Increasing Production Machine Capacity In Food Product Msmes Using A Linear Proramming Approach

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Abstrak

This study aims to optimize production capacity in a small and medium-sized enterprise (SME) that produces three types of meatballs: beef meatballs, chicken meatballs, and fish meatballs, by considering both cost aspects and demand fulfillment. A mathematical model was developed to minimize total costs, including operational costs, machinery costs, capacity expansion costs, loss costs, and outsourcing costs. Decision variables include the optimal quantity of demand fulfilled, , actual cycle time, the total number of machines operated, and the number of additional machines required. The optimization results show an objective function value of IDR 89,065,838, achieved through selective machine additions and the use of overtime during peak periods. Chicken meatball production exhibited a steady increase without requiring overtime, while beef and fish meatballs required overtime in certain periods. Sensitivity analysis indicates that normal operational costs are the most influential factor affecting total costs, followed by machinery costs and overtime costs. These findings emphasize the importance of proper capacity planning, cost control, and efficient production scheduling strategies to ensure sustainable demand fulfillment.

***Keyword**: Mathematics model, Production, Operation cost, Optimize*

INTRODUCTION

The dynamics of modern industry are characterized by shorter product life cycles, high demand variations, and "fast-paced" service pressures encourage companies to continuously evaluate the adequacy of their production capacity. Globalization expands markets while adding to volatility, while digitalization (IoT, real-time demand analytics) makes market signals faster to the factory. On the downstream side, customers demand short lead times, higher customization, and near-perfect order fulfillment rates (service levels) (Avraam et al., 1999; Read & George, 1990). On the upstream side, supply chains face supply uncertainty, long procurement lead times, and limited skilled manpower. This combination of factors makes adding capacity—whether in the form of debottlenecking, overtime, subcontracting, shift additions, new line investment, automation, or facility expansion a strategic decision (Contuzzi et al., 2025; Veena et al., 2024).

Capacity decisions are "lumpy" and long-term: unlike inventory adjustments, capacity cannot be subtly lowered every day (Wang et al., 2025). Buying machinery, building a building, or adding a line requires large capital expenditure (capex), installation time, and operator training. In addition, capacity is not only about the number of machines, but also the balance between processes (bottleneck vs non-bottleneck), the availability of tooling, utilities (electricity, steam, compressed air), and supply chain readiness (Meng et al., 2025). Because the financial and operational implications are wide-ranging, companies need an approach that can quantify the trade-offs between costs and services (Attia, 2025). This is where mathematical optimization, especially Integer Linear Programming (ILP), becomes relevant, as it can formulate "discrete" decisions (yes/no, how many units of capacity modules) with complex business constraints, while also finding optimal solutions globally (C. Y. Chen & Liao, 2011).

The novelty of this research lies in the formulation of a mathematical model based on Integer Linear Programming that determines the optimal decision on the use of production capacity with realistic limits. The model incorporates capacity module options (machine addition/shift/overtime), cross-process balance, setup time, skilled labor limitations, raw material availability, and budget limits and service SLAs (L. Y. Chen et al., 2025; Nandakumar et al., 2025; Simonis & Nickel, 2025). Objective functions minimize total costs (investment, operations, inventory, back order, outsourcing) and ensure multi-period demand fulfillment. In addition, the formulation considers the ramp-up curve, utility capacity, and limitations of finished warehouses, as well as internal production quality risks (Crema, 1995). The validation was carried out through a case study on a food company in the city of Bandung, with historical data on demand, processing time, OEE, and cost parameters. In this study, the authors ran seasonal and promotional scenarios, as well as sensitivity analysis to supplier lead time and engine downtime, to test the reliability of the solution. The results of the model are interpreted into implementable policies such as optimal combination of lines and working hours, when expansion is needed, and safe outsourcing levels aimed at improving operational efficiency, delivery accuracy, and company competitiveness.

METHOD

The methodology of this research is designed as an integrated flow that moves from goal formulation to implementation planning, with a focus on capacity determination using linear programming with discrete decisions. The research flow that is usually displayed in the flowchart is now narrated as follows. The research begins by defining the objectives, scope, horizon, and performance indicators. After that, demand, process, capacity, and cost data are collected and cleaned (Mezatio et al., 2022; Tan et al., 2016). Demand is forecasted and effective capacity is calculated. Capacity modules and flexible policies such as overtime and outsourcing are designed (Burdett et al., 2017; Jabeur et al., 2024; Tavaghof-Gigloo et al., 2016). The model formulation is built and implemented on the solver, then carried out until a solution that can be accounted for is obtained. Results are internally verified and validated against historical data. A series of scenarios and sensitivity analyses are executed to test the resilience of the policy. The findings are then synthesized into expansion, overtime, and production plans, which are followed by the preparation of implementation plans, system integration, and performance monitoring mechanisms. With such a flow, this methodology ensures that the resulting capacity decisions are not only mathematically optimized, but also realistic, transparent, and ready to execute. The research commenced with a clearly defined scope: a food manufacturing company in Bandung, with the main production stages consisting of grinding, mixing, and finishing; a one-year planning horizon; and performance indicators such as total cost. At this initial stage, operational assumptions and constraints were explicitly stated to ensure that every decision generated by the model could be traced and audited.

The next stage involved data acquisition and processing. Demand data were compiled from historical sales, promotional plans, and customer orders; process data were obtained from standard times per SKU, process routes, and information on setup and changeover; capacity data included the number of lines and machines, regular working hours, additional shift options, OEE metrics, and machine reliability profiles; while cost data covered machinery investment, labor and energy costs, inventory costs, delay penalties, outsourcing costs, overtime rates, and annual budget limitations. The data were cleaned of outliers and missing values, then demand forecasting was carried out using consistent methods such as exponential smoothing or ARIMA, providing both baseline values and reasonable uncertainty ranges. Effective capacity was calculated by multiplying available hours by OEE and line efficiency, after which standard times were converted into capacity consumption coefficients per SKU and process. At the same time, capacity modules were operationally defined—such as one module representing one machine plus one operator and tooling, or an additional shift—so that investment decisions could be represented as integer variables.

The model formulation was expressed in business terms rather than symbols alone, defining how many capacity modules to add to each line, how many overtime hours to allocate as flexible capacity, and what levels of inventory and order fulfillment delays would be permitted. The model's objective was to minimize the discounted total cost over the planning horizon, including investment, operating, inventory, delay penalty, outsourcing, and overtime costs, while maintaining service levels in line with targets. A balance between demand, internal production, outsourcing, inventory, and potential backorders was enforced in each period. Capacity constraints ensured that total process time requirements did not exceed regular capacity plus accumulated capacity from installed modules and overtime contributions. Other realistic constraints were added to ensure implementable solutions, such as annual investment ceilings, labor availability based on skills matrices, warehouse capacity, utility and peak load limits, and minimum service rules. Once formulated, the model was implemented in a reliable optimization solver. Formulation strengthening practices were applied to accelerate convergence, such as avoiding overly loose linking parameters, setting tight variable bounds, and preprocessing to fix obviously infeasible variable values. The solution process recorded the solution status, computation time, and optimality gap, ensuring measurable solution quality. The main results were translated into actionable policy plans, including schedules for module additions by line and period, optimal overtime allocation, safe outsourcing strategies, and an aggregate production plan consistent with warehouse and utility constraints.

RESULT AND DISCUSSION

1. Problem Description

In this study, the object studied is a food processing MSME that produces various variants of meatballs. The business unit operates at one production site with semi-automatic equipment, daily labor, and marketing to local retailers. The focus of the research is limited to three main products: beef meatballs, fish meatballs, and chicken meatballs, as these three absorb most of the demand and have different process characteristics. The process flow includes raw material acceptance and sorting, seasoning formulation, milling, emulsification in bowl cutters, molding, boiling to cooking, rapid cooling, packaging, labeling, and cold storage. Demand is seasonal with peaks on weekends, while capacity is determined by machine availability and working hours.

2. Mathematical Model

The cost components analyzed include the addition of machines, operations, production, and overtime. All elements of the research model are summarized and shown in Table 1, as a reference for the cost structure used in evaluation, capacity scenario comparison, and decision-making related to process efficiency and demand fulfillment. This information facilitates the transparency of the analysis and replication of the study.

a. Purpose Function is Minimizing production costs. Decision Variables are The number of products produced by the company in normal times
b. The number of products the company produces in overtime
c. Number of machines produced each period

Performance criteria are cost of increasing production capacity with the purchase of machinery, cost of adding overtime hours.

The objective function in this model is to minimize the total cost as in equations (1) and (2)

$$Z = \min\ (Mechine\ cost + Operation\ cost + b + Overtime\ Operational\ Costs$$

$$= \min \sum_{t \in T} \Bigg| ((Xmp_t CMp) + (Xmo_t CMo) + (Xmm_t CMm) + (Xmj_t CMj) + (XS_t CMs)) + \left(\left(\sum_{i \in I} XEmp_t . COMp_i \right) + \left(\sum_{j \in J} XEmo_t . COMo_j \right) + \left(\sum_{k \in K} XEmm_t . COMm_k \right) + \left(\sum_{l \in L} XEmj_t . COMj_l \right) + \left(\sum_{s \in S} XEms_t . COMs_s \right) \right) + \sum_{\alpha \in A} \sum_{p \in P} CP_\alpha . YP_{pt} \Bigg|$$

3. Applied in real case

A mathematical model that has been designed and applied to the real case of MSME X in the city of Bandung. Data was obtained from MSMEs, and various official websites were collected and Processed. Data parameterization is used in calculations to find solutions to increase capacity needed by MSMEs.

Tabel 1. Machine Specifications and Annual Production Capacity

Machine type	Price (Rp)	Cap Kg/day	Actual cap Kg/day	Annual cap Kg/year
Meat grinding machine	30,185,000	5	4	1440
Dough mixing machine	6,500,000	3	2.4	864
Meatball Molding Machine	49,100,000	200	160	57600
Ice chopper machine	1,000,000	50	40	14400
Vacuum packaging machine	6,255,000	35	28	10080

This calculation is carried out using a linear programming method using the model in the Mathematical Model chapter. The model is used to optimize the total cost required by the company by considering capacity additions. Data parameterization is used in calculations to find solutions to increase capacity needed by MSMEs. The model is used to optimize the total cost required by the company by considering capacity additions. The objective fauction is Rp 89.065.838.

Table 2. Optimation results

Var. Decision	6	7	8	9	10
Meat grinding machine	0	0	0	0	2
Dough mixing machine	0	0	0	0	2
Meatball Molding Machine	3	0	0	0	0
Ice chopper machine	2	0	0	0	0
Vacuum packaging machine	0	0	0	0	0
Beef meatballs	15.715	15.183	14.451	13.719	12.981
Chicken meatballs	21,881	22,538	23,214	23,910	24,628
Fish meatballs	14,800	15,244	15,702	16,173	16,658
Beef meatballs	0	3.044	5.143	6.241	6.542
Chicken meatballs	0	0	0	0	0
Fish meatballs	0	0	0	0	0

Table 2 presents production and capacity decisions for periods labeled 6 through 10, representing a distinct operational era in the planning horizon. The first section lists the number of machines added for each type. In this era, meat grinding and dough mixing machines remained at zero additions until period 10, where two units of each were introduced—indicating a capacity expansion in the final phase. Meatball molding machines showed an initial presence of three units in period 6, which were subsequently reduced to zero in the following periods, suggesting that either demand leveling or process optimization reduced the need for additional molding capacity. Ice chopper machines followed a similar pattern, with two units added in period 6 and no further additions thereafter. Vacuum packaging machines had no additions across the entire era, implying sufficient existing capacity.

The second section of the table records normal-time production volumes. Beef meatball production started at 15,715 units in period 6 and declined steadily to 12,981 units by period 10, possibly reflecting demand shifts or resource reallocation. Chicken meatball output consistently increased, from 21,881 units in period 6 to 24,628 units in period 10, showing strong and growing market demand. Fish meatball production also trended upward, from 14,800 to 16,658 units across the era.

The final section shows overtime production. Beef meatballs were produced in overtime from period 7 onward, peaking at 6,542 units in period 10, highlighting that this product required supplemental capacity during later stages. Chicken and fish meatballs recorded no overtime production in this era, suggesting that their demand was fully met within normal operating hours.

Overall, the era from period 6 to 10 reflects a strategic balance between selective machine additions, targeted overtime use for beef meatballs, and gradual output growth for chicken and fish meatballs, aligning resources with evolving demand patterns.

4. Sensitivity Analysis

Sensitivity analysis aims to assess the extent to which changes in input parameters or variables affect model results. This analysis can identify the factors that have the most influence on output, assess risks, and formulate more precise and efficient decision-making strategies. Table shows the results of sensitivity analysis per product.

Table 3. Sensitivity analysis per product

Product	Baseline Fee (Rp)	+10% Request (Rp)	-10% Request (Rp)	Delta+10% (Rp)	Delta-10% (Rp)
Beef Meatballs	30386288	33424917	27347659	3038628	-3038628
Chicken Meatballs	21311841	23443025	19180657	2131184	-2131184
Fish Balls	15101248	16611373	13591123	1510124	-1510124

Based on the results of the sensitivity analysis per product, it can be seen that chicken meatballs account for the largest portion of costs due to their consistently high production volume throughout the period. An increase or decrease in demand of ±10% on this product will have a significant impact on total costs, especially on the normal operating cost component, considering that there is no overtime production or outsourcing to meet demand. In other words, a small change in the volume of chicken meatballs is directly proportional to the increase or decrease in overall operating costs. For beef meatballs, cost sensitivity is also quite felt, especially during peak periods that require overtime production. The ±10% increase in demand affects not only normal operating costs, but also overtime costs, which are proportionally more expensive per unit. Therefore, capacity management in peak periods is important to reduce cost spikes. Fish balls have the smallest cost contribution among the three products, but in the early period there was overtime which made cost sensitivity quite high at that stage. Although the total impact is not as big as chicken or beef meatballs, overtime control strategies at the beginning of the period can help reduce costs.

Overall, the greatest efficiency can be achieved by optimizing chicken meatball production to remain efficient in high volumes, reducing the need for overtime for beef and fish meatballs, and considering adding machines in peak periods to avoid expensive overtime costs.

CONCLUSION

Based on the results of the study, it can be concluded that the production capacity planning strategy implemented is able to optimize the use of resources and reduce total costs to reach the objective function value of Rp 89,065,838. The addition of machines is carried out selectively, especially in periods of surge in demand, to reduce the reliance on overtime production which has a higher cost per unit. Chicken meatball production consistently increased without requiring overtime, indicating adequate capacity, while beef meatballs and fish meatballs took advantage of overtime in certain periods to meet peak demand. Sensitivity analysis showed that normal operating costs were the most influential factor in total costs, followed by machinery investment costs, while overtime costs had a smaller but still significant impact during peak periods. These findings underscore the importance of proper capacity management, operational cost control, and optimization of production schedules to maintain efficiency and meet market demand in a sustainable manner.

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