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Bottleneck Analysis and Improvement in Apparel Manufacturing Production Processes Using Integration Design of Experiments and Discrete Event Simulation

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Abstract. Bottlenecks in apparel manufacturing often cause unbalanced production flows, increased waiting times, and reduced system performance. This study aims to analyze and eliminate bottlenecks by integrating Design of Experiments (DOE) and Discrete Event Simulation (DES). Four workstations (X1–X4) were selected as experimental factors, while system performance was evaluated using bottleneck indicators across six production stages (Y1–Y6). DOE was used to design capacity scenarios, and DES assessed system performance under each configuration. Results show that partial capacity increases at selected workstations are insufficient to fully eliminate bottlenecks. Complete elimination was achieved only in specific scenarios (Experiments 13–16), where all bottleneck indicators reached zero. Among these, Experiment 13 was identified as the optimal solution, as it eliminated all bottlenecks with the minimum additional capacity. These findings indicate that targeted capacity enhancement at critical workstations is an effective and economical strategy. The integration of DOE and DES proves to be a reliable data-driven approach for identifying bottlenecks and selecting optimal capacity improvements. This study also provides a structured and replicable framework for bottleneck analysis in apparel manufacturing, contributing to the limited application of DOE–DES integration in this sector.

Keywords: bottleneck analysis, design of experiments, discrete event simulation, production capacity, apparel manufacturing

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1. **Introduction**

Improving production system efficiency has become a strategic agenda in the manufacturing industry, particularly in the apparel sector, which is characterized by high process time variability, labor-intensive operations, and dynamic demand patterns. Under such conditions, the presence of bottlenecks represents a primary determinant that constrains throughput and directly degrades operational performance. Digital transformation within the Industry 4.0 framework has enabled production systems to perform more comprehensive process monitoring and to support capacity constraint detection through real-time analytics [1]. The integration of cloud-based cyber–physical systems further extends these capabilities by ensuring connectivity, data processing speed, and accurate bottleneck identification within distributed production environments [3]. Beyond throughput considerations, bottleneck analysis has also been applied to industrial energy systems for optimizing power consumption through efficiency gap diagnostics [3]. Predictive approaches based on digital twin technology mark a new phase in production control, enabling anticipation of potential bottlenecks before actual disruptions occur through simultaneous modeling of physical and virtual system interactions [4]. The bottleneck phenomenon also transcends manufacturing boundaries, as evidenced by its application in healthcare compliance assessment [5], information system analysis [6], and biological flow modeling [7], reinforcing the argument that bottlenecks are a universal characteristic of complex systems with inherent capacity constraints.

Within industrial contexts, process mapping and process mining have emerged as essential techniques for extracting actual value stream representations and identifying system constraints [8]. Bottleneck drivers are multidimensional, encompassing operator limitations, workload imbalance, and process activity variability [9]. In the textile and apparel industry, knowledge graph–based representations have been employed to systematically map process dynamics and detect bottlenecks [10], while the advancement of Industrial Internet of Things (IIoT) technologies has further enabled automated bottleneck detection, enhancing system responsiveness to capacity imbalances [11]. Even in quantitative analytical research contexts, the bottleneck concept has been utilized to predict the precision of register-based healthcare studies, demonstrating its broad methodological applicability [12].

Simulation has become one of the most dominant approaches for analyzing, evaluating, and optimizing modern manufacturing systems. In the apparel context, simulation is employed not only to model production flows but also to visualize product–user interaction dynamics through 4D motion simulations [13]. Factory software–based industrial simulations have proven effective in capacity analysis and bottleneck identification [14], and the use of simulation for general manufacturing process improvement has expanded its application across diverse industrial sectors [15]. In textile production, numerical simulation is utilized to analyze and optimize process conditions [16], while simulation studies in the automotive industry confirm its effectiveness in evaluating capacity structures and workflow improvements [17]. Production line operation simulations have also been shown to increase resource utilization and minimize waiting times [18], and simulation-based line balancing has been demonstrated through workload scenario modeling [19]. In the apparel industry specifically, simulation modeling has been applied to assess and improve sewing line flows using algorithmic techniques [20], and simulation-based lean system evaluation has been implemented to identify waste and reduce process variability [21]. Simulation further supports sustainable scheduling [22], transitions toward Just-In-Time production systems [23], and evaluation of reconfigurable manufacturing systems using multi-objective approaches [24]. Comprehensive reviews confirm the broad utility of industrial simulation software in automated system optimization [25], and simulation-based line balancing in aircraft spare parts maintenance further highlights the flexibility of this method across sectors [26]. Additional applications extend to energy system analysis [27], apparel supply chain dynamics [28], logistics bottleneck elimination [29], ceramic manufacturing modeling [30], and resource utilization optimization in tire manufacturing [31]. DES-based bottleneck identification and mitigation have been extensively discussed in food manufacturing [32] and lean-oriented production environments [33], while simulation-based cellular manufacturing models in sewing departments illustrate the strategic benefits of process redesign through DES [34]. Modeling complex systems through simulation demonstrates the capability of this technique to handle nonlinear and interdependent process dynamics [35], and DES-based job-shop simulations are widely applied to evaluate performance in dynamic production environments [36] [37]. Simulation also plays a critical role in manufacturing system design and real-time decision-making [38], in the development of flexible manufacturing systems [41], and in optimizing production planning configurations in the packaging industry [39] [40]. Recent approaches integrate DES with machine learning to generate adaptive and optimal resource allocation strategies in seasonal operational environments [41].

The integration of DOE with simulation has emerged as a focused research direction, with applications spanning AGV performance evaluation [42], production system optimization using combined DEA and DOE approaches [43], and productivity improvement through Response Surface Methodology [44]. However, existing DOE–DES studies predominantly address non-apparel industrial contexts, and existing apparel simulation studies [20] [21] [37] rely on ad hoc scenario testing rather than a structured factorial experimental design, limiting their ability to systematically assess factor main effects and interactions. No prior study has integrated both methods specifically to identify and eliminate bottlenecks in apparel production using a structured 2^k factorial design. This study addresses this gap by operationalizing DES as the execution environment for each DOE experimental run within an apparel manufacturing bottleneck context, providing a structured, reproducible, and data-driven decision-support framework for capacity improvement [45].

The complexity of apparel production flows — driven by inter-process coordination, manual activities, and cycle time variability — renders bottleneck identification and mitigation a strategic challenge that demands robust analytical methods. The integration of DOE and Discrete Event Simulation (DES) addresses this by combining the structured exploratory power of factorial design with the dynamic modeling capability of event-driven simulation, enabling the development of systemic and empirically validated solutions for bottleneck mitigation. This study contributes a validated DOE–DES framework applicable to labor-intensive, cost-sensitive manufacturing environments. The remainder of this paper is organized as follows: Section 2 describes the research methodology; Section 3 presents and discusses the experimental results; and Section 4 concludes with key findings and directions for future research.

2. **Methods**

2.1. Research Approach

This study adopts a quantitative experimental approach combined with Design of Experiments (DOE) and Discrete Event Simulation (DES). DOE is employed to evaluate the factors influencing the performance of bottleneck workstations, while DES is utilized to comprehensively model the production system and assess the impact of the proposed improvement scenarios.

2.2. *Research Stages*

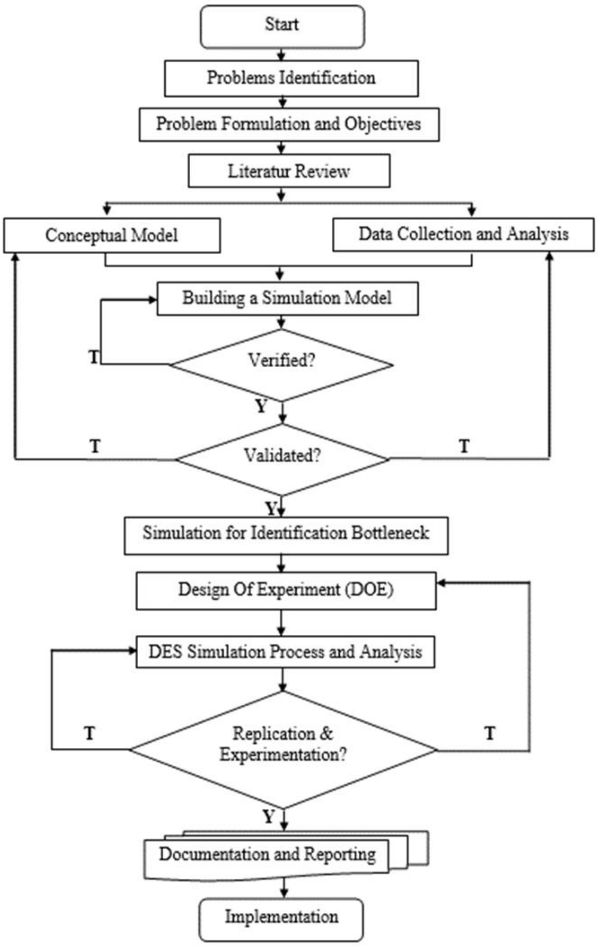

Figure 1. Step of Research

The study begins with problem identification in an apparel production line at a manufacturing company located in Purwakarta, West Java, Indonesia. The product under study is a short-sleeve shirt. Preliminary observations indicate workload imbalances among workstations, leading to work-in-process (WIP) accumulation and output delays. Based on these conditions, the research problem is formulated to determine bottleneck workstations, identify their contributing factors, and develop improvement alternatives aimed at enhancing production system performance through statistical and simulation-based methods. Subsequently, data are collected, including processing times, workstation capacities, number of operators and number of shift, production sequence and transfer times. These data are used to develop a conceptual model of the production system that represents process flows, resource capacities, and queuing rules. A Discrete Event Simulation (DES) model is then constructed using actual system parameters and subsequently verified and validated against real production data to ensure model accuracy.

After model validation, bottlenecks are identified through simulation of the real system. Once the bottleneck locations are determined, the study analyzes various parameters that potentially contribute to bottleneck formation. A Design of Experiments (DOE) is then developed based on the identified factors and response variables, and all experimental scenarios are executed within the simulation environment.

The final stage of the study involves analyzing the simulation results and formulating implementation recommendations, such as adjustments in the number of operators, workstation capacities, or workload redistribution. These recommendations aim to mitigate bottlenecks and improve the overall efficiency and productivity of the apparel manufacturing production system.

2.3. *Design Of Experiment (DOE)*

This study is aimed at identifying parameters that exert significant influence on bottleneck improvement. Therefore, a structured method is required to systematically analyze and address the research problem. Design of Experiments (DOE) is a statistical technique used to design and evaluate experiments [24]. In DOE, factors represent controllable parameters determined by the researcher, whereas responses are dependent variables, in this case, bottleneck indicators.

The 2^k factorial design is one of the most widely used DOE approaches, as each factor is assigned two levels, namely High and Low. This method is recognized for its efficiency and effectiveness in identifying both main effects and interaction effects among factors [46]. Accordingly, this study applies a 2^k factorial design to evaluate the impact of multiple parameters on bottleneck performance. The procedure for implementing the 2^k factorial design can be summarized as follows [23]:

Step 1. Identification of factors, levels, and response variables: At the initial stage, the response variables to be observed are defined. Subsequently, factors assumed to influence the experimental outcomes, along with their corresponding levels, are determined based on expert judgment to ensure that all relevant conditions are adequately represented.

Step 2. Development of the initial model: The 2^k factorial design is then constructed based on the selected factors and response variables. In this study, a 2^4 factorial design is employed, indicating that four factors are each set at two levels, resulting in all possible combinations of experimental treatments.

Step 3. Execution of experiments: At this stage, the simulation model is developed, and each treatment combination is executed according to the experimental design. The outcomes of each experiment or scenario are subsequently collected for analysis.

Step 4. Interpretation of results: The final stage involves analyzing data obtained from each experiment to understand variations in the response variables. The interpretation results are then used to evaluate factor effects and assess their implications for the system under investigation.

Having established the experimental framework, the following section presents and interprets the simulation outcomes across all sixteen experimental configurations

3. **Results and Discussion**

3.1. *Data Collection and Analysis*

Data were collected through direct observation, time studies, and production document analysis. The primary data included processing time at each workstation, workstation capacities, the number of operators and number of shift, total working hours for each workstation, production sequence, as well as transfer times between workstations within the production line.

Processing times for each work element were measured using a stopwatch and standard time study techniques. The data were then checked for consistency before further analysis. Table 1 presents the number of operators, number of shift and total working hours for each workstation:

Table 1. The number of operators, number of shift and total working hours for each workstation

Location	Number of operators	Number of shift	Number of hours per day
Design	1	1	10
Patterns & Markers	2	1	10
Spreading & Cutting	2	1	10
Bundling & Numbering	2	1	10
Sewing Preparation	5	1	10
Sewing	40	1	10
Sewing QC	6	1	10
Install Buttons	3	1	10
Buttons QC	2	1	10
Ironing	2	1	10
Finishing & Packing	3	1	10

Table 2 presents the capacity, processing time, and transfer time for each workstation in the production line. Capacity represents the maximum number of units that can be processed simultaneously at each workstation, while processing time indicates the average duration required to complete a single unit of work. Transfer time refers to the duration needed to move materials to the subsequent workstation. These data serve as key parameters for modeling and analyzing the performance of the production system.

Table 2. Capacity, process times and transfer time

Location	Capacity	Process Times (Min)	Transfer Time (Min)
Design	50	0,600	0.010
Patterns & Markers	50	0,600	0.300
Spreading & Cutting	50	0,750	0.208
Bundling & Numbering	50	0,100	0.325
Sewing Preparation	30	0,100	0.010
Sewing	40	1,700	-
Sewing QC	6	1,060	0.570
Install Buttons	3	1,725	0.533
Buttons QC	2	1,064	0.116
Ironing	2	0,750	0.230
Finishing & Packing	3	2,549	-

3.2. Conceptual Model

To analyze this case, a conceptual model of the apparel production process was developed. The production process begins with the design stage, followed by pattern and marker creation as references for cutting. Subsequently, spreading and cutting operations are carried out to cut the fabric according to the predetermined patterns. The cut pieces are then grouped and numbered during the bundling and numbering stage before entering sewing preparation. The next stage is sewing, where the pieces are assembled into the final product. After sewing, products undergo quality inspection (Sewing QC). In certain cases, products are directed to the button attachment process and then return to the inspection flow. Products that meet quality standards proceed to ironing and re-inspection. The final stage involves finishing and packaging, where the products are prepared for storage and distribution.

The conceptual model of the production line was extracted in the form of a flow diagram through direct observation of the production line and interviews with the production staff. The resulting conceptual model is illustrated in Figure 2.

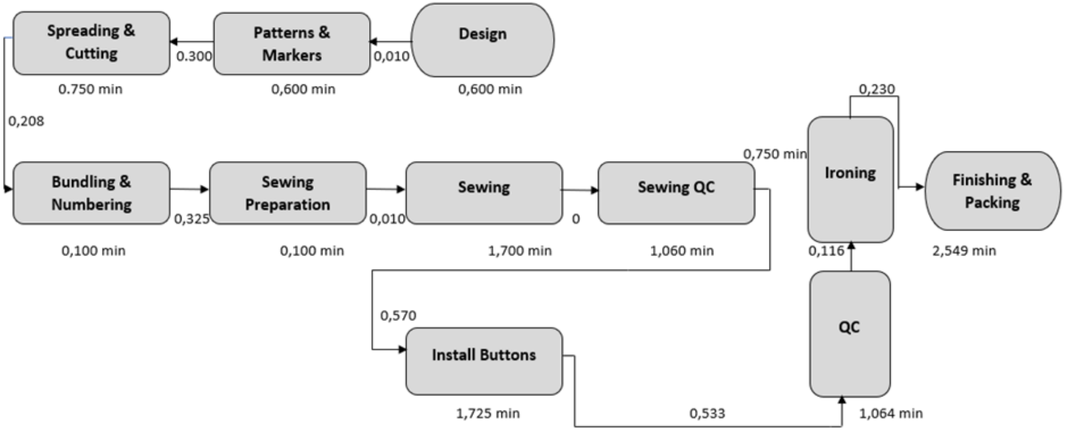

Figure 2. Conceptual Model

3.3. Simulation Model

In this study, the conceptual model of the production line for the investigated case was implemented into a simulation framework. Required data were collected and used to construct the simulation model, allowing the generation of system performance outputs. The simulation model captures the dynamics of the production process, including processing times, workstation capacities, material flows, and transfer times, providing a virtual environment to analyze bottlenecks and evaluate potential improvement scenarios. Since all processing times were modeled as deterministic fixed values derived from standard time study measurements, each experimental scenario produces consistent and repeatable outputs without stochastic variation. Accordingly, a single replication per scenario is sufficient to yield reliable results, and the reported bottleneck percentages reflect stable simulation outputs under fixed input conditions.

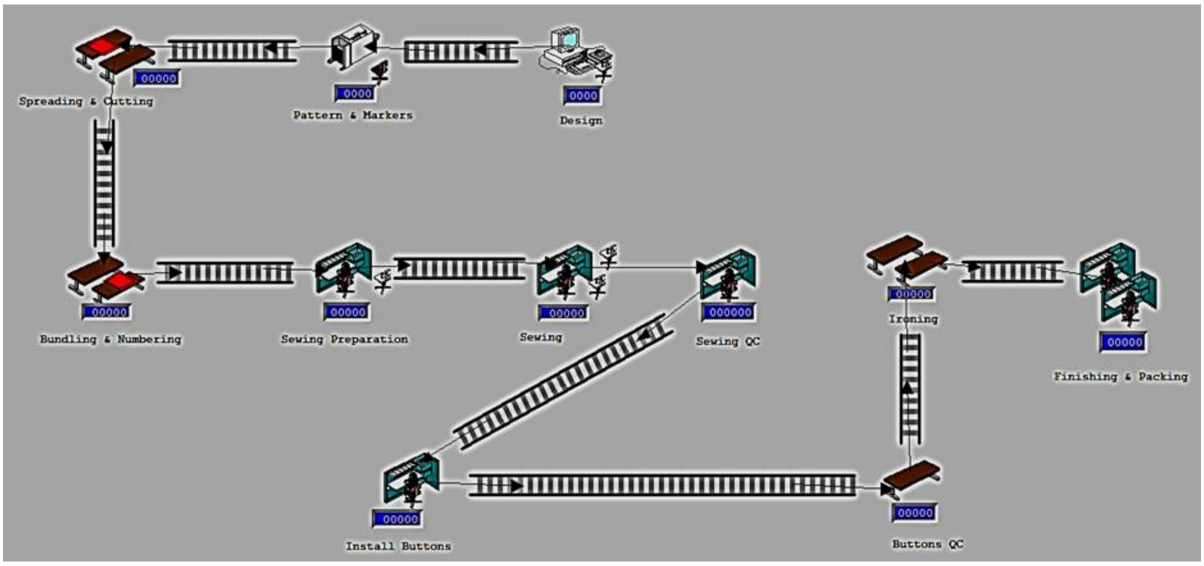

Figure 3. Stimulation Model

3.4. Verification and Validation of Model Simulation

Verification and validation were conducted to ensure the correctness and realism of the developed simulation model. Model verification focused on confirming that the logical structure, process flow, and resource allocation were implemented in accordance with the conceptual model derived from process mapping and expert interviews, which was further examined through animation-based inspection to identify potential modeling errors [14], [19]. Model validation was performed by comparing key performance indicators obtained from the simulation with historical production data, as commonly applied in manufacturing simulation studies [1], [15], [18]. Due to limited access to direct time measurements, input data were confirmed through expert judgment and company records. To strengthen the validity of the simulation model, key output metrics from the simulation — including daily throughput and workstation utilization rates — were compared against historical production records provided by the company. The simulated values demonstrated close agreement with actual data, with percentage deviations remaining within an acceptable threshold of below 5%, which is consistent with validation standards applied in manufacturing simulation studies [1][15][18]. This level of agreement confirms that the model reliably represents the real production system and is suitable for scenario-based experimentation.

3.5. *Bottleneck Analysis*

To determine the factors for improving bottlenecks within the system, the first step was to identify bottlenecks from real system data through simulation.

Based on the simulation of the actual system, bottlenecks were identified at the Button QC workstation, accounting for 5.77% of total system delay, and at the final workstation, Finishing and Packing, accounting for 45.84%. In this study, the Design of Experiments (DOE) was subsequently applied in combination with simulation to investigate strategies for eliminating these bottlenecks.

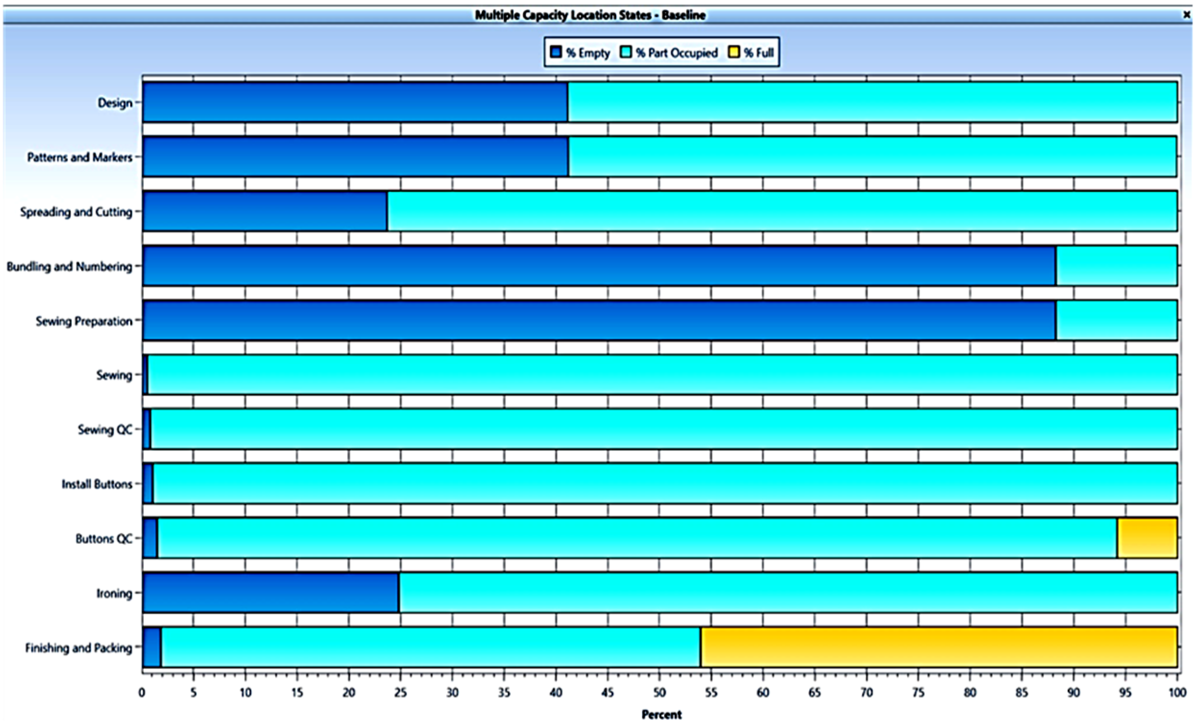

Figure 4. Percent bottleneck in real system

3.6. *Bottleneck Improvement*

After the bottlenecks were identified, the researchers evaluated and analyzed various parameters that could potentially reduce them. Factors considered influential were selected and further evaluated until a final list was established. Factors considered influential were initially screened through a structured expert consultation process involving production supervisors and process engineers familiar with the apparel line. Candidates were evaluated based on three criteria: (1) direct association with the identified bottleneck workstations, (2) operational controllability within the company's capacity planning decisions, and (3) potential magnitude of impact on downstream flow. This screening process resulted in the selection of four final factors: Capacity of Sewing (X1), Capacity of Sewing QC (X2), Capacity of Buttons QC (X3), and Capacity of Finishing and Packing (X4).

In the final stage, four factors were determined to be the most significant: Capacity of Sewing (X1), Capacity of Sewing QC (X2), Capacity of QC Install Buttons (X3), and Capacity of Finishing and Packing (X4). It should be noted that increasing the levels of factors X1, X2, X3, and X4, which represent the capacities at the respective workstations, will directly impact operational costs. Table 3 presents these factors along with their corresponding levels.

Table 3. Factors and Levels.

Factor	Level	
	Low (-1)	High (+1)
Capacity of Sewing (X1)	35	45
Capacity of Sewing QC (X2)	4	8
Capacity of Buttons QC (X3)	2	3
Capacity of Finishing and Packing (X4)	2	4

The response variables in this study were defined as the percentage of bottlenecks at key workstations, consisting of: bottleneck of Sewing (Y1), bottleneck of Sewing QC (Y2), bottleneck of Install Button (Y3), bottleneck of Button QC (Y4), bottleneck of Ironing (Y5), and bottleneck of Finishing and Packing (Y6). Table 4 presents the response variables used in the study.

Table 4. The response variables

Variable	**Description**	**Current state**
Y1	Bottleneck of Sewing	0 %
Y2	Bottleneck of Sewing QC	0 %
Y3	Bottleneck of Install Button	0 %
Y4	Bottleneck of Button QC	5,77 %
Y5	Bottleneck of Ironing	0 %
Y6	Bottleneck of Finishing and Packing	45,84 %

After the Design of Experiments (DOE) was established and the simulations were conducted, the simulation results were obtained, as presented in Table 5:

Table 5. Result of simulation experiment.

Run Order	Factors				Factors and Their Values				Respons (Bottleneck%)					
	X1	X2	X3	X4	X1	X2	X3	X4	Y1	Y2	Y3	Y4	Y5	Y6
1	-	-	-	-	35	4	2	2	71,39	93,10	57,73	58,34	88,29	80,60
2	+	-	-	-	45	4	2	2	64,87	93,10	57,73	58,34	88,29	80,60
3	-	+	-	-	35	8	2	2	68,75	90,48	57,73	58,34	88,29	80,60
4	+	+	-	-	45	8	2	2	62,25	90,48	57,73	58,34	88,29	80,60
5	-	-	+	-	35	4	3	2	70,70	92,47	53,38	57,85	88,29	80,60
6	+	-	+	-	45	4	3	2	64,18	92,47	53,38	57,85	88,29	80,60
7	-	+	+	-	35	8	3	2	68,14	89,85	53,38	57,85	88,29	80,60
8	+	+	+	-	45	8	3	2	61,60	89,85	53,38	57,85	88,29	80,60
9	-	-	-	+	35	4	2	4	0	0	0	5,77	0	0
10	+	-	-	+	45	4	2	4	0	0	0	5,77	0	0
11	-	+	-	+	35	8	2	4	0	0	0	5,77	0	0
12	+	+	-	+	45	8	2	4	0	0	0	5,77	0	0
13	-	-	+	+	35	4	3	4	0	0	0	0	0	0
14	+	-	+	+	45	4	3	4	0	0	0	0	0	0
15	-	+	+	+	35	8	3	4	0	0	0	0	0	0
16	+	+	+	+	45	8	3	4	0	0	0	0	0	0

Based on the simulation results presented in Table 6, this study analyzes and improves bottlenecks in an apparel manufacturing production process through the integration of Design of Experiment (DOE) and Discrete Event Simulation (DES). Four experimental factors (X1, X2, X3, and X4) represent capacity levels at critical workstations along the production flow. Increasing the factor levels corresponds to capacity expansion, which directly leads to higher operational costs. Therefore, the evaluation of the simulation outcomes is focused on two main criteria: complete bottleneck elimination and selection of the most cost-efficient capacity configuration.

To provide a statistically rigorous interpretation of the experimental results, a 2^4 factorial ANOVA was conducted on the response variables. The analysis reveals that X4 (Capacity of Finishing and Packing) is the dominant factor with the largest main effect across all responses, consistent with its initial bottleneck contribution of 45.84%. Factor X3 (Capacity of Buttons QC) emerges as the second most influential factor, as its inclusion at the high level is the distinguishing condition between Experiments 9–12 (incomplete elimination) and Experiments 13–16 (complete elimination). Interaction effects between X3 and X4 are also found to be significant, indicating that complete bottleneck elimination requires the simultaneous adjustment of both factors rather than isolated capacity increases. Factors X1 and X2 show comparatively smaller main effects, as their variation alone does not alter the bottleneck elimination outcome.

The simulation results indicate that in Experiments 1 to 8, bottlenecks remain significant across most responses, particularly Y1 and Y2, with relatively high values. This condition suggests that partial capacity improvements at selected workstations are insufficient to eliminate flow constraints throughout the system. These findings confirm that bottlenecks in manufacturing systems are systemic in nature, consistent with previous studies on bottleneck behavior in complex production environments [1], [7], [8]. In Experiments 9 to 12, substantial bottleneck reduction is observed, as reflected by zero values in responses Y1, Y2, Y3, Y5, and Y6. However, response Y4 still exhibits a bottleneck value of 5.77%, indicating that these configurations do not satisfy the criterion of complete bottleneck elimination. This result demonstrates that even after capacity increases at dominant workstations, residual bottlenecks may persist at other stages of the production line. Similar phenomena have been reported in data-driven and intelligent bottleneck analysis studies, where bottlenecks may shift or remain after partial improvements [3], [10], [11].

The persistence of Y4 (Button QC bottleneck at 5.77%) in Experiments 9–12, despite capacity improvements at X1, X2, and X4, can be explained by the upstream dependency structure of the production flow. The Button QC workstation processes output exclusively from the Install Buttons station, meaning that increasing sewing capacity (X1), sewing QC capacity (X2), or finishing capacity (X4) does not relieve the constraint at this node. It is only when X3 — the capacity of Buttons QC itself — is increased from 2 to 3 units in Experiments 13–16 that this bottleneck is fully resolved. This result highlights a critical implication for practitioners: bottleneck elimination in interconnected production systems requires targeting the specific dependency chain of each constraint, rather than broadly expanding capacity across all dominant workstations. From an operational standpoint, this finding supports a selective, node-specific capacity investment strategy for the studied apparel company, particularly at the Buttons QC and Finishing and Packing workstations.

Complete bottleneck elimination is achieved only in Experiments 13 to 16, where all bottleneck responses (Y1 to Y6) reach 0%. These four experiments are therefore classified as technically feasible solutions. However, because capacity expansion is directly associated with increased costs, the final selection of the optimal solution must also consider economic efficiency, represented by the extent and distribution of capacity increases across factors X1 to X4. Among the feasible configurations, Experiment 13 involves the minimum level of capacity expansion, as capacity increases are applied selectively to specific factors. In contrast, Experiments 14 to 16 require broader and more uniform capacity increases across multiple workstations. Consequently, Experiment 13 is identified as the optimal solution, as it achieves complete bottleneck elimination at the lowest cost among all feasible alternatives. Specifically, Experiment 13 applies capacity increases only to X3 (Buttons QC, from 2 to 3 units) and X4 (Finishing and Packing, from 2 to 4 units), resulting in a total additional capacity of 3 units across two workstations. In contrast, Experiments 14–16 require additional capacity increases in X1 and/or X2 on top of these, leading to a higher total resource investment without any improvement in bottleneck elimination outcome. This demonstrates that the cost advantage of Experiment 13 is not marginal but structural: it achieves the same technical result with fewer resource commitments, which is particularly significant in labor-intensive apparel manufacturing where each additional operator unit directly translates to recurring labor costs. This finding demonstrates that bottleneck elimination does not necessarily require uniform capacity expansion, but can instead be achieved through targeted and strategic capacity adjustments at critical workstations.

The results of this study are consistent with prior research highlighting the effectiveness of simulation-based approaches for analyzing and improving production systems, particularly in textile and apparel manufacturing contexts [20], [21], [25], [37]. However, compared to conventional simulation or bottleneck identification methods [7], [10], the integrated DOE–DES approach applied in this research provides significant methodological advantages. DOE enables systematic exploration of factor effects and interactions with a limited number of experiments, while DES accurately represents the dynamic and stochastic behavior of production systems. Similar benefits of combining DOE with simulation have been reported in simulation-based optimization studies across various manufacturing domains [22], [23], [24]. Overall, this study demonstrates that the integration of DOE and Discrete Event Simulation is effective not only for identifying the primary sources of bottlenecks, but also for evaluating alternative improvement scenarios to obtain solutions that are optimal from both technical and economic perspectives. The proposed framework offers a robust decision-support tool for capacity planning and performance improvement in complex, dynamic, and cost-sensitive apparel manufacturing systems.

4. **Conclusion**

This study demonstrates that the integration of Design of Experiment (DOE) and Discrete Event Simulation (DES) provides an effective and systematic framework for analyzing and improving bottlenecks in apparel manufacturing production systems. By evaluating sixteen experimental configurations, the proposed approach enables comprehensive assessment of capacity adjustments and their impacts on bottleneck behavior across multiple workstations. The simulation results reveal that bottlenecks in the apparel production process are systemic rather than isolated. Partial capacity increases, as observed in Experiments 1–8, were insufficient to eliminate bottlenecks, while Experiments 9–12 achieved significant bottleneck reduction but still exhibited residual constraints. Complete bottleneck elimination was attained only in Experiments 13–16, confirming that coordinated capacity adjustments at critical workstations are required to achieve balanced production flow.

Among the fully feasible configurations, Experiment 13 emerged as the optimal solution, achieving total bottleneck elimination with the minimum level of capacity expansion. This finding highlights that effective bottleneck resolution does not necessarily require uniform or excessive capacity increases, but can instead be accomplished through targeted and strategic capacity improvements. Such an approach is particularly relevant for apparel manufacturing systems, which are characterized by high variability and strong cost sensitivity. From a methodological perspective, this research confirms the advantages of the DOE–DES integration over conventional simulation or bottleneck identification approaches. DOE enables structured exploration of factor effects and interactions with a limited number of experiments, while DES captures the dynamic and stochastic characteristics of real production systems. As a result, the combined framework functions not only as a diagnostic tool for bottleneck identification but also as a prescriptive decision-support method for selecting technically feasible and economically efficient improvement strategies. In conclusion, this study contributes to both theory and practice by demonstrating that a DOE–DES-based framework can support informed capacity planning and performance improvement in complex apparel manufacturing systems. The proposed approach can be extended to other labor-intensive and dynamic manufacturing environments, and future research may incorporate additional performance indicators, real-time production data, or Industry 4.0 technologies to further enhance the robustness and applicability of the framework.

Declaration of AI and AI assisted technologies in the writing process

The author(s) declare that no artificial intelligence (AI) or AI-assisted technologies were used in the preparation, writing, or editing of this manuscript. All aspects of the work were conducted and written solely by the author(s).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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