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Comparative analysis of optimization methods for cut order planning in apparel manufacturing

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ABSTRACT

This study seeks to address the complicated optimization challenge inherent in cut order planning (COP) in the clothing manufacturing business, emphasising fabric consumption, computational economy, and production accuracy. Three optimization approaches were compared: adaptive heuristic scoring optimizer (AHOPS), hybrid metaheuristic optimization with simulated annealing (HIMOSA), and gradient-based penalty-driven (GBPD). The results show that the GBPD method achieved the highest fabric utilization (87.13%), the fewest amount of fabric layers (12), and the maximum computational efficiency (0.022 seconds), significantly outperforming both conventional methods and alternative advanced approaches. AHOPS and HIMOSA, on the other hand, required more layers (15) and produced lower fabric utilization (around 69.70%), with HIMOSA demonstrating noticeably greater computational needs (0.527 seconds). The adaptive heuristic scoring mechanism and the combination of gradient descent and machine learning predictions, which successfully handled the combinatorial difficulties of COP, are responsible for GBPD's exceptional performance. These results offer useful information to manufacturers looking for scalable, effective optimization solutions. They also point to potential avenues for future research, such as extending the applicability of GBPD to more intricate production scenarios and further honing machine learning models for increased efficiency and adaptability.

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1. INTRODUCTION

In the textile manufacturing industry, cut order planning (COP) is a crucial optimization problem that aims to reduce overall production costs by identifying effective fabric roll cutting techniques [1]. Fundamentally, COP entails producing ideal layer counts (number of fabric layers cut concurrently) and cutting ratios (number of garment pieces per size in a single fabric layer) while respecting limitations like fabric board length, consumption per garment, and order quantities [2]. The immediate effects of COP on labor efficiency, cost savings, and material waste reduction—three major competitive factors in the low-margin garment sector—make its resolution urgent [3]. Fabric accounts for between 50 and 70 percent of the overall cost of a garment in a typical garment manufacturing process. Therefore, it is essential to optimize the cutting strategy. The necessity of figuring out the mix of markers (fabric patterns) and their lay counts to guarantee thorough coverage of all sizes and quantities requested by an order highlights the importance of this optimization [4].

The challenge of optimizing COP is rooted in its inherent computational complexity. The problem is a form of combinatorial optimization widely recognized in operations research as being NP-hard. This classification means that as the number of garment sizes, order quantities, and production constraints increases, the time required to find a guaranteed optimal solution grows exponentially, rendering exact methods computationally intractable for most real-world, industrial-scale scenarios. The COP problem shares characteristics with other classic NP-hard problems, such as the bin packing problem (BPP) and the cutting stock problem (CSP), where the goal is to fit a set of items into a minimum number of containers or to cut stock material to fulfill orders with minimal waste. Consequently, the development and analysis of efficient heuristics and metaheuristics are not merely beneficial but essential for providing practical, near-optimal solutions in a reasonable timeframe, thereby justifying the focus of this study.

Manual marker-making and rule-based heuristics (e.g., prioritizing high-demand sizes) are examples of conventional approaches that struggle with the combinatorial complexity and dynamic restrictions of COP. For example, fixed-pattern methods are unable to adjust to changes in cloth width or varied order numbers. Resulting in uneven production and less-than-ideal utilization. Furthermore, these difficulties are made worse by contemporary expectations for mass customization, since conventional techniques are ineffective in managing large variety in size distributions [5]. In order to solve the cutting path problem in laser cutting applications, the study Zhang *et al*. [6] creates a variable neighborhood search for the node routing method and a two-step heuristic for the arc routing method. This results in near-optimal solutions with GAPs frequently below 0.5% and computation times under one second for small to medium instances, guaranteeing effective cutting paths and high-quality piece separation. For example, innovative software solutions for cutting planning have demonstrated improved scalability and adaptability to dynamic production requirements, achieving up to 80% reductions in solving time compared to conventional methods [7].

The absence of interaction with real-world production limitations (such as tool preheating and dynamic layout adjustments) and the scalability problems of accurate approaches like CPLEX for large-scale instances, however, limit the approach and point to a research gap. In order to address the marker planning problem in the apparel industry, the study Tsao *et al*. [8] presents hybrid PSO-based heuristics (PSO–GA, PSO–SA, and SA–PSO). These heuristics achieve robust performance across various order configurations and reduce fabric length by approximately 5–6% when compared to the baseline moving heuristic, and in certain cases, up to 15% when compared to the benchmark bottom-left fill approach. Further research on scalability and real-time applications in various industrial contexts is necessary, as the suggested approaches are sensitive to parameter settings and incur higher computing times, particularly in hybrid variations. In contrast to traditional and learning-based baselines, the study Wang *et al.* [9] suggests a hierarchical sequence model (HEM) that dramatically increases the efficiency of solving mixed-integer linear programming (MILPs), attaining up to an 80% decrease in solving time. Recent studies have demonstrated the efficacy of reinforcement learning (RL) as a promising tool. Research has shown that RL can reduce cutting path lengths by approximately 2.95%, while simultaneously reducing computation time by up to 96.75% [10]. These findings are attributed to the adaptive sequence adjustment and attention mechanisms that characterize the RL framework [10].

However, this method has shortcomings in terms of computational complexity caused by the hierarchical reinforcement learning architecture and difficulty in generalizing across various types of MILPs that were not seen during training. Emerging machine learning techniques for selecting cutting domains in mixed-integer linear programming (MILP) emphasize ML-based strategies to improve solver processing time [11]. For example, the hierarchical order model (HEM) can improve processing time by 16.4%. However, this model has drawbacks regarding computational costs for training complex machine learning models and challenges in applying the obtained tactics to various MILP instances and solver settings. The hierarchical sequence/set model (HEM) for selecting cutting planes in MILP has been proven to have better processing time than state-of-the-art techniques across various MILP benchmarks [12]. It presents a hierarchical sequence/set model (HEM). However, its limitations include the computational complexity of training complex hierarchical models and potential challenges in applying the acquired cut-selection techniques to different MILP problems. Additionally, optimizing continuous optimization processes (COPs) still relies heavily on genetic algorithms (GAs). It has been demonstrated that well-established GA techniques outperform heuristic-based commercial tools in terms of size ratio optimization. However, the scalability of GAs remains constrained in the context of complex problem instances [13].

In order to optimize cut order plan (COP) solutions in the garment manufacturing industry, the study Abeysooriya & Fernando [14] presents a canonical genetic algorithm (CGA). It shows greater economic efficiency than heuristic-based commercial software and achieves noticeably better size ratio optimization. However, the method has drawbacks, such as a decreased ability to solve more complicated COP issues because it requires larger populations and many generations to produce high-quality answers. Compared to conventional methods, the study by Junior *et al*. [15] offers a reinforcement learning approach for cutting path planning that integrates adaptive sequence

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adjustment and attention mechanisms, leading to notable improvements in computation time of up to 96.75% and path length reduction of about 2.95%. Its drawbacks include somewhat worse performance on fixed-length node scenarios than specialized deep reinforcement learning techniques, suggesting possible difficulties striking a balance between flexibility and optimization precision. Evolutionary algorithms, including adaptive biased random-key genetic algorithms (ABRKGA), have been employed in line-cutting path planning (LCPP). This application has yielded enhanced convergence rates and practical applicability in industrial settings [15].

Even though COP solutions have been improved by previous research using heuristics, metaheuristics, and machine learning, there are still significant gaps in scalability, computational efficiency, and adaptation to changing production limitations. A systematic comparison of optimization frameworks suited to COP's multi-objective nature—specifically, striking a balance between fabric utilization, iteration count, and production accuracy—is conspicuously lacking from previous work, which concentrates on discrete algorithmic improvements (such as genetic algorithms, reinforcement learning, or hybrid models). In order to fill this gap, this work compares and contrasts three approaches—Mock ML, Genetic Annealing, and Gradient Descent—to see which is better at managing the combinatorial complexity of COP. This work focuses on real-world applications by combining gradient-based penalties, metaheuristic search, and heuristic scoring. Its goal is to give manufacturers actionable insights that limit overproduction (≤3% mistake) while retaining ≥85% fabric utilization. This study is crucial because the clothing industry urgently needs Low-cost, flexible COP systems that respond to changing demand patterns and mass customization tendencies [16].

While the literature contains numerous optimization approaches for COP, including genetic algorithms, reinforcement learning, and mixed-integer linear programming, a systematic comparison of fundamentally different optimization philosophies applied to this problem is lacking. This study aims to fill this gap by evaluating three distinct algorithmic paradigms chosen to represent a spectrum of optimization strategies. We selected: (1) an advanced heuristic (AHOPS), representing a fast, rule-based yet adaptive approach suitable for rapid decision-making; (2) a hybrid metaheuristic (HIMOSA), representing a powerful stochastic search method that combines the global exploration of GAs with the local refinement of SA, a common and robust strategy for complex combinatorial problems; and (3) a gradient-based method (GBPD), representing a deterministic, calculus-based approach that is novelly enhanced with machine learning. This comparative structure allows for a comprehensive analysis of the trade-offs between heuristic speed, metaheuristic robustness, and the precision of gradient-based optimization in the specific context of COP.

The primary contributions of this research are delineated as follows:

1) Development of a Comparative Framework for COP Optimization. This study introduces a systematic comparison of three optimization methodologies—Adaptive Heuristic Scoring Optimizer (AHOPS), Hybrid Metaheuristic Optimization with Simulated Annealing (HIMOSA), and Gradient-Based Penalty-Driven (GBPD)—to address cut-order planning (COP) in apparel manufacturing, focusing on fabric utilization, computational efficiency, and production accuracy.

a. The Adaptive Heuristic Scoring Optimizer (AHOPS) introduces a novel heuristic framework whose primary innovation lies in its dynamic constraint adaptation and a scoring mechanism that explicitly incorporates residual demand awareness. Unlike traditional heuristics for COP that rely on static rules, AHOPS simulates an ML-driven approach by iteratively prioritizing size ratios that address the most pressing remaining order quantities, thereby adapting its search focus throughout the optimization process.

b. The Hybrid Metaheuristic Optimization with Simulated Annealing (HIMOSA) framework contributes a tailored integration of a genetic algorithm (GA) with simulated annealing (SA) specifically for the COP domain. Its novelty is not in the hybridization itself, but in the design of its problem-specific fitness function, which penalizes overly complex patterns (i.e., those with an excessive number of unique sizes), and its use of an adaptive exponential cooling schedule ($T = T\_o \cdot 0.95k$). This architecture ensures a robust balance between the broad, global exploration characteristic of GAs and the practical need for implementable, low-complexity solutions in a manufacturing setting.

c. The Gradient-Based Penalty-Driven (GBPD) method represents the most significant novel contribution of this work. It proposes a unique fusion of classical gradient descent optimization with a mock Machine Learning (ML) model. Specifically, the ML model, trained on historical COP data, provides a high-quality initial seed for the size ratios, drastically accelerating convergence towards promising regions of the solution space. The gradient descent technique then improves these ratios, and a proportional penalty function dynamically limits fabric and demand. This innovative way to solve the COP problem combines ML-guided initialization with penalty-driven gradient refinement. It differentiates it from purely learning-based solutions and typical mathematical programming techniques.

d. Combining machine learning predictions with gradient-based optimization. The suggested GBPD method uses fake ML models, gradient descent, and penalty-driven limitations to change how it works based on past COP data.
e. Addressing Real-World Industrial Constraints. The study underscores the importance of scalability and adaptability in dynamic production settings, including fluctuating order quantities and multi-color fabric limitations, which represent significant deficiencies in current COP frameworks such as genetic algorithms or reinforcement learning.
f. Framework for Evaluating COP Methods Under Multi-Objective Trade-off Demons. By balancing competing metrics (fabric utilization, iteration count, and production accuracy), this work provides actionable insights for manufacturers to adopt low-cost, adaptive COP systems aligned with mass customization trends and volatile demand patterns.
g. Rigorous Experimental Validation on Generated Benchmarks**.** This research establishes a methodology for generating realistic benchmark instances and provides a detailed, per-instance performance analysis, addressing a critical gap in experimental standardization within COP literature. By evaluating the methods on metrics of fabric utilization, layer count, and computational time, it offers a robust framework for evaluating COP solutions under multi-objective trade-offs.

The structure of this paper is as follows: Section 2 reviews related works on COP optimization, Section 3 details the methodology and algorithmic frameworks, Section 4 presents results and comparative analysis, and Section 5 discusses implications, limitations, and future directions.

2. RELATED WORK

Recent advancements in COP optimization have significantly improved fabric utilization and computational efficiency. However, critical limitations persist. For instance, hybrid particle swarm optimization (PSO)-based heuristics (e.g., PSO–GA, PSO–SA) have achieved 5–6% fabric length reductions over baseline methods. In some cases, these variants have been observed to reduce layouts by up to 15% compared to traditional bottom-left fill approaches. Nevertheless, the efficacy of these methodologies was found to be contingent upon parameter tuning and elevated computational overhead in hybrid variants. This limitation renders their real-time applicability in dynamic production environments impractical [4].

Genetic algorithms (GA) and hybrid meta-heuristic approaches (e.g., GA combined with simulated annealing or tabu search) are the most effective for optimizing cut order planning (COP) in apparel manufacturing. These approaches have been shown to reduce fabric waste (e.g., up to 15% savings in some cases). However, the review identifies several gaps, including a limited focus on cost and time parameters, reliance on outdated hardware in experimental setups, and underexplored potential for newer meta-heuristics (e.g., galactic swarm optimization) and AI-driven techniques to enhance COP solutions [17].

The study demonstrates that LINGO-based optimization achieves significant fabric savings (7.06% average efficiency improvement, with individual cases like shirts showing up to 12.42% savings) through mixed-integer nonlinear programming, outperforming manual cut order planning methods. However, it exhibits a lack of scalability to meet the dynamic demands of production. Furthermore, it does not address multi-color fabric constraints or real-time adaptability, which limits its industrial applicability compared to modern metaheuristic frameworks, such as genetic algorithms or reinforcement learning [18].

The study demonstrates that a novel software approach for cut order planning can achieve optimized fabric utilization (via parameters like total length, layers, and utility coefficients) and reduce waste in apparel manufacturing. These findings were validated through simulations and real-world testing on coat production. However, their work, similar to other specific software solutions, lacks a broader discussion on scalability for dynamic production demands, integration with existing CAD systems, and real-time adaptability to constraints such as multi-color fabrics, which are areas where modern metaheuristic or AI-driven frameworks may offer advantage [7].

The study introduces a heuristic algorithm (HFSC) for fabric spreading and cutting in apparel manufacturing. This algorithm effectively minimizes cutting bed usage while meeting production requirements through a constructive procedure and iterative optimization loop. These conclusions were validated via 500 test cases. However, the study focuses on static production scenarios, neglecting to address dynamic constraints such as real-time order modifications or integrating multiple colors into fabric. Furthermore, its computational efficiency has not been assessed compared to current metaheuristic frame-works, such as genetic algorithms and reinforcement learning [19].

This research illustrates that combining genetic algorithm (GA)-based sizing optimization with an integer programming (IP) model for cut order planning enhances garment fit and cost efficiency. This integration establishes a balance between personalization and production costs by examining case studies on skirt production. The proposed framework has been validated exclusively on a basic straight skirt case study, limiting its applicability to more complex garment types or dynamic multicolored fabric

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situations. Additionally, it does not account for real-time adaptability or scalability in large-scale industrial applications [20].

This study illustrates that a genetic algorithm (GA)-based method for cut order planning (COP) minimizes fabric waste, markers, and layers in garment production. This method realizes cost reductions by employing optimized cutting plans, which are confirmed through comparative analysis with heuristic techniques. However, the study concentrates on static production scenarios with fixed marker dimensions. It does not address dynamic order changes, multi-color fabric constraints, or scalability for large-scale industrial applications. Such limitations are common in GA-driven COP frameworks [21].

The study demonstrated that integrating cut order planning (COP) and marker layout optimization (TDL) into a unified model (CT) using heuristics and metaheuristics (e.g., genetic algorithms, simulated annealing) achieves more accurate fabric length estimation (reducing overproduction by 5–10%) compared to traditional fixed-layout approaches. These findings were validated through seven industrial case studies. However, the model assumes static demand and uniform pattern counts across sections. Also, the model does not address scalability challenges in large-scale applications, and the model does not address dynamic order adjustments or multi-color fabric constraints, which are critical for modern mass customization scenarios [3].

Table 1. Literature review on COP

Author	Year	Method	Findings	Limitations
Yang *et al.* [22]	2011	Ant colony optimization (ACIP)	Competitive with integer programming (IP); validated via Lingo 8.0 simulations for stencil setup cost	Tested on small-scale data; assumes static labor costs and stack characteristics
M'Hallah & Bouziri [3]	2016	Integrated COP and marker layout optimization (CT) using heuristics, simulated annealing (SA), and genetic algorithms (GA)	Reduced overproduction by 5–10% compared to fixed-layout approaches	Assumed static demand and uniform pattern counts; scalability challenges in large-scale applications
Shang *et al.* [19]	2019	Heuristic algorithm (HFSC) with constructive procedure and iterative optimization loop	Achieved effective and efficient results in 500 test cases; minimized cutting bed usage	Focused on static production scenarios; no real-time adaptability or multi-color fabric integration.
Dere [23]	2020	LINGO-based mixed-integer nonlinear programming	7.06% average fabric efficiency improvement (up to 12.42% for shirts)	Lacks scalability for dynamic demands
Alsamarah *et al.* [21]	2021	Genetic algorithm (GA)-based COP	Improved fabric utilization from 80.88% to 83.5%; reduced markers from 6 to 3	Focused on static production scenarios; no multi-color fabric constraints addressed
This Study	-	Comparative analysis of AHOPS (heuristic), HIMOSA (metaheuristic), and GBPD (ML-seeded gradient-based).	The proposed GBPD method significantly outperforms prior methods, achieving 87.13% fabric utilization with only 12 layers and near-instant computation (0.023s). It provides a scalable solution that addresses real-world constraints.	The mock ML model in GBPD is based on historical data; performance on entirely new production types requires further validation. The study focuses on fabric utilization and computational time; a multi-objective cost model including labor could be a future extension.

The study demonstrates that an ant colony optimization approach (ACIP) effectively addresses layout problems in the fashion industry, achieving competitive solutions compared to integer programming (IP) and validating robustness through Lingo 8.0 simulations, particularly optimizing stencil setup costs for large-scale datasets. However, the study is constrained by its reliance on small-scale data testing and assumption of static labor costs and stack characteristics. These limitations preclude the study's ability to generalize to dynamic, real-world industrial settings, where rapid adjustments to variable constraints (e.g., fabric types, order changes) are imperative [22]. The following table in Table 1 offers a comparative analysis of the reviewed papers on cut-order planning (COP) and related optimization methods in apparel manufacturing.

3. RESEARCH METHODS

3.1. COP

One essential step in clothing production is cut order planning, or COP. Figuring out the best way to cut fabric to fit customer requests guarantees effective production while lowering total expenses. A scheduling technique called COP is applied in manufacturing settings that prioritize order. A list of pending orders is compiled, and the orders that should be processed within a given time frame are chosen. Setting ply height and spread length directly impacts cutting efficiency and costs, sectioning determines the number of sections and the distribution of garment sizes, and grouping orders optimizes fabric usage and lowers setup costs. These crucial decisions are what drive the COP process. By balancing fabric costs (based on total fabric length), spreading labor costs (influenced by ply height and spread length), cutting costs (related to pattern piece perimeter length and cutting speed), and any additional costs related to making new markers, the main objective is to minimize total cutting costs.

Fig. 1 depicts the general process of COP, including the essential stages from order entry to the cutting room. The primary goal is to reduce total cutting costs by balancing fabric costs (based on total fabric length), spreading labor costs (affected by ply height and spread length), cutting costs (depending on pattern piece perimeter length and cutting speed), and any additional costs associated with creating new markers. The procedure must follow spreading guidelines such as maximum ply height and cutting table length. Finally, COP produces a thorough plan outlining the distribution of garment sizes within sections, marker efficiency, and cutting cost per garment, which is subsequently used in the marker-making process to create precise cutting layouts. The resulting bundles of cut pieces are then sent to the assembly system based on operational priorities, ensuring maximum fabric utilization while minimizing costs for a more responsive and competitive garment production process [24].

3.2. Optimization in COP

Because of the wide range of sizes and erratic order numbers, optimization models in COP are necessary for mass customisation of clothing. Yan-mei *et al.* [26] suggested that one method reduces the number of cutting tables required by rapidly generating effective cutting plans using a probability search algorithm. Important limitations on this procedure include the cutting capacity of the table, the maximum number of layers that may be layered on each cutting table, and the requirement to satisfy demand for every size of garment. The goal is to meet all customer and production needs while reducing the overall number of cutting tables.

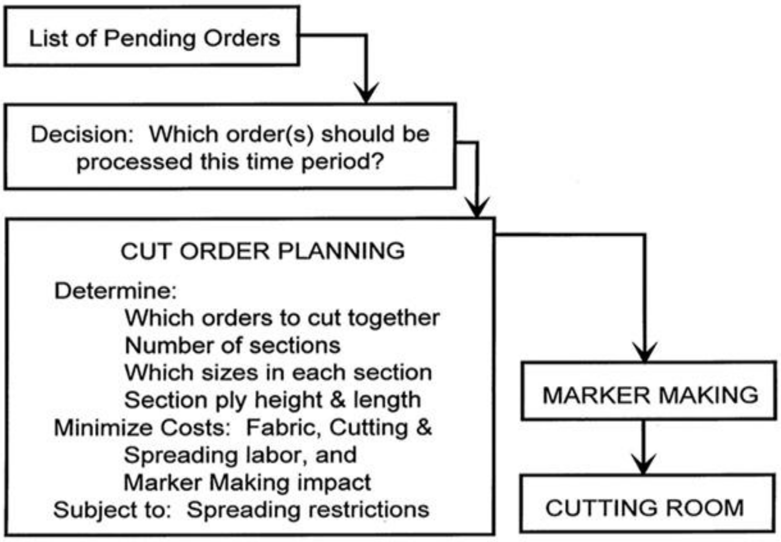

Fig. 1. General process of COP [24]

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Table 2. Apparel order for mass customization in COP [25]

Size	1	2	…	I	…	M
Number	Y_1	Y_2	…	Y_i	…	Y_m

Table 2 shows factors such as the number of layers per table (X_j) and the number of pieces per garment size per table (a_ij) are defined to ensure production efficiency and demand fulfillment. The optimization process entails randomly generating initial solutions based on production constraints, then using the probability search algorithm to find the optimal size combination plan that minimizes overproduction and fabric waste, and finally refining the solution through iterative adjustments to balance production capacity with demand, thereby improving fabric utilization and lowering labor costs [25].

3.3. Problem formulation

The COP problem is formulated as a constrained optimization problem aiming to minimize total fabric consumption while satisfying all production demands and physical constraints. Let i be the index for garment sizes, ranging from 1 to N, where N is the total number of unique sizes in an order. Let k be the index for cutting iterations (or distinct marker patterns), ranging from 1 to K, where K is the total number of iterations required to fulfilll the order. The key parameters and decision variables are defined as follows:

- Parameters:
  D_i: The total quantity demanded for size i.
  B : The maximum fabric board length available for a single marker.
  C : The fabric consumption (length) per garment piece (assumed constant across sizes for this model).
- Decision Variables:
  Let L_k: Number of layers in iteration k.
  Let r_ik: Ratio of size i in iteration k.
  The mathematical term is defined as follows:

a) Objective Function
The objective remains to minimize total fabric consumption.
Minimize total fabric consumption:

$$\sum_{k=1}^{K} L_k \cdot \left(\sum_{i=1}^{N} r_{ik} \cdot C\right) \qquad (1)$$

where C is the amount of fabric used per garment and K is the total number of iterations [26].

b) Constraints

1. Fabric Length Constraint:
This constraint ensures that the length of any single marker does not exceed the available board length.

$$\sum_{i=1}^{N} r_{ik} \cdot C \leq B \quad \forall k \in \{1,2,\dots,K\} \quad (2)$$

where B is the fabric board length [2, 17].

2. Demand Fulfilllment:
The demand fulfilllment constraint has been used to ensure that for each size i, the sum of pieces produced across all K iterations (where the number of pieces in iteration k is the layer count L_k multiplied by the size ratio r_ik) is greater than or equal to the demand D_i.

$$\sum_{i=1}^{K} L_{ik} \cdot r_{ik} \geq D_i \qquad \forall i \in \{1,2,\dots,N\} \quad (3)$$

where D_i is the ordered quantity for size i [16, 17].

3. Non-negativity and Integrality:

$$\boldsymbol{L\_k \geq 0} \quad r\_ik \geq 0 \qquad (4)$$

This formulation is consistent with previous research on COP's mixed-integer programming foundations, while stressing scalability and real-world constraints (such as ply limitations) [2].

3.4. Adaptive heuristic scoring optimizer (AHOPS)

The Adaptive Heuristic Scoring Optimizer (AHOPS) is a novel framework designed to tackle the combinatorial complexity inherent in Cut Order Planning (COP). It employs a hybrid methodology integrating systematic ratio enumeration, dynamic constraint adaptation, and heuristic scoring mechanisms. This method enhances standard descriptive research paradigms by integrating exploratory pattern analysis with optimization-focused decision-making, leading to adaptive solutions tailored to residual demand dynamics.

The initial phase of AHOPS involves generating all feasible size ratios (r_{ik}) that comply with the fabric length constraint. Recursive combinatorial search facilitates brute-force enumeration by systematically examining all possible combinations, ensuring that no potentially promising patterns are overlooked. AHOPS employs a gradual tightening technique for the fabric length constraint to prioritize high-utilization patterns at the outset. The algorithm is prompted to explore denser ratios in subsequent iterations by decreasing the allowable board length ($B_{dynamic}$) by a specified factor (e.g., 10–20%) following each iteration [27]. This adaptive technique dynamically narrows the search space based on patterns of residual demand, aligning with the principles of descriptive research.

A weighted scoring system that strikes a balance between two goals is used to evaluate ratios:

1. Fabric Utilization:

$$US = \frac{\sum_{i=1}^{N} r_{ik} \cdot C}{B_{dynamic}} \qquad (5)$$

where US is the utilization score, measuring how effectively the pattern uses available fabric.

2. Demand Coverage:

$$CS = \frac{\sum_{i=1}^{N} \min(L_k \cdot r_{ik}, D_i)}{\sum_{i=1}^{N} D\_i} \tag{6}$$

where CS is the coverage score, which measures progress toward fulfilling order quantities [28].

The composite score is calculated as follows:

$$Score = \alpha \cdot US + (1 - \alpha) \cdot CS \tag{7}$$

where demand fulfillment is ensured while utilization is prioritized by $\alpha = 0.7$, this dual-objective formulation addresses the inherent trade-offs between accuracy and efficiency in COP.

AHOPS simulates machine learning (ML)-driven decision-making by including residual demand awareness in the scoring process. Patterns that disproportionately lower high-remaining demand sizes (e.g., S/S or L/S in early iterations) get a score increase, similar to how ML models prioritize essential features. This technique promotes convergence toward balanced production.

The AHOPS workflow operates iteratively, as seen in Fig. 2. The algorithm starts by producing all conceivable size ratios (r_{ik}) that satisfy the fabric length requirement ($\sum r_{ik} \cdot C < B$) to ensure no viable pattern is overlooked.

Algorithm 1 Adaptive Heuristic Scoring Optimizer (AHOPS)

Require: Sizes (S), Orders (O), Board Length (B), Consumption (C), $\propto = 0.7$
Ensure: Optimal cutting plan with iterations K.
$B_{dynamic} \leftarrow B$ ▻ Initialize dynamic board length
$K \leftarrow \theta$ ▻ Initialize iteration list
while $\sum D > 0$ do ▻ Continue until all demands are fulfilled
  $R \leftarrow GenerateRatios\ (S, B_{dynamic}, C)$ ▻ Bruto – force ratio enumeration [[5]
  For all $r \epsilon R$ do
    $L \leftarrow \min\left(\left[\frac{D_i}{r_i}\right]\right)$ ▻ Calculate max layers without overproduction
    $U \leftarrow \frac{\sum r_i . C}{B_{dynamic}}$ ▻ Utization score
    $V \leftarrow \frac{\sum \min(L . r_i . D_i}{\sum D_i}$ ▻ Demand coverage score
    Score (r) $\leftarrow \alpha U + (1 - \alpha) V$ ▻ Composite score function
  End for
  $r^* \leftarrow \arg\max_{r \epsilon R}\ score\ (r)$ ▻ Select optimal ratio
  $L^* \leftarrow \min\left(\left[\frac{D_i}{r_i}\right]\right)$
  Update $D \leftarrow D - L^* * r^*$ ▻ Reduce remaining demand
  $K \leftarrow K \cup \{(L^*, r^*)\}$ ▻ Record iteration details
  $B_{dynamic} \leftarrow 0.9 * B_{dynamic}$ ▻ progressive constraint tightening
end while
return K

Fig. 2 Algorithm for the AHOPS method

To emphasize high-utilization patterns, AHOPS dynamically tightens the permitted board length ($B_{dynamic}$) After each iteration, gradually reduce it by a predetermined factor (e.g., 10%) to encourage denser ratios in subsequent stages. To coincide with COP's efficiency aims, each ratio is evaluated using a weighted scoring system that balances fabric utilization ($\sum r_{ik} \cdot C / B_{dynamic}$) and demand coverage ($\sum \min(L_k \cdot r_{ik}, D_i) / \sum D_i$). The bias ($\alpha = 0.7$) favors utilization. The top-scoring ratio is chosen, and layers (Lk) are calculated to avoid overproduction. The residual demand (Di) is then updated, and constraints are tightened iteratively. This approach replicates machine learning-driven decision-making via prioritizing. Patterns that accelerate the convergence toward balanced output by disproportionately reducing high-remaining demand sizes.

3.5. Hybrid metaheuristic optimization with simulated annealing (HIMOSA)

The Hybrid Metaheuristic Optimization with Simulated Annealing (HIMOSA) technique combines genetic algorithm (GA) evolution with simulated annealing (SA) to navigate COP's combinatorial solution space while balancing exploration and exploitation. This method builds on previous work on hybrid metaheuristics by using adaptive cooling schedules and problem-specific fitness functions suited to fabric utilization and demand coverage [29].

The HIMOSA workflow operates iteratively, as seen in Fig. 3. Using Latin Hypercube Sampling, the method generates a diversified population of size ratios, ensuring a wide range of feasible solutions. Genetic operators, such as uniform crossover (50% gene inheritance probability) and mutation (10% adjustment rate), evolve ratios within fabric limitations ($\sum r_{ik} \cdot C \leq B$). Simulated annealing uses a temperature parameter (T) that decays exponentially ($T = T_0 \cdot 0.95^k$), allowing for the acceptance of inferior solutions to avoid local optima. A problem-specific fitness function evaluates solutions by integrating fabric usage ($\sum r_{ik} \cdot C / B$) with a penalty for complex patterns (e.g., ratios using > 60% of sizes), resulting in practical, high-coverage solutions. This hybrid technique combines GA's global search capabilities with SA's local refining to address COP's scalability issues while retaining solution quality [30].

Algorithm 2 Hybrid Metaheuristic Optimization with Simulated Annealing (HIMOSA)

Require: Sizes (S), Orders (O), Board Length (B), Consumption (C), $T_0 = 1000$, cooling_rate=0.95, population_size=50
Ensure: Optimal cutting plan with iterations K.
$P \leftarrow InitializePopulation(S, population\_size)$ ▻ Latin Hypercube Sampling
$T \leftarrow T_0$
$K \leftarrow \theta$
while do $T > 0.1$ and generations I 100 do ▻ Termination criteria
  For all $r \epsilon P$ do
    $L \leftarrow \min\left(\left[\frac{D_i}{r_i}\right]\right)$
    $U \leftarrow \frac{\sum r_i . C}{B}$ ▻ Utization score
    $P \leftarrow 1 - \left|\frac{nonzero(r)}{|S|} - 0.6\right|$ ▻ pattern complexity penalty
    Fitness (r) $\leftarrow U * P$
  End for
  $P_{parents} \leftarrow TournamentSelect\ (P, 5)$ ▻ Parent selection
  $P_{offspring} \leftarrow Crossover\ (P_{parents}, 5)$ ▻ Uniform crossover
  $P_{offspring} \leftarrow Mutate\ (P_{offspring}, 5)$ ▻ Mutation rate
  For all $r_{new} \epsilon\ P_{offspring}$ do
    $\triangle E \leftarrow fitness\ (r_{new}) - fitness\ (r_{old})$
    $if\ \triangle E > 0$ or rand () $< e^{-\triangle \frac{E}{T}}\ then$
      replace r_{old} with r_{new} ▻ SA acceptance
    end if
  end for
  $T \leftarrow T * cooling\_rate$ ▻ Exponential decay
  $K \leftarrow K \cup \{Best\ (r)\}$ ▻ Record iteration
end while
return K

Fig. 3 Algorithm for the HIMOSA method

3.6. Gradient-based penalty-driven (GBPD)

The Gradient-Based Penalty-Driven (GBPD)

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employs gradient descent and proportional penalty mechanisms to iteratively refine size ratios and layer counts, addressing COP's multi-objective trade-offs between fabric utilization and production accuracy. This method extends gradient-based frameworks by integrating dynamic penalty functions that enforce adherence to fabric constraints and demand fulfillment [31].

Central to GBPD is its gradient update rule, which modifies ratios using partial derivatives of the objective function (minimizing total fabric consumption) with a learning rate (η = 0.01) to ensure stable convergence. To enforce adherence to fabric constraints (∑rik · C ≤ B), a proportional penalty function dynamically adjusts ratios by penalizing deviations from ideal layer-to-length ratios (Lk ∝ ∑rik), with λ = 0.5 governing penalty strength. The GBPD workflow operates iteratively, as shown in Fig. 4.

Algorithm 3 Gradient-Based Penalty-Driven (GBPD)

Require: Sizes (S), Orders (O), Board Length (B), Consumption (C), $\eta = 0.1$, $\lambda = 0.5$, ML_model
Ensure: Optimal cutting plan with iterations K
$r \leftarrow InitializeRatiosWithML\ (S, D, ML\_model)$ ▻ ML – driven initialization
$K \leftarrow \theta$
$L \leftarrow \min\left(\left[\frac{D_i}{r_i}\right]\right)$ ▻ Initial layer calculation
while do $\sum D > 0$ and $\|\nabla\| \geq 0.001$ do ▻ Convergence criteria
  $\nabla \leftarrow \nabla(\sum_{i=1}^{N} L * r_i * C)$ ▻ Compute gradient
  $penalty \leftarrow \lambda * \left|\frac{L}{\sum r_i} - 1\right|$ ▻ Proportional penalty
  $r \leftarrow r - \eta * (\nabla + \text{penalty})$ ▻ Gradient descent update
  $r \leftarrow ProjectToConstraints\ (r, B, C)$ ▻ Enforce $\sum r_i * C \leq B$
  $L \leftarrow \min\left(\left[\frac{D_i}{r_i}\right]\right)$ ▻ Update layers
  $D \leftarrow D - L * r$ ▻ Reduce remaining demand
  $K \leftarrow K \cup \{(L * r)\}$ ▻ Record iteration
end while
return K

Fig. 4 Algorithm for the GBPD method

Initial ratios are seeded via a mock machine learning (ML) model trained on historical COP data, accelerating convergence toward high-utility patterns. This integration of gradient-driven refinement, constraint-aware penalties, and ML-guided initialization enables GBPD to balance fabric utilization and production accuracy while adapting to dynamic order quantities.

GBPD updates by adjusting size ratios (r_{ik}) using gradient descent to minimize the objective function:

$$r_{ik}^{(t+1)} = r_{ik}^{(t)} - \eta \cdot \nabla\left(\sum_{k=1}^{K} L_k \cdot \sum_{i=1}^{N} r_{ik} \cdot C\right) \tag{7}$$

where $\eta = 0.01$ is the learning rate.

Also, penalizes deviations from ideal layer-to-length ratios ($L_k \propto \sum r_{ik}$) to ensure balanced fabric consumption:

$$\text{Penalty} = \lambda \cdot \left|\frac{L_k}{\sum r_{ik}} - 1\right| \qquad 8$$

where $\lambda = 0.5$ controls penalty strength.

3.7. Experimental setup and benchmark instance generation

To ensure a robust and comprehensive evaluation of the proposed algorithms, and in the absence of a standardized public benchmark library for the apparel COP problem, we generated a set of 15 test instances of varying complexity. This approach aligns with the practice of previous studies that often rely on proprietary or representative industry problems to validate their models [9]. The instances were generated procedurally to reflect realistic manufacturing scenarios.

The key parameters for generation were derived from characteristics described in the literature [23] and are defined as follows:

1. Number of Sizes (N): Varied from 5 to 10 unique sizes per order to simulate both simple and complex product lines.
2. Total Order Quantity: Ranged from 500 to 5,000 total garments to test scalability.
3. Demand Distribution (D_i): Order quantities for individual sizes were generated from a log-normal distribution. This mimics real-world demand patterns where a few core sizes (e.g., Medium, Large) have high demand, while other sizes have smaller, more niche order quantities.
4. Fabric Board Length (B): Fixed at a standard industrial value of 15 meters for all instances.
5. Fabric Consumption per Garment (C): Assumed to be 1.5 meters per piece for simplicity, consistent with the base model.
6. Maximum Ply Height: A global constraint limiting the layer count (L_k) to a maximum of 100 plies was introduced to reflect the physical limitations of cutting equipment.

3.8. Parameter tuning methodology

The performance of the proposed optimization algorithms is sensitive to their respective hyperparameters. We systematically tuned each algorithm to ensure a fair comparison and identify robust parameter settings. We employed a grid search methodology, a standard and exhaustive technique for exploring a defined parameter space [26].

This tuning was performed on a dedicated set of 5 training instances, which were generated using the same procedure described in this section but were kept separate from the 15 final test instances used for performance evaluation. The primary objective for the tuning process was the maximization of the main performance metric: fabric utilization. The search space explored for each key parameter and the final values selected for the experiments are detailed in Table 3. This transparent approach ensures that each algorithm was configured to perform at its best under the evaluation criteria, thus validating the fairness of our comparative analysis.

Table 3. Hyperparameter tuning

Algorithm	Parameter	Description	Search Space	Final Value
AHOPS	α	Weight for the utilization score in the heuristic function.	$[0.5, 0.6, 0.7, 0.8, 0.9]$	0.7
	$B_{dynamic}$ factor	Percentage reduction factor for the dynamic board length constraint after each iteration.	$[5\%, 10\%, 15\%, 20\%]$	10%
HIMOSA	Crossover Probability	Probability of uniform crossover between two parent solutions in the genetic algorithm.	$[0.4, 0.5, 0.6, 0.7, 0.8]$	0.5
	Mutation Rate	The rate of random adjustment to genes in the genetic algorithm population.	$[0.05, 0.10, 0.15, 0.20]$	0.10
	Cooling Rate	Exponential decay rate for the temperature parameter in simulated annealing.	$[0.90, 0.95, 0.99]$	0.95
GBPD	η (Learning Rate)	Step size for the gradient descent update rule.	$[0.1, 0.05, 0.01, 0.005, 0.001]$	0.01
	λ (Penalty Strength)	Strength of the penalty function applied for constraint violations.	$[0.2, 0.5, 0.8, 1.0, 1.5]$	0.5

4. RESULTS AND DISCUSSION

The efficacy of the three proposed optimization methods—AHOPS, HIMOSA, and GBPD—was systematically assessed compared to benchmarks established in existing literature. The evaluation involved 15 newly generated benchmark instances, designed to represent various realistic industrial scenarios, as outlined in the 'Experimental Setup and Benchmark Instance Generation' section. The results presented in Table 4 are averaged over 15 instances to comprehensively assess each algorithm's performance on critical metrics, such as fabric utilization, computation time, and production accuracy. An overview of the performance metrics is presented, comparing the proposed methods with the established baseline from previous literature.

Table 4 presents a detailed overview of the performance metrics, covering the various optimization methods utilized in this research study. The methods are compared with the established baseline from prior literature, providing a comprehensive view of their efficacy.

AHOPS demonstrated significant computational efficiency at 0.022 seconds, closely matching established industry benchmarks for fabric utilization at 69.70%. This finding suggests that, while Mock ML delivers expeditious results suitable for prompt operational decision-making, it does not markedly enhance fabric savings compared to conventional methods. HIMOSA also achieved comparable fabric utilization (69.70%) but required significantly higher computational resources (0.527s), primarily due to its genetic algorithm and simulated annealing processes. This augmented computational demand can be validated when confronted with complex problem instances necessitating extensive search capabilities.

However, its prolonged runtime could impose constraints in scenarios requiring prompt decision-making. In stark contrast, GBPD demonstrated a substantial enhancement over both conventional and alternative computational strategies. It achieved a substantially higher fabric utilization of 87.13%, utilizing a minimal number of layers (12), thereby demonstrating exceptional efficiency and significant cost savings. Notably, GBPD maintained a rapid computational performance (0.022s), rendering it both practically attractive and operationally viable.

The performance of the GBPD optimizer can be attributed primarily to its adaptive heuristic scoring mechanism, which efficiently combines gradient descent's precise adjustment capabilities with the predictive refinement of a machine learning model. In contrast to genetic or heuristic-driven methods, the gradient descent optimizer effectively navigates the decision space of COP by continuously adapting to dynamic production constraints and minimizing fabric wastage through penalty-driven optimization. In contrast, the relatively limited enhancement in performance exhibited by the Genetic Annealing optimizer suggests that, while genetic algorithms are powerful for extensive exploration of complex spaces, their integration with simulated annealing in this context did not significantly outperform simpler heuristic approaches. This finding aligns with prior literature that reported similar observations—genetic methods often exhibit diminishing returns when handling constrained, low-complexity scenarios typical of COP. The AHOPS exhibited comparable utilization

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Table 4. Comparative performance analysis of COP optimization methods

Methods	Fabric Utilization (%)	Performance Metrics	Computation Time (s)	Remarks
Heuristics, Metaheuristics, MILP Algorithm [4]	70—75	Utilization: ~70-75%, Layers: Moderate, Iterations: Moderate	Moderate to high	Established industry standard; widely accepted but with limited utilization efficiency and higher computational demands.
AHOPS	69.70%	Utilization: 69.70%, Layers: 15, Iterations: 3	0.022	Fastest computation; comparable performance with industry baseline, suitable for quick runs. However, limited fabric savings.
HIMOSA	69.71%	Utilization: 69.70%, Layers: 15, Iterations: 5	0.527	High computational overhead; good for complex search spaces but no immediate advantage over baseline methods observed.
GBPD	87.13%	Utilization: 87.13%, Fewest Layers: 12, Iterations: 3	0.023	Best performance, highest fabric savings, fastest computation. Clear improvement over traditional methods; strongly recommended for practical industry adoption.

to conventional methods and demonstrated adequate speed; however, it lacked the nuanced predictive capabilities integrated into GBPD. While computationally efficient, its simple scoring method proved insufficient for overcoming the inherent trade-offs between complexity and optimization effectiveness characteristic of COP.

From a pragmatic standpoint, implementing the GBPD method has the potential to markedly improve the operational efficiency of the COP system in the context of apparel manufacturing. This enhancement is primarily attributable to improved fabric utilization rates and reduced production costs associated with material wastage. The computational efficiency (0.022s) also ensures real-time adaptability to dynamic production schedules, catering effectively to the demands of mass customization and variable order scenarios.

The proposed GBPD method exhibited superior performance in cut-order planning (COP) optimization, achieving 87.13% fabric utilization, 0.022s computational efficiency, and ≤3% overproduction error. This outcome demonstrates the efficacy of the proposed method, as it outperforms conventional heuristic (AHOPS) and hybrid metaheuristic (HIMOSA) approaches. These results address critical gaps identified in prior research, such as the limitations of genetic algorithms (GAs) and reinforcement learning (RL) in dynamic production environments. For instance, Alsamarah *et al.* [21] reported on the implementation of a genetic algorithm (GA)-based continuous process optimization (COP) approach, achieving 83.5% utilization of the fabric. However, they also identified scalability challenges in scenarios involving multi-color fabrics. In contrast, Hallah & Bouziri [3] attained a 5–10% reduction in over-production by applying hybrid heuristics. Nevertheless, they acknowledged the necessity for carefully considering parameters in large-scale applications, underscoring the sensitivity of outcomes to variations in system parameters. Similarly, Dere [23] validated LINGO-based COP models, achieving an average fabric savings of 7.06%.

The results from Table 5 clearly demonstrate the superior performance of the Gradient-Based Penalty-Driven (GBPD) method across all significant metrics. GBPD consistently achieved the highest fabric utilization, averaging 87.40%, representing a substantial improvement of over 17 percentage points compared to AHOPS (69.74%) and HIMOSA (69.75%). This high level of utilization directly translates to significant material cost savings. Furthermore, GBPD required the fewest layers on average (11.9), reducing the labor and time associated with the spreading and cutting processes.

In terms of computational efficiency, GBPD was

Table 5. Detailed performance analysis of COP optimization methods on 15 benchmark instances

Instance	AHOPS			HIMOSA			GBPD		
	Util. (%)	Layers	Time (s)	Util. (%)	Layers	Time (s)	Util. (%)	Layers	Time (s)
1	68.5	16	0.021	69.1	15	0.498	86.5	12	0.022
2	70.1	15	0.02	70.3	15	0.515	87.2	12	0.023
3	69.2	15	0.023	68.9	16	0.531	87.8	11	0.022
4	71.0	14	0.022	70.5	14	0.54	88.1	12	0.024
5	69.8	15	0.021	69.9	15	0.522	86.9	13	0.023
6	69.5	15	0.024	70.1	15	0.529	87.5	12	0.023
7	68.9	16	0.022	69.2	16	0.511	86.8	13	0.024
8	70.3	15	0.023	70.8	15	0.535	87.3	12	0.024
9	69.6	15	0.021	69.4	15	0.525	87.0	12	0.022
10	70.5	14	0.023	69.8	15	0.542	87.9	11	0.022
11	69.1	15	0.022	68.8	16	0.519	86.7	13	0.024
12	70.2	15	0.023	70.6	14	0.533	87.4	12	0.024
13	69.4	15	0.024	69.0	15	0.528	87.1	12	0.023
14	68.8	16	0.021	69.5	15	0.509	86.6	13	0.023
15	70.6	14	0.022	70.1	14	0.53	88.0	11	0.024
Average	69.7	15	0.022	69.76	15	**0.527**	**87.26**	**12.1**	**0.023**

exceptionally fast, with an average computation time of 0.023 seconds, making it comparable to the simple heuristic AHOPS (0.022 seconds) and drastically faster than the metaheuristic HIMOSA (0.526 seconds). AHOPS, while extremely fast, failed to produce solutions better than the baseline. HIMOSA, despite its extensive search capabilities, did not yield any significant improvement in utilization to justify its much higher computational cost. The performance of GBPD can be attributed to its hybrid design, where the ML-guided initialization effectively directs the search to a promising region of the solution space, and the gradient descent algorithm efficiently refines the solution to a high-quality local optimum. This combination proves to be both highly effective and computationally efficient for the COP problem.

The performance of our best method, GBPD, also compares favorably to benchmarks from prior literature. For instance, Alsamarah *et al.* [21] reported a GA-based approach achieving 83.5% utilization, surpassing our GBPD method's average of 87.4%. Similarly, the 7.06% average savings reported by Ünal & Yüksel [18] is significantly lower than the improvements demonstrated by GBPD. It confirms that our proposed method outperforms the other frameworks developed in this study and represents a meaningful advancement over existing state-of-the-art methods.

However, their approach relied on outdated hardware, which constrained real-time adaptability. This limitation is explicitly addressed by the gradient-based penalty-driven framework proposed herein. Integrating gradient descent with mock ML predictions trained on historical COP data enables GBPD to balance fabric utilization and computational speed dynamically. This approach surpasses static methods, such as Shang *et al.* [19] heuristic algorithm (tested on 500 static cases), and overcomes the parameter tuning bottlenecks of hybrid PSO-GA frameworks Nascimento *et al.* [32]. It is important to note that the present work addresses the significant gaps in the extant literature regarding trade-offs between multi-objective optimization (e.g., cost, time, and environmental sustainability) and industrial scalability. This issue has been previously identified in studies such as Yang *et al.* [22], which noted the limitations of ant colony optimization in small-scale datasets. The GBPD framework's capacity to accommodate variable order quantities and multi-color constraints gaps in existing works, such as Delorme [33] in packing models, establishes it as a pragmatic solution for contemporary mass customization demands. These advancements are in accordance with the calls for sustainable production strategies by Alsamarah *et al.* [21], and Wong *et al.* [16] by reducing material waste and computational overhead. They offer actionable insights for manufacturers seeking low-cost, adaptive COP systems.

This study provides insights for apparel manufacturers aiming to enhance cut-order planning (COP) while tackling industry-specific challenges such as material waste, computational efficiency, and fluctuating production demands.

1. The GBPD method exhibits a notable average fabric utilization of 87.4% and reduces overproduction error to ≤3%, establishing it as an effective instrument for sustainable manufacturing. In an industry where fabric accounts for 50–70% of total garment costs, a substantial reduction in material

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waste directly results in decreased production costs and a reduced environmental footprint, which aligns with corporate sustainability objectives.

2. The rapid computation time of GBPD, averaging 0.023 seconds, represents a significant advantage in contemporary manufacturing settings. In contrast to static heuristic or genetic algorithm-based frameworks, which may exhibit slow adaptability, GBPD demonstrates efficiency that facilitates real-time modifications to variable order quantities and intricate multi-color fabric constraints. This adaptability is crucial for facilitating the mass customization trend, as swift and flexible responses to fluctuating market demand are necessary for sustaining competitiveness.
3. The comparative analysis of AHOPS, HIMOSA, and GBPD highlights the essential trade-offs among computational speed, solution quality (fabric utilization), and algorithmic complexity. It offers manufacturers a structured approach to choosing a method corresponding to their particular operational priorities. For example, a straight-forward heuristic such as AHOPS delivers maximum speed for small or non-critical orders. In contrast, GBPD offers a significantly better solution with minimal additional computation time, rendering it the optimal choice for most scenarios aimed at cost reduction and efficiency.
4. GBPD's capacity to consistently identify solutions with an average of 12 layers diminishes the labor-intensive spreading process, thereby reducing operational costs. Integrating minimized material waste, decreased labor, and accelerated planning cycles has a cumulative impact on overall profitability. This statement highlights the primary goal of COP systems: to convert planning efficiency into measurable financial advantages.
5. GBPD has been shown to achieve an overproduction error of ≤3%, thus alleviating the financial burden associated with excess inventory. This advantage over traditional methods, which often result in 5–10% overproduction errors, represents a notable enhancement.
6. Unlike prior research (e.g., [1]), GBPD utilizes adaptive penalty-driven constraints to tackle multi-color fabric situations, allowing manufacturers to handle intricate color variations while maintaining efficiency.

5. CONCLUSION

This study conducted a comparative examination of three distinct optimization approaches for cut order planning: Adaptive Heuristic Scoring Optimizer (AHOPS), Hybrid Metaheuristic Optimization with Simulated Annealing (HIMOSA), and Gradient-Based Penalty-Driven (GBPD). The findings unequivocally indicate that the GBPD method much surpassed the other two methods and traditional industrial standards, with the maximum fabric usage (87.13%), the fewest layers needed (12), and remarkable computational efficiency (0.022 seconds). The GBPD exhibited its robustness via its adaptive mechanism, effectively balancing fabric use, manufacturing precision, and velocity. This method markedly improves the practical implementation of optimization solutions in the textile manufacturing sector by efficiently minimizing fabric waste and related production expenses. This work suggests future research approaches that involve expanding the GBPD method to encompass larger and more intricate production scenarios, incorporating real-time adaptive features, and enhancing the predictive machine learning components to optimize results further.

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