

Research on Steel Plate Path Optimisation Based on Genetic and Ant Colony Interaction Algorithm

Yanhui Gu*, Xinhao Hu, Zhixin Guan, Lei Huang, Zhangquan Gong

Engineering Training Centre, Nanjing Institute of Technology, Nanjing 211167, China

* Corresponding author: Farid Uddin Ahmed (Email: 19825801917@163.com)

Abstract: In the steel plate cutting production process, path optimisation is crucial for improving cutting efficiency, reducing material costs and invalid cutting paths. In this paper, an interactive optimisation strategy combining genetic algorithm and ant colony algorithm is proposed to optimise the cutting sequence, overpass connecting structure, and empty distance of different distribution of steel plates by constructing a multi-objective mathematical model. The ant colony algorithm was used to solve the traveller's problem (TSP) path optimisation problem to optimise the cutting path of N1 steel plates. The improved genetic algorithm, on the other hand, handled the bridge crossing constraints for N4 steel plates and balanced the air travel distance with the number of bridges. The experimental results show that the ACO algorithm achieves better air-travel paths in N1 steel plates compared to the conventional optimisation algorithms, while the genetic algorithm significantly improves the material utilisation and satisfies all the geometrical constraints in the optimisation of N4 steel plates. The strength of this study lies in the contributory research in the related field, which validates the effectiveness and robustness of the proposed algorithms and provides an efficient solution to the complex steel plate cutting problem.

Keywords: Steel Plate Cutting, Path Optimisation, Ant Colony Algorithm, Genetic Algorithm, Bridging Technology.

1. Introduction

In the context of intelligent transformation of manufacturing industry, steel plate cutting technology has evolved from traditional manual operation to fully automated nesting system [1]. This progress has significantly improved the production efficiency. However, in the actual production process, the cutting path planning still faces many challenges. On the one hand, it is common for enterprises to 'focus on cutting but not on optimisation', and they are only satisfied with completing the cutting task, which leads to an increase in the distance of empty travel and a serious waste of material. On the other hand, the complex geometric constraints of steel plates increase the difficulty of path planning. This unreasonable path planning leads to the reduction of cutting efficiency, which becomes a key factor in production cost control.

In the field of path optimisation, traditional methods such as dynamic programming and branch-and-bound method are only applicable to simple layout problems, but their computational efficiency is significantly reduced when facing complex problems with multiple constraints. With the depth of research, intelligent algorithms have gradually become the focus of research [2]. Ant colony algorithms have shown excellent performance in traveller problem (TSP) optimization by simulating the foraging behaviour of ant colonies. In their study, Yiheng Qian and Wenzhuo Zhang applied the improved ACO algorithm to mobile robots and achieved success in the problem of safe path optimisation under integrated repulsive field rules [3]. This research effectively solved the challenges of mobile robots to perform fast and smooth operation, obstacle avoidance and prolonged service life in complex environments. Genetic algorithms are widely used in related fields due to their advantages in dealing with combinatorial optimisation and dynamic calibration problems. Chen Liudan, Zhu Yanfei and Li Guangying used two-step genetic algorithm to analyse the dynamic path

optimization of electric vehicles, which effectively meets the energy-saving needs and cost-saving needs of the vehicles [4].

However, the adaptability of the existing algorithms for steel plate-specific geometric constraints, such as over-bridge technical cuts and sequential limitations, still needs to be further improved. In particular, research on multi-algorithm optimisation synergy is still insufficient. In this paper, we propose a framework for the interaction between genetic algorithms and ant colony algorithms for two typical steel plate cutting scenarios, i.e., the TSP-type path optimisation problem for N1 plates and the over-bridge constraint-type optimisation problem for N4 plates[5].

2. Research methodology

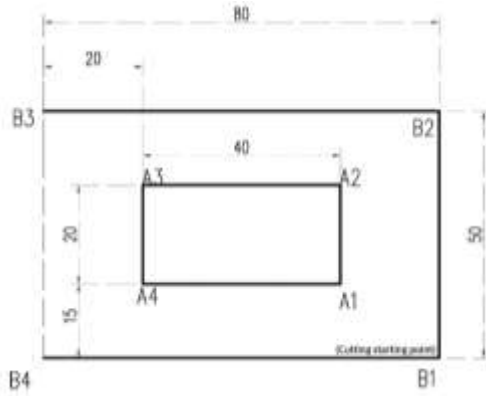
2.1. Data description

(1) Steel plate type N1: the size of this plate is 80mm x 50mm. inside the plate, two rectangular areas need to be cut precisely, one of which is 40mm wide and the other 20mm wide. point B1 is the starting point for the cutting operation of the plate, and the line from point B3 to B4 represents the boundary line of the plate, where no cutting operation is required. There is no need to perform any cutting operation in this boundary line area. The cutting path of the steel plate is shown as (a) in Fig. 1.

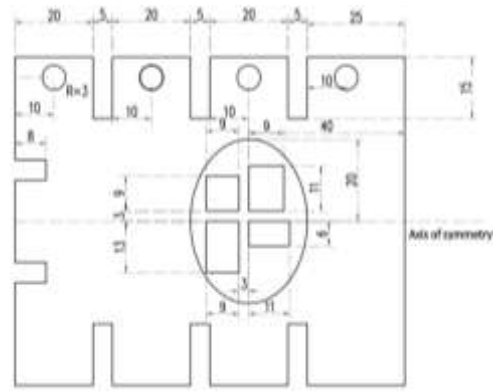
(2) Steel plate type N4: This plate measures 100 mm x 80 mm and has to be precisely cut into four rectangular parts. In the design of these parts, special attention was paid to the fact that the parts are connected to each other by means of so-called 'bridges', which are designed to ensure that the rectangular parts do not fall off during subsequent processing or use. In order to ensure the integrity and safety of the parts, the design specification requires that the minimum distance between the 'bridges' and the vertices of each rectangular part must be at least 1 mm. In addition, the width of the bridge is set at 2mm, which ensures a secure connection without restricting the use of the part too much. The width of the

'bridge' must be taken into account when calculating the air distance to ensure an accurate cutting path. The cutting path of the steel plate is shown in Figure 1 (b), which illustrates in

detail the exact layout of the cutting path and the final shape of the part.



(a) N1 steel plate cutting diagram



(b) N4 steel plate cutting diagram

Figure 1. Cutting diagram of N1 and N4 steel plates

2.2. Data preprocessing

(1) Geometric modelling uses elliptic equations with rectangular vertex coordinates defined by the part location. For example, the N1 steel plate path problem is mapped to a TSP path, and the N4 steel plate problem is converted to a combinatorial optimisation problem with geometrical constraints on the moving scale.

(2) When dealing with the cutting process of complex parts, due to the small size of the small parts, it is necessary to apply the 'bridge' technique to solve the problem of the distance between two small parts. At the same time, the initial cutting point of the steel plate is located in the lower right corner by default.

2.3. Methods

2.3.1. Ant colony algorithm to solve N1 paths

Firstly, in this study, the typical traveller's problem (TSP) algorithm and ant colony algorithm (ACA) are used for path optimisation for N1 steel plate. The Ant Colony Algorithm simulates ants foraging to find the optimal solution, and then, the set of points in Figure 1 is set in the building model as.

$$V = \{B1, B2, B3, B4, A1, A2, A3, A4\} \quad (1)$$

In this particular problem, B1 represents the starting point of the path, and the problem we need to solve is to find a path that starts at B1, passes through all the other points in the graph, passing through each of them exactly once, and is able to end up back at B1, and which has the shortest total length. To achieve this goal, we must ensure that the path satisfies all relevant constraints.

2.3.2. Improved genetic algorithm for solving N4 paths

In this study, a geometrically constrained model is constructed for the 'bridge crossing' problem of N4 steel plates. The model transforms the problem into a combinatorial optimisation problem by cutting four small rectangular parts in an ellipse and determining the number and location of 'bridges'. The goal is to find the 'bridge' solution and the cutting order that minimises the total length of the air travel. The geometrical properties of the ellipse are described by mathematical equations, and the positions of the small rectangular parts are defined by vertex coordinates. At the same time, the geometrical properties of the 'bridge' are specified, i.e. a width of 2 units of length and a minimum

distance of at least 1 unit of length from the vertices of the rectangular widget. These constraints need to be considered when constructing the model.

3. Modelling and solving

3.1. Steel Plate Path Optimisation Based on TSP Algorithm and Ant Colony Algorithm

The research objective of the optimal cutting path problem for N1 steel plates is to solve the problem of minimising the total air travel length, which can be classified as a classical problem in the field of path planning. In this study, a variant of the ant colony algorithm is used for modelling and solving. In the process of constructing the mathematical model, the path optimisation problem is solved by taking the starting point of the cut as the starting point, which requires the solution of the shortest path that starts from, passes through all the nodes only once, and finally returns.

Objective function:

$$D = \text{Min} \sum_{i \in v} \sum_{j \in v} D_{ij} X_{ij} \quad (2)$$

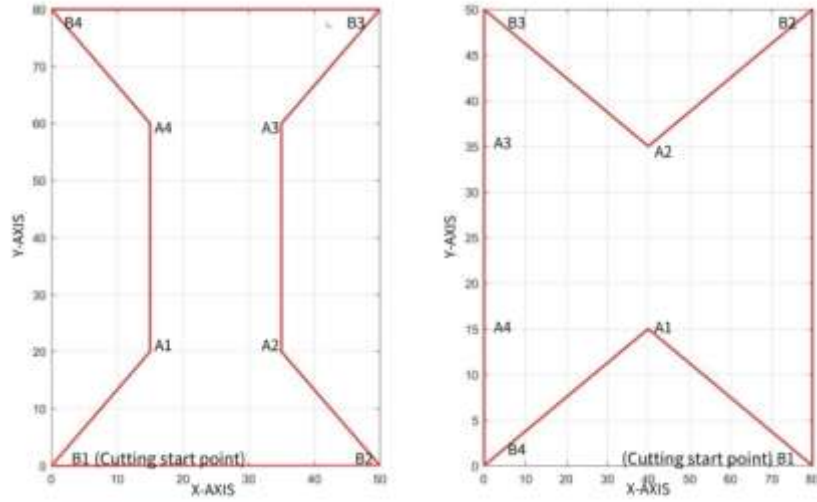
Constraints:

$$\begin{cases} \sum_{i \in v} X_{ij} = 1, \\ \sum_{j \in v} Y_{ij} = 1, \\ u_i - u_j \leq n + 1, \end{cases} \quad (3)$$

where equations (2) (3) in the X_{ij}, Y_{ij} represents the binary variable, if the first i rectangle and the first j rectangle has a 'bridge' connection, then $X_{ij} = 1$, otherwise $X_{ij} = 0$; define the distance matrix, where D_{ij} denotes the Euclidean distance between the point i and the point j .

For this problem, the results obtained by the TSP traditional path are shown in Figure2. (a): the total length of the empty path is 280.00mm, the optimal cutting path: $B1 \rightarrow A1 \rightarrow A4 \rightarrow B4 \rightarrow B3 \rightarrow A3 \rightarrow A2 \rightarrow B2$; and for the results obtained by the ACO algorithm, the results are shown in Figure2.(b): the total length of the empty path is 270.88mm, and the optimal path order is $B1 \rightarrow B2 \rightarrow A2 \rightarrow B3 \rightarrow A4 \rightarrow B4 \rightarrow B1$. The results are not much different, but the results obtained by using ACO are slightly better. $B3 \rightarrow A3 \rightarrow A4 \rightarrow B4 \rightarrow B1$. The results are not much different but the total length of the empty path obtained by

using the ACO algorithm is slightly better.



(a) Optimal cutting path (b) Optimal cutting path of ant colony algorithm
Figure 2. Comparison of conventional optimisation and ACO optimization

3.2. Optimisation of steel plate paths based on genetic algorithms

In order to solve the ‘bridge’ problem in N4 steel plate, this study firstly constructs a corresponding geometric model. In this model, the problem is transformed into a combinatorial optimisation problem by cutting four small rectangular parts in an ellipse and determining the number of ‘bridges’ and their positions. The objective of the study is to find a ‘bridge’ solution and its cutting order to minimise the total length of the empty paths of the cutting paths. The geometrical properties of an ellipse can be described by standard mathematical equations, specifically the equations:

$$\frac{X^2}{a^2} + \frac{Y^2}{b^2} = 1 \quad (4)$$

where the parameters a and b represent the lengths of the long and short semi-axes of the ellipse, respectively.

In the case of the rectangular widget, its position can be defined in terms of the vertex coordinates. In addition, the geometrical properties of the ‘bridge’ are specified, i.e. the width of the ‘bridge’ is 2 units of length and the shortest distance from the vertices of the rectangular widgets is ensured to be at least 1 unit of length. These constraints need to be taken into account during the modelling process.

3.2.1. Modelling

(1) Modelling the number and location of ‘bridges’

The goal is to make the bridge connection effective in preventing small parts from falling while minimising the number of bridges used, provided that the shortest distance between the bridge and the vertices of the rectangular small parts is at least 1. The number of bridges used is minimised.

Objective function:

$$D = \text{Min} \sum_{i=1}^3 \sum_{j=i+1}^4 X_{ij} \quad (5)$$

Constraints:

$$\begin{cases} d_{ij} \geq 1, \\ X_{ij} = X_{ji}, X_{ij} \in 0,1, \\ \sum_{j \neq i} X_{ij} \geq 1, (i = 1,2,3,4), \end{cases} \quad (6)$$

where for (5)(6) X_{ij} denotes the binary variable, if there is a ‘bridge’ connection between the first rectangle and the first rectangle, then $X_{ij} = 1$, otherwise $X_{ij} = 0$; d_{ij} denotes the

shortest distance between the matrix i and the rectangle j .

(2) Optimal Cutting Path Modelling

After determining the number and location of ‘bridges’, design the optimal cutting path starting from the lower right corner of the steel plate, S , so that the total length of the air travel is the shortest. Let the cutting sequence be $P = (p_1, p_2, p_3, p_4)$, where P_i denotes the number of the cut rectangle i .

Objective function:

$$D = \text{Min} L_{idle} \quad (7)$$

Constraints:

1) The cutting path must not exceed the boundary of the ellipse.

2) The width of the ‘bridge’ is taken into account when calculating the air distance.

3) The cutting path must pass through all rectangles and ‘bridges’.

where equations (7) L_{idle} denotes the total length of the air distance of the cut path.

3.2.2. Model solution

(1) Number and location of ‘bridges’ to be solved

For the number of bridges problem, integer programming algorithms, such as the branch-and-bound method, can be used to optimally solve for the number of bridges and their layouts. By exhausting all possible bridge connection schemes, the bridge layout scheme that minimises the value of the objective function is determined while satisfying the given constraints.

(2) Optimal cutting path solution

In this study, an improved genetic algorithm is proposed for the optimal cutting path problem, taking into account the effect of the ‘bridge’ operation on path optimisation. A dual-coding hybrid mechanism is used to generate the initial solution, in which the ‘bridge’ configuration is encoded in binary and the cutting path is encoded in real number arrangement. A dynamic penalty function is introduced, and the cutting sequence is continuously optimised by adjusting the dynamic penalty coefficient η with the objective of minimising the total length of the air distance.

3.2.3. Design of the parameter structure of the genetic algorithm

(1) Adaptation function

In genetic algorithms, the fitness function is one of the core components, and its role is carried through the key operations of the algorithm such as selection, crossover and mutation, setting the function as follows:

$$L = \alpha \cdot (L_{max} - L_{idle}) + \beta \cdot \sum X_{ij} + \gamma \cdot P(d) \quad (8)$$

$$P(d) = \sum \text{Max}(0, l - d_{ij}) \quad (9)$$

where equations (8)(9) L_{max} denote ellipse perimeter estimates (penalty criterion); $P(d)$ denote distance constraint penalty items; and weighting coefficients $\alpha = 0.6$, $\beta = 0.3$, and $\gamma = 0.1$ were determined by orthogonal experiments.

(2) Genetic operator design

In the genetic algorithm, crossover operator and mutation operator are the core operation to drive the evolution of the population, and their design way and role directly affect the search ability and convergence of the algorithm, the improved

algorithm for the crossover operator set: bridge segment: uniform crossover (probability $pc1=0.85$) path segment: OX crossover (probability $pc2=0.75$); mutation operator: bridge segment: bit flipping (probability $pm1=0.05$) path segment: exchange mutation + reversal mutation (probability $pm2=0.15$).

3.2.4. Analysis of results

In the research and application of genetic algorithms, the introduction of a variety of different crossover and optimisation operators can have a significant impact on the results of the experiments, as shown in Table 1 demonstrates how by varying the number of operators for the optimal paths and the empty backhaul journeys, the process of finding the optimal solution can be affected. Through a series of experiments it is concluded that when the total cluster size is set to 100, the cost of finding the optimal empty backhaul route can be reduced to 21.7, and such a result shows that the algorithm is optimally cost-effective with this particular parameter setting.

Table 1. Parameter sensitivities

Population size	Convergent algebra	Return stroke (mm)	Calculation time (s)
50	152	23.4	68
100	127	21.7	119
200	105	20.9	237

After determining the overall population size, the solution is carried out by three models: integer programming model, basic genetic algorithm and improved genetic algorithm, and

the results are shown in Table 2. After analysing the results, it is found that the improved genetic algorithm performs better in terms of performance-price ratio as shown in Figure 3.

Table 2. Comparative experiments

Norm	Integer programming	Basic GA	Current model
Return stroke (mm)	142.7	148.3	143.9
Number of bridge crossings (pcs)	2	3	3
Calculation time (s)	240	119	153
Number of binding violations	0	2	0
Material utilisation (%)	85.7	88.3	92.3

The optimal combination of bridges 1 - 2 was identified, with a shortest total air travel length of 142.7 mm, and the optimal configuration of the two bridges was successfully determined through careful optimisation analysis. Specifically, bridge 1 is responsible for connecting rectangles A and B with geometric centre coordinates (56.2, 42.8), while

bridge 2 connects rectangles C and D with centre coordinates (58.7, 67.3). In the path optimisation strategy, an 'inside-out' cutting sequence is adopted, i.e., the four internal rectangular parts and their connecting bridges are cut first, followed by the elliptical contours, and then the external circular parts are finally cut.

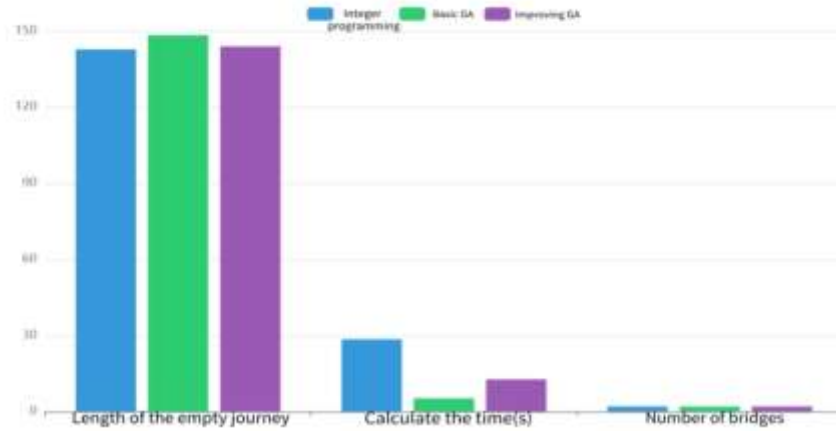


Figure 3. Comparative experimental diagram

The optimal cutting path is shown in Fig. 4 starting from the lower right corner of the steel plate, sequentially cutting 4 small rectangular parts inside the ellipse, connecting neighbouring parts through 2 overpasses, and finally cutting

the outer contour of the ellipse. The integer planning model determines the path with the shortest air distance and meets all the constraints.

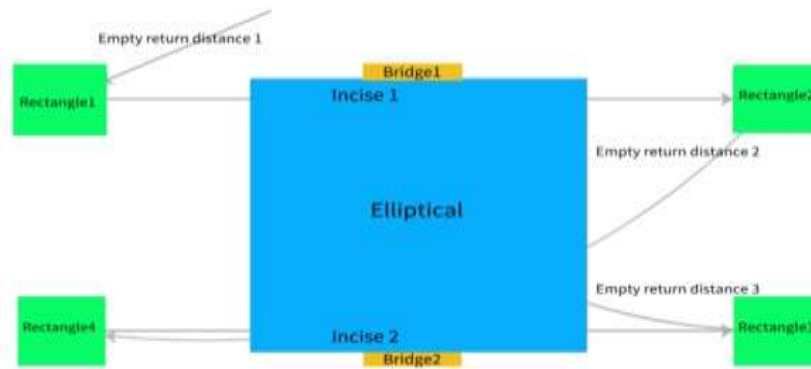


Figure 4. Display of optimal cutting path

4. Conclusions

In this study, we present an innovative application of a modified genetic algorithm combined with an ant colony algorithm. This novel approach, which combines the advantages of the two algorithms, demonstrates a more significant performance improvement in terms of optimisation results compared to the traditional single algorithm. Through in-depth theoretical research and experimental verification, it is found that these improved algorithms can find the optimal solution more efficiently when dealing with complex problems, and maintain high stability in multiple runs. Future research directions can consider combining these algorithms with reinforcement learning techniques to achieve adaptive adjustment of algorithm parameters and further improve the intelligence and adaptability of the algorithms.

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