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Development and Optimization of a Supplier Selection Model for the Agro-Hub Supply Chain Network: A Case Study of Banten Province, Indonesia

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ABSTRACT

The increasing demand for agricultural products requires more efficient and sustainable supply chain systems, particularly in regions where logistics and market connectivity remain limited. In Banten Province, Indonesia, the government is developing an agro-hub as a local collection hub to improve agricultural distribution efficiency. However, the current system lacks an integrated decision-support model to guide procurement, transportation, production, and inventory planning. This study aimed to develop an integrated Mixed-Integer Linear Programming (MILP) model to minimize the total operational cost within the agro-hub supply chain network. The model simultaneously optimizes supplier selection, procurement quantity, and product allocation across multiple suppliers, commodities, and distribution channels. A cost-based heuristic algorithm was also developed as a comparative benchmark to evaluate the performance and robustness of the MILP solution. The results showed that the MILP model achieved a minimum total operational cost of IDR 337,808,445, confirming its ability to identify optimal sourcing and logistics strategies under capacity and demand constraints. The heuristic algorithm produced a comparable total cost of IDR 384,111,503, demonstrating its practicality and consistency, though at a slightly higher cost (13.7% difference). Three sensitivity scenarios were further conducted, revealing that the model remained stable and responsive to changes in demand, transportation cost, and commodity price. In conclusion, this study provided a novel optimization framework and a complementary heuristic method for planning agro-hub operations. The findings offered strategic insights for policymakers in designing cost-efficient and adaptive food distribution systems in developing regions.

1. INTRODUCTION

Global food demand continues to grow sharply, driven by population expansion, urbanization, and rising per capita income. Between 2012 and 2050, demand for agricultural products is projected to increase by nearly 50% [1], raising serious concerns over long-term food availability [2, 3]. This condition highlights the urgent need for a more efficient and sustainable agro-food management system [4]. The central challenge lies not only in increasing production but also in ensuring that agricultural products are distributed, processed, and delivered efficiently while maintaining their quality, affordability, and speed of delivery [5, 6]. A reliable agro-food supply chain is therefore essential to achieve sustainability across upstream and downstream stages [7, 8]. To address these challenges, the global agro-food sector must enhance its overall system performance through improved productivity and coordinated distribution mechanisms. The increasing demand for agro-food products must be met through increased production and effective distribution to meet consumption needs [9].

The Food and Agriculture Organization (FAO) has emphasized the importance of strengthening agro-food systems to support the Sustainable Development Goals (SDGs), particularly through improved logistics, technology integration, and policy coherence [9-11]. Effective coordination among government, industry, and research institutions is necessary to ensure the efficient distribution of perishable agricultural products [12-14]. When these enabling conditions are met, an agro-hub system, a centralized collection and distribution hub linking upstream producers with downstream markets, can play a critical role in improving supply chain performance [15-17]. In such systems, time-sensitive goods are consolidated, processed, and redistributed, reducing losses and enhancing value-added processes. The FAO estimates that nearly 30-40% of fresh produce is lost before reaching consumers, mainly due to poor storage and transportation [18]. Thus, the implementation of agro-hubs can contribute to reducing food loss, improving quality control, and supporting sustainable development.

From a modeling perspective, supply chain networks (SCNs) for perishable goods require analytical approaches that integrate economic, logistics, and operational variables. Previous studies have explored various methods to address supplier selection and flow optimization problems. Under the theme of supplier selection models, numerous decision-making approaches such as neural networks [19], hybrid and game-theoretic models [20, 21], and efficiency-based weight models [22] have been proposed to evaluate supplier performance. Likewise, methods such as Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), and other Multi-Criteria Decision-Making (MCDM) techniques have been widely used to rank suppliers according to both qualitative and quantitative indicators [23-25]. However, these methods mainly focus on prioritization rather than on operational optimization, such as determining quantities and timing of procurement.

Under the theme of agro-food SCNs, simulation and mathematical models have been recognized as powerful tools for understanding real-world processes and improving system efficiency [26-28]. Studies in this area underscore the importance of integrating logistics, supplier management, a figured inventory control within perishable product networks to reduce waste and support circular economy goals [29, 30]. Nevertheless, the high complexity of integration requires mathematical rigor to ensure tractable solutions that can still be applied in practice.

Mixed-Integer Linear Programming (MILP) is extensively used as an optimization framework for supply chains involving multiple products, periods, and echelons. Its advantage lies in the ability to simultaneously handle discrete decisions, constraints, and trade-offs among interdependent elements. MILP allows integrated optimization that connects supplier selection, demand planning, and procurement scheduling, offering a systematic means of minimizing total operational cost while maintaining service quality [31-36].

This study aims to develop an integrated MILP model structured around the configuration of an agro-hub supply chain network. The model is designed to support end-to-end decision-making across multiple echelons of the supply chain from upstream suppliers to downstream distributors, retailers, and end customers by simultaneously addressing both strategic and operational dimensions. Specifically, the model determines the optimal supplier selection and the allocation of commodity flows, including the type and quantity of commodities to be procured, their conversion into products at the agro-hub, and the distribution of these products to various market channels over the planning horizon. This integrated modeling approach ensures that supplier selection is directly aligned with downstream demand requirements, thus enhancing supply chain responsiveness and efficiency [37, 38]. In this study, the model is applied to optimize the agro-hub supply chain in Banten Province, Indonesia. The agro-hub supply chain in Banten plays a crucial role in improving the efficiency of agricultural product distribution, shortening the supply chain, and increasing value-added through product standardization and processing. This model is needed for Banten because the province is currently developing a government-led agro-hub system aimed at improving the efficiency of agricultural distribution. Despite being located near Jakarta, the largest consumer market in Indonesia, Banten's agricultural supply chain remains fragmented, involving multiple intermediaries that increase logistics costs. The absence of an integrated decision-support framework has limited the province's ability to manage procurement, transportation, and storage efficiently. Therefore, the proposed MILP model provides a strategic planning tool that enables the government to allocate resources, select suppliers, and coordinate logistics based on cost-minimization principles rather than profit maximization. Thus, it supports the province's policy objectives of enhancing food system resilience, improving price stability, and ensuring affordable food access. To the best of current knowledge, this research is original and has not been conducted before. Hence, the novelty of this study is the development of a MILP model for a multi-echelon hub supply chain network that integrates supplier selection and flow allocation based on the structure of an agro-hub supply chain network in Banten Province, Indonesia. In addition, a cost-based heuristic algorithm is developed as a comparative benchmark to evaluate the efficiency of the MILP solution.

2. MATERIALS AND METHODS

2.1 General framework

In this research, the agro-hub acts as a mediator between the suppliers and customers. Agro-hub collects the commodities from the farmers in bulk quantities, and then the commodities are packaged at the warehouse site to meet the consumer-friendly requirements. The packaged commodities are called products. Thus, simultaneously, each agro-food commodity gets one conversion factor to become a product. The packaging process is done by batch production, meaning there will be a batch size for each product production. Farmers sell their commodities to the agro-hub, then the agro-hub can determine the types and quantity of commodities purchased from farmers in the most cost-effective manner and distribute the packaged products to distributors, retailers, and customers, as shown in Figure 1. The decision variables that are considered in the model (see Figure 1) consist of (1) what type of commodities, (2) how many quantities of commodities are bought from farmers, and (3) how many of the products are to be sent to distributors, retailers, and customers after being packaged in the agro-hub. A mathematical model is developed to minimize the total operational cost by considering the limitations as constraints. A critical constraint in the model is the machine capacity available in the agro-hub, which will determine the production capacity. The transportation cost will occur when the commodities or products are taken from farmers and distributed to the distribution channels (distributors, retailers, and customers). The model treats each commodity type as a distinct product, using a constant conversion factor to represent the transformation from raw commodity to finished product. Inventory costs are incurred when the production of agro-hub products exceeds actual demand. The model can be solved using Lingo software and validated with a series of data tests.

2.2 Mathematical model

MILP optimization is developed to determine the types of commodities obtained from farmers and their quantity, which are considered the most cost-effective for distribution through the agro-hub network. The model is addressed as a deterministic-dynamic model, meaning the parameter data must already be known in each period in the planning horizon.

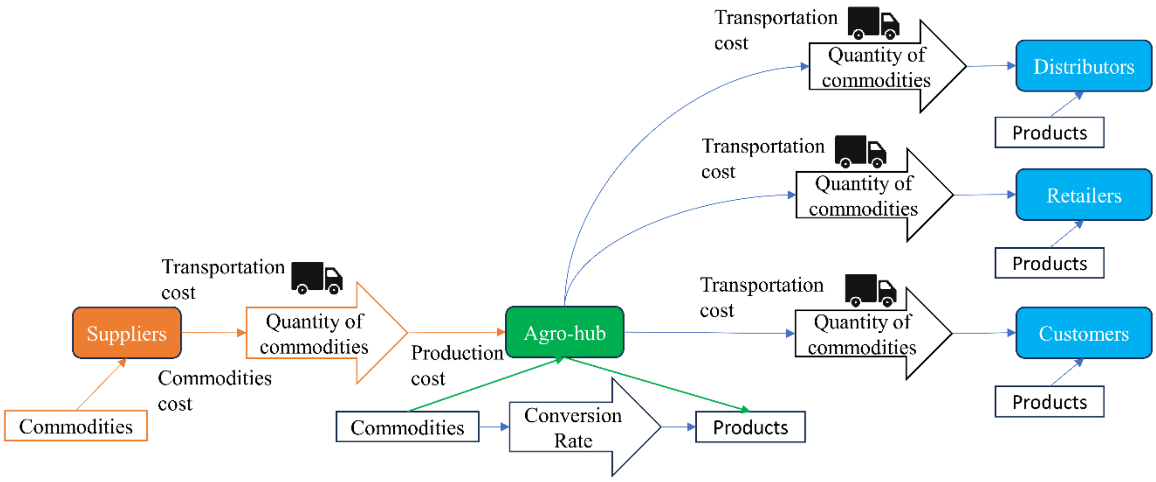

Figure 1. The framework of the agro-hub supply chain

Objective function:

$$\text{Min } Z = A + B + C + D + E + F + G \tag{1}$$

$$A = \sum_k \sum_j \sum_t S_{kjt} P_{kj} \tag{1a}$$

$$B = \sum_k \sum_j \sum_t NT_{kjt}\, TC_{kj} \tag{1b}$$

$$C = \sum_i \sum_t \frac{Q_{it}}{B_i} PC_i \tag{1c}$$

$$D = \sum_d \sum_i \sum_t NT_{dit}\, TC_{di} \tag{1d}$$

$$E = \sum_r \sum_i \sum_t NT_{rit}\, TC_{ri} \tag{1e}$$

$$F = \sum_c \sum_i \sum_t NT_{cit}\, TC_{ci} \tag{1f}$$

$$G = \sum_i \sum_t Inv_{it}\, IC_i \tag{1g}$$

s.t:

$$Q_{it} \le W_{ij} \sum_k S_{kjt}, \forall i, \forall j, \forall t \tag{2}$$

$$Q_{it} \ge \sum_c S_{cit} + \sum_r S_{rit} + \sum_d S_{dit}, \forall i, \forall t \tag{3}$$

$$S_{dit} \ge D_d, \forall i, \forall t, \forall d \tag{4}$$

$$S_{rit} \ge D_r, \forall r, \forall i, \forall t \tag{5}$$

$$S_{cit} \ge D_c, \forall i, \forall t, \forall c \tag{6}$$

$$\sum_i Q_{it} \le Cap, \forall t \tag{7}$$

$$NT_{kjt} >= \frac{S_{kjt}}{C_j}, \forall_k, \forall_j, \forall_t \tag{8}$$

$$NT_{dit} >= \frac{S_{dit}}{C_i}, \forall_d, \forall_i, \forall_t \tag{9}$$

$$NT_{rit} >= \frac{S_{rit}}{C_i}, \forall_r, \forall_i, \forall_t \tag{10}$$

$$NT_{cit} >= \frac{S_{cit}}{C_i}, \forall_c, \forall_i, \forall_t \tag{11}$$

$$Inv_{it} = Q_{it} - \left(\sum_c S_{cit} + \sum_r S_{rit} + \sum_d S_{dit}\right), \forall i, \forall t \tag{12}$$

$$NT_{kjt}, NT_{cit}, NT_{rit}, NT_{dit} \in integer \tag{13}$$

The objective function presented in Eq. (1) aims to minimize the total operational cost of the agro-food supply chain network. This total cost comprises several components that capture all major activities within the system.

The first component, expressed in Eq. (1a), represents the procurement cost of commodities, which includes the purchasing expenses incurred when obtaining raw materials from suppliers. Eq. (1b) accounts for the upstream transportation cost from farmers to the agro-hub. Eq. (1c) defines the processing cost, which covers the transformation of commodities into final products within the agro-hub facility.

Subsequently, Eqs. (1d)-(1f) capture the downstream transportation costs associated with product distribution to various market channels, namely distributors (Eq. (1d)), retailers (Eq. (1e)), and end customers (Eq. (1f)). Finally, Eq. (1g) represents the inventory holding cost at the agro-hub, which arises when the volume of produced goods exceeds current demand. This cost component discourages overproduction and promotes efficient synchronization between production and demand levels.

Eq. (2) defines the conversion relationship between commodities and products processed at the agro-hub. This constraint ensures that the total quantity of products produced at the agro-hub does not exceed the total amount of commodities supplied by farmers and suppliers, adjusted by the corresponding conversion factor.

Eq. (3) governs the distribution balance between the quantity of products produced at the agro-hub and the volume distributed to downstream channels. This constraint ensures that the total quantity of products delivered to all market nodes, including distributors, retailers, and end customers, does not exceed the total amount of products processed and available at the agro-hub.

Eqs. (4)-(6) represent the demand satisfaction constraints at different downstream levels of the agro-food supply chain. Each constraint ensures that the total quantity of products distributed from the agro-hub is sufficient to meet the corresponding demand at every market node, namely distributors, retailers, and end customers.

Eq. (7) establishes the production capacity constraint at the agro-hub. This constraint ensures that the total quantity of products processed and produced within the agro-hub during each period does not exceed the facility's available production capacity.

Eq. (8) defines the relationship between the number of vehicle trips and the volume of commodities transported from farmers (suppliers) to the agro-hub. Eqs. (9)-(11) determine the number of transportation trips required to deliver products from the agro-hub to each downstream channel, including distributors, retailers, and end customers. This constraint ensures that the total number of trips required in each period is consistent with the total shipment volume and the capacity of each vehicle.

Eq. (12) introduces the inventory variable at the agro-hub, which represents the quantity of products remaining at the end of each period. Inventory occurs whenever the production volume at the agro-hub exceeds market demand.

Eq. (13) imposes the integer condition on all variables representing the number of vehicle trips, both in the upstream (from farmers to the agro-hub) and downstream (from the agro-hub to distributors, retailers, and end customers) segments of the supply chain. This constraint ensures that the model captures the discrete nature of transportation activities. This integer constraint allows the model to accurately represent fixed transportation costs per trip, regardless of whether a vehicle is fully loaded or not. In practice, every vehicle dispatch incurs the same trip cost once it is operated, even if its capacity is partially utilized. This formulation enhances the model's operational realism by reflecting actual logistics behavior, ensuring that transportation costs are computed on a per-trip basis rather than proportionally to shipment volume.

2.3 Development of the heuristic algorithm

To complement the optimization model, a heuristic algorithm is developed to provide a simplified decision rule for allocating supply and demand within the agro-food supply chain network. The heuristic serves as a benchmark approach for comparison with the MILP model, enabling an evaluation of the model's effectiveness in minimizing total operational cost.

The algorithm is designed based on a cost-priority logic, where suppliers are ranked according to their effective unit cost, and demand is sequentially fulfilled from the lowest-cost sources until all requirements are met. This procedure reflects a practical decision-making process that can be easily applied in real-world agro-hub operations when computational optimization tools are not available.

The step-by-step procedure of the developed heuristic algorithm is presented as follows:

1. Compute the effective unit cost for each supplier (k) and commodity (i): purchase price_{jk} + transport cost_{jk}.
2. Sort all suppliers in ascending order of the effective unit cost from lowest to highest cost.
3. Calculate the required demand for each product (i) and period (t), including the conversion factor.
4. Starting from the lowest-cost supplier, allocate supply to meet the required demand from Step 3, subject to each supplier's available capacity.
5. Stop when the required demand for that period is fully satisfied.
6. Calculate the total operational cost.

2.4 Data collection

The dataset in this study includes information on the number of available suppliers and the types of commodities they provide, as well as the structure of downstream entities, including customers, retailers, and distributors, along with their corresponding product demand levels. Additional data parameters involve transportation costs between each supply chain echelon and conversion factors that reflect the transformation of raw commodities into finished products within the agro-hub. These input parameters serve as the foundation for implementing and testing the proposed MILP model. The data for this study are derived from internal records from the Banten Provincial Agriculture Office and the agro-hub. Given that the agro-hub initiative in Banten is still in progress, with the government currently updating and refining its operational blueprint, only limited but verified data are available for modeling purposes. There are two commodities and three suppliers used in this numerical example, with the agro-hub operating at an installed production capacity of 30,000 kg per period. The selection of two commodities and three suppliers reflects the most active and data-complete actors within this pilot phase. This simplified configuration corresponds to the early operational structure of the agro-hub and provides a realistic baseline for testing the model's effectiveness in minimizing operational costs and improving logistical efficiency.

Detailed data for the numerical example are presented in Tables 1-5. To facilitate model formulation and numerical analysis, certain simplifications are adopted. First, commodities are represented using numerical indices (e.g., Commodity 1, Commodity 2, etc.) instead of their actual product names. Each indexed commodity corresponds to a specific agricultural item, such as rice, maize, and other staples. Second, the planning horizon is segmented into discrete periods denoted by integers (e.g., Period 1, Period 2, etc.), rather than explicitly labeling them by weeks or months. These abstractions are commonly used in mathematical modeling to streamline variable representation and enhance scalability, without compromising the model's applicability to real-world supply chain contexts. A fixed number is assigned to the farmer as the supplier. In this research, three farmers are suppliers of two types of commodities for six weeks (6 periods) of production. The downstream structure of the agro-hub network consists of three retailers, two direct customers, and two distributors. The conversion factors for transforming Commodity 1 and Commodity 2 into Product 1 and Product 2 are assumed to be 0.80 and 0.85, respectively. These values represent the average conversion rates observed at the agro-hub company in Banten Province and are used as fixed parameters in this study. Tables 1-5 show the parameter data as input for the model. Table 1 presents the weekly demand from each downstream channel for the agro-hub's products. This demand data serves as the basis for determining the quantity of raw commodities that must be procured from suppliers and subsequently processed or converted into the desired products to fulfill downstream requirements.

Table 2 presents the purchasing prices of Commodity 1 and Commodity 2 from individual farmers who serve as upstream suppliers within the agro-hub network.

Table 1. Product demand in each period for each distribution channel (kg)

Channel	No.	Product Type	Period (Week)					
			1	2	3	4	5	6
Direct Customer	1	1	299	180	179	195	279	222
		2	170	105	106	193	202	254
	2	1	189	271	142	114	245	165
		2	271	120	246	299	102	232
Retailer	1	1	1085	1101	1362	1199	1334	1034
		2	1026	1189	1476	1425	1468	1304
	2	1	1357	1311	1180	1213	1272	1193
		2	1421	1057	1028	1095	1055	1169
	3	1	1423	1430	1444	1163	1101	1220
		2	1394	1037	1093	1352	1246	1002
Distributor	1	1	3474	3936	4642	4500	4583	4609
		2	4649	3881	3383	4116	3522	3284
	2	1	3481	3109	4629	4264	3401	4871
		2	4155	3856	4099	3665	4005	4095

Table 2. Commodity prices offered by each supplier (in IDR/kg)

Farmer	Type of Commodity	
	1	2
1	200	1800
2	250	1400
3	150	2000

Table 3. Supplier capacity for commodities per period (weekly, in kg)

Farmer	Commodity	
	1	2
1	10000	11000
2	9000	12000
3	1000	2000

Table 3 presents the supply capacities of each supplier for the respective commodities they provide to the agro-hub. These capacity values represent the maximum quantity that each supplier can deliver per period (weekly) within the defined planning horizon and are applied as upper-bound constraints in the optimization model.

Table 4 summarizes various capacity-related constraints used in the model. These include:

(i) the vehicle capacity for transporting commodities from suppliers to the agro-hub (kg);

(ii) the vehicle capacity for delivering finished products from the agro-hub to downstream channels (kg);

(iii) the production batch size at the agro-hub (kg);

(iv) the production cost incurred per batch (IDR). These parameters are critical for accurately modeling logistical and operational limitations within the agro-hub supply chain network.

Table 4. Transportation and production capacity (kg)

Commodity or Product Type	Transportation Capacity for Each Commodity	Transportation Capacity for Each Product	Production Batch Size for Each Product	Production Cost for Each Product	Inventory Cost for Each Product
1	3000	2000	1000	500	200
2	2000	3000	800	700	350

Table 5. Transportation cost per trip from agro-hub to each distribution channel (IDR)

Channel	No.	Commodity/ Product	
		1	2
Farmer	1	2500000	2500000
	2	3000000	2000000
	3	4000000	3000000
Customer	1	10000	10000
	2	10000	10000
Retailer	1	50000	80000
	2	60000	100000
	3	70000	85000
Distributor	1	150000	130000
	2	200000	180000

Table 5 displays the transportation cost per trip between the agro-hub and each connected channel, both upstream actors (farmers as suppliers) and downstream actors (retailers, distributors, and direct customers). The variation in transportation costs reflects differences in logistical complexity, including distance and required service levels.

2.5 Data processing

All parameter data (Tables 1-5) are inserted into an optimization software. Lingo software is used to generate the optimal solution. The proposed MILP model is solved using LINGO optimization software. The computation is performed on a standard personal computer with an Intel® Core™ i7-8750H CPU @ 2.20GHz and 16GB of RAM.

3. RESULTS AND DISCUSSIONS

3.1 The proposed MILP model

The proposed MILP model is solved using LINGO optimization software, which successfully obtained the optimal solution in less than one second (see Figure 2). The objective function is formulated to minimize total operational cost, resulting in a total operational cost of IDR 337,808,445. The corresponding optimal decision strategy comprising supplier selection, product allocation, quantity purchased, and delivery timing is detailed in Tables 6 to 9.

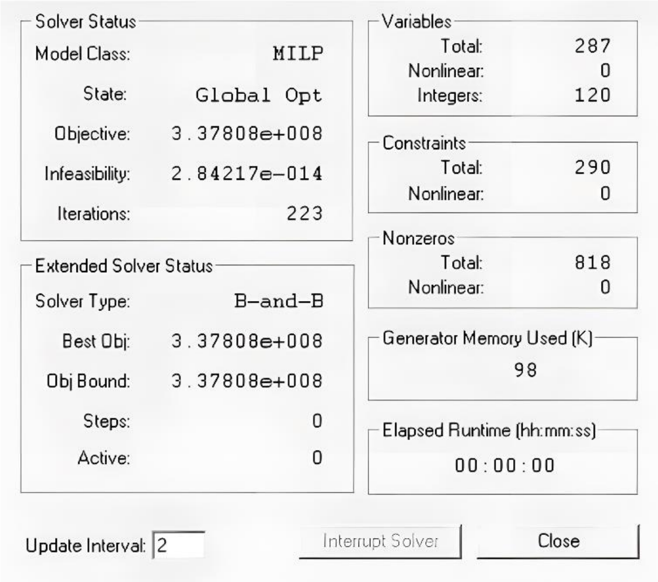

Figure 2. LINGO output display showing objective value and computation time

To achieve this objective value, LINGO provides a set of technical strategies involving supplier selection and weekly procurement decisions over the six-week planning horizon. These detailed decisions, including the type and quantity of commodities to be purchased from each supplier in each time period, are presented in Table 6. The results indicate that only two out of the three available suppliers are selected throughout the planning horizon. In Week 1, for example, the agro-hub is advised to procure 9,000 kg of Commodity Type 1 and 3,395 kg of Commodity Type 2 from Supplier 1, and 5,135 kg of Commodity Type 1 and 12,000 kg of Commodity Type 2 from Supplier 2. These procurement decisions are generated by the model based on a simultaneous evaluation of multiple constraints, including commodity prices offered by each supplier, supplier capacity limits, and transportation costs between suppliers and the agro-hub.

Table 7 presents the delivery strategy from the agro-hub to distributors, as generated by the LINGO optimization results. Table 7 specifies the type, quantity, and timing of product shipments required to meet distributor demand over the six-week planning horizon. For instance, in Week 1, the agro-hub is required to deliver 3,474 kg of Product Type 1 to Distributor 1. This quantity and product type precisely correspond to the distributor's stated demand in Table 1 for the same period. The consistency between planned deliveries and actual demand across all downstream entities further confirms the model's ability to effectively and accurately satisfy the requirements of each distribution channel.

Table 8 presents the delivery strategy from the agro-hub to retailers, as determined by the LINGO-generated solution. Table 8 details the type, quantity, and timing of product shipments required to fulfill retailer demands throughout the six-week planning horizon. For example, in Week 1, the agro-hub is scheduled to deliver 1,085 kg of Product Type 1 to Retailer 1. This quantity precisely matches the demand specified by the retailer in Table 1 for that period. Such alignment indicates that the model is capable of accurately fulfilling the needs of various downstream channels, ensuring timely delivery and product availability as required.

Table 6. The types and quantities of agro-food products bought from farmers as suppliers (kg)

Supplier	**Commodity**	**Week Period**					
		1	**2**	**3**	**4**	**5**	**6**
1	1	9000	9000	9000	10000	10000	9000
	2	3395	1229	1448	2288	1647	1341
2	1	5135	5173	7973	5810	5269	7643
	2	12000	12000	12000	12000	12000	12000
3	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
Total		29530	27402	30421	30098	28916	29984

Table 7. The types and quantities of agro-food products sold to distributors (kg)

Distributor	**Product**	**Week Period**					
		1	**2**	**3**	**4**	**5**	**6**
1	1	3474	3936	4639	4497	4583	4605
	2	4649	3881	3383	4116	3522	3284
2	1	3481	3109	4629	4264	3401	4871
	2	4155	3856	4099	3665	4005	4095
Total		15760	14784	16753	16546	15516	16861

Table 8. The types and quantities of agro-food products sold to retailers (kg)

Retailer	**Product**	**Week Period**					
		1	**2**	**3**	**4**	**5**	**6**
1	1	1085	1101	1362	1199	1334	1034
	2	1026	1189	1476	1425	1468	1304
2	1	1357	1311	1180	1213	1272	1193
	2	1421	1057	1028	1095	1055	1169
3	1	1423	1430	1444	1163	1101	1220
	2	1394	1037	1093	1352	1246	1002
Total		7706	7125	7583	7447	7476	6922

Table 9. The types and quantities of agro-food products sold to customers (kg)

Customer	Product	Week Period					
		1	2	3	4	5	6
1	1	299	180	179	195	279	222
	2	170	105	106	193	202	254
2	1	189	271	142	114	245	165
	2	271	120	246	299	102	232
Total		930	678	676	805	833	879

Table 9 presents the delivery strategy from the agro-hub to direct customers as determined by the MILP model over the six-week planning horizon. The results show that the quantity of each product delivered to direct customers in every period exactly matches their respective demand levels. For instance, in Week 1, the agro-hub is required to deliver 299 kg of Product Type 1 to Customer 1, which is identical to the demand stated in Table 1 for that period. This alignment demonstrates that the model effectively satisfies customer requirements with precision, thereby validating its capability to ensure timely and accurate fulfillment across the planning horizon.

The results demonstrate the effectiveness of the proposed MILP model in generating an integrated and feasible procurement and distribution strategy across a multi-echelon agro-hub supply chain. Selecting the most cost-efficient suppliers and optimizing commodity purchasing decisions based on price, capacity, and transportation costs enables the model to successfully maximize total profit. Furthermore, it ensures full alignment between downstream demand and delivery plans across all channels, including direct customers, retailers, and distributors, through precise allocation of product type, quantity, and timing. The optimization results from numerical approximation show promise for application in the agro-food supply chain in the real world, specifically in Banten Province, Indonesia.

3.2 Sensitivity analysis

To evaluate the robustness and responsiveness of the proposed MILP model, a sensitivity analysis is conducted under three different scenarios. Each scenario is designed to assess how changes in key parameters affect the model's total operational cost and allocation decisions across the agro-food supply chain network. Through these scenarios, the model's sensitivity to market demand, transportation efficiency, and supplier pricing is analyzed to validate its applicability under varying operational conditions.

Scenario 1: Reduced demand across all channels. In this scenario, the demand levels from all downstream channels (distributors, retailers, and customers) are decreased by up to 50%, while all other parameters are kept constant. This adjustment examines how lower market demand influences procurement quantities, production volumes, and total operational cost.

The model produces a total operational cost of IDR 168,764,309. This value is significantly lower than the base-case scenario, indicating that reduced market demand leads to a proportional decrease in overall procurement, transportation, and processing activities throughout the supply chain network. Table 10 presents the procurement quantities of each commodity from the respective suppliers over six planning periods.

The results indicate that only Supplier 1 (Commodity 1) and Supplier 2 (Commodity 2) remain active under the reduced-demand condition, while the remaining suppliers are not utilized. This reflects the model's cost-minimizing behavior, where procurement is restricted to the most cost-efficient suppliers. The overall procurement volume decreases consistently across periods, aligning with the halved market demand and supporting the model's capacity to dynamically adjust purchasing and production levels in response to demand fluctuations.

Scenario 2: Reduced transportation cost from farmers to the agro-hub. The second scenario simulates an improvement in upstream logistics efficiency by reducing transportation costs from farmers (suppliers) to the agro-hub. This case aims to observe how decreased transport costs affect supplier selection and cost distribution within the network. The modified parameter values used in this scenario are presented in Table 11. These values represent lower transportation costs per route compared to the base case.

Table 10. The types and quantities of agro-food products bought from farmers as suppliers (kg) under Scenario 1

Supplier	Commodity	Week Period					
		1	2	3	4	5	6
1	1	7068	7086	8486	7905	7634	8321
	2	0	0	0	0	0	0
2	1	0	0	0	0	0	0
	2	7698	6615	6724	7144	6824	6671
3	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
Total		14765	13701	15210	15049	14458	14992

Table 11. Transportation cost per trip from farmer to agro-hub channel (in IDR)

Channel	No.	Commodity	
		1	2
Farmer	1	2500000	2500000
	2	2500000	2500000
	3	500000	500000

Table 12. The types and quantities of agro-food products bought from farmers as suppliers (kg) under Scenario 2

Supplier	Commodity	Week Period					
		1	2	3	4	5	6
1	1	9000	9000	9000	9000	9000	9000
	2	2000	0	0	2000	0	0
2	1	5135	5173	7973	5810	5269	7643
	2	12000	12000	12000	12000	12000	12000
3	1	0	0	0	1000	1000	0
	2	1395	1229	1448	288	1647	1341
Total		29530	27402	30421	30098	28916	29984

Table 13. Commodity prices offered by each supplier (in IDR/kg) under Scenario 3

Farmer	Type of Commodity	
	1	2
1	200	1800
2	250	1400
3	50	500

Under Scenario 2, where the transportation cost from farmers to the agro-hub is reduced, the model produces a total operational cost of IDR 334,178,328. The detailed procurement quantities of each commodity from the respective suppliers over the six planning periods are summarized in Table 12. The results reveal a notable behavioral shift in supplier participation. Due to the reduced transportation cost, Supplier 3, previously inactive in the base-case scenario, becomes active in this configuration. This change indicates that lower logistics costs increase the competitiveness of suppliers located farther from the agro-hub.

Scenario 3: Lower commodity prices from Supplier 3. In the third scenario, the commodity prices offered by Supplier 3 are adjusted to be lower than in the base case. This modification evaluates how price competitiveness from a specific supplier influences sourcing decisions and overall system cost. The adjusted price parameters used in this scenario are presented in Table 13, where the price of Commodity 1 supplied by Supplier 3 is reduced to IDR 50 per kg, and the price of Commodity 2 is reduced to IDR 500 per kg. These adjustments represent a condition in which Supplier 3 offers a significant price advantage over other suppliers.

The model produced a total operational cost of IDR 326,142,092. This indicates a cost reduction compared to the base case and Scenario 2, suggesting that lower commodity prices substantially improve overall system efficiency. Table 14 presents the detailed procurement allocation of each commodity from the respective suppliers across six planning periods.

Table 14. The types and quantities of agro-food products bought from farmers as suppliers (kg) under scenario 3

Supplier	Commodity	Week Period					
		1	2	3	4	5	6
1	1	9000	9000	9000	10000	10000	9000
	2	1395	0	0	288	0	0
2	1	5135	5173	7973	5810	5269	7643
	2	12000	11229	11448	12000	11647	11341
3	1	0	0	0	0	0	0
	2	2000	2000	2000	2000	2000	2000
Total		29530	27402	30421	30098	28916	29984

The sensitivity analysis is conducted through three scenarios to evaluate how variations in key parameters, demand, transportation cost, and commodity price affect the model's performance and decision-making structure. The findings collectively demonstrate the robustness and adaptability of the proposed MILP model in optimizing procurement and minimizing total operational cost under different operational conditions. Overall, the sensitivity analysis reveals that the model responds logically and consistently to parameter variations. Reductions in demand or input cost parameters (either transport or commodity prices) directly lead to lower total operational costs and adaptive reallocation of procurement sources. These results confirm that the model provides a stable, responsive, and policy-relevant decision-support tool for managing the agro-hub's supply chain under changing economic and logistical conditions.

3.3 The proposed heuristic algorithm

This section presents the application and performance results of the proposed heuristic algorithm. The heuristic is implemented using the same input parameters and operational settings as the MILP model to ensure a consistent basis for comparison.

Applying Steps 1 and 2 of the heuristic algorithm results in a ranking of suppliers based on the lowest effective unit cost. For Commodity 1, the order of increasing cost is Supplier 1, Supplier 2, and Supplier 3. Meanwhile, for Commodity 2, the suppliers are ranked as Supplier 2, Supplier 1, and Supplier 3, respectively (Table 15).

Table 15. Ranking of suppliers based on effective unit cost for each commodity

Supplier	Commodity	
	1	2
1	2500200 (rank-1)	2501800 (rank-2)
2	3000250 (rank-2)	2001400 (rank-1)
3	4000150 (rank-3)	3002000 (rank-3)

Step 3 of the heuristic algorithm involves calculating the cumulative demand for each product across all distribution channels, namely distributors, retailers, and end customers.

The aggregated product demand is then adjusted using the corresponding conversion factor to determine the total quantity of each commodity that must be procured by the agro-hub. This step ensures that procurement volumes at the upstream level accurately reflect the processed product requirements downstream. The detailed computation of the cumulative product demand and the corresponding converted commodity quantities is presented in Table 16.

Table 16. Cumulative product demand from all channels adjusted by the conversion factor for commodity procurement

Commodity (j)	Period (t)					
	1	2	3	4	5	6
1	13570	13606	16294	15178	14658	15977
2	15049	12932	13146	13967	13340	13041

Steps 4 and 5 of the heuristic algorithms focus on the allocation of commodity procurement based on the ranked supplier costs obtained in the previous steps. In this stage, the agro-hub begins procuring commodities starting from the supplier offering the lowest effective unit cost. Procurement continues from this supplier until its available capacity is fully utilized or the total commodity requirement is met. If additional volume is still required, the algorithm proceeds to procure from the supplier with the next lowest cost, and the process repeats until the full demand for each commodity is satisfied. This sequential allocation ensures that procurement decisions remain cost-efficient while respecting supplier capacity constraints. The resulting distribution of commodity purchases from each supplier across all planning periods is presented in Table 17.

Table 17. Allocation of commodity procurement from each supplier (heuristic steps 4–5)

Supplier	Commodity	Week Period					
		1	2	3	4	5	6
1	1	10000	10000	10000	10000	10000	10000
	2	3049	932	1146	1967	1340	1041
2	1	3570	3606	6294	5178	4658	5977
	2	12000	12000	12000	12000	12000	12000
3	1	565	566	678	632	611	666
	2	346	297	302	321	307	300
Total		29530	27402	30421	30098	28916	29984

Step 6 involves calculating the total operational cost resulting from the procurement and distribution strategy generated by the heuristic method. All cost components, including procurement, transportation, processing, and inventory, are aggregated to obtain the overall system expenditure associated with the heuristic allocation strategy. From this computation, the total operational cost achieved by the heuristic approach is IDR 384,111,503. This value reflects the total expenditure required to operate the agro-food supply chain under the heuristic strategy and serves as a benchmark for comparison against the optimal solution obtained from the MILP model.

3.4 Comparison between MILP and heuristic results

The performance comparison between the MILP model and the proposed heuristic algorithm highlights the superior efficiency of the MILP-based optimization framework. The MILP model achieves a total operational cost of IDR 337,808,445, whereas the heuristic approach results in IDR 384,111,503, which is approximately 13.7% higher than the optimal solution.

This result confirms that the MILP model successfully provides the global minimum operational cost through an integrated optimization of procurement, transportation, and processing decisions. In contrast, the heuristic algorithm, while simpler and faster to implement, can only approximate the optimal result due to its sequential and cost-priority logic.

Overall, the findings reinforce that the proposed MILP model serves as the primary decision-support framework, offering a robust, data-driven basis for strategic planning within the agro-hub, while the heuristic provides supportive insight for quick operational evaluations.

3.5 Limitations of the study

Although the proposed MILP model provides a robust and practical framework for optimizing the agro-food supply chain network in Banten province, several limitations should be acknowledged to contextualize the findings and guide future improvements.

First, the current model operates under a deterministic assumption, where all parameters (such as demand, transportation cost, supplier capacity, and product prices) are treated as fixed and known in advance. This assumption simplifies computation and ensures model tractability. However, it does not account for uncertainty and variability commonly observed in real-world agro-food systems, such as seasonal demand fluctuations, weather-related disruptions, and price volatility.

Second, the model applies a fixed conversion rate between commodities and final products at the agro-hub. In practice, this conversion efficiency may vary due to raw material quality, processing losses, or equipment performance. A constant conversion factor can therefore limit the accuracy of production-procurement linkage and the estimation of total processing cost.

Third, the model assumes constant commodity prices across all planning periods, implying stable market conditions. This assumption may overlook temporal price fluctuations that typically occur in agricultural markets due to supply-demand dynamics or external shocks.

Finally, production and delivery lead times are not incorporated into the model. This exclusion is intentional to maintain model simplicity and focus on cost-minimization logic. However, it restricts the model's ability to capture scheduling delays and time-based coordination between upstream and downstream actors.

Despite these simplifications, the model successfully demonstrates the potential of an integrated optimization framework for policy-driven agro-hub management.

4. CONCLUSIONS

This study develops an integrated MILP model to optimize the agro-food supply chain network in Banten Province, Indonesia. The model is designed to minimize the total operational cost of the system by integrating procurement, transportation, processing, and inventory decisions across multiple suppliers, products, and distribution channels.

The optimization results demonstrate that the proposed

MILP model effectively identifies the most cost-efficient allocation of commodities from suppliers to the agro-hub and from the agro-hub to downstream markets. The model achieves a minimum total operational cost of IDR 337,808,445, representing the optimal balance among procurement, logistics, and production costs within the defined system constraints.

To validate the robustness of the proposed framework, sensitivity analyses are conducted under three scenarios: reduced demand, lower transportation costs, and decreased commodity prices. The results show that the model behaves logically and remains stable under parameter changes, adjusting supplier selection and procurement volumes accordingly. Additionally, a heuristic algorithm is developed to provide a simplified comparison method. Although the heuristic produces a slightly higher total cost (13.7% above the MILP optimum), it confirms the consistency and superiority of the MILP solution, reinforcing the model's effectiveness as a strategic decision-support tool.

The model's deterministic nature, along with assumptions of fixed conversion rates, constant commodity prices, and the exclusion of production and delivery lead times, is acknowledged as a limitation. Nevertheless, these simplifications ensure tractability and clarity of results in this early-stage modeling effort.

Overall, the proposed MILP framework contributes a practical, data-driven foundation for optimizing agro-hub operations and regional food supply chain management. The model can assist policymakers and practitioners in designing efficient sourcing and distribution strategies that enhance cost efficiency, resource utilization, and local food system resilience. Future research should extend this framework by incorporating stochastic elements, variable conversion efficiency, and time-dependent constraints to improve its applicability to dynamic real-world supply chain environments.

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NOMENCLATURE

Indices

i	Index of product
j	Index of commodity
c	Index of customer
r	Index of retailer
d	Index of distributor
k	Index of farmers

Parameters

$\boldsymbol{P_{kj}}$	Price of commodity $\boldsymbol{j}$ from farmer $\boldsymbol{k}$

TC_{kj}	Transportation cost to carry commodity *j* from farmer *k*
B_i	Production batch size of product *i*
C_i	Transportation capacity for product *i*
C_j	Transportation capacity for commodity *j*
PC_i	Production cost of product *i*
TC_{ci}	Transportation cost to carry product *i* to customer *c*
TC_{ri}	Transportation cost to deliver product *i* to retailer *r*
TC_{di}	Transportation cost to deliver product *i* to retailer *d*
D_{cit}	The demand of customer c on product *i* at period *t*
D_{rit}	The demand of retailer r on product *i* at period *t*
D_{dit}	The demand of distributor *d* on product *i* at period *t*
W_{ij}	Conversion rate of product *i* from commodity *j*
Cap	Production capacity
IC_i	Inventory cost of product *i*

Variables

S_{cit}	Quantity of product *i* to customer *c* at period *t*
S_{rit}	Quantity of product *i* to customer *r* at period *t*
S_{dit}	Quantity of product *i* to customer *d* at period *t*
S_{kjt}	Quantity of commodity *j* from supplier *k* at period *t*
Q_{it}	Quantity of product *i* packaged at period *t* in the hub
NT_{cit}	Number of trips required to deliver product *i* from agro-hub to customer *c* at period *t*
NT_{rit}	Number of trips required to deliver product *i* from agro-hub to retailer *r* at period *t*
NT_{dit}	Number of trips required to deliver product *i* from agro-hub to distributor *d* at period *t*
NT_{kjt}	Number of trips required to deliver commodity *j* from supplier *k* to agro-hub at period *t*
Inv_{it}	Inventory level of product *i* at the agro-hub at period *t*