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AN MDP MODEL-BASED REINFORCEMENT LEARNING APPROACH FOR THE NESTING PROBLEM: A CASE STUDY IN SHIP DESIGN

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ABSTRACT

The nesting problem in the shipbuilding industry calls for an increase in the utilization rates of plates and a decrease in the scrap ratio. To improve the efficiency of part nesting in ship design, this paper proposes an approach that uses a reinforcement learning algorithm to determine an efficient arrangement of parts. We frame the ship nesting problem as a Markov Decision Process (MDP) to apply the Proximal Policy Optimization (PPO) model, a reinforcement learning algorithm. A case study on a real-life nesting design is provided to validate and compare the proposed approach.

1 INTRODUCTION

The initial stage in the process of shipbuilding is cutting steel plates into various shapes to assemble the blocks that make up the hull of the ship. It is critical to optimally position these various shapes onto a rectangular plate material, to minimize the area wasted in the process. This arrangement, known as ship nesting, requires advanced techniques due to the intricate shapes of the materials and complex design constraints, such as the need for composite nesting for multiple ships. Prior research on nesting has explored the determination of placement sequences and overlap evaluations of parts, utilizing geometric shapes, bitmap representations, and heuristic methods. A recent study (Taniguchi et al. 2021) has incorporated metaheuristic methods for determining the sequence of part placement, while the placement location was decided using MDP. This methodology outperforms the widely used Bottom-Left-Fill (BLF) method, yet it often falls short when compared with the results of an experienced designer. With reference to previous studies, our experiments seek to bridge this gap by leveraging with the PPO algorithm, to define an efficent arrangement of pieces on specified steel sizes.

2 PROBLEM DEFINITION

Reinforcement learning is powerful tool in which an agent learns a policy to perform actions in an environment, with the objective of maximizing the rewards. We use the reinforcement learning algorithm to decide the component's placement positions and angles, targeting the minimization of unutilized space. The MDP for ship nesting probelem is formulated as follows:

- **State:** The plate and parts are represented in pixel format where an occupied area is denoted as 1 and an unoccupied one as 0. The parts to be placed are sorted by size, from largest to smallest. The state includes the plate shape with the ith part placed, and the shapes of parts from $i+1$ to $i+6$ yet to be placed.

- **Action:** The action of placing the ith part involves determining the position and angle of the part. The bottom-left corner of the plate is defined as the origin and parts are placed to minimize the area of the smallest rectangle enclosing the placed parts.
- **Reward:** The yield,

$$E = \frac{Area_{\text{PlacedComponents}}}{Area_{\text{plate}}},$$

  refers to the ratio of the total area of the placed parts to the smallest rectangle that can enclose them. Upon completion of the episode, where all parts are placed, the yield is taken as the reward. If all parts are not placed, a penalty is applied as a negative reward.

3 RESULTS AND CONCLUSION

PPO (Schulman et al. 2017) is a high-performing model-free reinforcement learning method that generates training data per step instead of per episode, thereby improving the learning effect. Figure 1 shows one of the the nesting results obtained by an experienced designer and by the proposed method using actual ship design. The results reveal a yield approximately lower with reinforcement learning than with the designer (Table 1). However, this is a result of training only on block shapes from two ships, suggesting that further training on part shapes can improve the yield. In conclusion, automated nesting design through reinforcement learning not only reduces design time significantly but also enhances the reproductivity of the design.

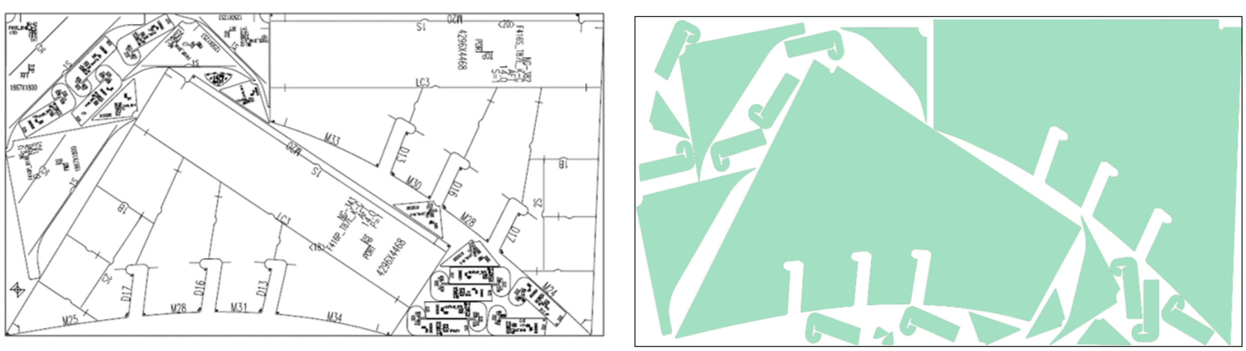

Figure 1: Placement result of (left) Designer and (right) PPO.

Table 1: Results.

efficiency	a	b	c
Designer	83.4%	53.5%	81.5%
PPO	75.9%	62.5%	70.5%

REFERENCES

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