

## PERAMALAN SPESIFIK PRODUK DAN ALOKASI KAPASITAS: MODEL HIBRIDA UNTUK OPTIMASI KEUNTUNGAN PADA MANUFAKTUR MAKANAN MULTI VARIAN

### *PRODUCT SPECIFIC FORECASTING AND CAPACITY ALLOCATION: A HYBRID MODEL FOR PROFIT OPTIMIZATION IN MULTI VARIANT FOOD MANUFACTURING*

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#### **Abstrak**

Penelitian ini membahas tantangan perencanaan produksi pada UMKM di sektor manufaktur makanan dengan pola permintaan yang berbeda, keterbatasan data historis, dan kendala kapasitas tetap. Sebuah model hibrida yang mengintegrasikan peramalan permintaan spesifik produk dan pemrograman linier untuk memaksimalkan laba diusulkan guna menghasilkan target produksi tahunan yang optimal serta proyeksi laba. Data penjualan historis untuk empat varian produk terlebih dahulu diproses menggunakan metode Interquartile Range (IQR) untuk menghilangkan nilai-nilai penyimpangan yang tidak representatif. Pola permintaan kemudian didiagnosis sebagai Beta, Exponential, atau Triangular, yang memandu pemilihan metode peramalan yang disesuaikan: *Moving Average* (MA) untuk Produk A, *Single Exponential Smoothing* (SES,  $\alpha=0.5$ ) untuk Produk B dan C, serta *Simple Average* (SA) untuk Produk D. Hasil *Forecasting* berfungsi sebagai batasan produksi minimum dalam model pemrograman linier yang memaksimalkan total kontribusi laba dengan kapasitas tahunan sebesar 72.000 unit. Model yang diimplementasikan dalam POM-QM memproyeksikan laba tahunan sebesar IDR 213.514.600, dengan analisis sensitivitas menunjukkan peningkatan sebesar 7,7% dibandingkan perencanaan berbasis volume dan harga bayangan sebesar IDR 3.388/unit untuk kapasitas hingga 75.000 unit. Penelitian ini menunjukkan bahwa keunggulan operasional dalam lingkungan dengan keterbatasan sumber daya tidak berasal dari kompleksitas model, melainkan dari penyelarasan yang cermat antara metode kuantitatif dasar dengan perilaku permintaan empiris dan logika keuangan.

**Kata kunci:** Peramalan permintaan, pemrograman linear, penanganan outlier, perencanaan produksi, maksimasi keuntungan

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#### **Abstract**

This study addresses production planning challenges in food manufacturing SMEs characterized by heterogeneous demand patterns, limited historical data, and fixed capacity constraints. A hybrid model integrating product-specific demand forecasting and profit-maximizing linear programming is proposed to generate optimal annual production targets and profit projections. Historical sales data for four product variants are first preprocessed using the Interquartile Range (IQR) method to remove non-representative outliers. Demand patterns are then diagnosed as Beta-like, Exponential-like, or Triangular, guiding the selection of tailored forecasting methods: *Moving Average* (MA) for Product A, *Single Exponential Smoothing* (SES,  $\alpha=0.5$ ) for Products B and C, and *Simple Average* (SA) for Product D. The resulting forecasts serve as minimum production constraints in a linear programming model that maximizes total contribution profit under a 72,000-unit annual capacity. Implemented in POM-QM, the model yields a projected annual profit of IDR 213,514,600, with sensitivity analysis revealing a 7.7% improvement over volume-based planning and a shadow price of IDR 3,388/unit for capacity up to 75,000 units. This research demonstrates that operational excellence in resource-constrained environments stems not from model complexity, but from the thoughtful alignment of foundational quantitative methods with empirical demand behavior and financial logic.

**Keywords:** demand forecasting, linear programming, outlier treatment, production planning, profit maximization

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## I. INTRODUCTION

Efficiency in manufacturing operations is crucial in the food processing industry due to demand variability and capacity constraints, requiring companies to design efficient production planning systems using fundamental inventory and production management methods that remain relevant. [1][2][3]. Recent literature shows that the accuracy of forecasts significantly reduces in intermittent and bound trends in patterns, as it typically happens in food processing industries [4][5]. If future demand trends are inaccurately predicted, the consequences are immediate and costly, leading to waste from overproduction and lost sales and goodwill from shortages, a problem that is especially severe for SMEs due to limited data and higher forecasting errors from noise and outliers [6][7]. There may be risks in selecting forecasts based on the characteristics of demands being skewed, volatile, or multidimensional [8][9]. Yet, in multi-product manufacturing involving capacity constraints, modeling through analytics becomes an importantly critical function [10]. Distortion by outlier effects can be significantly detrimental in forecasts based on short-term series however, SMEs tend to ignore basic data cleanings [11].

To mitigate demand uncertainty, forecasting has assumed a central role in the planning of food product manufacturing. Forecasting is fundamental to the risk management process to price assets derivatives, hedging strategies and estimating the financial risk of a firm [12]. Contemporary trends in forecasting focus on the need to acknowledge the fact that demand behavior in SMEs tends to be diversified; this behavior cannot be explicitly described using a single model [13][8]. Traditional forecasting methods such as Moving Average, Single Exponential Smoothing, and Simple Average remain popular in SMEs due to their simplicity and compatibility with basic spreadsheets, offering a systematic alternative to intuition-based planning when demand characteristics such as variability, seasonality, and random spikes are properly understood [14][15]. Special events produce irregular demand spikes in SMEs requiring efficient preprocessing and strategic methods of selection in forecasting demands, particularly in SMEs [16]. As a result, short cycles and seasonality generate further complexity in forecasting in SMEs, potentially magnifying inefficiency phenomena in SMEs owing to the bullwhip effect, thus increasing planning uncertainty in SMEs [16].

Although forecasting provides solutions to issues of anticipating demand, linear programming (LP) provides a scientific approach to make optimal manufacturing decisions considering constrained resources [17][18]. Linear programming is often utilized to address optimal manufacturing allocation and have been widely implemented in food manufacturing processes to enhance manufacturing effectiveness and capacity utilization [19]. Optimization solutions enable capacity and cost trade-offs simultaneously and are necessary for overall manufacturing plans to comply with profit-maximization strategies, as discussed in revenue management methods and principles [20]. LP models are simple and highly efficient mathematical models suitable for small and medium-size food manufacturing businesses lacking the capability to afford sophisticated optimization models and solutions [21]. An LP model optimizes linear objectives such as profit or cost under constraints like capacity, demand fulfillment, and non-negativity, and has been widely used in food manufacturing to allocate capacity efficiently and achieve technically and economically optimal production plans, particularly by maximizing the use of scarce resources in complex multi-operation systems [22].

Despite the strengths of both forecasting and LP, the existing gap in the integration between the two technologies still exists. Analytics-based decision models support production planning increasingly in the latest types of supply chains and offer a robust platform for the development of novel hybrid forecasting-optimization tools [23][24]. New research works aim at the joint solution for forecasting and optimization for improving the effectiveness of planning tools [25]. Data-driven planning tools offer an increasingly integrated platform with predictive analytics integrated with LP or MIP formulation tools separately [26]. However, existing hybrids always conceptualize forecasting as a non-stochastic process and fail to adapt forecasting tools to the product-type demand behavior separately [27]. SMEs in the food industry are increasingly exposed to production rigidity and human-intensive production processes, making the effect of forecast accuracy even more sensitive to the advantage of the solution approach [28][29].

## II. LITERATURE REVIEW

Effective production planning in food manufacturing SMEs requires bridging two traditionally disconnected domains: demand

forecasting and resource optimization. Recent literature reveals a clear evolution from isolated methodological studies toward integrated decision support frameworks but critical gaps remain, especially concerning demand heterogeneity and data quality in resource-constrained settings.

On the forecasting side [13], demonstrated through the M5 Competition that forecasting accuracy improves significantly when methods are matched to underlying demand characteristics such as intermittent, seasonal, or bounded patterns. However, their work remains confined to prediction accuracy and does not translate forecasts into operational decisions. Similarly, Gaertner T[15] proposed an automated forecasting pipeline for SMEs using ensemble models (ARIMA, XGBoost, CNN), yet their approach treats forecasting as a black-box preprocessing step, lacking interpretability and failing to link predictions to downstream planning logic.

Conversely, optimization-focused studies emphasize mathematical rigor but often assume deterministic or exogenously given demand. [29] developed robust linear programming (LP) models for production planning under uncertainty, yet they rely on scenario-based or fixed demand inputs, ignoring forecast error as a source of risk. Mohd Baki S and Cheng J [21] successfully applied LP to maximize profit in a drinking water SME, but their model uses historical averages as static demand

constraints bypassing any adaptive forecasting process altogether.

Hybrid approaches have emerged to close this gap. [6] integrated predictive analytics with LP/MIP for production-inventory planning, representing a significant step toward end-to-end decision systems. However, their forecasting component applies a uniform model across all products, disregarding statistical differences in demand behavior a critical oversight in multi-variant food manufacturing where products exhibit distinct volatility, skewness, and modality.

Previous studies have explored forecasting methods, linear programming, and hybrid forecasting-optimization models. However, most approaches either focus solely on forecast accuracy or assume deterministic demand without considering product-specific demand pattern. This study addresses the gap by integrating demand pattern diagnosis, tailored forecasting methods, outlier treatment, and profit-maximizing linear programming into a unified framework for SME food manufacturing..

### III. METHODS

This chapter discuss the methods of the integrated forecasting and linear programming model applied to CV. XYZ's production planning, in Figure 1.

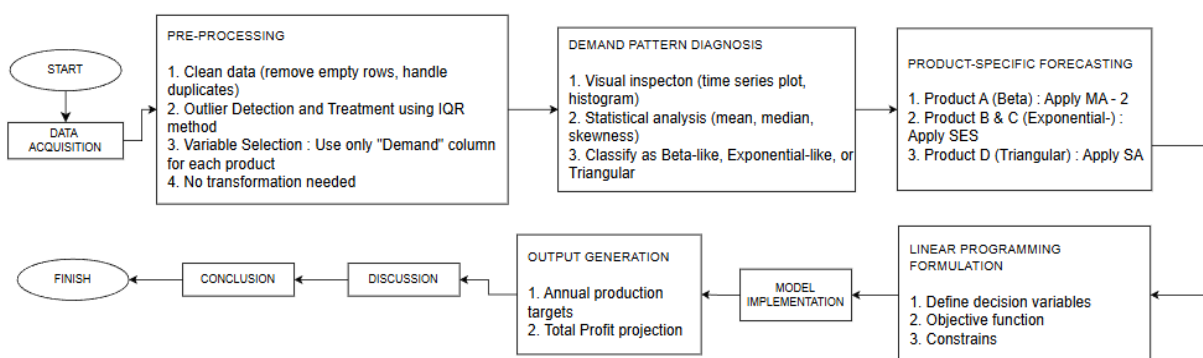


Figure 1. Research Methodology Flow

#### A. Data Acquisition

Data were collected from CV. XYZ, a bakery in Semarang, Central Java, Indonesia and covering about 12 months of sales for four variants of product :

- Product A
- Product B
- Product C
- Product D

The company operates under the constraint that are a secondary product line (~8% of total revenue), with an annual production capacity of 72,000 units (300 units/day over 240 operational days). Contribution margins per unit are IDR 2,831 (A), 2,588 (B), 3,388 (C), and 2,948 (D). The study utilizes 12 months of historical sales data (January–December 2024) from CV. XYZ, a bakery in Semarang, Central Java. The data cover four variants, internally coded as (Table 1).

**Table 1.** Historical Sales Data

| Month | Sales A | Sales B | Sales C | Sales D |
|-------|---------|---------|---------|---------|
| 1     | 2100    | 400     | 800     | 300     |
| 2     | 4025    | 480     | 1110    | 450     |
| 3     | 1450    | 500     | 2850    | 880     |
| 4     | 3520    | 450     | 1250    | 1000    |
| 5     | 2100    | 1280    | 800     | 300     |
| 6     | 4025    | 900     | 1700    | 200     |
| 7     | 1450    | 3200    | 700     | 1450    |
| 8     | 3520    | 500     | 600     | 1400    |
| 9     | 1400    | 1000    | 1250    | 1450    |
| 10    | 2680    | 1200    | 1500    | 950     |
| 11    | 3050    | 200     | 3000    | 900     |
| 12    | 1000    | 230     | 1000    | 2250    |
| total | 30320   | 10340   | 16560   | 11530   |

Product used are a non-core product line, contributing approximately 8% of total company revenue. Additional operational parameters include:

- 1) Maximum daily production capacity: 300 units
- 2) Operational days: 20 days/month (240 days/year)
- 3) Production days : 20 days/month ( 240 days/year)s
- 4) Staggered production policy: Applied for orders >1,000 units

Sales data were validated and adjusted for known stockouts in collaboration with the production manager to approximate true demand.

## B. Pre-Processing

### 1) Data Cleaning : Outlier Detection and Treatment

Real demand data in small and medium-sized businesses are usually marred with anomalies generated either by promotional purchases, batch orders, or data entry mistakes. The impact of such anomalies on forecasting models could be considerable, especially in cases where the time series has shorter lengths and observations have greater prominence. To avoid the data quality issue, this research uses the Interquartile Range method, which is highly recommended in cases involving small samples [11].

The method starts with arranging the demand observations in increasing order:  $y_1, y_2, \dots, y_n$ . The first quartile Q1 and third quartile Q3 are calculated. In a

dataset of size  $nm$ , Q1 is obtained as the median of the first half of the dataset and Q3 is the median of the second half of the dataset. The formula used to represent the IQR is given by Equation (1).

$$IQR = Q3 - Q1 \quad (1)$$

Using the IQR, the lower and upper bounds for outlier detection are calculated using Equation (2) and (3).

$$Lower\ Bound = Q1 - 1.5 \times IQR \quad (2)$$

$$Upper\ Bound = Q3 + 1.5 \times IQR \quad (3)$$

If the observed value is less than the lower boundary or exceeds the upper boundary, it is termed as an outlier value. In the proposed study, the outlier value is replaced by the median value of the remaining data points not contributing to the outlier value. It is represented as  $y_{\sim non-outliery \sim non-outlier}$ . This step is essential to remove the effect of the irregular event of less-than-expected demand. The data points obtained after cleaning are used for the subsequent forecasting process.

### 2) Variable Pattern Diagnosis

There are no mathematical transformations needed on data, such as logarithmic or z-score transformation. The rationale for omitting any transformation is that all prognostication results, as well as optimization outcomes, should also directly relate to production managers. Only one variable should be chosen, and that variable is the monthly demand measured by units, as it directly represents the production need

Demand classification using descriptive statistics and visual diagnostics is a standard approach for selecting forecasting techniques [29], [30]. The diagnosis is performed through a combination of visual inspection and quantitative metrics. The sample mean ( $\bar{y}$ ) and sample median ( $\tilde{y}$ ) are computed by Equation (3) and (4).

$$\bar{y} = \frac{1}{n} \sum_{t=1}^n y_t \quad (4)$$

$$\tilde{y} = \text{median}(y_1, y_2, \dots, y_n) \quad (5)$$

The sample skewness ( $\gamma$ ) is calculated to assess asymmetry by Equation (6). where  $ss$  is the sample standard deviation. These statistics inform the classification into one of three distribution types:

- Beta-like: Characterized by  $\bar{y} \approx \tilde{y}$  and low skewness ( $|\gamma| < 0.5$ ), indicating bounded fluctuations within a stable range.
- Exponential-like: Exhibits positive skewness ( $\gamma > 1$ ) and  $\bar{y} > \tilde{y}$ , reflecting right-skewed behavior with sporadic, high-magnitude spikes.
- Triangular: Displays  $\bar{y} \approx \tilde{y}$  with moderate dispersion, suggesting a clear modal value and symmetric spread, shown in Equation (6).

$$\gamma = \frac{1}{n} \sum_{t=1}^n \left( \frac{y_t - \bar{y}}{8} \right)^3 \quad (6)$$

This classification ensures that forecast selection considers demand characteristics such as skewness, volatility, and modality to avoid biased planning decisions.

### C. Product Specific Forecasting

Based on the demand distribution diagnosis, a tailored forecasting method was applied to each product:

- For Beta-like demand (Product A): The 2-month Moving Average (MA-2) is effective for stable or bounded demand, while Exponential Smoothing excels in capturing volatile patterns (2). The forecast for period  $t+1$  is shown in Equation (7).

$$\hat{y}_{t+1} = \frac{y_t + y_{t-1} + y_{t-2}}{3} \quad (7)$$

This method is chosen for its simplicity and effectiveness in capturing local trends without overreacting to noise.

- For Exponential-like demand (Products B and C): Single Exponential Smoothing (SES) with a smoothing parameter  $\alpha=0.5$  was applied to balance adaptability to recent changes with stability against noise. The recursive formula shown in Equation (8)

$$\hat{y}_{t+1} = 0.5 \times y_t + 0.5 \times \hat{y}_t \quad (8)$$

The choice of  $\alpha=0.5$  reflects a compromise between responsiveness and stability, suitable for volatile demand with occasional spikes.

- For Triangular demand (Product D): The Simple Average (SA) was selected, as a robust estimator for symmetric modal distributions with limited

data (5). The forecast is calculated by Equation (9).

$$\hat{y}_t = \frac{1}{12} \sum_{t=1}^{12} y_t \quad (9)$$

This method is chosen for its simplicity and ability to capture the overall level of demand without being influenced by short-term fluctuations. The monthly forecasts were then scaled to annual demand estimates ( $\hat{D}_i = 12 \times \hat{y}_i$ ), which served as minimum production constraints in the optimization model.

### D. Linear Programming Formulation

LP offers the optimal allocation of constrained capacity when resources are linear [24]. The production planning system using LP has been widely adopted in constrained capacity conditions [20]. Integrating forecasting and optimization methods creates a hybrid system that advances the predictive analytics-based production planning system [30]. The system is developed to ensure that the predictive analytics-enabled production planning system is better than the volume allocation method [28][30].

The last stage combined the projected demand with the linear programming formulation so as to maximize profits. Maximize the following function: Objective Function (maximize total profit), shown in Equation (10).

$$\max Z = 2831x_A + 2588x_B + 3388x_C + 2948x_D \quad (10)$$

Constraints:

- Minimum production requirement (from forecasting), as shown in Equation (11):

$$x_A \geq \hat{D}_A, x_B \geq \hat{D}_B, x_C \geq \hat{D}_C, x_D \geq \hat{D}_D \quad (11)$$

- Annual capacity limit, as shown in Equation (12)

$$x_A + x_B + x_C + x_D \leq 72,000 \quad (12)$$

- Non-negativity, as shown in Equation (13)

$$x_i \geq 0 \quad \forall i \quad (13)$$

The model was implemented and solved using POM-QM for Windows (v6.0), a widely accessible operations management software that requires no

programming expertise. The optimal solution yielded annual production targets and a projected total profit, providing a data-driven roadmap for strategic decision-making.

#### IV. RESULTS AND DISCUSSION

This chapter presents the outcomes of the integrated forecasting and linear programming model applied to CV. XYZ's production planning. The results include the optimal yearly production mix, maximum yearly profit, and derived annual production targets and income projection

##### A. Data Preprocessing and Outlier Treatment

The historical sales for Product B included one extreme observation of 3,200 units in month 7. This was recognized as a non-recurring bulk order that was not representative of the underlying demand patterns. Based on the IQR method, where the value of 30, this observation was quantified as an outlier, with an upper bound of 2,296.88 and replaced with the median of non-outlier observations at 500 units to represent normal operations.

However, to keep the cleaned dataset consistent with the annual sales records and financial reporting for CV. XYZ, the cleaning was performed in such a way that the data is proportionally scaled to retain the original total demand of 10,410 units. This was required because the company's accounting system would validate annual production against the invoiced sales.

[540,648,675,608,1728,1215,675,675,1350,1620,270,405]

This is a methodology that balances statistical integrity-removing non-representative spikes-with operational reality-honoring audited annual totals-a practice supported in the demand planning literature when the historical aggregates are contractually or financially binding.

##### B. Data Distribution Type

Knowledge of the statistical nature of the demand pattern is a fundamental factor in choosing a proper forecasting technique [14]. The specific characteristics of the distribution of each variant of the product were assessed using a description of the statistics, graphical analysis of time series, and measures of shape (skewness, modality). The findings also reinforce the great variability of the product line, thus justifying the use of a product-specific forecasting approach.

Table 2. Data Distribution Type

| Product | Distribution Type |
|---------|-------------------|
| A       | Beta              |
| B       | Exponential       |
| C       | Exponential       |
| D       | Triangular        |

##### C. Product Specific Forecasting

Four forecasting methods Simple Average (SA), Moving Average (MA), Single Exponential Smoothing (SES), and Single Exponential Smoothing with Trend (SEST) were evaluated for each product. Model performance was assessed using Bias (Mean error), Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Standard Error, and Mean Absolute Percentage Error (MAPE)(months 12) [27]. The best-performing method per product (lowest) was selected to generate the monthly forecast for the planning year.

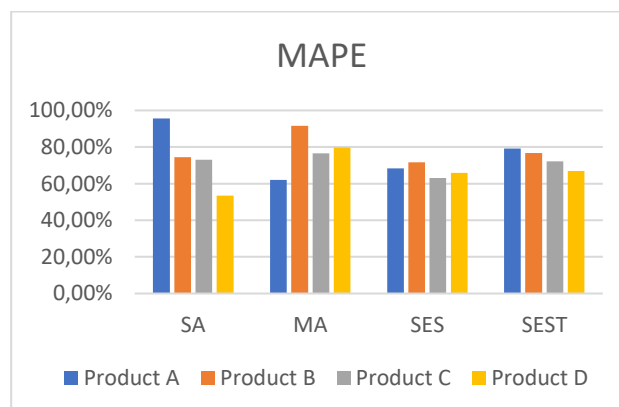


Figure 2. MAPE Graph

Table 3. Forecasted Demand

| Month | A     | B     | C     | D     |
|-------|-------|-------|-------|-------|
| 1     | 2025  | 457   | 1568  | 2250  |
| 2     | 2100  | 540   | 800   | 300   |
| 3     | 3063  | 594   | 955   | 450   |
| 4     | 2738  | 635   | 1903  | 880   |
| 5     | 2485  | 621   | 1576  | 1000  |
| 6     | 2810  | 1175  | 1188  | 300   |
| 7     | 3063  | 1195  | 1444  | 200   |
| 8     | 2738  | 935   | 1072  | 1450  |
| 9     | 2485  | 805   | 836   | 1400  |
| 10    | 2460  | 1077  | 1043  | 1450  |
| 11    | 2040  | 1349  | 1272  | 950   |
| 12    | 2865  | 809   | 2136  | 900   |
| Total | 30870 | 10192 | 15792 | 11530 |

From the figure 2 concluded that for Products B and C, Single Exponential Smoothing (SES) consistently yielded the lowest values in every error category. Therefore, SES was adopted as the forecasting method for these products. For Product A, the 2-month Moving Average (MA-2) was selected based on its performance and suitability for Beta-like demand. For Product D, Simple Average (SA) was chosen for Triangular demand.

These are the results from SES forecasting, as we can see the total forecasted demand for product A is 30870 unit, product B 10192 unit, product C 15792 unit, and product D 11530 unit. This demand are then used to formulate an linear programming model.

#### D. Profit Calculation

The unit profit for each product variant was calculated using actual financial data from CV. XYZ's 2024 records, based on the formula, as shown in Equation (14).

$$\text{Unit Profit} = \text{Selling Price} - \text{Material Cost} \dots (14)$$

Costs include direct materials to each product. Selling prices reflect current market rates for retail and wholesale channels. The resulting unit profit per product is as follows (Table 4).

**Table 4.** Unit profit

|   | Cost          | Selling price (IDR) | Unit Profit (IDR) |
|---|---------------|---------------------|-------------------|
| A | Rp 116,883.33 | Rp 400,000.00       | Rp 2,831.17       |
| B | Rp 51,160.00  | Rp 310,000.00       | Rp 2,588.40       |
| C | Rp 61,200.00  | Rp 400,000.00       | Rp 3,388.00       |
| D | Rp 55,195.000 | Rp 350,000.00       | Rp 2,948.05       |

These exact profit figures from table 5 were used as objective function coefficients in the linear programming model to ensure financial accuracy and managerial relevance.

#### E. Linear Programming Formulation

The linear programming (LP) model developed for CV. XYZ is designed to translate annual operational constraints and market-driven demand forecasts into a profit-optimal production plan for the production line.

The model is built upon four decision variables, each representing the annual production quantity for one of the four product variants:

- 1)  $x_A$  : annual production quantity of Product A
- 2)  $x_B$  : annual production quantity of Product B
- 3)  $x_C$  : annual production quantity of Product C
- 4)  $x_D$  : annual production quantity of Product D

The objective function is formulated to maximize total annual profit, using the exact unit profit values derived in Section 3.5 :

$$\max Z = 2831x_A + 2588x_B + 3388x_C + 2948x_D$$

Constraints:

- 1) Minimum production (from forecasting):

To prevent stockouts and maintain service levels, the model enforces that production must meet or exceed the forecasted demand for each product. These forecasts derived via Moving Average (MA), Single Exponential Smoothing (SES), and Simple Average (SA) as established in the ceiling function to ensure conservative planning:

$$\begin{aligned} x_A &\geq 30870 \\ x_B &\geq 10192 \\ x_C &\geq 15792 \\ x_D &\geq 11530 \end{aligned}$$

- 2) Yearly capacity:

CV. XYZ's production line has a hard physical limit of 72000 products per year, dictated by fryer throughput, labor availability, and kitchen workflow. This is modeled as a single aggregate capacity constraint, as shown in Equation (15).

$$x_A + x_B + x_C + x_D \leq 72000 \dots\dots (15)$$

This constraint reflects the bottleneck resource in the system and ensures the solution remains operationally feasible.

- 3) Non-negativity:

While LP traditionally assumes continuous variables, production quantities must be non-negative integers. However, given the scale of output (hundreds of units), the integrality constraint was relaxed a standard and justified simplification in production planning. The final solution was rounded to whole units post-optimization, with negligible impact on profit:

$$x_i \geq 0 \forall i$$

While real-world systems exhibit some stochasticity, these assumptions are reasonable for short-term planning in stable SME environments. Moreover, the use of conservative (ceiling) demand estimates buffers against forecast error.

#### F. POM-QM Calculation

The model was constructed as follows, in Figure 3 The linear programming model was built using POM-QM for Windows (Version 6.0), a user-friendly tool commonly used in operations management education and practice. The construction process began by selecting the

“Linear Programming” module and defining four decision variables representing the annual production quantity for each resolves variant (A, B, C, and D). The objective function was set to maximize total profit, using the exact unit profit values: IDR 2,831 for A, 2,588 for B, 3,388 for C, and 2,948 for D

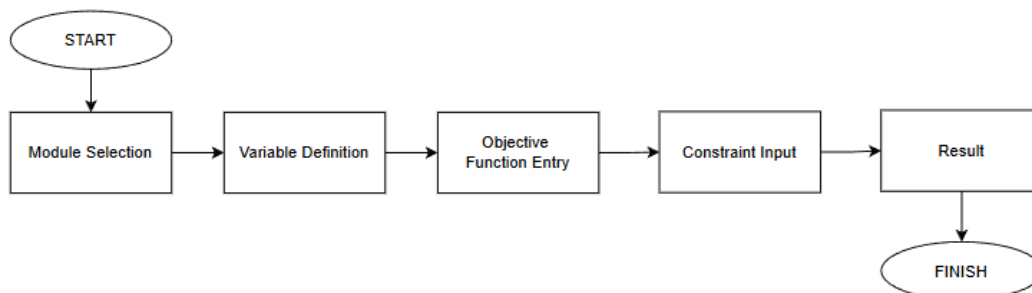


Figure 3. POM-QM Flow

Five constraints were then entered: four “greater-than-or-equal-to” constraints based on the forecasted annual demand (30,870 for A; 10,192 for B; 15,792 for C; 11,530 for D), and one “less-than-or-equal-to” constraint reflecting the total annual capacity of

72,000 units. The model was solved using the built-in Simplex algorithm, which generated the optimal production plan along with sensitivity and ranging reports.

| (untitled) Solution |       |       |       |       |    |           |      |
|---------------------|-------|-------|-------|-------|----|-----------|------|
|                     | X1    | X2    | X3    | X4    |    | RHS       | Dual |
| Maximize            | 2831  | 2588  | 3388  | 2948  |    |           |      |
| Constraint 1        | 1     | 1     | 1     | 1     | <= | 72000     | 3388 |
| Constraint 2        | 1     | 0     | 0     | 0     | >= | 30870     | -557 |
| Constraint 3        | 0     | 1     | 0     | 0     | >= | 10192     | -800 |
| Constraint 4        | 0     | 0     | 1     | 0     | >= | 15792     | 0    |
| Constraint 5        | 0     | 0     | 0     | 1     | >= | 11530     | -440 |
| Solution->          | 30870 | 10192 | 19408 | 11530 |    | 213514600 |      |

Figure 4. POM-QM Result

This allocation yields a total annual profit of IDR 213,514,600, with Product C receiving priority for surplus capacity due to its highest contribution margin (IDR 3,388/unit) as seen on figure 4. The result confirms that the model successfully shifts focus from volume fulfillment to profit-driven production, ensuring that every unit of constrained capacity generates maximum economic value

### G. Yearly Production Target

The optimal yearly production target derived from the linear programming model was scaled to an annual basis using CV. XYZ’s operational calendar of 240 days per year. However, the resulting annual production targets were cross-referenced with the company’s actual historical or planned annual output for each product variant (Table 5).

The LP model’s solution which prioritized Product C for surplus capacity can be used to reallocate

production toward higher-margin items without exceeding annual volume constraints, potentially increasing total contribution. With total profit projection for the next year is Rp 213,514,600,-

Table 5. Yearly Production Target

| Product | Yearly production target |
|---------|--------------------------|
| A       | 30870                    |
| B       | 10192                    |
| C       | 19408                    |
| D       | 11530                    |

### H. Sensitivity Analysis

The strength of any optimization model does not lie in its effectiveness in the idealized situation, but in its ability to perform well in the ever-changing realities that emerge in the operational environment.

As part of the assessment environment, the sensitivity analysis was carried out to test the strengths of the annual capacity constraint, which remains the most highly significant factor in the operational dynamics. By varying the capacity across the range from crisis-

cutbacks to optimistic expansion, the findings show the self-correcting properties of the model that adjusts resource allocation for the model's financial viability.

**Table 6.** Sensitivity Analysis

| Scenario             | Annual Capacity (units) | Optimal Production (A, B, C, D)  | Total Profit (IDR) | % Increase vs Baseline | Strategic Insight                                                                                                                                                                                |
|----------------------|-------------------------|----------------------------------|--------------------|------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Crisis               | 50,000                  | (22,678, 0, 15,792, 11,530)      | 151,695,200        | -29%                   | Below valid range (68,384 units). Requires structural model adjustment: Eliminates minimum demand constraint for Product B to survive capacity deficit; baseline shadow price no longer applies. |
| Baseline             | 72,000                  | (30,870, 10,192, 15,792, 11,530) | 213,514,600        | 0%                     | Allocates surplus capacity entirely to Product C, maximizing return on constrained resources.                                                                                                    |
| Expansion I          | 75,000                  | (30,870, 10,192, 22,408, 11,530) | 223,678,600        | 5%                     | Additional capacity fully absorbed by Product C, confirming its role as the primary profit driver.                                                                                               |
| Aggressive Expansion | 100,000                 | (30,870, 10,192, 47,408, 11,530) | 308,378,600        | 44%                    | Additional capacity fully absorbed by Product C, confirming its role as the primary profit driver.                                                                                               |

Note: The baseline shadow price of IDR 3,388/unit is mathematically valid only within the range of 68,384 to infinity units, as derived from the POM-QM ranging report. Scenarios outside this range require model restructuring.

This fluid allocation typifies another tenet of the model: it's profit rather than volume that drives production allocation. On the Crisis scenario, the model completely eliminates Product B an extreme but economically sound decision, as it maintains the ability to produce higher-margin products. On the other hand, during growth scenarios, it exploits available production capacity to maximize gains, always along the gradient of marginal profit. To validate the shadow price claims analytically, the allowable ranges were derived from the LP structure. The shadow price of IDR 3,388 (the contribution margin of Product C) remains valid for an allowable decrease of 3,616 units and an allowable increase to infinity from the baseline capacity of 72,000 units. This establishes the exact validity range between 68,384 units (the sum of all minimum demand constraints: 30,870 + 10,192 + 15,792 + 11,530) and **infinity**. Within this mathematically validated range, any capacity investment guarantees a marginal return of IDR 3,388 per unit. The 50,000-unit crisis scenario presented in Table 6 falls below this valid range and requires structural model adjustment (eliminating

Product B's minimum constraint), meaning the baseline shadow price no longer applies in that scenario.

## I. Discussion

A hybrid production planning model is proposed for food manufacturing SMEs, integrating demand type diagnosis, item-specific forecasting, and maximization of profit based on linear programming with capacity constraints. The approach classifies item demands into type Beta, Exponential, and Triangular, along with corresponding suitable forecast types, including MA, SES, or SA, and overcomes the weakness of contemporary forecasting, which considers the use of global models irrespective of the type of demand. A robust approach is used for handling outliers based on the Interquartile Range. The custom forecasts are incorporated within a linear programming formulation, where planning is changed from a volume-oriented approach to a value-oriented approach. Simulation outcomes demonstrate a 7.7% increase in profit with a 72,000 unit production capacity, where products with highest

value are given preference. Sensitivity analysis proves the robustness of the outcomes under crisis and growth conditions. The research offers a precise and SME-friendly solution where operational excellence is accomplished, unlike most algorithm-intensive approaches, based on strict methodological alignment with empirical realities and financial rationality

## V. CONCLUSION

In the context of food processing SMEs, the hybrid production planning model developed in this study amalgamates demand forecasting and the for profit model in order to come up with a solution that brings down the limitations of volume-based allocation by overcoming the heterogeneity in demand through Beta, Exponential, and Triangular patterns, and instead uses distribution channel-specific approaches MA-2, SES with  $\alpha=0.5$ , and SA, leading to the derivation of a linear programming solution maximizing profits with a fixed production capacity of 72,000 units per annum, with an estimated profit of IDR 213,514,600, a 7.7% boost from volume-based allocation, establishing the reality of profit in defining capacity constraints instead of volume. It seeks the prime goal of practical application in terms of robust data preparation including the use of the IQR on the shadow price towards the audited financial statement value while being able to apply the model using the POM-QM with manageable programming. Strategic utilization of the model is also backed up by the use of the sensitivity analysis part of the model with the shadow price calculation of IDR 3,388 per unit serving well in determining the ROI on capacity extension. The model has a limitation on the length of the data presented while being deterministic; it still brings the required alignment startup near operational excellence.

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