Journal of Optimization and Supply Chain Management

JOSCM

2025, Volume xx, Issue xx, pp. xx-xx
ISSN-Print: 3079-1022
ISSN-Online: 3079-1030
https://joscm.refconf.com

Production-Energy Mode Control and Decision Support System Development for Assemble-to-Order Systems

Fuat Emre Zengin [a*], Eylül Akcanb [b], İrem Geyik [b], Mevlüt Furkan Yılmaz [b], Neslihan Güner [b], Onur Deda [b] and Sinem Özkan [b]

[a] *Graduate School of Natural and Applied Sciences, İzmir Democracy University, İzmir, Turkey*
[b] *Department of Industrial Engineering, Faculty of Engineering, İzmir Democracy University, İzmir, Turkey*

Abstract

Cost management is vital in today's competitive business environment. Achieving a balance between energy and inventory management is essential for sustainable production and economic growth. This study examines an assemble-to-order system with multiple products, components, and customer types. Assemble-to-order is a strategy where components are pre-stocked and assembled into the final product once an order is received. In this system, machines producing semi-finished products operate in different energy modes with varying energy consumption. For this system, we optimize the parameters of production and order control policies that are both user-friendly and efficient. The goal is to determine which machines should produce the semi-finished products, in which energy modes, and when production should begin as inventory levels drop. Similarly, we establish when and how much to reorder when inventory levels of semi-finished products fall. Additionally, because there are multiple customer types for each final product, different allocation policies are analyzed to optimize the allocation of finished products. A general simulation model has been developed to support these analyses, designed to accommodate the system's complexity and facilitate experimental study of its structure. Finally, a decision support system is developed by adapting the simulation model to meet user requirements, allowing for practical application and further system optimization. The numerical results reveal that as customers' tolerance limits increase, average total costs rise due to higher waiting costs. In contrast, lost sales costs decrease as more time is available to fulfill demand. Additionally, On-Idle modes are more cost-effective when customer arrivals are frequent, whereas On-Off modes perform better when arrivals are less frequent. These insights highlight the importance of dynamically selecting energy modes based on demand patterns to achieve cost efficiency and improved service levels.

Keywords: Assemble-to-Order; Production-Energy Mode Control; Simulation; Decision Support System.

1 Introduction

The importance of assembly lines and assembly-based production systems has grown exponentially, particularly in sectors such as the automotive industry, where they have become indispensable. These systems, first introduced by Henry Ford, continue revolutionizing manufacturing today. One widely adopted approach is the assemble-to-order system, where manufacturers hold components in inventory and assemble final products only after receiving customer orders. This method offers numerous advantages: a component can be used in multiple final products, and final products may require varying subsets of components. Companies can reduce lead times and meet a wide range of customer needs by maintaining stock at the component level and assembling products based on customer demand.

*Corresponding author email address: 2417110007@std.idu.edu.tr
DOI: 10.22034/ISS.2025.8317.1018

Assemble-to-order systems are especially advantageous because of two key characteristics. First, component replenishment times are typically longer than final assembly times, meaning that holding component stock eliminates much of the delay associated with component production. Second, the commonality of components across different products creates economies of scale, reducing both inventory levels and overall costs through risk pooling. Additionally, this strategy is particularly suited to environments with short product life cycles, where holding finished goods inventory could lead to waste due to obsolescence. The flexibility of assemble-to-order systems allows manufacturers to respond quickly to diverse customer demands, making it an attractive strategy in many industries.

Production control policies are crucial in managing production processes and optimizing inventory levels in these systems. One common strategy is the (s, S) policy, where production starts when inventory falls to a certain level (s) and stops when it reaches an upper threshold (S). Another approach is the base stock policy, a particular case of (s, S), where s=(S-1). Similarly, the (Q, r) policy is used to manage orders, where a fixed quantity (Q) is ordered once inventory reaches a threshold (r). These policies enable businesses to maintain efficient inventory management, adapting to fluctuations in demand while controlling costs.

In addition to production control, component allocation policies are vital for ensuring that components are used efficiently in the assembly process. These policies allocate components based on order specifications, minimizing errors, optimizing inventory usage, and enhancing flexibility. This, in turn, allows manufacturers to respond quickly to changes and ensures higher production quality while keeping costs low. Effective component allocation is key to improving overall business competitiveness and customer satisfaction.

The assemble-to-order system is widely used in electronics, furniture, and automotive manufacturing industries. Notably, Eiji Toyoda and Taiichi Ohno of Toyota Motor Company introduced the concept of just-in-time (JIT) manufacturing in the 1970s, which shares similarities with assemble-to-order systems. The core principle of JIT is to minimize waste by maintaining low inventory levels and producing goods only when there is demand, resulting in reduced costs and more efficient use of resources. JIT’s focus on continuous improvement and flexibility has made it a benchmark for lean production processes. Companies like Dell Technologies have successfully implemented the assemble-to-order model. Dell allows customers to customize personal computers by choosing various components such as CPUs, monitors, and processors. Once an order is placed, the product is assembled and shipped, exemplifying the efficiency and customer-centric approach of assemble-to-order systems. In manpower-driven assembly lines, such as those found in the textile and automotive industries, variability in worker performance can significantly affect production outcomes. In these contexts, relying solely on deterministic models may lead to inaccurate results, underscoring the need for more comprehensive and realistic assumptions in system modeling.

Specifically, this study focuses on evaluating the performance of assemble-to-order systems in the context of production-inventory control policies, emphasizing customer prioritization based on lost sales costs. Furthermore, the study explores the impact of stochastic variations in production and demand lead times on the performance of these policies. A distinguishing feature of this research is its incorporation of different energy modes and energy costs, an aspect not widely addressed in the existing literature on assemble-to-order systems.

By developing a simulation model, the study provides a perspective on solving complex production and order management problems with real-world applicability. The insights gained from this study will help businesses optimize their production and ordering processes, ultimately contributing to improved efficiency and competitiveness.

The structure of this paper is as follows: Section 2 provides a literature review. Section 3 introduces the definition of the problem and its assumptions. Section 4 describes the production control policies and the simulation model. Section 5 presents a decision support system based on user input values. Finally, Section 6 concludes with numerical results and analysis.

2 Literature Review

To analyze the evolution of assemble-to-order systems over the years, we examined articles published from 2003 to the present. Table 1 summarizes key features common to the reviewed articles, including component status, component allocation policies used to assign components to final products, the distribution of random variables, costs incurred when customer demand is not met on time (e.g., backordering/lost sales), the type of optimization used as the objective function, assembly time structures, methods applied, and energy usage.

In today's global business environment, increasing competition and rapidly evolving technological dynamics highlight the importance of collaboration and innovation. In this context, component partnerships have emerged in the literature as a strategic form of collaboration that allows organizations to combine their strengths and gain a competitive advantage. This has motivated researchers to classify systems according to the degree of component commonality, the number of components, and system configurations influenced by final products. For example, ElHafsi et al. (2017) examines factors such as time-varying lead times, random demand arrival, and lost sales to gain a more comprehensive understanding of assembly system performance. In particular, the study analyzes the effects of W-configuration orders on assembly systems.

This research seeks to reveal the potential impact of continuous-time dynamics on the efficiency and performance of the assembly process. For instance, Nadar et al. (2014) analyzes the M-system, which consists of two components and three final products. One final product is assembled from both components, while the other two products are made from one of the components. In comparison, the N-system involves two components and two final products, where one product is assembled from both components and the other from one component. The objective in both systems is to minimize the expected long-run average cost under linear holding and procurement costs for components, as well as linear delay costs for final products. Both the N- and W-systems share a common component between two final products, while the other components are unique to each product. The M-system differs in that it has three products sharing two common components. The systems are named according to the shapes of their configurations.

The "First Come, First Served (FCFS)" policy is recognized as an effective strategy, particularly in inventory management and material flow processes. This strategy ensures that items in inventory are processed in the order they were received. Many assemble-to-order systems manage the inventory of common components according to customer demand and use the FCFS allocation rule. Jin et al. (2021) introduces a framework for handling heterogeneous demand, using closed-form expressions to investigate the performance of the IWTP policy under conditions of component scarcity and demand variability. Similarly, Jaarsveld and Wolf (2015) developed a stochastic programming (SP) algorithm focused on the FCFS allocation of components to products. However, other allocation policies have also been proposed in the literature. The NHB allocation rule, for example, allocates a component to product demand only when it ensures immediate fulfillment. Lu et al. (2015) examines the NHB and CBS (Coordinated Base Stock) policies to develop heuristic approaches for systems with asymmetric costs.

A distinguishing feature of assemble-to-order systems is that multiple customer classes may demand the same final product, but the cost of losing some customers is higher than others. As a result, orders from lower-cost customer classes are sometimes rejected to prioritize high-cost customers, even when components are available. This strategy, known as "rationing," ensures that high-value customers are not lost. Another focus of research is the development of inventory allocation policies for different customer types to determine effective inventory thresholds. Reiman and Wang (2015) shows that the optimal production policy for a component is typically base stock, depending on the inventory of other components. Additionally, the optimal inventory allocation policy is often a multi-level rationing strategy, with rationing levels determined by the inventory of all components.

Base stock policies maintain the inventory position of each component—accounting for both on-hand and backordered stock—at a constant level to clear the backlog. For example, ElHafsi et al. (2008) examines a system in which components are stocked before demand arrives, with holding costs incurred per unit of time. Demands follow a Poisson process, and orders are continuously placed for each product. The demand is met if all components are in stock; otherwise, it results in lost sales. Managers must decide when to produce a component and whether to fulfill an incoming product order from stock. Assembly time, often considered negligible in the literature, refers to the total time required to complete production operations.

Table 1. Summary of the related studies

Articles	Component Commonality (Yes/No)	Component Allocation Policy	Distributions of Random Variables	Backorder (B) / Lost Sale (L)	Optimization Type	Assemble Time	Applied Methods	Energy Use	Applied Energy Policy
Saracalıoglu et al. (2022)	Yes	Stock Rationing	Production and Delivery Time: Erlang k	L	Inventory Optimization	Negligible	Genetic Algorithms and Simulation	No	No
Jin and Wang (2021)	Yes	FCFS	Demand for the Product: Poisson	B	Order-Based Backorders and Order Fulfillment Rate	Negligible	Simulation and Modeling	No	No
Atan et al. (2017)	Yes	Continuous Review and Periodic Review	Demand for the Product: Poisson, Production Times: Exponential	L	Minimum Cost and High Level of Customer Service	Negligible	Markov Decision Chain and Queueing Theory	No	No
Fu et al. (2011)	No	FCFS	Arrival of Requests: Poisson, Processing Times: Exponential	B	System Optimization	Negligible	Upper and Lower Bound Method, Matrix-Geometric Approach	No	No
Jaarsveld and Wolf (2015)	Yes	FCFS	Demand for the Product: Poisson	B	Minimization of Component Availability and Product Backorder Costs	Negligible	Simulation	No	No
Nadar et al. (2014)	Yes	Stock Rationing	Demand for the Product: Poisson, Production Times: Exponential	L	Optimization of Stock Replenishment and Allocation Policies	Negligible	Markov Decision Chain	No	No
Elhafsi and Camus (2008)	Yes	Base Stock Policy	Demand for the Product: Poisson, Production Times: Exponential	L	Optimization of Production and Stock Allocation Policy	Negligible	Markov Decision Chain	No	No
Lu et al. (2003)	Yes	FCFS and Base Stock Policy	Component Lead Times: Exponential	B	Minimization of Unfulfilled Orders	Negligible	Simulation	No	No
Lu et al. (2015)	Yes	NHB Allocation Rule	Continuous Distribution	L	Optimal Control Policies for The Made-to-Order Assembly System	Negligible	Example Path Analysis, Linear Programming	No	No
Reiman (2015)	Yes	Dynamic Stock Rationing	Demand : Stochastic, Production Times: Stochastic	B and L	Cost of Holding in Inventory	Yes (Stochastic)	Asymptotic	No	No
Chen et al. (2021)	Yes	Dynamic Stock Rationing	Demand: Poisson	B and L	Inventory Policy	Yes	Heuristic Methods	No	No
ElHafsi et al. (2017)	Yes	Stock Rationing	Delivery Time: Normal Distribution, Demand: Exponential Distribution	L	Optimal Component Allocation Policy	Yes (Erlang)	Heuristic Methods	No	No
Nadar et al. (2018)	Yes	Dynamic Stock Rationing	Delivery Time: Deterministic, Demand: Stochastic	B and L	Optimal Component Allocation Policy	Negligible	Heuristic Methods	No	No

Simulation, the process of creating models replicating real-world systems or processes, offers various benefits such as cost and time savings, optimization, scenario testing, and the ability to model stochastic systems. Several studies, among those reviewed, have used simulation models. Saracalıoğlu et al. (2022) developed a flexible simulation model that could be adapted to various configurations, allowing researchers to experiment with different system structures.

Markov decision processes are commonly used to solve decision problems by modeling systems and helping decision-makers select optimal actions. Nadar et al. (2014) modeled an assemble-to-order system as a Markov decision process with an infinite time horizon. This mathematical framework allows for analyzing states and transitions between them governed by a certain probability distribution. The goal is to determine the optimal policy for producing components and meeting product demand. Similarly, ElHafsi et al. (2008) uses Markov decision processes to show that the optimal production policy for each component depends on the system's state, leading to the generation of a base stock policy. Dadaneh et al. (2023) explores the complexities of production planning and inventory management in environments characterized by demand uncertainty. Their research incorporates a wide range of assumptions, including multiple regions, suppliers, components, products, and time periods.

Nicla Frigerio et al. (2024) addresses the challenge of incorporating switch-off and switch-on modes for machines, focusing on determining the optimal times to switch machines on and off. Their study proposed a buffer-based threshold policy for a serial production line with multiple machines, aiming to enhance energy efficiency. Ozkan and Tan (2025) focused on optimizing energy consumption and inventory control in make-to-stock systems. In their work, they examine a problem involving holding costs, backorder costs, and energy consumption costs. They optimize costs and energy usage by determining the operational modes (busy, idle, turned-off, set-up) of the server at certain times. Tan and Karabag (2024) managed the energy policies of a single machine system in deterministic processes. The machine in the system can operate in four different energy modes: running, off, warming and idle. The study aims to develop an optimum control system to meet production targets while minimizing energy consumption.

As shown in the table, the topic of energy consumption has only recently begun to gain attention in the literature on assemble-to-order systems. Tan et al. (2023) notes in their study that energy efficiency in manufacturing can be improved by dynamically controlling energy modes and production processes. They examine a make-to-stock system that operates in on, idle, and off-energy modes, with costs varying based on the mode. In their optimal policy structure, two thresholds were used to determine both production and energy control policies, allowing for transitions between on, idle, and off modes. In our study, we analyze the performance of assemble-to-order systems using the energy mode control policies proposed in Tan et al. (2023).

This study aims to incorporate energy considerations into assemble-to-order systems by modeling machines with specific energy modes (on, idle, off) and determining the most efficient operating modes.

3 Problem Definition

The primary goal of this study is to provide a detailed perspective on production, inventory, and energy control for assemble-to-order systems. The significance of efficient production and inventory processes is increasing in today's competitive industry. Companies focus on minimizing production and storage costs to maintain a competitive edge. This study aims to minimize cost by examining these processes under specific assumptions.

We focus on production-inventory control with consideration of energy efficiency in W-type assembly systems, as illustrated in Figure 1. A W-type assembly system involves the production of two distinct final products using three different components. In our analysis, two of these components are manufactured within the system, while the third is sourced externally. The system operates with a single machine responsible for component production. Final Product 1 requires Components C and D, while Final Product 2 requires Components D and E, with Component D acting as a common component between the two products.

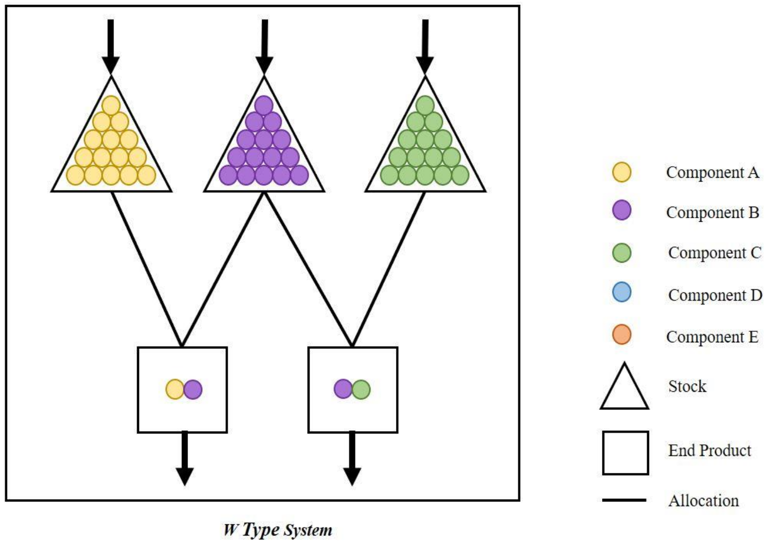


Figure 1. A W-type assemble-to-order system

W-type systems are particularly effective for heavy-load transportation, preventing component separation during transit. These systems are commonly employed in the automotive industry, where they are used to assemble complex parts such as transmissions, engine blocks, and differentials. The widespread application of W-type systems underscores their reliability and efficiency in handling complex product assemblies.

In the following of this section, we first explain the sub-problems we address and the assumptions in order.

3.1 Sub-Problems of Assemble-To-Order Systems

This paper addresses three main problems, with different parameters studied under specific assumptions: (1) production and supply control considering energy efficiency in the production of semi-finished components, (2) allocation of final products for different customer classes, and (3) component allocation to the final product.

Production and Supply Control Considering Energy Efficiency of Components. One of the key challenges in assemble-to-order systems is determining the right production and inventory policies. This study applies the (s, S) policy for component production. When the inventory level drops to s, production starts and stops when the level reaches S. For externally sourced components, the (Q, r) policy is used. In this policy, when the inventory position of a component reaches the reorder point r, the component is replenished by ordering a lot size of Q.

Allocation of Final Products for Different Customer Classes. Different customer classes exist for final products, requiring specific allocation strategies. Two rationing options are considered:

Static Rationing. Customer classes have fixed rationing levels for components. Here, rationing levels are based only on stock levels. If the stock is at or above the critical level for a customer class, its demand is fulfilled; otherwise, it is not.

Dynamic Rationing. This policy uses information on the status of replenishment orders and adjusts the rationing levels for each customer class dynamically as state variables (e.g., the number of active production lines) change.

Component Allocation to Final Product. Prioritization and ranking criteria are used in this method. Customers have varying tolerance limits. If a customer's tolerance limit is zero and their order is not fulfilled immediately, a lost sales cost is incurred. If the tolerance limit exceeds zero, the customer waits, and the waiting cost is incurred until the demand is fulfilled; if this limit is exceeded, a lost sales cost is incurred.

3.2 Problem Assumptions

- Final products share common components.
- Multiple components exist in the system, with some produced as semi-finished products and others procured from external suppliers.
- For semi-finished components, production begins when inventory drops to s and continues until it reaches S.
- For externally sourced components, orders are placed when inventory drops to r and replenished with a lot of Q size.
- Production and supply times for components are stochastic.
- There is only one machine in the system.
- Assembly times are considered negligible.
- Customer demand is variable and follows a random distribution, arriving one at a time.
- Customers have tolerance limits. If the limit is 0, lost sales costs are incurred if the demand is not met immediately.
- If sufficient stock is available, demand is fulfilled directly; otherwise, customers wait until their demand is met or exit the system as lost sales if their tolerance time is exceeded.
- Each customer has a specific lost sales cost.
- The machines in the system operate in three modes: On, Idle, and Off.
- The system includes various costs: holding costs, production startup costs, lost sales costs, customer waiting costs, order costs, and energy costs (based on machine operating modes: on, idle, or off).

In this system, where all assumptions are considered together, the goal is to manage and optimize variables such as customer demand, inventory levels, costs, and machine energy status in a balanced way.

4 Model

This study uses the simulation method to analyze the assemble-to-order system, which shares characteristics with real-world assembly systems. Simulation models of stochastic assemble-to-order systems are developed to understand, optimize, and evaluate real-life assembly processes. Demand is often uncertain in such systems, and customer orders arrive randomly. Simulation models address these uncertainties and allow system performance evaluation under various scenarios. Additionally, they provide the advantage of analyzing how different production strategies and inventory policies will impact the system.

Through simulation, businesses can develop optimized solutions for improved inventory management, delivery processes, and overall system performance. Simulation is a powerful tool for understanding and continuously improving the complexities of stochastic assemble-to-order systems while also provides an opportunity to assess critical factors such as cost efficiency and customer satisfaction. Therefore, simulation models of stochastic assemble-to-order systems are indispensable for successfully operating in real-world conditions and gaining a competitive advantage. This study uses the simulation method as the modeling approach for these reasons.

A simulation model has been developed for an assemble-to-order system that incorporates the abovementioned assumptions and shares characteristics with real-world assembly systems. The model was designed using Arena simulation software. A steady-state analysis was conducted to optimize the average total cost, and the results were examined until they were stable to two decimal places. Therefore, the results were evaluated using a single replication.

Figure 2 shows the entry of customers into the system. Customers enter the system with a certain random distribution. First, lost sales cost and waiting tolerance limit of the customer entering the system are determined. Then, customers continue to the system from one branch of the simulation model according to the product they demand.

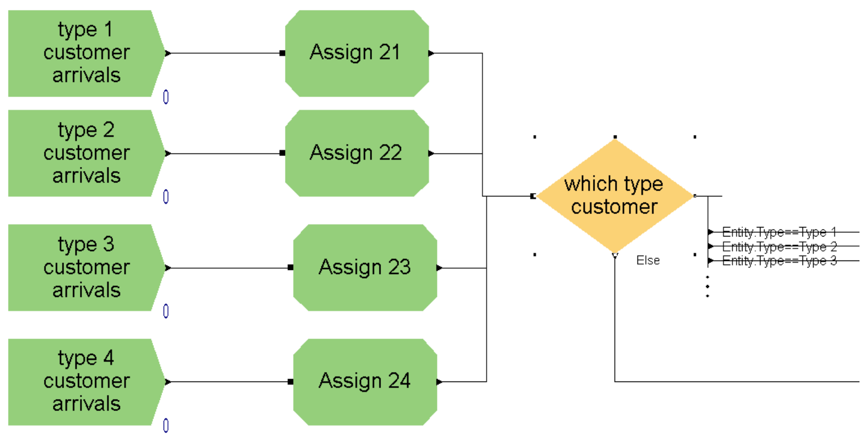


Figure 2. Customer arrivals for different types of products

In Figure 3, once customers are categorized into different types according to their demands, the current stock levels of the components required to create the product requested by each customer are meticulously checked. Suppose it is determined that the relevant components are in stock in sufficient quantities. In that case, the required components are deducted from the inventory, and the requested product is quickly prepared and included in the process to be delivered to the customer. The customer exits the system once the product is delivered and the process is completed. However, in cases where stock levels are insufficient, the customer is put on hold for a certain period within the waiting tolerance limits defined in the system. Suppose the stocks are replenished, and the product can be produced during this waiting period. In that case, the relevant components are deducted from the stock, the customer demand is met, and the customer exits the system. However, suppose the demand cannot be met during this period. In that case, the customer exits the system without receiving the product, and this transaction is recorded as lost sales, and the process is terminated.

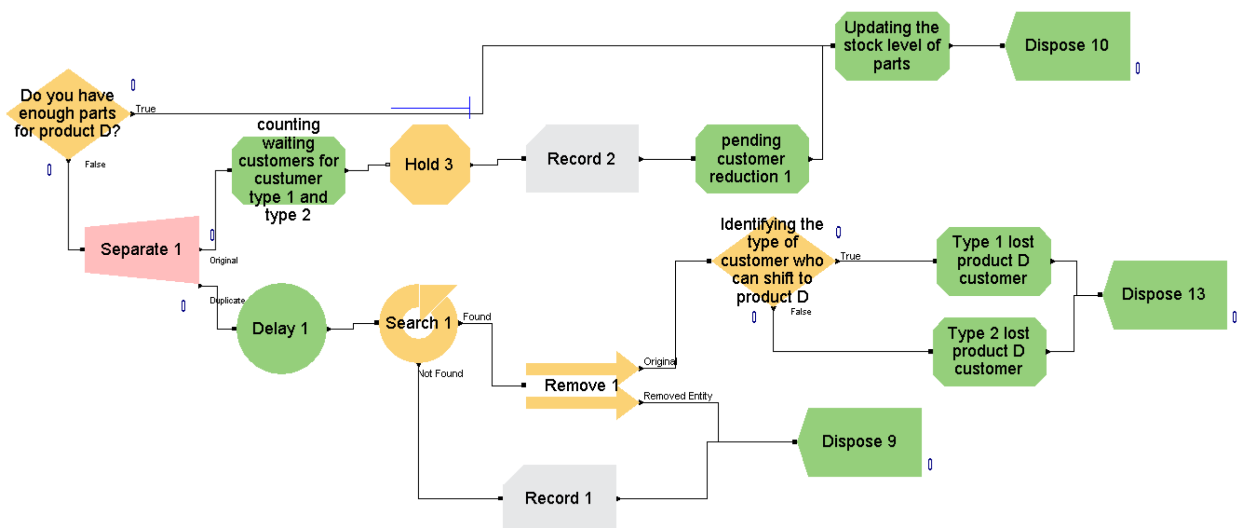


Figure 3. Meeting customers' demands for product D

In Figure 4, the procurement and production of product components are integrated into the simulation model through an Excel file. The components are included in the system according to (s, S) policies if they are produced and according to (r, Q) policies if they are outsourced. These (s, S) and (r, Q) values are determined by the decision support system user based on data entered into Excel. A module in the Arena Rockwell program reads this data and classifies the components according to their type. The system is then simulated based on the data from Excel.

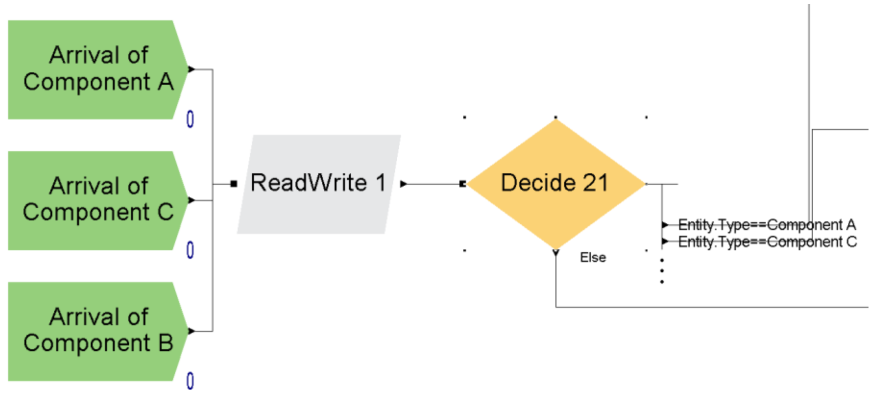


Figure 4. Arrivals of components

As shown in Figure 5, the production process is integrated into the simulation model in detail. According to this model, incoming components to the system are stored in a predetermined module, and a continuous inventory is monitored. When the stock level of each component falls below certain thresholds of s or r levels, the production process of the relevant component is initiated. Specific rules and conditions govern the production process; for example, it cannot simultaneously produce more than one component. If the production of one component is already in progress or preparations are being made for that component, the production of another component cannot be started. However, when all the conditions for production are met, and there are no other inhibiting factors, the production process of the relevant component starts. This production process continues without interruption until the stock level exceeds the set maximum level S.

On the other hand, a different process is followed for outsourced components. If the stock level of these components falls below r, the system automatically orders Q units for this component. However, including these components is not immediate; they are added to the system after a stochastically determined period. These outsourcing and production processes continue continuously and dynamically until the end of the simulation period. Maintaining accurate stock levels for each component in the system is critical for the successful operation of the simulation model.

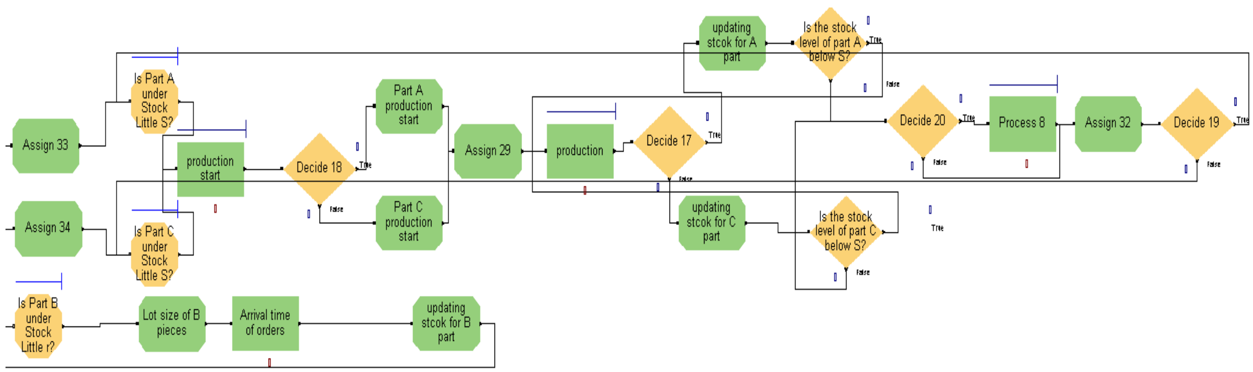


Figure 5. Production and Order Area

5 Decision Support System

A Decision Support System (DSS) is a computer-based system that provides information and analytical tools to assist users in complex decision-making processes. These systems collect and process data and provide meaningful reports or recommendations. DSSs help users make data-driven decisions, enabling them to achieve more effective and efficient results. They accelerate decision-making processes, reduce risks, improve performance and provide flexibility.

Arena Simulation program is used to model complex systems and evaluate the performance of these systems. Changing parameters using Excel in the Arena Simulation program provides a user-friendly interface, enables fast updates, facilitates data visualization and management, reduces errors and makes the program more accessible.

In this study, the control parameters defined in the Arena Simulation program are defined in an Excel file and the user is asked to enter values for these parameters. In the interface created, the values entered for the parameters ("Q" value, "r" value, "S" value for component A, "s" value for component A, "S" value for component C, "s" value for component C) are saved to the Excel file as CSV extension. The file is integrated into the model with the "File" command in the Arena program. Another command, "ReadWrite", performs the function of reading data from and writing data to files. This command allows reading data from a file or writing data generated during simulation to a file. Finally, when the model is run, the parameters are updated and it can be observed how the values entered by the user create changes in the model outputs. Figure 6 shows an example of Arena and Excel working in an integrated way.

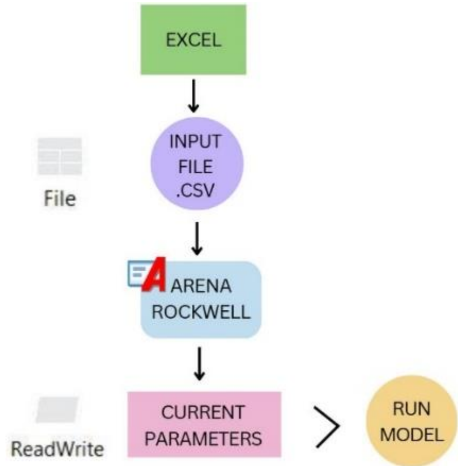


Figure 6. Explanation of how the decision support system works

In today's companies, users who do not know how to use the Arena program can easily enter values for control parameters via Excel files. These values are instantly applied to the simulation model, allowing users to quickly test different scenarios and parameter changes. This approach enables companies to effectively use simulation tools with a broader user base, increasing operational efficiency and optimizing decision-making processes. In addition, the automation and integration features provided by DSS allow users to obtain accurate and reliable results without requiring modeling and simulation knowledge. This reduces training and development costs for companies while increasing the accuracy and speed of simulation processes.

6 Numerical Results

Numerical studies were conducted to see the system's functioning developed to help businesses manage their production and ordering processes more efficiently and test its accuracy. In this context, a comprehensive analysis was carried out considering the interaction of various variables in the study.

Figure 7 shows the costs that arise as customers' tolerance limits increase. We see that the average total cost graph increases as the tolerance limits increase. The average total cost increases as the customers' tolerance limits increase because waiting costs are more involved. Again, as the tolerance limits of the customers increase, the total lost sales costs are observed to decrease because there is more time to meet the customer's demand as the limit increases.

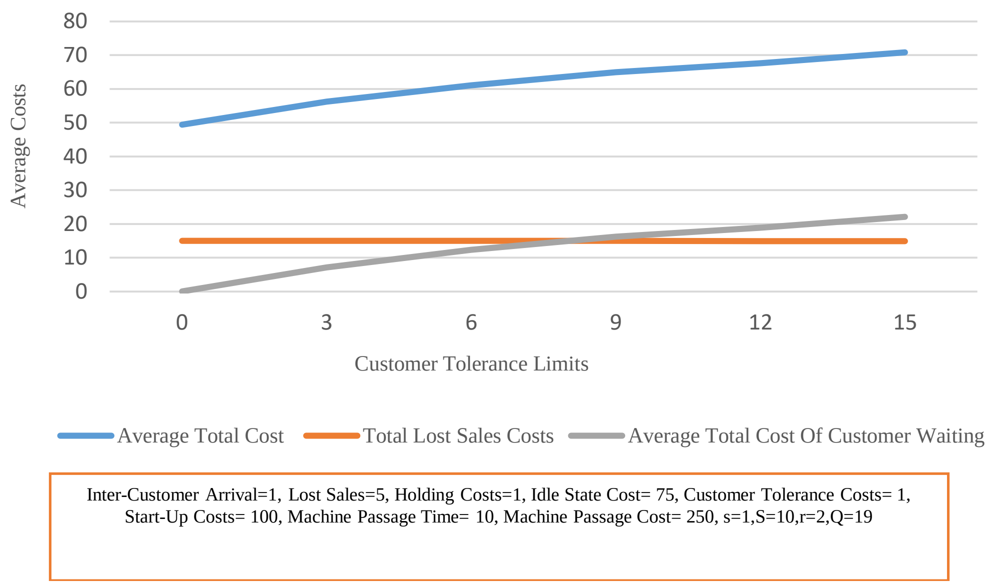
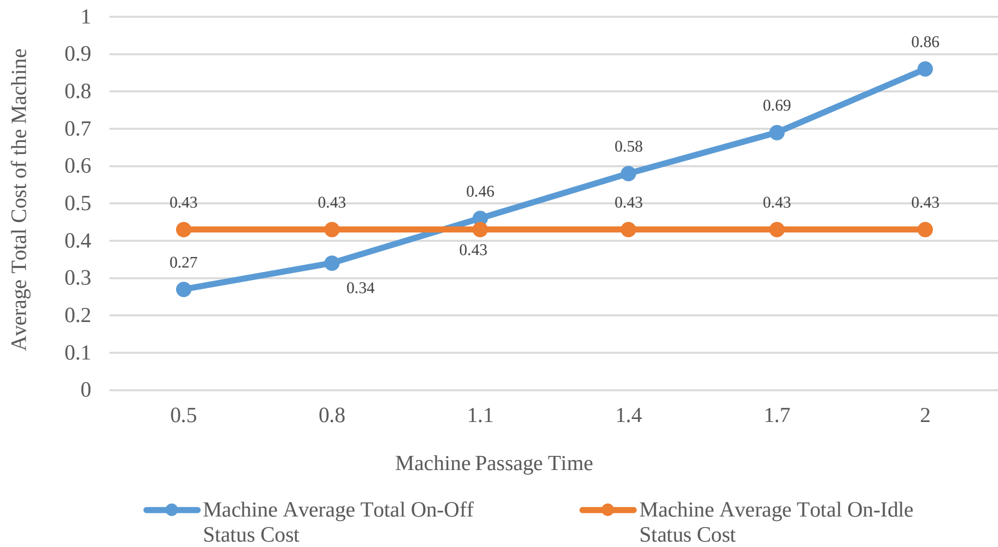


Figure 7. Average cost according to customers' tolerance limits

In Figure 8, On-Off and On-Idle modes are analyzed according to the change in the machine's transition times. Costs increase in the On-Off case when the passage times of the machine increase. There is no change in On-Idle costs. When the machine is On-Idle, no transit time is processed. Therefore, there is no change in On-Idle costs.

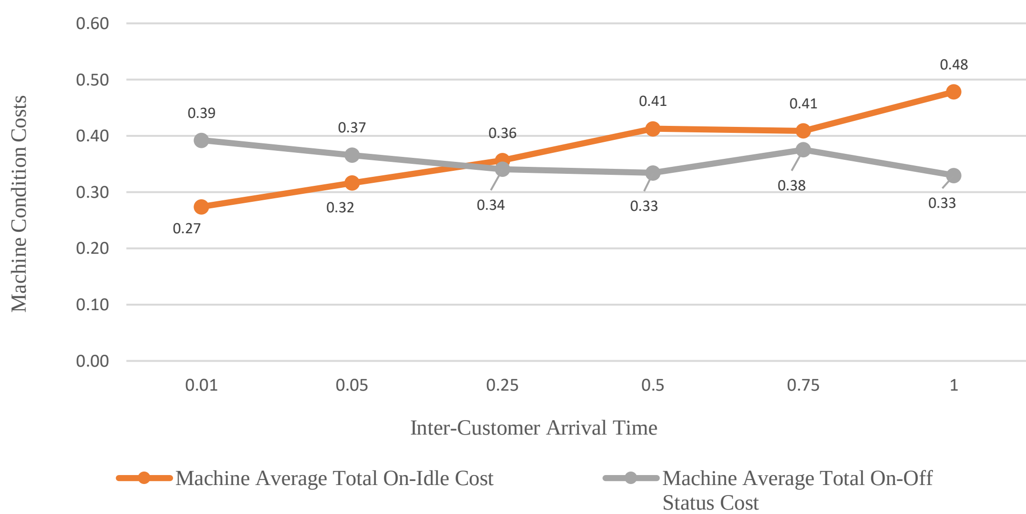
Figure 9 shows which energy mode works better for the machine according to the arrival rate of the customers. According to the figure, it is observed that as the arrival time between customers decreases, i.e. when customers start to arrive more frequently, On-Idle state costs give better results than On-Off state costs. As the inter-customer arrival times increase, i.e. when customers enter the system less frequently, the On-Off case is more advantageous than the On-Idle case. This is because when customers come to the system less, the machine stays in Idle state more. Therefore, Idle state costs come into play more. When customers come to the system more frequently, the machine is in Idle state less, and Idle state costs are more advantageous in this scenario.

Figure 10 shows the graph of customers who waited and received the final product according to their tolerance limits. According to the results, we see that as the tolerance limits of the customers increase, the rate of customers whose demand is met after waiting increases. At the same time, while the increase rate is constant, the increase in the number of customers whose demand is met gradually decreases. The reason for this is that there is only one machine in the system and the machine produces only one component at any time in the simulation, and if the stock levels of the other component are insufficient, the other final product is lost. In this context, the ratio in the graph can be increased depending on the production rate and the number of machines.



Inter-Customer Arrival Times = 1, Lost Sales Costs = 5, Holding Costs= 1, Idle Costs = 75, Customer Tolerance Costs = 1, Production Start-up Costs = 100, Customers' Tolerance Limits = 5, Machine Passage Costs = 250, s = 1, S = 10, r = 2, Q = 19

Figure 8. Variation of on-off and idle-off state costs according to machine changeover time



Lost Sales Costs = 5, Holding Costs = 1, Idle Cost = 75, Customer Tolerance Costs = 1, Customer Tolerance Limits = 5, Production Start-up Costs = 100, Machine Passage Time = 10, Machine Passage Cost = 250, s = 1, S = 10, r = 2, Q = 19

Figure 9. Machine condition costs graph according to time between customer arrivals

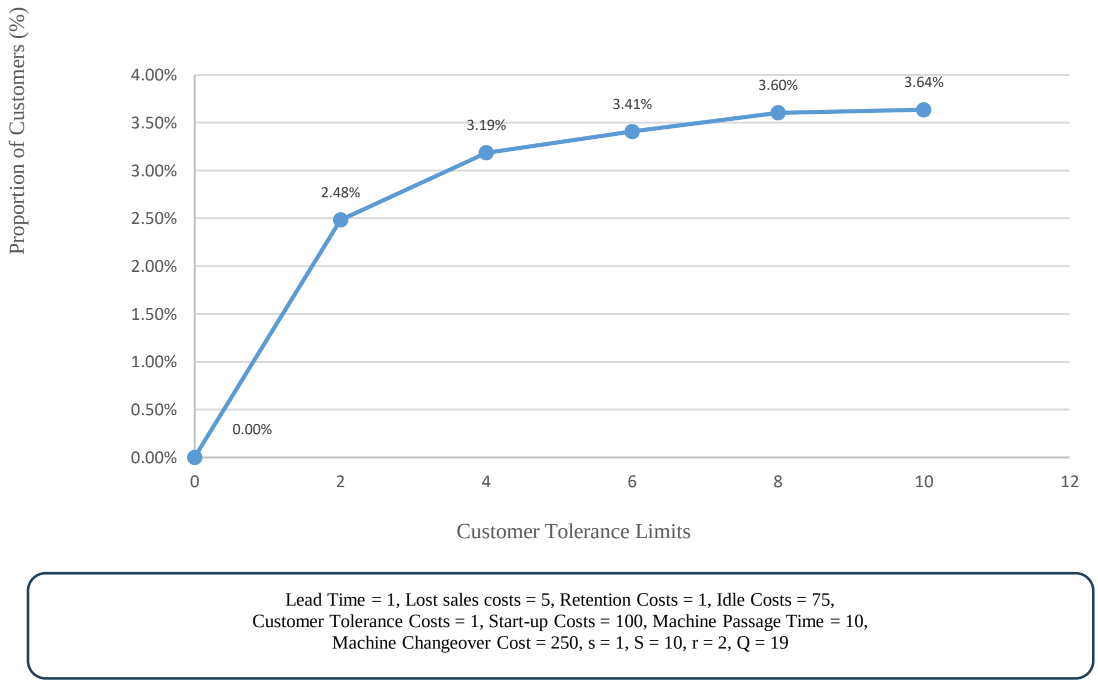


Figure 10. Proportion of customers whose requests were met after waiting

7 Conclusion

In this study, past and present studies were analyzed and the purpose of the system was determined. The order-based assembly system with various features is modelled, the simulation model is verified by generating different scenarios, and parameter effects are observed. The observed results are calculated numerically and presented graphically. In this study, cost analyses in areas such as machine management, inventory management, customer management in the order-based assembly system are performed and these issues are examined in detail.

As a result, optimal results can be obtained for (s, S) and (Q, r) parameters by following a policy according to retention costs, production start-up costs, lost customer costs, energy costs, etc. in the system. Depending on the customers' inter-arrival time, policies can be created for the machine or machines. If the inter-arrival time of the customers is short, open-waiting policy can be followed; if the inter-arrival time of the customers is longer, open-closed policies can be followed. Depending on the tolerance limits of the customers, customers can be prioritized according to lost sales costs, production speed can be increased, the number of machines can be increased, or the ratio of customers whose demand is met after waiting in the scenario where the tolerance limits of the customers cannot be increased can be increased by keeping the values of (s, S) and (Q, r) small and keeping the values of S and Q low by considering the costs of starting production and ordering costs.

This study is an important step in increasing efficiency in industrial processes and achieving sustainability goals. Cost analyses and policy determination processes in assemble-to-order systems can potentially increase enterprises' competitiveness and shape their future success.

Future research could expand the scope by increasing the number of machines and designing production systems that prioritize customers based on lost sales costs, deviating from the conventional FIFO principle. A detailed carbon footprint analysis could also be conducted, incorporating the machine utilization rate to evaluate environmental impact. Additionally, machine shutdown costs could be integrated into the model to reflect real-world operational dynamics more accurately. These extensions would provide deeper insights into cost optimization, sustainability, and customer-centric production strategies in assemble-to-order systems.

Acknowledgments

This study was funded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under the "2209-A - Research Project Support Program for Undergraduate Students" (grant number 1919B012334408).

Disclosure of Interests. The authors have no competing interests to declare relevant to this article's content.

References

Atan, Z., Ahmadi, T., Stegehuis, C., de Kok, T., & Adan, I. (2017). Assemble-to-order systems: A review. European Journal of Operational Research, 261(3), 866-879.

Baris, T., Oktay, K., & Siamak, K. (2023). Production and energy mode control of a production-inventory system.

Chen, S., Lu, L., Song, J. S. J., & Zhang, H. (2021). Optimizing assemble-to-order systems: decomposition heuristics and scalable algorithms. HKUST Business School Research Paper, (2021-33).

Dadaneh, D. Z., Moradi, S., & Alizadeh, B. (2023). Simultaneous planning of purchase orders, production, and inventory management under demand uncertainty. *International Journal of Production Economics*, *265*, 109012.

ElHafsi, M., Camus, H., & Craye, E. (2008). Optimal control of a nested-multiple-product assemble-to-order system. International Journal of Production Research, 46(19), 5367-5392.

ElHafsi, M., Fang, J., & Camus, H. (2017). Optimal control of a continuous-time W-configuration assemble-to-order system. European Journal of Operational Research, 267(3), 917-932.

Frigerio, N., Tan, B., & Matta, A. (2024). Simultaneous control of multiple machines for energy efficiency: a simulation-based approach. *International Journal of Production Research*, *62*(3), 933-948.

Fu, K., Hsu, V. N., & Lee, C. Y. (2011). Approximation methods for the analysis of a multi component, multiproduct assemble-to-order system. Naval Research Logistics (NRL), 58(7), 685-704.

Jin, X., & Wang, Z. (2021). Performance Analysis and Evaluation of Assemble-to-Order Systems With Non-Stationary Demands. IEEE Access, 10, 25834-25849.

Lu, L., Song, J. S., & Zhang, H. (2015). Optimal and asymptotically optimal policies for assemble-to-order n-and W-systems. Naval Research Logistics (NRL), 62(8), 617-645

Lu, Y., Song, J. S., & Yao, D. D. (2003). Order fill rate, lead time variability, and advance demand information in an assemble-to-order system. Operations Research, 51(2), 292-308.

Muharremoglu, A., Yang, N., & Geng, X. (2024). Single-product assemble-to-order systems with exogenous lead times. *Operations Research*, *72*(3), 916-939.

Nadar, E., Akan, M., & Scheller-Wolf, A. (2014). Optimal structural results for assemble-to-order generalized M-systems. Operations Research, 62(3), 571-579.

Nadar, E., Akcay, A., Akan, M., & Scheller-Wolf, A. (2018). The benefits of state aggregation with extreme-point weighting for assemble-to-order systems. Operations Research, 66(4), 1040-1057.

Özkan, E., & Tan, B. (2025). Asymptotically optimal energy consumption and inventory control in a make-to-stock manufacturing system. *European Journal of Operational Research*, *320*(2), 375-388.

Reiman, M. I., & Wang, Q. (2015). Asymptotically optimal inventory control for assemble-to-order systems with identical lead times. Operations Research, 63(3), 716-732.

Saracalıoğlu, N., Sonbahar, Y., Akdeniz, G. A., Ünsal, M., Yıldız, Y. Y., Çakmakçı, S. K., ... & Hökenek, C. (2022). Production and inventory control of assemble-to-order systems. In Digitizing Production Systems: Selected Papers from ISPR2021, October 07-09, 2021 Online, Turkey (pp. 757-771). Springer International Publishing.

Tan, B., & Karabağ, O. (2024). A deterministic fluid model for production and energy mode control of a single machine. *International Journal of Production Economics*, *278*, 109418.

Van Jaarsveld, W., & Scheller-Wolf, A. (2015). Optimization of industrial-scale assemble-to-order systems. INFORMS Journal on Computing, 27(3), 544-560**.**