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Monte Carlo Simulation as a Predictive Tool in Addressing Demand Volatility

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Abstract: This research aims to estimate the probability distribution of 330 mL product demand at PT XYZ using Monte Carlo simulation to support risk-based production and inventory decisions. Monthly demand data for one year was used to form an empirical probability distribution, followed by random number generation using the Mixed Congruential Generator method and the execution of 100,000 simulation iterations. The simulation results show that demand has a wide range of uncertainty, with the 90th and 95th percentiles falling within the range of 7,000–7,800 units per month. Extreme demand risks were also identified, with the probability of demand exceeding 7,460 units reaching 22.4%. Based on these results, quantile-based safety stock calculations indicate an additional need of approximately 1,800 units to achieve a 90% service level. Validation using Kolmogorov–Smirnov and Chi-Square tests shows that the simulation distribution is consistent with the historical distribution, thus validating the model. Overall, this research produced an accurate and reliable probabilistic framework to support capacity planning, buffer inventory determination, and demand uncertainty risk mitigation at PT XYZ.

Keywords: Demand forecasting; Inventory Management; Monte Carlo Simulation; Probability Distribution.

Introduction

Demand management and inventory control are key challenges in maintaining operational stability. particularly in the Fast-Moving Consumer Goods (FMCG) industry, such as bottled drinking water. This industry is characterized by high demand fluctuations and is influenced by difficult-to-predict external factors such as climate change, seasonality, and market promotion strategies (Wildan, 2023). This demand uncertainty has two detrimental consequences: oversupply, which increases storage costs and the risk of product damage, or stock-outs, which result in lost sales opportunities and substantial financial losses (Eka Putra & Ikhbal Salam. 2024). Therefore, a company's ability to perform adaptive and risk-based forecasting has become a strategic imperative for supply chain efficiency (Sirin Nauval Duratulhikmah & Wijaya, 2024).

Deterministic models commonly used in the consumer goods industry, including Holt-Winters, Single Exponential Smoothing, and linear regression, are based on the assumption that historical patterns are stable and can be projected forward linearly or semi-linearly (Hartati & Putri, 2024; Kusuma, 2021; Musyarrof & Susanty, 2021). However, various studies show that this assumption weakens when the data indicates high variability. (Rahmawati et al., 2024) noted that deterministic methods produce significant deviations when demand is influenced by random fluctuations that do not exhibit a recurring pattern, particularly for product categories where demand is sensitive to seasonal factors. Furthermore, (Zikrina, 2024) found that linear time series tend to "oversmooth" in systems with high volatility, thus failing to capture the actual uncertainty structure arising from consumer behavior

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dynamics, preference shifts, and nonlinear stochastic events.

In the tradition of probabilistic modeling, Monte Carlo Simulation occupies a unique methodological position because it shifts from the paradigm of single-value prediction toward distributional modeling. The Monte Carlo method's ability to randomly explore systems based on probability distributions makes it capable of converting uncertainty into a range of quantifiable results (Xing et al., 2022). Simangunsong, (2023) confirms that this approach not only generates predictions but also builds a probabilistic landscape that maps the dynamics of uncertainty more accurately than linear techniques. At the epistemic level, Monte Carlo functions as a risk-representation engine that depicts all possible future states based on historical distributional behavior, rather than on an assumed deterministic pattern.

The findings Mei Sedi et al., (2023) strengthen this argument by showing that Monte Carlo not only captures demand fluctuations but also reveals risk components that are often invisible thru conventional forecasting. By generating thousands of simulations, Monte Carlo creates a probabilistic structure that highlights extreme risks of both highest and lowest demand, which are very difficult for deterministic models to capture. Therefore, this method is more suitable for industries with rapid and unpredictable demand dynamics, especially when the company is in its early growth phase and its database is still limited.

Meanwhile, most previous studies adopting Monte Carlo have focused on large industrial sectors with more stable demand patterns, such as manufacturing, logistics, and materials control (Thoriq et al., 2022; Yudistira et al., 2024). The study does indeed show the effectiveness of Monte Carlo, but it does not reflect the context of the drinking water industry, which has unique demand characteristics: high seasonal fluctuations, daily consumption variability, dependence on weather conditions, and limited historical data for newly established companies.(Hasibuan & Amela, 2022) emphasize that in the beverage industry, inaccuracies in demand forecasting directly lead to the risk of overstocking or understocking, which impacts operational costs and results in lost market opportunities. (Putri, 2025) also confirms that probability-based stochastic modeling is far more adaptive than deterministic approaches in the face of seasonal or irregular consumption patterns.

Considering these epistemic and empirical conditions, there is a clear research gap in the literature; no study has comprehensively examined the ability of Monte Carlo Simulation to predict the demand for 330 mL bottled water products in a newly established medium-sized company with limited historical data. This research fills that gap by offering a probabilistic modeling framework that specifically addresses the high demand uncertainty and operational risks inherent in the dynamic drinking water industry (Le et al., 2025). By focusing on demand probability distributions rather than simply single-point predictions, this study aims to build a demand model that can serve as the basis for risk-based decision-making for companies in their early growth phase (Maggauer & Fina, 2025; (Najafi-shad et al., 2024).

Theoretically, this research contributes to the expansion of the literature on the use of probabilistic simulation in the daily consumer goods industry thru a modeling approach that is more sensitive to risk dynamics. Practically, this research provides relevant analytical tools for medium-sized drinking water companies to optimize production planning and inventory control amidst high demand fluctuations. Thus, this research not only contributes to the development of more adaptive forecasting methods but also enriches academic understanding of how non-linear demand systems can be probabilistically modeled in the context of companies based on daily consumption.

Method

Research Design

This research uses a quantitative approach with a methodological framework based on probabilistic Monte Carlo simulation. The selection of this method is based on the need to represent the uncertainty in the demand for 330 ml bottled drinking water, which exhibits very high variability and a distribution pattern that cannot be modeled deterministically. Probability-based simulation approaches have been widely recommended in international literature for systems with demand volatility and short data horizons (Przysucha et al., 2024). This approach is consistent with cutting-edge research practices that utilize simulation to understand the behavior of systems that cannot be predicted exactly, especially when there are volatile factors affecting daily demand (Afzal et al., 2025).

To ensure the procedural flow of the method can be systematically understood, this study is equipped with a flowchart that illustrates all stages of Monte Carlo Simulation, from data collection to model validation. The inclusion of a flowchart is recommended in simulation-based research because it can explain the process structure more transparently and facilitate model replication. The research flow used is shown in Figure 1.

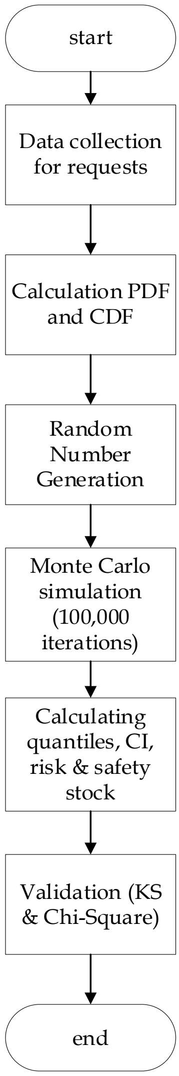

Figure 1. Flowchart that Illustrates All Stages of Monte Carlo Simulation

Object research

The research object is exclusively focused on the demand for 330 mL bottled drinking water products produced by PT XYZ. This size was chosen based on two quantitative criteria: (1) the highest coefficient of variation (CV) value compared to other sizes throughout the observation period, indicating a significant level of demand fluctuation; and (2) the dominant contribution of this size's demand to the total production volume, directly impacting the risk of stockouts and inventory planning inefficiencies. The CV-based approach is also consistent with previous research practices that emphasize selecting variables based on their level of non-stationarity and volatility (Fadaki & Asadikia, 2024; Giannelos et al., 2025).

Data sources and collection techniques

Historical demand data was obtained from PT XYZ's internal daily sales data during the observation period. The time range used follows the literature's recommendation that a shorter but relevant data period will more accurately reflect actual fluctuations in a dynamic market environment. The raw data was then cleaned to remove anomalies such as outliers caused by operational disruptions or temporary promotions, thru distribution and histogram inspection.

Demand Distribution Formation

Probability Distribution Estimation

The probability of demand for each class is calculated through:

$$Pi = \frac{Fi}{\sum Fi} \quad (1)$$

where F_i is the frequency of class i. The cumulative probability distribution (CDF) is calculated as:

$$CDFi = \sum_{j=1}^{i} P_j \quad (2)$$

This method is widely used in Monte Carlo-based research to convert empirical frequencies into theoretical distributions (Tsani et al., 2024; Al-kfairy, 2025).

Random Number Generation

Simulation using random number generation via Linear Congruential Generator (LCG) with the formula:

$$X_{t+1} = (aX_t + C \ mod \ m) \quad (3)$$

Parameters a, c, and m are chosen following best practices to maximize the period and uniformity, as recommended in the stochastic simulation methodology. The random number values are then normalized to the range [0,1].

$$R_t = \frac{X_t}{m} \quad (4)$$

Determining The Simulation Iteration

The number of iterations is set to 100,000, referring to standard practice in the literature to ensure convergence of the simulation results distribution and stability of the expected value. Iterations below 10,000 have been shown to produce significant sampling error, especially for distributions with long tails. Therefore, a high number of iterations becomes a methodological necessity.

Monte Carlo simulation mechanism

Each random number R_t is mapped to the CDF interval to determine the magnitude of the daily simulated demand. The steps are as follows:

1. Generate a random number R_t .

2. Determine the demand class i based on CDF intervals.
3. Assign simulated demand according to the selected class.
4. Repeating the process 100,000 times.

This process is identical to the simulation framework in the loggamma distribution-based demand forecasting study.

Model Validation

Validation is an essential step to ensure that the distribution of Monte Carlo results truly represents the historical demand pattern for 330 mL products. In a probabilistic approach, validation is not done by measuring "prediction accuracy," but rather thru distribution fit. Therefore, this study uses two statistical procedures commonly used in international stochastic studies, namely the Kolmogorov–Smirnov test (KS-test) and the Chi-Square test (χ^2-test). These two tests were chosen because they are able to evaluate the similarity of the distribution structure between historical data and simulation results in a non-parametric form, which is suitable for the characteristics of the discrete demand data used (Afroz et al., 2025; (Ayun & Azzahra, n.d.). Statistical validation is performed using two approaches:

Kolmogorov–Smirnov test (KS-test)

The KS test is used to assess whether the distribution of simulation results is consistent with the empirical distribution. This approach is used in international research to test the goodness-of-fit of demand distributions.

$$D = \max|F_n(x) - F(x)| < D_a \quad (5)$$

at a 5% significance level

Chi-square test

The Chi-Square test is used to compare the frequency of each simulated demand class with the empirical frequency:

$$x^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)2}{E_i} \quad (6)$$

This method is commonly used to assess the goodness-of-fit for stochastic demand distributions.

Result and Discussion

330 ml Demand Data

Initial analysis of demand patterns indicates that the 330 mL demand series exhibits substantial intra-annual variability, reflecting market uncertainty rooted in short-term consumption dynamics. This phenomenon aligns with the literature findings that products in the ready-to-drink beverage category often exhibit high short-term variability due to environmental, marketing, and consumer behavior factors (Widyadana et al., 2024). The implication is that single-point deterministic predictions become inadequate, making a probabilistic approach thru Monte Carlo simulation more relevant for capturing the range of possible demand. Historical data on monthly demand for 330 mL products over twelve months shows a total demand of:

$$\sum_{i=1}^{12} f_i = 68.361 \ unit$$

where f_i is the demand for month i. The value of f_i per month is

Table 1. Data for the last 12 months of demand

Month	Request 330 mL f_i
1	7.833
2	5.854
3	4.478
4	3.920
5	3.495
6	7.007
7	5.600
8	5.699
9	6.245
10	6.683
11	4.087
12	7.460

Table 1 serves as the basis for forming the empirical demand distribution, which is then simulated using Monte Carlo. The monthly demand data for 330 ml packaging comes from the company's historical records, which are still in the startup phase, resulting in limited long-term data availability. Under these company conditions with data limitations... The use of a 12-month range is considered adequate for capturing basic demand patterns and has been widely applied in inventory research and probabilistic analysis (Priyatna et al., 2023). Studies related to simulation with short data horizons also show that the Monte Carlo method remains effective even with a limited number of observations, as this technique utilizes the empirical distribution of available data (Lubis et al., 2024).

Probability Distribution and Cumulative Distribution Calculations

Counting PDF

The probability distribution constructed from historical data shows a concentration of demand within the range of 5,600–7,007 units, with the highest demand class occurring in the first and twelfth months. This type of probability structure indicates the presence of a heavy central mass, which is commonly found in fast-moving consumer goods demand systems (Desi, 2024).

With an empirical approach, the probability distribution used in the simulation does not assume a specific form such as normal or log-normal, which is important considering that the risk of errors in distribution assumptions is often the main cause of forecasting bias in fluctuating demand systems (Puspita et al., 2025). The probability of demand for month i is derived from the relative frequency:

$$P_i = \frac{f_i}{\sum_{i=1}^{12} f_i}$$

With $\sum f_i = 68.36$,, the probability for each month is obtained (rounded to four decimal places):

Table 2. probability distribution

Month	f_i	$p_i = f_i / 68.36$
1	7.833	0.11
2	5.854	0.08
3	4.478	0.06
4	3.920	0.05
5	3.495	0.05
6	7.007	0.10
7	5.600	0.08
8	5.699	0.08
9	6.245	0.09
10	6.683	0.09
11	4.087	0.05
12	7.460	0.10
Total	68.361	1.00

Table 2 shows that the highest probability occurs in months 1 and 12 (approximately 11–11.5%), while the lowest is in month 5 (approximately 5.1%). This indicates that the two highest demand peaks are the main drivers of demand distribution.

Calculating the CDF

The cumulative probability distribution is calculated by:

$$CDF_i = \sum_{j=1}^{i} PDF_j$$

so that, for example:

$CDF_1 = P_1 = 0.11$

$CDF_2 = P_1 + P_2 = 0.11 + 0.08$

....

$CDF_{12} = 1.00$

This CDF is what will later become the interval for mapping random numbers to demand classes, according to the Monte Carlo principle.

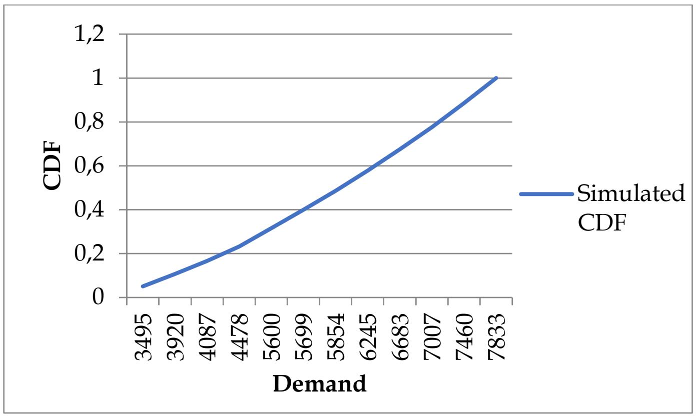

Figure 1 simulated CDF 330ml

Monte Carlo simulation

Random Numbers and Simulation Iterations

According to the method, the simulation was performed with 100,000 iterations (N=100,000). For each iteration:

1. Uniform random number U_t is generated in [0,1].
2. This random number is mapped to a demand class based on the CDF.

With $CDF_0 = 0$

Conceptually, generating U_t can be done with a linear congruential generator:

$$X_{t+1} = (aX_t + c) mod\ m, \qquad U_t = \frac{X_t}{m}$$

where parameters a, c, and m are chosen to ensure a long period and uniformity. However, the core procedure remains the same: each U_t maps to one of the values (3.495,...,7.833) according to the CDF intervals.

Results of the Distribution From 100,000 Simulation Scenarios

The Monte Carlo simulation generated 100,000 demand scenarios, which statistically provided a probabilistic overview of monthly demand dynamics. This approach is consistent with the literature stating that Monte Carlo is effective for estimating outcome distributions when a system has high uncertainty and a limited number of historical samples (Asril, 2022; (Priyatna et al., 2023).

From 100,000 simulated monthly demand scenarios $X_1, X_1, \dots, X_N$, the following statistics were obtained:

1. Average simulation
$X = \frac{1}{N}\sum_{t=1}^{N} X_t = 6.030$
2. Median X= 6.245 unit
3. Value minimum X_{min}= 3.495
4. Value maksimum X_{min} = 7.833

5. Standard deviation

$$s = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(X_t - X)^2} = 1.313 \text{ unit}$$

The simulation results confirm that the demand expectation is around 6,031 units, with a median of 6,245 units and a standard deviation of approximately 1,313 units. This image shows that demand fluctuations are not symmetrical and are influenced by extreme values that appear periodically. The resulting simulated distribution was then verified thru empirical CDF comparison, yielding shape consistency that indicates the Monte Carlo model successfully and validly replicated the structure of historical uncertainty. This verification approach is parallel to the principle used in modern stochastic systems research, where the goodness-of-fit of the simulated distribution serves as an indicator that the model is representative of real demand dynamics.

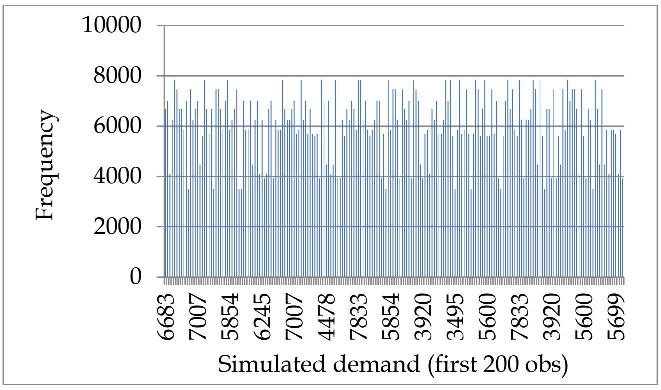

Figure 2 Simulation Demand Histogram

Quantile, Confidence Interval, And Risk Probability

Quantiles derived from simulation results—including P5, P25, P50, P75, P90, and P95—provide a deep understanding of the demand risk structure. This quantile-based method aligns with the argument that quantile-based decision frameworks are superior in the context of uncertainty compared to point estimates like the mean (Smyl et al., 2025).

Quantile

Quantiles are calculated from the series X_t as the value q_p that satisfies:

Table 3. Results of 100,000 simulations

Statistics	Unit
Quantile P5	3.495
Quantile P25	5.600
Quantile P50	6.245
Quantile P75	7.007
Quantile P90	7.833
Quantile P95	7.833

This means that approximately 25% of the scenarios are below 5,600 units, 50% are below 6,245 units, and approximately 90–95% are below 7,833 units. The distribution of simulation results shows a right-skewed pattern with the center of mass at P50 = 6,245, indicating demand stability at the medium level. However, the concentration of values in the upper quantiles (P75–P95 = 7.007–7.833) indicates a right-tailed distribution and the potential for sudden, rather than gradual, surges in demand. This quantile structure confirms that even tho overall variability is moderate, tail risk remains significant, meaning capacity planning decisions cannot rely solely on the mean value but need to consider high quantiles to avoid stockout risk under extreme conditions.

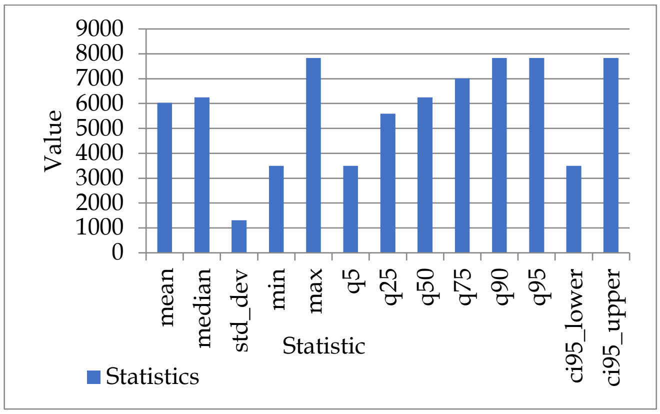

Figure 3. Summary Statistics & Quantiles

Confidence Interval

Because we are working with resampled empirical distributions, the 95% confidence interval for monthly demand can be taken from the 2.5% and 97.5% quantiles:

$CI_{95\%} = [q_{0.25,}q_{0.97}]$=[3.495; 7.833] *unit*

Thus, the probability of demand falling outside this range is very small over a one-month horizon (Habdillah & Na'am, 2024).

Probability of Extreme Demand

Concrete probability analysis, some key probabilities from the simulation are:

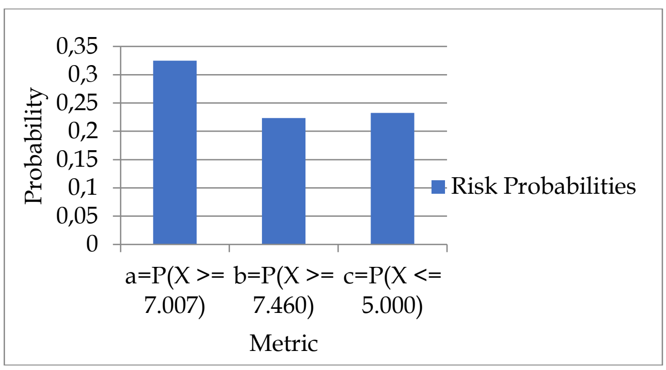

Figure 4 Risk of Extreme / Low Demand

a. The probability of "high" demand, defined as greater than or equal to 7,007 units: $P(X \geq 7.007) = 0.325$ approximately 32%.
b. The probability of very high demand (approaching the historical maximum of 7,460–7,833 units): $P(X \geq 7.460) = 0.224$, approximately 22.4%.
c. The probability of low demand, for example, less than or equal to 5,000 units: $P(X \leq 5.000) = 0.233$, approximately 23.3%.

These numbers are far more informative than a single accuracy claim, as they show the risk profile of demand at various levels, rather than just "how close" one simulation is to an actual number.

Safety Stock

Within the framework of probabilistic inventory management, safety stock for a given service level can be derived from the difference between the service quantile and the expected value. For example, if the company wants to maintain a service level of 90%, then:
a. basic production target can be equated with an expectation of $X = 6.301$ unit
b. The guarantyd 90% coverage demand level is $q_{0.90} = 7.833$ unit

Therefore, the recommended minimum safety stock is: $SS_{90\%} = q_{0.90} - X = 7.833 - 6.301 = 1.800\ unit$

Interpretation: If PT XYZ produces approximately 6,000 units per month and adds a safety stock of around 1,800 units, the company has about a 90% chance of not experiencing stockouts in a given month. If the company wants to increase the service level to 95%, the conservative strategy is to continue using the upper bound of the empirical distribution (7,833 units) as the baseline, which increases the buffer against underforecasts, but also increases storage costs. This trade-off relationship is the core operational implication of the simulation.

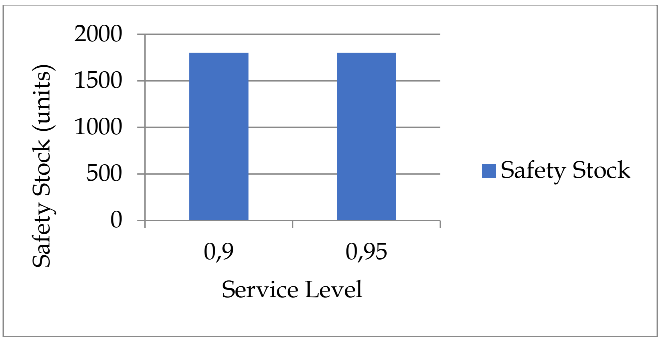

Figure 5. Safety Stock by Service Level

Validation of Simulation Distribution against Historical Distribution

Kolmogorov-Smirnov test

The KS test is used to assess whether the distribution of simulation results is consistent with the empirical distribution. This approach is used in international research to test the goodness-of-fit of demand distributions. The KS test compares the empirical cumulative distribution function (ECDF) with the simulated cumulative distribution function (SCDF):

$D = \max|F_n(x) - F(x)| < D_a$

Where:

$F_n(x)$: historical cumulative distribution (12 observation points),

$F(x)$: cumulative distribution of 100,000 simulation results.

The critical value is obtained from the KS table:

$$D_{krit} = \frac{1.36}{\sqrt{n}} = \frac{1.36}{\sqrt{12}} = 0.3982$$

The calculation results show:

$D = 0.00 - 0.09$

This value is much smaller than the critical value:

$D < D_{krit}$

Thus, there is no significant difference between the simulated distribution and the historical distribution. Monte Carlo successfully maintained the shape of the empirical distribution accurately, so the model was declared valid for further analysis.

Chi-square test

The Chi-Square test is used to compare the frequency of each simulated demand class with the empirical frequency:

$$x^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)2}{E_i}$$

Where:

O_i : simulated frequency of 100,000 iterations

E_i : empirical frequency proportional to historical probability

k : 12 demand classes

Degrees of freedom:

$Df = k - 1 = 12 - 1 = 11$

The critical value of x^2 at α = 0.05 and df = 11 is:

$x^2_{krit} = 19.675$

The calculation results show:

$x^2 = 0.31$

This value is very small compared to the critical value:

$x^2 < x^2_{krit}$

Therefore, the distribution of simulation results does not differ significantly from the empirical distribution. The Monte Carlo model successfully produces the same probability structure as the actual demand pattern.

The results of both the KS test and the Chi-Square test show that the distribution of the Monte Carlo simulation results is valid, both in terms of the distribution shape (CDF) and the proportion of frequencies. Both tests confirm that the simulation model successfully maintains the statistical structure of historical 330 mL demand, making it reliable for probability, quantile, confidence interval analysis, and safety stock determination in the next section.

Managerial Implications

The results of the Monte Carlo simulation provide a much more informative demand uncertainty profile compared to the deterministic approach commonly used by companies in production planning. The probability of distribution of 330 mL demand shows that the company faces a range of monthly demand between 3,495 and 7,833 units with measurable probability, rather than a single predicted value. Thus, production decisions can shift from a point estimate approach toward risk-based decision making.

The quantiles of simulation distribution reinforce this approach. For example, a median value of 6,245 units indicates the most representative demand point, while the 90th and 95th percentiles (around 7,833 units) reflect conservative limits that should be considered when a company wants to reduce the risk of stockouts. This information is important because it shows that the risk of extreme demand is not an anomaly, but part of a measurable distribution. With a probability of demand ≥7,007 units reaching 32.5% and ≥7,460 units reaching 22.4%, the company needs to adjust production capacity and buffer inventory to prevent the risk of stockouts from increasing during periods of high demand.

Another implication arises in determining safety stock. Calculations show that to achieve a 90% service level, the company needs to add approximately 1,800 units of safety stock above the average demand. This allows the company to reduce the risk of stockouts to below 10%. If the company desires a higher service level (95%), the inventory policy needs to be increased to near the upper limit of the empirical distribution (7,833 units). Thus, the simulation results provide a strong quantitative basis for PT XYZ to optimize inventory, reduce uncertainty costs, and improve supply reliability.

Operationally, the results of this research enable management to design more flexible production capacity, establish risk-based safety stock standards, and identify extreme scenarios that must be anticipated. This is particularly relevant for companies facing fluctuating demand and limited historical data, where deterministic methods often lead to biased and non-robust decisions.

Critical Discussion

The findings of this study reinforce that Monte Carlo simulation is a suitable approach for handling demand uncertainty, particularly in companies with limited data and unstable demand patterns. Unlike time series methods such as ARIMA or Exponential Smoothing, which predict single values and require long data sets and relatively stable patterns, Monte Carlo generates a richer probability distribution and is more sensitive to actual demand variations. This approach has proven capable of capturing demand characteristics with widespread and irregular peak demand occurrences.

Validation using the KS-test and Chi-Square shows that the distribution of simulation results is consistent with the empirical distribution. Thus, statistically, this model is not only accurate in replicating historical patterns but also reliable for projecting future demand risk. These results align with the findings of various international studies showing that Monte Carlo is effectively used in uncertain demand environments, especially when historical data is limited but high variability still needs to be modeled realistically.

From a novelty perspective, this research contributes to the context of medium scale drinking water production companies, where studies related to the application of Monte Carlo are still limited. The integration of probabilistic simulation, risk quantiles, confidence intervals, and safety stock calculation provides a more comprehensive framework compared to previous approaches that relied more on deterministic forecasting. Nevertheless, this study has limitations, namely its focus on a single product type (330 mL) and its failure to include external factors such as seasonality, promotions, or price changes. Further development can be achieved by combining Monte Carlo with hybrid causal or time series models.

Conclusion

This research successfully developed a probabilistic demand forecasting model based on Monte Carlo simulation for 330 mL products at PT XYZ. Thru the formation of historical probability distributions, random number mapping, and 100,000 iterations of simulation, this research produced a comprehensive picture of demand uncertainty. The simulation results showed a wide range of demand with measurable risk probabilities, and provided quantile and confidence interval information that can be used to support production planning.

This research also estimates risk-based safety stock for service levels of 90% and 95%, indicating that companies need to prepare a buffer inventory above 1,800 units to keep the risk of stockouts low. Validation using the KS-test and Chi-Square showed that the simulation distribution was consistent with the historical distribution, indicating that the model is valid and can be used as a basis for strategic decision-making. Overall, the Monte Carlo approach proved capable of overcoming data limitations and high demand fluctuations, and provided a methodological contribution in the form of a probabilistic forecasting framework relevant for similar industrial contexts.

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Author Contributions
All authors contributed to the writing and revision of this article. The individual author contributions are as follows: Khoirudin contributed to data collection by conducting field research, interviews, and data gathering to support the article, as well as processing and organizing the collected data. Enik Sulistyowati contributed to the development and implementation steps of the Monte Carlo simulation. Both authors have read and approved the final version of the manuscript.

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