Coil Slitting

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Abstract

Coil slitting is a critical process in metal processing industries, aiming to produce smaller pieces from wide metal strips efficiently. This paper leverages the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a robust multi-objective optimization algorithm, to enhance the coil slitting process. Optimization focuses on obtaining best-quality pieces, keeping their sizes as big as possible, but also considering constraints such as coil width, minimum length of the piece, and material properties. The experiments demonstrate various solutions for different population sizes and probability mutation variables. NSGA-II's ability to generate a Pareto-optimal front enables the exploration of trade-offs between competing objectives, offering decision makers a range of optimal solutions.

Keywords: Coil slitting, NSGAII, Genetic Algorithms

1. Introduction

Coil slitting is an essential process in the metal processing industry, where large coils of material are slit into smaller pieces to meet specific requirements for downstream applications. The quality and efficiency of this process significantly impact operational costs and product usability. Optimizing the coil slitting process involves addressing complex, competing objectives, making it an ideal candidate for multi-objective optimization techniques.

We try to trade-off *size* of the cuts with their *quality*. The latter is defined by a physical measure obtained by a scanning performed on the entire sheet of metal.

This study focuses on optimization employing the non-dominated classification genetic algorithm II (NSGA-II), a widely used evolutionary algorithm for solving multi-objective problems.

Maximizing the average rectangle size ensures efficient utilization of the raw coil material by increasing the average size of usable rectangular sections derived from the slitting process.

The quality of a rectangular cut is defined by the 95th worst percentile of the sensor readings. To aggregate quality across the entire slitting, the average weighted by their size is taken. This focuses on reducing variability and improving quality penalizing the worst performing segments, ensuring reliable performance across all slit sections.

In addition to these objectives, the optimization process incorporates the following constraints:

The minimum length constraint, which forces the length of each piece to be at least 20 percent of the total length of the sheet, ensuring practical usability of the resulting sections.

Moreover, a simple cut constraint requires cuts only in vertical and horizontal directions, reflecting practical limitations in the industrial environment.

2. Related Work

The optimization of the coil slitting process has been a significant focus in industrial research. Therefore, it is worth mentioning two notable works related to this study.

"An exact model for a slitting problem in the steel industry," [1] introduces a mixed-integer linear optimization model. This model aims to reduce scrap, fulfill customer requirements, and improve order accuracy while adhering to operational constraints. Although our research also addresses customer requirements and optimizes the use of steel coils, it differs significantly in both methodology and problem formulation. We employ the Non-dominated Sorting Genetic Algorithm II (NSGA-II), focusing on a two-objective optimization approach. Additionally, our work incorporates constraints that are not addressed in the exact model, such as ensuring a minimum length of each rectangle (at least 20 percent of the total sheet length) and limiting cuts to vertical and horizontal directions. These limitations reflect real-world operational considerations and introduce additional complexity to the optimization process.

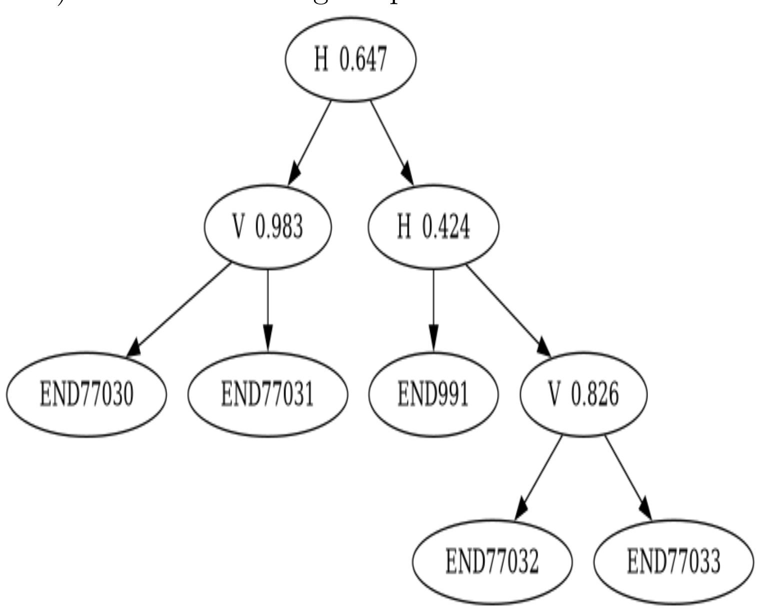
"Hybrid heuristic algorithm for two-dimensional steel coil cutting problem" [2], tackles a two-dimensional cutting problem for small rectangular items. The authors propose a Hybrid Heuristic Algorithm (HHA) to minimize trim loss and optimize the layout of items on large rectangular plates. Unlike classical two-dimensional cutting problems, this study introduces the concept of "nonclassical cutting," focusing on balancing conflicting objectives to enhance utility and efficiency. Our work differs by targeting the optimization of simple, practical cuts limited to vertical and horizontal directions, using a slicing-tree representation. Additionally, while HHA seeks optimal layouts, our approach explicitly incorporates domain-specific constraints, such as minimum piece length and quality variability, into the NSGA-II framework.

3. Algorithm

The implementation of the NSGA-II algorithm for optimizing the coil slitting process was designed to efficiently handle the problem's objectives and constraints. To represent and manipulate the slitted sheets, a *slicing tree* [3] data structure was employed.

The slicing tree provides a hierarchical representation of the coil slitting process, where each node corresponds to a cutting operation. This structure is well-suited for managing the constraints of simple cutting in vertical and horizontal directions while allowing efficient traversal and modification of the solution space.

Each node contains information on the direction of the cut (horizontal or vertical) and offset marking the position of the cut relative to the parent cut.



The algorithm was implemented using the Pymoo [4] Python library, a versatile toolkit for multi-objective optimization.

3.1. Crossover

To perform the crossover operation, subtrees within the slicing tree were randomly selected and swapped between two parent solutions. This operation enables the exchange of structural information, promoting diversity, and exploration of the solution space. The simplicity of subtree swapping ensures computational efficiency while maintaining the integrity of the slicing-tree representation.

3.2. Mutation

The mutation operation was implemented by randomly moving random a cut in a node within the slicing tree. This involves selecting a cut position within a node and shifting it to a new location, subject to the minimum length constraint (20 percent of the sheet length). This operation introduces variability in the population, allowing the algorithm to escape local optima and explore alternative solutions.

The combination of these customized crossover and mutation operations, in conjunction with the inherent capabilities of the NSGA-II framework, ensures effective optimization of the coil slitting process. The compatibility of the slicing tree with the algorithm's operations and constraints further enhances the efficiency and accuracy of the solution search.

4. Experiments

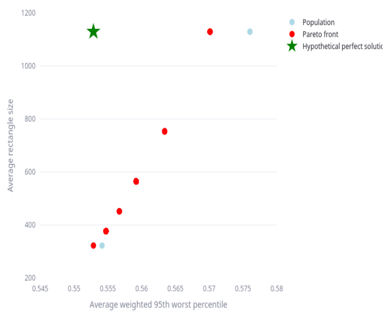
To evaluate the performance of the proposed optimization approach, we conducted a series of experiments using different configurations for the probability of mutation and population size.

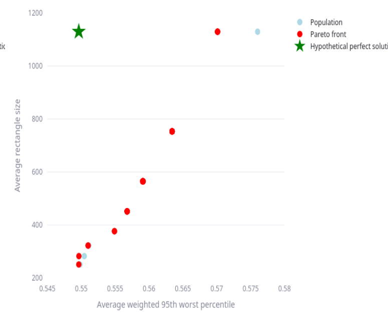
The probability of mutation, which controls the likelihood of introducing variability into the population, was tested at three levels: 0.3, 0.6, and 0.9.

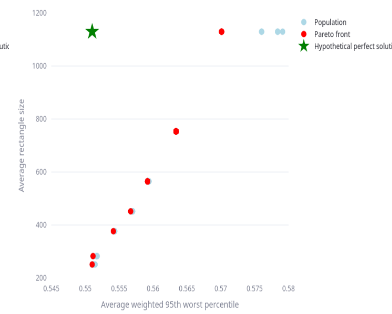
In addition, we tested two different population sizes: 200 and 400. This combination of parameters allowed us to analyze the algorithm's sensitivity to mutation probability and the effect of larger populations on the quality of solutions and computational performance.

These parameter configurations were applied to a real-world example to demonstrate the practical applicability of the approach.

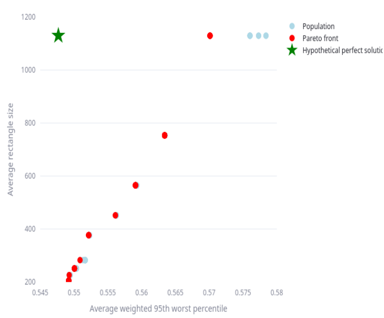
The 3 following pictures show the algorithm result as a pareto-optimal front for population equal to 200 and mutation probability variable set, respectively, to 0.3, 0.6, 0.9.

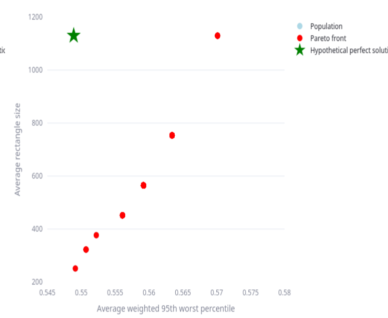


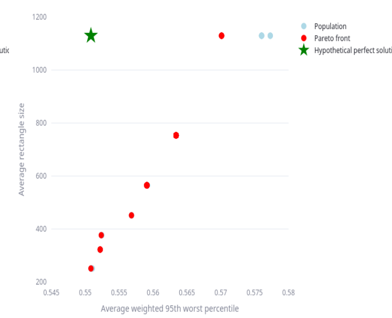




The next 3 following pictures show the algorithm result as a pareto-optimal front for population, in this case, equal to 400 and mutation probability variable set, respectively, to 0.3, 0.6, 0.9.



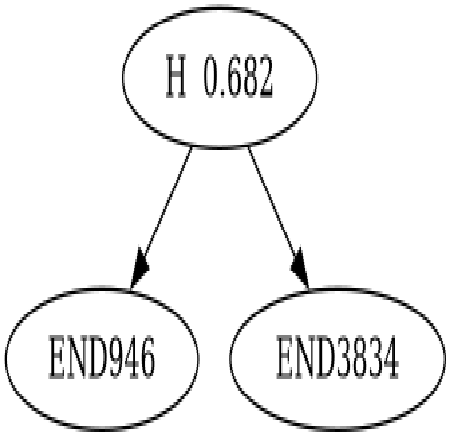


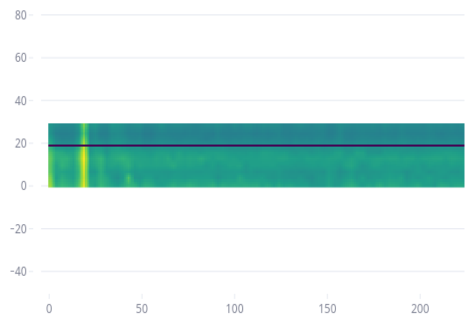


As the result shows great variability, we obtained for the configuration in which the population is equal to 400 and the mutation probability variable is set to 0.3.

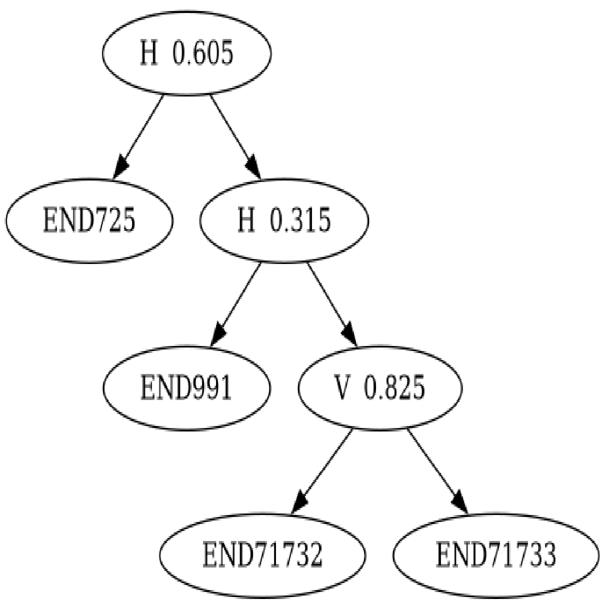
The following pictures illustrate the structures of example trees. Each node of the tree has the letter H or V, which represents type of cut: horizontal or vertical, and offset as a floating point number in range from 0 to 1, which represents relative position of the cut in the current node.

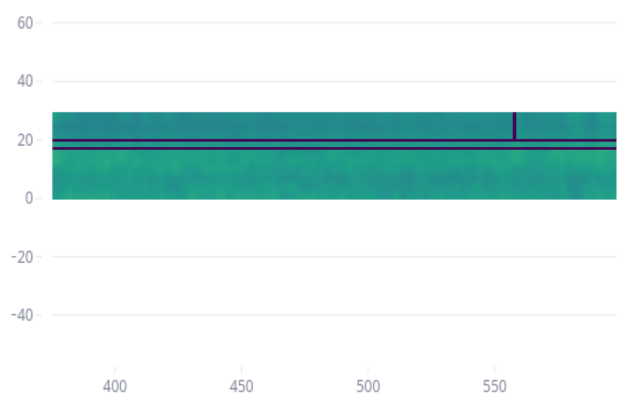
The first tree presents part of the pareto-optimal front, with the biggest average of the rectangle but with the worst quality. As the graph shows, it is only a simple horizontal cut, which can be seen on the steel sheet.



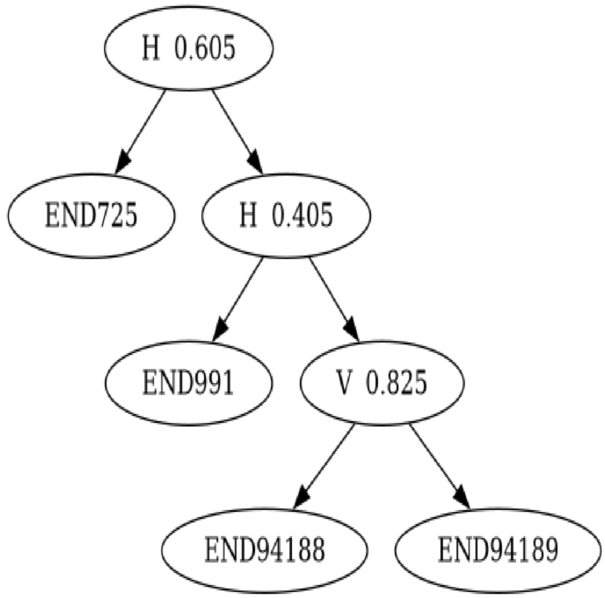


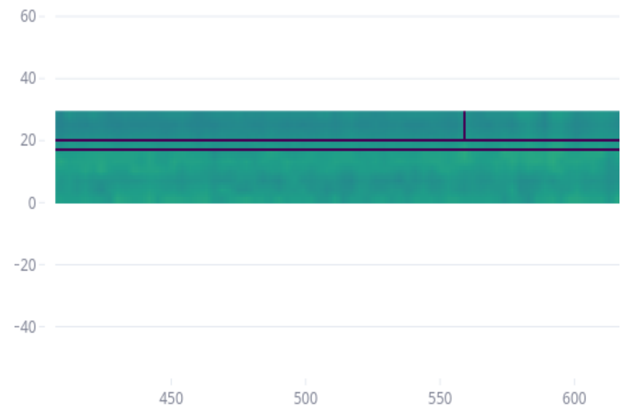
The next graphs present tree and slit sheet, which is trying to meet both objective functions.





The last graphs illustrate minimization of the second objective, the average weighted 95th worst percentile.





In conclusion, the results show that most trees have a similar structure. The differences are only in position of the cut, which seems to be the effect of the restricted constraints.

5. Conclusions

This study explored the optimization of the coil slitting process using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). By considering two competing objectives, maximizing the average rectangle size and minimizing the average weighted 95th worst percentile, our approach addresses key challenges in the steel industry, including material efficiency and quality consistency. The incorporation of practical constraints, such as a minimum piece length and simple vertical and horizontal cutting directions, ensures that the proposed solutions are both feasible and applicable in real-world scenarios.

The visualization of Pareto fronts for each parameter combination highlighted the trade-offs between the objectives and provided insights into the influence of parameter tuning on algorithm performance. The test on a real-world example further validated the practical utility of the approach, demonstrating its ability to generate diverse and high-quality solutions tailored to operational requirements.

Compared to existing methods, which often focus on minimizing scrap or optimizing layouts through linear models or heuristic algorithms, our slicing tree-based NSGA-II implementation offers a flexible and effective framework for handling multi-objective optimization problems with complex constraints. The results underscore the potential of evolutionary algorithms to address practical challenges in industrial applications, paving the way for future research into adaptive and domain-specific optimization techniques.

Future work could explore the integration of dynamic constraints, such as variable material properties or evolving customer demands, and extend the approach to other industries requiring optimized cutting processes. Additionally investigating hybrid methods that combine evolutionary algorithms with heuristic approaches may further enhance solution quality and computational efficiency.

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