Chemical Inventory Planning Using the EOQ Model and Monte Carlo Simulation

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Abstract. This study analyzes the application of the Economic Order Quantity (EOQ) method to determine the optimal and efficient order quantity for chemical materials at Perumda AMDT in Penajam Paser Utara Regency. It also examines the use of Monte Carlo Simulation to estimate fluctuating chemical demand, enabling more accurate determination of safety stock levels and reorder points. The company faces two major challenges: uncertainty in chemical consumption and high inventory costs, both of which may hinder smooth operational performance. The EOQ method provides optimal order quantities of 38,219 kg for Alum, 10,133 kg for Chlorine, 23,318 kg for Soda Ash, and 28,126 kg for PAC. These quantities correspond to an ideal ordering frequency of 1–2 orders per year, an ordering cycle of 40–60 days, an average safety stock of approximately 735 kg, and a reorder point of around 5,600 kg. The application of EOQ reduces the total annual inventory cost to IDR 24,002,484.71, supporting more economical and efficient procurement planning. Monte Carlo Simulation yields higher demand estimates 80,514 kg of Alum, 18,115 kg of Chlorine, 49,221 kg of Soda Ash, and 55,425 kg of PAC indicating considerable demand variability attributable to raw water quality fluctuations and operational intensity. These findings highlight the importance of integrating EOQ with stochastic simulations to enhance the accuracy of inventory management in water treatment operations.

Keywords: Chemical Inventory Planning, EOQ; and Monte Carlo Simulation.

1. Introduction

The availability of clean water is a fundamental prerequisite for public health, environmental sustainability, and regional economic development. In Indonesia, increasing population, spatial expansion, and industrial growth have driven a rising demand for reliable drinking water services. This situation compels public service providers, including regional water utilities, to enhance operational efficiency and ensure the continuity of clean water supply for communities. In this context, the Regional Drinking Water Company Danum Taka (Perumda AMDT) of Penajam Paser Utara plays a strategic role in providing and managing drinking water services in the areas of Sepaku, Waru, and Babulu. With service coverage exceeding 14,000 household connections in 2024 and a targeted expansion of up to 41% by 2025, the company must implement a robust inventory planning system to maintain uninterrupted water production and distribution.

A critical component of the water treatment process is the availability of treatment chemicals such as Aluminium Sulfate, Chlorine, Soda Ash, and Poly Aluminium Chloride (PAC). These chemicals are essential to ensure that treated water meets quality and safety standards for consumption. However, Perumda AMDT chemical inventory data for 2024 indicate substantial fluctuations in monthly ending stock levels for each chemical type, suggesting a potential imbalance between demand and availability. Such imbalances may lead to stockouts that disrupt production or excessive inventories that increase storage costs and strain operational budgets. Consequently, an inventory control approach is required that can minimize total inventory costs while maintaining the continuity of chemical supplies.

The Economic Order Quantity (EOQ) model is one of the classical inventory management methods used to determine the optimal order quantity by balancing ordering and holding costs. [1] demonstrated that the application of EOQ in a drinking water company can generate savings in ordering costs while maintaining the availability of key chemicals such as Alum, Chlorine, and Soda Ash to support uninterrupted production. Similarly, [2] found that the EOQ method improved the efficiency of chemical inventory management at the Regional Public Service Agency (BLUD) Air Minum in Cimahi by enabling more optimal ordering decisions. In another context, [3] showed that EOQ provides the most efficient results in controlling raw material inventories for brownies production, with lower total inventory costs compared with alternative methods. These findings collectively reinforce the relevance of EOQ for managing inventories of production inputs, including water treatment chemicals.

Nevertheless, the EOQ model essentially assumes relatively stable and predictable demand, whereas in practice, the consumption of chemicals in water utilities is subject to considerable fluctuations. Variations in raw water quality, changes in rainfall patterns, and shifts in plant production levels contribute to demand uncertainty

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W. Sari et al. (eds.), *Proceedings of the 5th Mulawarman International Conference on Economics and Business (MICEB 2025)*, Advances in Economics, Business and Management Research 406,
https://doi.org/10.2991/978-94-6239-815-3_23

over time. To accommodate these uncertainties, an additional approach is needed that can represent demand variability more realistically. Monte Carlo Simulation is a probabilistic method that can model demand fluctuations based on historical data and generate multiple possible future scenarios. [2] Utama and Siswanto (2017) demonstrated that combining EOQ with Monte Carlo Simulation provides a more effective solution for raw material planning by reducing operational costs while ensuring production continuity. Furthermore, [1] reported that the integrated use of Monte Carlo Simulation and EOQ is effective in addressing demand uncertainty in pharmacy settings through more accurate inventory planning. These conditions indicate a research gap concerning the development of an inventory planning model for water treatment chemicals that simultaneously accounts for cost efficiency and demand uncertainty.

Therefore, this study seeks to address these gaps by analyzing chemical inventory planning at Perumda AMDT Penajam Paser Utara using a combination of the EOQ method and Monte Carlo Simulation. Specifically, the study aims (1) to determine the optimal order quantity for each chemical using the EOQ model, and (2) to estimate variable chemical demand and to determine more accurate safety stock levels and reorder points through Monte Carlo Simulation. The findings are expected to provide policy recommendations for a more efficient, adaptive, and sustainable inventory control strategy, thereby supporting the continuity of clean water production and improving service quality for the community.

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2 Literature Review

2.1. Chemical Inventory Planning

According to [4], planning is a fundamental and initial activity within managerial functions. Planning activities are consistently followed by organizing, staffing, directing, and supervising or controlling. Essentially, planning involves determining the goals and objectives of an organization and outlining the actions required to achieve them. The preparation of production operation plans begins with forecasting aggregate demand for the medium-term horizon. This is then followed by general planning aimed at meeting demand requirements by determining work output, finished goods, inventory levels, and service capacity. Furthermore,, [4], explains that raw material inventory refers to the stock of tangible goods used in the production process, which may be sourced directly from natural resources or purchased from suppliers or manufacturers that produce raw materials for the company. Raw materials are required by factories to be processed, and through a series of production stages, they are expected to be transformed into finished goods.

2.2. Economic Order Quantity (EOQ)

According to [5], *Economic Order Quantity* (EOQ) is one of the oldest and most widely recognized inventory control techniques. Research on its application began with a publication by Ford W. Harris in 1915, and the technique continues to be used by a large number of organizations today. The EOQ model is relatively easy to implement; however, several underlying assumptions must be satisfied for the model to function effectively. The fundamental assumptions of the EOQ model are as follows:

1. Demand is known and constant over time.
2. Lead time, that is, the time between placing an order and receiving it, is known and constant.
3. Inventory replenishment is instantaneous, meaning that items from an order arrive in a single batch at one point in time.
4. The purchase cost per unit remains constant throughout the year, implying that quantity discounts are not considered.
5. The only variable costs are ordering and holding costs. Ordering costs per order and holding costs per unit per year are constant throughout the planning period.
6. Orders are placed in a manner that completely prevents stockouts or shortages.

2.3. Monte Carlo Simulation

According to [5], explain that the Monte Carlo Simulation method is developed through the use of probability distributions and random numbers. Random-number intervals are established to represent the possible outcomes for each probabilistic variable within the model. These random numbers are then selected from a random-number table or generated by a computer to simulate the behavior of the variables. The simulation procedure is performed over multiple time periods to evaluate the long-term effects of each policy value under consideration. Monte Carlo Simulation is commonly illustrated in inventory control, queuing systems, and machine maintenance problems. Furthermore, according to [6], describe the Monte Carlo technique as a method for selecting random numbers from a probability distribution for use in simulation. Meanwhile, according to, state that the Monte Carlo method is a simulation technique that incorporates random elements when probabilistic behavior is present in a system.

2.4. Research Conceptual Framework

Chemical inventory is a key component in ensuring the continuity of the water treatment process. The availability of chemicals used in water treatment must be consistently ensured. Any imbalance between existing

inventory levels and actual needs can pose operational risks, such as excessive inventory leading to higher storage costs or insufficient inventory that disrupts production. Therefore, an effective chemical inventory planning approach is required. In this study, the measurable variable of interest is chemical inventory planning, which considers ordering patterns, usage frequency, and material requirements within the company. Referring to previous studies, two commonly used approaches to improve inventory planning efficiency are the Economic Order Quantity (EOQ) method and Monte Carlo Simulation.

The EOQ method offers advantages in calculating the optimal order quantity that minimizes total inventory costs, including ordering and holding costs. [2]. However, EOQ does not account for uncertain demand fluctuations or potential delays in raw material procurement. Therefore, EOQ is complemented by Monte Carlo Simulation, which can predict various demand and procurement risk scenarios based on historical data and probability distributions [8]. The integration of these two methods provides a more adaptive and accurate solution for inventory planning. Moreover, research conducted by [9] demonstrated that the combined application of EOQ and Monte Carlo Simulation results in more effective raw material inventory control with lower total inventory costs. Similarly, [10] and [11] reported that Monte Carlo Simulation provides realistic insights into raw material inventory needs under demand uncertainty, enabling companies to minimize the risk of both overstocking and stockouts.

This study aims to examine the effectiveness of combining the EOQ method and Monte Carlo Simulation in reducing the total inventory cost of chemicals required for water treatment. The findings are expected not only to provide insights into optimal inventory planning strategies but also to contribute practical benefits in enhancing the company's operational efficiency. Thus, this study is expected to produce an inventory planning model capable of addressing fluctuations in demand and operational requirements while reducing inefficiencies associated with inventory costs.

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3 Research Method

3.1. Operational Definition

1. Chemical Inventory Planning

Chemical inventory planning is the process of determining the optimal quantity of chemicals that should be available in storage to support smooth operational activities. The primary objective of this planning is to ensure the availability of chemicals in optimal amounts to facilitate uninterrupted production processes, prevent shortages that may disrupt operations, and avoid excessive stock levels that could increase storage costs.

2. Economic Order Quantity (EOQ)

The Economic Order Quantity (EOQ) method is an approach used to determine the optimal order quantity by considering both ordering costs and holding costs. The formula used to calculate the Economic Order Quantity (EOQ), as proposed by [6] is as follows:.

$$Q^* = \sqrt{\frac{2.D.S}{H}}$$

Where.

Q : Number of Unit Ordered
Q* : Optimal order quantity per unit (EOQ)
D : Annual demand in units for inventory items
S : Setup or ordering cost for each order
H : Holding cost per unit per year

3. Monte Carlo

Monte Carlo is a simulation technique used to model variations in chemical demand based on probabilistic distributions. This method assists in forecasting future requirements by incorporating demand uncertainty into the analysis.

3.2. Data Analysis

Data analysis in this study was conducted using the Economic Order Quantity (EOQ) method and Monte Carlo Simulation, with the objective of determining the optimal order quantity for chemical materials and forecasting future requirements based on demand variability. The analysis was supported by data processing using Microsoft Excel.

4 Results And Discussion

4.1. Economic Order Quantity / EOQ

The Economic Order Quantity (EOQ) is an inventory planning method used to determine the optimal order quantity for each purchase of chemical materials, enabling the minimization of total inventory costs, which consist of ordering costs and carrying costs. The EOQ calculation is presented in Table 1 below.

Table 1. Results of Economic Order Quantity Calculations

No.	Chemical Material Name (i)	Annual Demand (Kg/tahun) (ii)	Ordering Cost (Rp) (iii)	Holding Cost (Rp) (iv)	EOQ (Kg) (v = ((√2 * iii * iv)/ v)
1	Aluminium Sulfate	67.109	1.750.000	160,80	38218,88
2	Chlorine	18.583	1.370.000	495,91	10132,67
3	Soda Ash	44.912	1.480.000	244,50	23317,99
4	Poly Aluminium Chloride (PAC)	47.525	2.110.000	253,53	28125,65
Total		178.129	6.710.000	1.154,74	99.795,19

Source: Processed Data (2025).

As shown in Table 5.4, the Economic Order Quantity (EOQ) calculations indicate notable variations in the optimal ordering quantities for each chemical material. Aluminium Sulfate has the highest optimal order quantity of 38,218.88 kg, reflecting its relatively high annual demand and lower holding cost. Chlorine shows a significantly lower EOQ of 10,132.67 kg, which is consistent with its smaller annual usage but higher storage cost. Soda Ash and Poly Aluminium Chloride (PAC) exhibit optimal order quantities of 23,317.99 kg and 28,125.65 kg, respectively, driven by differences in ordering and holding cost structures. The total EOQ requirement across all chemical materials amounts to 99,795.19 kg per cycle. These results demonstrate that applying the EOQ method enables Perumda AMDT to determine an efficient and economically optimal procurement plan by balancing ordering and holding costs. The substantial variation among EOQ values also highlights the importance of calculating order quantities individually rather than adopting a uniform procurement strategy, as each chemical possesses distinct demand characteristics and cost parameters. Next, the Total Inventory Cost (TIC) is calculated, as presented in Table 2 below.

Table 2. Total Inventory Cost (TIC) Calculation Results

No.	Chemical Material Name (i)	Annual Demand (Kg/tahun) (ii)	EOQ (Kg) (iii)	Order Frequency (iv = ii / v)	Time Between Order (v = 365 / vi)	Total Inventory Cost (Rp) (viii = (ii/ v)*iii + (v/2)*iv))
1	Aluminium Sulphate	67.109	38218,88	1,76	207,87	6.145.693,61
2	Chlorine	18.583	10132,67	1,83	199,03	5.024.936,78
3	Soda Ash	44.912	23317,99	1,93	189,51	5.701.157,14
4	Poly Aluminium Chloride (PAC)	47.525	28125,65	1,69	216,01	7.130.697,18
Total		178.129	99.795,19	7,21	50,65	24.002.484,71

Source: Processed Data (2025).

As shown in Table 2, the Total Inventory Cost (TIC) varies across chemical materials due to differences in demand levels, ordering frequency, and holding costs. Aluminium Sulfate accounts for the highest TIC at IDR 6,145,693.61, reflecting its substantial annual usage and relatively frequent ordering cycle. This is followed by Poly Aluminium Chloride (PAC) with a TIC of IDR 7,130,697.18, which, despite a lower ordering frequency, incurs higher storage-related expenses. Soda Ash contributes a TIC of IDR 5,701,157.14, while Chlorine results in the lowest TIC at IDR 5,024,936.78, consistent with its smaller demand volume. Overall, the total annual TIC

for all chemical materials amounts to IDR 24,002,484.71. The following presents the results of the safety stock calculations, as shown in Table 3 below.

Table 3. Safety Stock (SS) Calculation Results

No.	Chemical Material Name (i)	Annual Demand (Kg/tahun) (ii)	Daily Demand (iii = ii / 365)	Lead Time (day) (iv)	Standard Deviation (kg/day) (v)	Service Level (vi = ii / v)	Safety Stock (vii = (vi*v* √iv)
1	Aluminium Sulphate	67.109	183,86	5	679,30	1,65	2.506,27
2	Chlorine	18.583	50,91	7	178,56	1,65	779,49
3	Soda Ash	44.912	123,05	10	418,91	1,65	2.185,78
4	Poly Aluminium Chloride (PAC)	47.525	130,21	7	471,34	1,65	2.057,63

Source: Processed Data (2025)

As shown in Table 3, the safety stock (SS) levels vary considerably among the chemical materials due to differences in daily demand, lead time, and demand variability. Aluminium Sulfate requires the highest safety stock of 2,506.27 kg, which is attributed to its high daily consumption rate and significant fluctuation in demand. Soda Ash follows with a safety stock of 2,185.78 kg, reflecting its relatively high standard deviation and longer lead time of 10 days. Poly Aluminium Chloride (PAC) requires a safety stock of 2,057.63 kg, influenced by both a moderate lead time and substantial demand variability. Meanwhile, Chlorine has the lowest safety stock requirement at 779.49 kg, consistent with its lower daily demand and smaller deviation in consumption. These findings illustrate that safety stock requirements are highly sensitive to variations in consumption patterns and lead time durations. Establishing differentiated safety stock levels for each chemical material is therefore essential to ensure adequate inventory buffers while minimizing the risk of stockouts. The results also underscore the importance of incorporating demand variability into inventory planning to maintain operational continuity in water treatment processes The following presents the results of the reorder point calculations as shown in Table 4 below.

Table 4. Reorder Point (ROP) Calculation Results

No.	Chemical Material Name (i)	Daily Demand (ii)	Lead Time (day) (iii)	Safety Stock (kg) (iv)	Demand During LT (kg) (v = ii * iii)	Reorder Point (kg) (vi = v + iv)
1	Aluminium Sulphate	183,86	5	2.506,27	919,30	3425,57
2	Chlorine	50,91	7	779,49	356,38	1135,87
3	Soda Ash	123,05	10	2.185,78	1230,47	3416,24
4	Poly Aluminium Chloride (PAC)	130,21	7	2.057,63	911,44	2969,07

Source: Processed Data (2025)

As shown in Table 4, the Reorder Point (ROP) values differ significantly across the chemical materials due to variations in daily demand, lead time, and safety stock levels. Aluminium Sulfate has the highest ROP of 3,425.57 kg, driven by its substantial daily consumption and relatively high safety stock requirement. Soda Ash follows closely with a ROP of 3,416.24 kg, reflecting its long lead time of 10 days and elevated demand variability, which necessitate a larger inventory buffer. Poly Aluminium Chloride (PAC) shows a ROP of 2,969.07 kg, influenced by its moderate daily demand and safety stock level. Meanwhile, Chlorine has the lowest ROP at 1,135.87 kg, consistent with its smaller daily demand and lower risk of consumption fluctuation. These results demonstrate that the determination of ROP is highly sensitive to both operational lead time and demand variability. Establishing material-specific ROP thresholds ensures timely replenishment, minimizes the risk of stockouts, and supports uninterrupted chemical supply for water treatment operations. The findings also highlight the need for inventory policies that integrate demand uncertainty into the calculation of replenishment triggers.

4.2. Monte Carlo Simulation

Monte Carlo Simulation is a method used to model uncertainty in inventory systems by generating random numbers based on the probability distribution of historical demand, as presented in Table 5 below.

Table 5. Probability and Random Number Interval Calculation Results in the Monte Carlo Simulation

Aluminium Sulphate							
			Probability		Expected Demand (v = iii * ii)	Interval	
No	Mounth (i)	Usage (kg) (ii)	Probability Distribution (iii = ii / Sii)	Cumulatif Probability (iv = iii + iii)		Lower Bound	Upper Bound
1	January	4.620	0,069	0,069	318,06	0,000	0,069
2	February	5.158	0,077	0,146	396,44	0,069	0,146
3	March	4.813	0,072	0,217	345,18	0,146	0,217
4	April	3.491	0,052	0,269	181,60	0,217	0,269
5	May	5.470	0,082	0,351	445,86	0,269	0,351
6	June	4.320	0,064	0,415	278,09	0,351	0,415
7	July	4.064	0,061	0,476	246,11	0,415	0,476
8	August	4.120	0,061	0,537	252,94	0,476	0,537
9	September	5.483	0,082	0,619	447,98	0,537	0,619
10	October	11.302	0,168	0,787	1.903,40	0,619	0,787
11	November	9.452	0,141	0,928	1.331,27	0,787	0,928
12	December	4.816	0,072	1,000	345,61	0,928	1,000
Total		67.109	1,000		6.492,54		
Average		5.592			541,04		
Chlorine							
			Probability		Expected Demand (v = iii * ii)	Interval	
No	Mounth (i)	Usage (kg) (ii)	Probability Distribution (iii = ii / Sii)	Cumulatif Probability (iv = iii + iii)		Lower Bound	Upper Bound
1	January	1.570	0,084	0,084	132,56	0,000	0,084
2	February	1.659	0,089	0,174	148,11	0,084	0,174
3	March	1.944	0,105	0,278	203,37	0,174	0,278
4	April	1.360	0,073	0,352	99,53	0,278	0,352
5	May	1.201	0,065	0,416	77,62	0,352	0,416
6	June	1.377	0,074	0,490	102,04	0,416	0,490
7	July	1.363	0,073	0,564	99,97	0,490	0,564
8	August	1.401	0,075	0,639	105,63	0,564	0,639
9	September	1.302	0,070	0,709	91,23	0,639	0,709
10	October	1.587	0,085	0,794	135,53	0,709	0,794
11	November	1.868	0,101	0,895	187,78	0,794	0,895
12	December	1.951	0,105	1,000	204,84	0,895	1,000
Total		18.583	1,000		1.588,22		
Average		1.549			132,35		
Soda Ash							
			Probability		Permintaan Harapan (v = iii * ii)	Interval	
No	Mounth (i)	Usage (kg) (ii)	Probability Distribution (iii = ii / Sii)	Cumulatif Probability (iv = iii + iii)		Lower Bound	Upper Bound
1	January	5.725	0,085	0,085	488,39	0,000	0,085
2	February	3.178	0,047	0,133	150,50	0,085	0,133
3	March	3.546	0,053	0,186	187,37	0,133	0,186
4	April	3.994	0,060	0,245	237,64	0,186	0,245

5	May	3.832	0,057	0,302	218,81	0,245	0,302
6	June	3.541	0,053	0,355	186,84	0,302	0,355
7	July	3.807	0,057	0,412	215,91	0,355	0,412
8	August	2.935	0,044	0,455	128,36	0,412	0,455
9	September	2.190	0,033	0,488	71,47	0,455	0,488
10	October	2.097	0,031	0,519	65,53	0,488	0,519
11	November	4.729	0,070	0,590	333,24	0,519	0,590
12	December	5.339	0,080	0,669	424,76	0,590	0,669
Total		44.912	2,417		2.708,82		
Average		3.743			225,73		
Poly Aluminium Chloride (PAC)							
			Probability		Expected Demand (v = iii * ii)	Interval	
No	Bulan (i)	Mounth (i)	Lower Bound	Lower Bound		Batas Bawah	Batas Atas
13	January	4.000	0,060	0,060	238,42	0,000	0,060
14	February	4.250	0,063	0,123	269,15	0,060	0,123
15	March	3.825	0,057	0,180	218,01	0,123	0,180
16	April	5.500	0,082	0,262	450,76	0,180	0,262
17	May	4.000	0,060	0,321	238,42	0,262	0,321
18	June	4.000	0,060	0,381	238,42	0,321	0,381
19	July	4.500	0,067	0,448	301,75	0,381	0,448
20	August	5.000	0,075	0,523	372,53	0,448	0,523
21	September	5.450	0,081	0,604	442,60	0,523	0,604
22	October	-	-	0,604	-	0,604	0,604
23	November	1.750	0,026	0,630	45,63	0,604	0,630
24	December	5.250	0,078	0,708	410,71	0,630	0,708
Total		47.525	2,558		3.226,40		
Average		3.960			268,87		

Source: Processed Data (2025)

As shown in Table 5, the probability distribution and random-number intervals derived from historical monthly usage reveal substantial variability in chemical demand across all four materials. For Aluminium Sulfate, the probability distribution ranges from 0.052 to 0.168, with the highest usage occurring in October and November. This results in an expected monthly demand of 6,492.54 kg, indicating strong seasonality driven by operational fluctuations in water treatment processes. The cumulative probabilities and corresponding random-number intervals provide a structured basis for generating simulation inputs in the Monte Carlo model, ensuring that randomized demand values accurately reflect historical consumption patterns.

For Chlorine, the probability distribution is more evenly dispersed, ranging from 0.065 to 0.105, with an expected total demand of 1,588.22 kg. This suggests relatively stable yet moderately fluctuating usage, which is consistent with the chemical's essential function in disinfection processes. The random-number intervals demonstrate a smooth cumulative distribution, facilitating precise stochastic modeling. Soda Ash shows wider monthly variation, reflected in its probability distribution range of 0.031 to 0.085 and an expected demand of 2,708.82 kg. This dispersion underscores the influence of fluctuations in raw-water alkalinity on chemical consumption. The cumulative probability curve forms a broader spectrum of random-number intervals, indicating a higher degree of uncertainty in monthly demand. Poly Aluminium Chloride (PAC) also displays notable variability, with probability distribution values between 0.026 and 0.082, and an expected demand of 3,226.40 kg. Several months, such as February, April, and September, show higher probabilities, suggesting increased reliance on coagulation chemicals during periods of poorer raw-water quality. The random-number intervals provide a probabilistic representation that aligns well with historical peaks. Overall, the probability distributions and expected demand values across all materials highlight the substantial stochastic behavior in chemical usage. These findings confirm that Monte Carlo Simulation is an appropriate method for modeling demand uncertainty, as it enables the generation of simulated demand patterns that closely mimic real-world variability. The resulting probabilistic insights provide a stronger foundation for inventory planning, particularly in determining safety

stock, reorder points, and annual procurement quantities under uncertain operating conditions. The accuracy level between actual demand and simulated demand is presented in Table 6 below.

Table 6. Accuracy Level of Actual Demand and Simulated Demand

Accuracy Level (Aluminium Sulphate)				
Mount	Actual Demand (kg)	Simulation Demand (kg)	Difference(kg)	Accuracy (%)
Jan	4.620	4.816	196	95,76
Feb	5.158	5.483	325	93,70
Mar	4.813	11.302	6.489	34,82
Apr	3.491	4.064	573	83,59
May	5.470	4.813	657	87,99
Jun	4.320	4.064	256	94,07
Jul	4.064	11.302	7.238	78,10
Aug	4.120	5.470	1.350	67,23
Sep	5.483	5.470	13	99,76
Okt	11.302	9.452	1.850	83,63
Nov	9.452	9.452	-	100,00
Dec	4.816	4.816	-	100,00
Total (Σ)	67.109	80.504		
Accuracy Level (Chlorine)				
Mount	Actual Demand (kg)	Simulation Demand (kg)	Difference(kg)	Accuracy (%)
Jan	1.570	1.659	90	94,30
Feb	1.659	1.944	285	82,82
Mar	1.944	1.360	584	69,96
Apr	1.360	1.360	-	100,00
May	1.201	1.587	386	67,86
Jun	1.377	1.868	491	64,34
Jul	1.363	1.587	224	83,57
Aug	1.401	1.360	41	97,07
Sep	1.302	1.201	101	92,24
Oct	1.587	1.201	386	75,68
Nov	1.868	1.401	467	75,00
Dec	1.951	1.587	364	81,34
Total (Σ)	18.583	18.115		
Accuracy Level (Soda Ash)				
Mount	Actual Demand (kg)	Simulation Demand (kg)	Difference(kg)	Accuracy (%)
Jan	5.725	3.541	2.184	61,85
Feb	3.178	3.994	816	74,34
Mar	3.546	3.994	448	87,38
Apr	3.994	5.725	1.732	56,64
May	3.832	5.339	1.507	60,67
Jun	3.541	3.546	5	99,86
Jul	3.807	2.097	1.710	55,09
Aug	2.935	4.729	1.794	38,88
Sep	2.190	3.178	988	54,89
Oct	2.097	5.725	3.628	73,01
Nov	4.729	3.546	1.183	74,98
Dec	5.339	3.807	1.533	71,30
Total (Σ)	44.912	49.221		
Accuracy Level Poly Aluminium Chloride (PAC)				
Mount	Actual Demand (kg)	Simulation Demand (kg)	Difference(kg)	Accuracy (%)
Jan	4.000	3.825	175	95,63

Feb	4.250	4.000	250	94,12
Mar	3.825	4.000	175	95,42
Apr	5.500	4.500	1.000	81,82
May	4.000	5.450	1.450	63,75
Jun	4.000	3.825	175	95,63
Jul	4.500	5.000	500	88,89
Aug	5.000	5.250	250	95,00
Sep	5.450	5.500	50	99,08
Oct	-	3.825	3.825	#DIV/0!
Nov	1.750	5.250	3.500	100,00
Dec	5.250	5.000	250	95,24
Total (Σ)	47.525	55.425		

Source: Processed Data (2025)

As shown in Table 6, the accuracy levels between actual demand and simulated demand vary considerably across the four chemical materials, reflecting the inherent stochastic nature of monthly consumption patterns. For Aluminium Sulfate, the simulation accurately captures demand in several months, notably in November and December (100%), as well as September (99.76%). However, large deviations appear in months with extreme consumption values, such as March and July, where simulation demand significantly exceeds actual usage. This suggests that the historical probability distribution for Aluminium Sulfate contains several high-demand outliers, causing the Monte Carlo Simulation to generate elevated consumption scenarios.

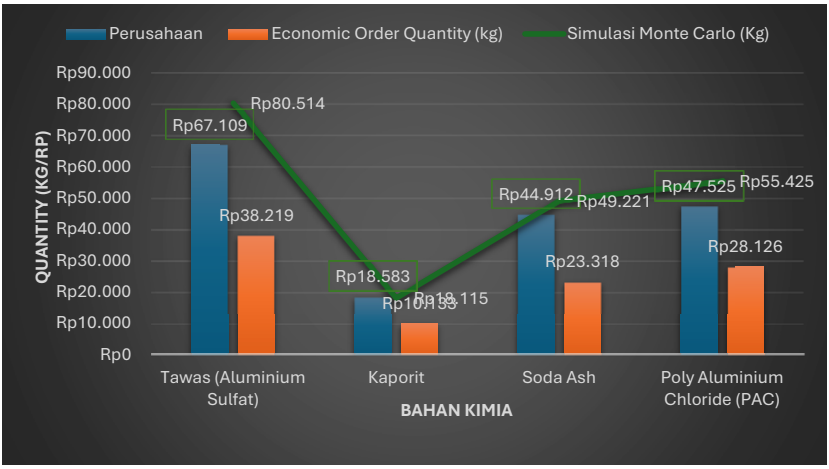
For Chlorine, the accuracy level remains moderately stable, with several months achieving values above 90%, such as January, August, and September. Nonetheless, fluctuations persist in months with irregular demand patterns (e.g., June and May), demonstrating that Chlorine's demand variability is moderately sensitive to probabilistic shifts in the simulation process. The total simulated demand (18,115 kg) closely approximates the actual total demand (18,583 kg), indicating generally reliable model behavior.

Soda Ash exhibits greater volatility, with accuracy levels ranging from 38.88% to 99.86%. These wide variations reveal substantial uncertainty in Soda Ash usage, likely driven by operational adjustments linked to raw water alkalinity. The simulation produces a higher total annual demand (49,221 kg) compared to actual consumption (44,912 kg), suggesting that the probabilistic distribution may overweight high-demand months due to seasonal peaks.

Poly Aluminium Chloride (PAC) also demonstrates mixed accuracy levels, with several months achieving values above 95%, including January, March, June, August, and December. However, substantial deviations occur in April and November, where simulated values differ markedly from actual usage. The simulation total (55,425 kg) exceeds actual consumption (47,525 kg), implying that demand variability for PAC is strongly influenced by water quality fluctuations and monthly operational intensity.

Overall, the results indicate that Monte Carlo Simulation is effective in capturing general demand trends, particularly for chemicals with relatively stable consumption. However, for materials exhibiting pronounced seasonality or extreme usage variation, the simulation outcomes tend to diverge more substantially from actual patterns. These findings underscore the importance of incorporating refined probability distributions, additional environmental variables, or multi-year datasets to enhance predictive accuracy in stochastic inventory modeling. The insights gained from the accuracy evaluation support more reliable procurement planning, allowing decision-makers to anticipate uncertainty and reduce the operational risk of stockouts or overstocking. The graphical visualization comparing actual demand, EOQ results, and Monte Carlo simulation outcomes is presented in Figure 1 below.

Figure 1. Actual Demand, Economic Order Quantity (EOQ), and Monte Carlo Simulation for Chemical Materials



Source: Processed Data (2025)

4.3. Discussion

1. Application of Economic Order Quantity (EOQ) in Chemical Inventory Planning

The analysis shows that the EOQ values for chemical reagents are 38,219 kg for alum, 10,133 kg for chlorine powder, 23,318 kg for soda ash, and 28,126 kg for poly aluminium chloride (PAC). These figures clearly differ from the company's current ordering quantities, which reach 67,109 kg for alum, 18,583 kg for chlorine powder, 44,912 kg for soda ash, and 47,525 kg for PAC. This discrepancy indicates that the company has been incurring higher storage costs due to ordering volumes that exceed the optimal EOQ levels. By adopting EOQ, the company could reduce these costs because the order quantities become smaller while still meeting operational needs effectively.

The gap between EOQ and actual ordering practices is crucial for managerial decision-making: whether the company prioritizes minimizing stockout risks by ordering larger quantities at once, or chooses cost efficiency by adhering to EOQ. From a modern management perspective, the latter option is more advisable as it is mathematically and empirically more efficient.

The analysis further shows that the application of EOQ significantly reduces the total inventory cost (TIC). Inventory costs calculated using the EOQ method are substantially lower than costs resulting from the company's current ordering pattern. For alum, the TIC based on EOQ is Rp405,880,400, markedly more efficient than the company's actual expenditure. For chlorine powder, the TIC is Rp83,786,900; for soda ash, Rp120,561,450; and for PAC, Rp176,702,400. These values demonstrate that EOQ can generate substantial cost savings while maintaining adequate chemical availability. The cost difference arises because EOQ identifies the optimal balance between ordering costs and holding costs. Excessively large order quantities, as currently practiced, inflate holding costs and burden total inventory expenditures. Conversely, ordering too frequently in small quantities would increase ordering costs. EOQ serves as a mathematical solution to determine the optimal order quantity that minimizes both cost components simultaneously.

2. Application of Monte Carlo Simulation in Chemical Inventory Planning

The application of Monte Carlo Simulation in chemical inventory planning is a strategic approach that provides a realistic representation of fluctuating chemical demand and serves as a foundation for developing inventory control policies that are more adaptive to uncertainty. Through processes such as random number generation, mapping to probability intervals, and conversion into simulated demand values, this method generates a range of possible outcomes that closely approximate actual field conditions.

The simulation results show that each chemical such as alum, chlorine powder, soda ash, and PAC exhibits distinct demand characteristics. Alum, for example, demonstrates high demand variability, ranging from 4,064 kg to over 11,302 kg, indicating that its usage is highly influenced by fluctuations in raw water quality across periods. Meanwhile, chlorine powder exhibits a relatively stable demand pattern with occasional extreme values; soda ash shows a consistent trend with smaller variations; and PAC records the smallest range of demand with relatively high stability. These patterns illustrate that Monte Carlo simulation not only produces numerical estimates but also

captures the actual dynamics of chemical demand faced by the water utility company, where factors such as weather, rainy seasons, and river water quality fluctuations significantly influence chemical usage.

In terms of overall accuracy, the simulation results are sufficiently convincing for use in inventory planning, with average accuracy levels of 80–90%, which are considered acceptable for stock planning studies under high uncertainty. This indicates that the simulation model can represent real-world conditions reasonably well and is thus suitable as a basis for operational planning. Moreover, the analysis suggests practical implications: the utility company should pay closer attention to chemicals with lower simulation accuracy, as these pose greater risks of deviation between projected and actual demand. Mitigation strategies may include increasing the frequency of inventory monitoring, adjusting ordering cycles, or integrating additional forecasting methods to complement the simulation results.

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5 Closing

5.1. Conclutions

1. The Economic Order Quantity (EOQ) method provides an efficient and measurable basis for chemical procurement planning. The calculation results indicate optimal order quantities of 38,219 kg for Alum, 10,133 kg for Chlorine, 23,318 kg for Soda Ash, and 28,126 kg for PAC. With these quantities, the ideal ordering frequency ranges from one to two times per year, with an ordering cycle of approximately 40–60 days, an average safety stock of about ±735 kg, and a reorder point of around 5,600 kg. The application of the EOQ method reduces the total annual inventory cost to IDR 24,002,484.71, supporting an economical and efficient inventory strategy while ensuring chemical availability for continuous water treatment operations.
2. The Monte Carlo Simulation method produces demand estimates that are more adaptive to uncertainty. The simulation results show projected requirements of 80,514 kg for Alum, 18,115 kg for Chlorine, 49,221 kg for Soda Ash, and 55,425 kg for PAC. These values are generally higher than the EOQ results, reflecting demand fluctuations driven by variability in raw water quality and operational intensity. The outcomes provide realistic and responsive demand estimates, supporting more accurate determination of safety stock levels and reorder points. Monte Carlo Simulation therefore complements the EOQ method by enhancing the robustness, adaptability, and efficiency of chemical inventory planning under uncertain operating conditions.

5.2. Research Limitations

1. The Economic Order Quantity (EOQ) method used in this study considers only classical parameters such as ordering costs, holding costs, and average demand, and therefore does not fully capture demand variations influenced by external factors such as weather, raw water quality, and distribution conditions.
2. The Monte Carlo Simulation relies on probability distributions constructed from limited historical data, making the simulation results highly dependent on the accuracy and completeness of the dataset used.
3. The study focuses only on four primary chemicals that used such as aluminium sulfate, chlorine, soda ash, and poly aluminium chloride thus not accounting for other chemical variations or potential substitutes that may be required under certain operational conditions. Non-technical operational factors such as supplier delays, procurement policies, and budget constraints were not incorporated into the model, even though these factors may influence the practical implementation of inventory strategies.

5.3. Recommendations

1. Future studies should collect longer-term and more detailed data on chemical demand and usage, enabling the Monte Carlo probability distributions to reflect actual conditions more accurately.
2. EOQ model development should incorporate external variables such as chemical price fluctuations, potential delivery delays, and seasonal or raw water quality effects to enhance adaptability.
3. Subsequent research may expand the scope to include additional types of chemicals, allowing for a more comprehensive and efficient inventory planning model.
4. The integration of EOQ and Monte Carlo Simulation with computerized inventory management systems is recommended to support real-time monitoring, evaluation, and decision-making.
5. From a managerial perspective, the findings can inform more flexible procurement strategies, such as bulk purchasing during stable price periods or establishing long-term contracts with suppliers to reduce supply uncertainty.

Acknowledgement

I am very grateful to Ardi Paminto and Irwansyah as supervising lecturers at Mulawarman University, Samarinda, East Kalimantan Province.

References

1. Safitri, D., Dahdah, S. S., & Andesta, D. (2018). Penerapan Metode Monte Carlo Pada Perencanaan Jumlah Produksi Pestisida (Studi Kasus : PT. Petrokimia Kayaku Plant Cair 1). *Jurnal Sistem Dan Teknik Industri*, 96–100.
2. Utama, I. T., & Siswanto, N. (2017). Inventory System Planning of Margarine and Shortening Ingredient With Monte Carlo Simulation in Addition To Economic Order Quantity (Eoq) Method on Pt . Smart Tbk. *Spirit Pro Patria*, *III*(September), 109–119. file:///F:/Bang Deddy/juranl internasional/jurnal internasional/Imam Trio Utama (2017).pdf
3. Dedrizaldi, Masdupi, E., & Roza Linda, M. (2019). Analisis Perencanaan Persediaan Air Mineral dengan Pendekatan Metode Monte Carlo pada PT. Agrimitra Utama Persada. *Jurnal Kajian Manajemen Dan Wirausaha*, *01*(1), 388–396. file:///F:/Bang Deddy/juranl internasional/jurnal internasional/Dedrizaldi (2019).pdf
4. Assauri, S. (2016). *Manajemen Operasi Produksi Pencapaian Sasaran Organisasi Berkesinambungan*. Rajawali Pers.
5. Render, B., Stair, R., Hanna, M. E., & Hale, T. S. (2018). *Quantitative Analysis for Management* (Thirteenth). Pearson Education Limited.
6. Rusell, R. S., Taylor, B. W., Bayley, T., & Castilo, I. (2020). *Operations Management : Creating Value Along the Supply Chain*. John Wiley & Sons Canada, Ltd.
7. Heizer, J., Render, B., & Munson, C. L. (2020). *Operations Management: Sustainability and Supply Chain Management* (.Thirteent). Pearson Education, Inc.
8. Pangaribuan, W. F. ., Rahman, A., & Eunike, A. (2016). Analisis Pengendalian Persediaan Bahan Baku Menggunakan Simulasi Monte Carlo (Studi Kasus : PT. Adiprima Suraprinta). *Jurnal Rekayasa Dan Manajemen Sistem Industri*, *4*(7), 1–12.
9. Cahya Wulandari, L. M., & Indrianto Putri, L. D. (2021). Inventory Control Analysis of Plastic Raw Materials Using Monte Carlo Simulation Approach. *Opsi*, *14*(1), 104. https://doi.org/10.31315/opsi.v14i1.4744
10. Chandra, A., Kristina, H. J., & Andres. (2022). Analisis Pengendalian Persediaan Bahan Baku Akrilik Menggunakan Metode EOQ Probabilistik Dan Simulasi Monte Carlo Pada PT. XYZ. *Jurnal Mitra Teknik Industri*, *1*(1), 94–105.
11. Heizer, J., Render, B., Munson, C., & Griffin, P. (2020). *Operations Management : Sustainability and Supply Chain Management* (Third Cana). Pearson Canada, Inc.

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