Managing Inventory and Production in an SME through ABC Categorization and an Optimization Approach

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ABSTRACT

Small and medium-sized enterprises (SMEs), which make up over 97.2% of all businesses, play a crucial role in Malaysia's economy by contributing significantly to GDP and employment. For these enterprises to maintain steady growth, production activities must be optimized to maximize resource utilization. This research highlights the vital role of effective production planning in stimulating growth and maximizing profits for SMEs in Malaysia. Acquiring data from a local SME, ABC categorization and optimization approach are employed in this study. A comparative analysis of linear programming and integer linear programming for profit maximization successfully reveals the potency of integer linear programming for profit maximization in real world scenarios, demonstrating a 4.53% increase in annual profit.

Keywords: SME, ABC Categorization, Optimization, Linear Programming, Integer Production Planning Linear Programming, Profit Maximization

INTRODUCTION

SMEs is an integral part of Malaysia's economy. These enterprises account for 97.2% of all business establishments, contribute 38.2% to the Gross Domestic Product (GDP) and offer job opportunities for 7.3 million individuals [1]. Therefore, it is essential for SMEs to achieve positive business growth for long term sustainability. Consequently, in order to increase productivity and maintain their profitability and competitiveness, SMEs must optimize their production processes and work towards making the best use of all of their resources [2].

Decision-making is essential in terms of optimizing business processes. In today's time, manufacturing industries encounter difficulties in producing goods that meet the appropriate criteria for quality, quantity, and turnaround times while keeping expenses down and profits up [3]. Luckily, the development of multiple decision-making tools such as dynamic programming, integer programming, linear programming, and others has greatly improved decision-making across various business areas and processes and increased the quality of the decisions made [4].

Operations research is a quantitative method that enables businesses to make significant decisions using quantitative data. It evaluates and offers support as needed to make the most of few resources to achieve objectives [5]. A fundamental tool within operations research that is one of the most effective optimization techniques is linear programming (LP), a mathematical method designed to determine the best use of scarce resources to accomplish desired goals [6]. Widely applied in operations research and management sciences, LP addresses a range of challenges such as allocation, transportation, and assignment problems, providing a systematic approach for making choices among different courses of action [7].

Capacity, encompassing the collective productive potential of all utilized resources, including personnel and equipment, plays a pivotal role in decision-making across various levels—strategic, tactical, and operational [8]. At its core, capacity decisions influence the organization's ability to meet objectives and efficiently utilize resources [9]. The underutilization of critical elements like machines, materials, and labor results in direct financial losses due to the costs associated with unused capacity. Consequently, the key to maximizing an organization's profit lies in prioritizing the optimization of resource utilization, with a subsequent focus on minimizing waste in manufacturing operations [10].

Aside from optimizing production capacity, a firm could also increase its profit by effectively managing its inventory [11]. Minimizing the quantity of products in inventory while meeting consumer demand is the aim of inventory management. A surplus of inventory can lead to significant expenses and negatively impact a company's financial performance [12]. As a result, inventory planning is essential for cutting down on the overall costs associated with ordering, holding, and shortage [13]. By practical means, ABC analysis is a popular inventory management method that groups products based on annual consumption rate. This approach is well known for its simplicity and ease of use, making it accessible to a broad audience [12].

This research focuses on key objectives within small and medium-sized enterprises (SMEs). Firstly, it aims to employ ABC categorization to classify SME inventory based on their value. Secondly, the research intents to define constraints impacting SME production for informed decision-making. Lastly, the research compares linear programming and integer linear programming approaches in profit maximization. Together, these objectives provide SMEs with a thorough framework for handling inventory management, production limitations, and optimization.

METHODOLOGY

This research was conducted using data sourced from local company in Selangor, Malaysia, which is a small and medium-sized enterprise (SME) specializing in engineering that is primarily engaged in machining processes. The company provides various services, such as material preparation, coarse grinding, finishing, and polishing. The data dates to 2022 and among the variables included are product ID, cost, sale price, profit, demand, CNC milling machine hours, lathe machine hours, cylindrical grinding machine hours, surface grinding machine hours and production time. Implementing the integrated approach of ABC categorization and optimization is hampered by a critical challenge: the requirement of data that must be reliable and complete. In both techniques, the key inputs include real-time demand forecasts, machine production rates, processing times, cost structures, and inventory levels. The optimization results stand to gain or lose greatly based on the input quality. Unfortunately, most SMEs operate without centralized data systems, relying instead on manual records or fragmented tools that essentially do not support any real-time analytic capability. In the absence of automated data collection and reporting infrastructure, data errors become rampant, and analysis for timely ABC reviews and optimization model adjustments to reflect changing conditions becomes cumbersome. Consequently, SMEs are likely to face data inaccuracy and inconsistency problems detrimental to their decision support system, which could lead to suboptimal performance despite the optimization model being sufficiently robust. The initiation of such an upgrade might require considerable investments in digital tools, inventory software, or basic ERP systems, which may prove a constraining factor for organizations with scanty resources.

ABC Categorization

ABC classification (or ABC analysis) is employed by inventory management teams to determine the most significant items within their product range and prioritize their management over less valuable ones [14]. The classification system recognizes that not all inventory holds equal worth and aligns with the Pareto Principle, where 20% of the stock contributes to 80% of the business's value [15]. The products are usually categorized into three groups based on their level of importance where group A represents items of high significance, group B denotes items of moderate importance, and group C signifies items of low or negligible importance.

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Considering these classifications, priority was given to Group A and Group B materials, while Group C materials were disregarded due to their minimal importance [16].

Classification of Products using ABC Categorization

Microsoft Excel was used to classify the products. The steps for ABC categorization are as follows:

Step 1: Determine the criteria for categorization. Typically, these criteria encompass crucial factors such as the value of sales, annual demand, the volume of sales, or the margin of contribution. Any one or a combination of these factors. In this study, ABC analysis is applied based on a cost-based calculation.

Step 2: Calculate the annual consumption value of each item using the Equation (1) below [17].

$$\text{Annual consumption value} = \text{annual demand} \times \text{cost per unit} \tag{1}$$

Step 3: Sort all the items according to annual consumption value in descending order, from highest to lowest [17].

Step 4: Calculate the value contribution of each item as a percentage of the total consumption value [17]. Mathematically, it is shown below in Equation (2).

$$\text{Item \% of total consumption value} = \frac{\text{item's annual consumption}}{\text{total consumption values}} \tag{2}$$

Step 5: Define percentage thresholds. Establish the specific percentages that will define each category. In this study, the ratio is divided into 70:20:10 where category A comprises the highest 70% of items based on their significance or worth, category B includes the subsequent 20% of items and category C represents the remaining 10% of items. These items hold the least importance or value and contribute to a relatively smaller portion of the total value when compared to Categories A and B [15].

Step 6: Group all the items according to their contribution to the overall inventory value.

Linear Programming

To solve the problem in this analysis, a linear programming model and integer linear programming model was developed. In linear programming, the variables can take any real value, including fractions or decimals whereas an integer linear programming (ILP) problem is a linear programming problem with the additional restriction that the decision variables must be integers [18]. The aim of the model is to maximize profitability by optimizing machinery production time [19].

Formulation of Mathematical Model

The software LINDO and LP Solve IDE were utilized to generate the model of this research. The four essential elements in formulating a linear programming and integer linear programming problems are: identifying the decision variables, constructing the objective function, defining the constraints, and explicitly stating the non-negativity constraint [19]. The steps are as follows:

Step 1: Define the decision variables of interest by expressing them as $X_1, X_2, \ldots, X_n$. In this study the decision variables are the number of products categorized under category A and B from the previous method. Category A and B products are prioritized in ABC categorization because they generally encompass items of greater value, significance, or overall influence when compared to Category C items.

Step 2: Find an objective function that includes a linear combination of decision variables. The objective

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function specifies the quantity that we aim to optimize, whether it is to maximize or minimize. In this study, the aim is to maximize profit, Z_{max}. The objective function model is as shown below in equation (3):

$$\begin{aligned} Z_{max} = {} & 11.50X_1 + 11.00X_2 + 12.50X_3 + 13.40X_4 + 11.75X_5 + 14.00X_6 + 15.65X_7 + \\ & 11.15X_8 + 14.30X_9 + 12.30X_{10} + 14.85X_{11} + 16.00X_{12} + 14.50X_{13} + 9.50X_{14} \\ & + 10.90X_{15} + 14.60X_{16} \end{aligned} \tag{3}$$

where X_i refers to the 16 different types of products.

Step 3: Formulate constraints that restrict possible values of decision variables by representing them as less than or equal to (≤) type inequality or greater than or equal to (≥) type inequality or 'equal to' (=) type equality respectively.

The constraints for this study are as below:

The machine processing time for CNC milling machine must be less than or equal to 240 hours (14400 minutes) per month and 2880 hours (172800 minutes) per year. Mathematically, the constraint in shown below in Equation (4).

$$\sum_{1}^{n} MM_i X_i \leq 172800 \tag{4}$$

The machine processing time for lathe machine must be less than or equal to 350 hours (21000 minutes) and 4200 hours (252000 minutes) per year. Mathematically, the constraint in shown below in Equation (5).

$$\sum_{1}^{n} LM_i X_i \leq 252000 \tag{5}$$

The machine processing time for cylindrical grinding machine must be less than or equal to 240 hours (14400 minutes) and 2880 hours (172800 minutes) per year. Mathematically, the constraint in shown below in Equation (6).

$$\sum_{1}^{n} CG_i X_i \leq 172800 \tag{6}$$

The machine processing time for surface grinding machine must be less than or equal to 240 hours (14400 minutes) and 2880 hours (172800 minutes) per year. Mathematically, the constraint in shown below in Equation (7).

$$\sum_{1}^{n} SG_i X_i \leq 172800 \tag{7}$$

Demand constraint for each type of product. Mathematically, the constraint in shown below in Equation (8).

$$\sum_{1}^{i} X_i \geq DM_i \tag{8}$$

The nonnegativity constraint. Mathematically, the constraint in shown below in Equation (9).

$$X_i \geq 0 \tag{9}$$

Integer constraint. Mathematically, the constraint in shown below in Equation (10).

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$$X_i \in Z \tag{10}$$

where:

MM_i = Machine processing time in CNC milling machine for each product, i

LM_i = Machine processing time in lathe machine for each product, i

CG_i = Machine processing time in cylindrical grinding machine for each product, i

SG_i = Machine processing time in surface grinding machine for each product, i

DM_i = Demand quantities for each product, i

Comparative Analysis of Optimization Approaches

A comparative analysis is conducted between linear programming (LP) and integer linear programming (ILP), where LP serves as the benchmark. While LP provides a foundational framework for optimizing decisions, the emphasis on ILP stems from its enhanced suitability for real-world scenarios [20]. Even though the combination of an ABC categorization along with some optimization techniques makes a potentially very powerful combination for improving production planning and inventory management, the main complexity comes with contacting the two methods together. ABC categorization, while conceptually straightforward, must be considered at time windows to be relaunched in terms of changing consumption patterns, new product introductions, and even changes in customer demand. In the absence of efficient regular updates, outdated categorization may happen, which causes a prioritization of inventory items that is not optimal.

The optimization component itself is math-intensive and software-intensive; it involves linear as well as integer linear programming. The development of accurate models requires careful and clear definition of the decision variables, objective functions, and several operational constraints. For small and medium enterprises (SMEs), this is a big obstacle as they do not have enough technical capacity, finance, and personnel trained in operations research or data analytics. Moreover, the actual implementation of these models into the real operations requires an accurate and up-to-date set of data-all of which a lot of SMEs do not have at this moment because of their manual systems for tracking or what would be termed siloed information. The very fact that they use software tools like LINDO and LP Solve IDE erects a further barrier to such companies, which do not use these kinds of software, because adoption would only be possible if there is a user-friendly interface or external consultancy.

Validation and Verification

The results obtained from the 2 optimization techniques, namely linear programming, and integer linear programming, are compared by checking if the solutions are consistent. When there is no major difference between both results, it proves that the techniques used are reliable. Furthermore, sensitivity analysis is carried out to check the model's adaptability to changes in parameters.

RESULTS AND DISCUSSION

This section will cover data-driven research findings.

ABC Categorization results obtained by Excel

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The ABC categorization analysis reveals the distribution and consumption patterns of the 24 products under consideration.

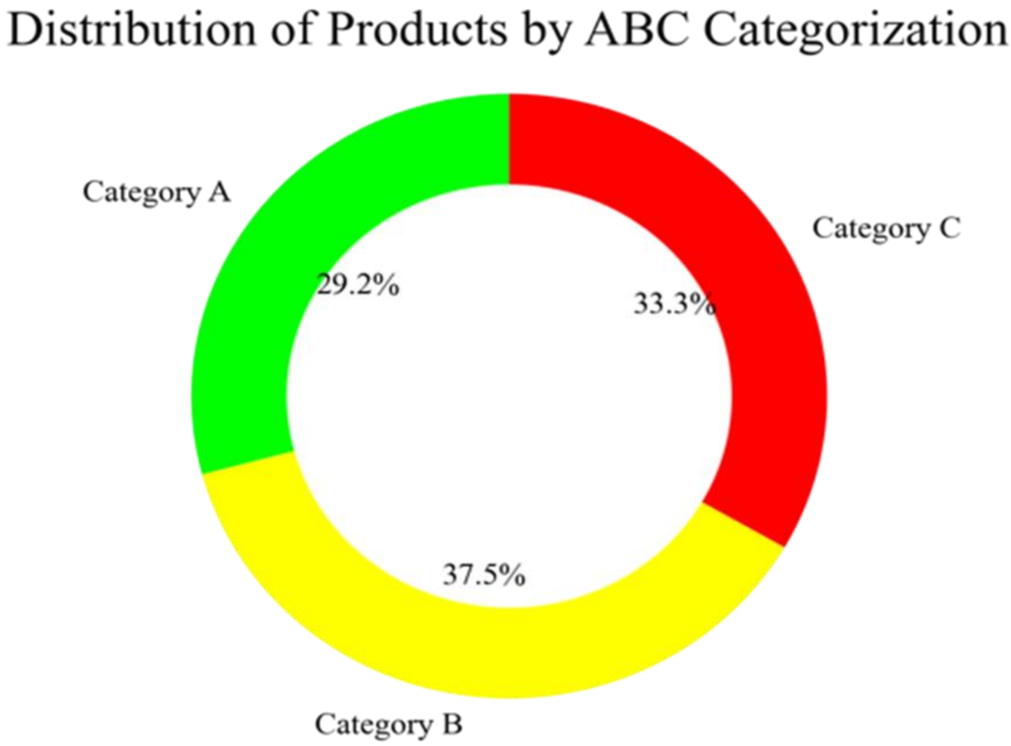

Fig. 1 Distribution of products by ABC categorization

From Fig. 1, it is apparent that the majority of the products are assigned to Categories 'A' and 'B.' Seven items, comprising 29.2% of the total, fall within Category 'A.' These products, despite being a minority, remarkably account for a substantial 67.0% of the overall consumption value. Nine items, constituting 37.5% of the total, are categorized as 'B.' Although they make up a larger portion of the product pool, their combined consumption value, 22.2%, is considerably lower compared to Category 'A.' In contrast, eight products, representing 33.3% of the total, are assigned to Category 'C.' Despite their relatively larger number, these products contribute only 10.6% of the consumption value.

For the subsequent stages of analysis, the focus will be exclusively on products falling within Category 'A' and 'B'. Category 'A' products, as highlighted earlier, have been identified as the most influential. Excluding the products in Category 'C' from further analysis due to their minimal impact on costs refines our strategies to maximize profitability based on the selected 16 products.

Comparison of Optimization Approaches

The analysis compares the optimal objective-function values obtained from linear programming model and integer linear programming model using two prominent optimization software, LINDO and LP Solve IDE.

Linear Programming Solution

The LP output from both LINDO and LP Solve IDE software for maximizing profits is shown in Table 1. The optimal objective-function value obtained in LINDO is RM 261,880.8, while LP Solve IDE produced a slightly higher value of 261,880.8375. Notably, the objective function, denoted as Z, is nearly identical in both software solutions.

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Table 1: Solution obtained for maximizing profit using LP

Variables	Optimum Value		Current Value
	LINDO	**LP Solve IDE**	
Z	261880.8	261880.8375	250492.95
X1	760.000000	760.000000	760.000000
X2	1345.000000	1345.000000	1345.000000
X3	995.000000	995.000000	995.000000
X4	1875.000000	1875.000000	1875.000000
X5	2450.000000	2450.000000	2450.000000
X6	1730.000000	1730.000000	1730.000000
X7	240.000000	240.000000	240.000000
X8	2015.000000	2015.000000	2015.000000
X9	2205.000000	2205.000000	2205.000000
X10	995.000000	995.000000	995.000000
X11	1666.861084	1666.861111	900.000000
X12	600.000000	600.000000	600.000000
X13	812.000000	812.000000	812.000000
X14	1055.000000	1055.000000	1055.000000
X15	1248.000000	1248.000000	1248.000000
X16	550.000000	550.000000	550.000000

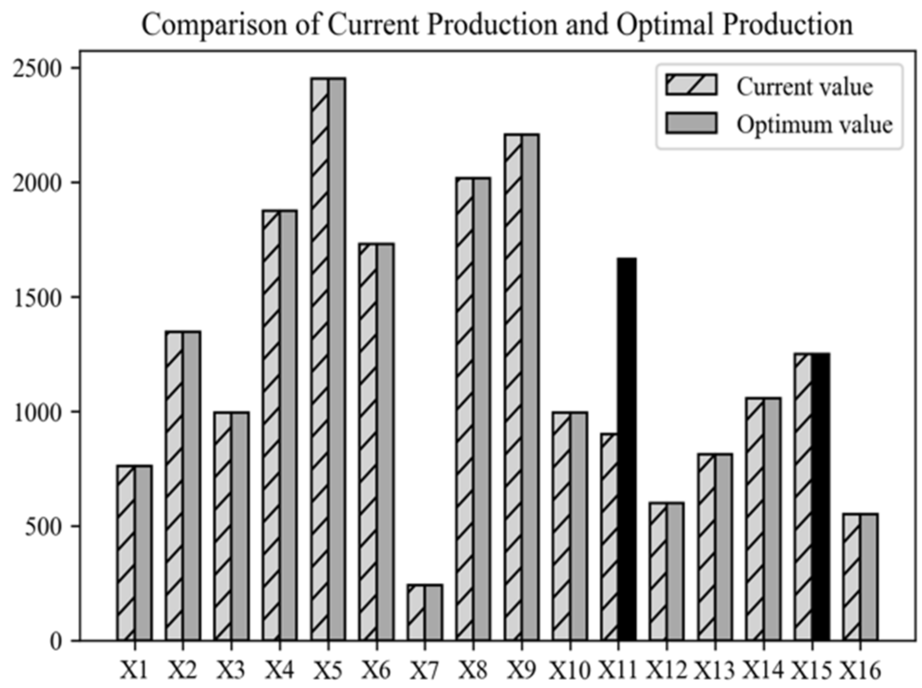

Fig. 2 Comparison of optimal production and current production using LP

Fig. 2 highlights a key observation: the company should consider increasing the production quantity of product X_{11} from 900 units to 1666.86 units while maintaining the production levels for all other products. This strategic insight, derived from the model, has pinpointed a clear opportunity for profit maximization by emphasizing the production of this specific product.

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Integer Linear Programming Solution

In Table 2, the integer linear programming results are displayed, revealing that both LINDO and LP Solve IDE software solutions converged on an identical optimal objective-function value, producing an outcome of RM 261,875.

Table 2: Solution obtained for maximizing profit using ILP

Variables	Optimum Value		Current Value
	LINDO	**LP Solve IDE**	
Z	261875	261875	250492.95
X1	760.000000	760.000000	760.000000
X2	1345.000000	1345.000000	1345.000000
X3	995.000000	995.000000	995.000000
X4	1875.000000	1875.000000	1875.000000
X5	2450.000000	2450.000000	2450.000000
X6	1730.000000	1730.000000	1730.000000
X7	240.000000	240.000000	240.000000
X8	2015.000000	2015.000000	2015.000000
X9	2205.000000	2205.000000	2205.000000
X10	995.000000	995.000000	995.000000
X11	1665.000000	1665.000000	900.000000
X12	600.000000	600.000000	600.000000
X13	812.000000	812.000000	812.000000
X14	1055.000000	1055.000000	1055.000000
X15	1250.000000	1250.000000	1248.000000
X16	550.000000	550.000000	550.000000

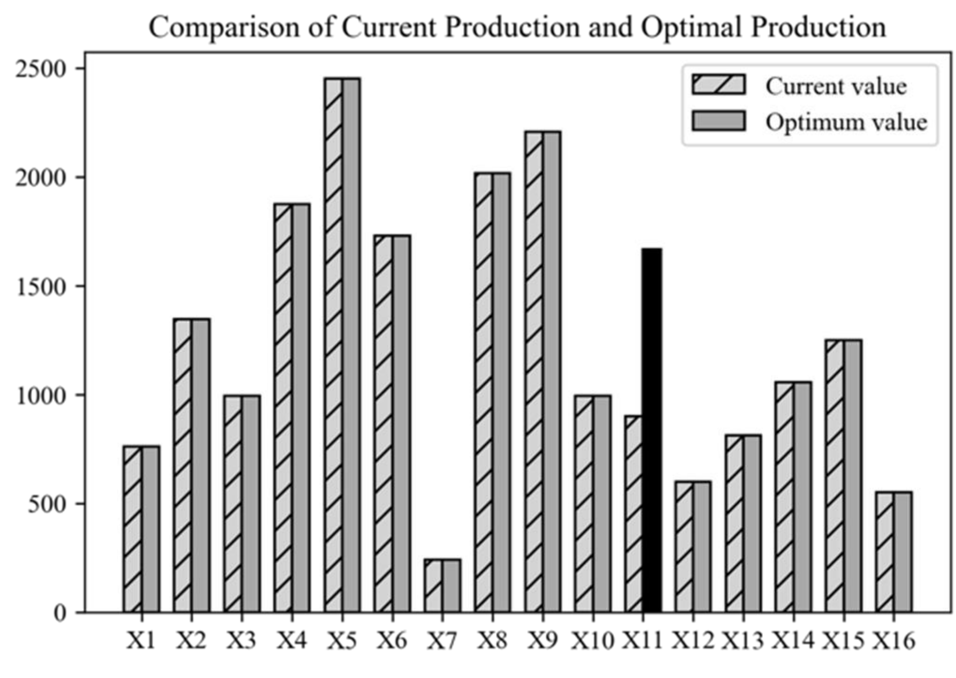

Fig. 3 Comparison of optimal production and current production using ILP

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Fig. 3 illustrates a clear path to optimizing profit – by increasing the production quantities of products X_{11} from 900 units to 1665 units and X_{15} from 1248 units to 1250 units while keeping the production levels for all other products constant. The model suggests that the company should concentrate its efforts on the production of products X_{11} and X_{15}, as these specific items are likely to generate the highest financial returns.

The application of LP served as a benchmark for evaluating the results derived from ILP. This is because the number of units to produce must be integers, the ILP model is more appropriate for this scenario. The LP solution, with an objective function value of RM 261,880.8, was marginally higher than the subsequent ILP solution, which yielded an objective function value of RM 261,875. This minimal variation highlights the consistency and reliability of the ILP approach, reinforcing its suitability for dealing with unique constraints associated with integer production quantities.

The SME's baseline annual profit, prior to any optimization initiatives, stands at RM 250,492.95. There is a noticeable change in profit after using the ILP model. The model systematically guides the production strategy, recommending specific adjustments that result in a maximized profit of RM 261,875. This shows a notable increase over the starting profit figure and demonstrates how well the ILP approach achieves financial optimization. Furthermore, it indicates a significant 4.53% increase in annual profit accomplished through the ILP optimization model.

Sensitivity Analysis

Sensitivity analysis was performed to show how variations in parameters influence the optimal solution.

Comparative Analysis with and without Product X_{11} and X_{15} Removal

The initial model provided a clear path for profit maximization by adjusting the production quantities of products X_{11} and X_{15}, while keeping the production levels of all other products constant. To assess the robustness of our initial solution, a sensitivity analysis was conducted by removing Products X_{11} and X_{15} from the model.

Table 3: Solution obtained for maximizing profit without X_{11} and X_{15} using LINDO

Variables	Optimum Value	Current Value
Z	261166.3	223525
X1	760.000000	760.000000
X2	1345.000000	1345.000000
X3	995.000000	995.000000
X4	1875.000000	1875.000000
X5	2450.000000	2450.000000
X6	1730.000000	1730.000000
X7	240.000000	240.000000
X8	2015.000000	2015.000000
X9	2205.000000	2205.000000
X10	995.000000	995.000000
X12	602.000000	600.000000
X13	812.000000	812.000000
X14	1055.000000	1055.000000
X16	3126.000000	550.000000

Based on Table 3, the model suggested an increase in the production quantity of Product X_{12} from 600 to 602 units and a significant adjustment for Product X_{16} from 550 to 3126 units. With the previous Products X_{11} and

X_{15} excluded, the revised solution yielded a profit of RM 261,166.3. While this represents a decrease in profit compared to the initial solution, it is imperative to note that the reduction is marginal, emphasizing the robustness of the optimization model. The minor decrease in profit without Products X_{11} and X_{15} suggests that the initial model's recommendations were already near the optimal solution. The sensitivity analysis demonstrated the model's ability to adapt and find alternative solutions when certain products are removed, showcasing its flexibility and reliability.

Increasing Binding Constraint to Maximize Profit

Binding constraints are those constraints that are active at their respective optimal values, indicating full utilization of the associated resources. In sensitivity analysis, the shadow price linked to a constraint shows how much the optimal value of the main goal changes when the right side of the constraint increases by one unit. If the shadow price is positive, it means the constraint is binding. Therefore, in our study, constraint 1 (Machine processing time for CNC milling machine) holds as a binding constraint, while the remaining constraints are deemed non-binding.

The model was resolved using LINDO software. The optimal solution was obtained and compared to the original proposed solution. Constraint 1 (C1) was increased as shown in Table 4 below.

Table 4: Changing right hand side for binding constraint

Variables	Original RHS	Current RHS
C1	172800.000000	345600.000000

Table 5: Comparison of optimal solution

Variables	Original Optimal Solution	New Optimal Solution
Z	261880.8	286929.3
X1	760.000000	760.000000
X2	1345.000000	1345.000000
X3	995.000000	995.000000
X4	1875.000000	1875.000000
X5	2450.000000	5550.963867
X6	1730.000000	1730.000000
X7	240.000000	240.000000
X8	2015.000000	2015.000000
X9	2205.000000	2205.000000
X10	995.000000	995.000000
X11	1666.861084	900.000000
X12	600.000000	600.000000
X13	812.000000	812.000000
X14	1055.000000	1055.000000
X15	1248.000000	1248.000000
X16	550.000000	550.000000

Table 5 provides a comparison between the initially proposed solution and the modified version with an altered right-hand side binding constraint. In the original proposed solution, the model placed a significant emphasis on the production of X_{11}, whereas the revised model prioritized the production of X_5. Notably, the objective function for the original proposed solution amounted to RM 261,880.8. However, with the introduction of the changed right-hand side binding constraint, the objective function saw a substantial increase, reaching RM

286,929.3. As a recommendation to the SME, it is suggested to increase the machine processing time for the CNC milling machine to capitalize on these profit-enhancing modifications.

Challenges of the Approach

Data Collection and Accuracy

Accurate and up-to-date data is essential for both ABC categorization and optimization modeling. Errors in cost, profit, or machine time values can significantly affect the final production strategy and profitability.

SMEs may lack systematic data recording systems, leading to incomplete or inconsistent datasets.

Simplification of Real-World Constraints

The study models only a fixed set of machine constraints and ignores potential issues such as machine downtime, maintenance schedules, and manpower limitations.

Other operational constraints like batch sizes, supplier reliability, or order variability are also not modeled.

Exclusion of Category C Products

While Category C products have minimal consumption value, excluding them entirely might overlook niche market demands or customer satisfaction factors that aren't purely profit-driven.

Fixed Demand Assumptions

The model assumes that demand is fixed and known. However, in real settings, demand is often uncertain and may fluctuate, affecting the robustness of the optimal solution.

Static Optimization

The optimization model is static—it does not account for dynamic changes such as seasonality, new product introductions, or discontinued items. This limits long-term applicability without regular model updates.

Scalability to Larger Product Sets

With a small set of products (16 prioritized items), the model is manageable. However, as the number of SKUs increases, maintaining and solving the model becomes more complex.

Complexity in Implementation

Mathematical and Software Expertise

Although the model uses accessible tools like Excel, LINDO, and LP Solve IDE, SMEs may lack personnel skilled in mathematical modeling or operations research to build and validate such models effectively.

Integer Linear Programming (ILP) Complexity

ILP problems are computationally more demanding than LP problems. They often require more processing time, especially with increased constraints or decision variables.

Solutions may involve long runtimes or may fail to converge quickly if not modeled efficiently.

Maintenance of the Model

For the model to remain effective, it must be regularly updated with new data (e.g., machine hours, product costs, new inventory entries), which may be difficult without automation.

Integration with Existing Systems

Many SMEs may not have existing ERP or inventory systems to integrate with the optimization model. Manual data extraction and input may introduce errors and delay decision-making.

Sensitivity and What-If Analyses

Performing sensitivity analysis (as done with constraint adjustments) adds value but requires technical expertise. Without proper interpretation, SMEs might misjudge the implications of small parameter changes.

Interpretation of Results

While models provide numerical solutions, strategic decisions (e.g., increasing machine time, changing production schedules) still require managerial judgment, which introduces subjectivity and potential resistance to change.

Over-Simplification of Demand Patterns

Overly simple demand patterns are assumed as they are treated as fixed and deterministic in this model. In reality, however, demand patterns are assumed to be dynamic, seasonal, and sometimes stochastic. On the static demand assumption, the model will fail to account for the fluctuations, which may impact production planning and inventory decision-makings. Such a simplification would lead to either overproduction or stockouts, either of which would affect operational efficiency and profitability in negative ways. Further, the model is not amenable to sudden changes in customer behavior or market trends or to external disruptors without the incorporation of stochasticity or scenario-based forecasting. Such inflexibility is detrimental to the practical applicability and long-term relevance of the model especially for SMEs whose demand is likely to be even more volatile due to their niche markets or limited customer base.

Assumption of Stable Demand

The optimization models examined in this study generally assume predictable and stable demand, which may not hold true in the case of an SME environment. In practice, demand is often volatile, influenced by seasonality, shifting customer preferences, market competition, economic conditions, and other external factors, or may suffer disruptions due to supply chain delays or policy alterations. Dependence on fixed demand parameters may create a major risk where the forecast might be miscalibrated or old. If the models do not replicate market dynamics correctly, SMEs could face inefficiencies in the form of excess inventory, unmet demand, or wasted resources". Since SMEs with their limited buffer stocks and tighter margins will be majorly affected by the consequences of such mismatches, it is therefore imperative that for optimization methods to remain relevant and actionable, techniques for demand forecasting require integrating flexibility for making market adjustments.

CONCLUSION

In conclusion, this research highlights the critical role of effective production planning, particularly in optimizing production capacity, for enhancing a company's profitability. The implementation of ABC categorization and integer linear programming has emerged as a transformative catalyst, resulting in increased production capacity and profitability. The application of the ABC categorization method led to a strategic focus on high-value products in Categories 'A' and 'B,' encompassing 16 out of the 24 total products. In further analysis, while the LP solution attained a marginally higher objective function value of RM 261,880.8, the subsequent ILP solution yielded RM 261,875. Nonetheless, the preference for the integer linear model is based on its suitability in situations where production quantities need to be whole numbers, aligning with practical constraints inherent in real-world scenarios. The application of the ILP optimization model has proven highly effective, resulting in a notable 4.53% increase in annual profit. One limitation of the current study is that it assumes a consistent set of products in the SME's inventory. Though, the company may eventually change the specs of its goods, launch new ones, or discontinue old ones. Consequently, dynamic modelling methodologies that can adapt to changes in the product portfolio over time can be used in future research.

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