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Profit Optimization for MSMEs in the Patchwork Fabric Industry Using Linear Programming and Simulated Annealing

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Abstract

Maximizing profitability is crucial for Micro, Small, and Medium Enterprises (MSMEs), especially in the patchwork fabric industry, where production optimization is a constant challenge. This study aims to optimize the production plans of MSMEs using a multi-constraint Linear Programming (LP) model integrated with Simulated Annealing (SA), with the goal of maximizing profits while considering resource constraints. The LP model identifies the most profitable product mix, while the SA heuristic explores alternative production plans with the same objective of maximizing profit. The SA approach uses parameters such as an initial temperature of 1000, a cooling rate of 0.95, and 5000 iterations to search for near-optimal solutions. The LP model achieves a maximum profit of IDR 14,070,000 by selecting Unicorn (M), Monkey (M), and Tote Bag as the optimal product mix under capacity constraints. The SA approach distributes production across all nine products, resulting in a total profit of IDR 11,568,000. Sensitivity analysis reveals that non-selected products carry negative reduced costs, indicating the minimum profit-per-unit increase required for each to enter the optimal solution. Shadow price analysis identifies three binding constraints: total production hours (IDR 22,500 per additional hour), the other plush group capacity (IDR 11,250 per additional unit), and the Tote Bag capacity (IDR 35,000 per additional unit), with the Tote Bag constraint yielding the highest marginal profit gain. The study concludes that LP is more effective for profit maximization in stable production environments, achieving a 17.8% higher profit than SA, while SA offers greater flexibility for production diversification under uncertain demand conditions. Future research should explore hybrid models combining the precision of LP with the flexibility of SA, which could enhance MSME production strategies under dynamic market conditions.

Keywords: Profit Maximization; Linear Programming; Simulated Annealing; MSMEs; Patchwork

1. Introduction

The textile industry, particularly Micro, Small, and Medium Enterprises (MSMEs), faces significant challenges in optimizing production due to fluctuating raw material prices, limited production capacity, and unpredictable market demand. These constraints make it difficult for MSMEs to maintain consistent profitability and stay competitive in a volatile market. Traditional optimization approaches often fall short in capturing the complexity and variability of real-world production environments. To address these challenges, this study introduces a combined

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multi-constraint Linear Programming (LP) and Simulated Annealing (SA) approach designed to maximize profit while maintaining practical feasibility for MSME production processes.

Simulated Annealing (SA) has been successfully applied across various industries due to its flexibility and effectiveness in solving complex, multi-constraint optimization problems. Its applications span multi-project linear scheduling [1], dial-a-ride logistical optimization [2], and product mix decisions [3], demonstrating its versatility in handling large solution spaces where conventional methods risk becoming trapped in local optima. Enhancements such as hybridization with tabu search have further strengthened SA's ability to escape local minima and find more globally optimal solutions [4]. SA is also highly adaptable to probabilistic constraints, offering flexible reliability-based decision-making frameworks [5]. In production contexts specifically, SA has proven effective in minimizing operational costs in steelmaking [6], optimizing raw material ordering and batch sizing [7], and determining optimum production quantities in the home textile industry [8]. Compared to other heuristic methods, SA frequently yields superior performance in just-in-time production environments [9] and aggregate production planning [10]. However, its effectiveness remains highly dependent on the specific constraint structure, and in highly constrained scenarios, alternative methods such as constraint programming may offer better performance [4, 11].

Linear programming (LP) has similarly demonstrated broad efficacy in optimizing costs, enhancing profitability, and maximizing resource utilization across multiple industries [12–14]. Studies have reported notable cost reductions through LP across various production and distribution contexts [13, 14], while Mixed-Integer Linear Programming and goal programming have been successfully applied in complex multi-product and facility optimization settings [15, 16]. Advanced variants such as fuzzy linear programming further facilitate handling of uncertain parameters and complex constraints [17], with successful applications in agriculture, manufacturing, and logistics [15, 18]. In MSME contexts specifically, LP has proven effective in optimizing production costs and profits across diverse sectors, including livestock farming [19], poultry production [12], and food manufacturing enterprises [20, 21], underscoring its practical relevance to small-scale production environments.

The effectiveness of LP in MSME contexts has also been demonstrated in trade and retail optimization. Sinulingga et al. [22] applied LP to maximize sales for a juice MSME, while Sabardi [23] employed LP to minimize production costs in a small-scale cashew chips enterprise. These studies highlight that LP provides a structured and reliable framework for profit and cost optimization in resource-constrained small businesses. Building on these findings, and recognizing that LP alone may not fully capture the dynamic and non-linear nature of real-world production environments, this study integrates LP with SA to develop a hybrid optimization approach tailored to the unique needs of MSMEs in the patchwork fabric sector. The combination leverages LP's mathematical precision in constraint handling with SA's heuristic exploration capabilities, aiming to maximize production profit and provide a practical optimization framework for small-scale manufacturers.

While numerous studies have applied LP and SA independently to various optimization problems, few have explored their combined application within the specific context of MSMEs in the patchwork fabric industry. Most existing research focuses on large-scale industries or overlooks the particular challenges faced by small and medium-sized enterprises, such as fluctuating material costs and limited operational capacity. This study addresses this gap by integrating LP and SA into a unified hybrid model tailored to the unique needs of MSMEs in the textile sector. The novelty of this research lies in its application of the LP-SA hybrid approach to a real-world case study involving patchwork fabric production, contributing to more effective production planning and profit maximization strategies for small-scale manufacturers.

2. Methods

This section describes the methodological framework used to formulate and solve the MSME production optimization problem. It begins with the mathematical formulation of the profit maximization model, followed by the simulated annealing procedure used to explore alternative feasible production plans.

2.1. Problem Formulation

This study develops a multi-constraint linear programming model integrated with the simulated annealing heuristic to maximize production profit for MSMEs in the patchwork fabric industry. Real-world data were collected from Laras Craft by Kahayu Larasati, an MSME specializing in patchwork fabric products based in Bali, Indonesia. Data collection was conducted through a structured questionnaire distributed via Google Form, supplemented by in-depth interviews to ensure the accuracy and reliability of the collected data.

The objective function aims to maximize total profit, expressed mathematically as:

$$\max Z = \sum_{i=1}^{n} C_i x_i$$

where C_i represents the profit per unit of product i, and x_i denotes the quantity of product i produced. The constraints are defined as follows.

Material Constraints. The total material used must not exceed the available supply. For each material k:

$$\sum_{i=1}^{n} a_{ik} x_i \leq b_k \qquad \forall k$$

where a_{ik} is the amount of material k required per unit of product i, and b_k is the total available quantity of material k.

Production Capacity Constraints. The total production time must not exceed available machine and labor capacity:

$$\sum_{i=1}^{n} t_i x_i \leq T$$

where t_i is the production time required per unit of product i, and T is the total available production time.

Product-Specific Capacity Constraints. Based on operational data from Laras Craft, the following product-specific upper bounds apply:

$$x_{\text{Unicorn,S}} + x_{\text{Unicorn,M}} \leq U_{\text{unicorn}}$$

$$\sum_{i \in \text{Plush}} (x_{i,S} + x_{i,M}) \leq U_{\text{Plush}}$$

$$x_{\text{Totebag}} \leq U_{\text{totebag}}$$

where U_{unicorn}, U_{Plush}, and U_{totebag} represent the maximum monthly production capacity for Unicorn, other plush toys, and Tote Bag respectively.

Demand Constraints. Production quantity for each product must meet market demand but not exceed it:

$$0 \leq x_i \leq D_i \qquad \forall i$$

where D_i is the maximum demand for product i.

Non-Negativity Constraints.

$$x_i \geq 0$$

2.2. Simulated Annealing Approach

Simulated Annealing (SA) is employed to explore a broader solution space and identify alternative production plans that maximize total profit. The SA algorithm is initialized with an initial solution and temperature, then iteratively explores neighboring solutions using a probabilistic acceptance criterion that allows occasional acceptance of worse solutions to avoid local optima. To ensure reproducibility of results, a fixed random seed of 42 was applied prior to initialization of the algorithm.

The formal pseudocode of the SA procedure is presented in Algorithm 1.

Algorithm 1 Simulated Annealing for Production Profit Maximization

```
Input: Initial solution $S_0$, initial temperature $T_0$, cooling rate $\alpha$, maximum iterations $N$, random seed $= 42$
Output: Best solution $S_{\text{best}}$
Set random seed $\leftarrow 42$
$S \leftarrow S_0$
$S_{\text{best}} \leftarrow S$
$T \leftarrow T_0$
for iteration $= 1$ to $N$ do
    $S' \leftarrow \text{GenerateNeighbor}(S)$
    $\Delta E \leftarrow f(S') - f(S)$ {$f(S)$ = total profit of solution $S$}
    if $\Delta E > 0$ then
        $S \leftarrow S'$ {Accept better solution}
    else
        $r \leftarrow \text{Uniform}(0,1)$
        if $r < \exp(\Delta E/T)$ then
            $S \leftarrow S'$ {Accept worse solution with probability}
        end if
    end if
    if $f(S) > f(S_{\text{best}})$ then
        $S_{\text{best}} \leftarrow S$ {Update best solution}
    end if
    $T \leftarrow \alpha \cdot T$ {Cooling schedule}
end for
return $S_{\text{best}}$
```

The SA parameters used in this study are summarized in Table 1.

3. Results and Discussion

This section presents the computational results obtained from the Linear Programming and Simulated Annealing models. The discussion begins with the explicit model formulation based on the case-study data, followed by the optimization results, sensitivity analysis, and comparison between the two approaches.

3.1. Model Formulation

This model optimizes production profit for MSMEs producing patchwork fabric products at Laras Craft by Kahayu Larasati, Bali, by integrating Linear Programming (LP) with Simulated Annealing (SA). The decision variables, objective function, and constraints follow the formulation presented in Section 2.

Table 1: Simulated Annealing Parameter Settings

Parameter	Value	Justification
T_0 (Initial Temperature)	1000	A high initial temperature enables broad exploration of the solution space in early iterations, reducing the risk of premature convergence.
α (Cooling Rate)	0.95	A cooling rate of 0.95 provides a gradual temperature reduction, balancing exploration and exploitation throughout the search process.
N (Iterations)	5000	A sufficient number of iterations to allow thorough exploration of the solution space and convergence toward an optimal or near-optimal solution.
Random Seed	42	A fixed random seed is applied to ensure full reproducibility of the SA results across independent runs.

Decision Variables. Let x_{ij} denote the number of units of product i produced in size j, where $i \in \{1, 2, \ldots, 8\}$ represents the product index (1–7 = plush toys; 8 = Tote bag), and $j \in \{S, M\}$ for plush toys or $j \in \{\text{one-size}\}$ for Tote bags.

Parameters are defined as follows: c_{ij} = unit production cost; p_{ij} = selling price per unit; t_{ij} = production time per unit (hours); $T_{\max} = 416$ hours (total available working hours per month, based on 2 workers × 8 hours/day × 26 days).

The objective function maximizes total profit:

$$\max Z = \sum_{i=1}^{8} \sum_{j} (p_{ij} - c_{ij}) x_{ij}$$

Subject to constraints are as follows:

Total Production Capacity. Total working hours must not exceed 416 hours/month (2 workers × 8 hours/day × 26 days):

$$\sum_{i=1}^{8} \sum_{j} t_{ij} x_{ij} \leq 416$$

Product-Specific Capacity Constraints. Based on operational data from Laras Craft, the following product-specific upper bounds apply:

$$x_{\text{Unicorn,S}} + x_{\text{Unicorn,M}} \leq 96$$

$$x_{\text{Sit.Eleph,S}} + x_{\text{Sit.Eleph,M}} + x_{\text{Monkey,S}} + x_{\text{Monkey,M}} + x_{\text{Giraffe,S}} + x_{\text{Giraffe,M}} \leq 120$$

$$x_{\text{Totebag}} \leq 96$$

Demand Constraints. Production quantity for each product must meet market demand but not exceed it:

$$0 \leq x_i \leq D_i \qquad \forall i$$

where D_i is the maximum demand for product i.

Non-Negativity Constraints.

$$x_i \geq 0$$

The material availability used in this model is summarized in Table 2.

Table 2: Material Availability

Material	Available Quantity
Patchwork Fabrics	10 kg
Fabrics	8 meters
Charm Pack	6 pcs
Jelly Roll	6 pcs
Dacron	15 kg
Thread	2 dozen
Interfacing	50 meters

3.2. Linear Programming Optimization Results

The LP model was solved using the PuLP library in Python with the CBC solver. With the inclusion of product-specific capacity constraints, the model selects three products for production: Unicorn (M), Monkey (M), and Tote Bag, fully utilizing all 416 available working hours. The optimal production plan yields a maximum profit of IDR 14,070,000, as presented in Table 3.

Table 3: LP Optimal Production Plan

Product	Optimal Quantity (units)	Profit per Unit (IDR)	Contribution (IDR)	Hours Used
Unicorn (S)	0	35,000	0	0
Unicorn (M)	22	45,000	990,000	44
Sitting Elephant (S)	0	35,000	0	0
Sitting Elephant (M)	0	42,000	0	0
Monkey (S)	0	38,000	0	0
Monkey (M)	120	45,000	5,400,000	180
Giraffe (S)	0	37,000	0	0
Giraffe (M)	0	44,000	0	0
Tote Bag	96	80,000	7,680,000	192
Total	238		14,070,000	416

The LP solution selects the size-M variants of Unicorn and Monkey alongside Tote Bag, all of which share the highest profit-per-unit values within their respective product categories. The Tote Bag remains the single largest contributor to total profit (IDR 7,680,000 or 54.6% of total), followed by Monkey (M) (IDR 5,400,000 or 38.4%).

3.3. Sensitivity Analysis of the LP Model

Sensitivity analysis was conducted to evaluate the economic feasibility of non-selected products. Table 4 presents the reduced costs for all decision variables, and Table 5 presents the shadow prices for active constraints.

Table 4: Reduced Costs of Decision Variables

Product	Profit per Unit (IDR)	Optimal Quantity (units)	Reduced Cost (IDR)	Status
Unicorn (S)	35,000	0	−10,000	Not selected
Unicorn (M)	45,000	22	0	Selected
Sitting Elephant (S)	35,000	0	−21,250	Not selected
Sitting Elephant (M)	42,000	0	−14,250	Not selected
Monkey (S)	38,000	0	−7,000	Not selected
Monkey (M)	45,000	120	0	Selected
Giraffe (S)	37,000	0	−19,250	Not selected
Giraffe (M)	44,000	0	−12,250	Not selected
Tote Bag	80,000	96	0	Selected

The reduced costs confirm that the three selected products: Unicorn (M), Monkey (M), and Tote Bag, are basic variables in the optimal solution, each with a reduced cost of zero.

Table 5: Shadow Prices of Constraints

Constraint	Shadow Price (IDR)	Slack	Binding	Interpretation
Total Production Hours (≤ 416 hours)	22,500	0	Yes	Each additional working hour increases maximum profit by IDR 22,500
Unicorn Group Cap (≤ 96 units)	0	74	No	Non-binding; only 22 of 96 available Unicorn slots are used
Other Plush Group Caps (≤ 120 units)	11,250	0	Yes	Each additional unit of plush capacity increases profit by IDR 11,250
Tote Bag Cap (≤ 96 units)	35,000	0	Yes	Each additional Tote Bag unit yields the highest marginal profit gain of IDR 35,000

Non-selected products carry negative reduced costs, indicating the magnitude by which their per-unit profit must increase before they become economically viable. For instance, Monkey (S) requires a profit increase of IDR 7,000 per unit, while Sitting Elephant (S) requires the largest adjustment at IDR 21,250 per unit.

Shadow price analysis reveals three binding constraints: total production hours (IDR 22,500 per hour), the other plush group capacity (IDR 11,250 per unit), and the Tote Bag capacity (IDR 35,000 per unit). The Unicorn group capacity is non-binding, with a slack of 74 units remaining. The highest shadow price belongs to the Tote Bag capacity constraint, indicating that relaxing this limit by one unit yields the greatest marginal profit gain. These findings imply that to increase total profit, the most effective levers are: (1) expanding Tote Bag production capacity, (2) extending available working hours, and (3) increasing the other plush group limit.

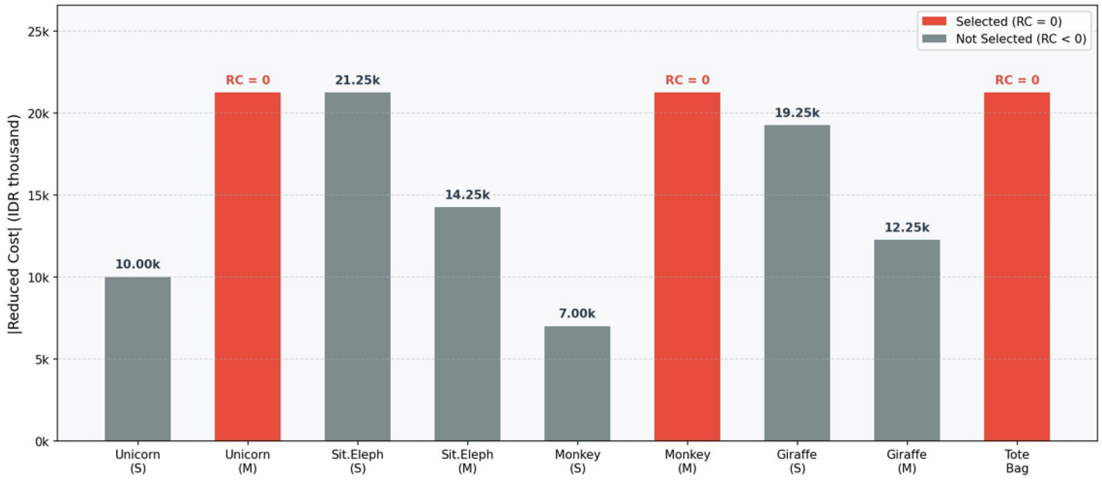

Fig. 1: Absolute reduced cost from LP sensitivity analysis

Red bars indicate selected products (actual RC = 0); grey bars indicate non-selected products, with bar height representing the required profit-per-unit increase to enter the optimal solution.

3.4. Simulated Annealing Optimization Results

The SA heuristic was applied with parameters $T_0 = 1000$, $\alpha = 0.95$, $N = 5000$ iterations, and a fixed random seed of 42 for reproducibility. Unlike LP, SA distributes production across all nine products while respecting all capacity constraints. The SA solution uses 415 of 416 available hours and achieves a total profit of IDR 11,568,000, as presented in Table 6.

3.5. Comparison of LP and SA Results

Table 7 summarizes the key differences between the two approaches. Fig. 2 and Fig. 3 present visual comparisons of production quantities and profit contributions per product.

Table 6: SA Optimal Production Plan

Product	Optimal Quantity (units)	Profit per Unit (IDR)	Contribution (IDR)
Unicorn (S)	50	35,000	1,750,000
Unicorn (M)	14	45,000	630,000
Sitting Elephant (S)	16	35,000	560,000
Sitting Elephant (M)	34	42,000	1,428,000
Monkey (S)	20	38,000	760,000
Monkey (M)	19	45,000	855,000
Giraffe (S)	13	37,000	481,000
Giraffe (M)	16	44,000	704,000
Tote Bag	55	80,000	4,400,000
Total	237		11,568,000
Hours Used	415 / 416		

Table 7: Comparison of LP and SA Optimization Results

Criteria	LP Model	SA Model
Selected Products	Unicorn (M), Monkey (M), Tote Bag	All 9 products
Total Profit (IDR)	14,070,000	11,568,000
Profit Gap	–	−17.8% vs LP
Hours Used	416 / 416	415 / 416
Product Mix	Concentrated (3 products)	Diversified (9 products)
Sensitivity Analysis	Available	Not applicable
Decision Basis	Exact profit maximization	Heuristic exploration
Best Suited For	Stable demand, profit maximization	Uncertain demand, production diversification

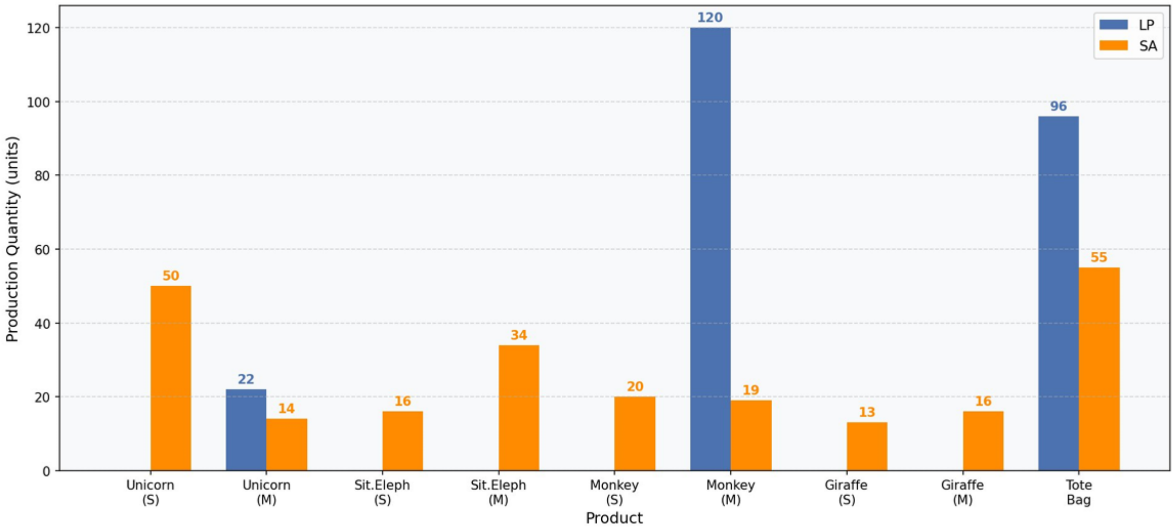

Fig. 2: Comparison of optimal production quantities: LP vs SA

The LP model outperforms SA by IDR 2,502,000 (17.8%). This gap arises because LP mathematically identifies the globally optimal allocation, concentrating resources on the three highest-yielding products. SA, being a heuristic, explores a broader solution space but cannot guarantee global optimality; its diversified output, while suboptimal in pure profit terms, provides a more balanced production portfolio that may better serve MSMEs facing uncertain or varied consumer demand.

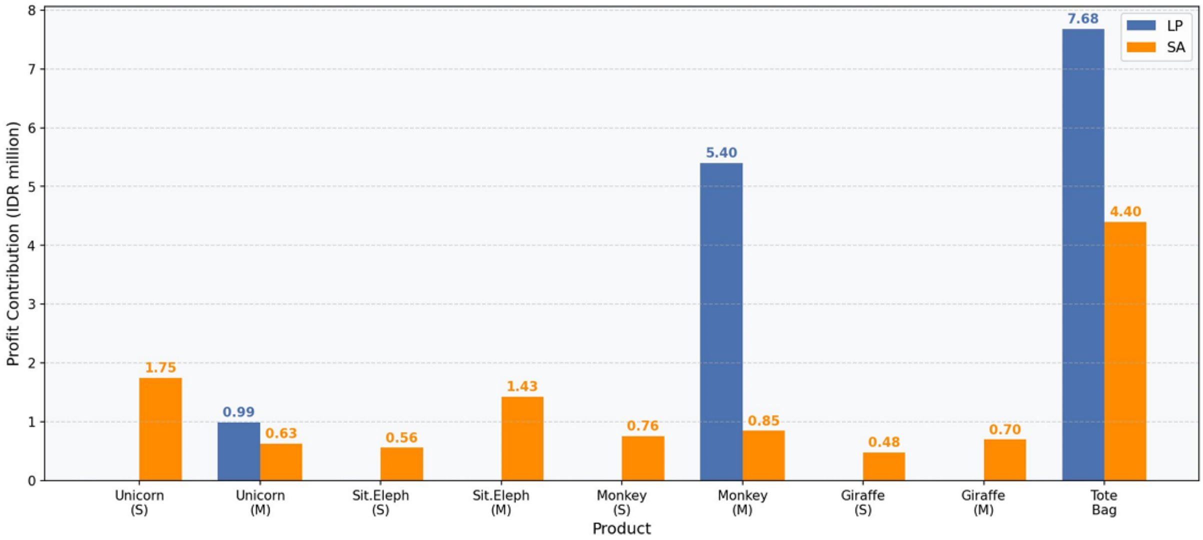

Fig. 3: Profit contribution per product: LP vs SA

4. Conclusion

This study compared the performance of Linear Programming (LP) and Simulated Annealing (SA) for maximizing production profit in MSMEs in the patchwork fabric industry, using Laras Craft by Kahayu Larasati in Bali, Indonesia as a case study. The results indicate that the LP model is more effective for profit maximization, achieving a total profit of IDR 14,070,000 by concentrating production resources on three products: Unicorn (M), Monkey (M), and Tote Bag; all of which carry the highest profit-per-unit values within their respective capacity groups. The SA model, while more exploratory in nature, distributed production across all nine products and achieved a total profit of IDR 11,568,000, representing a 17.8% gap relative to the LP solution.

The LP model's superiority in this context stems from its ability to identify and exploit the globally optimal product mix with mathematical precision, fully utilizing all 416 available working hours. In contrast, the SA approach's diversification of the product mix, while suboptimal in pure profit terms, reflects a more flexible production strategy that may be preferable in contexts where market demand is uncertain or MSME owners wish to maintain product variety for customer retention purposes.

While LP excels in stable conditions with well-defined constraints, SA provides a viable alternative in dynamic environments where demand fluctuates and rigid optimization may not be practical. The stochastic nature of SA, however, necessitates the use of a fixed random seed to ensure reproducibility of results, a practice that should be standardized in future computational studies of this kind. Future research should explore hybrid models that combine the mathematical precision of LP with the adaptive search capabilities of SA, potentially offering MSMEs a more robust framework for production planning under uncertainty.

This study offers several actionable insights for MSME production planning. First, MSMEs operating in stable market conditions should prioritize LP-based optimization to maximize profit, as demonstrated by its selection of the three highest-yielding products under capacity constraints. Second, in environments with fluctuating or uncertain demand, SA provides a flexible alternative that distributes production risk across a broader product portfolio, supporting customer variety and reducing dependency on a single product line. Third, efficient resource utilization, as demonstrated by the LP solution's full utilization of 416 available working hours, is critical for profit maximization in capacity-constrained settings. Fourth, the development of hybrid LP-SA models represents a promising direction for MSMEs seeking to balance profitability with production flexibility in dynamic market environments.

CRediT Authorship Contribution Statement

Afnaria: Conceptualization, Methodology, Software, Formal Analysis, Writing–Original Draft Preparation, Writing–Review & Editing. **Rina Fillia Sari:** Data Curation, Validation, Writing–Review & Editing. **Isnaini Halimah Rambe:** Investigation, Visualization, Writing–Review & Editing.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools (ChatGPT-4 and Claude 3.5 Sonnet) were used to assist with literature review organization, proofreading, and formatting consistency. All technical content, methodologies, and results were independently developed and validated by the authors.

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

The dataset and code supporting the findings of this study are available from the corresponding author upon reasonable request.

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