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Hybrid Demand-Based Goal Programming for Product Portfolio Optimization in B2B Lubricant Distribution Under Deadstock Risk

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Abstract

The increasing complexity of B2B lubricant distribution requires purchasing decisions that simultaneously consider sales targets, profitability, and inventory risk. However, purchasing policies are often based solely on historical demand, resulting in inefficient product portfolios and increased deadstock risk. This study aims to develop a product portfolio optimization model by integrating goal programming, hybrid demand forecasting, and inventory risk analysis. A quantitative operations research approach was employed using sales, inventory, profitability, and customer relationship management data from a lubricant distributor in Indonesia. Hybrid demand was estimated by combining historical demand with CRM-based opportunity demand using an expected value approach, while inventory risk was evaluated through inventory ageing and reinforced by integrated FSN–XYZ–ABC classification. The optimization model successfully achieved the purchase volume target of 2,000 barrels, generated an optimal profit of IDR 931.31 million, and maintained deadstock purchase value within the company's risk tolerance. Compared with actual purchasing practices, the proposed model reduced the proportion of purchase value allocated to non-moving products while improving profitability and working capital efficiency. These findings demonstrate that integrating goal programming with hybrid demand provides an effective decision-support approach for balancing multiple purchasing objectives and optimizing product portfolio management in B2B lubricant distribution.

Keywords

B2B, Goal Programming, Hybrid Demand, Product Portfolio Optimization.

1. Introduction

The development of the modern industrial sector has increased the need for efficient, adaptive, and data-driven distribution systems, particularly in the lubricant industry, which supports various operational sectors such as manufacturing, mining, transportation, construction, and energy (Leung & Chan, 2009). In the B2B environment, distributor performance is not only determined by sales volume but also by the ability to optimize product portfolios and maintain sustainable profitability (Ratnasari et al., 2025). However, lubricant distributors often face challenges in balancing sales growth and profit margins, as high-volume products may generate limited or negative returns due to discount strategies, promotional activities, and inventory considerations (Singh et al., 2011; Whitby, 2022). This condition is reflected in PT XYZ, where several business lines with high sales volumes contribute lower profitability than products with smaller sales volumes. Therefore, a comprehensive evaluation approach integrating sales performance and profitability analysis is required to support more effective strategic decision-making, as presented in Figure 1.

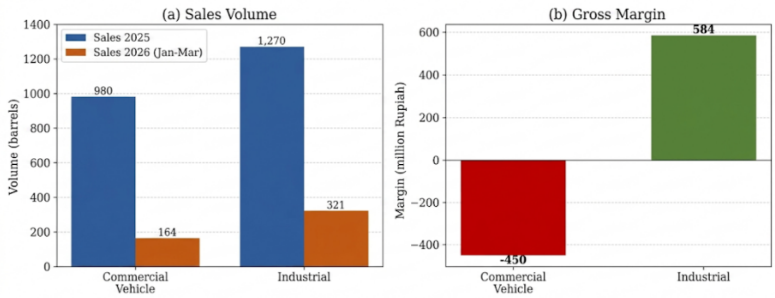

Figure 1. Historical Sales Volume and Margin by Business Line

Beyond profitability issues, distributor performance is also affected by inefficient inventory management, particularly the accumulation of slow-moving and non-moving products. Excessive inventory holding increases storage costs, risks of quality deterioration, and potential loss of economic value, leading to deadstock (Silver et al., 2016). Products stored for more than 180 days are considered high-risk due to declining sales potential and increased pressure on cash flow (Rachmawati & Lentari, 2022). At PT XYZ, approximately 40% of inventory value consists of products held beyond 180 days, indicating significant unproductive working capital and the need for improved inventory optimization strategies, as illustrated in Figure 2.

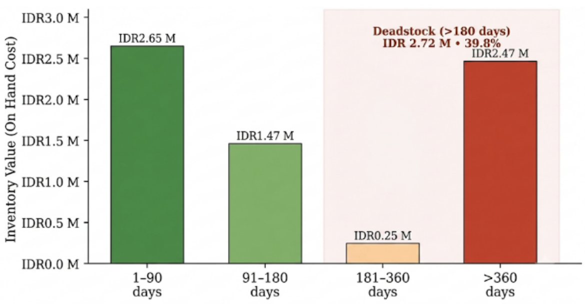

Figure 2. Inventory Value by Inventory Ageing

Product portfolio management becomes more complex when distributors must achieve annual purchase (sell-in) targets set by principals while ensuring that products are converted into sales (sell-out) without increasing inventory accumulation or reducing profitability (Rodriguez & Boyer, 2020). This condition creates conflicting objectives between maximizing purchase volume, profitability, and minimizing deadstock risk. Moreover, B2B demand dynamics are often difficult to predict using historical data alone (Kumar & Reinartz, 2018). Therefore, a hybrid demand approach that combines historical demand with sales opportunity data from Customer Relationship Management (CRM) systems provides a more accurate demand estimation (Wang et al., 2023). Sales opportunities can be transformed into demand forecasts using an expected value approach by considering the probability of success at each stage of the sales pipeline as presented in Figure 3.

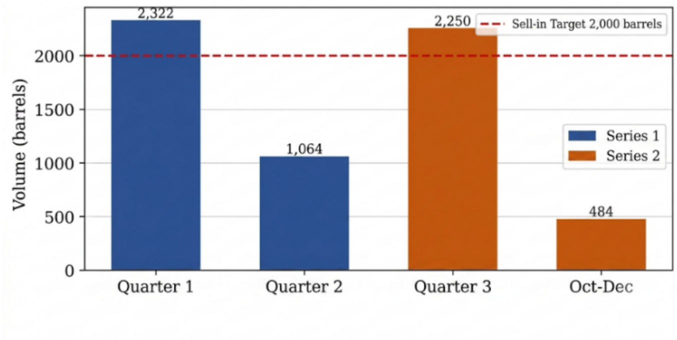

Figure 3. Historical Sell-in (Purchases) and Sell-out (Sales)

From a theoretical perspective, multi-objective decision-making requires optimization methods capable of balancing competing goals simultaneously. Goal programming, an extension of linear programming, is widely used to minimize deviations from multiple predefined targets and is suitable for complex decision problems (Charnes & Cooper, 1961; Rahmah et al., 2025). Previous studies by Herdiyanti et al. (2024) have applied goal programming to production optimization and resource allocation. However, its application in B2B distribution product portfolio optimization remains limited, particularly in integrating profitability, purchase targets, and deadstock risk. Existing studies also predominantly rely on historical demand data without incorporating CRM-based sales opportunities. Therefore, this study addresses the research gap by integrating goal programming, hybrid demand estimation, and inventory ageing-based risk measurement in lubricant distribution.

To address this research gap, this study proposes a product portfolio optimization model integrating goal programming, hybrid demand estimation, and inventory risk analysis based on inventory ageing, supported by FSN, XYZ, and ABC classification methods. Unlike previous studies focusing mainly on volume or cost optimization, this research quantifies deadstock risk in monetary terms to provide more financially relevant decision support. The integration of CRM-based sales opportunities with historical demand also enhances demand estimation accuracy by capturing dynamic market conditions. This study aims to analyze the current lubricant purchasing portfolio at PT XYZ, develop a hybrid demand-based goal programming model for multi-objective purchasing optimization, and evaluate the effectiveness of the proposed model by comparing its purchasing performance with the company's existing practices. This research contributes to operations management and B2B distribution optimization, while practically supporting profitability improvement, inventory efficiency, deadstock reduction, and sustainable supplier relationships.

2. Literature Review

2.1. Goal Programming in Multi-Objective Optimization

Goal programming is an operations research technique designed to address optimization problems involving multiple objectives simultaneously (Taha, 2017). Unlike linear programming, which aims to optimize a single objective function, goal programming allows decision-makers to define multiple goals and minimize deviations from these predetermined targets (Hillier & Lieberman, 2015). This approach is particularly suitable for multi-objective decision-making contexts where objectives are often conflicting, such as maximizing profitability, fulfilling purchase volume targets, and reducing inventory risk (Romero, 1991; Ehrgott, 2005). This concept aligns with multi-criteria optimization theory, which emphasizes achieving a satisfactory compromise solution rather than pursuing a single optimal outcome (Deb, 2001).

Previous studies have confirmed the effectiveness of goal programming in solving various business and industrial decision-making problems. Tamiz et al. (1998) highlighted that the method is widely applied in strategic planning due to its ability to accommodate multiple objectives with different levels of priority. Similarly, Zuhanda et al. (2022) demonstrated that goal programming can balance operational cost efficiency and profitability objectives, while Kaban and Siregar (2024) found that its implementation improved production target achievement and financial performance. This is consistent with Prameswari et al. (2024), who demonstrated that inventory optimization can improve ordering efficiency and resource allocation while considering economic objectives. These findings indicate that goal programming provides a relevant framework for optimizing product portfolios in B2B lubricant distribution, where companies must simultaneously manage purchase targets, profitability objectives, and deadstock risk.

2.2. Hybrid Demand and Customer Relationship Management (CRM)

Demand forecasting represents a fundamental component of purchasing decision-making and inventory management. Conventional forecasting methods generally rely on historical sales data as the primary basis for estimating future demand (Makridakis et al., 1998). However, in B2B environments characterized by irregular and intermittent demand patterns, historical data alone may not sufficiently capture actual market conditions. Therefore, the concept of hybrid demand has emerged by integrating historical demand with opportunity demand generated from Customer Relationship Management (CRM) systems, enabling more accurate and responsive demand estimation that reflects dynamic market changes (Brau et al., 2023).

CRM is a strategic business approach that utilizes information technology to systematically manage customer relationships and sales-related information (Buttle & Maklan, 2019). Chen and Popovich (2003) emphasized that effective CRM implementation requires the integration of people, business processes, and technology. In practice, CRM platforms, such as Salesforce, enable organizations to track sales pipelines and estimate the probability of successful conversion for each sales opportunity (Pookandy, 2024). These opportunity data can subsequently be transformed into opportunity demand using an expected value approach, providing a more forward-looking and market-responsive basis for purchasing decisions compared with approaches that rely solely on historical demand patterns.

2.3. Inventory Management and Deadstock Risk

Inventory management aims to achieve an optimal balance between product availability and the costs associated with inventory holding. Excessive inventory levels may increase storage costs, reduce working capital efficiency, and raise the risk of deadstock accumulation (Chopra & Meindl, 2016). Hudori (2018) demonstrated that inventory control through the implementation of safety stock and reorder point policies can improve inventory performance compared with existing company practices. Furthermore, Sintiana et al. (2023) found that integrating the ABC classification method with the Economic Order Quantity (EOQ) model enhances inventory control effectiveness by categorizing products based on their economic value contribution.

In lubricant distribution, deadstock risk represents a critical challenge because products stored for extended periods may experience quality degradation while generating increasing holding costs. Inventory ageing analysis is commonly applied to identify items with a high probability of becoming deadstock based on storage duration, whereas Fast–Slow–Non-Moving (FSN) analysis evaluates product movement and turnover characteristics (Fadilah et al., 2023). The integration of these approaches provides a more comprehensive assessment of inventory risk profiles, enabling companies to formulate purchasing decisions that prioritize products with higher turnover potential and lower risks of inventory accumulation.

3. Methods

This study employed a quantitative research design with a descriptive-quantitative and mathematical optimization approach, focusing on processing numerical data to generate optimal product purchasing decisions using a goal programming model based on hybrid demand (Sugiyono, 2016). A quantitative approach was selected because it enables the objective measurement of relationships among variables through mathematical modeling and statistical analysis, making it particularly suitable for addressing multi-objective optimization problems in operations management (Taha, 2017). The study was conducted at PT XYZ, a B2B lubricant distributor, using both primary and secondary data. Primary data were collected through field observations and semi-structured interviews with the sales team, operations management, and personnel involved in purchasing decision-making (Buttle & Maklan, 2019). Secondary data were obtained from company records, including historical sales data, purchase records for 2024–2025, product margin data, inventory records, inventory ageing reports, sales opportunity data extracted from Salesforce CRM, and relevant academic literature (Pookandy, 2024).

Data were collected through observation, interviews, documentation, and literature review to ensure comprehensive and reliable information. The data processing procedure began with data validation and cleaning, followed by the calculation of historical demand, estimation of opportunity demand using the expected value approach, construction of hybrid demand, and deadstock risk assessment based on inventory ageing, complemented by FSN–XYZ–ABC classification. Subsequently, a preemptive priority goal programming model was formulated to determine the optimal purchasing portfolio. Data analysis included descriptive statistics, coefficient of variation analysis, expected value estimation, goal programming optimization, model validation, and sensitivity analysis to evaluate the robustness of the proposed solution under changes in model parameters (Makridakis et al., 1998).

The selection of this methodology was driven by the nature of the research problem, which involves multiple conflicting objectives, namely achieving purchase volume targets, maximizing profitability, and minimizing deadstock risk. Consequently, a multi-objective optimization approach capable of simultaneously balancing these competing objectives was required. The significance of this study lies in the growing need for B2B lubricant distributors to adopt more adaptive, data-driven, and evidence-based decision-making systems in response to increasingly dynamic market demand. This research is expected to advance the application of goal programming and hybrid demand within the field of operations management. It provides managerial recommendations for developing more efficient purchasing strategies, improving profitability, reducing deadstock risk, optimizing working capital utilization, and strengthening long-term business relationships with principals.

4. Results

Among the 67 active products, the total inventory value (On Hand Cost) amounted to IDR 6,585,419,530, of which IDR 2,619,370,839 (39.8%) was tied up in inventory aged more than 180 days. Based on this inventory ageing criterion, 28 products were identified as being at risk of becoming deadstock. A comparative FSN analysis produced consistent findings, classifying 41 products as non-moving, accounting for IDR 4,636,442,056, or 70.4% of the total inventory cost. Furthermore, the integrated FSN–XYZ–ABC classification provided a more refined assessment by identifying 11 critical SKUs that were simultaneously classified as non-moving, highly variable (Z), and high-value (Class A). These products collectively tied up IDR 3,380,684,747 in working capital. From a purchasing perspective, Table 1 presents the historical purchasing allocation associated with deadstock risk, showing that the proportion of purchase value allocated to products with inventory ageing risk declined from 66.7% in 2024 to 35.2% in 2025. This reduction indicates an improvement in purchasing allocation; however, the remaining proportion of risky purchases demonstrates that inventory risk remains a significant concern. The 2025 proportion of 35.2% was subsequently used as the empirical reference for determining the Tolerance Risk (TR) parameter in the proposed optimization model.

Table 1. Actual Purchase Value in 2024 and 2025 by Deadstock Risk Category

Indicator	2024	2025
Purchase Volume (barrels)	2,321.6	1,063.9
Total Purchase Value (IDR)	13,563,694,882	9,251,389,531
Inventory Value of Products Aged >180 Days (IDR)	9,047,468,099	3,253,316,200
Risky Inventory Value Proportion	66.7%	35.2%

Based on Table 1, PT XYZ's primary purchasing challenge is the allocation of a substantial portion of purchase value to products associated with deadstock risk. Although the proportion declined from 66.7% in 2024 to 35.2% in 2025, the value remains significant and indicates that purchasing decisions still require stronger consideration of inventory characteristics and demand patterns. The inventory ageing analysis identified 28 products at risk of becoming deadstock, with a total inventory value of IDR 2.62 billion (39.8%), while the FSN analysis classified 41 products as non-moving, accounting for 70.4% of total inventory cost. Furthermore, the integrated FSN–XYZ–ABC analysis identified 11 critical SKUs characterized by low inventory turnover, high demand variability, and high investment value, making them the main contributors to unproductive working capital. These findings indicate that the existing purchasing approach has not fully incorporated demand uncertainty and inventory risk factors. Therefore, a goal programming model based on hybrid demand is required to optimize purchasing decisions by simultaneously balancing purchase volume targets, profitability objectives, and deadstock risk reduction, thereby improving working capital efficiency.

Table 2. Summary of Goal Achievement

Goals	Target	Result	Status
Purchase Volume (barrels)	2,000.00	2,000.00	Achieved
Profit (IDR million)	1,000.00	931.31	Not Achieved
Deadstock Purchase Value (IDR million)	6,785.60	6,785.43	Achieved

The pre-emptive goal programming model generated the optimization results summarized in Table 2. The purchase volume target was fully achieved at 2,000.00 barrels, resulting in zero negative deviation ($d_1^- = 0$). The model also generated an optimal profit of IDR 931.31 million, representing 93.1% of the predetermined target of IDR 1,000 million. Although the profit target was not fully achieved, the remaining shortfall was limited to IDR 68.69 million, indicating that the solution closely approached the desired objective. The deadstock purchase value target was successfully achieved, with an optimized value of IDR 6,785.43 million, which was slightly below the maximum allowable target of IDR 6,785.60 million ($d_3^+ = 0$). Compared with the actual purchasing condition in 2024, this result represents a 25.0% reduction in purchases associated with deadstock risk. These findings demonstrate that the proposed goal programming model successfully satisfied the highest-priority objectives while maintaining inventory risk within the predetermined tolerance level. The non-binding nature of the deadstock constraint further indicates that the optimal solution was able to control inventory risk without compromising the achievement of the higher-priority purchasing objectives.

Table 3. Comparison of Actual Conditions and Goal Programming Results

Indicator	2024	2025	GP Results
Purchase Volume (barrels)	2,321.6	1,063.9	2,000.0
Profit (IDR million)	-565.2	868.6	931.3
Deadstock Purchase Value (IDR million)	9,047.5	3,253.3	6,785.4
Proportion of Deadstock Purchase Value	66.7%	35.2%	50.9%
Proportion of Non-Moving Purchase Volume	44.5%	35.5%	29.2%
Proportion of Non-Moving Purchase Value (FSN)	48.6%	43.1%	35.0%

Table 3 compares the actual purchasing performance in 2024 and 2025 with the results generated by the proposed Goal Programming (GP) model. The GP solution achieved the targeted purchase volume of 2,000.0 barrels, while generating a profit of IDR 931.3 million, representing a substantial improvement over the IDR 565.2 million loss recorded in 2024 and exceeding the IDR 868.6 million profit achieved in 2025. Although the optimized deadstock purchase value (IDR 6,785.4 million) remained higher than the 2025 level (IDR 3,253.3 million), it was considerably lower than the 2024 value (IDR 9,047.5 million). Similarly, the proportion of deadstock purchase value declined from 66.7% in 2024 to 50.9% under the GP solution. The lower proportion reported in 2025 (35.2%) should be interpreted with caution because it was achieved with a substantially lower purchase volume of only 1,051.2 barrels, well below the optimization target of 2,000.0 barrels. The same pattern was observed in the FSN analysis, where the GP model reduced the proportion of purchase volume allocated to non-moving products to 29.2%, compared with 44.5% in 2024 and 35.5% in 2025, while the proportion of purchase value allocated to non-moving products decreased to 35.0%, compared with 48.6% and 43.1%, respectively.

The results indicate that the hybrid demand-based goal programming model produced a more balanced purchasing strategy than the company's historical purchasing practices. The model fully satisfied the purchase volume target without deviation ($d_1^- = 0$) while generating a profit close to the predetermined target, with a remaining shortfall of only IDR 68.69 million. At the same time, the optimized purchasing allocation reduced both deadstock exposure and non-moving inventory, demonstrating a better balance between profitability and inventory risk. These findings suggest that the proposed model is capable of simultaneously supporting purchasing volume commitments, improving financial performance, and controlling inventory risk. This result is consistent with goal programming theory, which emphasizes achieving the best compromise among competing objectives according to their priority structure (Taha, 2017), and supports previous findings reported by

Tamiz et al. (1998), Zuhanda et al. (2022), and Kaban and Siregar (2024) regarding the effectiveness of goal programming in multi-objective optimization.

Table 4. Sensitivity of the Optimization Solution to Changes in the Purchase Volume Target

Purchase Volume Target (barrels)	Optimal Profit (IDR)	Deadstock Purchase Value (IDR)
1,500	1,029,844,437	4,590,389,750
1,651	1,000,088,309	5,253,291,752
1,800	970,726,301	5,907,413,596
2,000	931,314,211	6,785,429,493
2,200	891,902,120	7,663,445,391

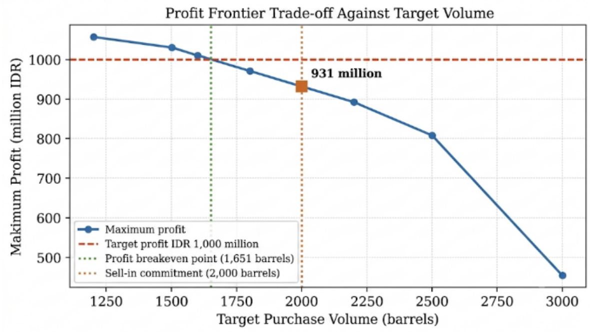

Figure 4. Profit–Purchase Volume Trade-off Frontier

The validation results confirmed that all model constraints were satisfied (ΣX_i = 2,000.00; $0 \leq X_i \leq D_i$). The complementarity condition ($d_j^- \times d_j^+ = 0$) was satisfied for each objective, and the Solver solution was identical to the independent greedy calculation (zero difference). Furthermore, a perturbation test involving 300,000 random reallocations failed to identify any superior solution. As presented in Table 4, the sensitivity analysis indicates that optimal profit decreases monotonically as the purchase volume target increases because additional purchases must be allocated to lower-margin products. The IDR 1,000 million profit target can only be achieved when the purchase volume target does not exceed 1,651 barrels, whereas the deadstock TR begins to be exceeded when the purchase volume target reaches approximately 2,200 barrels. The profit–purchase volume trade-off illustrated in Figure 4 further demonstrates that increasing the sell-in target beyond the profit breakeven point results in a gradual decline in profitability. These findings suggest that the 2,000-barrel sell-in commitment represents the primary structural constraint preventing the company from fully achieving its profit target. Nevertheless, this target remains within an acceptable range for controlling inventory risk while maintaining a favorable balance between profitability and purchasing commitments.

5. Discussion

The findings indicate that the primary challenge faced by B2B lubricant distributors is not merely the high inventory value itself but rather the mismatch between the product portfolio composition and market demand characteristics. Although PT XYZ successfully reduced the proportion of purchase value allocated to products with deadstock risk from 66.7% in 2024 to 35.2% in 2025, inventory ageing analysis still identified 28 products with inventory exceeding 180 days, while FSN analysis classified 41 products as non-moving. Furthermore, the integrated FSN–XYZ–ABC analysis identified 11 critical SKUs that accounted for a substantial proportion of the company's working capital. These findings indicate that purchasing decisions based solely on historical sales performance are insufficient to capture the complexity of fluctuating B2B demand. Instead, effective purchasing decisions require consideration of both product movement characteristics and inventory risk to ensure that working capital is allocated to products with greater sales potential. This result is consistent with Chopra and Meindl's (2016) and Heizer and Render's (2017) inventory management theory, which emphasizes balancing customer service, inventory efficiency, and working capital utilization to achieve effective supply chain performance.

The proposed hybrid demand approach provides a more adaptive basis for purchasing decisions by integrating historical demand with opportunity demand derived from the CRM system using the expected value approach. This integration enables the optimization model to represent better actual market conditions, particularly in B2B markets characterized by irregular and intermittent demand patterns. Rather than relying exclusively on historical transactions, the model incorporates potential future sales opportunities recorded in the CRM system, allowing purchasing decisions to become more responsive to changing market conditions. Consequently, the estimated demand more accurately reflects actual business opportunities and reduces the likelihood of excessive purchasing for products with limited market potential. These findings are supported by Makridakis et al. (1998), Kumar and Reinartz (2018), Brau et al. (2023), and Pookandy (2024), suggesting that incorporating CRM information into demand forecasting enhances operational decision-making and improves purchasing accuracy.

From an optimization perspective, the preemptive goal programming model successfully achieved the 2,000-barrel purchase volume target, generated an optimal profit of IDR 931.31 million, and maintained the deadstock purchase value at IDR 6.79 billion, remaining within the company's predefined risk tolerance. Although the profit target of IDR 1 billion was not fully achieved, the remaining gap was relatively small and primarily reflected the structural characteristics of the product portfolio, where many available purchasing opportunities generated relatively low profit margins. Moreover, the comparison with the company's actual purchasing performance demonstrates that the proposed model produced a substantially better compromise among purchase volume, profitability, and inventory risk. The reductions in both the proportion of purchase value allocated to non-moving products and the proportion of purchase volume associated with slow-moving inventory further indicate that the optimization model improved the overall quality of purchasing allocation. These findings are consistent with Cho et al. (2017) and Taha (2017), multi-objective optimization theory, which argues that competing objectives require compromise rather than simultaneous maximization.

This study contributes both theoretically and practically to product portfolio optimization in B2B lubricant distribution. It extends the application of goal programming by integrating hybrid demand with inventory risk assessment based on inventory ageing, thereby providing a more comprehensive framework for multi-objective purchasing optimization than approaches relying solely on historical demand or inventory volume indicators. The proposed framework demonstrates that combining demand forecasting, inventory classification, and multi-objective optimization can improve decision quality in complex purchasing environments. The proposed model can serve as a decision support tool for developing purchasing plans that simultaneously consider principal purchase targets, profitability, and inventory risk. By providing a balanced allocation of purchasing decisions, the model enables companies to improve working capital efficiency, reduce deadstock risk, strengthen inventory performance, and support more sustainable business operations in B2B lubricant distribution.

6. Conclusion

This study developed a hybrid demand-based goal programming model to optimize product portfolio purchasing decisions in a B2B lubricant distribution company. The findings demonstrate that the proposed model successfully achieved the 2,000-barrel purchase volume target, generated an optimal profit of IDR 931.31 million, and maintained the deadstock purchase value within the company's acceptable risk threshold. Compared with the company's actual purchasing practices, the model improved purchasing allocation by reducing the proportion of purchases associated with non-moving and deadstock-risk products while maintaining profitability. These results confirm that integrating hybrid demand, inventory risk analysis, and goal programming provides a more effective decision-making framework than relying solely on historical sales data. The study therefore contributes to the literature on multi-objective optimization by extending goal programming through the incorporation of CRM-based demand information and inventory ageing into purchasing decision models.

Despite these contributions, this study has several limitations. The proposed model was developed using data from a single B2B lubricant distributor and assumes deterministic demand estimates and fixed business targets, which may limit its generalizability to other industries or more dynamic market environments. Furthermore, the optimization model focuses primarily on purchase volume, profitability, and deadstock risk without considering additional operational factors such as warehouse capacity, logistics costs, supplier constraints, or uncertain demand. Future research should validate the proposed framework across different industries and distribution contexts while incorporating stochastic demand, multi-period planning, and additional operational constraints. Integrating advanced optimization techniques or machine learning-based demand forecasting may also further enhance purchasing decision quality and inventory performance.

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