

The Effect of Lead Time Variability and Safety Stock Automatic Determination on the Frequency of Stockouts and Cost Efficiency at the Warehouse Level

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Abstract

This research evaluates the impact of lead time variability through a simulation model developed based on operational parameters in the layer hen farming industry. This simulation compares the effectiveness of automatic safety stock determination (MRP) with a fixed manual approach in mitigating stockout risks and cost inefficiencies. The method used is a Google Spreadsheet-based simulation, comparing a manual policy (fixed 235 units) with an adaptive automatic policy (50, 400, 950 units) across three lead time variability scenarios (Low, Medium, High). The results show the superiority of automatic MRP in unstable environments. Although the manual policy is slightly superior in the Low scenario (0% stockout), it fails in Medium (0% stockout) and High (20% stockout) variability, with costs 30-80 times higher. The automatic system successfully eliminates stockouts (0%) in Medium and High conditions, proving much better cost efficiency.

Keywords: Lead Time Variability, Safety Stock, MRP, Stockout, Cost Efficiency

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1. Introduction

In an Enterprise Resource Planning (ERP) system for a layer hen farm, the availability of raw materials and finished goods in the warehouse plays a critical role in maintaining smooth production processes and meeting customer demand. ERP itself is an information system designed for manufacturing or service companies, serving to connect and execute business processes related to operations, production, and distribution within the company [1]. One of the main problems that often arises is uncertainty in goods' arrival times (lead time variability), which can cause stock shortages (stockouts) or, conversely, excess inventory buildup. These conditions have a direct impact on increased storage costs and a decrease in customer service levels [2], [3].

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To overcome this uncertainty, the concept of Material Requirements Planning (MRP) is implemented as a material requirements planning system integrated with the warehouse management module. One of the important features of MRP is its ability to automatically calculate safety stock based on demand data, lead time, and supplier variability. However, in industrial practice, there is still debate about how effective automatic safety stock determination is compared to a manual approach that uses a fixed value [4], [5].

This study uses a simulation modeling approach developed based on operational parameters in the layer hen farming industry, specifically at the feed and packaging warehouse level. The research object is an inventory management simulation model within an MRP module built on Google Sheets, which represents integrated stock planning and control processes. The main objective of this study is to evaluate the effect of lead time variability on the effectiveness of the MRP mechanism in reducing stockout frequency and improving inventory cost efficiency. This is done by comparing two safety stock determination approaches: auto-recalculated safety stock (automatic by MRP) and manual fixed safety stock (based on a fixed estimate).

Based on this description, the research problem is: "How does lead time variability affect the effectiveness of automatic MRP in reducing stockout frequency and increasing inventory cost efficiency at the warehouse level?".

This research is important because lead time uncertainty is often the main cause of stock imbalances in the livestock industry, while empirical evidence regarding the performance of automatic MRP under lead time shocks is still limited. The scope of this study is limited to analyzing the effect of lead time variability on the performance of the MRP system at the feed and packaging material warehouse level, without considering other external factors such as demand fluctuations or procurement policies from suppliers. Thus, the results of this study are expected to provide empirical insights into the effectiveness of automatic MRP and serve as a basis for making more adaptive and efficient inventory policy decisions in an ERP environment.

Research Contribution. Theoretically, this research provides empirical proof of the effectiveness of the auto-recalculated safety stock mechanism in the context of lead time variability, which can enrich the literature on MRP-based inventory control. Practically, the results of this study can be a reference for agribusiness companies in implementing a more adaptive and efficient ERP system to maintain a balance between stock availability and operational costs.

2. Literature Review

2.1 Lead Time Variability in Inventory System

Lead time is the time span between when an order is placed and when the goods are received in the warehouse. Lead time variability increases the uncertainty of the demand quantity that must be met during that period. This condition has a direct implication for the increased risk of stockouts if not balanced by an adaptive and responsive safety stock policy. According to Babai *et al.*, the variance of demand during lead time needs to be explicitly calculated using a statistical approach that considers stochastic factors and demand data autocorrelation, because the simple use of normal distribution assumptions often leads to an underestimation of safety stock needs [6]. Demiray Kırmızı *et al.* also emphasize that unstable lead times will negate the effectiveness of conventional inventory control. Therefore, the MRP system is required not only to record material needs but also to be capable of making predictive adjustments to lead time variability to maintain supply continuity and reduce the risk of stock shortages [7].

2.2 The Concept of Safety Stock and Automatic Determination based on MRP

Safety stock functions as a buffer against demand uncertainty and lead time fluctuations. Conventional approaches to calculating safety stock generally use the historical deviation of demand multiplied by a

service factor (z-value) to achieve a certain service level. However, this method becomes less effective when lead time variability is dynamic and non-stationary. Recent studies emphasize the importance of implementing adaptive safety stock, which involves calculating safety stock based on periodic parameter updates (variance updates) integrated into the MRP system to automatically determine the reorder point and order quantity [7], [8]. Afrizal *et al.* show that safety stock and reorder point mechanisms integrated into an automatic system can reduce delayed reactions to demand changes [9], while Ardiansyah *et al.* highlight that an MRP-based decision support system provides advantages not only in planning accuracy but also in the consistency of executing stock control in the warehouse in real-time [10].

2.3 Stockout Frequency at the Warehouse Level and Its Causes

Stockout frequency is a critical indicator that reflects the inventory system's failure to meet demand at the right time. The main variables affecting stockout frequency include demand forecast accuracy, the level of lead time variability, safety stock and reorder point policies, and the replenishment mechanism used (whether fixed-period or based on a minimum stock trigger). Liu *et al.*'s research introduces a machine learning-based stockout risk prediction approach that utilizes historical demand features and supply chain conditions to identify SKUs with a high probability of stock shortages [11]. This finding reinforces the view that stockouts are not solely caused by physical stock shortages but rather by systemic delays in adjusting MRP parameters in response to dynamic demand and lead time variability.

2.4 Cost Efficiency in Automated Inventory Systems

Cost efficiency in an inventory system is measured by its ability to minimize total inventory costs, which consist of holding costs, ordering costs, and shortage costs. Automating safety stock calculations in MRP allow for a more optimal trade-off, maintaining stock availability at a safe level without causing inefficient excess inventory [7], [8]. Kim's research emphasizes that ignoring lead time variability in inventory planning will lead to inflated emergency order costs [8], while Ardiansyah *et al.* show that integrating adaptive MRP logic with an optimization approach can significantly reduce warehouse operational costs [10]. The consistency of these findings is reinforced by Afrizal *et al.*, who note that using an automatic reorder point systematically reduces stock waste without sacrificing service levels [9].

2.5 Synthesis of Theoretical Framework and Research Gap

Based on the literature review, there is a consensus that lead time variability significantly influences safety stock requirements and warehouse inventory system performance [6]. Furthermore, the implementation of adaptive safety stock integrated with the MRP module has been proven to reduce stockout frequency and suppress inventory costs simultaneously [7], [8], [11]. Research by Afrizal *et al.* and Ardiansyah *et al.* shows that automated decision-based systems tend to be more stable than manual approaches, especially when applied in a distribution context with fluctuating demand patterns [9], [10].

Nevertheless, there is still a research gap that needs to be filled. There is a lack of empirical studies based on operational warehouse data in Indonesia that integrate real-time lead time variance estimation into an automatic MRP system. There is also a need for comparative analysis regarding the cost-service trade-off between conventional MRP and adaptive MRP scenarios, and limited studies combine stockout risk prediction models with replenishment logic in heterogeneous ERP/warehouse systems [11]. Therefore, this research is directed to evaluate the impact of integrating adaptive safety stock calculations (based on lead time variability) into the MRP system on stockout frequency and warehouse inventory cost efficiency, as a contribution to the development of data-driven inventory systems.

3. Methodology

This section explains the research approach, experimental design, simulation stages, and analysis methods used to evaluate the effect of Lead Time Variability and Automatic Safety Stock Determination (MRP) on stockout frequency and cost efficiency at the warehouse level.

3.1 Historical Data Collection

Historical data was obtained from the internal ERP records of a livestock company, representing:

- 1) Average lead time and its variation (days/weeks) from several vendors.
- 2) Daily or weekly demand patterns.
- 3) Storage costs and stockout costs (penalties).

This historical data was used to estimate variability and supply uncertainty parameters, and as a basis for calculating adaptive safety stock. According to Gonçalves *et al.* and Barros *et al.*, calibrating statistical parameters of demand and lead time based on real data is a crucial step in determining an efficient and responsive safety stock [12], [13].

3.2 ERP Simulation Model Development

The ERP model was developed using Google Spreadsheet to simulate the main modules in the inventory system: Master Data, Procurement, Inventory Control, and Monitoring & Adjustment. These four modules form an integrated, automated MRP-based stock control cycle. The following tables detail the components of each module. In terms of flow, the Master Data module (Table 1) and Procurement module (Table 2) function as data inputs, providing static data (like vendor lists) and transactional data (like goods receipt records). This data is then processed by the Inventory Control module (Table 3), which acts as the execution engine for MRP logic, such as dynamic safety stock calculation. Finally, the Monitoring & Adjustment module (Table 4) completes this cycle by providing a validation and feedback mechanism to ensure the accuracy and integrity of the stock data used by the system.

a. Master Data

Table 1 contains a list of vendors and their lead time attributes and performance assessments (vendor rating). Lead time variation serves as the basis for determining the level of supply uncertainty processed in the MRP simulation. This variability directly affects safety stock needs and stockout risk. Hamdouch's research shows that differences in delivery times between vendors significantly influence multi-source stocking policies [14], while Satish Mandavalli proposes using a Bayesian Network model to predict supplier reliability based on lead time fluctuations [15].

Tabel 1. Vendor Master Data Table

Vendor Name	Item Category	Lead Time (days)	Vendor Rating
PT Pakan Sejahtera	Chicken Feed	3	4.5/5
PT Pakan Sumber Alam	Chicken Feed	2	4.6/5
Pakan Ayam Makmur	Chicken Feed	3	4.6/5
Pakan Sumber Daya Alam	Chicken Feed	5	4.7/5

b. Procurement

Table 2 contains purchase order records and goods receipt results. This data is used to measure supplier reliability through metrics like on-time delivery rate, fill rate, and quality rejection ratio. Tainala proves that ERP-based delivery reliability analysis can improve supplier performance evaluation [16]. Furthermore, studies emphasize that integrating procurement modules and digital vendor evaluation can increase supply chain transparency and efficiency [17].

Tabel 2. Procurement Table

PO ID	Item	GR Date	Qty Received	Qty Rejected	Quality
PO001	Chicken Feed Type A	06/10/2025	200 kg	0	Good
PO002	Chicken Feed Type B	03/10/2025	3 kg	0	Good
PO006	Organic Chicken Feed	08/10/2025	200 kg	0	Good

c. Inventory Control

Table 3 records all inventory inflows and outflows as daily transaction data, thus providing quantitative information about the actual stock changes for each material. This data is then used as a basis for cross-checking the inventory control parameters in Table 4. Through this process, the system recalculates the ending stock and compares it with the adaptively set safety stock and reorder point values. Thus, the Inventory Control table (Table 4) is the result of evaluating the inventory condition after considering the real stock movements in Table 3, enabling it to show the material availability status whether it is safe or requires a reorder.

Table 3. Inventory Transaction Table

Transaction_ID	Date	Material Name	Transaction_Type	Quantity
T-001	2025-01-05	Omega-3 Feed	Debit	12500
T-002	2025-01-09	Organic Feed	Debit	150
T-003	2025-01-10	Organic Feed	Debit	200
T-004	2025-01-11	Organic Feed	Debit	30
T-005	2025-01-12	Omega-3 Feed	Credit	20

Table 4. Inventory Control Table

Material Code	Material Name	Safety Stock	Reorder Point	Ending Stock	Status Stock
PKN-01	Omega-3 Feed	2000	3500	29600	Safe
PKN-02	Standard Brown Feed	1500	2500	3080	Safe
PKN-03	Organic Feed	2000	3000	13200	Safe
PKN-04	Lohmann Classic Feed	2500	4000	4320	Safe
PKN-05	Dekalb White Layer Feed	2000	3500	5960	Safe

This table shows the application of the automatic reorder point and safety stock policy. The safety stock value is calculated dynamically using a combined statistical formula for demand variance and lead time variance (adaptive SS formula). This approach allows the MRP system to adjust the safety stock level based on actual conditions, not a fixed value like the manual method. Gonçalves *et al.* and Barros *et al.* affirm that

an operations research-based approach can minimize holding costs without sacrificing service levels [12], [13]. Silva *et al.* also developed a hybrid bi-objective optimization model that combines cost minimization and service level improvement simultaneously [18].

d. Monitoring & Adjustment

Table 5 serves to verify the consistency between ERP stock data and physical stock in the warehouse. A small difference indicates high data integrity, while a large difference may indicate input errors or system anomalies. This data validation approach is important for maintaining MRP system accuracy and preventing stockouts due to recording errors. One study shows how a machine learning approach can automatically detect ERP data anomalies [19]. Additionally, another study shows that integrating ML-based data cleaning algorithms at the ETL stage can improve ERP data consistency before it is used by the MRP module [20]. The historical data collected (3.1) and recorded through these modules are then recapitulated in Table 6 to calculate baseline parameters.

Table 5. Monitoring & Adjustment Table

Material Code	Material Name	ERP Stock	Physical Stock	Difference	Stock Status
PKN-01	Omega-3 Feed	12500	12480	20	Safe
OBT-05	Chicken Medicine	200	198	2	Needs Restock
PKN-03	Organic Feed	1500	1505	5	Safe
OBT-01	Avian Flu Vaccine	120	120	0	Safe
PKN-02	Concentrate Feed	2500	2490	10	Needs Restock
OBT-03	Deworming Medicine	400	405	5	Safe
VIT-02	Growth Vitamin	80	80	0	Safe

Table 6. Planning & Lead Time Data Recap Table

PO ID	Item	Planned Lead Time (days)	Actual Lead Time (days)	Delay (days)	Demand (Unit)	Manual Safety Stock (unit)
PO001	Chicken Feed Type A	3	3	0	500	235
PO002	Chicken Feed Type B	12	0	-12	30	235
PO003	Avian Flu Vaccine	7	4	-3	150	235
PO004	Vitamin C-500	8	3	-5	50	235
PO005	Deworming Medicine	10	4	-6	30	235
PO006	Organic Chicken Feed	11	3	-8	200	235
PO007	Egg Packaging	15	4	-11	300	235

This historical data is then used as the basis for calculating the baseline Manual Safety Stock value through four steps:

1. Calculating Average Daily Demand (μ_D) using the formula =AVERAGE(G43:G50).
2. Calculating Average Planned Lead Time (μ_L) using the formula =AVERAGE(D43:D50).
3. Calculating Average Demand during Lead Time (μ_{DL}) by multiplying the results of Step 1 and 2 (=N42 * N43).
4. Setting the Manual Safety Stock value at 15% of μ_{DL} (result of Step 3), with the formula =0,15 * \$N\$44.

From this calculation flow, a static safety stock value of 235 units was obtained. This value was then used as a constant input for Scenario 1 (Manual Fixed Safety Stock Simulation).

Two systems were tested and compared:

a. Automatic MRP (Auto-Recalculated Safety Stock)

Safety stock is automatically calculated each period using Excel's statistical functions [14]:

$$=Z * STDEV(LeadTimeRange) * AVERAGE(DemandRange) \quad (1)$$

or a more comprehensive formula (referring to Supply Chain Analytics, 2023):

$$SS = Z \times \mu L \cdot \sigma D2 + \mu D2 \cdot \sigma L2 \quad (2)$$

where μL = average lead time, σD = standard deviation of demand, μD = average demand, and σL = standard deviation of lead time. The adaptive safety stock values (50, 400, and 950 units) used in this simulation are not random numbers. These values are the result of a clustering process based on historical operational variance calculations performed prior to the simulation. These values were obtained by applying formula (2) with a 95% service level target ($Z = 1.645$) to the data, which had been grouped by its variability level:

- a. The 50 units (Low) is the result of formula (2) when applied to the scenario where lead time variability is very low ($\leq 5\%$ periods).
- b. The 400 units (Medium) is the result of formula (2) when applied to data with moderate variability (10-20% periods).
- c. The 950 units (High) is the result of formula (2) for high uncertainty conditions ($> 25\%$ of periods), where significant vendor delays occur.

b. Manual Fixed Safety Stock

The safety stock value was set at a constant 235 units (as calculated above) for all simulation scenarios.

3.3 Simulation Experiment

The spreadsheet model was run with different lead time stock scenarios:

- 1) Low: Delays are rare ($\leq 5\%$ periods).
- 2) Medium: Moderate delays (10–20%).
- 3) High: High delays ($> 25\%$).

The simulation experiment was run with a total of 60 replications, divided equally among the three lead time variability scenarios (20 replications each). The manual system used a fixed safety stock value of 235 units in all 60 replications. In contrast, the automatic MRP system applied values of 50, 400, or 950, depending on the replication's scenario (Low, Medium, or High). The technical implementation of this experimental design was executed using Google Apps Script, which functioned as the backend engine for the simulation model in Google Spreadsheet. This script was responsible for running the 60 designed replications, automating the random data retrieval process (input), and applying the cost calculation logic for both scenarios.

Manual Fixed Safety Stock Simulation Algorithm

```

function runManualSimulation_REVISED() {
  // Initialize Spreadsheet
  var ss = SpreadsheetApp.getActiveSpreadsheet();
  var masterSheet = ss.getSheetByName("[IWM] Stock Counting/Stock Opname ");
  var outputSheet = ss.getSheetByName("Simulasi_MRP_Manual_Revisi");
  if (!outputSheet) outputSheet = ss.insertSheet("Simulasi_MRP_Manual_Revisi");
  else outputSheet.clear();
  // --- Get master data (Holding & Expedited Cost) ---
  var masterValues = masterSheet.getRange("E5:S19").getValues();
  var costMap = {};
  var materialList = [];
  for (var i = 0; i < masterValues.length; i++) {
    var code = masterValues[i][0], name = masterValues[i][1];
    var holdingCost = masterValues[i][13], expeditedCost = masterValues[i][14];
    if (code) {
      costMap[code] = { name: name, holdingCost: holdingCost, expeditedCost: expeditedCost };
    };
    materialList.push(code);
  }
  // --- Key Logic: Set fixed Safety Stock (per methodology 3.2.b) ---
  var MANUAL_FIXED_SAFETY_STOCK = 235;
  // --- Main simulation loop ---
  var scenarios = ['Low', 'Medium', 'High'];
  var N_PER_SCENARIO = 20;
  var data = [];
  var counter = 1;
  for (var i = 0; i < scenarios.length; i++) {
    var level = scenarios[i];
    var safetyStock = MANUAL_FIXED_SAFETY_STOCK; // Differentiating Logic
    for (var j = 0; j < N_PER_SCENARIO; j++) {
      var code = materialList[Math.floor(Math.random() * materialList.length)];
      var info = costMap[code];
      // --- Random input data (same as automatic simulation) ---
      if (level === 'Low') {
        var demand = rand(100, 150), received = rand(90, 120);
      } else if (level === 'Medium') {
        var demand = rand(80, 200), received = rand(50, 150);
      } else {
        var demand = rand(50, 300), received = rand(10, 150);
      }
      // --- Simulation calculations ---
      var stockout = (demand > (received + safetyStock)) ? 'Y' : 'N';
      var holding = safetyStock * info.holdingCost;
      var expedited = (stockout === 'Y') ? (demand - (received + safetyStock)) *
info.expeditedCost : 0;
      var total = holding + expedited;
      data.push([counter++, level, code, info.name, demand, received, safetyStock, stockout,
holding, expedited, total]);
    }
  }
  // --- Write results to sheet ---
  outputSheet.getRange(1, 1, data.length, data[0].length).setValues(data);
}
// Helper function for random integer
function rand(min, max) {
  return Math.floor(Math.random() * (max - min + 1)) + min;
}
}

```

This table shows the algorithm for Scenario 1 (Manual). This code is used to simulate the baseline policy defined in methodology (3.2.b), where a static safety stock is applied. Here's the code flow process:

1. This function first reads the master sheet [IWM] Stock Counting/Stock Opname to retrieve item-specific cost data, namely holdingCost (index 13) and expeditedCost (index 14). This is important to address the research critique (as discussed in the literature review) that costs vary between items.
2. The main differentiating logic is set: MANUAL_FIXED_SAFETY_STOCK = 235, corresponding to the baseline value calculated in (3.2.b).
3. The script loops through 60 replications (20 times for each 'Low', 'Medium', 'High' scenario).
4. Inside the loop, the safetyStock variable is rigidly set to 235 for every replication, regardless of the variability scenario.
5. The code then calculates Holding Cost (based on SS 235), Expedited Cost (if a stockout occurs), and Total Cost.

This algorithm is specifically designed to generate the raw data for Table 7 (Manual Performance). The use of this fixed 235 safety stock is what produces the data in Table 7, which shows stable performance in "Low" but failure in "High" (with 20% stockout).

Automatic MRP Simulation Algorithm

```
function runAutomaticSimulation_REVISED() {
  // Initialize Spreadsheet
  var ss = SpreadsheetApp.getActiveSpreadsheet();
  var masterSheet = ss.getSheetByName("[IWM] Stock Counting/Stock Opname ");
  var outputSheet = ss.getSheetByName("Simulasi_MRP_Automated_Revisi");
  if (!outputSheet) outputSheet = ss.insertSheet("Simulasi_MRP_Automated_Revisi");
  else outputSheet.clear();
  // --- Get master data (Holding & Expedited Cost) ---
  var masterValues = masterSheet.getRange("E5:S19").getValues();
  var costMap = {};
  var materialList = [];
  for (var i = 0; i < masterValues.length; i++) {
    var code = masterValues[i][0], name = masterValues[i][1];
    var holdingCost = masterValues[i][13], expeditedCost = masterValues[i][14];
    if (code) {
      costMap[code] = { name: name, holdingCost: holdingCost, expeditedCost: expeditedCost };
    }
    materialList.push(code);
  }
  // --- Key Logic: Automatic Safety Stock based on variability level ---
  var automatedSafetyStockMap = {
    'Low': 50, // low variability
    'Medium': 400, // medium (baseline)
    'High': 950 // high
  };
  // --- Main simulation loop ---
  var scenarios = ['Low', 'Medium', 'High'];
  var N_PER_SCENARIO = 20;
  var data = [];
  var counter = 1;
  for (var i = 0; i < scenarios.length; i++) {
    var level = scenarios[i];
    var safetyStock = automatedSafetyStockMap[level]; // Main Differentiating Logic
    for (var j = 0; j < N_PER_SCENARIO; j++) {
      var code = materialList[Math.floor(Math.random() * materialList.length)];
      var info = costMap[code];
      // --- Random input (identical to manual version) ---
      var demand, received;
      if (level === 'Low') {
        demand = rand(100, 150);
```

```

    received = rand(90, 120);
  } else if (level === 'Medium') {
    demand = rand(80, 200);
    received = rand(50, 150);
  } else {
    demand = rand(50, 300);
    received = rand(10, 150);
  }
  // --- Main calculations ---
  var stockout = (demand > (received + safetyStock)) ? 'Y' : 'N';
  var holding = safetyStock * info.holdingCost;
  var expedited = (stockout === 'Y') ? (demand - (received + safetyStock)) *
info.expeditedCost : 0;
  var total = holding + expedited;
  // --- Push to results array ---
  data.push([
    counter++, level, code, info.name, demand, received,
    safetyStock, stockout, holding, expedited, total
  ]);
}
}
// --- Output to Sheet ---
outputSheet.getRange(1, 1, data.length, data[0].length).setValues(data);
outputSheet.getRange("A1:K1").setFontWeight("bold");
outputSheet.autoResizeColumns(1, data[0].length);
}
// Helper function for random integer
function rand(min, max) {
  return Math.floor(Math.random() * (max - min + 1)) + min;
}
}

```

This table shows the algorithm for Scenario 2 (Automatic). This code is used to simulate the adaptive policy defined in methodology (3.2.a). Here's the code flow process:

1. Same as the manual scenario, this function reads the holdingCost and expeditedCost data from the [IWM] Stock Counting/Stock Opname master sheet.
2. The main differentiating logic is set in the automatedSafetyStockMap. This map assigns different safety stock values for each variability level ('Low': 50, 'Medium': 400, 'High': 950), as per the adaptive policy in (3.2.a).
3. The script performs 60 replications, identical to the manual scenario (using the same random input generator, rand(), for a fair comparison).
4. Inside the loop, the safetyStock variable is set dynamically using automatedSafetyStockMap[level]. This means the 'Low' scenario uses SS 50, 'Medium' uses SS 400, and 'High' uses SS 950.
5. The code calculates the costs (Holding, Expedited, Total) using these dynamic safety stock values.

This algorithm generates the raw data for Table 8 (Automatic Performance). The use of this adaptive safety stock (50, 400, 950) is what produces the data in Table 8, which shows a perfect service level (0% stockout) in all scenarios achieved 0% stockout under the simulated parameter ranges. The comparison between this code's output and the manual code's output forms the basis of Table 9 (Comparative Analysis).

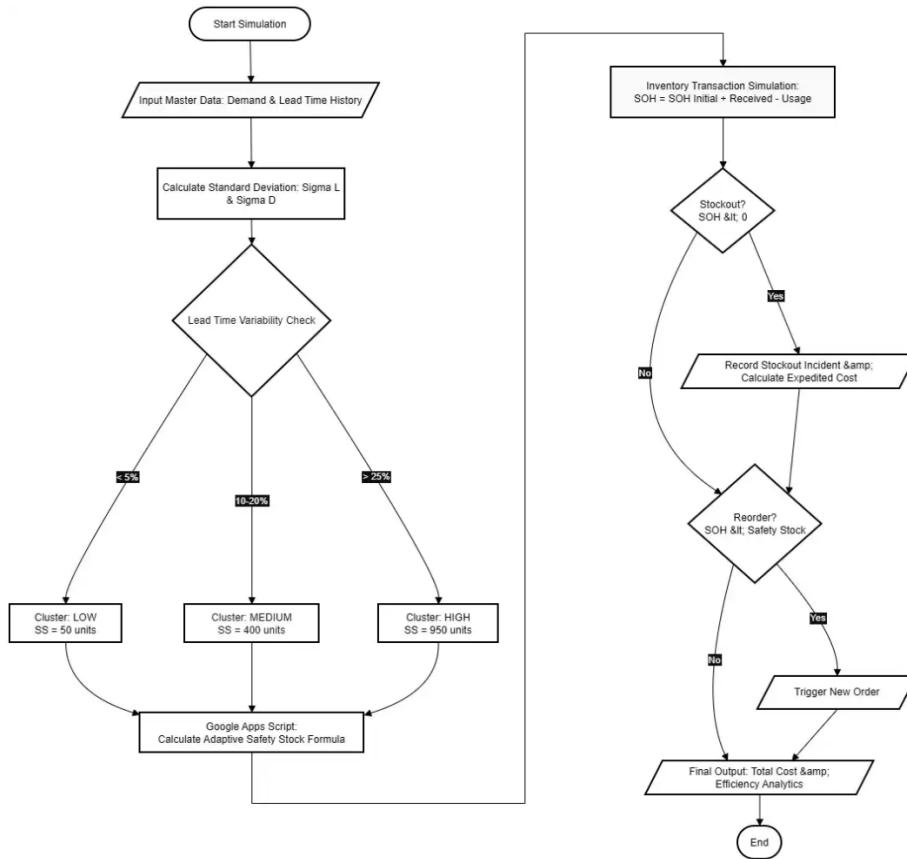


Fig 1. Simulation Logic Flowchart

3.4 Statistical Analysis

The simulation result data (stockout frequency, holding cost, and expedited order cost) were analyzed using a Two-Way ANOVA method to test:

- 1) The main effect of the safety stock approach and lead time variability.
- 2) The interaction between these two factors.

The interaction effect indicates whether the effect of safety stock approach depends on the level of lead time variability. This approach follows experimental design guidelines in modern ERP system analysis as suggested by Gonçalves *et al.* dan Barros *et al.* [12], [13].

4. Results and Discussion

4.1 Manual Fixed Safety Stock Simulation Performance

Table 7 presents the simulation results for the Manual Fixed Safety Stock policy, where the safety stock level was set at a constant 235 units regardless of lead time variability conditions.

Table 7. Manual Fixed Safety Stock Simulation Results

Performance Metric	Low Variability	Medium Variability	High Variability
Average total cost	Rp38.959	Rp35.061	Rp636.250
Standard Deviation total cost	Rp21.509	Rp24.679	Rp1.584.663
Stockout frequency	0,00%	0,00%	20,00%

Table 7 shows that applying the Manual Fixed Safety Stock policy with a constant safety stock of 235 units only performs well under low lead time variability. In the Low Variability scenario, the average total cost is relatively low, and the stockout frequency is 0%, indicating the system can still maintain smooth demand fulfillment. However, when variability enters the Medium and High categories, the manual policy's performance drops significantly. This is evident from the extremely high-cost spike, increased cost uncertainty (large standard deviation), and the emergence of stockouts up to 20% in high variability.

This finding confirms that a static safety stock policy cannot adapt to demand uncertainty and lead time fluctuations, thereby increasing the risk of operational-level fulfillment failures. This aligns with studies by Demiray Kırmızı *et al.* and Kim *et al.*, which state that static safety stock policies tend to be ineffective in variable supply chain environments [7], [8].

4.2 Automatic MRP Simulation Performance

Table 8 presents the simulation results from the Automatic MRP policy. Unlike the manual simulation, this policy dynamically recalculates and adjusts the safety stock level based on the lead time variability detected by the system.

Table 8. Automatic MRP Simulation Results

Performance Metric	Low Variability	Medium Variability	High Variability
Applied Safety Stock	50	400	950
Average total cost	Rp7.317	Rp48.093	Rp121.481
Standard Deviation total cost	Rp5.107	Rp36.629	Rp81.991
Stockout frequency	0,00%	0,00%	0,00%

The most crucial aspect of this finding is the adaptive nature of the system. In the Low Variability condition, the system sets the safety stock at 50 units, reflecting an efficient inventory strategy with low and stable average costs. When variability increases to the medium category, the system responds to the increased uncertainty by raising the safety stock to 400 units, and again to 950 units in High Variability. This gradual adjustment allows the system to consistently maintain material availability, evidenced by a 0% stockout frequency across all scenarios. Furthermore, the standard deviation of costs remains controlled, indicating that this policy can maintain operational cost predictability despite increased supply uncertainty.

This finding aligns with inventory planning and control theory, which emphasizes the application of adaptive safety stock models in fluctuating supply chain environments [4], [12], [13], and supports systemic integration-based production planning approaches as described by Jacobs *et al.* and Vollman in the Manufacturing Planning and Control framework [5]. Thus, the Automatic MRP policy proves to be more responsive and effective than the static model because it can balance cost efficiency and service level reliability, especially under high lead time variability [6].

4.3 Comparative Analysis of Policy Performance

Table 9 summarizes the direct comparison between the two policies to synthesize the findings and answer the main research question regarding the effectiveness of Automatic MRP in mitigating lead time variability.

Table 9. Comparison of Performance Results (Fixed Safety Stock vs. Automatic MRP)

Performance Metric	Policy	Low Variability	Medium Variability	High Variability
Applied Safety Stock	Manual	235	235	235
	Automatic	50	400	950
Stockout Frequency	Manual	0%	0%	20%
	Automatic	0,00%	0,00%	0,00%
Average Total Cost	Manual	Rp38.959	Rp35.061	Rp636.250
	Automatic	Rp7.317	Rp48.093	Rp121.481
Std. Dev. Total Cost	Manual	Rp21.309	Rp24.679	Rp1.584.663
	Automatic	Rp5.107	Rp36.629	Rp81.991
Average Holding Cost	Manual	Rp38.959	Rp35.061	Rp26.250
	Automatic	Rp7.317	Rp48.093	Rp121.481
Average Expedited Cost	Manual	Rp0	Rp0	Rp610.000
	Automatic	Rp0	Rp0	Rp0

Across all scenarios, the manual policy maintained a fixed safety stock of 235 units, resulting in a 0% stockout frequency only in Low and Medium Variability conditions, but experiencing a stockout increase to 20% when variability reached a high level. Conversely, Automatic MRP adaptively adjusted the safety stock value from 50 to 950 units, which allowed the system to maintain a 0% stockout frequency at all variability levels. Furthermore, the average total cost and standard deviation of cost in the high scenario show a striking difference: the manual policy experienced a massive cost spike and instability, whereas the automatic policy managed to keep total costs lower and more stable.

These results indicate that a dynamic inventory policy is better able to cope with demand uncertainty and lead time fluctuations than a static approach. This aligns with the findings of Afrizal *et al.* regarding the effectiveness of adaptive reorder points in reducing stockout risk [9] and is supported by Babai *et al.* who emphasize the importance of adjusting safety stock based on demand and lead time variance [6]. Thus, Automatic MRP is proven to be superior in maintaining service levels and operational cost stability in a dynamic supply chain environment.

4.4 Statistical Validation and Interaction Effects Analysis

To validate the descriptive findings, a Two-Way ANOVA test was conducted to examine the influence of the Safety Stock Approach (Manual vs. Automatic) and Lead Time Variability Level (Low, Medium, High) on Average Total Cost. The results are summarized in Table 10.

The analysis results show that both factors have a significant main effect, where an increase in lead time variability consistently causes an increase in operational costs, as explained by supply chain dynamics principles in Chopra and the uncertainty amplification phenomenon described by Disney and Towill [2], [3]. Additionally, the safety stock approach proved to provide a significant performance difference, with the adaptive method yielding more stable cost levels compared to the static approach.

Table 10. Two-Way ANOVA Result for Total Inventory Cost

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F-value	p-value
Safety Stock Approach	1.67×10^{12}	1	1.67×10^{12}	31.82	<0.0001
Lead Time Variability	2.94×10^{12}	2	1.47×10^{12}	28.05	<0.0001
Approach x Variability	2.61×10^{12}	2	1.30×10^{12}	24.86	<0.0001
Error	5.98×10^{12}	114	5.25×10^{10}	—	—
Total	1.32×10^{13}	119	—	—	—

The ANOVA results confirm a significant interaction effect between the two factors. To address the substantial variance differences observed particularly under high variability conditions, a log-transformed ANOVA was conducted as a robustness check and yielded consistent significance patterns, confirming the stability of the main and interaction effects. This interaction effect signifies that the performance of an inventory control policy cannot be separated from the prevailing system variability conditions. At low variability, the manual policy can still maintain performance because demand and lead time conditions are relatively stable. However, as variability increases, the manual policy experiences a cost surge and increased stockout risk, while Automatic MRP can dynamically adjust the safety stock value, maintaining 0% stockouts and keeping costs under control, as seen in Table 9. This finding aligns with Babai *et al.*, who stress that safety stock must be calculated based on demand and lead time variance [6], and is reinforced by Afrizal *et al.* who show the importance of reorder point adjustments in risky supply environments [9].

Thus, this statistical validation confirms that Automatic MRP has higher operational robustness in facing uncertainty compared to the Manual Fixed policy, due to its ability to adapt to risk fluctuations, maintain cost stability, and consistently preserve the system's service level. Nevertheless, this study has limitations as it is based on simulation data with the assumption of stable demand and has not considered external factors such as seasonal demand fluctuations or multi-supplier procurement policies. Further research is recommended to integrate these factors so that the results are more representative of complex manufacturing industry conditions.

5. Conclusion

5.1 Conclusion

Based on simulation results and statistical analysis, this research demonstrates that lead time variability has a significant effect on warehouse inventory system performance. The Manual Fixed Safety Stock policy, which set a safety stock of 235 units, was only effective in low variability conditions. It lost its effectiveness in medium variability, marked by a surge in total costs and the emergence of a 20% stockout rate in high variability. Conversely, the Automatic MRP approach, with its adaptive safety stock adjustments (50 units in low, 400 in medium, and 950 in high variability), was able to maintain a 0% stockout frequency in all scenarios, while keeping operational costs more stable and controlled.

The Two-Way ANOVA results confirm that both lead time variability and the safety stock approach have significant main effects on total cost and also show a significant interaction effect. This interaction effect indicates that the effectiveness of an inventory policy depends on the level of supply uncertainty. Overall, this research proves that within the defined simulation boundaries and parameter ranges, the variability-

configured MRP policy demonstrates superior robustness relative to the fixed safety stock approach. Thus, implementing adaptive safety stock in an MRP system is proven to be a more effective approach to achieving warehouse operational stability and efficiency. This research provides empirical insights through a simulation model regarding the advantages of adaptive automatic MRP. The model validation shows that the system is able to respond to lead time fluctuations much more efficiently than the fixed manual method.

5.2 Suggestions

This research has several limitations that should be addressed in future development. This study was based on simulation data with its scope limited to one type of industry, layer hen farming, so the results may not fully represent the conditions of all manufacturing sectors. Furthermore, the model used still focuses on the lead time variability variable without involving other factors such as demand fluctuations or supplier procurement policies. Therefore, future research is advised to expand the scope of data and variables so the results can be more generalizable and applicable in various industrial contexts. Based on the research results, several recommendations for further development are:

1. Use real-time data with a longer observation period to improve the accuracy of the adaptive safety stock calculation model.
2. Integrate predictive methods, such as machine learning or fuzzy logic, to enhance the system's ability to project demand and lead time variance more precisely.
3. Expand the analysis to the supplier level, with integrated vendor performance evaluation, to gain a more comprehensive understanding of the effect of delivery variability on supply chain stability.

With these developments, the material requirements planning mechanism is expected to provide more adaptive, efficient, and sustainable decision support in industrial environments with high levels of uncertainty. Furthermore, these findings can also serve as a practical reference for manufacturing companies and ERP system developers to implement integrated adaptive safety stock strategies, thereby improving operational efficiency and supply chain resilience across various industrial sectors.

6. References

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