, \forall i, \forall r, \forall o, \forall t \quad (14)$$

Constraint (14) defines the number of trips required for delivering products from retailers to customers located outside Banten Province. This is determined by dividing the total quantity of goods sent to each outside customer by the vehicle's carrying capacity.

$$q_{iro}^t = \sum_{v=1}^V Q_{viro}^t, \forall i, \forall r, \forall o, \forall t \quad (15)$$

Constraint (15) ensures that the total quantity of products delivered to each outside Banten customer is obtained by summing all deliveries made by vehicles from the assigned retailers.

$$\sum_{a=1}^A q_{iar}^t \geq \sum_{o=1}^O q_{iro}^t + \sum_{b=1}^B q_{irb}^t + \sum_{c=1}^C q_{irc}^t, \forall i, \forall r, \forall t \quad (16)$$

Constraint (16) represents the flow-balance relationship at each retailer. It ensures that the total quantity distributed from a retailer to all customer categories, including end customers, B2B customers, and customers outside Banten, does not exceed the quantity received by that retailer from the agro-hub. Combined with Constraint (9), this constraint ensures that if a retailer is not open, both inbound and outbound flows associated with that retailer are forced to zero.

$$D_{ic}^t \leq \sum_{v=1}^V \sum_{r=1}^R Q_{virc}^t, \forall i, \forall c, \forall t \quad (17)$$

$$D_{ib}^t \leq \sum_{v=1}^V \sum_{r=1}^R Q_{virb}^t, \forall i, \forall b, \forall t \quad (18)$$

$$D_{io}^t \leq \sum_{v=1}^V \sum_{r=1}^R Q_{viro}^t, \forall i, \forall o, \forall t \quad (19)$$

Constraints (17)–(19) ensure that the demand from all customer segments is fully satisfied. These constraints are applied respectively to: End-customers (Constraint 17), B2B customers (Constraint 18), and Outside Banten customers (Constraint 19).

Each constraint guarantees that the total quantity of products delivered to each customer group is at least equal to their stated demand.

$$\begin{aligned} & \sum_{i=1}^I \sum_{a=1}^A \sum_{r=1}^R NT_{viar}^t + \sum_{i=1}^I \sum_{r=1}^R \sum_{c=1}^C NT_{virc}^t \\ & + \sum_{i=1}^I \sum_{r=1}^R \sum_{b=1}^B NT_{virb}^t \\ & + \sum_{i=1}^I \sum_{r=1}^R \sum_{o=1}^O NT_{viro}^t \\ & \leq \text{Max Trip}, \forall v, \forall t \end{aligned} \quad (20)$$

Constraint (20) ensures that the number of trips assigned to each vehicle in a given period does not exceed the maximum allowable limit. This constraint reflects real-world operational limitations such as driver working hours, vehicle fatigue, delivery windows, and regulatory compliance.

$$y_r \in \{0,1\} \tag{21}$$

Constraint (21) introduces a binary decision variable that governs the selection of retailer facility locations. This variable takes the value of 1 if a particular retailer location is selected and 0 otherwise.

$$NT_{viar}^t, NT_{virc}^t, NT_{virb}^t, NT_{viro}^t \in integer \tag{22}$$

Constraint (22) ensures that the number of trips assigned to each vehicle is treated as an integer value.

2.4 Heuristic approach

To complement the MILP formulation, this study uses a simple LP-relaxation-based rounding heuristic as a computational comparison with the feasible MILP solution. The heuristic is not intended as a standalone methodological contribution but as a practical procedure for generating a feasible solution with lower computational effort. The method starts by relaxing the integer constraint on the number of vehicle trips (Constraint 22), allowing the solver to generate continuous trip values. The fractional trip values are then rounded up to the nearest integer to ensure that the assigned vehicle capacity is sufficient to transport the required product quantity. The steps are outlined below:

- Step 1. Constraint relaxation: Remove the integer requirement for the number of vehicle trips, allowing them to take positive real values.
- Step 2. Initial solution generation: Solve the relaxed MILP model to obtain the total cost and trip values for each vehicle.
- Step 3. Identification of non-integer trips: All trip variables with non-integer values are identified. For each non-integer trip, the shortage required to reach the nearest upper integer value is computed.
- Step 4. Additional transportation cost calculation: Compute the additional cost by multiplying the shortage of each trip by the vehicle operating cost per kilometer and the corresponding travel distance.
- Step 5. Heuristic total cost computation: Add the total additional cost from Step 4 to the initial solution cost obtained in Step 2.

3. DATA COLLECTION

To validate the proposed model, a real-case dataset derived from the AFSC system in Banten, Indonesia, was utilized. The data were collected from the ongoing development of the Banten agro-hub and represent actual supply chain characteristics observed in the region. The dataset includes several key components, including (1) information on product types handled in the supply chain, (2) consumer data consisting of demand quantities, geographic locations (distance), and the number of consumers served, (3) planning data for supporting distribution facilities, i.e., retailers,

covering potential locations, estimated capacities, and planned numbers, (4) vehicle data including capacity and available fleet size, and (5) the planning horizon used for distribution scheduling. To simplify model implementation and enhance readability, commodity names such as rice, corn, and others were anonymized and grouped as Product Type 1, 2, and so on. Similarly, supporting facilities, vehicles, and planning periods were labeled using generic identifiers such as Retailer-1, Vehicle-1, and Week-1, respectively.

In this numerical example, the dataset comprises 3 types of agro-food products, 8 potential retailer locations, and a total of 27 customers. The customer segment consists of 12 direct customers, 14 B2B customers, and 1 customer located outside Banten Province. Additionally, 6 delivery vehicles are available for the distribution process, categorized into 3 different capacity types to reflect the heterogeneous nature of the transportation fleet. The planning horizon is divided into 2 discrete time periods to capture short-term distribution dynamics. Customer demand data covers three product types over two planning periods and shows considerable variation across customer segments. For the 12 direct customers, demand ranges from a minimum of 4 tons to a maximum of 5 tons per period. Among the 14 B2B customers, demand varies more widely, with values ranging from 10 to 60 tons per period. Meanwhile, the single customer located outside Banten Province has the highest demand, ranging from 60 to 100 tons per period. The opening cost for each retailer’s location is Indonesian rupiah (IDR) 4,500,000 per period.

A detailed overview of all input data used for model validation is presented in Tables 1–6. Table 1 presents the classification of available vehicle types, their respective capacities, and associated per-kilometer transportation costs. Table 2 summarizes the planned retailer locations along with their respective capacity limits. Table 3 provides the distance matrix from the agro-hub to each retailer. Table 4 shows the distances in kilometers from each retailer to the 12 direct customers, used as input for routing and allocation decisions in the model. Table 5 presents the distances in kilometers from each retailer to the 14 B2B customers, while Table 6 provides the distances in kilometers from each retailer to the customer located outside Banten Province.

Table 1. Vehicle types, capacities, and transportation costs per kilometer

Vehicle	Capacity (tons)	Cost per km (Indonesian rupiah (IDR)/km)
1	1	3550
2	2.5	4600
3	5	5620
4	5	5620
5	5	5620
6	5	5620

Table 2. The planned retailer’s locations

Retailer	Capacity (tons)
1	200
2	200
3	200
4	200
5	200
6	200
7	200
8	200

Table 3. Distance between agro-hub and retailer locations (in km)

From/To	Retailer-1	Retailer-2	Retailer-3	Retailer-4	Retailer-5	Retailer-6	Retailer-7	Retailer-8
Agro-hub	23	7	15	65	50	78	83	35

Table 4. Distance between retailers (R) and direct customers (C) (in km)

From/To	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
R1	5	5	5	5	5	25	25	25	25	25	25	20
R2	25	25	25	25	25	5	5	5	5	5	5	15
R3	20	20	20	20	20	15	15	15	15	15	15	5
R4	85	85	85	85	85	65	65	65	65	65	65	60
R5	70	70	70	70	70	50	50	50	50	50	50	55
R6	98	98	98	98	98	78	78	78	78	78	78	65
R7	103	103	103	103	103	85	85	85	85	85	85	50
R8	55	55	55	55	55	35	35	35	35	35	35	35

Table 5. Distance between retailers and business-to-business (B2B) customers (in km)

From/To	B2B-1	B2B-2	B2B-3	B2B-4	B2B-5	B2B-6	B2B-7	B2B-8	B2B-9	B2B-10	B2B-11	B2B-12	B2B-13	B2B-14
Retailer-1	5	5	5	5	5	25	25	25	25	25	25	25	25	20
Retailer-2	25	25	25	25	25	5	5	5	5	5	5	5	5	15
Retailer-3	20	20	20	20	20	15	15	15	15	15	15	15	15	5
Retailer-4	85	85	85	85	85	65	65	65	65	65	65	65	65	60
Retailer-5	70	70	70	70	70	50	50	50	50	50	50	50	50	55
Retailer-6	98	98	98	98	98	78	78	78	78	78	78	78	78	65
Retailer-7	103	103	103	103	103	85	85	85	85	85	85	85	85	50
Retailer-8	55	55	55	55	55	35	35	35	35	35	35	35	35	35

Table 6. Distance between retailers and outside Banten's customers (in km)

From/To	Retailer-1	Retailer-2	Retailer-3	Retailer-4	Retailer-5	Retailer-6	Retailer-7	Retailer-8
Outside Banten Customer	120	100	95	35	50	30	140	130

4. RESULTS AND DISCUSSION

4.1 Numerical example

The LINGO optimization software was used to determine the minimum total operational cost of the proposed supply chain configuration. The LINGO software produced a feasible solution with a total supply chain cost of IDR 221,650,020, based on the given input data and model configuration. The largest cost component is Z1 of the total cost. The breakdown of the total operational cost is presented in Table 7. The optimization output includes key strategic decisions, such as selected retailer locations, vehicle utilization, and product flow allocations.

Table 7 presents the cost breakdown of the proposed supply chain configuration. Z1 was the largest cost component, accounting for 42.08% of the total cost, followed by Z3 at 32.45%. The remaining components were Z5, Z4, and Z2, contributing 14.21%, 7.11%, and 4.15%, respectively.

Based on the optimization results, the model selected 7 out of the 8 planned retailer locations. Specifically, all retailers were open except Retailer-6. This decision was driven by the model's consideration of distance constraints and transportation costs, ensuring that only locations contributing to total cost minimization were activated. Retailer-6 was not selected because its overall contribution to the distribution network was weaker than that of the other candidate locations. Although this location may offer some outbound access advantages, these advantages were not sufficient to offset its less favorable position in the overall inbound and outbound logistics structure. The selected retailers serve as key

distribution points in the optimized supply chain configuration. Details of the activated retailer's locations are presented in Table 8.

Table 7. Cost breakdown

Cost Component	Value (Indonesian Rupiah (IDR))	Share of Total Cost (%)
Z1	93,269,520	42.08
Z2	9,190,600	4.15
Z3	71,925,800	32.45
Z4	15,764,100	7.11
Z5	31,500,000	14.21
Total cost	221,650,020	100

Table 8. Selected retailer's locations

Location	1	2	3	4	5	6	7	8
Value	1	1	1	1	1	0	1	1

Table 9. Summary of total trips by flow segment and planning period

Flow Segment	Period 1	Period 2	Total Trips
Agro-hub to retailer	246	246	492
Retailer to end customer	96	96	192
Retailer to business-to-business (B2B) customer	170	171	341
Retailer to outside-Banten customer	44	44	88
Total	556	557	1,113

Table 10. Total inbound flow to retailer locations by period

Retailer Location	Period 1	Period 2	Total
Location 1	390	330	720
Location 2	0	65	65
Location 3	320	360	680
Location 4	80	100	180
Location 5	200	140	340
Location 6	0	0	0
Location 7	30	30	60
Location 8	210	205	415
Total	1,230	1,230	2,460

Table 11. Total outbound flow by customer category

Customer Category	Period 1	Period 2	Total
End customers (C)	160	160	320
Business-to-business (B2B) customers (B)	850	850	1,700
Outside Banten (O)	220	220	440
Total	1,230	1,230	2,460

Table 12. Vehicle-3 deployment and delivery strategy for each product and retailer across two periods (in tons)

Vehicle–Product–Agro-Hub–Retailer (V–I–A–R)	<i>t</i>	
	1	2
3,1,1,2	25	90
3,1,1,4	55	65
3,1,1,7	5	0
3,1,1,8	75	0
3,2,1,4	0	40
3,3,1,5	0	65

Table 13. Vehicle-3 routing and product delivery from retailers to direct customers across two periods (in tons)

Vehicle–Product–Retailer–Customer (V–I–R–C)	<i>t</i>	
	1	2
3,1,5,10	0	5
3,1,7,12	5	5
3,2,7,12	5	0
3,3,1,2	5	0
3,3,1,5	5	5
3,3,2,6	5	5
3,3,2,8	0	5
3,3,2,9	5	0
3,3,2,10	0	5
3,3,2,11	5	0
3,3,4,4	5	0
3,3,4,7	0	5
3,3,4,12	5	5

Given the large size of the complete allocation output, the results are presented using summary-level tables and selected detailed outputs. Tables 9–11 report the total trips by planning period and the total flow by retailer. Meanwhile, Tables 12–15 present selected outputs for Vehicle-3 to illustrate the detailed deployment and delivery decisions across products, retailers, and planning periods.

Table 9 summarizes the total number of trips assigned across all vehicle types for each flow segment and planning period. The model generated 556 trips in Period 1 and 557 trips in Period 2, resulting in 1,113 trips over the two-period planning horizon. The agro-hub-to-retailer segment accounted for the largest number of trips, with 492 trips, followed by retailer-to-B2B customer distribution with 341 trips. Retailer-

to-end customer and retailer-to-outside-Banten customer flows required 192 and 88 trips, respectively.

Table 10 presents the total inbound flow from the agro-hub to each retailer's location across the two planning periods. Location 1 received the largest total inbound flow, with 720 units, followed by Location 3 with 680 units and Location 8 with 415 units. Location 6 received no inbound flow in either period, which is consistent with the optimization result that this location was not selected as an operating retailer.

Table 11 summarizes the total outbound flow from retailers to each customer category across the two planning periods. The outbound flow was balanced across periods, with 1,230 units distributed in Period 1 and 1,230 units in Period 2, resulting in 2,460 units over the planning horizon. B2B customers received the largest allocation, with 1,700 units, followed by outside-Banten customers with 440 units and end customers with 320 units. The total outbound flow is consistent with the total inbound flow, indicating that the model maintains flow balance between products received by retailers and products distributed to customers.

Table 12 presents the delivery strategy for Vehicle-3 determined by the optimization model, detailing vehicle utilization, product type, origin and destination locations, as well as the quantity delivered across two planning periods. Each row describes a specific shipment scenario, using a structured notation: Vehicle–Product–Agro-hub–Retailer (V–I–A–R). For example, the entry “3–1–1–2” indicates that Vehicle-3 is used to deliver Product Type-1 from Agro-hub (node 1) to Retailer-2. In this case, 25 tons were shipped in Period 1 and 90 tons in Period 2. This level of detail provides insights into how the model effectively allocates transport resources to fulfill demand while minimizing total costs.

Table 13 outlines the delivery strategy from retailers to the 12 direct customers, capturing vehicle assignments, product types, routing paths, and shipment quantities across two planning periods. The structured notation Vehicle–Product–Retailer–Customer (V–I–R–C) is used to describe each delivery instance. For example, the entry “3–1–7–12” indicates that Vehicle-3 is assigned to deliver Product Type-1 from Retailer-7 to Customer-12. In this particular case, 5 tons were delivered in each period. This information reflects how the model allocates vehicles to satisfy direct customer demand with cost efficiency and routing feasibility.

Table 14 displays the delivery configuration from retailers to the 14 B2B customers, including vehicle allocation, product type, source and destination points, and quantity shipped across two planning periods. The structured notation used is Vehicle–Product–Retailer–B2B Customer (V–I–R–B). For example, the entry “3–1–1–4” in the second row, that Vehicle-3 is assigned to deliver Product Type-1 from Retailer-1 to B2B Customer-4, with 40 tons shipped in Period 1 and no product shipped in Period 2. This detailed delivery mapping demonstrates the model's ability to allocate transport resources efficiently in meeting B2B customer demands.

Table 15 presents the delivery strategy from retailers to the customers located outside Banten Province. The table follows the same structured format using the notation Vehicle–Product–Retailer–Outside Customer (V–I–R–O). For instance, the entry “3–1–5–1” indicates that Vehicle-3 is used to deliver Product Type-1 from Retailer-5 to the out-of-Banten customer. In this case, 30 tons were shipped in Period 1, while no delivery occurred in Period 2. This data supports the model's ability to plan long-distance shipments while considering vehicle capacity and transportation efficiency.

Table 14. Vehicle-3 routing and product delivery from retailers to business-to-business (B2B) customers across two periods (in tons)

Vehicle-Product-Retailer-B2B Customer (V-I-R-B)	<i>t</i>	
	1	2
3,1,1,4	40	0
3,1,2,7	0	20
3,1,2,10	5	0
3,1,2,12	5	0
3,1,2,13	0	20
3,1,3,5	30	0
3,1,4,3	0	25
3,1,4,8	0	20
3,1,4,12	15	0
3,1,4,14	20	15
3,1,5,6	20	0
3,1,5,12	0	20
3,1,8,11	20	20
3,2,1,1	0	20
3,2,2,13	5	0
3,2,4,9	20	0
3,2,5,11	20	20
3,2,5,13	15	0
3,2,7,14	0	20
3,2,8,8	0	20
3,2,8,13	0	20
3,3,2,7	0	10
3,3,2,9	0	20
3,3,2,10	10	0
3,3,2,11	15	0
3,3,2,12	5	10
3,3,3,4	10	0
3,3,4,1	0	10
3,3,4,4	0	10
3,3,4,9	20	0
3,3,4,14	0	10
3,3,5,2	10	0
3,3,5,13	10	0
3,3,8,11	5	0

Table 15. Vehicle-3 routing and product delivery from retailers to outside-Banten customers across two periods (in tons)

Vehicle-Product-Retailer-Outside Customer (V-I-R-O)	<i>t</i>	
	1	2
3,1,5,1	30	0
3,1,8,1	30	0
3,2,1,1	60	0
3,3,4,1	0	40

The numerical results demonstrate the applicability and effectiveness of the proposed MILP-based facility location and allocation model for agro-food distribution in Banten. By incorporating real-world data, including customer segmentation, vehicle heterogeneity, and multi-period planning, the model successfully identifies cost-efficient delivery strategies that align with operational constraints. The optimized configuration, including selected retailer locations, vehicle assignments, and detailed product flows, highlights how the model can support data-driven decision-making in agro-hub development. These findings not only validate the model's structure but also provide practical insights for regional planners seeking to design more efficient and

responsive food supply chain systems.

To complement the feasible MILP optimization result, a simple heuristic method was implemented as a comparative solution strategy. The heuristic was based on the relaxation of Constraint (22), which initially enforced integer values for the number of vehicle trips. After relaxing this constraint, the model produced an initial solution cost of IDR 218,472,904. However, this solution contained non-integer values for several trip variables and therefore could not be directly implemented in practice. To restore feasibility, the fractional trip values were rounded up to the nearest integer, and the associated cost adjustment was recalculated. The additional cost incurred from this rounding adjustment was IDR 7,113,796, resulting in a total heuristic cost of IDR 225,586,700. Compared with the feasible MILP solution of IDR 221,650,020, the heuristic solution was 1.78% higher in total cost.

4.2 Sensitivity analysis

A sensitivity analysis was conducted to evaluate how the proposed agro-hub supply chain model responds to changes in demand and vehicle capacity. Demand was selected as the sensitivity parameter because it directly affects product allocation, retailer activation, vehicle utilization, and total operational cost. Four demand scenarios were examined: a pessimistic scenario with a 50% demand reduction, the most-likely scenario representing the baseline demand, an optimistic scenario with a 25% demand increase, and a high-demand stress-test scenario with a 50% demand increase. All other model parameters were kept constant to isolate the effect of demand variation on the optimization results.

The results in Table 16 show that the proposed model is highly sensitive to demand changes. Under the most-likely scenario, the model generated a feasible solution with a total operational cost of IDR 221,650,020, requiring seven out of eight available retailer locations to be opened. This scenario was used as the main reported solution because it represents the expected demand condition and provides the most relevant operational configuration for the proposed supply chain system.

When demand was reduced by 50%, the total operational cost decreased substantially to IDR 58,438,720, and only four retailer locations were required. This indicates that under lower demand conditions, the model can consolidate product flows into fewer retailer facilities, thereby reducing distribution and facility-related operational costs. In contrast, when demand increased by 25%, the total operational cost rose to IDR 349,362,880, and all eight available retailer locations had to be opened. This result suggests that the supply chain network has limited spare capacity under the baseline configuration, since a moderate increase in demand already requires full retailer activation.

The final scenario, in which demand was increased by 50%, resulted in an infeasible solution. This infeasibility occurred because the total capacity of all available retailer locations, even when fully opened, was insufficient to accommodate the increased demand. Therefore, the result highlights a critical capacity limitation in the proposed network. If demand grows beyond the 25% increase level, additional capacity expansion, new retailer facilities, larger storage capacity, or alternative distribution arrangements would be required to maintain supply chain feasibility.

To extend the sensitivity analysis, vehicle capacity varied

by increasing and reducing the capacity of all vehicle types by 50%. The results are presented in Table 17. When vehicle capacity was increased by 50%, the total cost decreased from IDR 221,650,020 in the base case to IDR 151,963,620, representing a 31.44% cost reduction. This decrease occurred mainly because higher vehicle capacity reduced the required number of trips from 1,113 trips in the base case to 899 trips.

Table 16. Sensitivity analysis of demand variation

Scenario	Demand Assumption	Feasibility Status	Total Operational Cost (IDR)	Retailers Opened
Pessimistic	50% lower than baseline demand	Feasible	58,438,720	4 of 8
Most likely	Baseline demand	Feasible	221,650,020	7 of 8
Optimistic	25% higher than baseline demand	Feasible	349,362,880	8 of 8
High-demand stress test	50% higher than baseline demand	Infeasible	Not applicable	Capacity insufficient

Note: IDR: Indonesian rupiah.

Table 17. Sensitivity analysis of vehicle capacity variation

Scenario	Vehicle Capacity Setting	Feasibility Status	Total Operational Cost (IDR)	Total Trips
Base case	Normal vehicle capacity	Feasible	221,650,020	1,113
Capacity +50%	All vehicle capacities increased by 50%	Feasible	151,963,620	899
Capacity -50%	All vehicle capacities reduced by 50%	Infeasible	-	-

Note: IDR: Indonesian rupiah.

In contrast, reducing vehicle capacity by 50% resulted in an infeasible solution. This occurred because the lower vehicle capacity increased the required number of trips beyond the maximum allowable trips per vehicle and period defined in the model. These results indicate that vehicle capacity is a critical logistics parameter in the proposed agro-hub supply chain configuration. Larger vehicle capacities can reduce trip requirements and total operational cost, while insufficient vehicle capacity may make the distribution plan infeasible unless additional vehicles, higher trip limits, or changes in distribution frequency are introduced.

5. CONCLUSIONS

This study developed and validated a multi-echelon MILP model to optimize facility location and product allocation decisions within an AFSC network, taking the structure of the Banten agro-hub as a case reference. The model incorporates vehicle heterogeneity, customer segmentation, and multi-period planning to generate a cost-minimizing distribution configuration under deterministic input assumptions. By using case-based data from Banten Province, Indonesia, the model identified retailer locations, assigned vehicle types, and

allocated product flows across customer categories and planning periods. The feasible MILP solution selected seven of the eight candidate retailer locations, namely Locations 1, 2, 3, 4, 5, 7, and 8, while Location 6 was not selected. The resulting total operational cost was IDR 221,650,020. These results show that the model can support structured facility-location and allocation analysis for the Banten agro-food logistics case, particularly when distance, capacity, vehicle use, and customer segmentation need to be considered jointly.

The numerical findings provide case-specific insights for agro-food distribution planning in Banten. First, the selection of seven retailer locations suggests that not all planned facilities need to be activated when their contribution to total cost reduction is limited. Second, the exclusion of Location 6 indicates that facility selection should be evaluated based on its role in the overall network, rather than on location availability alone. Third, the vehicle-capacity sensitivity analysis shows that increasing vehicle capacity by 50% reduced the total cost from IDR 221,650,020 to IDR 151,963,620 by lowering the required number of trips from 1,113 to 899. In contrast, reducing vehicle capacity by 50% produced an infeasible solution because the required number of trips exceeded the maximum allowable trip limits. In addition, a 50% demand increase also resulted in infeasibility, indicating that the current network configuration has limited capacity to absorb large demand expansion without additional vehicle capacity, higher trip limits, or facility adjustments. Finally, a simple LP-relaxation-based rounding heuristic was tested to complement the feasible MILP solution. The heuristic solved with a total cost of IDR 225,586,700, which was 1.78% higher than the feasible MILP solution. The purpose of this procedure is to show how a relaxed solution can be converted into an implementable feasible solution through a rounding step. When Constraint (22), which enforces integer values for vehicle-trip variables, is relaxed, the model can generate a relaxed solution within seconds. However, when this integer restriction is activated, the solution search time increases substantially because the model involves binary and integer decision variables associated with the location-allocation structure. This is consistent with the computational nature of location-allocation problems, which are generally classified as NP-hard.

Despite its strengths, the model assumes deterministic input parameters, including demand, travel time, and transportation costs. This simplification may not fully capture real-world uncertainties. Future research should enhance the current model by incorporating stochastic parameters to reflect real-world uncertainties, such as demand variability, fuel price fluctuations, and traffic conditions. Integrating probabilistic demand scenarios and robust optimization techniques would improve the model's resilience and decision-making accuracy under uncertainty. In addition, future studies could expand the model's scope by including product transformation or processing activities at the agro-hub, enabling a more comprehensive representation of value-added operations in AFSCs.

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NOMENCLATURE

i	Products
a	Agro-hub
r	Retailers
o	Outside Banten Customers
c	Customers inside Banten
b	B2B customer in Banten
v	Vehicle types
t	Time periods

Parameters

D_{ic}^t	Demand of product i by customer c in period t
D_{ib}^t	Demand of product i by B2B customer b in period t
D_{io}^t	Demand of product i by outside customer o in period t
TC_{viar}^t	Transportation cost by truck v of processed product i from agro-hub to retailer r in period t
TC_{viro}^t	Transportation cost by truck v of processed product i from retailer r to outside customer o in period t
TC_{virc}^t	Transportation cost by truck v of processed product i from retailer r to customer c in period t
TC_{virb}^t	Transportation cost by truck v of processed product i from retailer r to B2B customer b in period t
CAP_v	Capacity of vehicle v

DS_{ar}	Distance from agro hub to retailer r
DS_{ro}	Distance from retailer r to outside customer o
DS_{rc}	Distance from retailer r to customer c
DS_{rb}	Distance from retailer r to B2B customer b
V_r	Retailers capacity

Variables

NT_{viar}^t	Number of trips required to deliver fresh product i from agro-hub a to retailer r using vehicle v at period t
NT_{viro}^t	Number of trips required to deliver fresh product i retailer r to outside customer o using vehicle v at period t
NT_{virb}^t	Number of trips required to deliver fresh product i retailer r to B2B customer b using vehicle v at period t
NT_{virc}^t	Number of trips required to deliver fresh product i retailer r to customer inside Banten c using vehicle v at period t

y_r	Binary variable, equal to 1 if the retailer r is opened, 0 otherwise, at period t
Q_{viar}^t	Distributed quantity by truck v of product i from agro-hub to retailer r in period t
q_{iar}^t	Total quantity of fresh product i from agro-hub a to retailer r in period t
Q_{viro}^t	Distributed quantity by truck v of product i from retailer r to outside customer o in period t
q_{iro}^t	Total quantity of fresh product i from retailer r to outside customer o in period t
Q_{virc}^t	Distributed quantity by truck v of product i from retailer r to customer c in period t
q_{irc}^t	Total quantity of fresh product i from retailer r to customer c in period t
Q_{virb}^t	Distributed quantity by truck v of product i from retailer r to B2B customer b in period t
q_{irb}^t	Total quantity of fresh product i from retailer r to B2B customer b in period t