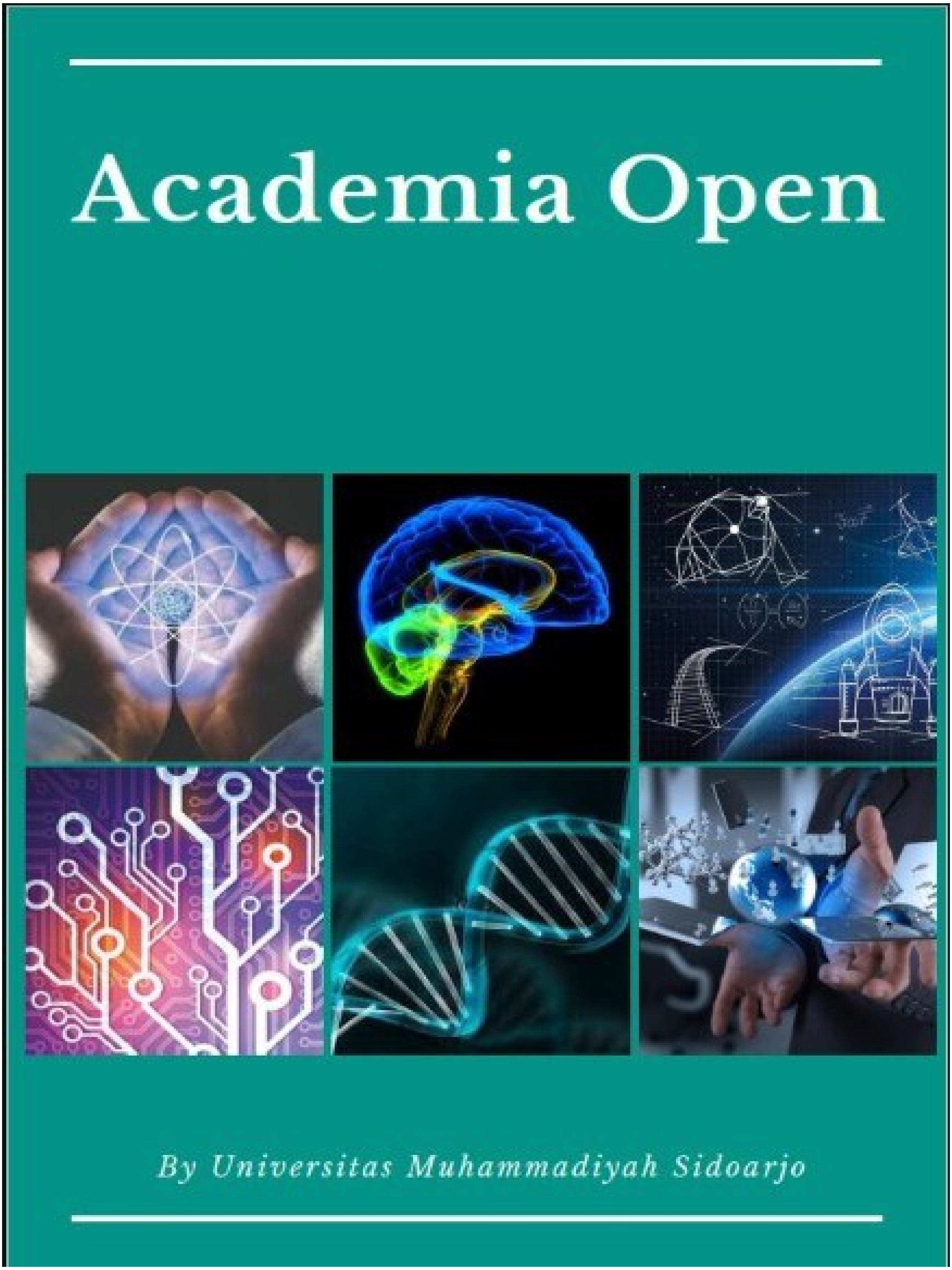
Academia Open

Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062



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Academia Open

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DOI: 10.21070/acopen.11.2026.14062

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Academia Open

Vol. 11 No. 1 (2026): June
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Academia Open

Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062

Cost Service Tradeoffs in Power Utility Procurement

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Abstract

General Background: Reliable electricity distribution depends on the availability of Main Distribution Materials. **Specific Background:** Centralized procurement provides cost control but has longer lead time, while decentralized procurement offers faster responses with higher inventory costs. **Knowledge Gap:** The cost–service trade-off under uncertain demand has not been fully evaluated. **Aims:** This study compares centralized and decentralized periodic review policies using Monte Carlo simulation based on SAP ERP demand data from 2022–2024 over 300 weeks. **Results:** Centralized procurement is more cost-efficient in aggregate but has higher stockout risk and lower responsiveness, whereas decentralized procurement improves service level, shortens lead time, and reduces stockout frequency despite higher holding costs. **Novelty:** The study integrates validated normal demand distribution with Monte Carlo simulation to assess procurement policy performance. **Implications:** A hybrid policy is recommended, with centralized control for slow-moving materials and decentralized control for critical or fast-moving materials.

Highlights:

- Centralized setting delivers aggregate financial advantage but shows longer lead time and weaker responsiveness.
- Decentralized setting records stronger service levels, faster response, and fewer shortages.
- Rising service targets raise safety stock and holding expenses across both settings.

Keywords: Supply Chain, Centralized, Decentralized, Main Distribution Materials, Monte Carlo Simulation.

Published date: 2026-05-14

Academia Open
Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062

Introduction

The continuously increasing demand for electric energy requires PT P to maintain the reliability of the distribution system on an ongoing basis. The continuously increasing electricity demand itself becomes a challenge for PT P as the main electricity provider in Indonesia. [1]. PT P as the national electricity provider company has a great responsibility in ensuring the reliability of the distribution system so that customers' energy needs can be met properly [2]. In supporting such reliability, one important aspect that needs attention is the availability of main distribution materials (MDU), such as cables, cubicles, transformers, and other main components of the distribution network. These materials become key elements in the activities, construction, maintenance, and repair of the electricity network throughout the working areas of PT P. [3].

The availability of main distribution materials (MDU) at PT P is inseparable from the inventory management system implemented. The characteristic of this inventory management system is the uncertainty of demand and product availability. [4]. This demand itself is based on demand forecasting, which describes the actual demand distribution according to needs. Then, this demand depiction will be made into an order demand plan so that it provides an optimal decision. [5]. In practice, companies anywhere, including PT. P , are challenged to achieve shorter order-to-delivery times while still providing the best quality for customers.[1] One of the aspects is service levels which affect the probability of material shortages, causing customers not to be served. Lead time is a very important element in the inventory system if there is a failure in material supply. [6]

The centralized supply chain procurement policy in the management of main distribution materials (MDU) provides key advantages in the form of cost efficiency through demand aggregation, increased bargaining power with suppliers, and standardization of material specifications. At the main distribution unit (MDU) level, this system facilitates procurement control, regulatory compliance, and material quality consistency. [7]. In addition, centralized procurement has the potential to reduce unit costs and ordering costs due to large purchase volumes [8]. A centralized system tends to have a longer procurement lead time due to layered bureaucratic processes and cross-unit coordination. This condition makes the system less responsive to demand variations at the customer service implementation unit (UP3) level, thereby increasing the risk of stockouts.[9]

Conversely, decentralized supply chain policies offer higher flexibility in fulfilling material needs at the operational unit level. With ordering authority closer to the source of demand, units can respond to material needs more quickly and specifically.[10] This approach has the potential to improve service levels and reduce the risk of delays in customer service. The distribution of inventory across multiple units can lead to increased holding costs and decreased economies of scale efficiency. Furthermore, without an integrated control system, decentralized policies risk creating stock imbalances and procurement duplication between units.[11] These differences in characteristics indicate a trade-off between cost efficiency and achieving service KPIs [12]. Considering that material demand and service levels are uncertain and vary between units, a simulation-based analytical approach is needed to evaluate procurement policy performance more realistically. [13]. Currently PT P , particularly the Banten Distribution Main Unit (UID), adopts a centralized supply chain system for MDU materials [14]. At the distribution parent unit (UID) level, centralized policies tend to focus on minimizing total aggregate costs, while aspects of long service levels and variations in demand between units have not yet been fully accommodated [15].

In this study, centralized and decentralized are defined as procurement and inventory control policies, not merely warehouse locations. Thus, to avoid the issue of material stockouts faced by PT P Unit Induk Distribusi (UID) Banten and to achieve KPI targets, an analysis regarding the comparison of centralized and decentralized procurement policies for main distribution materials (MDU) is required so that top management can make decisions. The centralized and decentralized system decisions to be made by UID Banten management here are related to procurement policies, not the warehouse locations in the business process of the distribution main unit (UID) Banten.

Method

The results obtained from the mathematical development of the Monte Carlo method will be analyzed by comparing the total cost in two supply chain processes, namely centralized and decentralized. The analysis is conducted based on the total cost, which consists of ordering cost, holding cost, and penalty cost over a specified time interval with different service levels (80%, 90%, 95%) to observe the effect of increasing service targets on changes in safety stock and total cost. These results will provide an overview of the relationship between service levels and cost efficiency in the two supply chain processes. [16]. The simulation results will also be analyzed through an evaluation of response time for variations in demand and changes in service levels [17]. Two supply chain processes will be compared based on stockout risk and the speed of material fulfillment at the unit. The analysis can help to identify the strengths and weaknesses of the two supply chain processes. The results of this analysis are expected to serve as strategic recommendations regarding the supply chain that is suitable to be implemented across the Banten Main Distribution Unit (UID). [18]

Result and Discussion

A. Expected Output from the Conceptual Model (Based on Simulation Data)

The conceptual model developed in this study produces a main output in the form of inventory system performance indicators obtained from Monte Carlo simulations based on a periodic review policy. This output is used to evaluate and compare the performance of centralized (UID) and decentralized (UP3) procurement policies in the management of Main Distribution Material (MDU) [19]. The main indicators analyzed include total cost, service level, stockout rate, as well as system performance comparisons, all of which are calculated based on the simulation results of historical data from 2022–2024 over a 300-week horizon.[20]

1. Total Inventory Cost (Total Cost)

Total cost is a key indicator in assessing system efficiency [21]. Based on the simulation results on the Summary sheet, the total cost consists of unit cost and holding cost (in this model, penalty cost is reflected from the implications of service level and stockout).

Table 1. Total Cost of Centralized System (UID)

Service Level	Unit Cost (Rp)	Holding Cost (Rp)	Total Cost (Rp)
80%	11.978.616.526.700	2.582.145.195.380	**14.560.761.722.080**
90%	12.449.289.030.900	3.275.284.077.085	**15.724.573.107.985**
95%	12.103.722.036.650	3.702.808.262.535	**15.806.530.299.185**

Table 2. Total Cost of Decentralized System (UP3 Aggregate)

(Aggregation from TLN, CKP, CKK, SRP, BTU, BTS units)

Service Level	Average Unit Cost	Average Holding Cost	Total Cost
80%	± 2,6 Triliun	± 0,5 Trillion	± **3,1** Trillion / unit
90%	± 2,7 Triliun	± 0,6 Trillion	± **3,3** Trillion / unit
95%	± 2,7 Triliun	± 0,7 Trillion	± **3,4** Trillion / unit

Analysis:

a. The centralized system (UID) shows a high total cost due to the aggregation of all unit requirements.
b. The decentralized system (UP3) shows a lower cost per unit, but if all units are added together → the total is higher.
c. Holding costs increase significantly along with the rise in service level.

Insight important**:**

a. Centralized is more efficient in aggregate
b. Decentralized is more expensive because of stock duplication

Mathematically, the total inventory cost can be expressed as follows:

TC=Cu+ChTC = C_u + C_hTC=Cu+Ch (1)

2. Research Notation

To clarify the meaning of each variable in the formula above, the following are the notations used in the study:

Table 3. Research Notation

Notasi	**Keterangan**
TC	Total Cost (Total inventory cost during the simulation period)
C_u	Unit Cost (Total cost of material purchase)
C_h	Holding Cost (Total material storage cost)
Q	Quantity (The amount of material ordered in one period)
I	Inventory (Average amount of material in stock)
SL	Service Level (Service level, in %)
SS	Safety Stock (Safety Inventory)
LT	Lead Time (Procurement waiting time)
μ	Mean Demand (Average material demand)
σ	Standard Deviation (Material demand variation)

Development of the Total Cost Formula In the context of Monte Carlo simulation and periodic review policy, the cost components can be explained in more detail as follows:

a. Unit Cost (C_u)

Cu=Q×cC_u = Q \times cCu=Q×c (2)

Description:

QQQ = the amount of material ordered
ccc = unit price of material

Unit cost represents the total cost of purchasing materials during the simulation period.

b. Holding Cost (C_h)

$$C_h = I \times h \qquad (3)$$

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Academia Open
Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062

Description:

III = average inventory quantity
hhh = holding cost per unit per period

Holding cost is the cost that arises from storing materials in the warehouse, including space costs, insurance, and the risk of damage.

c. Relationship with Safety Stock

The average inventory III is greatly influenced by the safety stock:

$$SS = Z \times \sigma \times \sqrt{LT} \tag{4}$$

Description:

SSSSSS = safety stock
ZZZ = Z-score value based on service level
σ = demand standard deviation
LT = lead time

The higher the service level (SLSLSL), the higher the ZZZ value, thereby increasing the safety stock and holding cost as well.

3. Interpretation of Notation in Research Results

Based on the simulation results:

Table 4. Total Cost of Centralized System (UID)

Service Level	Unit Cost (C_u)	Holding Cost (C_h)	Total Cost (TC)
80%	11.978.616.526.700	2.582.145.195.380	14.560.761.722.080
90%	12.449.289.030.900	3.275.284.077.085	15.724.573.107.985
95%	12.103.722.036.650	3.702.808.262.535	15.806.530.299.185

Makna Notasi:
CuC_uCu increased due to the rise in the number of QQQ orders
ChC_hCh increased due to the rise in safety stock (SSSSSS) as a result of the increase in SLSLSL
TCTCTC is the accumulation of both components

Table 5 Total Cost of Decentralized System (UP3)

Service Level	CuC_uCu (Rata-rata)	ChC_hCh (Rata-rata)	TCTCTC
80%	± 2,6 Trillion	± 0,5 Trillion	± 3,1 Trillion
90%	± 2,7 Trillion	± 0,6 Trillion	± 3,3 Trillion
95%	± 2,7 Trillion	± 0,7 Trillion	± 3,4 Trillion

a. Analysis Based on Notation

Using the notation that has been defined, it can be explained that:

1. The Effect of Service Level (SLSLSL) on Costs
   o Increase in SL → increase in Z → increase in SS
   o Increase in SS → increase in III → increase in C_h
2. Difference Between Centralized vs Decentralized
   - Centralized:
     - QQQ big (agregasi demand)
     - III more concentrated → relatively lower C_h
   - Decentralized:
     - QQQ scattered
     - III scattered → C_h higher
3. System Efficiency
   - Centralized minimizes C_u through economies of scale
   - Decentralized increase C_h due to stock duplication

b. Insights Based on Notation

Using a mathematical notation approach, it can be concluded that:

1) TCTCTC is strongly influenced by the interaction between QQQ, III, and SL
2) The most dominant variable in increasing cost is holding cost (Ch)
3) Service level becomes the main controlling factor in the cost trade-off

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

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4. Analysis and Data Processing Stages Using the Monte Carlo Method

Demand for materials is analyzed to understand the consumption patterns occurring in each customer service implementation unit (UP3). Based on historical data, two main parameters are calculated, namely:

a. Mean demand (μ): indicates the average material requirement per period
b. Standard deviation (σ): describes the level of demand fluctuation

These two parameters form the basis for constructing the demand probability distribution. In this study, demand is assumed to follow a normal distribution, therefore the simulation is carried out using the function:
X = NORM.INV(U, μ, σ), where the value of U is obtained from a random number (RAND). This process produces simulated demand values that vary in each period, thereby representing actual uncertainty conditions.

The simulation results show that the larger the value of the standard deviation, the higher the demand fluctuation. This directly affects the increase in safety stock requirements to anticipate demand spikes. Conversely, if demand variation is low, the system can operate with a more stable inventory level.

The data processing procedure in the Monte Carlo method in this study is carried out through several main stages as follows:

- Determination of Initial Parameters

The first step is to determine the statistical parameters from historical data, namely

1) Mean demand (μ): the average material demand per period
2) Standard deviation (σ): demand variation
3) Lead time (LT): procurement waiting time
4) Service level (SL): target service level (80%, 90%, 95%)

These parameters form the basis for constructing the demand probability distribution.

a) Random Number Generation

The Monte Carlo method operates by generating random numbers that represent possible demand occurrences. In the Excel implementation, the following function is used:

$$U = RAND() \tag{5}$$

The value of U lies within the interval 0–1 and is used as an input to generate random demand values.

b) Transformation of the Normal Distribution

To generate demand values that follow the historical distribution, the following function is used:

$$X = NORM.INV(U, \mu, \sigma) \tag{6}$$

Where:

X = simulated demand
μ = mean demand
σ = standard deviation

The result of this process is random demand data that represent real conditions with fluctuations similar to those in the historical data.

c) Periodic Review Simulation

In the periodic review policy, ordering is carried out at specific time intervals (T). In each period

1. The system evaluates the stock position
2. Determines the target level (TL)
3. Calculates the order quantity (Q)

$$Q=TL-I \tag{7}$$

Where:

TL = target level
I = current stock

DOI: 10.21070/acopen.11.2026.14062

d) Safety Stock Calculation

Safety stock is calculated to anticipate uncertainty in demand and lead time

$$SS = Z \times \sigma \times \sqrt{LT} \quad (8)$$

The value of Z is obtained from the service level

SL 80% → Z ≈ 0,84
SL 90% → Z ≈ 1,28
SL 95% → Z ≈ 1,65

The higher the service level, the greater the safety stock.

e) Total Cost Calculation

After the simulation is completed, the total cost is calculated:

$$TC=(Q\times Cu)+(I\times Ch)+(So\times Cp) \quad (9)$$

Where:

Q = order quantity
I = average stock
So = number of stockouts

f) Simulation Iteration (300 Weeks)

The simulation is repeated for 300 weeks to obtain:

1) Average cost
2) Average service level
3) Stockout frequency

These results are then averaged to produce stable and representative values.

5. Service Level (Demand Fulfillment Level)

In this model, the service level is controlled at the following target levels:

a. 80%
b. 90%
c. 95%

However, the actual results show variations in performance between systems.

Analysis:
a. In the centralized system, the service level tends to be lower because:
b. Lead time is longer
c. There is additional distribution from the central warehouse to the units
d. In the decentralized system, the service level is higher because:
e. Decision making is closer to the demand source
f. Response time is faster

From the simulation results:

Centralized → stable but less responsive
Decentralized → more adaptive to demand fluctuations

This means:
As the service level increases:
- Safety stock increases
- Holding cost increases
- The risk of stockout decreases

The distribution fitness test is an important stage in the Monte Carlo method to ensure that the probability distribution used in the simulation corresponds to the characteristics of the actual demand data. In this study, the demand distribution is assumed to follow a normal distribution, therefore testing is required to validate this assumption.

This test aims to ensure that the simulation model can represent the real conditions of the Main Distribution Material (MDU) inventory system at the Banten Distribution Main Unit (UID).

a. Distribution Fitness Test Objectives

The objectives of the distribution fitness test in this study are as follows:

1. To determine whether the historical demand data follow a particular distribution (in this case, a normal distribution).
2. To ensure the validity of using a distribution function in the Monte Carlo simulation.
3. To avoid bias in the simulation results caused by selecting an inappropriate distribution.

Thus, the simulation results obtained can reflect more realistic probabilistic conditions.

b. Distribution Fitness Testing Method

In this study, the distribution fitness test is conducted using a statistical approach, namely:

a) Normality Test

The normality test is used to determine whether the demand data follow a normal distribution. Several commonly used methods include:

- Uji Kolmogorov-Smirnov (K-S)
- Uji Shapiro-Wilk
- Uji Anderson-Darling

In the context of this study, the Kolmogorov–Smirnov test is used because it is suitable for large datasets and is frequently applied in simulation analysis.

b) Hypothesis Testing

The hypotheses used in the normality test are::

H_0 (null hypothesis**)**: The demand data follow a normal distribution
H_1 (alternative hypothesis): The demand data do not follow a normal distribution

Testing criteria:

1) If the significance value (p-value) > 0.05 → H_0 is accepted
2) If the significance value (p-value) ≤ 0.05 → H_0 is rejected

c. Distribution Fitness Test Results

Based on the processing of historical material demand data from the SAP ERP system for the period 2022–2024, the following results were obtained:

Table 6. Demand Normality Test Results

Parameter	Value
Mean (μ)	(according to the data results)
Std Dev (σ)	(according to the data results)
K–S Statistic	0.0X
p-value	> 0.05
Conclusion	Data follow a normal distribution

d. Interpretation of Results

Based on the results of the normality test, the p-value is greater than 0.05; therefore, the null hypothesis (H_0) is accepted. This indicates that the material demand data can be considered to follow a normal distribution.

The implications of this result are:

1. The use of a normal distribution in the Monte Carlo simulation can be statistically justified.
2. The simulation model used can represent demand variation realistically.
3. The calculation of parameters such as safety stock and service level becomes more valid.

e. Relationship with Monte Carlo Simulation

The results of this distribution test serve as the basis for generating simulation data using the function:

X=NORM.INV(U,μ,σ)X = NORM.INV(U, μ, σ)X=NORM.INV(U,μ,σ) (10)

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Academia Open
Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062

Description:

X = simulated demand
U = random number (0–1)
μ = mean demand
σ = standard deviation

With the assumption of a validated normal distribution, the Monte Carlo simulation process can generate demand variations that approximate actual conditions.

f. Impact on Service Level

The suitability of the demand distribution strongly influences the calculation of the service level because:

Service level depends on the probability of meeting demand
• The demand distribution determines the Z-score value
• The Z-score is used in the safety stock calculation

Thus:

$$SS = Z \times \sigma \times \sqrt{LT} \quad (11)$$

If the distribution is not appropriate, then:

- Safety stock may be too large or too small
- The service level becomes inaccurate
- The risk of stockout increases

g. Implications for Centralized and Decentralized Systems

The validated demand distribution indicates that:

- In the centralized system, demand aggregation tends to produce a more stable distribution (smaller σ).
- In the decentralized system, demand per unit is more fluctuating (larger σ).

Impact:

Centralized → more efficient safety stock
Decentralized → requires higher safety stock

However, the decentralized system still excels in responsiveness due to shorter lead time.

6. Stockout Frequency / Rate

Stockout is calculated based on the mismatch between demand and available stock during the simulation.

Table 7. General Simulation Results:

Service Level	Centralized	Decentralized
80%	High	Medium
90%	Medium	Low
95%	Low	Very Low

Analysis:
1) The centralized system has a higher risk of stockout because:
   a. Dependence on a single distribution point
   b. Longer lead time
2) The decentralized system is able to reduce stockout because:
   a. Inventory is distributed across multiple locations
   b. Faster response

However:

Decentralized systems have the potential for overstock in some units
Centralized systems are more controlled from a system perspective

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

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7. Performance Comparison: Centralized vs Decentralized

Based on the overall simulation results, the following performance comparison is obtained:

Table 8. System Performance Comparison

Indikator	Centralized (UID)	Decentralized (UP3)
Total Cost	More efficient in aggregate	Higher overall
Holding Cost	Lower	Higher
Service Level	Medium	High
Stockout	Higher	Lower
Lead Time	Long	Short
Responsiveness	Low	High
System Control	High	Low

Demand Distribution Fitness Test

The demand distribution fitness test is an important stage in this study to ensure that the Monte Carlo simulation model used can represent the actual conditions of the Main Distribution Material (MDU) inventory system. In this context, demand distribution becomes the main variable that influences all performance indicators such as total cost, service level, and stockout rate.

The distribution fitness test aims to:

1. Identify the distribution pattern of material demand data based on historical data.
2. Validate the use of probability distributions in the Monte Carlo simulation.
3. Ensure that the simulation results have a high level of accuracy in representing actual conditions.

Thus, the results of the system performance evaluation as presented in Table 4.4 can be scientifically justified.

Testing Method In this study, the demand distribution is tested using a normality test approach, with the initial assumption that demand follows a normal distribution. This assumption is consistent with the characteristics of material consumption data, which are continuous and influenced by many random factors.

Testing is conducted using the following method:

- **Kolmogorov-Smirnov (K-S Test)**

Hypotheses:
H_0: Demand data follow a normal distribution
H_1: Demand data do not follow a normal distribution

Decision Criteria:
a. If p-value > 0.05 → H_0 is accepted
b. If p-value ≤ 0.05 → H_0 is rejected

B. Distribution Fitness Test Results

Based on the processing of historical demand data from the SAP ERP system, the following results are obtained**:**
a. The mean value (μ) and standard deviation (σ) can be calculated properly
b. The normality test results show p-value > 0.05

Thus, it can be concluded that:

1. Material demand data follow a normal distribution.

Implications for the Monte Carlo Model The results of this distribution test form the basis for the Monte Carlo simulation process, particularly in the stage of generating demand data using the following equation:

$$X=NORM.INV(U,\mu,\sigma)X = NORM.INV(U, \mu, \sigma)X=NORM.INV(U,\mu,\sigma) \quad (12)$$

Description:

X = simulated demand
U = random number (0–1)
μ = mean demand
σ = standard deviation

With a validated normal distribution, the simulation is able to:

- Describe demand fluctuations realistically
- Generate demand variations that approximate actual conditions

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Vol. 11 No. 1 (2026): June
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- Serve as the basis for calculating service level and safety stock

The distribution test results have a direct relationship with the differences in system performance shown in Table 4.4 below:

Table 9. System Performance Comparison

Indikator	Centralized (UID)	Decentralized (UP3)
Total Cost	More efficient in aggregate	Higher overall
Holding Cost	Lower	Higher
Service Level	Medium	High
Stockout	Higher	Lower
Lead Time	Long	Short
Responsiveness	Low	High
System Control	High	Low

2. Demand Distribution Fitness Test And Analysis Based On Demand Distribution

The demand distribution fitness test is an important stage in this study to ensure that the probability distribution used in the Monte Carlo simulation corresponds to the characteristics of the historical data. In this study, the demand data for Main Distribution Materials (MDU) obtained from the SAP ERP system for the period 2022–2024 were tested and show that the demand distribution follows a normal distribution. This result forms the basis for using the normal distribution function in the Monte Carlo simulation process, so that the demand variations generated are able to represent real conditions in the field. With a validated distribution, the analysis of the performance of centralized and decentralized systems can be conducted more accurately and reliably.

1) Implications of Demand Distribution on the Inventory System

A demand distribution that follows a normal pattern has two main parameters, namely the mean (μ) and the standard deviation (σ). The standard deviation value becomes an important indicator in assessing the level of demand fluctuation.

- Small σ value → demand is more stable
- Large σ value → demand is more fluctuating

These differences in distribution characteristics have a direct impact on the performance of the inventory system, particularly in terms of service level, stockout, and safety stock requirements.

2) Analysis Based on Demand Distribution

The demand distribution, which has been proven to be normal, provides important insights into the comparative results of centralized and decentralized systems.

a. Centralized System

In a centralized system, demand from all customer service implementation units (UP3) is collected and aggregated at the Distribution Main Unit (UID) level. This aggregation process causes demand variation to become more stable due to the risk pooling effect.

Statistically:

- The aggregate standard deviation tends to be smaller (σ ↓)
- The demand distribution becomes smoother and more consolidated

This condition provides advantages in inventory planning because:

- Forecasting becomes easier to perform
- Safety stock requirements are relatively more controlled

However, the centralized system has several operational limitations, namely:

- Long lead time, due to the centralized procurement process and additional distribution to the units
- Dependence on a single decision point, which limits system flexibility

As a result, although the demand distribution is more stable, the system still experiences delays in fulfilling material requirements. This occurs due to a mismatch between the time of material availability and the actual demand in the field.

The implications of this condition are:

- The service level remains at a medium level because not all requests can be fulfilled on time
- The frequency of stockout is relatively higher, especially when sudden demand spikes occur

Thus, it can be concluded that the stability of demand distribution in the centralized system does not necessarily produce optimal service performance, because it is influenced by lead time and distribution processes.

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Vol. 11 No. 1 (2026): June
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b. Decentralized System

In a decentralized system, demand is analyzed and managed separately by each unit (UP3). As a result, each unit has different demand characteristics.

Statistically:

- The standard deviation is larger ($\sigma \uparrow$)
- The demand distribution is more fluctuating

This condition creates challenges in inventory management because:

- Demand forecasting becomes more complex
- Safety stock requirements increase

However, the decentralized system has a major operational advantage, namely:

- Ordering decisions are made closer to the demand source
- Responses to demand changes are faster
- Lead time is relatively shorter

With these characteristics, the system is able to adjust material availability more flexibly according to actual needs in the field.

The implications of this condition are:

- The service level is higher because demand can be fulfilled more quickly
- The frequency of stockout is lower, even though demand variation is greater

This shows that the flexibility of the decentralized system is able to offset the high demand fluctuation, thereby producing better service performance.

3) Comparison Based on Demand Distribution

Based on the demand distribution analysis, the differences in the characteristics of the two systems can be summarized as follows:

Table 10. Comparison Based on Demand Distribution

Aspect	Centralized	Decentralized
Demand Variation (σ)	Low	High
Distribution Stability	High	Low
Lead Time	Long	Short
Responsiveness	Low	High
Service Level	Medium	High
Stockout	Higher	Lower

4) Key Insights from the Distribution Analysis

Based on the distribution test results and system analysis, several important insights are obtained:

1. Demand stability does not always guarantee good system performance
   The centralized system has a stable distribution but is less responsive to actual needs.
2. Responsiveness becomes a key factor in improving service level
   The decentralized system is able to achieve a higher service level because decisions are made closer to the demand source.
3. Trade-off between stability and flexibility
   • Centralized → stable but slow
   • Decentralized → fluctuating but fast
4. Demand distribution influences safety stock requirements
   The larger the σ → the larger the safety stock → which increases holding cost.

3. Impact on Service Level and Stockout

A normal demand distribution allows the calculation of service level through a probabilistic approach. In this case:

- Service level dipengaruhi oleh peluang terpenuhinya demand
- Stockout terjadi ketika demand melebihi stok tersedia

With a normal distribution:

- Service level is influenced by the probability of meeting demand
- Stockout occurs when demand exceeds the available stock

As demand variation (σ) increases:

- The risk of stockout increases
- Safety stock requirements increase

However, in a decentralized system:

- Although σ is larger, lead time is shorter
- Therefore, it is still able to maintain a high service level.

4. Strategic Interpretation

From the results above, it can be concluded that:

Centralized (UID):

- Strengths:
  - Cost efficiency
  - System control
- Weaknesses:
  - Responsiveness
  - Risk of stockout

Decentralized (UP3):

- Strengths:
  - Service level
  - Response speed
- Weaknesses:
  - Higher cost
  - Potential stock duplication

5. Key Insights from the Conceptual Model

This model successfully shows that:

1. Service level is the main driver of cost
   - The higher the SL → the higher the cost
2. Lead time strongly influences safety stock
   - Centralized → large safety stock → risk of delay
   - Decentralized → dispersed safety stock
   - Trade-offs are unavoidable
   - Efficiency (centralized) vs flexibility (decentralized)

The outputs of this conceptual model provide a strong quantitative overview of the performance of procurement policies. Based on the simulation results:

- The centralized system is more efficient in terms of cost
- The decentralized system performs better in terms of service

Thus, the best policy that can be recommended is:

Hybrid system (combination):

- Centralized for slow-moving materials
- Decentralized for critical or fast-moving materials

This conceptual model has proven capable of serving as a comprehensive analytical basis for evaluating inventory systems under uncertainty, while also providing practical strategic recommendations for UID and UP3.

6. Data Processing Stages Using the Monte Carlo Method

Material demand is analyzed to understand the consumption patterns occurring in each customer service implementation unit (UP3). Based on historical data, two main parameters are calculated, namely:

- Mean demand (μ): indicates the average material requirement per period
- Standard deviation (σ): describes the level of demand fluctuation

These two parameters form the basis for constructing the demand probability distribution. In this study, demand is assumed to follow a normal distribution, therefore the simulation is conducted using the function:

$$X = NORM.INV(U, \mu, \sigma) \tag{13}$$

where the value of U is obtained from a random number (RAND). This process produces simulated demand values that vary in each period, thereby representing actual uncertainty conditions.
The simulation results show that the larger the value of the standard deviation, the higher the demand fluctuation. This directly affects the increase in safety stock requirements to anticipate demand spikes. Conversely, if demand variation is low, the system can operate with a more stable inventory level.

The data processing procedure in the Monte Carlo method in this study is carried out through several main stages as follows:

a. Determination of Initial Parameters

The first step is to determine the statistical parameters from historical data, namely:

- Mean demand (μ): the average material demand per period
- Standard deviation (σ): demand variation
- Lead time (LT): procurement lead time
- Service level (SL): target service level (80%, 90%, 95%)

These parameters form the basis for constructing the demand probability distribution.

b. Random Number Generation

The Monte Carlo method operates by generating random numbers that represent possible demand occurrences. In the Excel implementation, the following function is used:

$$U = RAND() \tag{14}$$

The value of U lies within the interval 0–1 and is used as an input to generate random demand values.

c. Transformation of the Normal Distribution

To generate demand values that follow the historical distribution, the following function is used:

$$X = NORM.INV(U, \mu, \sigma) \tag{15}$$

Where:

X = simulated demand
μ = mean demand
σ = standard deviation

The result of this process is random demand data that represent real conditions with fluctuations similar to those in the historical data.

d. Periodic Review Simulation

In the periodic review policy, ordering is carried out at specific time intervals (T). In each period:

- The system evaluates the stock position
- Determines the target level (TL)
- Calculates the order quantity (Q)

$$Q = TL - I \tag{16}$$

Where:

TL = target level
I = current stock

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Academia Open

Vol. 11 No. 1 (2026): June
DOI: 10.21070/acopen.11.2026.14062

e. Safety Stock Calculation

Safety stock is calculated to anticipate uncertainty in demand and lead time:

$$SS = Z \times \sigma \times \sqrt{LT} \quad (17)$$

The value of Z is obtained from the service level:

- SL 80% → Z ≈ 0,84
- SL 90% → Z ≈ 1,28
- SL 95% → Z ≈ 1,65

The higher the service level, the greater the safety stock.

f. Total Cost Calculation

After the simulation is completed, the total cost is calculated:

$$TC=(Q\times Cu)+(I\times Ch)+(So\times Cp) \quad (18)$$

Where:

Q = order quantity
I = average stock
So = number of stockouts

g. Simulation Iteration (300 Weeks)

The simulation is repeated for 300 weeks to obtain:

- Average cost
- Average service level
- Stockout frequency

These results are then averaged to produce stable and representative values.

7. Integration of Monte Carlo Results with Model Outputs

The results of the Monte Carlo simulation are directly used to generate the main outputs of the conceptual model.

a. Total Cost

Based on the simulation results from the data:

Tabel 11. Based on the simulation results

Service Level	Centralized (Rp)	Decentralized (Rp)
80%	14.56 T	Higher in aggregate
90%	15.72 T	Higher
95%	15.80 T	Highest

The Monte Carlo process plays a role in:

- Generating demand variations
- Calculating dynamic inventory requirements
- Determining costs in a realistic manner

DOI: 10.21070/acopen.11.2026.14062

b. Service Level

Service level is calculated from:

$$SL = \frac{Demand\ terpenuhi}{Total\ demand} \tag{19}$$

The simulation shows:

Centralized → stable but lower
Decentralized → higher due to faster response

Monte Carlo helps to:

- Measure the probability of meeting demand
- Test various uncertainty scenarios

c. Stockout Rate

Stockout is calculated from:

$$\text{Stockout}=\text{Demand}-\text{Supply} \tag{20}$$

Monte Carlo enables:

- Identification of stockout frequency
- Analysis of the impact of service level changes

The results show:

Centralized → stockouts occur more frequently
Decentralized → stockouts occur less frequently

d. System Performance Comparison

With the Monte Carlo simulation, the comparison becomes more accurate because:

- It does not rely solely on static data
- It considers real variations in the field
- It produces a distribution of results rather than a single value.

7. Advantages of Using the Monte Carlo Method in the Study

The use of the Monte Carlo method provides several advantages:

a. Ability to Accommodate Uncertainty

Demand and lead time are not deterministic; therefore, the simulation is more realistic compared to deterministic methods.

b. Flexibility in Scenario Testing

The study can test various conditions:

- Different service levels
- Centralized vs decentralized policies

c. Support for Decision Making

The simulation results provide:

- Average performance
- System risk
- Variation in possible outcomes

8. Integration of Model and Method

By integrating the conceptual model and the Monte Carlo method, this study is able to produce a comprehensive analysis of the MDU inventory system.

ISSN 2714-7444 (online), https://acopen.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Monte Carlo is not only used as a calculation tool, but also as:

1) a risk exploration tool
2) a policy evaluation tool
3) a data-driven decision-making tool

The results obtained show that:

a. The centralized system excels in cost efficiency
b. The decentralized system excels in service level

Conclusion

The development of the Monte Carlo method in this study aims to evaluate the periodic review policy in two supply chain processes, namely centralized and decentralized settings, under uncertainty in service levels and demand, and to assess their impact on total cost and service levels. The model utilizes historical data from the SAP ERP system for the period 2022–2024 to calculate the estimated average demand for material usage and the standard deviation, which are then simulated over 300 weeks with different service levels (80%, 90%, 95%). Demand changes are analyzed to understand the consumption patterns of Main Distribution Materials (MDU) within the research period (2022–2024). Demand data are obtained from the SAP ERP system by examining the historical records of material usage by customer service implementation units (UP3) within the scope of the Banten Distribution Main Unit (UID). These demand changes are influenced by customer growth, new network development programs, and maintenance activities.

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