

Development of Inventory Policy Using Demand Driven Material Requirements Planning (Ddmrp) and Probabilistic Inventory Model: A Case Study on the Water Tank Industry in Indonesia

Ghoffar Albab Maarif*, Iwan Vanany

Institut Teknologi Sepuluh Nopember, Indonesia

Email: ghoffar123@gmail.com*, vanany@ie.its.ac.id

Abstract. PT. X, a water tank manufacturer in Indonesia, has long faced inventory management challenges due to the lack of a structured policy. The current MRP system relies heavily on subjective employee judgment, leading to a reactive and imbalanced inventory system with frequent stockouts or overstock. This study aims to develop a more structured inventory policy that is examined using Monte Carlo simulations in order to achieve more effective and efficient control. Materials are first classified into two groups, namely general components and special components and mixtures. These two groups receive different treatment according to their characteristics. The general components utilize a probabilistic inventory model (R, s, S) to create structured inventory parameters, which are then evaluated against the existing system. Special and mixed components improve the existing MRP system to DDMRP (Demand Driven Material Requirements Planning) with buffer levels across different materials. This adjustment is necessary because the behavior of the MRP system causes system instability, as it is highly dependent on the estimated demand for the final product. Overall, the selected inventory policy resulted in total cost savings of IDR 494,464,820 per week, equivalent to IDR 25,712,170,632 per year. This study proves that pull-based inventory system adjustments, namely DDMRP for special and mixed components and probabilistic inventory models (R, s, S) for general components, are effective in minimizing overstock, stabilizing demand variability, and significantly improving service levels.

Kata kunci: inventory management, periodic review model (r, s, s), material requirement planning (mrp), demand driven material requirement planning (ddmrp), simulasi monte carlo

INTRODUCTION

In the last decade, supply chains have undergone dynamic changes, constantly evolving in terms of their size, structure, and organization, as well as in how they are coordinated, controlled, and managed (Bressanelli et al., 2022; Gawusu et al., 2022; Ning & Yao, 2023; Richey Jr et al., 2023). Efficient operations and supply chain management are essential for most businesses, and implementing the right strategy is crucial for practitioners in competitive industries and markets (MacCarthy et al., 2016). Various planning, management, and supply chain control systems are generally applied in practice. However, optimizing these systems is quite challenging, especially in a VUCA (Volatility, Uncertainty, Complexity, Ambiguity) environment (Bennett & Lemoine, 2014; Marzougui et al., 2020).

This new reality requires a dynamic production environment in which products, processes, and production schedules change frequently (Johnson et al., 2022; Oluyisola et al., 2022; Zhou et al., 2022). Thus, companies are under pressure to lower total costs across the entire supply chain, shorten processing times, drastically reduce inventory, expand product options, provide more reliable delivery dates and better customer service, as well as improve quality to achieve competitive advantage (Rondeau, 2001; Cox III, 2010). Amirjabbari and Bhuiyan (2014) explain that reducing the booking cycle becomes a significant competitive advantage, as it directly impacts the level of customer satisfaction. Reducing inventory levels while maintaining or improving customer service can provide a positive advantage over competitors. Companies that want to stay competitive must therefore build strong competitive advantages. In this context, lowering inventory costs is very important for increasing competitiveness (Jones & Riley, 1985; Kaewchur et al., 2021).

Taking into account the factors mentioned above, choosing a suitable Manufacturing Planning & Control (MPC) system is considered important (Bozzi et al., 2023; Gómez Paredes et al., 2022; Oluyisola et al., 2022; Rahmani et al., 2022; Salatiello et al., 2024). In the last century, many MPC systems were developed, the most extensive of which were Material Requirements Planning (MRP), Just in Time (JIT), and Theory of Constraints (TOC) (Abuhilal et al., 2006). However, these conventional planning systems are not designed to operate effectively in an unstable environment (Kortabarria et al., 2018).

This problem also occurs at PT. X, which is engaged in the water tank industry. PT. X faces challenges related to demand uncertainty caused by fluctuating demand from the retail market and from various construction projects that are difficult to predict. This demand uncertainty has an impact on suboptimal inventory management conditions. PT. X does not yet have standardized inventory policies to address VUCA (Volatility, Uncertainty, Complexity, Ambiguity) environmental conditions.

PT. X currently uses an MRP system, but many parameters for controlling the supply of raw and supporting materials are determined based on subjective judgment. The existing MRP also operates without a proper inventory policy; there is no structured and formal guidance to determine the optimal stock levels to be held in inventory.

In the period from January to April 2024, there was a positive deviation in which the actual finished goods stock was greater than sales orders. This positive deviation shows that PT. X's performance can meet and even exceed sales orders. However, different conditions occur when the deviation is negative, where the actual finished goods stock is lower than the sales order, which results in unfulfilled customer demand.

From the explanation above, this study aims to develop a better and more structured inventory policy at PT. X to achieve more effective and efficient inventory control. Using 465 final products produced by PT. X, this study will classify materials based on their use in the final product as well as the characteristics of the material itself. The rationale behind this classification is to determine the most appropriate inventory policy strategy for each material category, taking into account the differences in characteristics in each category. The material classification will be divided into general, special, and mixed components.

Common components refer to components used by all final products. Common components are more suitable for removal from the MRP system because they are required across all final products and therefore must always be available in inventory for production. Thus, rather than using MRP, which relies on demand forecasts, analyzing historical data and using probabilistic review models to determine the right inventory policy is more appropriate and effective. The periodic review model (R, s, S) is considered an appropriate method to calculate inventory parameters as a cost-saving option for class A items. Previous research indicates that, under fairly common assumptions, the (R, s, S) system results in lower replenishment, storage, and shortage costs compared to three other systems (Scarf, 1960).

Custom components refer to components used in only one final product. Meanwhile, mixed components are a combination of common and special materials. This means that the purchased material is used as a component in more than one final product, but not in all products. Both types of components tend to have fluctuating and unstable demand, highly dependent on higher-level final products. Therefore, using an MRP system based on forecast data that considers future demand and events, rather than solely historical data, would be more appropriate.

Nevertheless, given the behavior of the MRP system that can cause system instability because it is highly dependent on the estimated demand for the final product, this study attempts to improve the MRP system. For this reason, the DDMRP (Demand Driven Material Requirements Planning) concept will be considered as a proposed improvement model, given that the basis of DDMRP is to protect and support the flow of information and materials.

DDMRP allows decoupling points to be placed throughout the bill-of-materials structure and enables demand signal distortion and supply continuity variability to be addressed consistently.

Because the full implementation of DDMRP requires substantial resources, this study will focus only on the first two phases of DDMRP, namely strategic inventory positioning and buffer profiles & levels, while still combining them with the basic concept of MRP through the implementation of MRP Rolling Horizon. The combination of simplified DDMRP and MRP is expected to manage uncertainty better than MRP alone through the principle of a pull approach. The use of DDMRP in this study aims to offer an alternative approach to MRP and to develop a more efficient material management model based on demand, taking into account an unstable manufacturing environment.

Based on the background and problems described above, this study aims to classify raw materials at PT. X into common components, special components, and mixed components based on their usage characteristics, in order to determine the most appropriate inventory control strategy for each category. Furthermore, this research seeks to develop a structured inventory policy for common components using a probabilistic periodic review model (R, s, S), evaluated through Monte Carlo simulation to minimize overstock and reduce total inventory costs. For special and mixed components, this study aims to improve the existing Material Requirements Planning (MRP) system by integrating the Demand Driven Material Requirements Planning (DDMRP) framework, specifically through strategic inventory positioning and buffer level determination, to enhance material flow stability and mitigate the bullwhip effect. This research also intends to compare the performance of the proposed inventory policies ((R, s, S) and DDMRP) against the company's existing MRP system in terms of total cost efficiency and service level (fill rate), ultimately providing PT. X with a comprehensive and data-driven inventory policy recommendation that can reduce overall operational costs while maintaining high customer service levels amid demand uncertainty.

The benefits of this research are multifaceted. For PT. X, this research provides a practical and structured inventory management framework that can be directly implemented. The proposed policies are expected to significantly reduce total inventory costs—as evidenced by the projected savings of IDR 25.7 billion annually—optimize stock levels to prevent both overstock and stockouts, and improve service levels to nearly 100%, thereby enhancing the company's operational efficiency and competitiveness in the dynamic water tank industry. For academic development, this study contributes to the existing body of knowledge by empirically comparing traditional MRP, probabilistic inventory models, and the DDMRP framework within the context of a real-world manufacturing case study in a developing country. It validates the application of combining pull-based strategies (DDMRP) and probabilistic models to address different material characteristics, offering a valuable reference for future research on inventory management under VUCA conditions. For industry practitioners, the findings offer valuable insights for other manufacturing companies facing similar inventory challenges. The material classification approach and the hybrid methodology, which combines DDMRP for demand-dependent items and probabilistic models for common items, can serve as a benchmark for developing resilient and efficient inventory policies in other industries characterized by demand uncertainty and complex bills of materials.

RESEARCH METHOD

Problem Identification Stage

The first stage carried out in this study is to identify problems that occur in the Planning Division of PT X. The problems identified are related to inventory control policies.

The problem identification stage was carried out through two studies, namely field studies and literature studies. A field study was conducted to find out directly the problems that occurred in PT X's inventory system. Literature studies are conducted to obtain several theories related to the problems in the research. The theory is used as a guideline for research work and research problem-solving methods.

Stages of Data Collection

At this stage, the data needed to solve inventory problems at PT X is collected. *lead time*; *Bill of Materials* (BOM) for finished products; historical demand for materials; components of inventory costs, such as purchase costs and reorder costs; existing MPS and MRP systems; and existing inventory policies and parameters.

Data Processing Stage

The data processing stage in this study is divided into two component groups, general components and special and mixed components. The following is an explanation of the steps taken for each component group.

Common Components

Historical demand data over the past year will be used to calculate inventory parameters on common components.

Critical Material Selection

The common components used by all finished products will be identified first, then the critical common components will be determined. Common components here refer to the materials used by all finished products. There are 5 common components that will be observed in this study.

Identify Uncertain Elements

An uncertain element in this study is demand. Demand distribution matching will be done to accommodate this uncertainty. The results of the distribution matching will be used as input for the Monte Carlo simulation. Microsoft Excel software will be used to perform distribution matching that will show distribution options based on their acceptance priority, along with the distribution parameters to be used.

Determination of Inventory Parameters and Model Development

This study shows that the demand is in stochastic conditions, so the model used comes from a probabilistic model, especially the periodic review model. The conceptual models that will be evaluated in this study include existing models and models (R, S, S). The service level used in the calculation is 90%.

The formula for calculating the inventory control parameters is as follows: (Smith, 1989)

$$(q_w = \sqrt{\frac{2kr}{h}} \quad 3.1)$$

$$F_{L+w}(K) = \frac{\pi r - hq}{\pi r} \quad (3.4)$$

$$SS = K \times \sigma_{L+w} \quad (3.2)$$

$$s = \mu_{L+w} + SS + \frac{rw}{2} \quad (3.3)$$

$$s = q_w + s - \frac{rw}{2} \quad (3.5)$$

With :

q_w = order quantity

r = total requests

k = booking fee

h = holding cost

π = cost shortage

K = safety factor

σ_{L+w} = Standard Demand Deviation

μ_{L+w} = average demand
L = lead time
w = period review

Parameter Simulation

Monte Carlo simulations will be performed to see demand uncertainties and observe how those uncertainties affect inventory levels, so that the results will take into account more precise parameters than the results of the previous calculations. The output of this simulation is the total cost and fulfillment rate.

Special and Mixed Components

For special and mixed (general-special) components, the DDMRP system is used as an upgrade of the traditional MRP system. The steps taken are described in the following sections.

Critical Material Selection

Custom components refer to materials that are only used by one final product. There are 5 special components that will be observed in this study. While mixed components refer to the materials used by less than 100 final products. Because mixed components are the most common components encountered in real conditions. There are 5 mixed components that are the focus of this research.

Identification of the BOM

Once the special components and critical mixed components are selected, the BOM that reflects the final product is identified. Furthermore, a BOM matrix was developed that displays the components in the column and the parent product in rows or vice versa, so that the need for mixed components can be easily summarized.

Determination of Inventory Parameters and Model Development

Current models use MRP as a material planning system. The DDMRP system will be developed as an upgrade of the MRP. The initial inventory parameters but not limited to safety stock, will be calculated as the basis of this system. The development of the parameters used in the DDMRP will be described in the following sections.

Strategic Inventory Placement

Strategic stockpiling is the determination of where decoupling points *should be placed on the BOM*. The sequence of steps taken is to identify the places in the BOM that represent the main raw materials purchased, sub-assemblies, and intermediate components. This is done through observations on the MRP and the BOM matrix. Then determine the placement of the separation point on the BOM. This placement can only be done on one level. Tier 1 or tier 2, and not at tier 0 as the final product. The position of the *decoupling points* will be one of the parameters that will be simulated in the development of the scenario later.

Buffer Levels

The profile and buffer level, as the second stage of the DDMRP, will determine the amount of *buffer* that should be provided at the separation point. The safety stock formula used is for variable demand and constant *lead time*. The calculation is made based on the average demand for materials with a service rate of 90%.

$$(3.6)SS = Z \times \sigma_D \times \sqrt{LT}$$

With :

SS = Safety Stock
Z = Z-value of normal distribution
 σ_D = Standard demand deviation (*Demand*)
LT = Lead Time

MRP with Rolling Horizon

Since the full implementation of DDMRP requires a lot of resources such as time and effort, DDMRP in this study only considers the first two stages with some simplification. This model is run in MRP with a rolling horizon, as this approach is better at mimicking periodic updates of MPS plans that generally occur in reality. Demand, or MPS, as an uncertain input will be calculated with a deviation from -10% to 10% to represent the real system. Rolling horizon will continuously display MRP planning for several weeks of the year, starting from the first week. When the week has passed, it will be removed from the MRP planning and replaced with a new calculation for future planning.

Data Analysis and Interpretation Stage

At this stage, an analysis was carried out on each inventory control method, namely the *periodic review* (R,s,S) and DDMRP methods, as well as the existing method. After that, a comparison of the total inventory costs of each of these methods is carried out. The inventory control method that provides the lowest total cost of inventory is the method chosen.

RESULTS AND DISCUSSION

Analysis of Existing Inventory Policy for Common Components

Kebijakan persediaan PT. X is currently run through an MRP-based Microsoft Excel worksheet without any default in the ordering process. Although the company stated that it was trying to maintain inventories (DOIs) for up to 14 days to meet the needs of two weeks, analysis of historical data showed significant deviations. The actual average DOI value exceeds 100%, such as BR1 which has a DOI of 80 days. This condition occurs in all common components.

The magnitude of the DOI value is in line with the high consumption of common components used in more than 13 final products. This explains why component stocks are so abundant and reinforces the *overstock* and *overcapacity* findings highlighted in Chapter 1. Figure 7.1 shows the average *fill rate* of existing conditions for all common components.

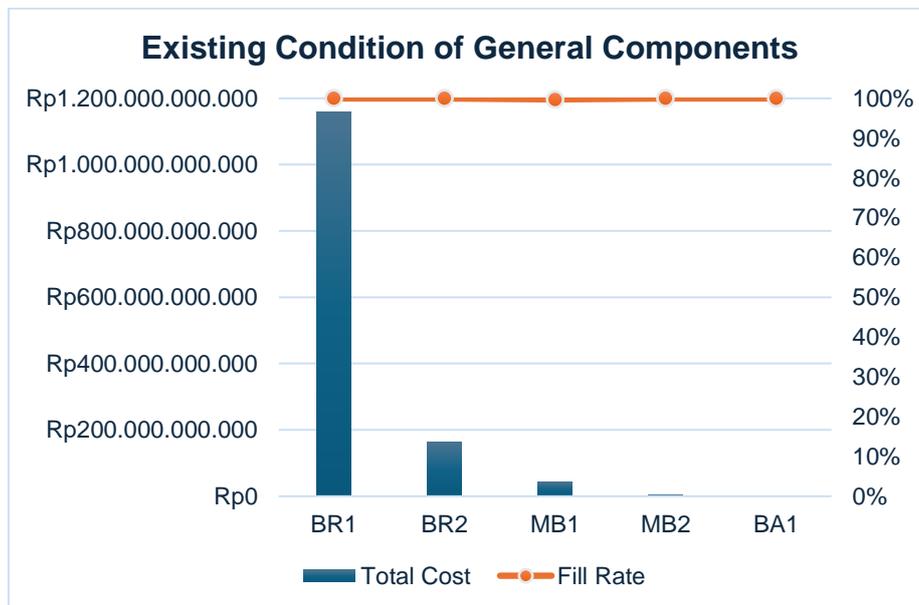


Figure 1. Total Cost and Fill Rate Existing Conditions of Common Components

Source: Primary data processed (2024)

Historical booking patterns show a low frequency of bookings, i.e. one to two times per month, so the number of bookings becomes very large to anticipate the needs of the

coming months. Replenishment decisions are often influenced by subjective factors due to the unavailability of mathematically calculated inventory parameters. Lack of human resources and high number of items are likely to be the reasons for the absence of a formal inventory policy, including the unavailability of PPIC KPIs that regulate minimum and maximum inventory limits.

Proposed Model Analysis for Common Components

The proposed inventory policy model utilizes the periodic review (R, s, S) approach as a cost efficiency strategy for category A components. All common components are excluded from the MRP mechanism due to the nature of the use of many final products, so they must always be available for production activities to run smoothly.

In this method, the review period (R) is the moment of evaluation whether the stock has reached the lower limit (s). If so, then it will be replenished until it reaches the upper limit of inventory (S). Since the order decision depends on the current stock conditions, *the quantity of replenishment* is always dynamic.

The results of the Monte Carlo simulation show that the proposed model is able to significantly increase *the fill rate* compared to the current system. The probability of *stockouts* decreases due to the existence of a minimum inventory limit, while the risk of *overcapacity* can be reduced through maximum inventory restrictions. Thus, the demand fulfillment rate is almost 100% and inventory becomes more controlled.

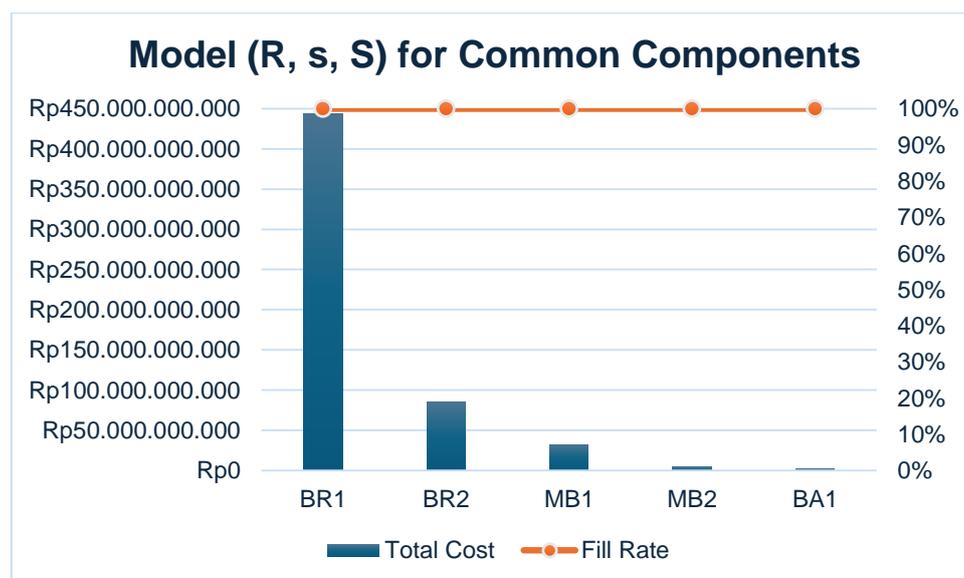


Figure 2. Total Cost and Fill Rate Model (R,s,S) Common Components

Source: Primary data processed (2024)

The proposed inventory model shows a very significant reduction in total costs compared to previous conditions. As an illustration, for the BR1 component, the total cost under the existing condition reached around **1.15 trillion rupiah**, while after using the (R, S, S) approach, the total cost dropped drastically to only **444 billion rupiah**. Thus, there is a **saving of 62%**. The cost reduction percentages for all components are then summarized in the following table.

Table 1. Deduction Total Cost Common Components

Material	Total Cost (Existing)	Total Cost (R, s, S)	Total Cost Reduction
BR1	IDR1.159.091.502.084	IDR 444,315,979,966	62%

BR2	IDR162.916.177.116	IDR85,040,535,042	48%
MB1	IDR43.128.972.192	IDR 32,227,403,106	25%
MB2	IDR 4,992,977,452	IDR 4,308,560,952	14%
BA1	IDR 2,208,075,328	IDR 2,068,930,160	6%
Total	IDR 1,372,337,704,172	IDR567.961.409.227	59%

Source: Primary data processed (2024)

The significant difference between the total cost under existing conditions and the proposed model is mainly triggered by the magnitude of the storage costs. Under current conditions, the volume of inventory held far exceeds the weekly real demand, resulting in excess storage capacity and resulting *in very high holding costs*. When analyzed based on its components, the purchase costs and storage costs on existing systems are much greater than the costs on periodic models (R, S, S).

In contrast, the cost of ordering on the proposal model is higher because the frequency of orders increases—inversely proportional to the existing condition of only making purchases about once every one to two months.

Common Component Sensitivity Analysis

Sensitivity testing is performed to evaluate changes in output performance due to fluctuations in demand uncertainty factors. This test is focused on selected inventory policy strategies. Five variations of demand conditions were used in this test, namely decrease and increase in demand by -15%, -5%, 0%, 5%, and 25%. The results of the sensitivity test are further discussed in the following sections.

The test results showed that the decrease in the level of demand was directly proportional to the decrease in total costs, while the increase in demand led to an increase in total costs. For example, in the BR1 Material shown in Figure 7.3, a 15% increase in demand from the initial condition resulted in a total cost increase from 444 billion rupiah to 449 billion rupiah.

This increase in total costs is due to the need to procure larger quantities of components to meet the increasing demand, which ultimately increases storage costs, purchase costs, as well as reordering costs. A similar pattern occurs across all other components, so it can be concluded that changes in demand consistently affect the total cost of inventory.

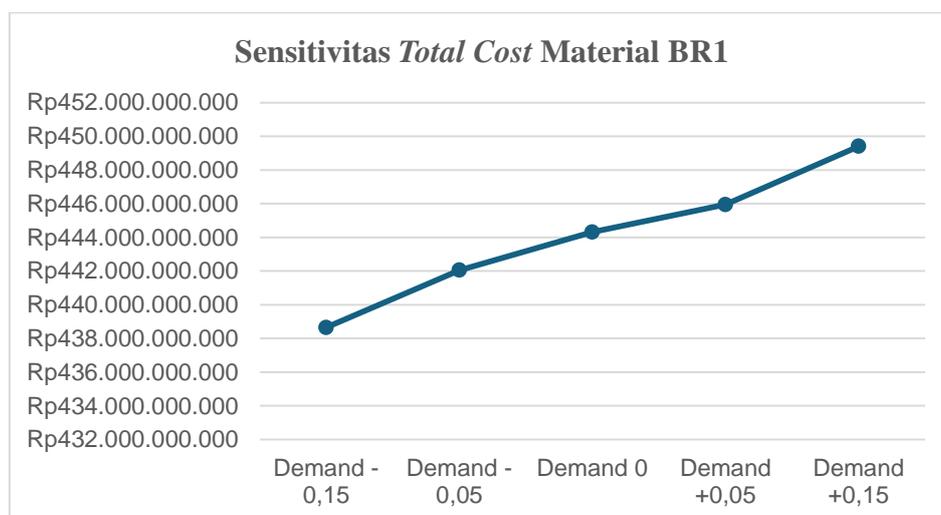


Figure 3. Sensitivity Total Cost Material BR1

Source: Primary data processed (2024)

Based on Figure 3, it can be concluded that the variation in demand does not have a significant impact on the *fill rate*. Despite changes in demand, the inventory system is still able to meet the *predetermined fill rate target*. These findings indicate that the proposed inventory model (R, s, S) has a high level of resilience in determining an adequate amount of inventory while minimizing the risk of *stockout*.

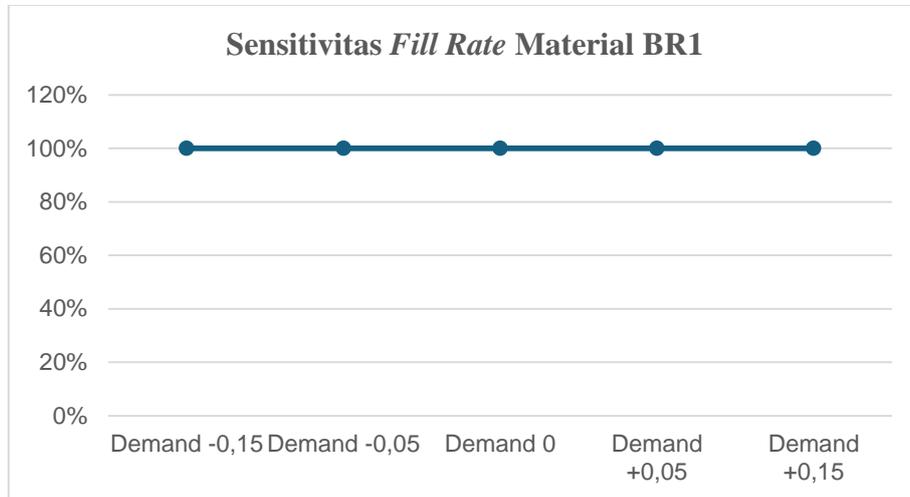


Figure 4. Sensitivity *Fill Rate* Material BR1

Source: Primary data processed (2024)

Analysis of Existing Inventory Policy for Specialty and Mixed Components

PT. X applies similar inventory policies for special, mixed, and common components. However, the DOI value of special components is much lower than that of mixed and common components. For example, the average DOI of ACC1 components is only about 17 days, and most specialty components are under 20 days, while mixed components reach 87 days, comparable to common components.

This difference arises because special components are associated with only one *parent* (final product), whereas mixed and common components are used by many end products. The larger number of *parents* increases the need for components significantly. In addition, the demand for special and mixed components tends to be small and uneven because their use depends on *less parent* production schedules than common components. In some weeks there is not even any use at all.

The recapitulation in Figures 5 and 6 indicates that special and mixed components experienced the occurrence of stock shortages, which had an impact on the low *fill rate*.

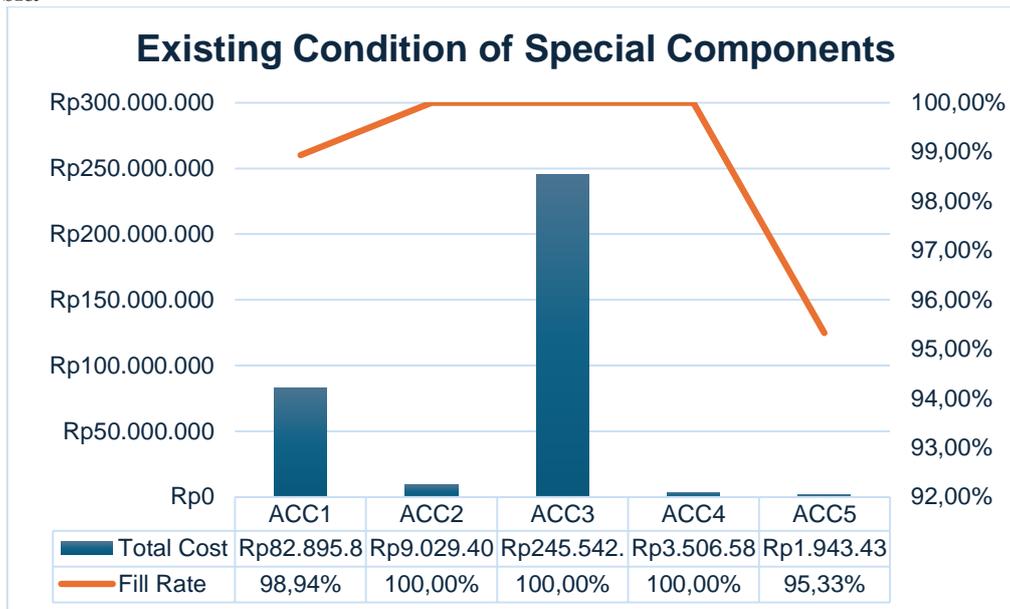


Figure 5. Average Total Cost and Fill Rate Existing Conditions of Special Components
Source: Primary data processed (2024)

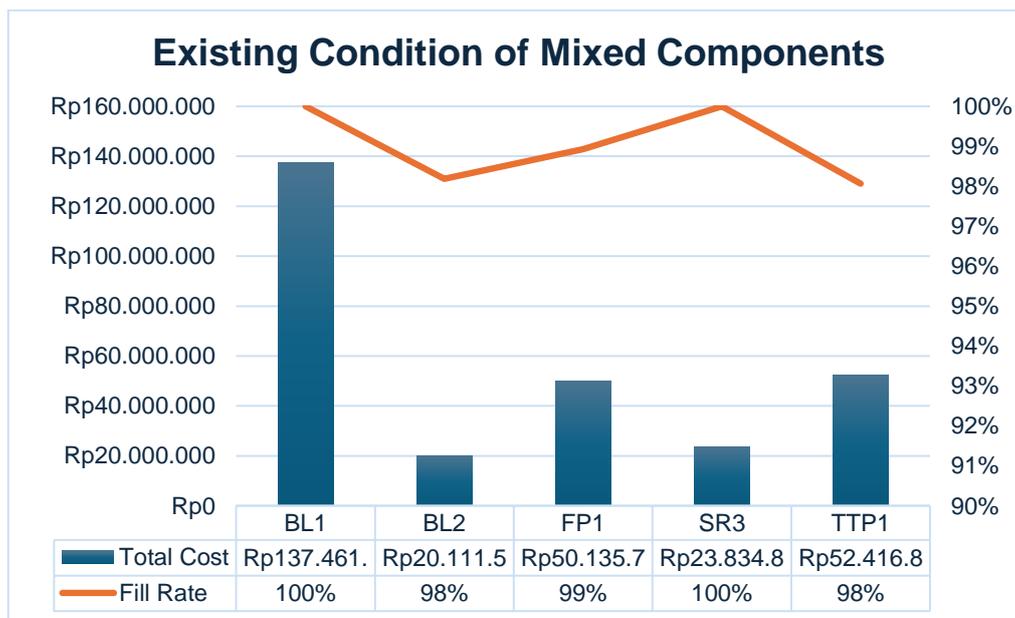


Figure 6. Friendly Total Cost and Fill Rate Existing Conditions of Mixed Components
Source: Primary data processed (2024)

The *replenishment process* that is still carried out manually is a challenge in itself, considering that the number of components that must be managed can reach hundreds of materials from various *end-products*. The complexity of multi-product and multilevel MRPs, coupled with limitations of human resources and technology, causes order cycles to be very long and order sizes to be excessive. The use of excel MRP that has been more than five years without updating the master data further increases the risk of errors and prolongs the calculation time.

With these conditions, this study proposes the implementation of a more structured and efficient MRP system. The next section presents an inventory policy designed to reduce total costs while increasing fill rates in response to weaknesses in existing conditions.

Analysis of Proposed Models for Specialty and Mixed Components

The proposed inventory policy model utilizes a more structured MRP system and runs using a 40-week rolling horizon to describe actual operating conditions when there are high demand fluctuations. Since the demand pattern for special and mixed components is much more unstable than for common components, the use of MRP systems is considered most appropriate. A detailed explanation of Excel that is more systematic and organized has been presented in Sub-Chapter 6.4.

In its application, there are a number of limitations and research assumptions related to the MRP system. First, each purchase *order* release is assumed to be received within a full period of one week so that the receipt functions as a *scheduled receipt*. Second, no fixed lot size or minimum order amount is applied; custom and mixed components using a Lot-For-Lot (LFL) policy. As such, the order quantity may change in each *replenishment cycle* as the system tries to ensure that there is no *inventory buffer* left each week.

After the implementation of the 40-week horizon with a uniform demand deviation of between -10% to +10%, there is a decrease in total costs with a maintained *fill rate*, as shown in Figure 7.5. With the *characteristics of demand being lumpy* and the implementation of the proposed MRP system, the number of orders can be adjusted to the needs of weekly demand so that the inventory level can be reduced to a minimum.

The use of the *rolling horizon* approach makes MRP planning more realistic. A positive demand deviation has the potential to lead to *stockouts*, while a negative deviation can lead to inventory buildup.

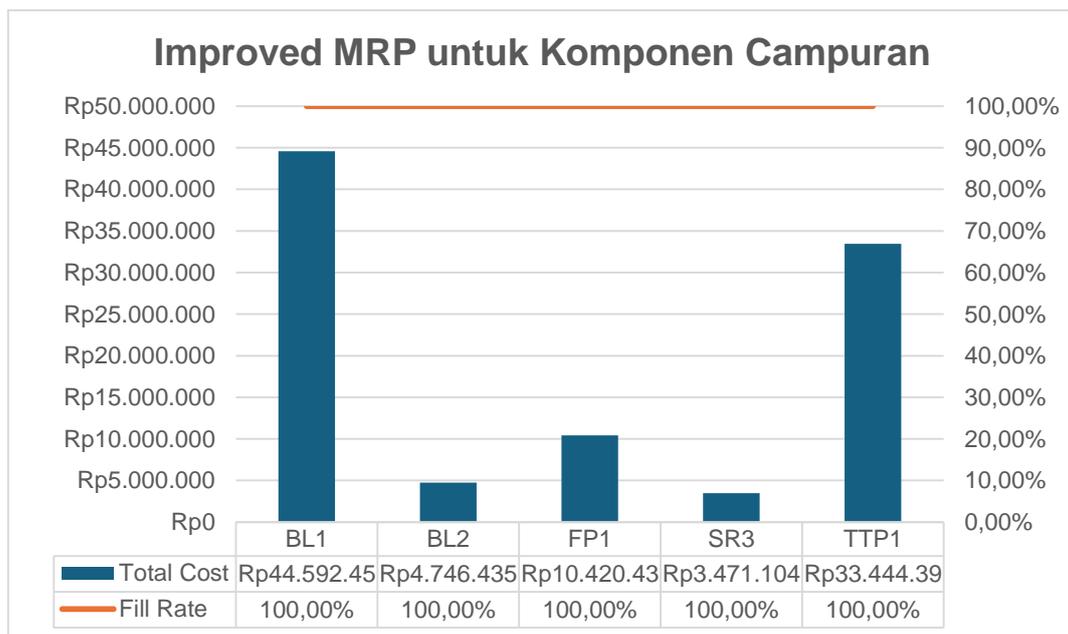


Figure 7. Friendly Total Cost dan Fill Rate Improved MRP Mixed Components

Source: Primary data processed (2024)

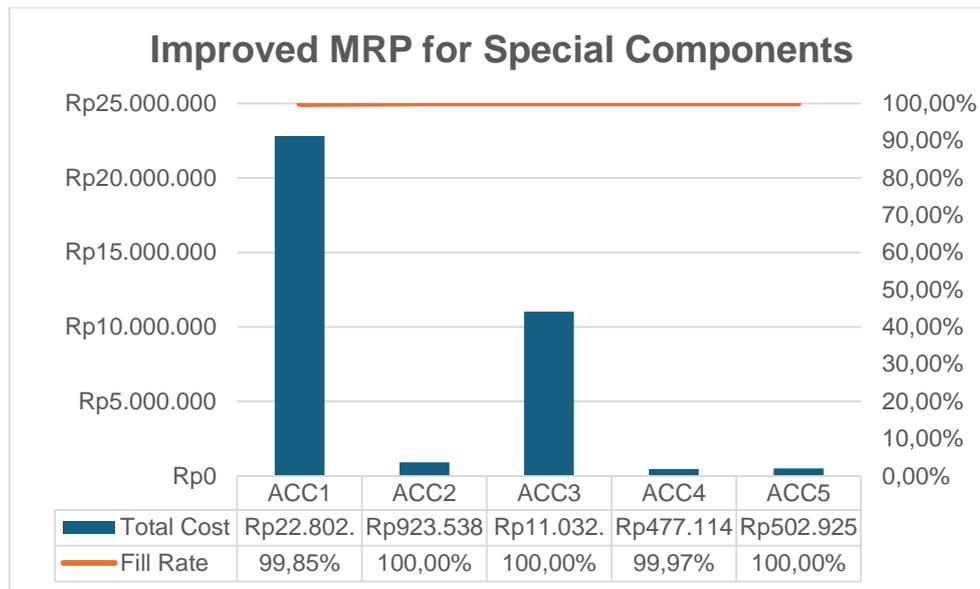


Figure 8. Friendly Total Cost dan Fill Rate Improved MRP Special Components

Source: Primary data processed (2024)

For example, Table 8 shows a comparison between the existing conditions, the proposed MRP, and the proposed DDMRP to the *fill rate* and *total cost* for the ACC5 component. Only one component is shown as an illustration, as the other components exhibit similar patterns of results — especially in terms of large cost reductions and high *fill rates*.

Table 2. Comparison of Inventory Policies for ACC5 Components

ACC5		
Skenario	Total Cost	Fill Rate
IDR		
Existing	1,943,432	95,33%
DDMRP Without Buffer	IDR402,330	97,96%
DDMRP Buffer	IDR 502,925	100,00%

Source: Primary data processed (2024)

The cost reduction from the existing condition to the initial MRP reached 90.53% for special components and 75.74% for mixed components. Meanwhile, the cost reduction from the existing condition to the proposed DDMRP is 89.58% for special components and 65.95% for mixed components. The average fill rate in the initial MRP is 97.77%, while in the proposed DDMRP it reaches 100%, except for the ACC1 and ACC4 components.

These substantial savings are likely affected by research limitations, as not all company data were available for further processing. Several assumptions needed to be made for data such as unit cost, MOQ, and lot size of special and mixed components, because in actual conditions there are no standard values for these parameters. Unit cost often changes, while MOQ and lot size usually follow previous purchase histories that vary over time. This causes the number of orders to be subjective under existing conditions and not supported by standardized calculations.

As in the previous subchapter, normalization and weighting processes were carried out for the existing condition, the proposed MRP model, and the proposed DDMRP model. The results consistently show that DDMRP obtained the highest weight value compared to

the existing condition and the initial MRP. The complete results can be seen in Table 6.28 in Chapter 6. Furthermore, Table 7.3 shows the total cost savings after implementing the selected inventory policy, which is around IDR 494,464,820 per week. Assuming one year consists of 52 weeks, the annual savings amount to IDR 25,712,170,632. These inventory cost savings are acceptable because the selected proposed model succeeded in achieving an average fill rate above 97.5%, in accordance with the predetermined target parameters.

Table 3. Savings Recapitulation Total Cost Per Week

Material	Existing	DDMRP Buffer	Savings
ACC1	IDR 82,895,889	IDR22.802.039	IDR 60,093,850
ACC2	IDR 9,029,409	IDR 923,538	IDR 8,105,871
ACC3	IDR245.542.613	IDR 11,032,827	IDR 234,509,786
ACC4	IDR 3,506,580	IDR477,114	IDR 3,029,466
ACC5	IDR 1,943,432	IDR 502,925	IDR 1,440,507
BL1	IDR 137.461.122	IDR44,592,452	IDR 92,868,670
BL2	IDR 20,111,571	IDR 4,746,435	IDR 15,365,135
FP1	IDR50,135,725	IDR 10,420,430	IDR 39,715,295
SR3	IDR 23,834,859	IDR 3,471,104	IDR 20,363,755
TTP1	IDR52,416,877	IDR 33,444,392	IDR 18,972,485
Total	IDR626.878.078	IDR 132,413,258	IDR494,464,820

Source: Primary data processed (2024)

The DDMRP model has been proven to maintain consistently higher fill rates, almost reaching 100% for all components. This is made possible by the presence of a buffer that functions as both safety stock and buffer supply to prevent stock shortages. The buffer is able to respond to high demand fluctuations, which generally occur in special and mixed components.

In this study, buffer placement was applied only to critical materials at Level 1. The reason is that most Level 1 components are special and mixed components, in contrast to Level 2, which consists mostly of common components. Ideally, buffers can be placed on all materials from Level 0, Level 1, to Level 2 to maintain customer satisfaction and minimize the risk of stockouts. However, implementing buffers at all levels has the potential to cause inventory build-up and a substantial increase in storage costs. Therefore, to maintain realism, the buffer is placed only on critical materials, namely components that have a high level of component commonality.

As in the previous condition, the large difference between the existing conditions, the proposed model, and the scenario model in terms of total cost is mainly due to the high holding cost. Under current conditions, the amount of inventory stored far exceeds demand for several weeks or even months, so the volume of goods that must be held becomes very large and results in very high storage costs.

As previously explained, this occurs due to the absence of a proper study or calculation of the percentage of holding costs. As a result, the actual storage costs are quite large and have not been adequately accounted for under existing conditions. The absence of standardized inventory parameters and KPIs also contributes significantly to this problem.

The situation is exacerbated by the manual replenishment process for a large number of special and mixed components, making inventory control even more inefficient.

CONCLUSION

This research develops a structured inventory policy system that divides materials into two groups. The common components use a probabilistic periodic review (R,s,S) model, which results in average annual operational cost savings of IDR 800 billion and simultaneously increases the average fill rate to 100% compared to the existing MRP system. Special and mixed components develop the existing MRP system into a DDMRP framework that results in a substantial weekly total cost reduction (89.58% for special components and 65.95% for mixed components) and achieves an average fill rate above 99.5%. Based on historical data calculations, the MRP system produces a bimodal distribution, resulting in simultaneous stock accumulation (overstock) and stock shortage risk. Service performance under this condition is unstable, with the average fill rate reaching only 91.8% for special components and 93.8% for mixed components. The application of DDMRP with buffer placement has been proven effective in dampening the bullwhip effect and improving material flow stability. The simulation results show a very significant improvement in service quality, with the average fill rate increasing to 100% for almost all components (with the exception of ACC1 at 99.85% and ACC4 at 99.97%). The implementation of the (R,s,S) and DDMRP policies results in combined total cost savings of IDR 494,464,820 per week, or around IDR 25,712,170,632 per year, by reducing overstocking and improving the accuracy of material requirements planning. This study successfully establishes and recommends a demand-based pull system (DDMRP) strategy for materials directly related to the Master Production Schedule (MPS) and probabilistic (R,s,S) strategies for common materials that are always needed, effectively mitigating the bullwhip effect.

REFERENCES

- Abuhilal, L., Rabadi, G., & Sousa-Poza, A. (2006). Supply chain inventory control: A comparison among JIT, MRP, and MRP with information sharing using simulation. *Engineering Management Journal*, 18(2), 51–57. <https://doi.org/10.1080/10429247.2006.11431694>
- Amirjabbari, B., & Bhuiyan, N. (2014). Determining supply chain safety stock level and location. *Journal of Industrial Engineering and Management*, 7(1), 42–71. <https://doi.org/10.3926/jiem.543>
- Bennett, N., & Lemoine, J. (2014). What a difference a word makes: Understanding threats to performance in a VUCA world. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2406676>
- Bozzi, A., Graffione, S., Sacile, R., & Zero, E. (2023). Dynamic MPC-based scheduling in a smart manufacturing system problem. *IEEE Access*, 11, 141987–141996.
- Bressanelli, G., Visintin, F., & Saccani, N. (2022). Circular economy and the evolution of industrial districts: A supply chain perspective. *International Journal of Production Economics*, 243, 108348.
- Cox, J. F., III. (2010). *Theory of constraints handbook*. McGraw-Hill.
- El Marzougui, M., Messaoudi, N., Dachry, W., Sarir, H., Bensassi, B., & Marzougui, M. El. (2020). Demand driven MRP: Literature review and research issues. HAL. <https://hal.science/hal-03193163>
- Gawusu, S., Zhang, X., Jamatutu, S. A., Ahmed, A., Amadu, A. A., & Djam Miensah, E. (2022). The dynamics of green supply chain management within the framework of renewable energy. *International Journal of Energy Research*, 46(2), 684–711.
- Gómez Paredes, F. J., Godinho Filho, M., Thürer, M., Fernandes, N. O., & Jabbour, C. J. C. (2022). Factors for choosing production control systems in make-to-order shops: A systematic literature review. *Journal of Intelligent Manufacturing*, 33(3), 639–674.
- Johnson, D., Chen, G., & Lu, Y. (2022). Multi-agent reinforcement learning for real-time

Development of Inventory Policy Using Demand Driven Material Requirements Planning (DDMRP) and Probabilistic Inventory Model: A Case Study on the Water Tank Industry in Indonesia

- dynamic production scheduling in a robot assembly cell. *IEEE Robotics and Automation Letters*, 7(3), 7684–7691.
- Jones, T. C., & Riley, D. W. (1985). Using inventory for competitive advantage through supply chain management. *International Journal of Physical Distribution & Materials Management*, 16–26.
- Kaewchur, P., Sritong, C., Sriard, B., & Nima, T. (2021). Role of inventory management on competitive advantage of small and medium companies in Thailand. *Turkish Journal of Computer and Mathematics Education*, 12(8).
- Kortabarria, A., Apaolaza, U., Lizarralde, A., & Amorrortu, I. (2018). Material management without forecasting: From MRP to demand driven MRP. *Journal of Industrial Engineering and Management*, 11(4), 632–650. <https://doi.org/10.3926/jiem.2654>
- MacCarthy, B. L., Blome, C., Olhager, J., Srari, J. S., & Zhao, X. (2016). Supply chain evolution – theory, concepts and science. *International Journal of Operations and Production Management*, 36(12), 1696–1718. <https://doi.org/10.1108/IJOPM-02-2016-0080>
- Ning, L., & Yao, D. (2023). The impact of digital transformation on supply chain capabilities and supply chain competitive performance. *Sustainability*, 15(13), 10107.
- Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2022). Designing and developing smart production planning and control systems in the Industry 4.0 era: A methodology and case study. *Journal of Intelligent Manufacturing*, 33(1), 311–332.
- Rahmani, M., Romsdal, A., Sgarbossa, F., Strandhagen, J. O., & Holm, M. (2022). Towards smart production planning and control: A conceptual framework linking planning environment characteristics with the need for smart production planning and control. *Annual Reviews in Control*, 53, 370–381.
- Richey, R. G., Jr., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, 44(4), 532–549.
- Rondeau, P. J. (2001). *Evolution of manufacturing planning and control systems: From reorder point to enterprise resource planning*.
- Salatiello, E., Vespoli, S., Guizzi, G., & Grassi, A. (2024). Long-sighted dispatching rules for manufacturing scheduling problem in Industry 4.0 hybrid approach. *Computers & Industrial Engineering*, 190, 110006.
- Scarf, H. (1960). The optimality of (S, s) policies in the dynamic inventory problem.
- Smith, S. B. (1989). *Computer-based production and inventory control*. Prentice-Hall.
- Zhou, L., Jiang, Z., Geng, N., Niu, Y., Cui, F., Liu, K., & Qi, N. (2022). Production and operations management for intelligent manufacturing: A systematic literature review. *International Journal of Production Research*, 60(2), 808–846.



© 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY SA) license (<https://creativecommons.org/licenses/by-sa/4.0/>).