

Optimizing Efficiency in a 1D CSP: A Computational Intelligence Study

Innovative Ant Colony Optimization Approaches for the Cutting Stock Problem: An Experimental Comparison

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# Introduction

# Problem Definition:

# Methodology

# Implementation

# Experimental Results

## Performance Metrics

The performance of each proposed solution was evaluated based on three primary metrics: the total cost of stock used, the extent of stock wastage, and the computational efficiency, measured in time from initiation to solution. These metrics help assess both the effectiveness and efficiency of the algorithms under different problem complexities.

* Solution Cost: The total cost of the stock used to meet all piece requirements, aiming for minimization.
* Waste Minimization: The total length of stock wasted, which should be minimized.
* Computation Time: Time taken to arrive at a solution, indicating the algorithm's efficiency.

## Results of Experiments

Figure 1 illustrates a comparative analysis of the total costs incurred by Solution 1 and Solution 2 across the three problem instances. While both solutions approached the provided optimal costs, Solution 2 consistently yielded closer approximations, suggesting a more effective optimization strategy under varied conditions.

Cost Based Experiments

|  |  |  |  |
| --- | --- | --- | --- |
| Problem ID | Optimal Cost | Solution 1 Cost. Mutation | Solution 2 Cost  Hybrid ACO with local search |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

# Analysis and discussion

## Comparative Analysis

In this study, two algorithms were evaluated based on their performance in solving a stock cutting problem across three different instances with varying complexities. The key metrics considered were solution cost, waste minimization, and computation time. Each metric provides insights into different aspects of the algorithms’ efficacy and efficiency in resource management and processing time.

Algorithm 1 tended to produce solutions that were closer to the optimal cost in instances where the optimal cost was known, indicating a potentially more precise optimization strategy. For instance, in Problem 2, Algorithm 1 achieved a cost that was closer to the optimal by approximately 1.6%, compared to Algorithm 2 which was around 2.4% away from the optimal cost. However, Algorithm 1 generally took longer to compute the solutions, with computation times significantly higher especially in more complex problems (e.g., 33.16 seconds for Problem 3 compared to 3.42 seconds for Algorithm 2). Furthermore, Algorithm 1 had mixed results regarding waste, performing better than Algorithm 2 in Problem 2 but worse in Problem 3.

Algorithm 2, on the other hand, demonstrated superior performance in terms of computation speed across all problems and was consistently faster than Algorithm 1, suggesting a more time-efficient approach which might be more suitable in scenarios where quick decision-making is critical. Despite this, it often resulted in higher solution costs and variable performance in waste minimization. Notably, in simpler problem setups (Problem 1), it matched Algorithm 1 in both cost and waste but with significantly faster computation time.

## Conclusion of Experimental Results.

The experimental results highlight the strengths and limitations of each algorithm, suggesting that the choice between these two should be context-dependent:

* **Context of Efficiency**: Algorithm 2 is preferable in scenarios where time efficiency is critical. Its faster computation times make it suitable for real-time or near-real-time applications where decisions need to be made quickly, even at the expense of some level of optimality in cost and waste.
* **Context of Cost and Precision:** Algorithm 1 appears more suitable for scenarios where the minimal cost is paramount and computation time is less critical. This algorithm's ability to come closer to the optimal cost might offset the longer computation times in high-stakes financial contexts or where material costs significantly impact overall expenses.
* **Waste Sensitivity:** If waste minimization is a critical factor, the choice might depend on the specific problem complexity, as both algorithms have shown varied performance. Algorithm 1 might be favored in more complex setups for better waste outcomes, while Algorithm 2 could be considered in simpler settings.

Overall, the study underscores the importance of aligning the choice of algorithm with specific operational priorities, such as cost efficiency, time sensitivity, and waste reduction. Future work might explore hybrid approaches or parameter tuning to enhance the performance of each algorithm according to identified weaknesses. Additionally, further testing across a broader range of problem scenarios would help refine these conclusions and potentially reveal more about the conditions under which each algorithm performs best.

# Conclusion:

# References:

1. Baba, N., & Kozaki, M. (1992). AN INTELLIGENT FORECASTING SYSTEM OF STOCK PRICE USING NEURAL NETWORKS. *Proceedings of the International Joint Conference on Neural Networks*, *1*, 371–377. https://doi.org/10.1109/IJCNN.1992.287183