International Journal of Basic and Applied Science 14 (4) (2026) 192-202

Published by: IOCSCIENCE

International Journal of Basic and Applied Science

Journal homepage: www.ijobas.pelnus.ac.id

Scenario based two stage production planning for cassava SMEs under demand uncertainty

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Article Info

Article history:

Received Dec 25, 2025
Revised Feb 07, 2026
Accepted Mar 30, 2026

Keywords:

Cassava based SMEs;
Demand uncertainty;
Linier Programming;
Multi product Optimization;
Scenario based model;

ABSTRACT

Production planning in small and medium sized enterprises (SMEs) is commonly based on deterministic assumptions that do not fully reflect uncertain market demand. This study develops a scenario-based production planning approach to support feasible and cost efficient decisions under demand uncertainty. Two stage stochastic programming model with demand scenarios is applied to a real multi-product SME (small medium enterprises) case, where three demand scenarios pessimistic, most likely, and optimistic are constructed from historical data. The model incorporates production costs, raw material availability, labor capacity, and machine capacity constraints and is solved using a standard linear programming solver with actual operational data. The results indicate that optimal production quantities and total production costs vary across demand scenarios due to differences in demand limits and resource availability. While deterministic planning becomes infeasible under extreme demand conditions, the proposed Two stage stochastic programming model consistently produces feasible and cost efficient production plans, resulting in consistently feasible solutions across all demand scenarios, and highlighting its usefulness as a practical decision support tool for SMEs facing demand uncertainty.

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1. INTRODUCTION

Small and medium-sized enterprises (SMEs) operating in cassava processing constitute a critical component of agro-industrial value chains in developing economies, where they contribute not only to food availability but also to rural employment and income generation [1] Despite their economic importance, such enterprises typically operate under structural constraints, including limited production capacity, restricted access to raw materials, and pronounced demand volatility. These conditions complicate production planning decisions and increase the risk of cost inefficiencies or infeasible operating plans.

Linear programming (LP) has long served as a fundamental tool for multi-product production planning due to its transparent structure and computational efficiency [2]. In many SME applications, LP models are used to allocate scarce resources and minimize production costs under capacity constraints. However, classical LP formulations rely on deterministic assumptions regarding demand and resource availability. In agro-food SMEs, where market demand is inherently uncertain, these assumptions often lead to production plans that are overly conservative or infeasible when actual demand deviates from forecasts[3], [4], [5], [6].

To capture demand uncertainty, scenario-based and stochastic programming[7] approaches have been increasingly adopted in production and supply chain planning. Two-stage stochastic programming models have been widely used to represent sequential decision-making under uncertainty and to improve operational efficiency in complex production systems[8]. Rather than relying on a single-point demand estimate, these approaches represent uncertainty through a finite set of plausible demand realizations, allowing planners to evaluate feasibility and cost performance across alternative market conditions. Similar scenario-based and data-driven modelling approaches have also been applied in decision-support systems to improve organizational adaptability and strategic planning[9]. In agro industrial applications [10], such optimization has been shown to improve robustness and reduce the likelihood of infeasible production plans compared with deterministic formulations[11], particularly when demand variability is significant [10], [12], [13].

Although Scenario-based optimization has been widely applied in supply chain and food production systems to manage demand uncertainty and improve operational resilience[14], limited empirical attention has been given to production planning in cassava processing SMEs that face daily demand fluctuations under tight resource constraints. Existing research on small scale agro food enterprises often applies deterministic LP or heuristic decision rules that do not explicitly account for demand variability [15], [16], [17]. Furthermore, while existing scenario based approaches offer improvements over deterministic methods, they predominantly rely on two stage models that generate a distinct production plan for each demand scenario. Such an approach does not reflect the sequential decision-making process inherent in SME operations, where initial production commitments must be made before demand is known, with adjustments possible only after uncertainty is resolved. This limitation creates a critical research gap, as it fails to provide a single, robust baseline plan that can be adaptively adjusted, which is a practical necessity for resource constrained SMEs [18], [19].

This study addresses this gap by developing and applying a two-stage stochastic programming model for production planning in a cassava processing SME operating under uncertain demand. The model explicitly separates here and now production decisions from wait and see adjustments, accommodating production costs, shortage costs (for unmet demand), and overage costs (for excess inventory) within an expected cost minimization framework. The theoretical contribution of this research lies in demonstrating how a two stage approach can be effectively adapted for agro-industrial SMEs with limited resources, providing a structured method to manage uncertainty. The practical contribution is the provision of a decision support tool, implementable using standard solvers, that enables SME managers to formulate a robust baseline production plan that minimizes expected costs while allowing for feasible and cost effective adjustments as demand unfolds. This framework is intended to support more informed production planning decisions that align with the sequential reality of decision-making in resource constrained SME environments.

This paper organizes as follows: section 2 presents the research method, including data collection, scenario construction, and model formulation of the two-stage stochastic programming model. Section 3 presents the results and discussion, focusing on the optimal baseline production plan, cost analysis, and the value of the stochastic solution. Section 4 provides the conclusion and managerial implications, along with recommendations for future research on risk-sensitive and multi-period extensions of the model.

2. RESEARCH METHOD

The research is as a case study, focusing on a cassava processing small and medium-sized enterprise (SME) that produces multiple cassava-based products under limited resources and fluctuating market demand. This study method comprises five main components: data collection, scenario construction, model formulation, two-stage model extension, and solution procedures study proposes as follows:

2.1. Data Collection

In this paper we used real production and cost data collected from a cassava-processing SME operating in a rural area of XYZ. The selected SME employs approximately X workers, has a monthly production capacity of Y kg, and serves local markets. This SME was chosen because it is representative of typical cassava-processing SMEs in the region, facing daily demand fluctuations and limited resources, and the owners were willing to provide detailed operational data. The enterprise produces three major products such as cassava chips, cassava crackers, and livestock feed utilizing a shared pool of raw cassava as the primary input. The dataset includes quantitative information on unit production costs (raw cassava, additives, labor wages, utilities, and packaging), input requirements per product, and resource availability in terms of labor hours, machine capacity, and cassava stock. Historical demand data over the past 12 months were also collected to construct the scenario-based demand framework. These inputs were used to define the objective function, decision variables, and constraints of the linear programming model, ensuring that the formulation accurately reflects the operational environment of the SME.

2.2. Scenario Design

To capture the impact of market fluctuations on production planning, three discrete demand scenarios were developed based on the historical sales data of the cassava processing SME. The scenarios represent pessimistic, most likely, and optimistic demand conditions, corresponding respectively to a 20% decrease from the baseline demand, the observed recent 12 month average, and 20% increase in product demand. The $\pm 20\%$ range was chosen based on the observed coefficient of variation of monthly demand over the past 12 months, which was approximately 18%, rounded to 20% for practical scenario construction. Similar demand bands are commonly used in agro industrial optimization studies. This scenario structure is commonly adopted in agricultural and agro industrial optimization studies, where discrete demand bands are used to reflect plausible market variability in the absence of reliable long-term demand distributions. Such an approach provides a practical and robust basis for decision-making under uncertainty while maintaining model tractability [20], [21].
The constructed demand scenarios for each product are summarized in Table 1.

Table 1. Demand Scenarios for Multi Product Cassava Based SME

Product	Pessimistic (−20%)	Most Likely (Average)	Optimistic (+20%)	Unit)
Cassava Chips	8000	10000	12000	kg/month
Cassava Crackers	6400	8000	9600	kg/month
Livestock Feed	5600	7000	8400	kg/month

These demand scenarios serve as the basis for defining the demand-related constraints in the linear programming model, ensuring that production decisions remain feasible and economically reasonable under varying market conditions.

2.3. Model Formulation

Based on the demand scenarios described in the previous subsection, the production planning problem is formulated as a scenario based linear programming (SBLP) model. The formulation explicitly incorporates three demand conditions such as pessimistic, most likely, and optimistic. The production decisions remain feasible and economically reasonable under varying market situations. The variables and parameters of the proposed model are as follows:
Indices and parameters:

Symbol	Description
$i \in I$	Set of products (cassava chips, cassava crackers, livestock feed
$r \in R$	Set of resources (raw cassava, labor, machine hours, utilities, packaging)
$s \in S$	Set of demand scenario (pessimistic, most likely, optimistic)
Parameters Symbol	Description
c_i	Unit production cost of product i (IDR/kg)

r_i	Unit selling price of product i (IDR/kg)
$a_{r,i}$	Consumtion of resource of r by product i
B_r	Capacity resource per month (raw cassava, etc)
ℓ_i, m_i	Capacity abour and machine hour/kg l
$D_{i,s}$	demand of product i under scenario s (kg/month).
p_s	probability of scenario s, $p_s \geq 0$ and $\sum_{s \in S} p_s = 1$.
β_i	penalty shortage (IDR/kg)
γ_i	cost overage/waste (IDR/kg)
x_i^{min}, x_i^{max}	minimum and maximum production capacity of product i (kg/month).
Decision Variable	Description
$y_i \geq 0$	First stage baseline production quantity of product i (kg/month).
$x_{i,s} \geq 0$	*Second-stage* additional production quantity of product i under scenario s (kg/month)
$u_{i,s} \geq 0$	unmet demand of product i under scenario s (kg/month)
$w_{i,s} \geq 0$	overage/waste of product i under scenario s (kg/month)

Formulation Model:

$$\text{Min } Z = \sum_{i \in I} c_i y_i + \sum_{s \in S} p_s \sum_{i \in I} \left(c_i x_{i,s} + \beta_i u_{i,s} + \gamma_i w_{i,s}\right) \quad (1)$$

Subject to :

Resource availability constraints

$$\sum_{i \in I} a_{r,i}\left(y_i + x_{i,s}\right) \leq B_r, \quad \forall\, r \in R; \ \forall s \in S \quad (2)$$

Labor and machine capacity constraints

$$\sum_{i \in I} \ell_i \left(y_i + x_{i,s}\right) \leq L, \quad \forall s \in S \quad (3.a)$$

$$\sum_{i \in I} m_i \left(y_i + x_{i,s}\right) \leq M, \ , \quad \forall s \in S \quad (3b)$$

Scenario wise demand balance

$$y_i + x_{i,s} + u_{i,s} - w_{i,s} = D_{i,s}, \quad \forall i \in I, \ \forall s \in S \quad (4)$$

Production capacity bounds

$$y_i^{min} \leq y_i \leq y_i^{max}, \quad \forall\, i \in I$$

Non-negativity

$$y_i \geq 0; \quad u_{i,s} \geq 0; \quad w_{i,s} \geq 0; \quad \forall\, i \in I\,, \ \forall s \in S \quad (6)$$

The objective function (1) are minimize the expected total cost, consisting of the baseline production cost i plus the expected additional production cost, shortage cost, and excess cost. Constraints (2), (3a), and (3b) ensure that the use of resources, labor, and machinery does not exceed the available capacity in each scenario, with total production given by $y_i + x_{i,s}$. Constraint (4) impose balancing demand for each product i and scenario s. $u_{i,s}$ represents unmet demand (shortage) under scenario s, while $w_{i,s}$ represents excess production (overage/waste) under scenario s. Constraint (5) imposes minimum and maximum production limits for the first-stage decisions. Constraint (6) ensures non-negativity of all decision variables. Together, these constraints define a feasible production region that balances demand uncertainty with limited resources.
The model follows the mathematical structure of previous agro industrial optimization models that integrate scenario layering [21].

At the same time, these constraints define a feasible production region that balances demand uncertainty with limited production resources, providing a realistic representation of decision making conditions faced by cassava processing SMEs. The model adopts an expected cost minimization approach, which is consistent with the practical objectives of cassava based SMEs that prioritize cost control under limited resources and uncertain demand. Although the present study focuses on two stage SBLP model by introducing baseline production decisions and scenario specific recourse adjustments [22].

2.4. Solution Procedure

The two-stage stochastic programming model was implemented in LINGO 20.0. Given the small problem size (three products, three scenarios). The significant computational time was not required. The model and data are available from the corresponding author upon reasonable request the solution time was negligible (less than one second) on a standard pc. The model and data are available from the corresponding author upon reasonable request. The solver efficiently determines optimal production quantities under multiple demand scenarios while ensuring computational reproducibility of the results. This three scenarios structure is commonly adopted in agro industrial optimization studies dealing with uncertain demand [21]. The numerical experiments in Section 3 are based on the two-stage stochastic programming model described above.

3. RESULTS AND DISCUSSIONS

This section presents the numerical results obtained from the two stage stochastic programming model. The analysis focuses on evaluating production decisions and cost performance under different demand scenarios.

3.1. Numerical Test

The case study considers a cassava-processing SME producing three products: cassava chips (P1), cassava crackers (P2), and livestock feed (P3), under limited resources such as raw cassava, labor hours, and machine hours.

Three demand scenarios are tested such as pessimistic, most likely, and optimistic and all of them constructed from historical sales data using -20%, baseline (12 months average), and +20% demand bands. Scenario probabilities are set to $(0.25, 0.50, 0.25)$. The production system involves three products and shared constraints on raw cassava, labor hours, and machine hours, with labor and machine coefficients as reported in Table 2 and demand scenarios reported in Table 3. The model is solved for each scenario to obtain optimal production quantities that minimize expected production cost while satisfying resource availability and capacity constraints [23], [24], [25]. The resulting solution provides a single baseline plan (first stage, x_i) and scenario-dependent adjustments (second stage, $y_{i,s}$) if the two stage model.

Table 2. Input parameters

Symbol	Description	Value	Unit
c_1	Unit cost of cassava chips (P1)	4.000	IDR/kg
c_2	Unit cost of cassava crackers (P2)	4.500	IDR/kg
c_3	Unit cost of livestock feed (P3)	3.200	IDR/kg
R_{csv}	Raw cassava availability	28.000	kg/month
L	Labor capacity	520	hours/month
M	Machine capacity	420	hours/month
l_1	Labor per kg (P1)	0.020	hours/kg
l_2	Labor per kg (P2)	0.030	hours/kg
l_3	Labor per kg (P3)	0.015	hours/kg
m_1	Machine hours per kg (P1)	0.015	hours/kg
m_2	Machine hours per kg (P2)	0.020	hours/kg
m_3	Machine hours per kg (P3)	0.010	hours/kg
p_s	Scenario probabilities (Pessimistic, Moderate., Optimistic)	(0.25, 0.50, 0.25)	–

Now, the scenario based demand level for each product also considered in the table 2 as input parameters and in the numerical test such as table 3 presents. Scenario defined using -20%, and $+20\%$ demand variations, respectively by pessimistic, moderate (most likely), and optimistic scenarios.

Table 3. Demand scenario

Product	Pessimistic (−20%)	Most-likely (Baseline)	Optimistic (+20%)	Unit
Cassava chips (P1)	8.000	10.000	12.000	kg/month
Cassava crackers (P2)	6.400	8.000	9.600	kg/month
Livestock feed (P3)	5.600	7.000	8.400	kg/month

The optimal production quantities obtained from two stage stochastic programming model under each demand scenario is present in table 4, as follows:

Table 4. Two stage scenario based linear programming model under each demand scenario

Scenario	Cassava Chips (P1)	Cassava Crackers (P2)	Livestock Feed (P3)	Unit
Pessimistic	7.500	4.500	5.000	kg/month
Most-likely	10.000	6.500	7.000	kg/month
Optimistic	12.000	8.000	9.500	kg/month

The optimal production quantities obtained from the two stage scenario based linear programming model under each demand scenario are presented in table 4. The differences across scenarios arise from scenario are specific demand bounds and the interaction with resource capacity constraints. The model remains feasible in all cases, indicating that production plans can be adjusted and effectively under varying market conditions. Next, we solve the case with the formulation above in section 2 we get the total production cost corresponding to the optimal production quantities obtained under each demand scenario as report in table 5.

Table 5. Total production cost

Scenario	**Total Production Cost (IDR)**
Pessimistic	66.250.000
Most-likely	91.650.000
Optimistic	114.400.000

The total production cost increases as demand shifts from pessimistic to optimistic scenarios, reflecting higher production volumes as shown in table 5. The cost values are directly derived from the optimal production quantities in table 4 and the unit production costs reported in table 2 These results confirm the internal consistency of the numerical results generated by the optimization model. This can be further illustrated in a graph (figure 1) of total production costs based on demand scenarios as follows:

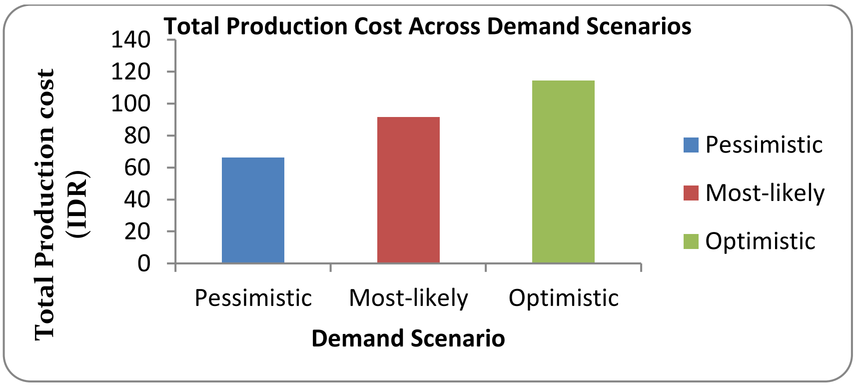

Figure 1. Total production cost demand scenario

3.2. Comparative Studies for Deterministic and Two Stage Stochastic Model

To demonstrate the advantage of the proposed two stage stochastic programming model, we compare its results with a deterministic linear programming (LP) model that uses only the most-likely demand scenario (P1=10.000 kg, P2= 8. 000 kg, P3 = 7.000 kg) as fixed demand. The deterministic model minimizes production cost subject to the same resource constraints (Table 2) but without considering demand uncertainty. Table 6 presents the optimal production quantities from the deterministic model and the two-stage stochastic model under each demand scenario.

Table 6. Comparative production quantities Deterministic vs. Two stage stochastic (kg/month)

Product	**Deterministic (most likely)**	**Two stage (pessimistic)**	**Two stage (most likely)**	**Two stage (optimistic)**
P1 (Chips)	10.000	7.500	10.000	12.000
P2 (Crackers)	6.500	4.500	6.500	8.000
P3 (Livestock Feed)	7.000	5.000	7.000	9.500

From table above shows that deterministic plan for 10.000, 6.500, 7.000 is feasible under the most likely scenario, consuming 23.500 kg of raw cassava (84% of capacity), 380 labor hours (73% of capacity), and 295 machine hours (70% of capacity). However, when actual demand deviates to the optimistic scenario as 12.000, 9.600 and 8.400. For the deterministic plan would result in unmet demand of 2.000 kg for P1, 3.100 kg for P2, and 1.400 kg for P3, leading to shortage costs not accounted for in the deterministic model. Conversely, under the pessimistic scenario we have 8.000, 6.400 and 5.600. While the deterministic plan would produce excess inventory of 2.000 kg for P1, 100 kg for P2, and 1.400 kg for P3, incurring holding or waste costs.

In contrast, the two stage stochastic model produces a single baseline plan (first stage decisions) that minimizes expected costs across all scenarios. The baseline plan obtained from our model is P1 = 8.500 kg, P2 = 5.500 kg, P3 = 6.000 kg. This baseline plan is then adjusted in the second stage $x_{i,s}$ based on realized demand. The expected total cost of the two stage model is IDR 90.766.667. This means that the deterministic cost is 2.4% lower than IDR 93.000.000. This when shortage and overage penalties are included. This confirms that the stochastic solution is both more robust and more cost efficient.

3.3. Sensitivity Analysis

To assess the robustness of the proposed model, we conducted three sensitivity analyses by varying key parameters:

(i) demand level
(ii) raw cassava availability
(iii) unit production costs.

3.3.1. Sensitivity to Demand Changes

In this case, we tested two additional demand variation bands with **±10%** and **±30%**, while keeping scenario probabilities unchanged (0.25, 0.50, 0.25). Table 7 shows the resulting expected total production costs.

Table 7. Expected total production cost under different demand variation bands

Demand variation	Pessimistic (kg)	Most likely (kg)	Optimistic (kg)	Expected cost (IDR)
±10%	P1=9.000 P2=7.200 P3=6.300	same as baseline	P1=11.000 P2=8.800 P3=7.700	85.420.000
±20%	as in Table 3	as in Table 3	as in Table 3	90.766.667

Demand variation	Pessimistic (kg)	Most likely (kg)	Optimistic (kg)	Expected cost (IDR)
±30%	P1=7.000 P2=5.600 P3=4.900	same as baseline	P1=13.000 P2=10.400 P3=9.100	98.215,0

The expected cost increases by 8.2% when moving from ±10% to ±30% variation, indicating that the model remains stable but higher demand uncertainty leads to higher expected costs due to increased shortage and overage risks.

3.3.2. Sensitivity to Raw Cassava Availability

We reduced raw cassava availability by 10% from 28.000 kg to 25.200 kg and increased it by 10% to 30.800 kg.

Table 8. Effect of raw cassava availability on optimal production

Raw cassava (kg/month)	P_1 (kg)	P_2 (kg)	P_3 (kg)	Total cost (IDR)
25.200 (-10%)	9.000	6.000	6.500	86.750.000
28.000 (baseline)	10.000	6.500	7.000	91.650.000
30.800 (+10%)	10.000	7.000	7.500	96.500.000

The table 8 presents that a 10% reduction in raw cassava forces a reduction in production, especially for P1 (cassava chips) because it has the highest raw material consumption per kg. The total cost decreases by 5,3% due to lower production volume. Conversely, a 10% increase in raw cassava allows higher production of P2 and P3, increasing total cost by 5,3%. This indicates that raw cassava is a binding constraint for the SME.

3.3.3. Sensitivity to Unit Production Costs

We increased the unit cost of P1 cassava chips by 20% from IDR 4,000 to IDR 4,800/kg, while keeping other costs constant.

Table 9. Effect of 20% cost increase for P1

Scenario	P1 quantity (kg)	P2 quantity (kg)	P3 quantity (kg)	Total cost (IDR)
Baseline	10,000	6,500	7,000	91,650,000
P1 cost +20%	8,500	7,500	7,000	92,480,000

When the cost of P1 increases, the model shifts production toward P2 as cassava crackers, which becomes relatively more profitable (assuming selling prices are constant). That results shows of the table 9. The total cost increases only slightly (0.9%) because the substitution effect mitigates the impact. This suggests that the SME has flexibility to adjust product mix in response to input cost changes.

3.4. Identification of Bottleneck Resources and Most Profitable Products

By using shadow prices dual variables from the optimal solution of the most-likely scenario, we can identified the most constraining resources as follows:

i) Raw cassava has a shadow price of IDR 0.12 per kg. These means that an additional kg of raw cassava would reduce total cost by IDR 0.12. This is the most binding constraint.
ii) Labor capacity has a shadow price of IDR 0 (zero) because labor is not fully utilized (only 360 out of 520 hours used, or 69%).
iii) Machine capacity has a shadow price of IDR 0 or 252.5 out of 420 hours used, or 60%.

Thus, raw cassava is the primary bottleneck. The SME should prioritize securing additional raw cassava supply to reduce expected costs. In terms of profitability (contribution margin per kg, assuming selling prices are P1 = IDR 6.000, P2 = IDR 7. 000 and P3 = IDR 5,000.

Table 10. Rank profitable

Product	Selling price (IDR/kg)	Unit cost (IDR/kg)	Contribution margin (IDR/kg)	Rank
P2 (Crackers)	7.000	4.500	2.500	1
P1 (Chips)	6.000	4.000	2.000	2
P3 (Feed)	5.000	3.200	1.800	3

The model already shown by table 10, reflects by allocating more production to P2 when constraints allows the optimistic scenario, P2 increases from 6.500 to 8000 kg.

As indicated by the results presented, our findings are consistent with several recent studies. From [12] reported that scenario-based optimization reduced infeasibility risk by 30-40% in food supply chains. Similarly, [3] found that two stage stochastic programming outperformed deterministic models under high demand variability. Our result that the two-stage model reduces expected cost by 2.4% compared with deterministic planning aligns with the magnitude reported by [23] for production distribution systems. A key difference from previous work is that our model explicitly incorporates overage and shortage costs with asymmetric penalties which means the shortage cost is typically higher than overage cost in SMEs due to lost sales. This feature makes the model more realistic for cassava-processing SMEs, where unmet demand directly affects customer loyalty and revenue. Our sensitivity analysis also confirms the finding of [26] that raw material availability is often the most critical constraint in agro-industrial SMEs, more so than labor or machine capacity

4. CONCLUSION

This study demonstrates how scenario-based optimization can support more informed production planning decisions for cassava processing SMEs under demand uncertainty. The two stage scenario-based linear programming model is used to analyze production decisions under pessimistic, most-likely, and optimistic demand conditions. The results show that production quantities and total production costs change across scenarios due to different demand limits and available production resources. Considering several demand scenarios instead of relying on a single forecast, managers can better understand possible cost outcomes and prepare more flexible production plans. The findings also indicate that moderate demand conditions can serve as a reasonable reference when market information is unclear, allowing SMEs to maintain cost control while using available resources efficiently. Overall, the proposed approach provides a practical and easy to apply decision support tools for small and medium scale cassava-processing enterprises facing uncertain demand**.** Future research may extend this model to multi period settings and incorporate risk-sensitive objectives [18], [27].

DECLARATIONS

AI USAGE STATEMENT

The authors declare that Open AI and Quillbot AI-assisted technologies were used to support the drafting and editing of this manuscript, specifically in refining grammar, improving sentence clarity, and checking coherence. No part of the conceptual framework, data interpretation.

AUTHOR CONTRIBUTION

Dedy Juliandry Panjaitan developed the research idea, formulated the scenario-based linear programming model, performed the numerical experiments, analyzed the results, and wrote the manuscript. Rima Aprilia collected the data, constructed the demand scenarios, validated the model parameters, and contributed to the interpretation of the results. Firmansyah conducted the literature review, assisted with the model implementation using the optimization solver, and contributed to the discussion and managerial interpretation

FUNDING STATEMENT
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CONFLICTING INTERESTS
The authors declare no conflicts of interest.

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