

Optimization of Aggregate Planning and Inventory in the Sunflower Supply Chain Based on Situational Analysis Using Soft System Dynamics Methodology

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Abstract:

Purpose: This study seeks to improve the international competitiveness of the Indonesian sunflower industry. The study includes several particular objectives to accomplish this goal: (1) To assess the present condition of the sunflower industry supply chain, and (2) To formulate an optimization model for production and inventory management.

Design/methodology/approach: The Soft System Dynamics Methodology (SSDM) was used for situational analysis, followed by optimization of production planning through demand forecasting using the Artificial Neural Network (ANN) method and aggregate planning using the Heuristic method. Furthermore, inventory optimization was carried out using the working capital and storage space restriction model with three algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA).

Findings: Based on the inventory optimization using the three algorithms, it was found that the Genetic Algorithm resulted in the lowest total inventory cost calculation, amounting to IDR2,943,675.

Research limitations/implications: This study investigates a sunflower industry located in Bandung Regency, Indonesia. The optimization models applied Genetic Algorithm, Particle Swarm Optimization, and Simulated Annealing were specifically adapted to the available operational data. As a result, the findings may not be directly generalizable to other industries operating under different conditions. Furthermore, limitations in resources, such as machinery and storage capacity, posed constraints on the system simulation for inventory planning.

Practical implications: This research offered practical methods and approaches for sunflower industries to enhance operational efficiency, reduce production costs, and optimize storage space utilization. Recommendations, such as the moderate production scenario, provided actionable insights for fulfilling consumer demand optimally while avoiding lost sales.

Social implications: The study had potential socioeconomic benefits, particularly for farmers and local workers involved in the industry. Improved planning systems can contribute to economic stability for these communities while also ensuring high quality sunflower derived products became more widely available and affordable to the public.

Originality/value: The integration of diverse methodologies, including the Soft System Dynamics Methodology, demand forecasting through Artificial Neural Networks, aggregate planning via heuristic methods, and inventory optimization using GA, PSO, and SA, distinguished this study as a unique,

comprehensive approach. This holistic framework added significant value to the academic field of production and inventory planning, especially for small scale industries like sunflower industries.

Keywords: aggregate heuristic, artificial neural network, demand; inventory, soft system dynamic methodology, storage space restriction

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1. Introduction

Indonesia, as a tropical country, has significant potential for cultivating various agricultural commodities, including sunflower (*Helianthus annuus* L.) (Aisyah et al., 2016). Despite favorable climatic conditions, domestic sunflower production remains insufficient to meet local demand, leading to dependence on imports (Baraki et al., 2024; Sharma & Deshmukh, 2024). Sunflower derived products, such as cooking oil and herbal oil (Nakonechna et al., 2024), have high economic value (Puttha et al., 2023), while production residues can be utilized as livestock feed supplements (Senkoylu & Dale, 2007), enhancing value creation along the supply chain (Fang & Ge, 2023; Nurhasanah, Natilla-Adlina et al., 2024). Globally, sunflowers rank among the leading oilseed crops, underscoring their strategic importance in industrial systems (Kaur et al., 2023; Peng et al., 2020).

However, the sunflower processing industry in Indonesia continues to face substantial challenges in production planning and inventory management. Current practices rely heavily on intuition and short-term orders, limiting the ability of firms to anticipate demand fluctuations and leading to inefficiencies such as excess inventory, lost sales, and high operational costs (Hasan & Habib, 2023; Luo et al., 2020). These issues indicate the absence of an integrated decision-making framework capable of capturing both systemic complexities and quantitative operational constraints.

Situational supply chain analysis provides a means to understand complex interactions among actors, processes, and resources within an agro-industrial system (Lyu et al., 2014). In this context, the Soft System Dynamics Methodology (SSDM), developed by Paucar-Caceres and Rodriguez-Ulloa, serves as a qualitative problem-structuring approach that facilitates the identification of key variables, feedback relationships, and organizational challenges within complex systems (Kırcı et al., 2018). Unlike predictive system dynamics simulations, SSDM is particularly useful in structuring ill-defined problems and supporting subsequent quantitative analyses.

Beyond qualitative analysis, effective decision making in production planning requires accurate demand forecasting and optimization of production and inventory levels (Rakholia et al., 2025). ANN have been widely adopted for demand forecasting (Kumar & Nayak, 2024; Singhroul & Agrawal, 2021) due to their ability to capture nonlinear patterns without restrictive assumptions of stationarity and linearity (El-Amarty et al., 2022; Tulli, 2020)

Aggregate planning as a medium term planning function (Aydin & Tirkolae, 2025), aligns production capacity with anticipated demand, while inventory optimization ensures efficient use of working capital and storage space (Liu & Yang, 2022; Mehdizadeh & Atashi, 2014). Recent studies highlight the potential of metaheuristic algorithms, such as GA, PSO, and SA (Abualigah et al., 2023), in solving complex production and inventory planning problems under real-world constraints, particularly in small-scale manufacturing environments (Abdul-Khannan et al., 2025).

Despite extensive literature on demand forecasting, aggregate planning, and inventory optimization, prior studies rarely integrate qualitative system structuring with quantitative optimization in a unified framework. Specifically, the linkage between systemic insights derived from methodologies such as SSDM and subsequent operational decision models remains underexplored (Kogetsidis, 2025), particularly in small scale industrial contexts (Maje, 2021).

To address this gap, this study proposes an integrated framework for optimizing aggregate production planning and inventory management in the Indonesian sunflower supply chain. SSDM is employed to structure the problem and identify key variables and constraints, while ANN is used for demand forecasting, heuristic methods for aggregate planning, and GA, PSO, and SA for inventory optimization. The results demonstrate that a moderate production scenario combined with GA yields the most cost-effective outcomes. This integrated approach contributes to improved operational efficiency and supports informed decision-making in small scale industries.

This paper was organized as follows. Section 2 described the research methodology, emphasizing the role of SSDM in structuring the decision-making framework. Section 3 presented the results and discussion, covering the qualitative insights from SSDM and the outcomes of demand forecasting, aggregate planning, and inventory optimization. This section presented the analysis following the sequence of the ten stages of the SSDM. Section 4 discussed the managerial and practical implications of the proposed framework. Finally, Section 5 concluded the paper and outlined directions for future research.

2. Methodology

2.1. Research Methodology

The improvement process began with recognizing that the sunflower supply chain still faced structural limitations. The lack of a comprehensive situational analysis left key risks, opportunities, and operational needs unidentified. Additionally, the absence of aggregate and inventory planning weakened the system’s ability to respond to demand changes, optimize production activities, and maintain storage efficiency.

Building on these gaps, the study applied SSDM to obtain a holistic view of the problem and identify effective intervention points. Insights from SSDM then guided the use of ANN forecasting, heuristic aggregate planning, and evolutionary algorithms for inventory optimization to improve decision making.

Through these improvements, the supply chain is expected to become more adaptive capable of meeting demand, reducing costs, and using storage space more efficiently while maintaining quality. Figure 1 provides a summary of the research process and proposed enhancements.

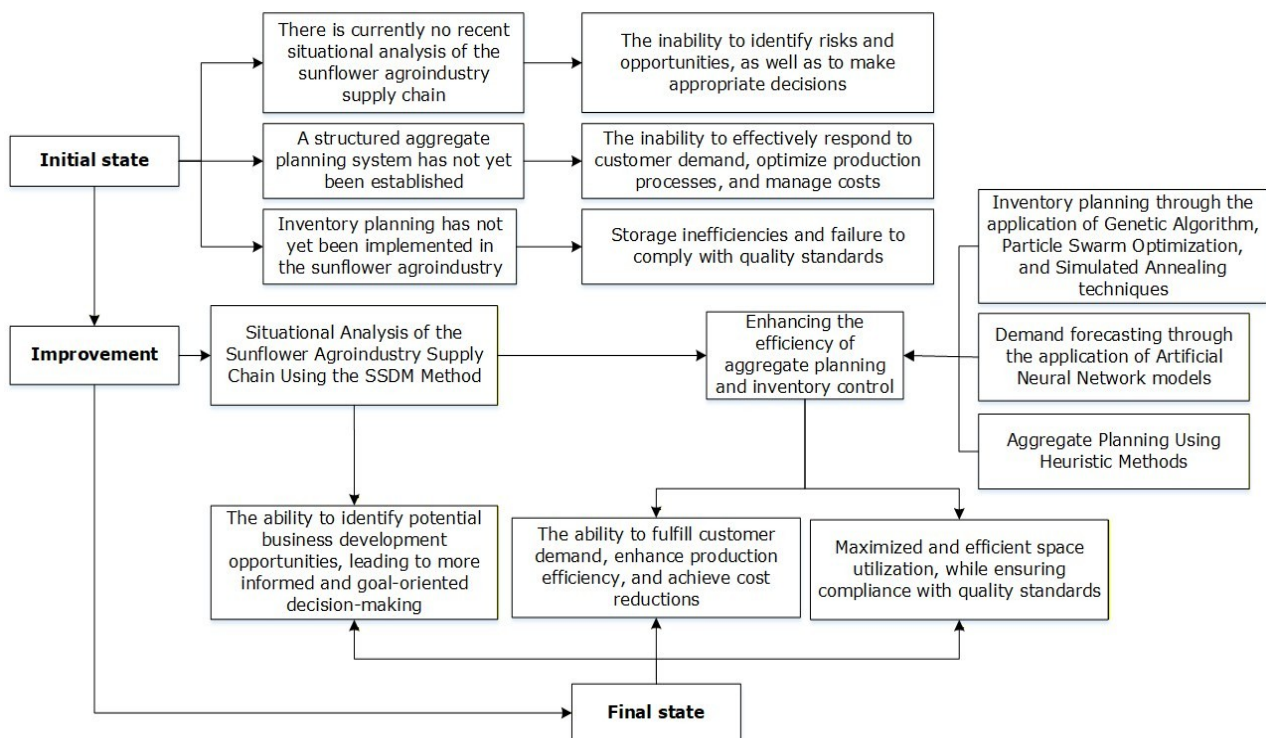


Figure 1. Research methodology

2.2. Ten Stages Soft System Dynamic Methodology

Figure 2 provided an integrated overview of the ten SSDM stages, illustrating how the method progressed from understanding the real-world problem to model construction, systemic reflection, and the implementation of feasible changes. These stages depicted SSDM as a learning process that guided practitioners through complexity toward meaningful system improvement (Paucar-Caceres & Rodriguez-Ulloa, 2007; Rodriguez-Ulloa & Paucar-Caceres, 2005).

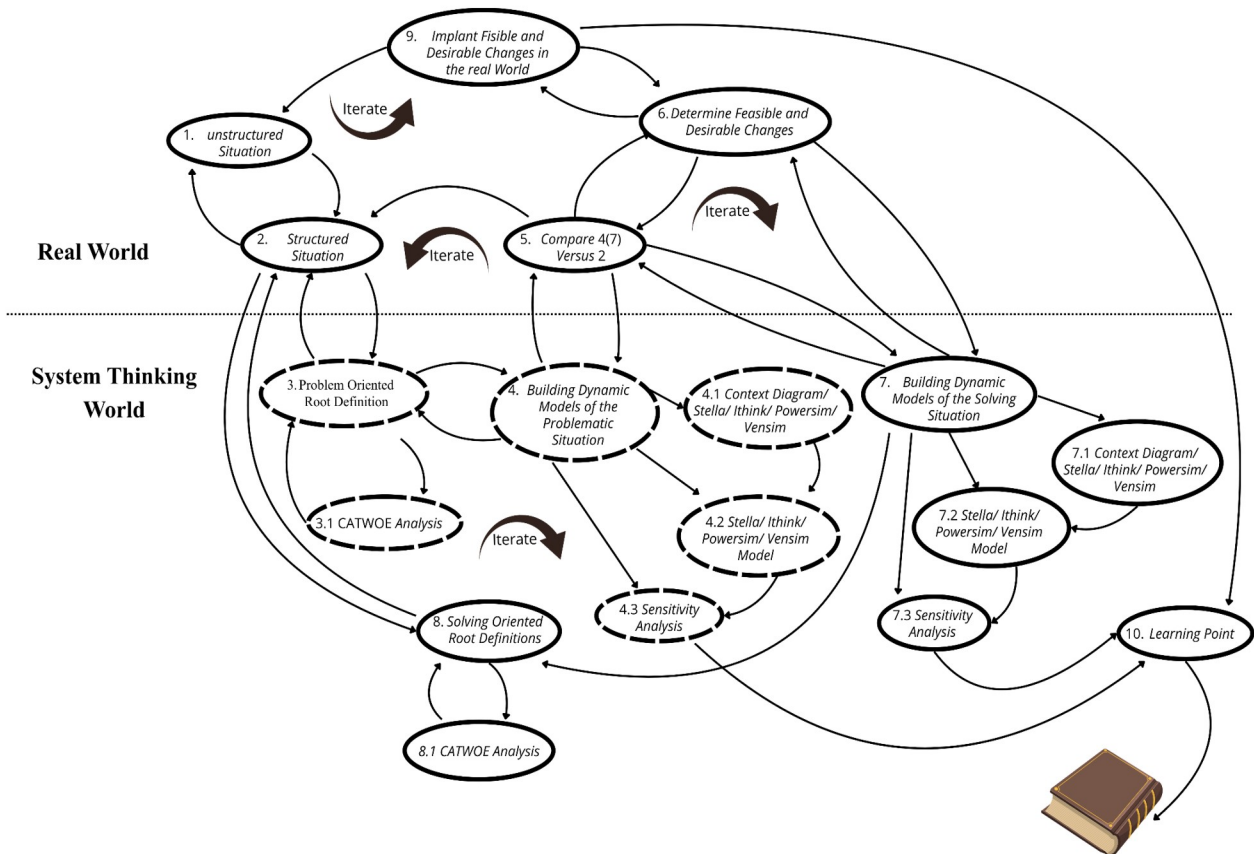


Figure 2. Research methodology

SSDM was applied as a structured pathway to move from a complex, ill-defined situation to quantitative decision models. First, a rich picture and CATWOE clarified the problem boundary, actors, and constraints. Next, these insights were formalized into a causal loop diagram (CLD) to identify key feedbacks (reinforcing and balancing). We then translated the CLD into a stock flow diagram (SFD), making explicit how inventory, production rate, capacity limits, and demand fulfilment evolve over time.

SSDM was applied as a structured pathway to transition from a complex, ill-defined situation to quantitative decision models. A rich picture and CATWOE clarified the problem boundaries, actors, and constraints. These insights were then formalized into a CLD to identify key reinforcing and balancing feedbacks, which were subsequently translated into a SFD to represent the dynamics of inventory, production rate, capacity limits, and demand fulfilment.

Finally, variables and constraints surfaced by the SFD directly informed the quantitative models: (1i) ANN for demand forecasting (to address demand uncertainty highlighted in the CLD), (2) a heuristic aggregate plan subject to capacity and cost constraints derived from the SFD, and (3) constrained inventory optimization (GA/PSO/SA) reflecting warehouse space and working capital limits identified in the SSDM stages.

2.3. Data Collection and System Understanding

The collected data were used not only to describe operational conditions but also to identify causal relationships underlying the SSDM model. Demand, inventory, capacity, drying time, and seed-availability data revealed bottlenecks affecting material flow, production cycles, and the industry's ability to meet demand. These variables, gathered through observations, interviews, and historical records, informed the reinforcing and balancing feedback structures represented in the CLD.

These datasets were integrated into the SSDM modelling process by translating quantitative variables such as capacity, processing times, labor costs, and raw material costs into stocks, flows, and auxiliary parameters in the SFD.

2.4. Demand Forecasting using Artificial Neural Network

Demand forecasting is conducted to address demand uncertainty identified in the SSDM CLD, particularly the feedback between demand fluctuation, inventory depletion, and stock out risk. ANN was selected because of their ability to model nonlinear demand patterns without assuming data stationarity.

A feedforward ANN with two hidden layers was used. The architecture was selected based on achieving the lowest Mean Squared Error (MSE) among several tested configurations, and was applied to forecast monthly demand for all product categories.

2.5. Aggregate Planning Model

Aggregate planning was developed to convert SSDM identified constraints such as labor shortages, pressing capacity limits, drying delays, and inventory buildup into a quantitative medium-term production plan. The model aimed to minimize total operational costs while meeting ANN-based monthly demand. It covered three product types (250 mL, 500 mL, and 1 L) and evaluated pessimistic, moderate, and optimistic scenarios using a heuristic approach to determine the most feasible production level under real operational constraints.

2.6. Inventory Optimization Model

Inventory optimization was formulated to address two systemic constraints emphasized in SSDM: limited warehouse space and restricted working capital for inventory investment. The model determines the optimal order quantity Q_i for each product.

Metaheuristic algorithms (GA, PSO, and SA) were implemented because the model is nonlinear and constrained, making analytical solutions impractical. These algorithms efficiently search the feasible region and identify minimum cost solutions consistent with SSDM's systemic insights.

3. Soft System Dynamic Methodology and Model Development

SSDM outputs guided the structure of all quantitative components. The CLD revealed demand uncertainty, capacity bottlenecks, and limits on warehouse space and working capital. Based on these insights, ANN generated short term demand for each SKU, a heuristic aggregate plan minimized operating costs under capacity and inventory balance constraints, and GA/PSO/SA optimized inventory within space (W) and investment (J) limits. This ensured that each quantitative result remained traceable to its corresponding SSDM insight.

3.1. Stage 1: Unstructured Problem Situation

The initial field observations, interviews, and site visits revealed that the sunflower industry operates with several structural limitations that affect its production and supply-chain performance. As a micro-scale industry, the company relies on limited labor, basic processing machinery, and constrained warehouse capacity. These constraints create bottlenecks in drying, pressing, and storing sunflower seeds and oil products.

Demand fluctuates significantly and is not supported by any forecasting system, leading to recurring stockouts and excess inventory. Production is reactive to short-term orders, creating inconsistent workloads and unstable inventory levels. Supply availability is also uncertain due to reliance on a single seed importer and weather dependent drying durations.

Multiple operational constraints, including limited capacity, uncertain demand, variable material supply, and restricted storage, form a complex and ill-structured problem situation. These challenges obstruct effective alignment of production and inventory with market needs, providing the basis for applying SSDM to identify key variables and systemic leverage points.

3.2. Stage 2: Structured Problems

The next SSDM stage involved describing the problem situation through a rich picture, which illustrated the company's operational issues. Figure 3 presents this rich picture, while Table 1 lists the actors involved.

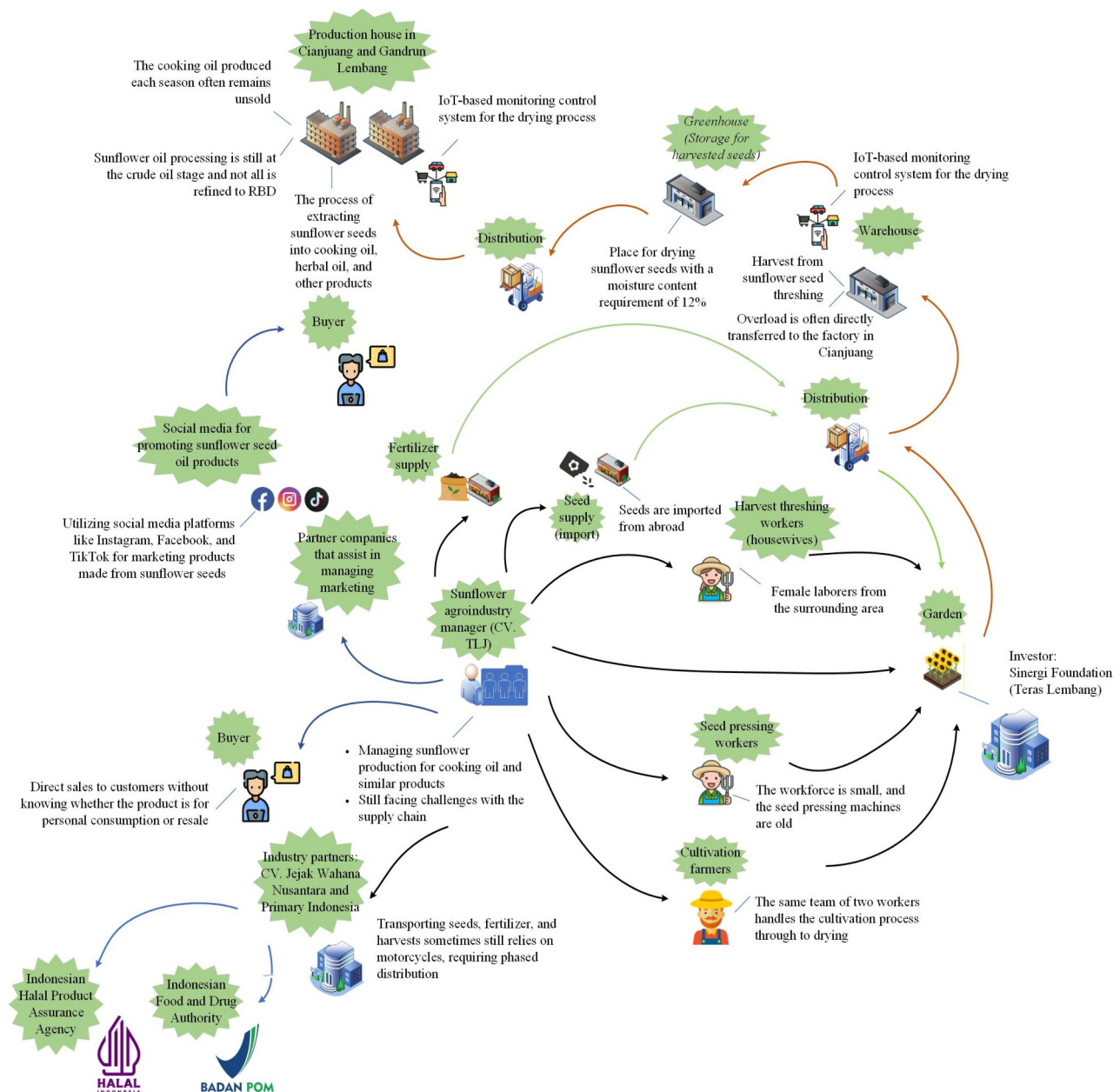


Figure 3. Rich picture of the sunflower industry

The rich picture provided a qualitative overview of the sunflower supply chain, summarizing key stakeholders, constraints, and material flows. It was used to delimit the system's scope and identify candidate variables for formalization in the CLD.

No	Actor	Description
1	Sunflower industry manager	Oversees production and overall operations under existing supply-chain constraints.
2	Farmer cultivation	Handle planting, harvesting, drying, and basic seed processing.
3	Female workers	Separate harvested seeds from calyxes.
4	Sunflower seed pressing machine operator	Operates the small-scale seed-pressing machine.
5	Partner companies that help manage marketing	Support product promotion through social media channels.
6	Buyer	Purchase products directly, either for personal use or resale.
7	Investor	Provides land endowment that supports cultivation activities.

Table 1. Actors in rich picture

3.3. Stage 3: Root Definition – Problem Oriented

To further structure the problem situation illustrated in the rich picture and supported by the list of actors in Table 1, the next step in SSDM is to analyze the case using the CATWOE framework. CATWOE helps categorize the elements of the system such as stakeholders, transformation processes, worldview, ownership, and environmental constraints into a structured format. This step ensures that all perspectives of the problematic situation are explicitly defined before constructing the causal loop diagram (CLD). Table 2 summarized the CATWOE elements identified in the sunflower supply chain.

No	CATWOE Elements	Description
1	Client	Sunflower seed processing industry and direct or online buyers.
2	Actor	Cultivation workers, seed peelers, machine operators, marketing partners, and investors.
3	Transformation	Converting raw sunflower seeds into processed oil products and utilizing by-products.
4	World View	Structured production and planning improve productivity and demand fulfilment.
5	Owner	Sunflower processing industry
6	Environment	Limited seed availability, machine capacity constraints, restricted storage, regulatory requirements, and suboptimal drying conditions.

Table 2. CATWOE Analysis

By integrating all elements identified in the CATWOE framework, a comprehensive root definition of the purposeful activity system can be formulated as follows. A transformation system, owned by the sunflower processing company and carried out by cultivation workers, seed peelers, machine operators, marketing partners, and investors, that converts raw sunflower seeds into processed oil products for direct and online buyers, in accordance with the worldview that structured and optimized production processes will increase productivity and demand fulfilment, within environmental constraints including seed availability, machine capacity limits, inadequate drying processes, restricted storage space, and regulatory compliance requirements.

The root definition clarified the purpose and structure of the activity system and summarized the key CATWOE elements. These elements guided the identification of the main state and rate variables used in the CLD and SFD, ensuring that qualitative insights from SSDM were systematically translated into the system dynamics formulation. They also provided the conceptual basis for defining parameters and constraints in the forecasting model, aggregate production planning, and inventory optimization. With this foundation, the analysis proceeded to Stage 4, where the problem situation was formalized into an operational system dynamics model.

3.4. Stage 4: Building a System Dynamics Model of the Problem Situation

Drawing on the CATWOE analysis and the problem structure depicted in the rich picture (see Figure 4), a CLD was constructed to represent the key feedback mechanisms within the sunflower supply chain. The diagram

captures reinforcing and balancing loops affecting capacity, inventory, drying, and utilization, and serves as the foundational step for formalizing the system into a system dynamics model

The CLD captured the main systemic relationships in the sunflower supply chain by linking demand patterns, production activities, resource constraint, and financial performance. Rising demand increases sales but depletes inventory and heightens stock out risk, which suppresses profit. These dynamics highlight the need for improved production and inventory planning as such planning directly affects production cost, labor use, and required cultivation technology factors that collectively shape operational efficiency.

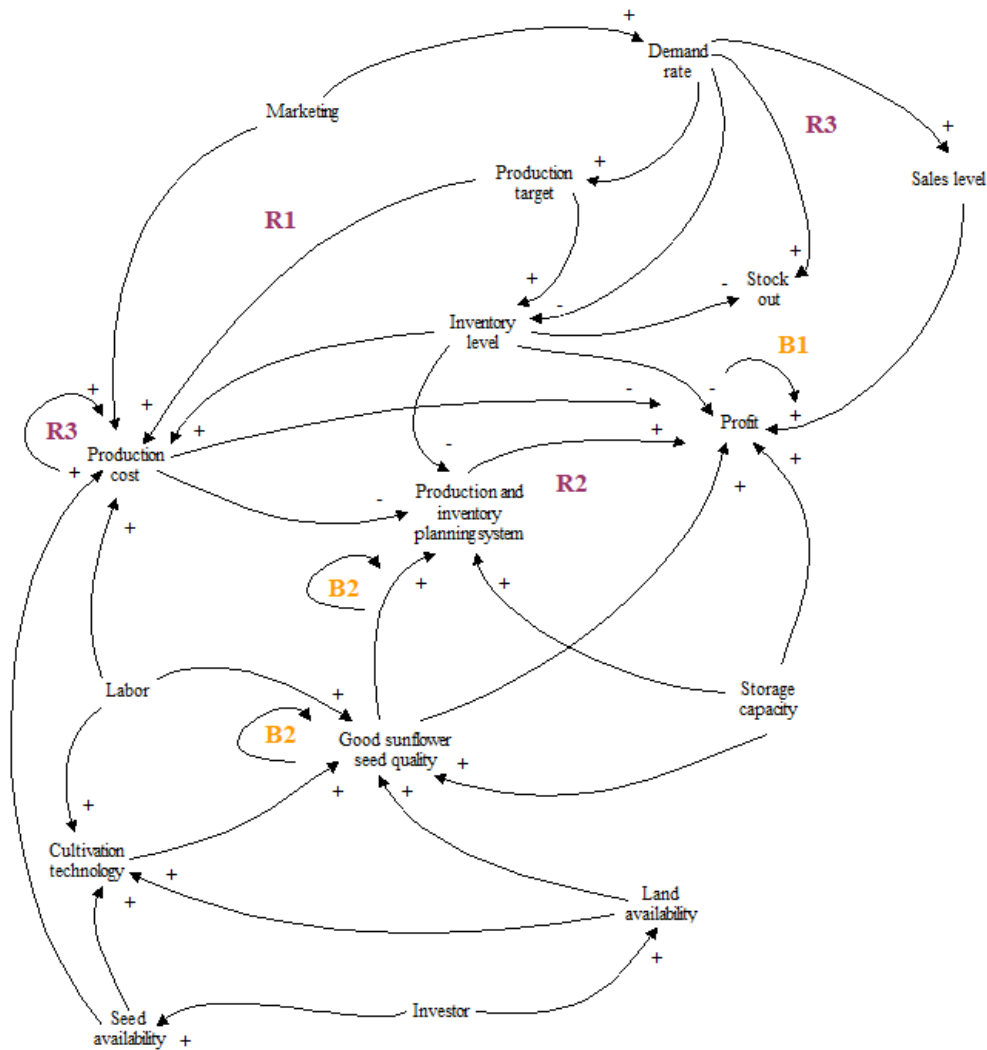


Figure 4. SSDM Causal Loop Diagram of Problematic Situation

The diagram also emphasized the role of seed availability and quality, where higher quality seeds improve production efficiency, lower costs, and increase profit. Increased profit then supports larger storage capacity and attracts investment, strengthening the industry’s ability to meet demand. The model further shows how land availability and investor involvement shape cultivation activities and raw material supply, generating reinforcing or balancing effects across the supply chain

To ensure clarity and traceability between the qualitative and quantitative stages of SSDM, each causal relationship shown in the CLD was explicitly mapped into the corresponding stock flow structure in the SFD (Figure 5).

This section converts the qualitative relationships identified in the CLD into a quantitative SFD. In this subsystem, Sales Value is treated as a stock that accumulates revenue, while Sales Value Rate acts as its inflow.

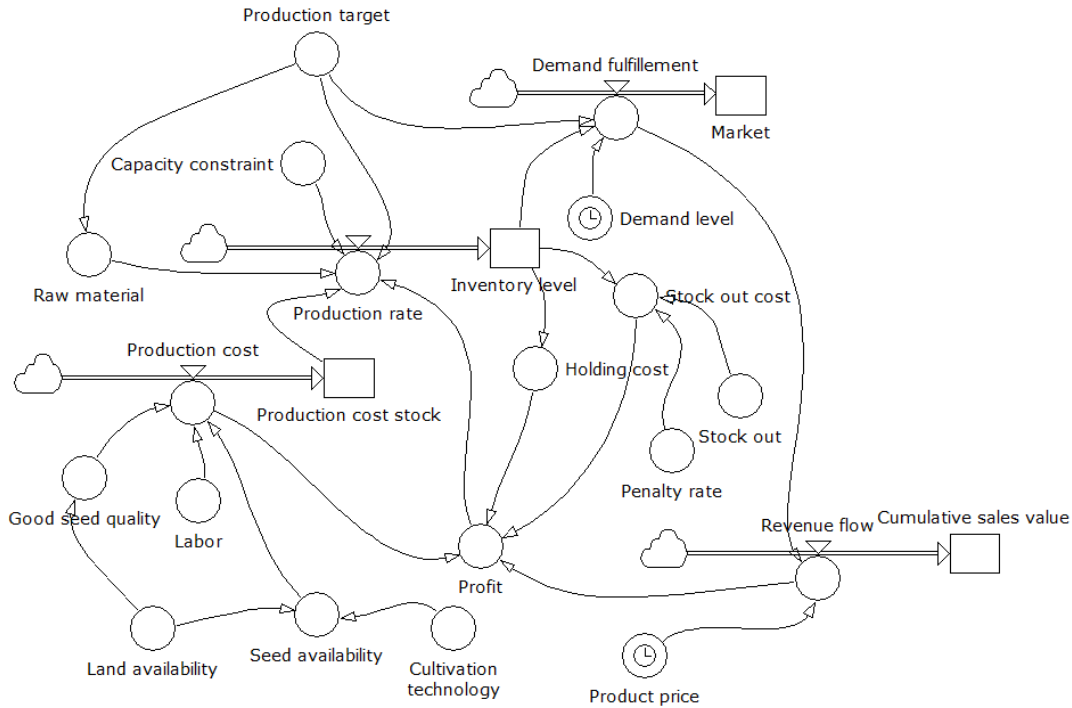


Figure 5. SSDM Stock Flow Diagram of Problematic Situation

The inflow structure follows the SSDM findings, where the number of products sold is constrained by both demand and production availability; therefore, it is modelled as the minimum of the two. Revenue per period is then obtained by multiplying units sold by the Product Price, and this inflow accumulates over time into the Sales Value stock. In this way, the Sales Value quantitatively represents the causal relationships identified in SSDM and allows simulation of how revenue flow (1), demand fulfilment (2), inventory level (3), production rate (4), and unit production cost (5).

$$\text{Revenue flow} = \text{product price} \times \text{demand fulfilment} \tag{1}$$

$$\text{Demand fulfilment} = \text{Min}(\text{Production rate}, \text{Inventory level}) \tag{2}$$

$$\frac{\partial(\text{Inventory level})}{\partial t} = \text{Inflow} - \text{Outflow} = \text{Production rate} - \text{Demand fulfilment} \tag{3}$$

$$\text{Production rate} = \text{MIN}(\text{Production target}, \text{Capacity constraint}) \tag{4}$$

$$\text{Unit production cost} = \left(\frac{\text{Labor cost}}{\text{Cultivation technology}} \right) \times \left(\frac{1}{\text{Good seed quality}} \right) \tag{5}$$

To connect the qualitative insights obtained from SSDM with the subsequent quantitative analyses, the following table summarizes how each SSDM finding informs the selection of forecasting, aggregate planning, and inventory optimization models used in this study.

The mapping in Table 3 illustrates how each SSDM insight informs the selection of variables, parameters, and constraints for the quantitative models. To consolidate these interconnected activities, Figure 6 introduces the conceptual model, which organizes the forecasting, planning, and optimization processes into a unified decision making structure.

SSDM output / insight	Decision implication	Quantitative model used	Input / parameter
Demand uncertainty and lost sales observed in interviews	Need forecast-based planning to reduce stockouts and overproduction	ANN demand forecasting	<ul style="list-style-type: none"> Historical monthly sales (Dec 2023–Dec 2024) Forecast (Jan–Jun 2024)
Limited pressing/drying capacity and labor constraints	Scenario-based production targets to match feasible capacity	Heuristic aggregate planning	<ul style="list-style-type: none"> Production targets (pessimistic/moderate/optimistic) Unit costs Labor cost
Warehouse space limitation (W)	Inventory must respect physical space	Constrained inventory optimization	<ul style="list-style-type: none"> W w_i (space per unit)
Working capital/investment limitation (J)	Inventory must respect investment budget	Constrained inventory optimization	<ul style="list-style-type: none"> J P_i (unit price / investment per unit)
Need for implementable policy in small-scale setting	Use metaheuristics to solve constrained nonlinear problem efficiently	GA, PSO, and SA	<ul style="list-style-type: none"> Objective function Constraints Algorithm parameters

Table 3. Mapping of SSDM Findings to Quantitative Models Used in the Study

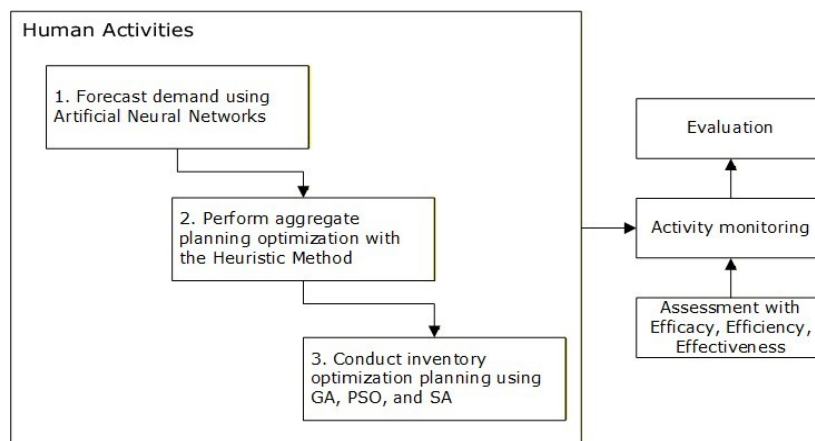


Figure 6. Conceptual Model

Figure 6 represents the conceptual model derived from the root definition and the system dynamics formulation. At this stage, the model serves only as a structured representation of the purposeful human activities within the system, and not yet as a proposed solution. With the conceptual model established, the analysis proceeds to Stage 5, where it is compared with the real-world problem situation to identify gaps and areas that require improvement before formulating feasible solutions in Stage 6.

The CLD and SFD from Stage 4 provided the structural foundation for all subsequent quantitative models. By deriving the variables and constraints (such as demand, capacity, and storage) directly from SSDM insights, the study integrated qualitative system understanding with quantitative decision-making. This ensured that the ANN, aggregate planning, and metaheuristic optimizations (GA, PSO, SA) remained coherent and fully guided by the systemic problem situation.

3.5. Stage 5: Comparison Between the Conceptual Model and the Problem Situation

The comparison between the conceptual model and the real operational conditions showed that the model was generally consistent with the key issues observed in the field, particularly demand fluctuations, capacity constraints, and limited storage space. This indicates that the model captures the main decision making needs of the sunflower industry.

At the same time, the comparison revealed several gaps, such as variations in seed quality, weather-dependent drying times, and machine limitations that behave more dynamically than the simplified model relationships. These differences provide important insights for refining feasible and systemically desirable improvements in the next stage.

3.6. Stage 6: Determine Solution Mechanisms

Stage 6 identified and formulated the solution mechanisms required to improve the system. These mechanisms took the form of quantitative models: ANN for forecasting, heuristic procedures for aggregate planning, and metaheuristic techniques for inventory optimization. These models formed the basis for generating improved outcomes in Stage 7.

3.6.1. Demand Forecasting

Demand forecasting was introduced in Stage 6 as a solution mechanism to address the demand uncertainty identified through the SSDM analysis, particularly its influence on inventory depletion, stock-out risks, and production imbalances. To generate reliable short-term estimates, this study employed an ANN architecture that had been previously validated using the same sunflower agro-industry dataset.

The selected feed forward backpropagation network consisted of six lagged inputs, two hidden layers with seven neurons, and a *logsig* activation function. The model was trained using the TRAINGDM and LEARNGDM algorithms (Han & Dong, 2023), with MSE used as the primary performance indicator. Historical demand data were normalized and transformed into input target pairs to capture the nonlinear and fluctuating patterns inherent in the system.

The resulting forecasts served as the monthly inputs for aggregate production planning and inventory optimization. By reducing uncertainty within key feedback loops, this forecasting mechanism was considered both systemically desirable and culturally feasible for application in a small scale industry context. Recent evidence showed that neural-network-based hybrid models outperformed traditional univariate approaches for manufacturing demand, particularly when exogenous drivers were included, reinforcing our choice of ANN for short term SKU level forecasting (Quiñones-Rivera et al., 2023).

3.6.2. Aggregate Planning Optimization

Aggregate planning was performed to determine an optimal medium-term production plan that balances demand forecasts, production capacity, workforce availability, and inventory levels. As identified in the SSDM causal loop diagram, production capacity, labor availability, and inventory accumulation are key variables influencing system performance. These systemic relationships form the basis for the quantitative aggregate planning model developed in this stage.

In this study, aggregate planning focuses on three sunflower oil products (250 mL, 500 mL, and 1 L) using the demand forecasts generated in Stage 6 (ANN model). The objective of aggregate planning is to minimize total operational costs, including regular production cost, labor cost, inventory holding cost, and potential shortage cost, while satisfying monthly demand. Three planning scenarios (pessimistic, moderate, and optimistic) were evaluated to reflect system behavior under different production targets, as suggested by the SSDM analysis regarding capacity limitations and demand uncertainty. The aggregate planning problem was formulated as an optimization model with the following decision variables:

Objective function:

$$\min TC = \sum_{t=1}^T (C_p P_t + C_l L_t + C_h I_t + C_s S_t) \quad (6)$$

Subject to:

Inventory balance:

$$I_t = I_{t-1} + P_t - D_t \quad (7)$$

Capacity constraint:

$$0 \leq P_t \leq C_{apt} \quad (8)$$

Shortage definition:

$$S_t \geq D_t - (I_{t-1} + P_t) \quad (9)$$

Non negativity:

$$P_t \geq 0, I_t \geq 0, S_t \geq 0 \quad (10)$$

where:

D_t = demand forecast in period t from the ANN model

P_t = production quantity in period t

I_t = ending inventory in period t

S_t = shortage quantity in period t

C_p = unit production cost

C_L = labor cost per unit of labor

C_b = holding cost per unit per period

C_s = shortage (penalty) cost per unit

C_{apt} = production capacity limit in period t based on SSDM findings (machine limits, drying delays, labor availability)

T = total number of planning periods

The heuristic method was adopted because it allows scenario based evaluation under real operational constraints and provides feasible solutions suitable for small scale industries. This method iteratively evaluates production levels for all scenarios and identifies the scenario that yields the best trade off between production cost and sales performance.

The scenario evaluation is consistent with findings from the SSDM Forrester diagram, where production decisions affect inventory accumulation, operational workload, and sales value, thus requiring an optimization mechanism that stabilizes these reinforcing and balancing loops.

This stage evaluated the aggregate planning scenarios using a heuristic approach that enabled scenario-based assessment under real operational constraints and suited small scale industry conditions. Instead of relying on a single optimization formula, the procedure compared production levels across pessimistic, moderate, and optimistic scenarios to identify the most efficient balance between production cost and sales performance. This evaluation reflected the systemic behavior shown in the SSDM Forrester diagram, where production decisions influence inventory levels, workload, and sales value, ensuring that the selected plan remained feasible and aligned with the dynamics of the sunflower supply chain.

The aggregate planning model was directly linked to the qualitative insights produced by SSDM. Capacity constraints identified earlier, such as labor shortages and machine throughput limits, were translated into quantitative restrictions within the planning model. The feedback relationships among production output, inventory levels, and stock out risk formed the basis of the inventory balance equations. Demand uncertainty highlighted in the SSDM analysis was addressed through ANN based forecasting, which supplied the demand estimates for scenario evaluation. Through this integration, the aggregate planning model functioned as a quantitative extension of the systemic relationships identified in SSDM and ensured that the resulting production plan was operationally feasible and aligned with the dynamics of the sunflower supply chain. All constraints (capacity, balance) are the same quantities formalized in the SFD, ensuring behavioral consistency. Prior work showed that integrating capacity constraints within metaheuristic frameworks, such as GA combined with constraint programming, was effective for scenario-based capacity planning under realistic shop-floor limitations (Leong et al., 2025).

3.6.3. Inventory Optimization

Inventory planning optimization in this study aimed to determine the most efficient inventory allocation using GA, PSO, and SA, based on the company’s operational data to ensure realistic results. In the calculations for inventory planning optimization, the Working Capital and Storage Space Restrictions models are used. Several equations are employed, including:

$$G = \text{order cost} + \text{holding cost}$$

$$G = \sum_{i=1}^n \left(\frac{R_i C}{Q_i} + \frac{Q_i P_i F}{2} \right) \tag{11}$$

Equation (11) represents the mathematical model for the objective function, which involves minimizing the total inventory costs.

$$g_1 = \sum_{i=1}^n w_i Q_i \leq W \tag{12}$$

$$g_2 = \sum_{i=1}^n \frac{P_i Q_i}{2} \leq J \tag{13}$$

Equation (12) represents the mathematical model for the maximum storage space value. Equation (13) represents the mathematical model for the maximum inventory investment.

$$Q_i^* = \sqrt{\frac{2CR_i}{FP_i + \lambda_1 P_i + 2\lambda_2 w_i}} \tag{14}$$

$$\lambda_2 \left(\sum_{i=1}^n \sqrt{\frac{2CR_i w_i^2}{FP_i + \lambda_1 P_i + 2\lambda_2 w_i}} - W \right) = 0 \tag{15}$$

$$\frac{\lambda_1}{2} \left(\sum_{i=1}^n \sqrt{\frac{2CR_i P_i^2}{FP_i + \lambda_1 P_i + 2\lambda_2 w_i}} - J \right) = 0 \tag{16}$$

Equation (14) represents the mathematical model for calculating the order quantities of products. Equations (15) and (16) represent the mathematical models for validating the value of $\lambda = 0$. Table 4 presents a description of the parameters for each variable notation and its unit of measurement.

Notation	Information	Unit
i	Sunflower oil/seed product index	Index
R_i	Annual product demand per item i	Bottle/Seed
C	Message fee	IDR
P_i	Price per unit of item i	IDR
F	Fraction	Constants
W	Total warehouse capacity volume for all items	m^3
w_i	Capacity requirement per unit of item i	m^3
J	Maximum inventory investment	Bottle

Table 4. Parameter Description

Table 5 presents the parameter of three oil products. Table 6 presents the parameters of sunflower seed products. Table 8 shows the decision variables for the linier programming modeling of storage space restrictions.

Notation	Oil (250 mL)	Oil (500 mL)	Oil (1 L)
R_i	$180 \leq x \leq 258$	$348 \leq x \leq 354$	$246 \leq x \leq 258$
C	IDR600000	IDR600000	IDR600000
P_i	$25000 \leq x \leq 40000$	$40000 \leq x \leq 55000$	$75000 \leq x \leq 90000$
F	$0.10 \leq x \leq 0.25$	$0.10 \leq x \leq 0.25$	$0.10 \leq x \leq 0.25$
W	33.60 m^3	33.60 m^3	33.60 m^3
w_i	0.03 m^3	0.03 m^3	0.03 m^3
J	49	65	55

Table 5. Parameters on Oil Products

Notation	Seed
R_i	$214308 \leq x \leq 226920$
C	IDR600,000
P_i	$500 \leq x \leq 1.000$
F	$0.10 \leq x \leq 0.25$
W	33.60 m^3
w_i	1.80 m^3
J	280

Table 6. Parameters of Sunflower Seed Products

The following definitions describe the key components of the constrained inventory optimization model, including the objective function, decision variables, and system constraints. These elements clarify how the model minimizes total inventory cost while incorporating limitations on storage capacity and working capital

G : The objective function for minimizing total inventory costs.

λ_1 : Decision variable related to the holding cost factor, associated with ordering cost per unit.

λ_2 : Decision variable related to the holding cost factor, associated with storage cost per unit.

Constraint 1: Function g_1 , related to maximum storage space.

Constraint 2: Function g_2 , related to maximum inventory investment for 250 mL oil products.

Constraint 3: Function g_2 , related to maximum inventory investment for 500 mL oil products.

Constraint 4: Function g_2 , related to maximum inventory investment for 1 L oil products.

Constraint 5: Function g_2 , related to maximum inventory investment for sunflower seeds.

Q_1 : Order quantities for 250 mL oil products, Q_2 : Order quantities for 500 mL oil products, Q_3 : Order quantities for 1 L oil products, Q_4 : Order quantities for sunflower seeds.

The storage space (W) and investment (J) constraints used in the optimization model were derived from the environmental limitations identified in the CATWOE analysis and represented in the CLD. In line with prior studies that successfully applied GA and PSO to multi-period inventory routing formulations, this research adopted GA, PSO, and SA to explore constrained, non convex solution spaces for minimizing total inventory cost (Rabbani et al., 2013).

3.7. Stage 7: System Dynamic Simulation and Optimization of the Solving Situation

3.7.1. Demand Forecasting Results

The historical sales patterns for all product types are shown in Figure 7, illustrating the nonlinear fluctuations and irregular movements characteristic of the sunflower agro-industry demand. These patterns formed the basis for constructing the input–target pairs used in the ANN model. The ANN structure applied in this study is the same architecture previously developed and validated in previous research on the upstream and midstream sunflower

supply chain (Nurhasanah, Noviyanti et al., 2024). The previous study demonstrated that this configuration consisting of six lag inputs, two hidden layers with seven neurons each, and a *logsig* activation function achieved the lowest MSE across all product categories.

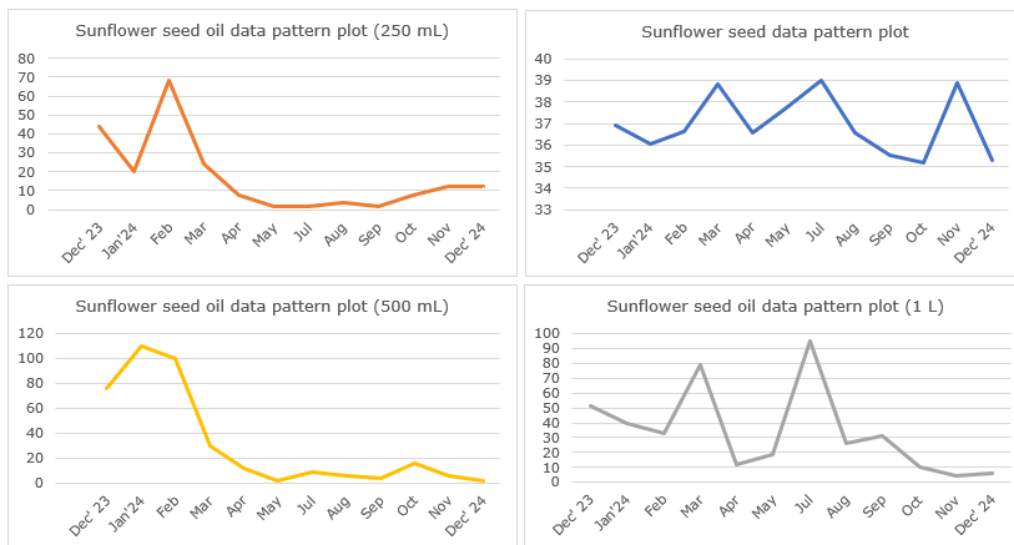


Figure 7. Sales history data pattern plot

Using this validated structure, the ANN model was retrained with the normalized historical data from the present study to generate short-term forecasts. The results, shown in Table 7, provide the projected monthly demand for each product category over the next six months and serve as essential inputs for subsequent stages, including aggregate production planning and inventory optimization.

Month	Demand Forecasting			
	Oil 1L	Oil 500 mL	Oil 250 mL	Sunflower Seeds
Jan-24	40.0	58.7	29.1	35717.57
Feb-24	40.9	57.9	29.1	36024.68
Mar-24	40.9	58.7	31.9	35875.15
Apr-24	41.4	58.8	31.9	36682,21
May-24	41.0	58.3	31.3	37287.60
Jun-24	42.2	58.6	42.8	37819.37

Table 7. Results of demand forecasting for all product types

3.7.2. Aggregate Planning Optimization Results

The calculation focused on three cooking oil variants (250 mL, 500 mL, and 1 L) across pessimistic, moderate, and optimistic scenarios. These scenarios determined production targets and the resulting total production costs, which were then compared with outputs from the stock and flow simulation. The simulation also provided the sales value for each scenario. To evaluate these scenarios quantitatively, the model required cost parameters drawn from the company's operational data.

The aggregate planning model utilized cost parameters obtained from field observations. The unit material cost for the sunflower oil products ranged from IDR 7,470 (250 mL) to IDR 29,970 (1 L) per bottle, and the daily labor cost was IDR 100,000. These cost components were incorporated into the objective function to estimate the total production cost under different planning scenarios.

For the 250 mL sunflower oil product, three production scenarios were evaluated: a pessimistic target of 30 bottles, a moderate target of 34 bottles, and an optimistic target of 100 bottles. The analysis shows that the moderate scenario provides the best performance, yielding higher sales while maintaining feasible production levels.

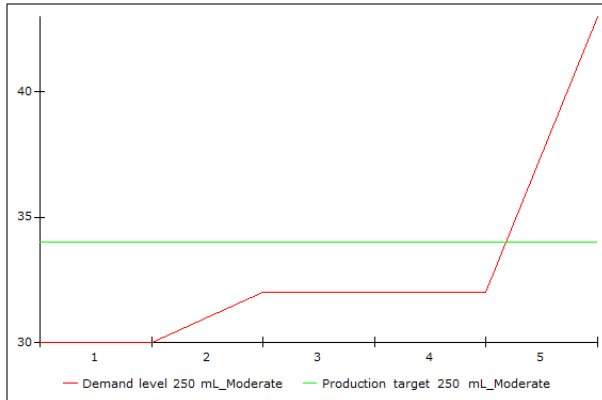


Figure 8. Graph of Demand Level vs. Target Production of Oil Products (250 mL) – Scenario: Moderate

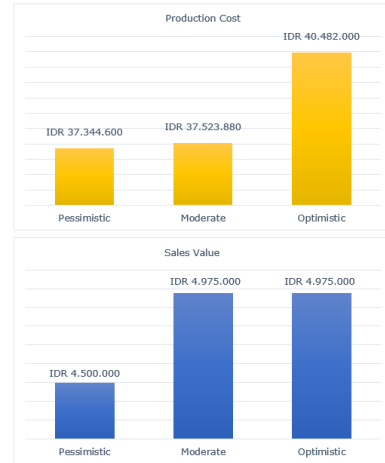


Figure 9. Comparison Chart of Production Cost Results and Sales Value of Oil Product Production (250 mL)

Figure 8 shows that the production target quantity could meet demand with available inventory. Figure 9 indicates that the moderate scenario was the optimal choice, with a sales increase of IDR4,975,000 and controlled production costs.

For the 500 mL sunflower oil product, three production scenarios were evaluated: a pessimistic target of 30 bottles, a moderate target of 59 bottles, and an optimistic target of 100 bottles. The analysis indicates that the moderate scenario provides the best performance, generating higher sales while remaining operationally feasible.

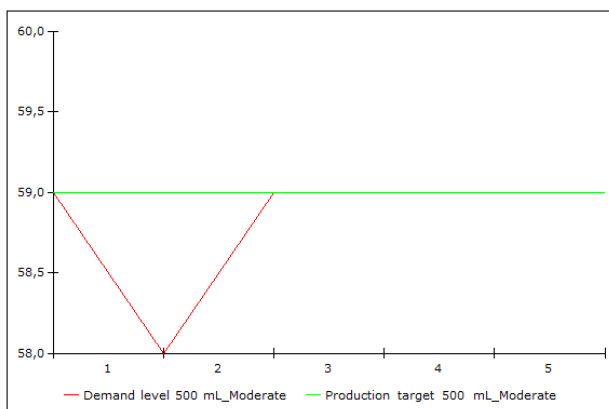


Figure 10. Graph of Demand Level vs. Target Production of Oil Products (500 mL) – Scenario: Moderate



Figure 11. Comparison Chart of Production Cost Results and Sales Value of Oil Product Production (500 mL)

Figure 10 shows that the production target quantity could meet demand with available inventory. Figure 11 indicates that the moderate scenario was the optimal choice, with a sales increase of IDR14,120,000 and controlled production costs.

For the 1 L sunflower oil product, three production scenarios were evaluated: a pessimistic target of 30 bottles, a moderate target of 42 bottles, and an optimistic target of 100 bottles. The analysis shows that the moderate scenario provides the best performance, generating higher sales while remaining operationally feasible.

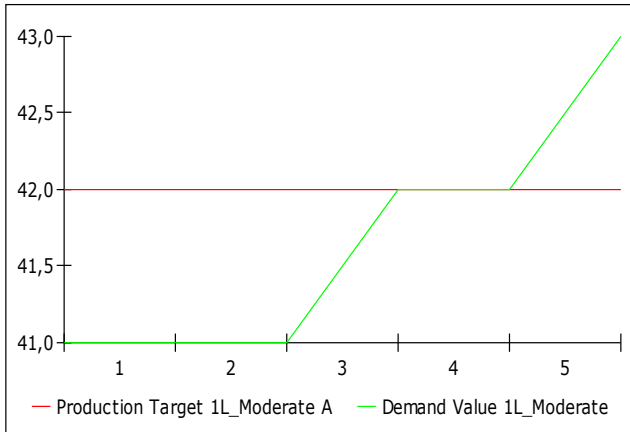


Figure 12. Graph of Demand Level vs. Target Production of Oil Products (1 L) – Scenario: Moderate



Figure 13. Comparison Chart of Production Cost Results and Sales Value of Oil Product Production (1 L)

Figure 12 shows that the production target quantity could meet demand with available inventory. Figure 13 indicates that the moderate scenario was the optimal choice, with a sales increase of IDR18,750,000 and controlled production costs. All scenarios faced the challenge of high production costs. As a solution, the company needed to reassess its operational cost components to find opportunities for savings.

3.7.3. Inventory Optimization Results

Tables 4-6 present the indices, parameters, and decision variables used as inputs in the Working Capital and Storage Space Restriction models. These inputs were then processed using the three optimization algorithms applied in this study. The simulation for GA, PSO, and SA generated convergence graphs that illustrate the reduction of the objective function across iterations, as shown in Figures 14, 15, and 16.

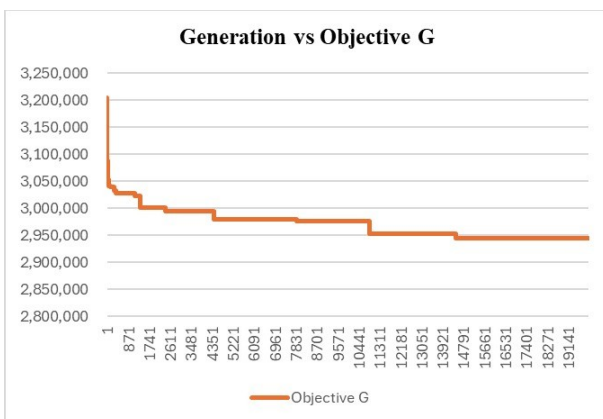


Figure 14. GA Method Result

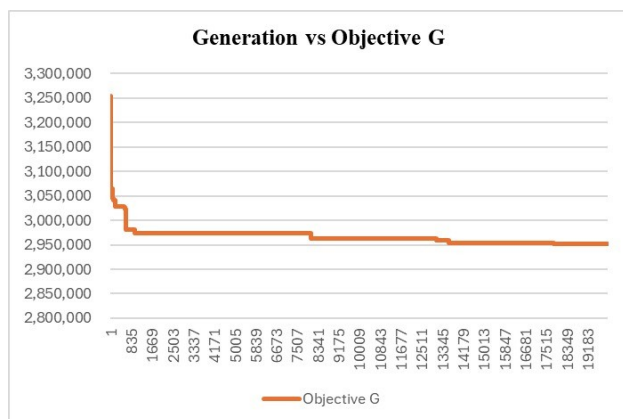


Figure 15. PSO Method Result

Figure 17 illustrates the comparison of total inventory costs obtained from the three metaheuristic algorithms. The GA produced the lowest cost at IDR 2,943,675, followed by PSO and SA with slightly higher values. Among the

three methods, GA demonstrated superior performance due to its stronger exploration capability supported by selection, crossover, and mutation operators, which help prevent premature convergence. PSO, although fast, tends to converge quickly and may become trapped in local optima, leading to a slightly higher cost. Simulated Annealing exhibited the highest cost among the three, reflecting its slower convergence and sensitivity to temperature dependent parameters. Overall, GA provided the most cost efficient and stable solution for this constrained inventory optimization problem.

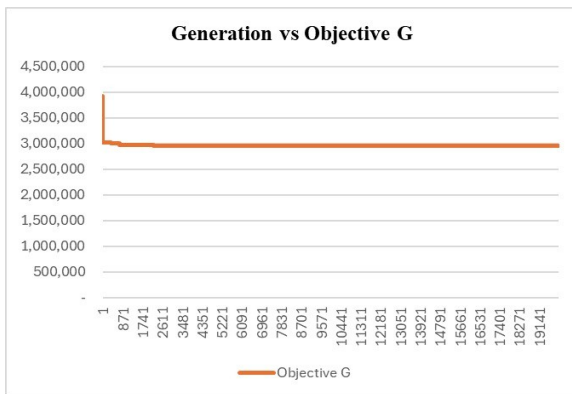


Figure 16. SA Method Result

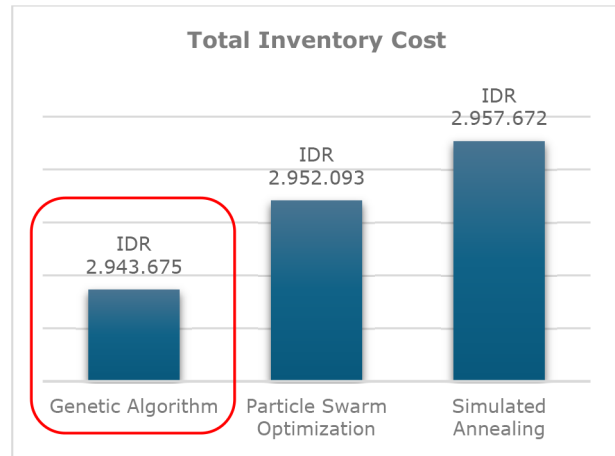


Figure 17. Comparison Chart of Total Inventory Costs in the Three Algorithm

3.8. Stage 8: Solving-Oriented Root Definitions of the Problem Situation

This stage compares the conceptual model with the actual operational conditions of the industry to identify the key gaps and derive improvement recommendations (Table 8).

Activity	Real World Conditions	Recommendation
1. Perform demand forecasting (ANN)	No demand forecasting is performed, resulting in frequent lost sales.	Implement ANN-based demand forecasting to reduce uncertainty and prevent lost sales.
2. Conduct aggregate planning using the Heuristic Method	No calculation of optimal production, workforce, or inventory levels.	Apply heuristic aggregate planning to align production capacity with forecasted demand and reduce costs.
3. Determine inventory planning (GA/PSO/SA)	Without inventory planning, storage and capital are used inefficiently.	Use constrained optimization to determine optimal order quantities and improve operational efficiency.

Table 8. Comparison of Models with Real World Conditions

3.9. Stage 9: Implement Culturally Feasible and Systemically Desirable Changes in the Real Word

Identifying Success Indicators and Stakeholders in Recommendations: The next step involves determining the key success indicators and identifying the stakeholders responsible for implementing the proposed recommendations (Table 9).

Recommendation	Success Indicators	Actor
1. Perform demand forecasting using ANN	Demand can be met and there are no lost sales, thereby increasing the company's profit capability.	Sunflower industry
2. Conduct aggregate planning using the Heuristic Method	Increased production efficiency and effectiveness, as well as reduced production costs	Sunflower industry
3. Determine inventory planning using GA, PSO, and SA	Increased efficiency and effectiveness of space use, which will improve operational efficiency and reduce costs.	Sunflower industry

Table 9. Success Indicators and Actors Implementing Recommendations

Recommendation Assessment: The assessment of recommendations using Efficacy, Efficiency, and Effectiveness was a comprehensive method for evaluating the quality of recommendations from various aspects. The assessment results were presented in Table 10.

No	Recommendation	Efficacy	Efficiency	Effectiveness
1	Perform demand forecasting using Artificial Neural Networks	Produces more accurate demand estimates.	Reduces time and effort through automated forecasting tools.	Minimizes lost sales and improves product availability.
2	Perform aggregate planning using the Heuristic Method	Provides feasible solutions for complex planning problems.	Improves production efficiency by aligning capacity with demand.	Enhances profitability through optimized production levels.
3	Determining inventory planning using GA, PSO, and SA	Yields better solutions than traditional methods.	Optimizes space utilization and reduces storage costs.	Improves operational performance and reduces total cost.

Table 10. Recommendation Assessment

3.10. Stage 10: Key Learnings

Point 1: Demand forecasting using ANN can increase company profits by minimizing lost sales and adapting to market changes.

Point 2: Aggregate planning with heuristic methods can optimize production, reduce costs, and increase company profits. This method is flexible and can address imbalances between production and demand.

Point 3: Scenario planning with SSDM helps the company anticipate future conditions and make better decisions, such as choosing the moderate scenario to boost sales and profits.

Point 4: Inventory planning using the three algorithms can enhance space efficiency and reduce operational costs.

The system dynamics model analysis has yielded several key insights for enhancing the performance of the sunflower industry. Implementing strategies such as demand forecasting, aggregate planning, scenario planning, and inventory optimization can help address operational challenges, improve profitability, and increase supply chain efficiency.

4. Implication

The integrated of SSDM, ANN, aggregate optimization, and inventory pipeline provides a practical way for small agro-industries to align capacity with short-term demand while honoring space and capital limits. First, the SSDM phases help managers focus on a small set of bottlenecks with the largest leverage (drying/pressing and storage). Second, the ANN produces SKU level demand that can be plugged directly into monthly production targets. Third, the heuristic aggregate plan translates capacity insights into feasible schedules and cost trade-offs, while the inventory optimizer allocates working capital and space across SKUs at minimum total cost. Together, these steps

reduce stock-outs and overproduction risk, make costs transparent, and create a repeatable planning routine that can be re-run as new data arrives or constraints change.

5. Conclusions

This study showed how SSDM could frame a complex sunflower supply chain and feed quantitative models that improved planning quality. Using ANN forecasts, a heuristic aggregate plan, and constrained inventory optimization, a coherent plan was obtained that (i) met demand under realistic capacity limits and (ii) minimized total inventory cost, where GA delivered the lowest objective among tested metaheuristics in the data. The approach is directly implementable in small-scale settings and can be updated as new data or constraints emerge. Future work should automate data ingestion and scenario runs, extend the optimizer to routing/warehouse layout decisions, and test alternative metaheuristics under the same SSDM derived constraints.

Declaration of Conflicting Interests

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Authors' contributions

Nunung Nurhasanah: Conceptualization; funding acquisition; project administration; supervision; writing – review & editing; corresponding author.

Tharra Azzahra Riyana: Data collection; data curation; formal analysis; data processing; writing – original draft.

Data availability

Data included in the article itself.

Use of Artificial Intelligence

The authors declare that artificial intelligence was used for language improvement and editing of the manuscript (e.g., ChatGPT/Grammarly). All content has been reviewed and validated by the authors.

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