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Inventory Analysis of Packed Red Cells Components Using Monte Carlo Simulation

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ABSTRACT

This study analyzes Packed Red Cells (PRC) inventory management at PMI Banyumas using a Monte Carlo simulation to evaluate different stock management strategies. The initial model shows a significant shortage of blood supply. Two alternative scenarios were simulated to address this issue: adding 55 additional units from external sources and increasing donor participation by 15%. The simulation results demonstrate that these strategies effectively reduce the shortage from 62 units to just 5 units without increasing expired inventory while achieving the lowest total cost of Rp. 9,927,682. These findings highlight that increasing donor participation offers the best performance in balancing supply and demand. This study provides simulation-based strategic recommendations that other PMI branches can replicate to improve bloodstock management, reduce shortages, and maintain optimal service levels.

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1. INTRODUCTION

Blood plays a vital role in the body, particularly in transporting oxygen and nutrients and supporting the immune system. The circulatory system facilitates blood distribution, with the heart as the primary pump. Any disruption in this flow can result in severe tissue damage or even death, underscoring the critical importance of maintaining sufficient blood availability, especially for medical procedures such as transfusions (Saviano *et al*., 2024).

In Indonesia, blood management is carried out by the Indonesian Red Cross (Palang Merah Indonesia or PMI) through its Blood Transfusion Units (Unit Kegiatan Transfusi Darah or UKTD). This process includes donor selection, blood collection, storage, and distribution. To ensure the availability of blood in optimal conditions, PMI implements Blood Supply Chain Management (BSCM), which consists of stages such as collection, production, storage, and distribution (Torrado & Barbosa-Póvoa, 2022). However, this management faces various challenges, including the perishable nature of blood, the need for specialized storage, and uncertainties in demand. Therefore, effective coordination among donors, blood banks, and healthcare facilities is essential to maintain stock balance and ensure smooth distribution (Jin *et al*., 2021).

The blood inventory management at PMI Banyumas system involves multiple stages, including donor recruitment, blood collection, testing, production of blood components, storage in blood banks, and distribution to hospitals. Each stage presents inventory management challenges, particularly in balancing operational and safety stock levels to meet fluctuating demand while minimizing expirations. Traditionally, inventory systems rely on historical data to determine reorder points and safety stock levels. However, due to the highly variable and unpredictable nature of blood demand affected by accidents, emergencies, seasonal factors, and medical procedures, historical averages alone may not provide sufficient accuracy for forecasting. Therefore, this study applies Monte Carlo simulation to realistically model demand uncertainty by generating probabilistic outcomes rather than static forecasts. This method facilitates the integration of demand uncertainty and risk considerations into inventory decision-making. This research addresses unmet demand (shortages) and evaluates key performance indicators of the inventory system, including stock availability, expiration rates, and cost efficiency. Through simulation, this study aims to provide a more comprehensive evaluation of the blood inventory system at PMI Banyumas to support more adaptive and data-driven decision-making.

The imbalance between supply and demand is a major challenge in blood inventory management. For instance, PMI Banyumas Regency often experiences

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shortages (out of stock) or overstock, which risks resource wastage. This challenge is particularly complex for blood type AB, which constitutes only about 8.38% of Indonesia's population, or approximately 3,175,187 people (Direktorat Jenderal Kependudukan dan Pencatatan Sipil, 2021). With limited supply compared to other blood types, even minor changes in demand or distribution can significantly impact its availability at PMI, including in Banyumas Regency.

Based on PMI Banyumas data from June 2023 to May 2024, there was a deficit of 688 units of Packed Red Cells (PRC) for blood type AB. Demand reached 4,825 units, while supply was only 4,137 units. This imbalance is particularly critical because blood type AB has the lowest proportion in the population, both nationally and in the Banyumas Regency. Data from UDD PMI Banyumas in 2020 shows that only about 7.5% of total PRC production comes from AB blood type, far lower than type O (38.5%), B (30.2%), and A (23.7%). The limited number of AB donors increases the vulnerability of AB stock to shortages. Moreover, AB patients can only receive transfusions from AB donors or, under specific conditions, from universal donors, although full compatibility is medically preferred to avoid transfusion reactions. In Banyumas, certain cases, such as thalassemia and chronic diseases, also require regular transfusions, making the availability of AB PRC crucial. This shortage could hinder critical medical procedures like surgeries or emergency care, increasing mortality risk due to delayed treatment (Jayaram et al., 2024). Additionally, stock imbalances increase expired blood units, which must be discarded, ultimately leading to higher costs (Anchinmane & Sankhe, 2022).

Monte Carlo simulation can be used as a predictive inventory management method to address blood demand uncertainties. This simulation utilizes probability distributions to estimate demand variations based on factors such as accidents, surgical needs, and blood donation trends. This approach has proven effective in reducing the risks of stockouts and overstock by considering dynamic demand patterns (Darnis *et al.*, 2020). The Monte Carlo technique employs random sampling and statistical evaluation to estimate a range of potential outcomes. This approach has been highly useful in health care planning treatments, evaluating risks, and managing resource distribution (Velikova *et al.*, 2024).

This research focuses on analyzing blood inventory management at PMI Banyumas, considering aspects such as storage costs, blood availability levels, and service levels. Monte Carlo simulation is implemented using Microsoft Excel due to its accessibility and ease of implementation in PMI's operational environment. This method has been shown to improve the accuracy of blood demand predictions and can serve as a basis for more effective decision-making in stock management strategies (Efendi & Zahmi, 2023). Additionally, information technology in blood inventory management can enhance transparency and responsiveness to demand fluctuations (monireh Ahmadimanesh et al., 2022). The results of this study are expected to provide more efficient recommendations for bloodstock management, not only for PMI Banyumas but also for other blood transfusion units in Indonesia.

2. RESEARCH METHODS

2.1. Blood Supply Chain

The Blood Supply Chain is a complex management and logistics system designed to ensure the availability and safety of blood for patients. This supply chain encompasses a series of processes, from blood collection from donors, separation of blood components such as Packed Red Cells (PRC), plasma, and platelets, and rigorous testing to guarantee safety (Imamoglu *et al.*, 2023). After these processes, blood is stored under controlled conditions, such as regulated temperatures, before being distributed to healthcare facilities for transfusion purposes. This process requires effective coordination among blood banks, hospitals, and related parties to ensure that the available blood meets the necessary quantity and quality standards.

Effective logistics management in the Blood Supply Chain is essential, given the perishable nature of blood and its direct impact on patient safety. Efficient inventory management and well-organized distribution can reduce the risks of stockouts and blood wastage due to expiration (monireh Ahmadimanesh et al., 2022). Additionally, accurate blood demand planning is crucial in preventing stock imbalances that could lead to wastage or increased patient health risks. One of the challenges in the Blood Supply Chain is predicting fluctuating blood demand and managing inventory while considering limited shelf life (Putri & Sitepu, 2024).

To optimize the Blood Supply Chain, simulation-based approaches such as Monte Carlo are often used to model uncertainties in blood demand and supply. This simulation enables risk analysis and evaluation of various inventory management scenarios, such as determining safety stock levels and optimal blood procurement policies (Abidovna, 2023). By leveraging historical data and probabilistic models, Monte Carlo simulation can help reduce uncertainties in planning and managing the blood supply chain, ensuring timely and efficient blood availability for needy patients.

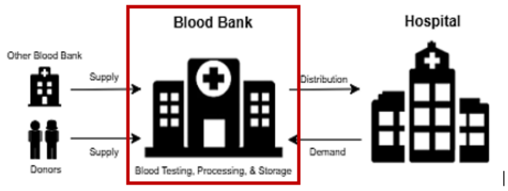

Fig. 1. Blood supply chain diagram at UTD PMI Banyumas with a focus on monte carlo simulation for bloodstock management

Fig. 1 illustrates the entire flow of the Blood Supply Chain, from the blood collection process by donors to the distribution of blood to hospitals for transfusion. In the context of this study, the focus of the Monte Carlo simulation is on the storage stage and bloodstock management at UDD PMI Banyumas. This simulation optimizes bloodstock management by considering blood demand and supply fluctuations uncertainties. By using Monte Carlo simulation, we can estimate blood requirements more accurately and reduce the risks of

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blood shortages or wastage that may arise from stock imbalances.

2.2. Packed Red Cells

Packed Red Cells (PRC) are blood components used to increase hemoglobin and hematocrit levels by separating plasma from whole blood. PRC is crucial in enhancing the body's oxygen-carrying capacity, aiding anemic patients by alleviating symptoms such as fatigue, and supporting various medical procedures, including surgeries and oncology treatments (Al-Farisy, 2023). Additionally, PRC is utilized in emergencies such as acute bleeding or trauma, where patients require rapid blood transfusions to maintain vital bodily functions (Maegele *et al*., 2023).

Managing PRC stock involves a series of processes, including blood collection, production, storage, and distribution. After being collected from donors, blood is processed into various products, stored in blood centers or hospitals, and then distributed for transfusion to ensure availability for needy patients (Sumbogo, 2021).

2.3. Monte Carlo Simulation

Monte Carlo simulation is a computational method used to model uncertainty by generating multiple samples from the probability distribution of a random variable (Harahap, 2024). This method works by repeatedly running random simulations based on predetermined probability distributions, producing various possible possible scenarios. As a result, Monte Carlo simulation enables a deeper analysis of data variability, which is particularly useful in situations where uncertainty and risk need to be carefully considered. The primary advantage of this method is its ability to provide a comprehensive overview of various possible outcomes, including extreme or rare events. It makes Monte Carlo simulation effective in analyzing data variability, allowing decision-makers to assess risks and determine strategies based on the distribution of possible outcomes (Maulana, 2024).

Monte Carlo simulation can be used to predict blood demand, estimate the risk of stockouts, and minimize wastage due to expiration (Awandani, 2022). For example, by modeling the probability distribution of blood demand and delivery times, this simulation can generate thousands of scenarios depicting possible outcomes of the inventory system. This allows for more accurate risk analysis and better planning to anticipate demand fluctuations. This method can also be used to optimize safety stock levels and determine the most efficient procurement policies (Maitra, 2024).

2.4. Simulation Workflow

The simulation process in this study is systematically designed to follow a series of steps that transform historical supply and demand data into a stochastic simulation model. These steps ensure that the generation of random variables, stock calculations, and cost evaluations are conducted in a structured and repeatable manner (Fig. 2). The complete simulation workflow is outlined as follows:

1. Data Input and Probability Calculation
   Historical supply and demand data are processed by calculating frequency, probability, and cumulative probability. Upper and lower bounds are then determined for each demand level to define the probability intervals.
2. Model Construction
   The simulation model is built in Excel with the following formulas:
   a) Random Number Generation:
      = RANDBETWEEN (0;99)
   b) Starting Stock:
      Stock at the beginning of the day equals the ending stock of the previous day.
   c) Supply Formula:
      =IF (Random Number Supply < UpperBound1, Supply Amount 2; IF (Random Number Supply < Upper Bound 3; Supply Amount 2, ...))
   d) Demand Formula:
      =IF (Random Number Demand < Upper Bound 2; Demand Amount 1; IF Random Number Demand < Upper Bound 3, Demand Amount 2, ...))
   e) Ending Stock:
      = IF (Starting Stock + Supply - Demand <=0; 0; Starting Stock + Supply - Demand)
   f) Shortage:
      = IF (Starting Stock + Supply < Demand; Demand - Supply - Starting Stock; 0)
   g) Expired Stock:
      Inventory that exceeds 25 days of storage.
3. Cost Accumulation
   Inventory costs are calculated as follows:
   a) Holding Cost:
      = ((Starting Stock + Ending Stock)/2) × Holding Cost per Unit
   b) Production Cost:
      = Supply × Production Cost per Unit
   c) Ordering Cost:
      = IF (Shortage > 0; 1 × Ordering Cost; 0)
   d) Shortage Cost:
      = IF (Shortage > 0; Shortage × Shortage Cost per Unit; 0)
   e) Expired Cost:
      = Number of Expired Units × Expiration Cost per Unit
4. Service Level Calculation
   Service level is calculated using the formula:
   = (Total Supply / (Total Supply + Total Shortage)) × 100%

2.5. Simulation Workflow

Replication in simulation aims to reduce result variance and ensure more stable and representative estimates. This study determines the number of replications (n) to enhance accuracy and reflect real-world conditions with a certain confidence level (Akerina & Adi, 2023). This process is carried out by running the simulation model repeatedly to analyze the distribution and variability of results.

Once the data is collected, the probabilities of PRC supply and demand are calculated to build a simulation model that enables the analysis of blood requirements based on supply and demand variability. An initial simulation is conducted with 10 replications to obtain the data's mean, standard deviation, and variance.

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Subsequently, the half-width value is calculated to assess the precision of the simulation results using the following formula:

$$Half\ Width = \frac{(t_{n-1,n/2}) \times S}{\sqrt{n}} \tag{1}$$

Based on the half-width value, the percentage error relative to the mean is calculated using the equation:

$$\%\ error = \frac{half\ width}{\bar{x}} 100\% \tag{2}$$

Next, the optimal number of replications (n') is calculated using the following formula:

$$n' = \left[\frac{t_{n-1,n/2} \times S}{Half\ Width'}\right]^2 \tag{3}$$

Once the optimal number of replications is determined, validation ensures the simulation model accurately represents the real-world system at the Indonesian Red Cross (PMI) in the Banyumas Regency. Based on the simulation results, inventory management scenarios are then developed to optimize service levels while minimizing storage costs, taking into account uncertainties in blood supply and demand.

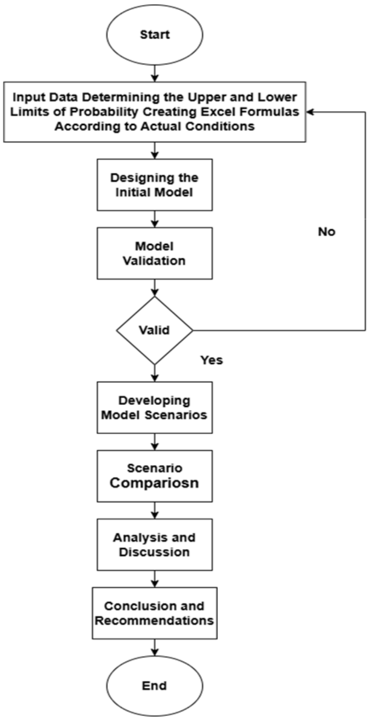

Fig. 2. Workflow of the simulation model development and analysis process

2.6. Validation

Models play a crucial role in decision-making by helping to predict outcomes based on assumptions and experiences. A model serves as a simplified representation of a complex real-world system, enabling the analysis of various scenarios without direct experimentation. However, validation is a critical step in ensuring the reliability of a model. Validation is necessary to confirm that the developed model aligns with the real-world system or actual conditions as a basis for comparison (Sadeghi, 2022). To be useful in decision-making, a model must closely approximate the characteristics of the real system. This includes the model's ability to represent key variables, relationships between variables, and the overall dynamics of the system. Model predictions can be misleading and potentially lead to suboptimal decisions without proper validation. Additionally, inadequately validated models can produce systematic errors that significantly impact the analysis results (Navarra, 2021). Therefore, model validation and calibration are essential steps to ensure the relevance and reliability of the model in real-world contexts.

In this study, an empirical distribution was used to represent supply and demand, derived directly from historical data. Due to the non-normality of the data, the Mann-Whitney U test was selected for model validation as a non-parametric alternative.

The hypotheses tested are:

a. H_0: The distribution of the model output is equal to the distribution of the real system data.
b. H_1: The distributions are different.

If the p-value > 0.05, H_0 is accepted, indicating no significant difference between the model and the real system, thus validating the model. This validation ensures the model's robustness despite the irregular and empirical nature of the blood supply-demand patterns.

3. RESULTS AND DISCUSSION

3.1. Historical Data Probabilities

Probability distributions were developed for supply and demand based on the data on the receipt and demand for Packed Red Cells (PRC) of blood type AB at PMI Banyumas from June 2023 to May 2024. The highest recorded receipt was 40 units, while the highest demand reached 52.

The empirical probability distributions were constructed directly from historical frequency data, as presented in Table 1 and Table 2 (demand). This approach was selected because the data did not conform to common theoretical distributions (such as normal or Poisson), reflecting the irregular and unpredictable nature of blood donations and requests. Initial goodness-of-fit tests supported the use of an empirical approach. These distributions from Table 1 and Table 2 were used as the basis for generating random values in the simulation by mapping random numbers to cumulative probability intervals to simulate daily supply and demand variations.

3.2. Cost Data

The cost data used in this study were obtained from official documents available at PMI Banyumas and adjusted based on previous studies to supplement cost components that were not explicitly recorded. The costs considered in this model include procurement, production, storage, expiration, and shortage costs. Other potential costs, such as transportation and donor promotion, were excluded due to unavailable data and were assumed negligible in their impact on the total cost. Transportation costs were assumed to be included in the shortage cost component, as blood procurement from other PMI units inherently includes purchasing and

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delivery expenses (Table 3).

Table 1. Probability distribution and random number interval for PRC receipts June 2023 – May 2024)

Number of Receipts	Frequency	Probability	Cum. Probability	Lower Bound	Upper Bound
0	48	0.132	0.132	0	13
1	6	0.016	0.148	13	15
2	15	0.041	0.189	15	19
3	10	0.027	0.216	19	22
4	10	0.027	0.244	22	24
5	20	0.055	0.299	24	30
6	15	0.041	0.340	30	34
7	13	0.036	0.375	34	38
8	11	0.030	0.405	38	41
9	16	0.044	0.449	41	45
10	16	0.044	0.493	45	49
11	14	0.038	0.532	49	53
12	18	0.049	0.581	53	58
13	19	0.052	0.633	58	63
14	20	0.055	0.688	63	68
15	15	0.041	0.729	68	73
16	13	0.036	0.764	73	76
17	7	0.019	0.784	76	78
18	4	0.011	0.795	78	79
19	11	0.030	0.825	79	82
20	4	0.011	0.836	82	84
21	10	0.027	0.863	84	86
22	9	0.025	0.888	86	89
23	9	0.025	0.912	89	91
24	5	0.014	0.926	91	93
25	3	0.008	0.934	93	93
26	2	0.005	0.940	93	94
27	4	0.011	0.951	94	95
28	6	0.016	0.967	95	97
29	2	0.005	0.973	97	97
31	2	0.005	0.978	97	98
33	1	0.003	0.981	98	98
34	1	0.003	0.984	98	98
37	1	0.003	0.992	99	99
38	2	0.005	0.997	99	100
40	1	0.003	1.000	100	100
Total	365	1	1	100	100

3.3. Determination of the Number of Replications

In this study, the absolute error method with a 95% confidence level is used to determine the sample size (n), which serves as the basis for setting the number of simulation replications. In the initial stage, the simulation is conducted with 10 replications (Table 4).

The next step is to determine the t-table value used in the half-width calculation. With a significance level of 5% and a sample size (n) of 10, the t-table value for t(n – 1; α/2) or t(9; 0.025) is 2.26. Once this value is obtained, the half-width is calculated using the following formula:

$$Half\ Width = \frac{(t_{n-1,n/2}) \times S}{\sqrt{n}} = \frac{2.26 \times 0.634}{\sqrt{10}} = 0.453 \quad (4)$$

The calculation results show that the half-width value is 0.453. Next, the percentage error relative to the average is calculated.

$$\%\ error = \frac{Half\ Width}{\bar{X}} 100\% = \frac{0.453}{23.687} 100\% = 1.914 \quad (5)$$

This error value needs to be reduced to improve the accuracy of the simulation results. Therefore, a target error reduction to 0.8% is set, requiring the half-width value to be adjusted to:

$$Half\ Width' = \bar{X} \times 0.8\% = 23.687 \times 0.008 = 1.914 \quad (6)$$

Thus, the desired half-width is 75.256. Subsequently, a recalculation is performed to determine the new number of replications (n') required. This calculation uses the latest half-width value previously determined, yielding the following result:

$$n' = \left[\frac{t_{\alpha/2,n-1)} \times S}{\mathrm{HalfWidth}'}\right]^2 = \left[\frac{2.26 \times 0.634}{0.189}\right]^2 = 57.47 \quad (7)$$

Based on the calculation results, the number of replications required to achieve the desired level of accuracy is 58 replications.

Table 2. Probability distribution and random number interval for PRC demands (June 2023 – May 2024)

Number of Receipts	Frequency	Probability	Cum. Probability	Lower Bound	Upper Bound
0	24	0.066	0.066	0	7
1	6	0.016	0.082	7	8
2	15	0.041	0.123	8	12
3	11	0.030	0.153	12	15
4	14	0.038	0.192	15	19
5	14	0.038	0.230	19	23
6	11	0.030	0.260	23	26
7	17	0.047	0.307	26	31
8	11	0.030	0.337	31	35
9	14	0.038	0.375	35	39
10	17	0.047	0.422	39	44
11	22	0.060	0.482	44	50
12	21	0.058	0.540	50	56
13	13	0.036	0.575	56	60
14	13	0.036	0.611	60	64
15	22	0.060	0.671	64	70
16	10	0.027	0.699	70	73
17	8	0.022	0.721	73	75
18	12	0.033	0.753	75	78
19	12	0.033	0.786	78	81
20	13	0.036	0.822	81	85
21	6	0.016	0.838	85	87
22	4	0.011	0.849	87	88
23	8	0.022	0.871	88	90
24	5	0.014	0.885	90	91
25	4	0.011	0.896	91	92
26	5	0.014	0.910	92	93
27	3	0.008	0.918	93	94
28	3	0.008	0.926	94	95
29	3	0.008	0.934	95	96
30	4	0.011	0.945	96	97
31	1	0.003	0.948	97	97
32	1	0.003	0.951	97	97
33	2	0.005	0.956	97	98
34	1	0.003	0.959	98	98
35	1	0.003	0.962	98	98
36	1	0.003	0.964	98	98
37	4	0.011	0.975	98	99
39	4	0.011	0.986	99	100
42	1	0.003	0.989	100	100
43	1	0.003	0.992	100	100
44	1	0.003	0.995	100	100
47	1	0.003	0.997	100	100
52	1	0.003	1.000	100	100
Total	365	1	1	100	100

Table 3. Inventory cost data

Cost Component	Cost
Procurement Cost	Rp. 117,388
Production Cost	Rp. 15,777
Storage Cost	Rp. 2,033
Expiration Cost	Rp. 490,000
Shortage Cost	Rp. 360,000

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Table 4. Initial replication output

n	Average Receipts	Average Demand	Total
1st Replication	10.740	12.049	22.789
2nd Replication	11.444	12.989	24.433
3rd Replication	11.803	12.688	24.490
4th Replication	10.816	12.285	23.101
5th Replication	11.611	12.244	23.855
6th Replication	11.005	12.619	23.625
7th Replication	12.115	12.200	24.315
8th Replication	11.274	12.792	24.066
9th Replication	11.112	11.964	23.077
10th Replication	11.101	12.014	23.115
Average ($\bar{x}$)			23.687
Standard Deviation (S)			0.634
Variance			0.403

3.4. Model Validation

To ensure the accuracy and reliability of the simulation model for decision-making, we performed validation using the Mann-Whitney U test. This non-parametric test compares two independent samples without assuming normality. The significance level (α) was set at 0.05, which is the threshold for determining whether any observed differences between the actual and simulated data are statistically significant. If the p-value is greater than 0.05, the null hypothesis (H_0), which states no significant difference between the actual and simulated distributions, cannot be rejected. Conversely, if the p-value is less than or equal to 0.05, the null hypothesis is rejected, suggesting a significant difference between the distributions.

1. Supply Simulation Validation
   Since the p-value of 0.419 is greater than the significance level of 0.05, we fail to reject the null hypothesis (H_0) (Fig. 3). This indicates that there is no significant difference between the actual PRC supply distribution and the simulated supply distribution, meaning the model effectively reproduces the actual system.

Test Statistics[a]

	Simulation Supply
Mann-Whitney U	64312.000
Wilcoxon W	131107.000
Z	-.809
Asymp. Sig. (2-tailed)	.419

a. Grouping Variable: Aktual Supply

Fig. 3. Mann-Whitney test results comparing actual and simulated blood supply data

Test Statistics[a]

	Simulation Demand
Mann-Whitney U	62489.500
Wilcoxon W	129284.500
Z	-1.449
Asymp. Sig. (2-tailed)	.147

a. Grouping Variable: Aktual Demand

Fig. 4. Mann-Whitney test results comparing actual and simulated blood demand data

2. Demand Simulation Validation
   With a p-value of 0.147, which is also greater than the significance level of 0.05, we fail to reject the null hypothesis (H_0) (Fig. 4). This suggests no significant difference between the actual PRC demand distribution and the simulated demand distribution, indicating that the model accurately reflects the real-world demand.

3.5. Scenario Development

Scenarios in the Monte Carlo simulation are designed to reduce inventory costs while improving service levels. Additionally, these scenarios are developed by considering uncertainties in demand and supply, making the resulting strategies more flexible and adaptable to real-world conditions (Table 5). The following scenarios have been designed:

a. Scenario 1
Adding a fixed supplement of 55 PRC units per month directly addresses the issue of blood shortages predictably. It's important to note that the 55 units were derived based on the average monthly shortage observed in the initial model. This ensures that the scenario mirrors real-world behavior and can effectively handle the average demand.

b. Scenario 2
By increasing the donor supply by 15%, Scenario 2 is designed to enhance availability, which could lead to a more consistent and robust blood supply. The multiplier of 1.15 is applied to the historical donor data, which helps maintain the empirical distribution while scaling up the supply to match increased demand.

Table 5. Scenario design

Scenario Type	Description
Initial Model	The validated replication results that represent the real-world system.
Scenario 1	The initial model with additional blood units from other PMI units to meet demand when inventory is insufficient, based on the average shortage of the initial model (55 units).
Scenario 2	Scenario 1 plus a 15% increase in the number of donors to improve blood availability (Hasanah, 2024)

3.6. Result

The simulation results for the Initial Model, Scenario 1, and Scenario 2 are summarized in Table 6 and Fig. 5, Fig. 6 and Fig. 7, providing a comprehensive comparison across key performance indicators shortage, expired units, service level, and total cost. These findings highlight the progressive improvements achieved through each scenario, offering valuable insights into the effectiveness of different inventory management strategies.

Based on the Fig. 5, it can be seen that the initial model (blue) has a higher and more frequent shortage compared to Scenario 1 (orange) and Scenario 2 (gray). Scenario 1 shows a significant reduction in shortages compared to the initial model, although there are still some periods with relatively high shortages. Meanwhile, Scenario 2 performs the best with the lowest and least frequent shortages, indicating that the 15% increase in donors is more effective in reducing shortages compared to simply increasing the supply from other PMIs. This suggests that Scenario 2 is better at maintaining blood availability while controlling costs.

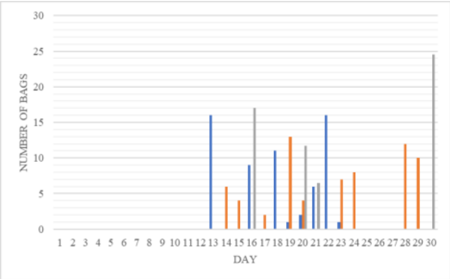

Fig. 5. Comparison of shortage levels from scenarios

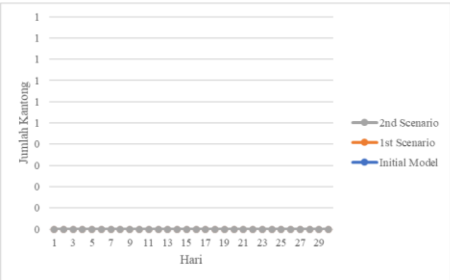

Fig. 6. Comparison of expired levels from scenarios

Across 30 time periods, all three scenarios (Initial Model, Scenario 1, and Scenario 2) consistently recorded zero expired units, demonstrating that their inventory control strategies effectively prevent wastage (Fig, 6). Despite varying shortage levels, each model achieved the primary goal of zero expirations, indicating no further adjustments are needed for expired stock management.

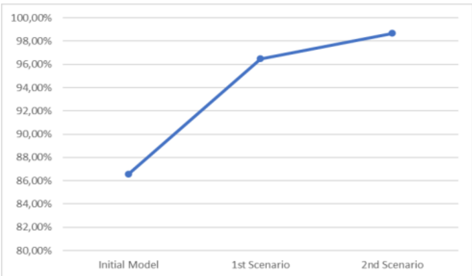

Fig. 7. Comparison of service level

The service level markedly improved from the Initial Model to Scenario 2. In the Initial Model, the service level stood at 86.58%, indicating that 13.42% of demand went unmet (Fig. 7). Under Scenario 1, where a fixed supply supplement was added, the service level rose sharply to 96.49%, a 9.91 percentage-point increase, thereby satisfying nearly all demand. Further enhancement in Scenario 2 via a 15% increase in donors boosted the service level to 98.66%, an additional 2.17 percentage points. Although the gain from Scenario 1 to Scenario 2 is smaller than the initial jump, achieving 98.66% demonstrates that virtually all demand is now met, approaching an ideal fulfillment rate.

Table 6. Comparison between scenarios

Parameter	Initial Model	Scenario 1	Scenario 2
Shortage (Units)	62	11	5
Expired (Units)	0	0	0
Service level (%)	86.58%	96.49%	98.66%
Total *Cost* (Rp)	30,816,533	10,968,042	9,927,682

This study evaluates various factors, including storage costs, stock shortages, expiration, and service levels, to determine the optimal inventory strategy. The simulation results show that Scenario 2 is the best option, with the lowest total inventory cost of Rp. 9,927,682 and a service level of 98.66% (Table 6).

3.7. Discussion

The simulation results show that the developed scenarios focus primarily on increasing supply to meet demand. While effective in improving service levels and reducing costs, this approach also highlights the continued importance of the existing inventory system. The inventory system plays a key role in preventing expirations, but its limited ability to handle demand variability is evident from the shortages observed in the initial model. Therefore, the inventory system needs improvement beyond increasing supply, such as incorporating reorder points or safety stock policies based on simulation results to better respond to fluctuations.

The use of Monte Carlo simulation offers advantages over traditional probabilistic methods by allowing more flexible, data-driven modeling of uncertainty without relying on rigid probability formulas. This provides more realistic and adaptable decision support for inventory management under uncertainty.

Compared to prior studies, this research has a narrower focus on a single-unit inventory system. Ahmadimanesh *et al.* (2023) addressed a broader multi-level inventory and distribution network with integrated routing optimization, while Efendi & Zahmi (2023) applied Monte Carlo simulation mainly to estimate optimal supply levels. In contrast, this study emphasizes scenario-based supply and inventory management using empirical data, offering a practical approach for localized decision-making.

4. CONCLUSION

The Monte Carlo simulation analysis of PRC inventory at PMI Banyumas showed that increasing supply from other units by 55 units and raising donor numbers by 15% reduced shortages from 62 to 5 units without increasing expiration while keeping costs at Rp. 9,927,682. PMI Banyumas can implement this strategy through donor campaigns, incentives, and partnerships with local organizations. Future studies should explore the long-term effects of these strategies, seasonal

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demand variations, and the integration of AI or behavioral factors to develop more adaptive and sustainable blood inventory systems. Ethical approval was obtained from PMI Banyumas for this research.

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