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# Analysis of Inventory Management Using The Demand Driven Material Requirements Planning (DDMRP) Approach in The Fast-Food Industry

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# **ABSTRACT**

Effective inventory management is a critical element in ensuring smooth operations and business success, particularly in the fast-food industry, which is characterized by highly dynamic demand. CV X, a fast-food company based in East Java, is currently facing challenges related to overstock and stockout conditions that hinder operational efficiency. Additionally, limited cold storage capacity further complicates efforts to maintain inventory balance amidst fluctuating demand. As the industry shifts from a push-based to a pull-based system—prioritizing flexibility and responsiveness in meeting customer demand—an adaptive inventory management approach becomes essential. This study analyzes the inventory management system at CV X using the Demand-Driven Material Requirements Planning (DDMRP) method to address overstock and stockout issues. DDMRP is chosen due to its ability to integrate dynamic buffer stock control and inventory adjustments based on real-time demand signals, enabling a more responsive supply chain while optimizing the use of limited cold storage capacity. This research employs secondary data from CV X for the year 2023, including production, sales, and inventory records, analyzed using descriptive and quantitative methods. The results indicate that the implementation of DDMRP successfully reduced the average inventory level by 6.62%, decreased overstock by 96.29%, and lowered stockout occurrences by 88.51%.

Keywords: DDMRP, Fast-Food Industry, Inventory Management, Overstock, Stockout.

## INTRODUCTION

Inventory refers to all goods stored to meet future demand [1], and it has a significant impact on a company's financial performance [2]. According to [3], inventory can be classified into three categories based on its form, function, and the interdependence among items. As noted by [4] in [5], inventory plays a crucial role in operational activities through three main functions: decoupling, economic lot sizing, and anticipation. Common performance indicators used in inventory management include Inventory Turnover Rate (ITR), Inventory Days of Supply (IDS), and fill rate (service level) [6][7]. Inventory management is defined as the control of assets used in production or ready for sale within the normal course of business operations [8][9]. Its primary function is to maintain stock levels at an optimal point, enabling cost efficiency in inventory handling [10][1]. Strategically, inventory management is vital to ensure product availability, minimize holding costs, and fulfill customer delivery expectations [11].

In the fast-food industry, inventory management becomes particularly critical due to high demand variability and associated risks such as overstock and stockout. Overstock leads to increased storage costs, while stockouts directly impact customer satisfaction and may result in lost sales opportunities. As indicated by [12], imbalances in inventory control can disrupt supply chain continuity and weaken a company's competitive edge. Nevertheless, many companies still rely on conventional forecasting methods, which often lack responsiveness to actual market dynamics.

To address these limitations, Demand Driven Material Requirements Planning (DDMRP) has emerged as an innovative, effective, and efficient approach that emphasizes real-time demand visibility and strategic buffer positioning within the supply chain [13]. The method integrates the principles of position, protect, and pull, aiming to minimize lead times, reduce variability, and optimize product availability [14]. Several previous studies have



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demonstrated that the implementation of DDMRP significantly improves inventory control efficiency. For example, a study by [15] analyzed organizational changes after transitioning from MRP to DDMRP, and the results showed that inventory levels decreased by 52.53%, material consumption increased by 8.7%, and service levels remained high. Another study by [16] evaluated DDMRP implementation in a complex manufacturing environment, focusing on customer satisfaction and inventory levels, and found that DDMRP was able to reduce lead time by up to 41%, lower inventory levels by 18%, and prevent both stockouts and overstock situations, where the success of DDMRP heavily depends on the strategic placement of buffers. Additionally, a study by [17] investigated the impact of buffer placement on industrial performance using the DDMRP method and revealed that buffer positioning could affect performance by up to 15 OTD points and 100% of working capital, and that no single buffer placement is universally optimal for all situations. Other studies have also concluded that DDMRP outperforms traditional methods such as MRP II and Kanban/Lean [18].

CV X, a fast-food company operating in East Java, Indonesia, faces similar challenges in managing inventory across its outlets. Data from 2023 revealed simultaneous overstock and stockout issues, particularly involving Products 1 through 12. The situation was further exacerbated by limited cold storage capacity. These challenges highlight the need for a more adaptive and responsive inventory planning method. DDMRP was selected as the preferred approach due to its alignment with CV X's operational characteristics, which include fluctuating demand, perishable food items, and constrained storage facilities.

This study aims to analyze the inventory management system at CV X by applying the DDMRP methodology. Using a simulation-based approach, the research evaluates the impact of DDMRP on key inventory performance indicators: Inventory Turnover Rate (ITR), Inventory Days of Supply (IDS), and Service Level (SL). The findings are expected to provide practical insights for the fast-food industry in adopting demand-driven inventory strategies and reducing reliance on purely historical forecasting models.

## **METHODS**

This Research employs a descriptive quantitative approach with a case study method to evaluate the effectiveness of Demand Driven Material Requirements Planning (DDMRP) as an inventory management system that adapts to actual customer demand. The research object is CV X, a fast-food company operating in East Java, Indonesia. Conceptually, DDMRP is an evolution of Material Requirements Planning (MRP) that integrates three core principles: position, protect, and pull [14]. The method is designed to minimize lead time, reduce variability, and improve product availability by strategically positioning buffers, protecting material flow with adaptive buffers, and triggering production and procurement based on actual demand. The five main components of DDMRP that serve as the theoretical foundation of this study are: Strategic Inventory Positioning, Buffer Profiles and Levels, Dynamic Adjustments, Demand-Driven Planning, and Visible and Collaborative Execution.

The research was carried out in the following stages:

- 1) Literature review, to understand the concepts, principles, and components of DDMRP as well as inventory performance indicators (ITR, IDS, and SL).
- 2) Field observation and interviews, to map the production process flow and identify the lead time at each stage, which was then used as the basis for determining the decoupling points. The primary data were collected through in-depth interviews with the operational manager of CV X, who was selected as an expert respondent due to his comprehensive knowledge of the company's production processes, inventory management, and supply chain operations. His expertise ensured that the information obtained was accurate and representative of the company's operational realities.
- 3) Collection of secondary data, including production, sales, and inventory data for 2023.
- 4) Pareto analysis, to identify the top 12 Category A products, out of a total 35 products, with the highest sales contribution, which became the focus for calculating DDMRP parameters.
- 5) Calculation of DDMRP parameters, including Average Daily Usage (ADU), order spike, lead time, and variability factor, as well as buffer levels for the red, yellow, and green zones.
- 6) DDMRP simulation, by calculating the net flow position and dynamically determining the reorder point for the 12 main products.



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- 7) Performance evaluation, by comparing inventory performance indicators before and after the DDMRP simulation, specifically Inventory Turnover Rate (ITR), Inventory Days of Supply (IDS), and Service Level (SL).
- 8) Model validation, through discussions with the CV X operations team to ensure that the developed model aligns with the company's actual conditions and operational requirements.

All data processing and simulations were performed using Microsoft Excel as the primary modeling tool. The validity of the approach was confirmed through triangulation by engaging with CV X's operational manager to ensure that the simulation results were relevant and applicable to real-world practices. These steps were designed to provide a comprehensive view of how DDMRP can be theoretically and practically implemented to enhance inventory management efficiency in an actual operational context.

## **RESULTS AND DISCUSSION**

## **Determining Decoupling Points**

The decoupling point serves to isolate variability between production processes by strategically positioning inventory buffers. Prior to determining its placement, a comprehensive mapping of CV X's production flow was conducted based on in-depth interviews with the company's operational manager. The production flow diagram, presented in Figure 1, uses the letters P for purchase (procurement of raw materials), M for manufacture (production process), and FP for final product, with lead times indicated on the left side of each process box in hours. Each code was derived directly from the company's internal documentation and interview responses and refers to specific operations within CV X's production flow: P001–P004 correspond to four main raw material procurement points, M001–M004 denote sequential manufacturing stages, and FP1 represents the final product stage. The mapping results reveal that the cumulative lead time for the final product (FP1) reaches 115.5 hours. Based on this analysis, DDMRP buffers were positioned at strategic points identified as vulnerable to delays and critical to the continuity of production flow. These decoupling points are represented by funnel-shaped icons in green–yellow–red and include P001, P002, P003, P004, M002, and FP1, as illustrated in Figure 1. Placing buffers at these locations enabled the company to significantly reduce the cumulative lead time from 115.5 hours to only 3 hours.

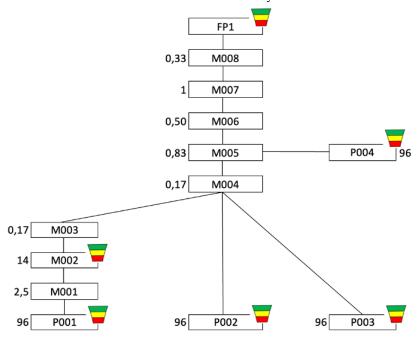
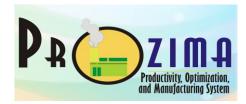


Figure 1. Decoupling Points Identification in the Production Flow



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The selection of decoupling points in Figure 1 was based on considerations of supply reliability, production efficiency, and responsiveness to market demand. Codes P001–P004 represent primary raw material procurement stages, chosen because they involve external suppliers with a long lead time of 96 hours. M002 corresponds to a manufacturing stage with a lengthy 14-hour process, which presents a high risk of becoming a bottleneck. FP1, the final product, was selected because it directly interfaces with highly volatile customer demand. All codes and their definitions were established based on the company's standard operating procedures (SOPs) and validated through expert interviews, ensuring their accuracy and relevance within CV X's production context.

#### **Determining Buffer Profile and Buffer Level**

The buffer profile in this research was established by focusing on 12 Pareto A products from CV X, which collectively accounted for 78.92% of total sales volume in 2023. Demand variability was measured using the Coefficient of Variation (CV), defined as the ratio of the standard deviation to the mean of historical demand. All analyzed products exhibited high demand fluctuations, with CV values exceeding 0.5. Notably, Products 7, 11, and 12 showed CV values greater than 1, indicating extremely high variability. Consequently, a variability factor of 99% of the safety base was adopted, in accordance with the "high variability" classification [14]. The lead time parameter for FP1, classified as short based on its decoupled lead time, was assigned a lead time factor of 1 to maximize supply chain speed and agility and particularly important given CV X's limited cold storage capacity for finished goods.

The buffer level was determined by calculating the three DDMRP buffer zones: red, yellow, and green [14]. The red zone was derived by summing the red base and red safety. The yellow zone was calculated by multiplying the Average Daily Usage (ADU) by the decoupled lead time. The green zone was determined by selecting the maximum value among the red base, ADU multiplied by the minimum order cycle, and the minimum order quantity. The final calculated buffer levels for each product are summarized in two separate graphs in Figure 2 & 3, which provides a clearer view of their respective results and calculation process.

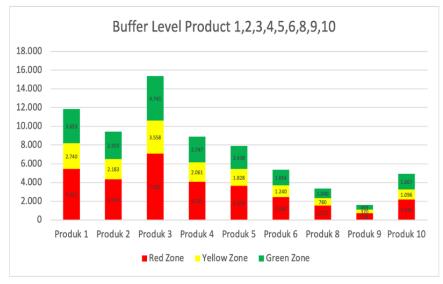


Figure 2. Buffer Level Values for Products 1,2,3,4,5,6,8,9,10

Figure 2 shows the buffer level composition—Red Zone, Yellow Zone, and Green Zone for Products 1,2,3,4,5,6,8,9,10. These buffer levels were calculated based on historical sales, lead time analysis, and DDMRP parameters, focusing on high-volume Category A products. Among these, Product 3 exhibits the largest total buffer of over 14,000 units, with the highest Red Zone allocation 7,081 units, reflecting its high variability and safety requirement. The calculation process involved determining ADU, CV, lead time, and applying the DDMRP formulas to compute buffer zones for each product.



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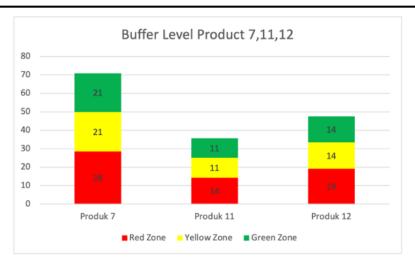


Figure 3. Buffer Level Values for Products 7,11,12

Figure 3 illustrates the buffer levels for Products 7, 11, and 12, which are characterized by low sales volume but high demand variability (CV > 1). The results show lower absolute buffer values compared to the other products, yet a balanced distribution across the Red, Yellow, and Green Zones. These buffer levels were also derived using DDMRP calculations, adapted to account for the products' unique demand patterns and operational importance. This separation of the graphs allows for a more detailed explanation of the differences between high-volume, moderate-variability products (Products 1–10) and low-volume, high-variability products (Products 7, 11, and 12), providing clearer insights into the buffering strategy adopted for each group.

## **Determining Net Flow Position**

The order spike threshold determination aims to identify abnormal demand surges, allowing the system to avoid overreacting to temporary fluctuations with excessive production or ordering decisions. In this study, two approaches were used to calculate the order spike threshold: 50% of the Red Zone and the Average Daily Usage (ADU) based on online sales data. These two methods were later evaluated to compare their effectiveness in managing demand variability, particularly in terms of average inventory levels, overstock occurrences, and stockouts throughout the year 2023. The Order Spike Horizon in this research was set at two days, derived from the sum of the decoupled lead time (one day) and an additional anticipatory day. This additional buffer time was introduced to account for high demand variability, especially among Pareto A products, which are characterized by fast-moving inventory and a coefficient of variation (CV) greater than 0.5. The Net Flow Position value is dynamic and fluctuates daily as a result of changes in on-hand stock, open supply orders, and qualified demand across all observed products, namely Products 1 through 12. The following is an example of the Net Flow Position calculation simulation for Product 1 in Figure 4.



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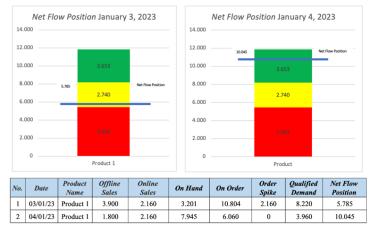


Figure 4. Net Flow Position of Product 1 on January 3–4, 2023

As shown in Figure 4, the Net Flow Position on January 3, 2023, was calculated by summing the on-hand inventory (3,201 units) and on-order supply (10,804 units), then subtracting the qualified demand (8,220 units), resulting in a Net Flow Position of 5,785 units. It is important to note that the order spike recorded on January 3 originated from an online sales order scheduled for January 4, amounting to 2,160 units exceeding the predefined Order Spike Threshold of 1,471 units.

#### **Determining Reorder Point**

The reorder point functions as a mechanism to identify replenishment needs for the subsequent period, thereby ensuring that inventory levels remain within safe boundaries. Figure 4 presents the reorder point simulation for Product 1 on January 3–4, 2023, with the buffer displayed at the center of the chart. The right-hand side of the buffer, labeled as Demand Side, shows sales order demand over the next two days within the defined Order Spike Horizon. The Order Spike Threshold value of 1,471 units is represented by a dashed line positioned within the red zone of the buffer. On the left-hand side, labeled as Supply Side, the incoming supply flow is visualized, where each negative value on the arrows indicates the number of days remaining until receipt.

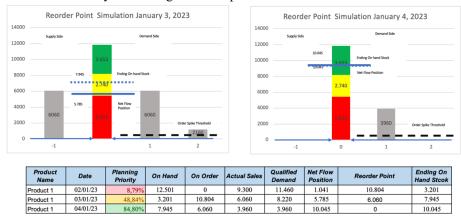


Figure 5. Reorder Point Simulation for January 3-4, 2023

In Figure 5, the beginning inventory on day 1 (January 3) was 3,201 units, and there was one open supply order of 6,060 units. A significant order spike of 2,160 units was scheduled for day 2 (January 4), with no overdue demand observed. The qualified demand totaled 8,220 units, resulting in a Net Flow Position (NFP) of 5,785 units, represented



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by a solid line within the yellow zone area. This corresponds to a yellow planning priority of 48.84%. Since the NFP (5,785 units) falls below the Top of Yellow Zone (8,192 units), a reorder point is triggered, calculated as the difference between the Top of Green Zone (11,845 units) and the NFP, yielding a replenishment quantity of 6,060 units. The ending on-hand stock for day 1 is 7,945 units, derived from beginning stock plus on-order quantity minus actual sales. To illustrate the profile of Net Flow Position and Ending On-Hand Stock over time, a simulation for Product 1 covering the entire month of January 2023 is presented in figure 6.

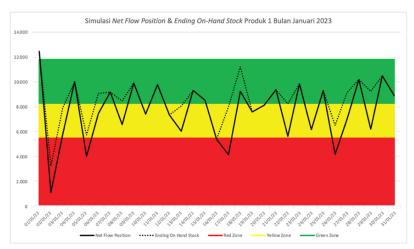


Figure 6. Net Flow Position and Ending On-Hand Stock for Product 1 in January 2023

Figure 6 presents the simulation of the Net Flow Position and Ending On-Hand Stock for Product 1 throughout January 2023. The solid line represents the Net Flow Position, while the dashed line indicates the daily ending on-hand stock. This visualization demonstrates that both Net Flow and ending inventory levels predominantly remained within the DDMRP buffer zones, indicating that the buffer system effectively absorbed daily demand fluctuations. Despite the occurrence of significant variability, the buffer consistently maintained sufficient supply to meet demand without resulting in stockouts. This finding confirms that the buffer strategy within the DDMRP framework operated efficiently and responsively during the simulation period.

#### **DDMRP Calculation Results for Products 1-12**

This research simulated the Demand Driven Material Requirements Planning (DDMRP) individually for each of twelve key products (Products 1 to 12). The results of these simulations were compiled and summarized in Table 1.

Parameter	Before DDMRP	After DDMRP	
Product Name	Product 1-12	Product 1-12	
Variability Factor (VF)	-	0,99	
Order Spike Threshold Method	-	50% Red Zone	ADU Online Sales
Average inventory in 2023	4.632	4.167	4.325
Overstock 2023 (Unit)	74.424	2.768	2.758
Stockout 2023 (Unit)	-101.513	-24.136	-11.664
% Decrease in Average Inventory	-	10,04%	6,62%
% Decrease in Overstock	-	96,28%	96,29%
% Decrease in Stockout	-	76,22%	88,51%

**Table 1.** DDMRP Calculation Results Summary for Products 1–12



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Table 1 illustrates improvements in inventory performance across Products 1 through 12, reflected in the reduction of average inventory levels, overstock, and stockout occurrences under two different order spike threshold approaches: 50% Red Zone and ADU Online Sales. While the 50% Red Zone method yielded a greater reduction in average inventory (10.04%), the ADU Online Sales approach demonstrated superior performance in minimizing overstock by 96.29% and stockout by 88.51%. Given its effectiveness in addressing the two primary inventory issues faced by CV X,overstock and stockout, the ADU Online Sales approach was selected as the preferred method for determining the order spike threshold in this DDMRP simulation.

## Inventory Management Analysis (ITR, IDS, SL)

The inventory analysis was conducted to evaluate the impact of DDMRP on stock management performance at CV X using three key indicators: Inventory Turnover Rate (ITR), which reflects how frequently inventory is cycled within a year; Inventory Days of Supply (IDS), which measures the average number of days inventory can meet demand before depletion; and Service Level (SL), which represents the system's ability to fulfill customer demand without stockouts.

Product Name	Parameter	Before DDMRP	After DDMRP
I	Inventory Turnover Rate	81	96
	Inventory Days of Supply	3,53	2,47
	Service Level	98,08%	99,42%

**Table 2.** Inventory Management Analysis for Products 1–12

As presented in Table 2, the simulation results indicate improved inventory management performance across all three indicators. The ITR prior to the DDMRP simulation was 81, suggesting that the company cycled its inventory 81 times annually. Following the DDMRP simulation, the ITR increased to 96, signifying faster inventory turnover. Meanwhile, IDS decreased from 3.53 days to 2.47 days, demonstrating that the company could maintain leaner inventory levels while remaining responsive to demand. Additionally, the Service Level improved from 98.08% to 99.42%, reflecting a heightened ability to fulfill customer orders on time. Collectively, these results affirm that the implementation of DDMRP positively influenced the efficiency and responsiveness of the company's inventory management system.

#### Discussion

This research demonstrates that the Demand Driven Material Requirements Planning (DDMRP) approach effectively addresses the imbalance between demand and stock availability in the fast-food industry. The results comprehensively align with the research objectives. First, the objective of analyzing the inventory management system at CV X was achieved by mapping the company's production flow, identifying decoupling points, and calculating DDMRP parameters tailored to operational characteristics, including highly fluctuating demand, perishable products, and limited cold storage. The decoupling points were strategically determined at stages vulnerable to delays (P001–P004, M002, and FP1), reducing cumulative lead time from 115.5 hours to only 3 hours. This indicates a significant improvement in process responsiveness and stability, meeting the requirement for a more adaptive inventory management method.

Second, the objective of evaluating the impact of DDMRP on inventory performance indicators was fulfilled through the simulation. The results revealed substantial improvements: overstock was reduced by 96.29%, stockout by 88.51%, and average inventory levels by 6.62%, directly optimizing cold storage utilization. The Inventory Turnover Rate (ITR) increased from 81 to 96, Inventory Days of Supply (IDS) decreased from 3.53 to 2.47 days, and Service Level (SL) improved from 98.08% to 99.42%. These findings confirm that DDMRP enhances stock rotation speed, improves demand fulfillment accuracy, and strengthens operational competitiveness.

Third, the research aimed to provide practical insights for the fast-food industry in adopting demand-driven inventory strategies. The simulation results and managerial implications indicate that CV X should adopt a phased implementation roadmap. In the short term, developing a structured database, digitizing buffer calculations, and



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conducting technical training on DDMRP fundamentals are recommended. In the medium term, integrating a DDMRP module into the ERP (OMEGA) and deploying real-time alerts based on actual demand are suggested. In the long term, developing an adaptive decision support system and preparing to adopt predictive analytics, IoT, and AI are advisable. Strengthening human resources through cross-functional training and ongoing capacity-building programs is essential to ensure sustainable implementation.

#### **Managerial Implications**

The DDMRP simulation results at CV X indicate a significant improvement in inventory management efficiency through optimized buffer allocation, reduced lead times, and enhanced service levels, all of which carry strategic implications for managerial decision-making. From a managerial perspective, the company should adopt buffer placement policies at critical control points, shift from forecast-driven planning to DDMRP-based systems, and adjust procurement strategies to be more flexible and aligned with real-time buffer status. It is also recommended that management establish seasonal stock scenarios, utilize performance indicators (KPI) such as Inventory Turnover Rate (ITR) and Inventory Days of Supply (IDS), and develop a phased digitalization roadmap from implementing simple dashboards to achieving full integration with the company's ERP system while also exploring advanced technologies such as Decision Support Systems (DSS), the Internet of Things (IoT), and Artificial Intelligence (AI). Furthermore, enhancing workforce capabilities through cross-functional training and reinforcing daily monitoring systems via dashboard-based tools are essential steps to ensure consistent, adaptive, and sustainable DDMRP implementation within CV X's operational environment.

#### **CONCLUSION**

This research concludes that the Demand Driven Material Requirements Planning (DDMRP) approach effectively addresses the imbalance between demand and stock availability in the fast-food industry. First, the analysis of CV X's inventory management revealed that the imbalance was caused by highly fluctuating demand, perishable products, and limited cold storage, which were identified through production flow mapping, decoupling points, and DDMRP parameter calculations. Second, the simulation results showed that DDMRP significantly improved inventory performance by reducing overstock by 96.29%, stockout by 88.51%, and average inventory levels by 6.62%, thereby optimizing cold storage utilization. Third, DDMRP improved inventory efficiency as evidenced by an increase in Inventory Turnover Rate from 81 to 96, a decrease in Inventory Days of Supply from 3.53 to 2.47 days, and an improvement in Service Level from 98.08% to 99.42%. Lastly, the research provided a practical implementation roadmap tailored to CV X's needs, recommending short-term actions, like database development, buffer digitization, technical training, medium-term integration into the ERP system with real-time alerts, and long-term adoption of advanced technologies such as predictive analytics, IoT, and AI, supported by continuous human resource development.

# **REFERENCES**

- [1] J. H. Heizer and B. Render, Manajemen Operasi: Manajemen Keberlangsungan dan Rantai Pasokan, 11th ed. 2015.
- [2] H. T. I. Driantami, "Analisis Manajemen Persediaan: Studi Kasus Distributor PT Bahagia Intra Niaga (Produk PT Perfetti Van Melle Indonesia)," Institut Teknologi Sepuluh Nopember Surabaya, Surabaya, 2023.
- [3] N. Pujawan and E. Mahendrawathi, *Supply Chain Management*, 3rd ed. Andi, 2017.
- [4] T. H. Handoko, Dasar-Dasar Manajemen Produksi dan Operasi. BPFE Yogyakarta, 1999.
- [5] S. T. P. Hutagalung, Analisis Pengendalian Spare Parts Di Perusahaan Perbaikan Alat Berat (Doctoral dissertation, Institut Teknologi Sepuluh Nopember)," 2023.
- [6] I. N. Pujawan, Supply Chain Management. Guna Widya, 2005.
- [7] D. Rahmayanti and A. Fauzan, "Optimalisasi Sistem Persediaan Bahan Baku Karet Mentah (Lateks) dengan Metode Lot Sizing (Studi Kasus: PT Abaisiat Raya)," 2013.
- [8] A. Keown, D. F. Scott, D. Martin J, and J. Petty W, *Dasar-dasar Manajemen Keuangan*. Jakarta: PT Gramedia Pustaka Utama, 2000.



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- [9] B. F. Rambitan *et al.*, "Analisis Penerapan Manajemen Persediaan Pada CV. Indospice Manado," *Jurnal EMBA*, vol. 6, no. 3, pp. 1448–1457, 2018.
- [10] R. Vikaliana, Y. Sofian, N. Solihati, D. Bayu Adji, and S. S. Maulia, *Manajemen Persediaan*. Media Sains Indonesia, 2020.
- [11] V. B. Zotov, S. S. Demin, and I. Y. Glazkova, "Features of Material Flow Accounting for the Efficient Supply Chain Management," 2019. [Online]. Available: http://excelingtech.co.uk/
- [12] N. Slack, S. Chambers, and R. Johnston, *Operations Management*. Pearson education, 2010.
- [13] G. A. Zachariah, "Demand Driven Material Requirements Planning (DDMRP): A New Method for Production and Planning Management [Master's thesis, Politecnico di Milano]," Politecnico Di Milano, 2017.
- [14] C. Ptak and C. Smith, *Demand Driven Material Requirements Planning DDMRP version 3*. Industrial Press.Inc., 2016.
- [15] A. Kortabarria, U. Apaolaza, A. Lizarralde, and I. Amorrortu, "Material management without forecasting: From MRP to demand driven MRP," *Journal of Industrial Engineering and Management*, vol. 11, no. 4, pp. 632–650, 2018, doi: 10.3926/jiem.2654.
- [16] A. P. Velasco Acosta, C. Mascle, and P. Baptiste, "Applicability of Demand-Driven MRP in a complex manufacturing environment," *Int J Prod Res*, vol. 58, no. 14, pp. 4233–4245, Jul. 2020, doi: 10.1080/00207543.2019.1650978.
- [17] S. Bayard, F. Grimaud, and X. Delorme, "Study of buffer placement impacts on demand driven MRP performance," in *IFAC-PapersOnLine*, Elsevier B.V., 2021, pp. 1005–1010. doi: 10.1016/j.ifacol.2021.08.119.
- [18] R. Miclo, M. Lauras, F. Fontanili, J. Lamothe, and S. A. Melnyk, "Demand Driven MRP: assessment of a new approach to materials management," *Int J Prod Res*, vol. 57, no. 1, pp. 166–181, Jan. 2019, doi: 10.1080/00207543.2018.1464230.