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Solving One-Dimensional Material Cutting Model Based on Genetic Algorithm

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Abstract. The cutting efficiency and material utilization challenges in window frame manufacturing represent a typical one-dimensional material cutting problem. Traditional linear programming algorithms encounter NP-hard issues, making effective solutions difficult. This study employs genetic algorithms to establish models for maximizing profits and developing optimal cutting schemes. For Problem 1, we designed specialized encoding strategies under genetic algorithm frameworks to effectively address partitioning challenges. The fitness function incorporates a strategy space concept, where solution costs serve as individual fitness values for iterative optimization. Matlab simulations demonstrate this approach achieves high raw material utilization while maximizing profits. For Problem 2, the model extends to defective sections by extracting valid cutting intervals with non-overlapping constraints, creating a new strategy space for defect avoidance. Applying this strategy space to genetic algorithm fitness functions enables rapid computation of optimal outcomes. Regarding Problem 3, we developed an evaluation molecule-based material assessment method for large-scale multi-type orders. When handling excessive materials, the scoring system prioritizes high-quality materials, significantly enhancing computational efficiency. The results show that under different complexity backgrounds, the model can output engineering feasible cutting schemes stably, and finally achieve more than 92% material utilization rate and significant profit income under the premise of full order coverage.

Keywords: One-dimensional cutting, Genetic algorithm, Defect interval processing, Large-scale order

1. Introduction

Window-frame production relies on precise cutting of elongated aluminum or steel stock to meet order specs, tolerances, and saw-kerf waste. Defects appear randomly, so plans must dynamically reroute cuts to dodge flaws while maximizing yield and quality..

Problem 1: Suppose each order contains multiple window frame requirements, with each frame having target width, height, and tolerance range (i.e., allowable dimensional deviations). During cutting, the impact of saw cut width on actual dimensions must be considered to meet order specifications within remaining material length while minimizing waste. Table 1 presents specific order requirements: width and height may vary by ±0.01 meters from given dimensions. Each

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window frame requires two heights and two widths. Given available materials measuring 5.5m,6.2m, and 7.8m in length at unit prices of ¥18, ¥22, and ¥28 per piece respectively, with unlimited quantities, and a saw cut width of 0.005 meters, please develop a mathematical model based on material lengths to establish an optimal cutting plan that maximizes profit (total cost-benefit difference) while meeting customer demands. Additionally, calculate the cutting loss rate and utilization rate for this solution [1].

Problem 2: Assuming each raw material contains irregular defects whose dimensions and locations are known, these defects will affect material cutting. The finished product must not contain any defective areas (each defect area is defined as a rectangular region). Each category of raw material defect information includes its starting position and length, as shown in Table 2 [2]. Based on these defects, we reconstruct the mathematical model from Problem 1 to formulate an optimal cutting plan, then calculate both the overall cutting loss rate and utilization rate of the adjusted plan.

2. Problem analysis

In one-dimensional material cutting problems, obtaining theoretically rigorous global optimal cutting solutions remains an NP-complete challenge. Genetic algorithms, inspired by natural evolutionary mechanisms, explore solution spaces through population iteration. This approach effectively avoids the common issue of traditional gradient descent methods getting trapped in local optima, making it widely adopted across multiple fields [3]. Therefore, we abandon conventional integer programming solutions and instead establish a cutting plan model that optimizes material usage and cutting patterns to achieve cost minimization and profit maximization.

2.1. Analysis of problem 1

To meet the goal of "model → optimal cut → max profit," we adopt a three-step framework:

(1) Profit view—fixed frame prices and ample raw stock make revenue constant, so profit hinges on minimizing material cost.

(2) Constraints—order quantities must be met and any cut pattern must fit within the chosen stock length.

(3) Model—encode material choice as chromosomes, use total cost as fitness, and evolve solutions via genetic operators (crossover, mutation, selection) until the best partitioning plan emerges.

2.2. Analysis of problem 2

Problem 2 introduces variables more closely aligned with real-world production scenarios: material defects. In actual manufacturing, certain raw materials contain unusable areas such as scratches, bubbles, and bends, whose locations and lengths are typically known [4]. Therefore, the original cutting plan must be adjusted to avoid these known defect areas while maintaining order fulfillment capabilities, preventing product rejection or quality issues caused by defects. This requirement complicates the cutting layout strategy. Building upon Problem 1, we have added constraint spaces for raw materials and developed the following analytical approach: 1. Profit Analysis: Same as Problem 1. 2. Constraint Determination: Considering variations in material length, defect space, and cost, each order requires products of different sizes and quantities. Unlike Problem 1, three constraints must be addressed: (1) Customer demand limitation – the number of cut products must meet client requirements; (2) Material length limitation – the total available length under any cutting

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pattern must not exceed the material's length; (3) Defect space limitation – cutting plans must avoid defective areas. 3. Model Establishment: Building on the Problem 1 model, genetic algorithm solutions are employed to determine raw material partitioning schemes by incorporating constraint space limitations.

3. Basic assumptions

1. The cutting process demonstrates optimal technical specifications with zero defects or defective products;

2. Cutting waste materials cannot be reused;

3. All raw materials (including defective ones) are sufficiently supplied without material shortages;

4. No restrictions apply to the number of cuts performed, and this quantity does not affect costs;

5. The cutting width is disregarded as it is specified at 0.005 meters in this case. Considering a product typically has approximately two cutting edges, the maximum error margin of 0.01 meters aligns with the specified tolerance criteria, thus the cutting width can be neglected.

4. Model development and solution

symbol	symbol description
S	A collection of cutting strategies
C	Total production cost
L_i	The length of the first type of raw material
l_j	The length of product j
q_j	Demand for product j
D_{ik}	The defect interval of the kth number of raw material type i
c_i	The price of raw material type I
n_{si}	The amount of the first material used in the second cutting strategy
m^j_{si}	The number of parts of type j produced from raw material type i under cutting strategy type s

The one-dimensional cutting problem involves dividing a raw material into specified quantities with minimal trimming and optimal cutting methods. In Problem 1, five raw materials (lengths L1, L2,..., L5, costs c1, c2,..., c5) are available. With four orders requiring two different length materials each, eight window frame products (labeled l1, l2,..., l8) must be produced [5]. Let S denote the set of all possible cutting configurations, and miisk represent the quantity of the i-th component generated by the j-th cutting method for the k-th material. The production cost C is calculated as follows:

$$C = \sum_{i=1}^{5} \sum_{s \in S} n_{si} c_i$$

The constraints of various variables are:

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$$\begin{cases} \sum_{j=1}^{8} l_j m_s^j \leq L_i \ (\forall s \in S, i = 1, 2, \cdots, 5) \\ \sum_{i=1}^{5} \sum_{s \in S} n_{si} m_s^j \geqq_j \ (\forall s \in S, j = 1, 2, \cdots, 8) \end{cases}$$

Step 1: Arrange the parts in descending order of length to reduce the search space; Step 2: For each material Lj, recursively generate all combinations that satisfy the constraints ∑ljmjsi≤Lj; Step 3: If the remaining length is insufficient or the part requirements are met, terminate the branch.

The one-dimensional cutting problem is a classic challenge in combinatorial optimization. To obtain a theoretically optimal global solution, all feasible cutting methods must be incorporated into the coefficient matrix of the linear programming model [6]. From computational complexity theory, this constitutes an NP-complete problem. Therefore, we employ genetic algorithms to determine the overall cutting scheme with the lowest cost.

$$f = \sum_{i=1}^{5} \sum_{s \in S} n_{si} c_i$$

Using the cost value under a specific strategy as the fitness function, we calculate the corresponding fitness function for each individual (which can be mapped to a cutting plan) during each iteration to determine its cost value. To solve nsi, we design a greedy algorithm-based solution method: Step 1: Decode chromosomes to obtain part sequences, initially setting the remaining space as an empty set; Step 2: Process parts sequentially. If the remaining space contains the part, update it (using it) and proceed to the next part; otherwise, execute Step 3; Step 3: Create new raw materials by traversing the strategy set. Select cutting strategies containing the part with cutting index I (s). Update the remaining space (record other models produced under cutting mode s), record corresponding material i, and accumulate nsi; Step 4: After processing all parts, record returned nsis and compute f.

The cutting index in the algorithm is defined as :

$$I(s) = \frac{kl(s)}{v(s)}$$

$$p_k^t = \frac{\frac{1}{f_k^t}}{\sum_{\nu=1}^{Q} \frac{1}{f_\nu^t}} = \frac{1}{\sum_{\nu=1}^{Q} \frac{f_k^t}{f_\nu^t}}, k = 1, 2, \cdots, Q$$

As can be seen from the above formula, individuals with lower fitness (smaller cost) are selected with a higher probability, while those with higher fitness are selected with a lower probability. Moreover, the sum of the selection probability of all individuals is 1.

The scheme not only achieves large profit, but also achieves high utilization efficiency of raw materials, which proves that the established model has good practical feasibility and optimization

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ability.

5. Conclusion

5.1. Model evaluation

The team devised a window-frame cutting optimization model tackling defect-free operations, defect-zone handling, and large-scale orders. It embeds core constraints, key factors, cutting-strategy sets, and a genetic algorithm for dynamic global scheduling, yielding feasible solutions that guarantee order fulfillment and material efficiency [7]. Continuous cutting is recast as an evolutionary problem, shrinking the search space and boosting speed while flexibly meeting varied demands..

5.2. Improvement direction

The model can be further streamlined and refined. Replace the current uniform edge-error treatment with an asymmetric tolerance mechanism that reflects each component's distinct dimensional sensitivity. When handling large-scale orders, abandon the five high-coefficient material filter in favor of particle-swarm optimization to avoid local optima. Drop the assumption of unlimited stock and fixed unit prices; integrate inventory levels, bulk-purchase discounts, and procurement-driven scheduling into a unified optimization loop. Finally, complement integer-linear programming with graph models and interval dynamic programming to enrich solution diversity and structural expressiveness.

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