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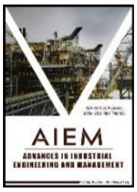

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RESEARCH ARTICLE

SIMULATION-BASED OPTIMIZATION IN PRODUCTION AND INVENTORY MANAGEMENT: THE IMPACT OF UNCERTAINTIES, FAILURES AND CUSTOMER DEMAND

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ABSTRACT

In today's competitive business environment, the efficiency of production and inventory management processes plays a critical role. This study presents a simulation model developed to understand the impact of production uncertainty, downtime, and customer demand on inventory management. Using the Arena simulation software, the model analyzes the dynamic management of inventory levels, identifies bottlenecks in the production process, and proposes strategies to enhance operational efficiency. The study aims to investigate the effects of downtime, repair processes, and demand uncertainty in a system where production is carried out on a single machine. The simulations reveal the impact of dynamic inventory management on production efficiency. Various scenarios were tested to optimize the production process. The simulation results indicate that machine failures directly affect customer losses, and reducing repair time improves delivery time by 86%. However, while increasing production capacity reduces customer losses by 85%, it also extends production times. From an inventory management perspective, low stock levels lead to higher customer losses, and merely increasing safety stock is insufficient to prevent these losses. The contribution of this study to the literature lies in offering an innovative approach to production and inventory management by utilizing dynamic simulation models to analyze uncertainty scenarios that are difficult to address with traditional methods. By presenting a simulation model that represents uncertainties in the production system, this study contributes to businesses' strategic decision-making processes. The model provides practical and applicable strategies for companies seeking to optimize their production and inventory management decisions.

KEYWORDS

Arena Simulation, Production Management,Inventory System, Lost Customers, Downtime

1. INTRODUCTION

In today's business world, effective management of production and inventory systems is critical to gain competitive advantage (Vidal 2022). Emphasizing the importance of inventory modeling in production systems, a comprehensive literature review of both deterministic and stochastic inventory models was conducted. The study proposes a methodology for enabling the management of manufacturing systems and analyzes various inventory modeling methods along with research strategies based on specific questions. The findings reveal that different inventory models are of scientific interest, especially in deterministic systems such as Economic Production Quantity (EPQ), Generational Model (QM) and Optimization-Linear Programming (OP). There is also a trend towards Optimization (OPT) and Simulation (SIM) models in stochastic supply chain management. It offers an important contribution to be considered in inventory management and decision-making processes.

Uncertainties in production processes, failures and variability of customer demands make optimization of these systems difficult. Therefore, simulation models need to be developed to help businesses better understand production and inventory management. For example, a study has shown how inventory management processes under stochastic demand can be improved with Monte Carlo Simulation (MCS) and optimization methods (Maitra 2024). By comparing periodic review (p, Q) and continuous review (r, Q) policies, this study demonstrates the impact of dynamically managing inventory levels according to customer demand and lead times on business profitability.

Similarly, different dynamic models have been developed in the literature for inventory management and optimization of production systems. The popular APIOBPCS model and a new variant, the 2APIOBPCS model, are compared and the system control parameters are determined using a multi-objective particle swarm optimization (MOPSO) algorithm (Al-Khazraji et al., 2021). These dynamic models have shown how inventory levels can be managed more flexibly and efficiently according to customer demands.

In a study that presents a simulation-optimization approach to inventory optimization in supply chain networks and considers the management of a three-level supply chain, optimal inventory policies are determined by considering the flow of products between the retail store, distribution center and manufacturer (Mahmoudi et al., 2023). The management of the products demanded by the customers according to the stock status and the delays that occur when the demand exceeds the stock are analyzed. The study evaluates system performance with performance indicators such as daily order cost, average daily cost and average waiting time. Such simulation and optimization approaches are critical to provide flexibility and efficiency in inventory management.

A researcher aimed to assess the state and performance of manufacturing processes by developing an integrated modeling approach (Vidal 2022). This work provides integrated management and control for digital twin models, taking into account the relevant flows in the areas of production, maintenance and quality. The system dynamics simulation model developed for the metallurgical process provides a digital manufacturing

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system organized by maintenance, quality and production strategies, enabling companies to increase profitability and customer service levels. The research makes an important contribution supporting the continuous optimization of production processes.

A researcher conducted a comprehensive literature review on inventory modeling; this paper presents a practical solution by integrating downtime and inventory management, targeting existing gaps (Vidal 2022). İn other study, author developed inventory management processes under stochastic demand, while this paper presents a more comprehensive model by considering downtime and customer losses in production processes (Maitra 2024). A group researchers demonstrates the effectiveness of dynamic control models, while this study provides additional depth in improving system performance by integrating inventory management and production failures (Ma et al., 2025). Some researcher also addresses supply chain optimization, while this study provides an integrated approach by including maintenance management (Mahmoudi et al., 2023). Finally, author provides dynamic management of manufacturing processes, while this paper provides different perspective by focusing on breakdown repair times to improve system performance (Vidal 2022).

In this paper, a simulation model based on the production and inventory system will be created and analyzed using Arena simulation software. Arena simulation software provides a comprehensive tool for modeling processes, helping users to understand the behavior of complex systems. By simulating the effects of real-world variables, simulation allows decision makers to optimize their strategic choices.

The main objective of the research is to simulate a single manufacturing process and its associated inventory management system, and to evaluate the performance of the system by analyzing downtime and lost customers. The production process is designed with a structure in which materials are processed on a single machine. The machine breakdowns and their repair times are the stochastic variables considered in the simulation. At the same time, customer demands and unmet demands will be analyzed within the framework of inventory management practices.

Existing studies in the field of production and inventory systems are limited in the number of simulation models that examine in detail the effects of uncertainties and failures in production processes. While the existing literature focuses on stochastic demand modeling, there is limited coverage of manufacturing process failures and their impact on inventory management systems. Breakdowns are an important uncertainty factor that directly affects system performance as well as inventory management. In this study, a comprehensive simulation model for system performance is presented by integrating both production process downtime and lost customer analysis.

Studies emphasizing the impact of critical factors such as lost customer analysis on system performance are often superficial and lack sufficient data analysis. This study aims to fill this gap in the literature by analyzing the number of lost customers as well as inventory levels and downtime in detail. Finally, the strategies proposed based on the simulation results will provide a basis for future research in this field by offering new approaches to the optimization of production and inventory systems. In this context, the study has the potential to be an important source for the development of applications in the field of production management by making important contributions to the literature.

2. CONCEPTUAL FRAMEWORK

The conceptual framework of this paper focuses on simulation analysis of production and inventory systems. Production and inventory management are critical areas to ensure that an organization uses its resources in the most efficient way. The study aims to evaluate production and inventory management processes through simulation analysis. Production and inventory management play a vital role in increasing operational efficiency and optimizing resource utilization in a business. Failure to manage these processes will result in failure to meet customer demands and increased customer churn. Simulation methods are used to analyze variables in production and inventory management, identify opportunities for performance improvement and reduce the impact of customer losses. In this study, the concepts of production processes, inventory management, the use of simulation and customer churn are discussed and a framework for making operational processes more efficient and sustainable is presented. The key concepts and components of this study are described below:

2.1 Production Processes

The production process is defined as an important component of industrial energy consumption that is influenced by operational strategies, control mechanisms and external price factors (Salahi and Jafari 2016). It is a series of activities that transform a product from raw material to final product. These processes, which usually use various inputs (raw materials, labor and machinery), play a critical role in terms of production efficiency, resource utilization and operational reliability. Various approaches to manufacturing processes are presented in the literature, where elements such as risk assessment and failure modes are prominent, especially in automated production systems (Sarwar et al., 2021). In addition, the remanufacturing process, unlike traditional manufacturing processes, involves uncertainties and variables. These factors contribute to the effective and optimized management of the remanufacturing process. Production process management is considered as an important area not only in terms of efficiency and quality, but also in terms of continuity of operations, environmental impact and sustainability (Peng et al., 2019).

2.2 Inventory Management

Inventory management is a discipline that enables businesses to effectively manage their material and product inventories. In a study that defines inventory management as a process that aims to meet demand while minimizing costs, minimum and maximum inventory levels for inventory capacity are determined, storage costs are defined and capacity expansion parameters are presented. In addition, mathematical models were developed to optimize inventory levels and the impact of inventory management on productivity was demonstrated by emphasizing the need to control inventory flow (Hosseinitabar et al., 2024). Inventory management is also a critical component of supply chain operations and requires strategic planning, especially in times of uncertainty. A global crisis such as the pandemic has reshaped inventory planning and demonstrated that low inventory levels may not be enough to manage consumer demand. A renewal of inventory management research is therefore needed to develop more resilient and flexible strategies to cope with supply chain disruptions. Determining optimal inventory levels and establishing demand-responsive inventory policies play a vital role in enhancing the operational sustainability of a business (Priyamvada and Kumar, 2022).

2.3 Simulation

Simulation is a method used to learn about complex systems and test new operational or resource policies, new concepts or systems before implementation (Patole, 2024). Simulation, which is defined as a powerful method used to analyze production processes and make performance improvements, helps businesses make effective decisions on their processes by simulating the effects of variables and uncertainties in the system, allowing users to visualize the dynamics of the system (Oljira et al., 2020). It is used to understand the performance of the current system, test different scenarios and predict the impact of future changes.

2.4 Lost Customers

In this study, a lost customer is defined as a customer whose demand cannot be met due to insufficient inventory and therefore whose orders cannot be fulfilled. Failures in inventory management processes, lack of production planning and errors in demand forecasting can lead to increased customer churn. High customer churn rate directly damages the revenues of businesses and reduces customer loyalty in the long run. Therefore, analyzing the number of lost customers plays a vital role in assessing the impact of inventory management on customer satisfaction. Effective inventory management helps you minimize customer churn and more accurately meet customer demand. Reducing the number of lost customers is directly related to increasing the efficiency of production and inventory systems. In this context, simulation analysis can be used to evaluate the impact of different inventory management strategies on customer losses and to develop more flexible and sustainable inventory policies.

3. PROBLEM

Uncertainties in production and inventory systems present significant challenges that can hamper operational efficiency and overall business performance. For example, fluctuations in demand, unpredictable lead times and equipment breakdowns lead to stock-outs, excess inventory and increased costs. These problems not only disrupt the supply chain, but also affect customer satisfaction and competitiveness. This paper focuses on the development of a simulation model of a production and inventory management system. In a given production process, materials are processed on a single machine tool and various uncertainties and failures arise in this process. The time between machine breakdowns leads to unexpected stoppages and the repair times affect the production efficiency. The overall flow in the plant consists of six stages as shown in

Figure 1.

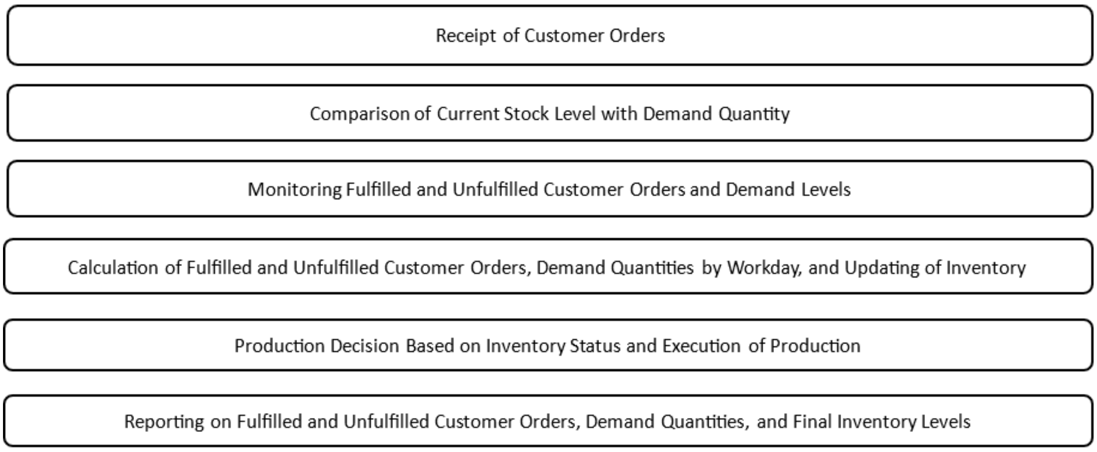

Figure 1: Order and Production Process Flow

The process that starts with the arrival of customer orders continues with the comparison of the incoming customer order, i.e. the amount of demand and the amount of available stock. According to the results of the comparison, the number of satisfied and unsatisfied customers and demand quantities are monitored daily. For this purpose, the number of met and unmet customers and demand quantities are calculated according to working days and stocks are updated. According to the current stock status, the production decision is made and production is made or orders continue to be met from stock. In the last stage, the number of satisfied and unsatisfied customers, demand quantities, and the last values of inventories are recorded and reported.

In the study, the actual production facility in ABC enterprise is taken as a reference. It is determined that the production time for each unit in production is 75 seconds. The products coming out of production are stored in a stock area with a capacity of 1000 units. If the stock area is full, production stops. Initially, the inventory level is 500 units and the safety stock is 150 units. Customer demands are fulfilled depending on the stock level, and the demands that cannot be fulfilled when there is not enough stock are considered as unfulfilled customer orders. In order to determine the statistical distribution of the times between incoming orders during the six-day working period, the following table was obtained by measuring the times between order requests from the first 20 customers.

Table 1: Demand Information

Order No	Demand Amount	Periods Between Demands	Order No	Demand Amount	Periods Between Demands
1	880	20	11	370	16
2	630	97	12	400	20
3	990	96	13	640	88
4	950	69	14	200	106
5	550	62	15	900	47
6	980	114	16	330	97
7	290	113	17	160	20
8	150	102	18	120	44
9	650	21	19	380	52
10	480	78	20	700	55

The data obtained by monitoring the times between failures and repair times observed during the study period are as given in the table below;

Table 2: Breakdown and Repair Information

Failure No	Time between failures (min)	Repair Time (min)	Failure No	Time between failures (min)	Repair Time (min)
1	71	60	11	51	76
2	39	32	12	37	55
3	102	76	13	64	23
4	105	61	14	34	53
5	30	16	15	81	64
6	108	32	16	74	47
7	69	23	17	57	50
8	78	64	18	45	65
9	79	10	19	90	37
10	114	5	20	98	48

In this study, answers to the following research questions will be sought:

- Which factors are effective for reducing the number of lost customers?
- How is the relationship between breakdown times and delivery times shaped?
- How does the frequency and duration of breakdowns in the

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production process affect total production efficiency?

- What strategies can be recommended to optimize production and inventory system performance?

This problem statement aims to develop a systematic approach to the research objective and to understand the effects of uncertainties in production and inventory management. The findings will contribute to the development of strategies to improve the efficiency of production systems.

4. METHOD

In this study, a model was developed using the Arena simulation program for production and inventory system simulation. Arena Packaging Edition provides a framework for learning how to build models and analysis by providing a five-step modeling methodology(Oljira, Abeya et al. 2020).

Figure 2: Arena Packaging Edition Methodology

- Installation and connection of equipment
- Define of equipment behavior
- Run the model
- View automatic statistics
- Experimenting with complex strategies

The model is designed according to the modeling methodology of the Arena program to analyze production processes and inventory management. Arena Packaging Edition is a powerful modeling tool for the simulation of production and inventory systems and provides users with a five-step methodology to effectively manage the simulation process. In the first step of the methodology, the layout and connections of equipment such as machines, conveyors, storage areas, etc. within the production line are modeled. Then, in the second step, the behavior of the equipment is defined and the operating rules for each component are determined. In the third step, the models are run to test the dynamics of the system. In the fourth step, the performance data is displayed with automatic statistics and analyzed. Finally, in the fifth step, experiments are conducted on complex strategies, alternative scenarios are evaluated and decisions are made to improve the system. This methodology provides an important framework for improving process efficiency and optimizing system performance.

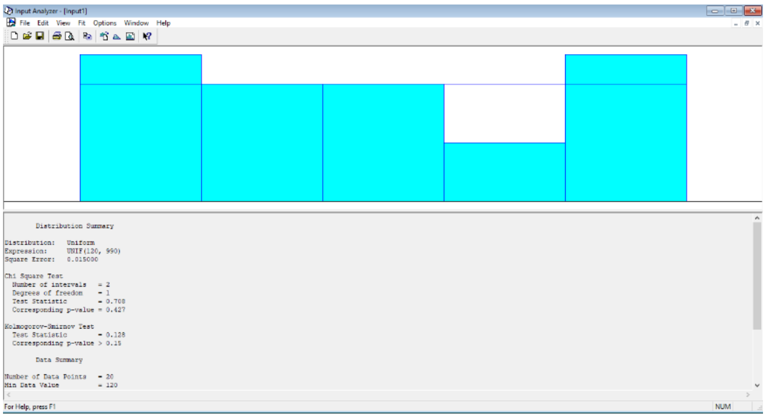
4.1 Model Design

The study involves a single production process and the associated inventory management system. The workbench is identified as the main unit where the materials are processed. The production process is associated with a stock area with a certain capacity. The parameters used in the model are; time between machine breakdowns, repair times, production batch size, production time, stock area capacity, initial stock level, safety stock, time between customer orders, customer demands.

4.2 Creating the Simulation Model

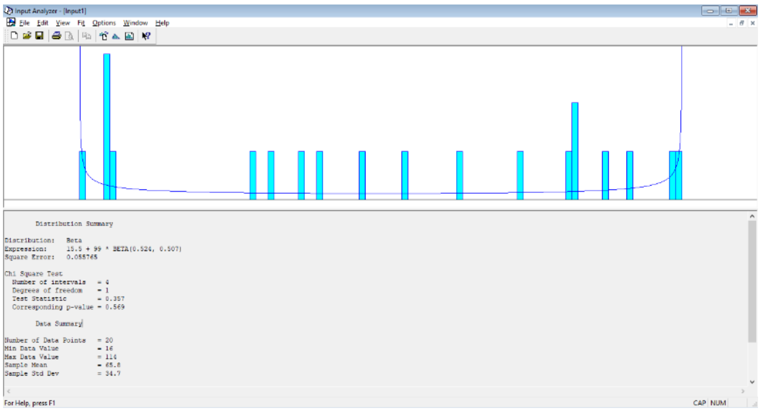
4.2.1 Data Acquisition and Input Analyzer (1. Place and connect equipment)

Considering the data in Table 1, the statistical distribution of demand quantities is determined as 11.5 + 88 * BETA(0.596, 0.646) units. The time distribution between the arrival of the requests is 15.5 + 99 * BETA(0.524, 0.507) minutes. Similarly, taking into account the data in Table 2, the statistical distribution of the time between breakdowns at the machine is 11.5 + 69 * BETA(0.759, 0.62) minutes. The repair time is 4.5 + 72 * BETA(0.899, 0.729) minutes, which represents the uncertainty in the repair process.



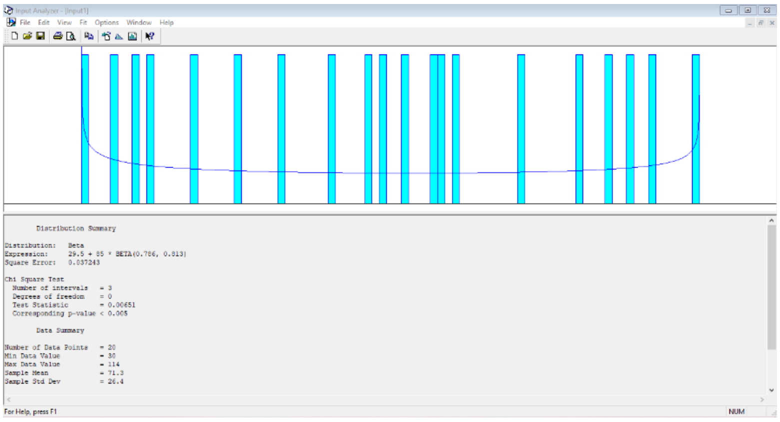
```
        Distribution Summary

Distribution:   Uniform
Expression:     UNIF(120, 990)
Square Error:   0.015000

Chi Square Test
  Number of intervals   = 2
  Degrees of freedom    = 1
  Test Statistic        = 0.708
  Corresponding p-value = 0.427

Kolmogorov-Smirnov Test
  Test Statistic        = 0.128
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 20
Min Data Value          = 120
```

Figure 3: Input Analyzer-Demand Amount



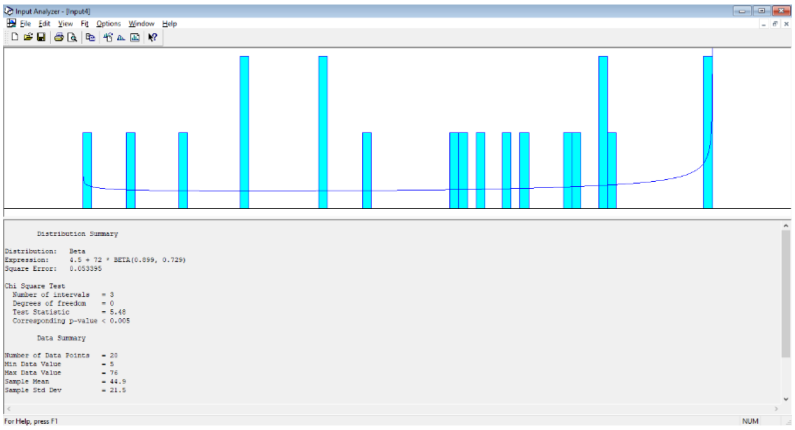
```
        Distribution Summary

Distribution:   Beta
Expression:     15.5 + 99 * BETA(0.524, 0.507)
Square Error:   0.055765

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 1
  Test Statistic        = 0.357
  Corresponding p-value = 0.569

        Data Summary

Number of Data Points   = 20
Min Data Value          = 16
Max Data Value          = 114
Sample Mean             = 65.8
Sample Std Dev          = 34.7
```

Figure 4: Input Analyzer- Time Between Demands



```
        Distribution Summary

Distribution:   Beta
Expression:     29.5 + 85 * BETA(0.786, 0.813)
Square Error:   0.037243

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 0
  Test Statistic        = 0.00651
  Corresponding p-value < 0.005

        Data Summary

Number of Data Points   = 20
Min Data Value          = 30
Max Data Value          = 114
Sample Mean             = 71.3
Sample Std Dev          = 26.4
```

Figure 5: Input Analyzer- Time Between Failures



```
        Distribution Summary

Distribution:   Beta
Expression:     4.5 + 72 * BETA(0.899, 0.729)
Square Error:   0.053395

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 0
  Test Statistic        = 5.48
  Corresponding p-value < 0.005

        Data Summary

Number of Data Points   = 20
Min Data Value          = 5
Max Data Value          = 76
Sample Mean             = 44.9
Sample Std Dev          = 21.5
```

Figure 6: Input Analyzer- Repair Times

Table 3 shows the statistical distributions obtained with Input Analyzer and the parameters used in the model, including information about the production facility.

Table 3: Parameters used in the model

Production time	75 seconds (for each unit)
Stock space capacity	100 unit
Initial stock level	500 unit
Safety Stock	150 unit
Customer requests	UNIF(120, 990) unit
Time between customer orders	15.5 + 99 * BETA(0.524, 0.507) min
Time between failures at the workbench	29.5 + 85 * BETA(0.786, 0.813) min
Repair time	4.5 + 72 * BETA(0.899, 0.729) min

4.2.2 Define equipment behaviors

In the Arena simulation program, a simulation model was created using the parameters defined above. The model includes the components of production process, breakdowns, stock status and customer demands. The model is graphically designed to simulate the flow of the production process and inventory management. Using Create, Assign, Decide, Hold, Process, Record and Dispose modules, the design provides a better understanding by visualizing each stage of the simulation.

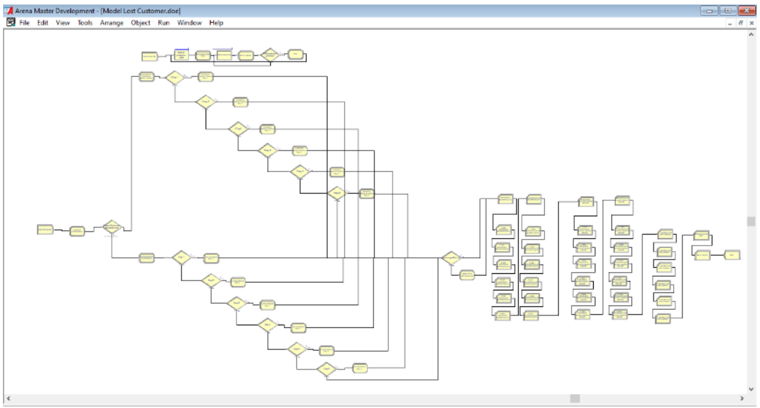


Figure 7: Arena Simulation Model

In the first part of the model Figure7a.Arena Simulation Model-Unit1, the availability of incoming customer orders from the available stock is checked.

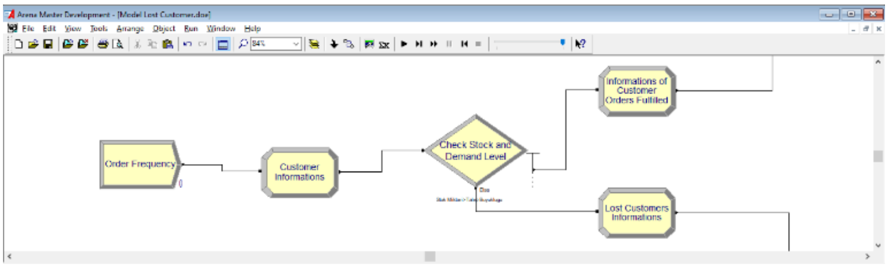


Figure 7a: Arena Simulation Model-Unit1 – Orders and Check Stock & Demand Level

When the quantity in stock meets the incoming customer order, it is recorded as fulfilled customer orders on a daily basis as shown in Figure7b.Arena Simulation Model-Unit2 - Daily Customer Orders Fullfilled.

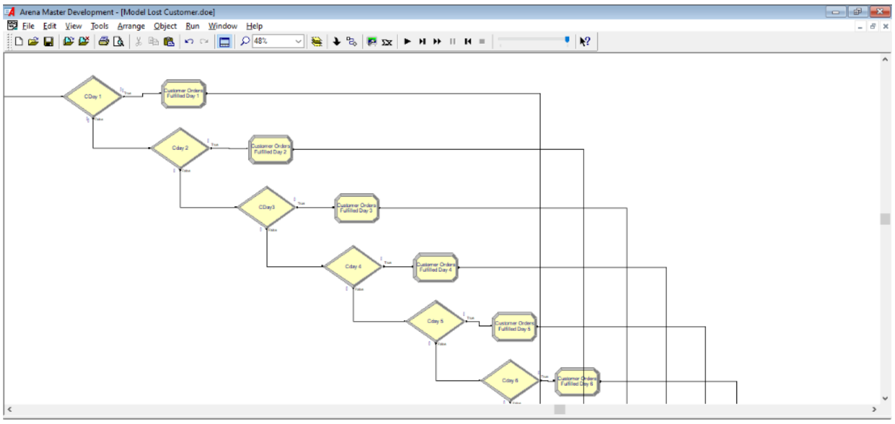


Figure 7b: Arena Simulation Model-Unit2 – Daily Customer Orders Fullfilled

When the incoming customer order cannot be met from the amount in stock, it is recorded as lost customer orders that cannot be met on a daily basis as in Figure5c.Arena Simulation Model-Unit2 - Daily Lost Customers.

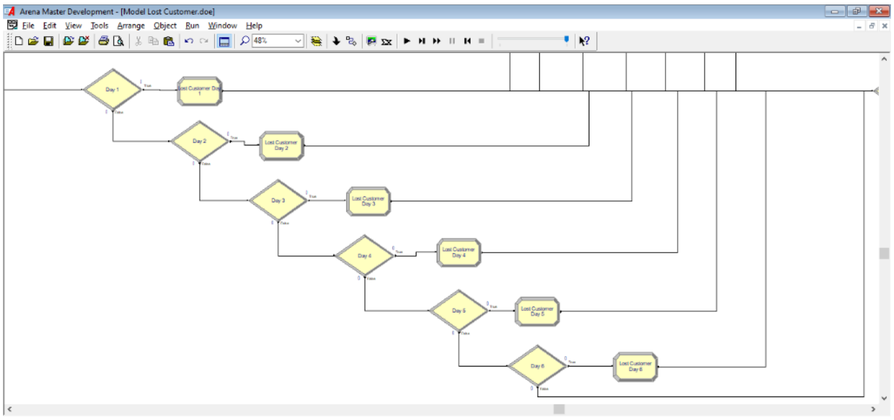


Figure 7c: Arena Simulation Model-Unit2 – Daily Lost Customers

Once these steps of the simulation model are completed, another part of the model shown in Figure7 is the process operation in the production facility. Here the quantity in stock is rechecked. As seen in Figure5d.Arena Simulation Model-Unit3, at the point where the incoming customer orders cannot be met from the amount in stock, the production process starts with the Production Work Order given to production. Production is carried out until the capacity of the stock area is full.

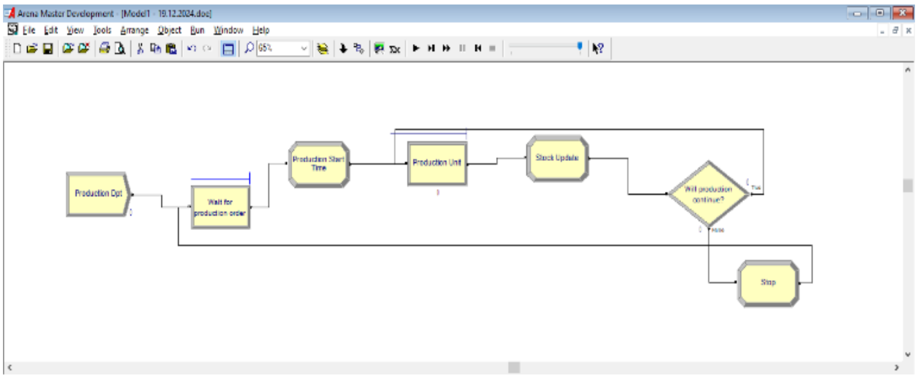


Figure 7d: Arena Simulation Model-Unit3

In the last section of the model, Figure7e.Arena Simulation Model-Unit4 - Production Begin and Results for Report, the number of Lost Customers, Lost Customer Order Quantity, Fulfilled Customer Number, Fulfilled Customer Order Quantity, Inventory Quantity and Production Quantity and Downtime information recorded daily are reported as output.

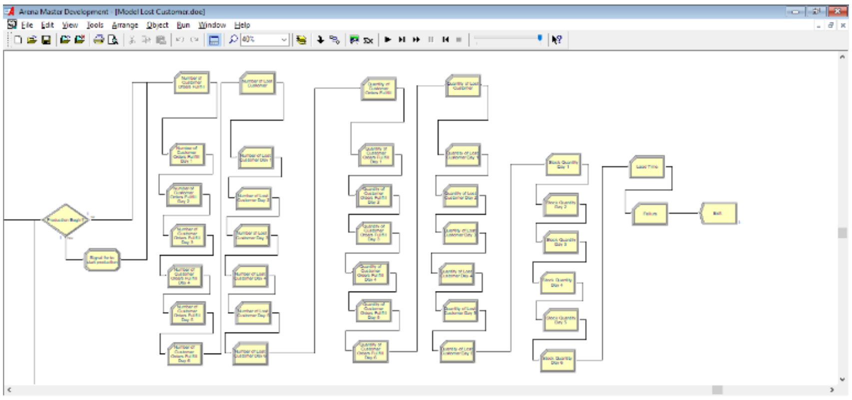


Figure 7e: Arena Simulation Model-Unit4 – Production Begin and Results for Report

4.3 Running the model

The simulation model was run for 6 days with a daily run time of 8 hours. At the beginning of each simulation, the initial stock level was set as 300 units and the faults and repair times in the production process and customer demands were generated according to the statistical distributions obtained by analyzing the available data in Input Analyzer. During the simulation, the number of satisfied customers, the number of unsatisfied customers and the daily stock status were recorded every day.

5. FINDINGS

5.1 Data Analysis

Simulation results are analyzed in terms of the number of lost customers per day and the overall performance of the system. The data obtained were evaluated in relation to inventory levels, production efficiency and customer demands. The results of the analysis were used to identify the effects of bottlenecks, failures and inventory management in the system. This study presents a holistic approach to analyzing the dynamics of the production and inventory system and provides valuable insights for evaluating system performance through simulation analysis.

As a result of the simulation, the number of unfulfilled customer orders per day was calculated and monitored over a period of time to identify the factors that are effective in reducing the number of lost customers from the research questions. These data reflect the ability of the production process and inventory management to meet customer demands. During the simulation, the evolution of inventory levels over time was also monitored. By checking whether the stock level exceeds certain thresholds, the effects of production stoppages and remanufacturing processes are evaluated.

The data obtained by monitoring the number of unfulfilled customers and inventory levels on a daily basis are shown in Table 4.

In the simulation results of the model where all orders are evaluated, the Number of Customer Orders Fullfill is 495, while the Number of Lost Customer is 540 customer orders.

Table 4: Daily Customer Order and Stock Quantity Information

Day	Number of Customer Orders Fullfill	Number of Lost Customer	Quantity of Customer Orders Fullfill	Quantity of Lost Customer	Stock Quantity
Day 1	161	110	64.150	61.575	20.432
Day 2	95	58	28.579	34.916	17.337
Day 3	39	106	22.813	73.206	13.624
Day 4	52	76	30.233	68.768	9.237
Day 5	94	111	56.115	66.317	7.819
Day 6	54	79	26.473	59.853	10.386
Total	**495**	**540**	**228.363**	**364.635**	**78.835**

Since the working period is planned on a weekly plan, it is determined as six days. In the work plan divided into days, the Unfulfilled Customer order on Day 1 is 41% of the total orders for that day. It was observed that this rate tended to decrease in the following days, but reached its peak on the 3rd day with a rate of 73%. On the 4th day, it decreased to 54%.

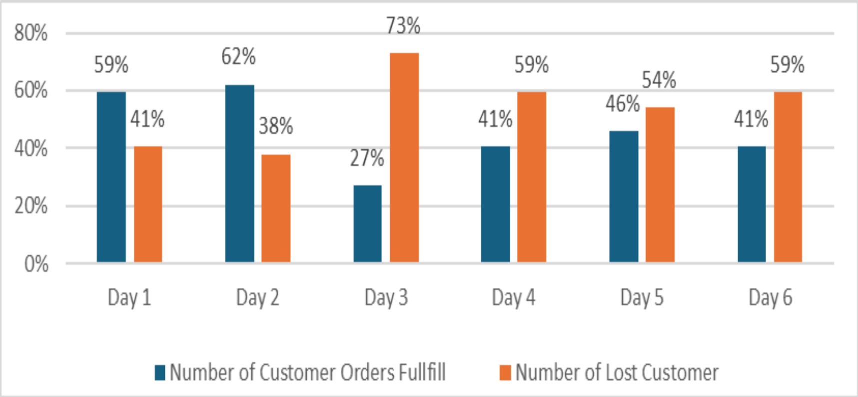


Figure 8: Ratio of Fulfilled Customer Orders to Lost Customer Orders Graph

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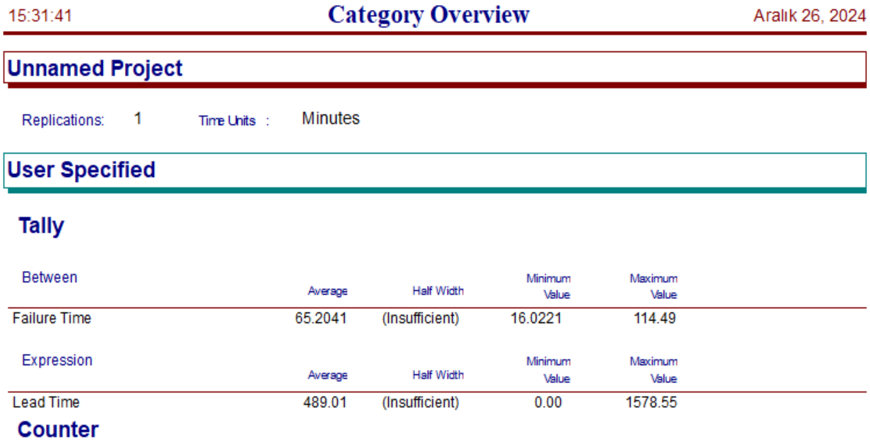
The maximum time in production was 1578.55 minutes. Total downtime was 114.49 minutes.



15:31:41 **Category Overview** Aralık 26, 2024

Unnamed Project

Replications: 1 Time Units : Minutes

User Specified

Tally

Between	Average	Half Width	Minimum Value	Maximum Value
Failure Time	65.2041	(Insufficient)	16.0221	114.49

Expression	Average	Half Width	Minimum Value	Maximum Value
Lead Time	489.01	(Insufficient)	0.00	1578.55

Counter

Figure 9: Production and Downtime Arena Simulation Program Report Results

5.2 Production Efficiency

The simulation results also show the efficiency of the production process. Production efficiency will be assessed by analyzing the number of products produced and the production time. The key data reflecting the efficiency of the production process are given in Table 5. When production is carried out with a single production station, 51.08% of orders cannot be fulfilled. This is a high rate for a manufacturing enterprise.

Table 5: Production Efficiency Table

Total Product Produced	Toplam Üretilen Ürün	307.198 Pieces
Total Order Quantity	Toplam Sipariş Miktarı	592.998 Pieces
Production Success Rate	Üretim Başarı Oranı	51,80%

5.3 Breakdown Times and Their Effects

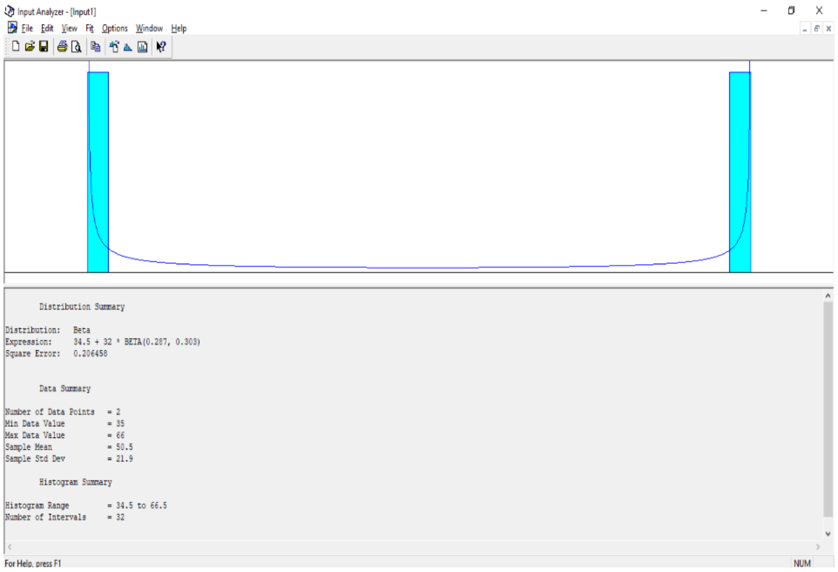
One of the research questions of the study is to determine how the frequency and duration of breakdowns in the production process affect the total production efficiency, and therefore the breakdown times on the machine were evaluated as an important variable during the simulation. The effect of breakdown times on the total process directly affects the production performance. The findings are given in Table 6. As can be seen here, the total breakdown time corresponds to 0.07% of the total production time.

Table 6: Failure Time Table

Total Production Time	1578,55 Min
Total Failure Time	114,49 Min
Total Number of failures	669 Pieces
Failure Frequency	% 0,07

The fault durations included in the model have a significant effect on the overall efficiency of the system. Long fault durations can reduce the overall production capacity by increasing the interruptions in the production process.

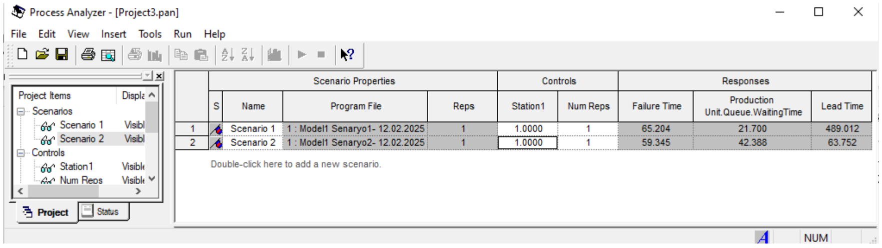
The statistical distribution of the repair duration in the current scenario is 4.5 + 72 * BETA(0.899, 0.729) minutes, the distribution of 34.5 + 32 * BETA(0.287, 0.303) obtained by increasing this distribution, which expresses the uncertainty in the repair process, by 10%, was applied to the model and re-run.



```
       Distribution Summary

Distribution:   Beta
Expression:     34.5 + 32 * BETA(0.287, 0.303)
Square Error:   0.206458


       Data Summary

Number of Data Points   = 2
Min Data Value          = 35
Max Data Value          = 66
Sample Mean             = 50.5
Sample Std Dev          = 21.9

       Histogram Summary

Histogram Range         = 34.5 to 66.5
Number of Intervals     = 32
```

Figure 10: Input Analyzer - Increased Repair Times

When examining the relationship between failure times and delivery times, it has been observed that a 10% increase in repair times reduces failure times in the production line by 9%. Despite doubling the waiting times in the line, it accelerates the average delivery time by 86%. Although the total production waiting time increases, the reduction in delivery times results in an improved ability of the company to respond quickly to its customers. The developed model differs from other models in the existing literature by better representing uncertainties in the system. In particular, the ability to simulate the impact of uncertainties on production performance is one of the most significant innovations of our model. For instance, modeling certain random variables (such as failure rates and demand fluctuations) provides managers with more realistic scenarios, establishing a stronger foundation for strategic decision-making. As a result, flexibility and adaptability in production processes are enhanced. These findings provide valuable insights into the performance of the production and inventory system and contribute to the development of strategies for system improvement.



	S	Name	Program File	Reps	Station1	Num Reps	Failure Time	Production Unit.Queue.WaitingTime	Lead Time
	Scenario Properties				Controls		Responses		
1		Scenario 1	1 : Model1 Senaryo1- 12.02.2025	1	1.0000	1	65.204	21.700	489.012
2		Scenario 2	1 : Model1 Senaryo2- 12.02.2025	1	1.0000	1	59.345	42.388	63.752

Double-click here to add a new scenario.

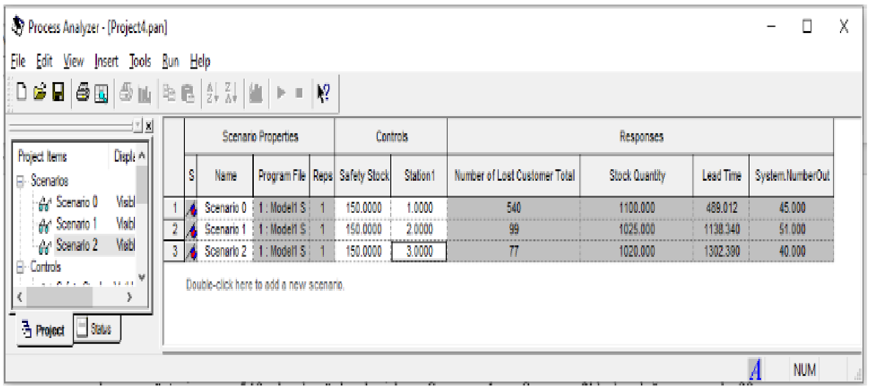
Figure 11: Process Analyzer - The Relationship Between Failure Times and Lead Times

5.4 Experiment with Complex Strategies

This section explains the strategies that can be implemented to optimize the performance of production and inventory systems, addressing one of the research questions. The **Process Analyzer** was used to determine the most effective strategies for increasing system efficiency and to test different scenarios. These analyses serve as a critical guide for achieving sustainable improvements in production and inventory management.

In the first applied strategy, scenario analysis was conducted to reduce customer loss. As shown in **Figure X**, system performance was evaluated for different machine configurations. In **Scenario 0**, the number of lost customers was observed to be **540**, whereas in **Scenario 1** and **Scenario 2**, this value decreased to **99** and **77**, respectively. However, the increase in production capacity led to changes in inventory levels and an extension of **lead time**. The **lead time** increased from **489.012 units** in the single-machine scenario to **1302.390 units** in the three-machine scenario. Additionally, changes in inventory and system outputs were examined.

The results demonstrated that increasing the number of production machines can significantly reduce customer loss. This analysis provides an important decision support tool for evaluating the impact of machine adjustments on customer satisfaction in the production process. In conclusion, while increasing the number of machines to enhance production speed proves advantageous in minimizing customer loss, it also results in an increase in production time. This analysis highlights the necessity of considering inventory management and process optimization when expanding production capacity.

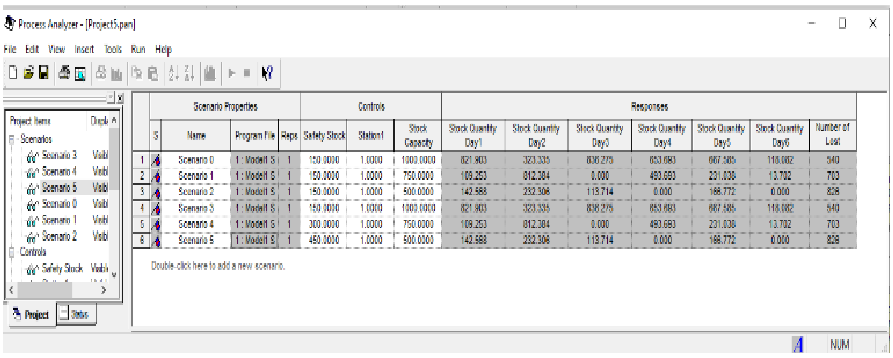


	S	Name	Program File	Reps	Safety Stock	Station1	Number of Lost Customer Total	Stock Quantity	Lead Time	System.NumberOut
	Scenario Properties				Controls		Responses			
1		Scenario 0	1 : Model1 S	1	150.0000	1.0000	540	1100.000	489.012	45.000
2		Scenario 1	1 : Model1 S	1	150.0000	2.0000	99	1025.000	1138.340	51.000
3		Scenario 2	1 : Model1 S	1	150.0000	3.0000	77	1020.000	1302.390	40.000

Double-click here to add a new scenario.

Figure 12: Process Analyzer-Relationship between failure times and lead times

Based on the simulation results, suggestions such as regular monitoring of stock levels, taking measures to reduce bottlenecks in the production process and developing error management strategies were evaluated.



	S	Name	Program File	Reps	Safety Stock	Station1	Stock Capacity	Stock Quantity Day1	Stock Quantity Day2	Stock Quantity Day3	Stock Quantity Day4	Stock Quantity Day5	Stock Quantity Day6	Number of Lost
	Scenario Properties				Controls			Responses						
1		Scenario 0	1 : Model1 S	1	150.0000	1.0000	1000.0000	821.903	323.335	836.275	653.683	667.585	118.082	540
2		Scenario 1	1 : Model1 S	1	150.0000	1.0000	750.0000	109.253	812.384	0.000	493.693	231.838	13.702	703
3		Scenario 2	1 : Model1 S	1	150.0000	1.0000	500.0000	142.588	232.306	113.714	0.000	166.772	0.000	828
4		Scenario 3	1 : Model1 S	1	150.0000	1.0000	1000.0000	821.903	323.335	836.275	653.683	667.585	118.082	540
5		Scenario 4	1 : Model1 S	1	300.0000	1.0000	750.0000	109.253	812.384	0.000	493.693	231.838	13.702	703
6		Scenario 5	1 : Model1 S	1	450.0000	1.0000	500.0000	142.588	232.306	113.714	0.000	166.772	0.000	828

Double-click here to add a new scenario.

Figure 13: Process Analyzer - Inventory Levels and Customer Loss Analysis

In the second strategy, inventory levels were monitored daily, and different scenarios were compared. This analysis examined the impact of inventory capacity and safety stock levels on the number of lost customers.

In Scenario 0, the inventory capacity was set at 1,000 units, with a safety stock level of 150 units. In this scenario, daily stock quantities were evenly distributed, and customer loss was maintained at 540. These results indicate that sufficient inventory capacity can meet a significant portion of customer demand.

In Scenario 1, the inventory capacity was reduced to 750 units, while the safety stock level remained at 150 units. These changes led to stockouts, particularly on days 5 and 6, increasing customer loss to 703. This outcome shows that reduced inventory capacity fails to meet customer demand adequately.

In Scenario 2, the inventory capacity was further reduced to 500 units, with the safety stock level still set at 150 units. In this scenario, stockouts occurred on days 4 and 6, causing customer loss to rise to 826. These results demonstrate that lower inventory levels significantly increase customer losses.

In Scenario 3, the inventory capacity was maintained at 1,000 units, while the safety stock level was increased to 450 units. The daily stock levels followed a distribution similar to Scenario 0, and customer loss remained at 540. This scenario revealed that higher safety stock levels did not provide any additional benefit in reducing customer losses.

In Scenario 4, the inventory capacity was reduced to 750 units, while the safety stock was increased to 450 units. However, similar to Scenario 1, stock shortages still occurred on certain days, resulting in 703 lost customers. This finding suggests that merely increasing safety stock is not sufficient to prevent customer losses.

Finally, in Scenario 5, the inventory capacity was lowered to 500 units, with the safety stock set at 450 units. Due to low inventory levels, stockouts occurred completely on days 4 and 6, leading to a customer loss of 826. This scenario highlights that insufficient inventory capacity makes it highly challenging to meet customer demand.

Overall, high inventory capacity plays a crucial role in minimizing customer loss. Simply increasing safety stock is not enough to reduce customer losses, and lowering inventory capacity below a certain threshold significantly increases customer losses. Therefore, determining an optimal inventory level that can accommodate demand fluctuations is essential in strategic inventory management.

6. CONCLUSION

In this study, the evaluation of simulation models developed for production and inventory systems using the Arena simulation program and the assessment of system performance were examined. Simulation integrates variables such as stock levels, production processes, customer demand, and breakdowns to help develop strategies for more effective process management. The research findings provide critical insights into understanding the impact of uncertainties in the production process, breakdowns, and customer demands on the system.

The first research question addressed in this study is identifying the effective factors in reducing customer loss. For this purpose, the fundamental factors affecting the performance of production and inventory systems were first analyzed. The simulation results indicate that monitoring stock levels regularly and implementing strategies to ensure uninterrupted production processes are necessary to reduce customer loss. In particular, reviewing stock replenishment strategies and minimizing production interruptions are crucial for improving customer satisfaction.

Scenario analysis conducted to explain the relationship between breakdown durations and delivery times revealed that long repair times lead to production breakdowns and negatively impact delivery times. The results show that simulation significantly reduces delivery times. This highlights the practical implications of simulation for better resource allocation and improved operational efficiency in supply chains. Evaluations on breakdown times and customer demands enable businesses to anticipate potential challenges in advance. Especially, enhancing the simulation model's ability to respond to future changes has been identified as a critical requirement in a dynamic production environment. Additionally, analysis of various scenarios showed that increasing the number of production machines significantly reduces customer losses but extends production times.

The third research question investigated how the frequency and duration of production breakdowns affect overall production efficiency. Minimizing breakdown durations and accelerating repair processes emerge as key factors for improving production efficiency. The simulation results clearly reveal the impact of uncertainties in production processes on inventory management and maintenance strategies. The findings provide managers with concrete data for making better strategic decisions and improving operational efficiency. The frequency and duration of production breakdowns directly affect production efficiency, reducing customer demand satisfaction and creating bottlenecks in system performance. Consequently, the most crucial factors for increasing production efficiency are minimizing breakdown times and accelerating repair processes. The simulation results suggest that optimizing downtime can help businesses improve operational efficiency and respond more quickly to customer demands. Furthermore, various scenario analyses indicate that increasing the number of production machines significantly reduces customer losses while extending production times.

The fourth research question explored the strategies that can be recommended to optimize the performance of production and inventory systems. According to the simulation results, strategies for regularly tracking inventory levels and ensuring uninterrupted production processes should be implemented to reduce customer loss. In particular, reviewing stock replenishment strategies and minimizing production disruptions are critical for increasing customer satisfaction. Analyses conducted to optimize the performance of production and inventory systems evaluated different scenarios to reduce customer loss and improve process efficiency. Increasing the number of production machines significantly reduces customer loss but leads to an extension of production time. From an inventory management perspective, it was observed that reducing stock capacity below a certain level increases customer losses, and simply increasing safety stock is not sufficient to prevent losses. Determining optimal inventory levels to prevent stockouts and meet customer demand appears to be a critical strategy. As a result, production capacity and inventory management should be balanced and strategies should be implemented to prevent bottlenecks in the processes.

Future studies may examine more complex production and inventory systems and allow the application of simulation techniques across different scenarios. Additionally, the findings of this study contribute to advancing the literature by presenting an integrated model that analyzes the impact of uncertainty on production systems in greater depth. Investigating applications across various industries and examining the effects of variables more comprehensively can serve as a guide for future research to enhance the generalizability of simulation models. Ultimately, this study contributes to understanding the complex dynamics of production and inventory systems and provides the decision-support tools necessary for companies to optimize their processes. By leveraging simulation technology more extensively in production management, companies can enhance their competitive advantage and develop more sustainable operational strategies for the future.

REFERENCES

Al-Khazraji, H., Cole, C., & Guo, W. (2021). Optimization and Simulation of Dynamic Performance of Production–Inventory Systems with Multivariable Controls. *Mathematics*, *9*(5). https://doi.org/10.3390/math9050568

Hosseinitabar, S. A., Sabouhi, F., & Bozorgi-Amiri, A. (2024). A resilient biofuel supply chain design based on Paulownia and Jatropha under uncertainty considering the water-energy nexus. *Industrial Crops and Products*, *222*. https://doi.org/10.1016/j.indcrop.2024.119607

Ma, M., Hu, L., Wang, L., & Yu, X. (2025). Stochastic modeling and optimization of discrete-time cold standby repairable systems with unreliable repair facility and retrial mechanism. *Journal of Computational and Applied Mathematics*, *453*. https://doi.org/10.1016/j.cam.2024.116134

Mahmoudi, F., Eshghi, A., Basirati, M., & Hassannayebi, E. (2023). A Simulation Optimization Approach to Inventory Optimization in Supply Chain Networks. In *Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures* (pp. 374-384). https://doi.org/10.1007/978-3-031-43670-3_26

Maitra, S. (2024). Inventory Management Under Stochastic Demand: A Simulation-Optimization Approach. https://doi.org/10.48550/arXiv.2406.19425

Oljira, D. G., Abeya, T. G., Ofgera, G., & Gopal, M. (2020). Manufacturing System Modeling and Performance Analysis of Mineral Water Production Line using ARENA Simulation. *International Journal of Engineering and Advanced Technology (IJEAT)*, *9* (5), 312-317. https://doi.org/10.35940/ijeat.D8033.069520

Patole, S. (2024). Using Simulation software Rockwell Arena for effective teaching of Value Stream Mapping in Undergraduate Lean Six Sigma Class. *The Future of Engineering Education*. https://doi.org/10.18260/1-2--48241

Peng, S., Li, T., Zhao, J., Guo, Y., Lv, S., Tan, G. Z., & Zhang, H. (2019). Petri net-based scheduling strategy and energy modeling for the cylinder block remanufacturing under uncertainty. *Robotics and Computer-Integrated Manufacturing*, *58*, 208-219. https://doi.org/10.1016/j.rcim.2019.03.004

Priyamvada, & Kumar, A. (2022). Modelling retail inventory pricing policies under service level and promotional efforts during COVID-19. *J Clean Prod*, *381*, 134784. https://doi.org/10.1016/j.jclepro.2022.134784

Salahi, N., & Jafari, M. A. (2016). Energy-Performance as a driver for optimal production planning. *Applied Energy*, *174*, 88-100. https://doi.org/10.1016/j.apenergy.2016.04.085

Sarwar, M., Akram, M., & Liu, P. (2021). An integrated rough ELECTRE II approach for risk evaluation and effects analysis in automatic manufacturing process. *Artificial Intelligence Review*, *54*(6), 4449-4481. https://doi.org/10.1007/s10462-021-10003-5

Vidal, G. H. (2022). Deterministic and Stochastic İnventory Models in Production Systems: a Review of the Literature. *Process Integration and Optimization for Sustainability*, *7*(1-2), 29-50. https://doi.org/10.1007/s41660-022-00299-3

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