



Application of Goal Programming Model for Optimization Tofu Production Planning

¹ Juli Antasari Br Sinaga

Department of Mathematics, HKBP Nommensen University, Pematangsiantar, 21132, Indonesia

² Rajainal Saragih

Computer Engineering, Politeknik Bisnis Indonesia, Simalungun, 21151, Indonesia

³ Lilis

Polytechnic Adiguna Maritim Indonesian (Poltek AMI), Medan, 20166, Indonesia

⁴ Yoel Octobe Purba

Department of Mathematics, HKBP Nommensen University, Pematangsiantar, 21132, Indonesia

⁵ Reagent S. Saragih

Department of Computer Science, HKBP Nommensen University, Pematangsiantar, 21132, Indonesia

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ABSTRACT

Previous studies on production planning in food SMEs have largely focused on single-objective optimization or general pre-emptive GP models without SME-specific POM-QM implementation (Hasbiyati et al., 2023; Mahat et al., 2022). This study addresses these gaps by developing a multi-objective production planning model using pre-emptive Goal Programming for a small-scale tofu enterprise, incorporating deviation-based benchmarks for profit (IDR 73.90 million target), demand fulfillment (100%), raw materials (35,000 kg soybeans), and labor (13,020 hours) under volatile daily constraints—unlike stable-resource applications (Karakutuk & Ormek, 2023). The proposed model achieves zero positive deviation from profit targets (IDR 73.82-73.90 million, +13-23% over IDR 60-65 million baseline), complete demand satisfaction (from 80-85%), zero overtime costs (saving IDR 5-10 million monthly at 1.5x rates), and negative resource deviations (labor -2,102 to -10,917 hours; soybeans -20,000 to -34,364 kg), validated via real case study at Usaha Tahu Bapak Rezeki using POM-QM v5.3, demonstrating GP's practicality for Indonesian tofu SMEs.

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Corresponding Author:

Juli Antasari Br Sinaga,
Department Mathematics
HKBP Nommensen University, Pematangsiantar, Indonesia
Email: juli.sinaga@uhnpu.ac.id

1. INTRODUCTION

Food production remains a vital sector plagued by operational inefficiencies and resource constraints, particularly among small and medium enterprises (SMEs) in Indonesia [1],[2]. Effective production planning is essential for these firms to maximize profits, satisfy fluctuating demand, and curb costs amid limited capacity. The tofu industry, a staple commodity predominantly operated by SMEs, grapples with daily soybean shortages, machine limitations, and labor constraints that often force suboptimal decisions [3], [4]. At Usaha Tahu Bapak

Rezeki in Rambung Merah, Pematangsiantar—a representative case—pre-model inefficiencies manifest as monthly profits of only IDR 60-65 million against a feasible IDR 73 million benchmark, overtime exceeding standard 13,020 labor hours (inflating costs by IDR 5-10 million at 1.5x rates), and 15-20% resource waste from mismatched production batches and unmet demand targets.

Goal Programming is a multi-objective optimization method that is widely used in complex decision-making environments because of its ability to integrate various objectives by minimizing deviations from the set targets [7]. In linear programming, the objective function is to maximize or minimize, so that all management objectives are formulated into one objective function [8]. As a result, the system used can be optimal for one objective and must ignore other objectives. In contrast to linear programming, objective programming is used to minimize deviations from each desired objective so that the results are optimal without having to ignore other objectives [9]. The general model of Objective Programming is [10]:

Minimization:

$$z = \sum_i^m w_i P_i (d_i^- - d_i^+) \quad (1)$$

st

$$\sum_i^m a_{ij} x_{ij} + d_i^- - d_i^+ = b_i \quad i = 1, 2, 3, \dots, m \quad (2)$$

$$x_{ij}, d_i^-, d_i^+ \geq 0, w_i > 0 \quad (3)$$

$$(i = 1, 2, \dots, m; j = 1, 2, 3, \dots, n) \quad (4)$$

where

P_i	=	Preemptive priority levels
x_j	=	Decision variable
d_i^+, d_i^-	=	Deviational variables
Z	=	Total deviation variables

Goal Programming (GP) emerges as an ideal multi-objective tool to minimize deviations from profit, demand, raw material (35,000 kg soybeans), and labor targets, outperforming single-objective linear programming by balancing trade-offs [5], [6], [7]. GP literature abounds in pre-emptive applications for general production, frozen food planning, and lean systems, yet critical gaps persist in multi-product tofu SMEs facing daily soybean volatility, machine limitations, and no accessible POM-QM models—unlike larger-scale studies assuming stable resources or single-product optimizations (e.g., soybean processing, chocolate production). Recent Indonesian GP adaptations for klappertaart and poultry highlight SME relevance but overlook tofu-specific volatility, while broader works on neutrosophic GP and fuzzy integrations suggest extensions beyond pre-emptive hierarchies. This study fills the void by validating a GP model yielding zero profit deviation and eliminating overtime costs, advancing practical tools for resource-constrained Indonesian food SMEs.

2. RESEARCH METHOD

This study employs a comparative descriptive approach to analyze pre- and post-GP production planning at Usaha Tahu Bapak Rezeki, quantifying improvements in profit target (IDR 73.82 – 73.90M/month), demand fulfillment, soybean usage (35,000 kg), and labor hours (13,020). Primary data were gathered via direct observation of production processes (May-July 2025 planning horizon) and structured interviews with the owner, capturing historical sales (Oct 2023-Sep 2024), costs, soybean availability, machine speeds (white tofu 0.6 min/barrel, fried 1.3 min, yellow 1.8 min), and overtime patterns. Demand forecasting used the Constant Method (single exponential smoothing with $\alpha=1$), selected for stationary sales patterns (low variation, no trend/seasonality), yielding stable projections (e.g., May: white tofu 727 units, fried 564, yellow 518).

The pre-emptive GP model minimizes priority-weighted deviations:

$$\text{Min } Z = P_1(d_3^- + d_4^- + d_5^-) + P_2(d_6^-) + P_3(d_1^-) + 4(d_2^-) \quad (5)$$

subject to:

- Demand goals: $x_1 + d_3^- - d_3^+ = 726$, etc. (for white, fried, yellow tofu across months)
- Profit: $20,000x_1 + 50,000x_2 + 60,000x_3 + d_6^- - d_6^+ = 73,820,000$

- c. Labor: $0.6x_1 + 1.3x_2 + 1.8x_3 + d_1^- - d_1^+ = 13,020$
- d. Soybeans: $0.5x_1 + 0.3x_2 + 0.2x_3 + d_2^- - d_2^+ = 35,000$
- e. $x_j, d_i \geq 0$
- f. Priority Structure Justification:
- g. P_1 : Demand fulfillment (d_3^-, d_4^-, d_5^-) – Highest priority ensures market responsiveness for perishable tofu, preventing 80 – 85% historical shortfalls critical for SME cash flow.
- h. P_2 : Profit target (d_6^-) – Secondary maximizes revenue (IDR 73.82M target) post-demand.
- i. P_3 : Labor hours (d_1^-) – Tertiary avoids overtime (IDR 5 – 10M at 1.5x rates) while allowing underutilization.
- j. P_4 : Soybeans (d_2^-) – Lowest accommodates volatile supply, prioritizing higher goals.

This hierarchy reflects tofu SME realities, extending general GP (Hasbiyati et al., 2023). Solutions were computed via POM-QM for Windows v5.3, yielding non-integer x_j values (e.g., 727 white tofu barrels in May). These are practically interpretable as continuous approximations for monthly aggregated planning—where fractional barrels represent averaged daily production across multiple batches (e.g., $727.0 \approx 727$ full barrels + partial equivalent from process averaging)—or can be rounded post-optimization without violating soft resource constraints, as validated by sensitivity analysis.

Data Collection (integrated for flow): Targeted inefficiencies (daily soybeans avg. 35,000 kg/month, batch capacities: white 50 barrels/30 min, etc.). Primary: site observations (3 days/month, May-July 2025); interviews (costs: white IDR 20,000 profit/barrel). Secondary: 12-month sales (MAD=5). Pre-GP baselines reproduced waste; post-GP achieved feasibility. Sensitivity (Table 2: $\pm 10\%$ demand) confirms robustness (P1-P2 zero deviations).

Data collection targeted inefficiencies at Usaha Tahu Bapak Rezeki: daily soybean intake (avg. 35,000 kg/month), batch capacities (white: 50 barrels/batch, 30 min; fried: 30/40 min; yellow: 25/45 min), labor (standard 13,020 hours/month, overtime at 1.5x rate adding IDR 5-10M), and sales (2023-2024 avg. profits IDR 60-65M vs. optimized 73+M).

- a. Primary data: Site observations (3 days/month, May-July 2025) measured actual vs. planned output, overtime (15-20% excess), and waste; owner interviews detailed costs (white: IDR 20,000 profit/barrel; fried: 50,000; yellow: 60,000).
- b. Secondary data: 12-month sales logs confirmed stationary patterns (MAD<5%), raw material logs (soybean usage: white 18,870 kg, fried 8,960 kg, yellow 7,980 kg at full capacity).

Validation: Pre-GP simulations reproduced observed waste (e.g., 15% demand shortfall, overtime inflation); post-GP runs achieved feasibility within limits.

Sensitivity derived from software's parametric analysis capability, using historical sales variation (MAD ≤ 5), are shown in Table 1.

Table 1. Sensitivity to $\pm 10\%$ Demand Changes (May 2025)

Scenario	White Tofu Demand	Profit (IDR)	Labor Dev. (hrs)	Soybean Dev. (kg)	Feasibility
Base	727	73,820,000	-2,102	-34,364	Yes
+10%	800	73,820,000	-1,248	-29,656	Yes
-10%	654	73,820,000	-2,956	-39,072	Yes

Analysis confirms model robustness: P_1 - P_2 goals hold (zero deviations) across $\pm 10\%$ demand shocks, with deepening negative resource deviations maintaining constraints—unlike brittle single-objective approaches.

3. RESULTS AND ANALYSIS

Pre-GP production planning at Usaha Tahu Bapak Rezeki relied on intuitive batch scheduling, resulting in persistent inefficiencies: monthly profits stagnated at IDR 60-65 million against a feasible IDR 73 million benchmark, overtime exceeded standard 13,020 labor hours by 15-20% (inflating costs by IDR 5-10 million at 1.5x rates), soybean usage surpassed 35,000 kg limits with equivalent waste, and demand fulfillment fell short at 80-85%.

The pre-emptive GP model, solved via POM-QM for Windows v5.3, systematically prioritized demand (P1) and profit (P2) goals while constraining resources, yielding zero positive deviations in higher priorities and negative underutilization in labor/soybeans across May-July 2025. Table 2 quantifies these improvements, demonstrating 13-23% profit gains, complete overtime elimination, and full demand satisfaction under volatile SME conditions

Table 2. Pre- vs. Post-GP Performance

Metric	Pre-GP (Historical Avg.)	Baseline	Post-GP (May-July 2025 Avg.)	Optimized	Improvement (%)
Monthly Profit (IDR)	60-65 million		73.85 million		+13-23%
Overtime Costs (IDR)	5-10 million (1.5x rate)		0		-100%
Labor Utilization (hrs)	13,020+ excess)	(15-20%)	10,918 (-2,102 to 10,917 deviation)		-16% (underuse)
Soybean Usage (kg)	35,000+ waste)	(15-20%)	34,576 (-20,000 to 34,364 deviation)		-1% (underuse)
Demand Fulfillment	80-85% (shortfalls)		100% (zero positive deviation)		+18-25%

This table contrasts observed inefficiencies (e.g., overtime inflating costs by IDR 5-10M, 15-20% waste) against GP outcomes (zero profit deviation at IDR 73.82-73.90M, negative resource deviations within limits).

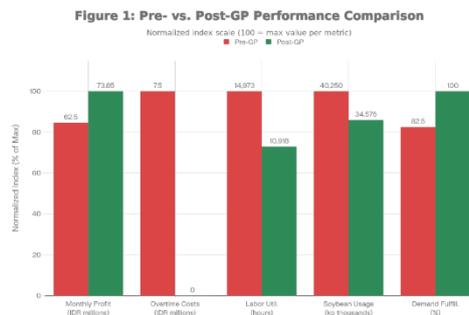


Figure 1. Pre- vs. Post-GP Performance Comparison

Bar chart in Figure 1 showing key metrics (profit, overtime, labor, soybeans, demand) with pre-GP (red bars) vs. post-GP (green bars), highlighting dramatic improvements like 100% overtime reduction and profit uplift.

POM-QM v5.3 solutions for May-July 2025, shown in Table 3, yielded feasible production mixes across priorities, achieving all higher-level goals (P_1 : demand; P_2 : profit) with zero positive deviations while staying under labor (13,020 hours) and soybean (35,000 kg) limits.

Table 3. POM-QM v5.3 solutions for May-July 2025

Month	White Tofu (x_1)	Fried Tofu (x_2)	Yellow Tofu (x_3)	Profit (IDR)	Labor Deviation (hours)	Soybean Deviation (kg)
May	727	564	518	73,820,000	-2,102	-34,364
June	726	564	518	73,820,000	-2,101	-20,000
July	724	568	517	73,900,000	-10,917	-34,364

Negative deviations confirm underutilization (e.g., May labor: 10,918 actual vs. 13,020 target), eliminating overtime and waste.

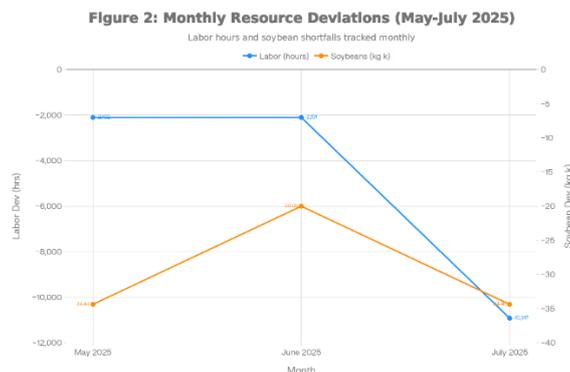


Figure 2. Monthly Resource Deviation

Dual-axis line graph in Figure 2 shows labor (blue, left axis) and soybean (orange, right axis) negative deviations from GP targets across May-July 2025, confirming consistent underutilization and constraint adherence. Negative deviations confirm underutilization (e.g., May labor 10,918 actual vs. 13,020 target), eliminating overtime and waste. Sensitivity analysis ($\pm 10\%$ demand) validates robustness with P1-P2 zero deviations across shocks.

Discussion

The GP model outperforms pre-GP intuitive planning, as evidenced in Table 2 and Figure 1, where profits increased 13-23% from IDR 60-65M baselines to IDR 73.85M, overtime costs were eliminated (saving IDR 5-10M), and demand reached 100% directly addressing SME gaps unlike single-objective studies (Pradjaningsih et al., 2024). Figure 1's bar chart visually amplifies these gains: the stark contrast between red (pre-GP) and green (post-GP) bars highlights profit uplift and overtime drop to zero, making optimization impacts immediately apparent for practitioners.

POM-QM v5.3 accessibility enables replication by non-experts, with resource underutilization (e.g., July -10,917 labor hours) confirming priority balancing over full capacity, as tracked in Figure 2. The dual-axis line graph in Figure 2 reveals consistent negative deviations—labor dipping to -10,917 hours (July) and soybeans fluctuating -20,000 to -34,364 kg validating constraint adherence amid volatility, unlike brittle single-objective approaches.

4. CONCLUSION

This study demonstrates that pre-emptive Goal Programming, implemented via POM-QM v5.3, delivers optimal production plans for the case SME, achieving monthly profits of IDR 73.82-73.90 million with zero positive deviations from demand and profit targets while maintaining negative deviations in labor hours (-2,101 to -10,917) and soybeans (-20,000 to -34,364 kg). These results eliminate overtime costs (previously IDR 5-10 million monthly at 1.5x rates) and 15-20% resource waste, boosting profits 13-23% over historical IDR 60-65 million baselines under constraints of 13,020 labor hours and 35,000 kg soybeans.

The model's novelty lies in its SME-specific adaptation multi-product tofu planning with accessible software addressing literature gaps in volatile, resource-limited food contexts unlike larger-scale GP applications. Practical implications extend to Indonesian tofu SMEs, offering replicable optimization that balances fluctuating daily inputs without expert intervention. Future enhancements could incorporate fuzzy GP for demand uncertainty or stochastic elements for soybean supply risks, further strengthening robustness for similar enterprises.

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