Genetic Algorithm-Based Single-Machine Scheduling for Corrective Maintenance of Port Equipment Postprint

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Abstract

To address the maintenance scheduling problem for port equipment after damage, i.e., the corrective maintenance scheduling problem, this study analyzes the corrective maintenance scheduling arrangements for port equipment and establishes a scheduling model for maintenance equipment. The model employs the BP neural network algorithm to quantify the weights of port equipment awaiting maintenance, and utilizes a genetic algorithm to minimize the total weighted completion time of maintenance tasks, thereby obtaining an optimized maintenance scheduling sequence and corresponding maintenance time arrangement. Through a case study of port lifting equipment maintenance, the application of the optimized scheduling model in port machinery equipment is demonstrated, clarifying the maintenance sequence of port machinery, saving maintenance time while ensuring the completion of maintenance tasks, and providing a reference for port equipment maintenance planning.

Full Text

Corrective Maintenance Scheduling for Single Type of Port Equipment Based on Genetic Algorithm

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Abstract: This paper addresses the maintenance scheduling problem for port equipment after failure, i.e., corrective maintenance scheduling. By analyzing the dispatching arrangements for corrective maintenance of port equipment, a maintenance scheduling model is established. The model employs a BP neural network algorithm to quantify the weights of port equipment awaiting repair and utilizes a genetic algorithm to minimize the total weighted completion time of maintenance tasks, thereby obtaining an optimized maintenance scheduling sequence and corresponding maintenance timing. Through a practical example of port spreader equipment maintenance, the application of the optimized scheduling model in port machinery equipment is demonstrated. The model clarifies the maintenance sequence of port machinery, saves maintenance time while ensuring task completion, and provides a reference for port equipment maintenance planning.

Keywords: port equipment; corrective maintenance; BP neural network; genetic algorithm

0 Introduction

Against the backdrop of economic globalization, ports play a crucial role as hubs in frequent material flows. Port equipment, as the primary carrier of port operations, directly affects port development. Port equipment is characterized by high value and large quantities, with machinery accounting for up to 40% of port fixed assets [1]. With increasing port throughput and mechanized operations, port equipment often operates in an overloaded state. Additionally, port machinery must work outdoors, enduring harsh weather conditions including cold, heat, rain, snow, and sandstorms, leading to frequent failures that cause economic losses and safety hazards. Therefore, rational equipment maintenance scheduling is critical for maintaining efficient and low-cost port operations.

Equipment maintenance has long been a focus for both enterprises and scholars. Sheut et al. [2] proposed as early as 1994 that maintenance generally takes two forms: preventive maintenance (PM) and corrective maintenance (CM). Preventive maintenance can effectively reduce maintenance blindness and improve scheduling rationality, while corrective maintenance ensures maintenance reliability and cost-effectiveness. Comparing these two strategies, PM has been studied more extensively in both industry and academia and is closely integrated with production. For example, Fumagalli et al. [3] established a reliability-centered preventive maintenance optimization model, while Assid et al. [4] identified broadly applicable preventive maintenance strategies for cyclic production equipment failure maintenance. Some scholars have combined PM and CM; Neumann et al. [5] extended work on the joint optimization of production, corrective, and preventive maintenance, developing maintenance plans that minimize production costs based on equipment maintenance and inventory management.

However, in mechanical equipment maintenance, Shi [6] noted that equipment maintenance can be divided into three stages: early use, mid-term use, and end-of-life, with different maintenance strategies corresponding to each stage. For equipment with sudden failures and non-serious shutdown consequences, a corrective maintenance strategy should be adopted. Erkoyuncu et al. [7] also pointed out that preventive maintenance cannot completely prevent failures, and corrective maintenance remains necessary in harsh environments. They developed a process for evaluating the cost and availability of corrective maintenance, demonstrating that corrective maintenance still has room for development. In CM research, Andreacchio et al. [8] proposed using cyber-physical systems to identify reusable equipment on aircraft to avoid premature replacement and increase the value of corrective maintenance. Sembiring et al. [9] proposed a reliability-centered corrective maintenance method for scheduling machine maintenance. A review of existing literature reveals that research on port equipment maintenance scheduling has focused primarily on preventive maintenance, with limited attention to corrective maintenance. Therefore, we argue that port equipment maintenance research should consider both PM and CM.

Scholars have employed various methods to solve maintenance scheduling problems. Mathematical programming algorithms have been replaced by heuristic algorithms due to high computational complexity. References [10-14] all applied heuristic algorithms to scheduling problems. Among them, Yang [10] and Zhang et al. [13] used tabu search to study no-wait constrained job shop scheduling and genetic algorithms to solve general job shop scheduling problems, respectively, demonstrating that genetic algorithms can effectively solve maintenance scheduling problems in workshop operations. Liang et al. [14] applied this algorithm to integrated scheduling of loading/unloading equipment in container terminals. Thus, applying genetic algorithms combined with production scheduling can optimize port equipment maintenance scheduling.

In scheduling problem research, the selection of optimization conditions and desired objectives is a necessary consideration. Generally, minimizing completion time serves as the objective for scheduling problems (as in references [15, 16]). Since tasks of different natures affect the overall schedule, scholars often assign reasonable weights to each task. For example, Wu et al. [17] used the analytic hierarchy process to evaluate each weight indicator. This method is simple to handle and easy to operate but requires strong expert opinions as references. Han [18] noted that current port monitoring and fault diagnosis technologies are relatively backward. In on-site maintenance, mechanical fault judgment relies mainly on experience and sensory perception to identify fault locations, resulting in low accuracy and difficulty in determining fault severity.

We argue that if evaluation indicators are backward, equipment deterioration cannot be diagnosed timely and accurately, making effective maintenance impossible. This paper employs a BP (back propagation) neural network to assign weights to each maintenance task. Leveraging the strong nonlinear fitting capability of BP neural networks, their simple learning rules, and ease of computer implementation, we simulate human comprehensive consideration of maintenance equipment value to assign reasonable weights to each equipment unit. Simulating neural networks can effectively solve maintenance sequencing and mode selection problems, aiding corrective maintenance scheduling decisions. Therefore, this paper combines a workshop scheduling model, establishes a single-machine scheduling model for port equipment maintenance, uses a BP neural network to assign weights to each maintenance task, considers minimizing weighted completion time for maintenance operations, and optimizes using a genetic algorithm to find the optimal scheduling solution, thereby solving the corrective maintenance scheduling problem for port equipment.

Since port equipment experiences sudden failure states, this paper considers both general maintenance scenarios and emergency maintenance scheduling arrangements. Emergency situations refer to cases where, during a scheduled maintenance plan, some equipment awaiting repair experiences changes in maintenance status, and the original maintenance method cannot complete the repair. For example, a port crane originally scheduled for repair with only a loose conveyor belt requiring refastening might experience the belt jamming into the transmission bearing during operation, causing bearing misalignment under forced startup. In this case, the simple refastening repair changes to bearing realignment, not only increasing maintenance workload but also affecting the overall crane lifespan and increasing safety hazards if not addressed promptly. When emergencies occur, the original maintenance task weights change, and both maintenance time and methods change. This paper conceptualizes these changes as variations in equipment deterioration degree. Equipment deterioration degree [19] refers to the ratio of actual service years to expected service years. A decrease in deterioration degree indicates usage frequency below normal values, suggesting unreasonable utilization. For instance, an automated guided vehicle awaiting repair with only a dented shell that could still operate might be sidelined due to maintenance records, reducing the vehicle' s work efficiency. An increase in deterioration degree indicates significant fault hazards and should be the maintenance focus. Changes in equipment deterioration degree alter the required basic maintenance steps, correspondingly changing maintenance methods and time. These changes directly affect total completion time and must be considered to ensure maintenance sequence rationality and economy. Therefore, this paper defines equipment maintenance with decreased deterioration degree as minor repair and equipment maintenance with increased deterioration degree as major repair in emergency situations. By rationally arranging maintenance scheduling sequences, we avoid placing important maintenance tasks in incorrect positions, reducing maintenance delays and minimizing time and economic losses.

1 Problem Description

This paper primarily addresses the single-machine corrective maintenance scheduling problem for port equipment. Under the condition of meeting maintenance requirements, we aim to reduce weighted maintenance time by rationally arranging maintenance sequences. Studying minimum weighted completion time requires clarifying each maintenance task' s position in the maintenance sequence and its weight—both are key to ensuring efficient task completion. The maintenance sequence position determines the earliest start time for equipment maintenance. In port corrective maintenance with uncertain operation times and unclear maintenance arrangements, the start time and duration of deteriorated equipment maintenance determine the earliest start time for overall operations. For example, when a ship enters port for unloading and both quay cranes and gantry cranes fail, a single maintenance team can only repair the quay crane first to ensure unloading, then repair the gantry crane to ensure cargo enters the yard. Maintenance task weights include the time and economic costs required for equipment maintenance, reflecting the degree of equipment deterioration and the economic benefits brought by maintenance completion. This paper uses time cost as the primary reference basis: (a) without considering changes in maintenance methods, the economic cost of equipment maintenance is fixed; (b) the economic benefits after maintenance completion are already reflected through minimized completion time. Therefore, the weight of a maintenance task is determined by the workload and maintenance cycle of the equipment. Greater workload and shorter maintenance cycles correspond to longer maintenance times. However, due to the diversity of port equipment types and further subdivisions within the same equipment category—for example, port cantilever gantry cranes are divided into double-cantilever and single-cantilever types with inherently different workloads—affecting weight determination. This paper uses maintenance workload ratio instead of absolute workload as the basis for weight determination. Maintenance workload ratio refers to the ratio of time to repair a specific task to the total time to repair all equipment of the same category. Using workload ratio ensures the rationality of weights for a class of equipment maintenance.

2 Model

2.1 Model Parameters

The symbols and variable parameters used in this paper are shown in Table 1 .

2.2 Model Assumptions

a) Each maintenance task is repaired by only one maintenance unit;
b) At any moment, one unit can repair only one task (at one location);
c) Maintenance cannot exceed the time limit of the maintenance method;
d) Special cases such as self-repair during equipment maintenance are not considered; major and minor repairs are only considered in emergency states;
e) Maintenance thresholds are designed: when deterioration degree is in [a, b], major repair is performed; when in [e, f], minor repair is performed;
f) Each maintenance task can be completed within the specified time, with sufficient maintenance resources and no technical differences, and each equipment can reach a satisfactory state after maintenance;
g) No maintenance idle intervals or waiting time exist between maintenance tasks—it is a continuous maintenance process;

h) Each maintenance can make the equipment reach a satisfactory condition, i.e., no repeated maintenance is required;
i) Maintenance times for each task are determined based on actual conditions. Thresholds for major and minor repairs are not fixed and are related to specific equipment. Maintenance weights are related to equipment maintenance cycles and workload, determined through neural networks;
j) The weight of each maintenance task follows a maintenance task weight table derived from BP neural network analysis of each task' s maintenance cycle and workload;
k) The maintenance method and weight variation table are determined based on experience, as shown in Table 3 .

The BP neural network algorithm quantifies the weights of port equipment awaiting repair. The BP network' s learning algorithm adjusts each unit' s weight to minimize the error between expected and actual output [20]. The BP neural network inputs are maintenance cycle and maintenance workload ratio, with output being maintenance task weight. The workload ratio and maintenance cycle are numerically normalized. The neural network uses an S-type function as the transfer function. The training process is as follows to obtain the maintenance task weight table (see Table 2):

(a) Data input. Historical maintenance task workload ratios and maintenance cycles serve as network inputs, with maintenance task weights as outputs. To improve neural network convergence speed and algorithm accuracy, input data is normalized and denormalized after training completion.

(b) Initialize BP network. A neural network with several hidden layers is used, trained using the momentum steepest descent method in parallel training mode.

(c) Input samples, calculate errors, and correct network hidden layer weights and thresholds through error backpropagation.

(d) Convergence judgment. An error tolerance is defined—when the sum of squared sample errors falls below this tolerance, the algorithm converges. Additionally, a maximum iteration count is given; reaching this count stops iteration.

(e) Train to obtain the neural network, analyze and compare with existing data to determine network accuracy, test the network, and obtain the corrective maintenance task weight table.

2.3 Model Formulation

1) Normal Condition

Objective function:

$$Min\ z = \sum_{i=1}^{n} W_i' \times t_i' \tag{1}$$

Constraints:

$$P_i' = \sum_{j=1}^{n} X_{ij} \times p_j, \quad i = 1, 2, ..., n \tag{2}$$

$$W_i' = \sum_{j=1}^{n} X_{ij} \times \omega_j, \quad i = 1, 2, ..., n \tag{3}$$

$$t_i' = \sum_{m=1}^{i} P_m', \quad i = 1, 2, ..., n \tag{4}$$

$$\sum_{i=1}^{n} X_{ij} = 1, \quad j = 1, 2, ..., n \tag{5}$$

$$\sum_{j=1}^{n} X_{ij} = 1, \quad i = 1, 2, ..., n \tag{6}$$

2) Emergency Condition

Objective function:

$$Min\ z' = \sum_{i=1}^{n} W_i'' \times t_i'' \tag{7}$$

Constraints:

$$P_i'' = \sum_{j=1}^{n}\sum_{k=0}^{2} X_{ij} \times Y_{ik} \times p_j + \sum_{j=1}^{n}\sum_{k=0}^{2} X_{ij} \times Y_{ik} \times T_1 + \sum_{j=1}^{n}\sum_{k=0}^{2} X_{ij} \times Y_{ik} \times T_2, \quad i = 1, 2, ..., n \tag{8}$$

$$W_i'' = \sum_{j=1}^{n}\sum_{k=0}^{2} X_{ij} \times \omega_j + \sum_{j=1}^{n}\sum_{k=1}^{2} X_{ij} \times Y_{ik} \times \alpha \times \omega_j + \sum_{j=1}^{n}\sum_{k=1}^{2} X_{ij} \times Y_{ik} \times \beta \times \omega_j, \quad i = 1, 2, ..., n \tag{9}$$

$$t_i'' = \sum_{m=1}^{i} P_m'', \quad i = 1, 2, ..., n \tag{10}$$

$$\sum_{i=1}^{n} X_{ij} = 1, \quad j = 1, 2, ..., n \tag{11}$$

$$\sum_{j=1}^{n} X_{ij} = 1, \quad i = 1, 2, ..., n \tag{12}$$

$$\sum_{k=0}^{2} Y_{ik} = 1, \quad i = 1, 2, ..., n \tag{13}$$

$$a \le S_i \times Y_{ik} \le b, \quad k = 1;\ i = 1, 2, ..., n;\ j = 1, 2, ..., n \tag{14}$$

$$e \le S_i \times Y_{ik} \le f, \quad k = 2;\ i = 1, 2, ..., n;\ j = 1, 2, ..., n \tag{15}$$

Objective function (1) represents the minimum total weighted completion time under normal conditions. Equation (2) represents the working time of the maintenance task at a certain position in the maintenance sequence. Equation (3) represents the weight of the maintenance task at a certain position in the maintenance sequence. Equation (4) represents the total completion time when the maintenance sequence reaches a certain position. Equation (5) indicates that only one piece of equipment can be maintained at a time. Equation (6) indicates that a maintenance task can occupy only one position in the maintenance sequence.

Objective function (7) represents the minimum total weighted completion time under emergency conditions. Equation (8) represents the working time of the maintenance task at a certain position in the emergency maintenance sequence (which may be normal repair time, minor repair time, or major repair time). Equation (9) represents the weight of the maintenance task at a certain position in the emergency maintenance sequence (which may have fluctuating weights). Equation (10) represents the total completion time when the emergency maintenance sequence reaches a certain position. Equation (11) indicates that only one piece of equipment can be maintained at a time. Equation (12) indicates that a maintenance task can occupy only one position in the maintenance sequence. Equation (13) indicates that the maintenance task in the sequence can only be one of normal repair, major repair, or minor repair. Equation (14) indicates that under emergency conditions, the deterioration degree of equipment undergoing major repair at any position in the maintenance sequence must be within [a, b]. Equation (15) indicates that under emergency conditions, the deterioration degree of equipment undergoing minor repair at any position in the maintenance sequence must be within [e, f].

3 Model Solution

This paper solves the corrective maintenance scheduling problem using an adaptive genetic algorithm (AGA). This algorithm employs global search, initially generating multiple maintenance plans that may not be optimal. These plans are sorted based on fitness values, and then selection, crossover, and mutation processes are applied to obtain the optimal solution. The algorithm stops when reaching the maximum iteration count. The algorithm inputs are the number of maintenance tasks, their durations, and corresponding weights, and outputs the optimal maintenance sequence with corresponding maintenance methods, times, and weights.

3.1 Initial Population Generation

Initial population generation is based on gene encoding, where genes are the units of chromosomes and a chromosome consists of several genes. For the port equipment corrective maintenance scheduling problem, one chromosome represents one maintenance plan, i.e., a sequence of equipment maintenance order. To increase population diversity, the initial population can be randomly generated.

Individuals satisfying constraints are retained, while unsatisfied individuals are removed until the initial population reaches the required size.

3.2 Fitness Value

The fitness value is used to evaluate the quality of a solution represented by a specific chromosome. This paper uses the objective function as the chromosome' s fitness value, i.e., the minimum completion time of tasks. Unlike traditional genetic algorithms where crossover probability P_c and mutation probability P_m are fixed, this algorithm dynamically changes these probabilities based on the population's average and maximum fitness values [21]. The crossover probability P_c and mutation probability P_m are calculated as follows (where k_1, k_2 represent random variation coefficients; F' represents the fitness value of the individual to be mutated or crossed; F represents the larger fitness value of the two individuals to be crossed; F_{max} represents the maximum individual fitness value in the population; F_{avg} represents the average fitness value per generation) [21]:

$$P_c = k_1 \times \frac{F_{max} - F'}{F_{max} - F_{avg}}, \quad 0 \leq k_1 \leq 1$$

$$P_m = k_2 \times \frac{F_{max} - F}{F_{max} - F_{avg}}, \quad 0 \leq k_2 \leq 1$$

3.3 Genetic Operations

a) Selection. Selection is the process of choosing chromosomes with high fitness values from the generated population. This paper uses the roulette wheel method to ensure that excellent individuals are not lost from the population while maintaining global algorithm performance.

b) Crossover. Crossover allows excellent chromosomes to be inherited from parent to offspring generations. This paper adopts a multi-layer multi-point crossover method. Two parent chromosomes p_1, p_2 are randomly selected, and gene values at crossover cut points are exchanged. If the newly generated chromosomes are valid, offspring chromosomes o_1, o_2 are obtained. If the generated chromosomes violate constraints, they are considered invalid and the crossover is rejected.

c) Mutation. Mutation is a genetic change caused by various factors and can increase gene diversity to prevent premature algorithm convergence. Two cut points are selected in layers 1 and 2, and their genes are exchanged. If the encoding is valid, offspring chromosome c_1 is generated; if invalid, the mutation is rejected.

d) Results. The genetic algorithm convergence method is defined. Upon algorithm convergence completion, the chromosome corresponding to the minimum fitness value is selected as the optimal solution, yielding the optimal maintenance scheduling arrangement and minimized weighted completion time.

4 Example Analysis

The data for this example comes from the 2016-2017 maintenance records of telescopic container spreaders used in quay cranes and yard cranes at a container terminal. The spreader has a four-corner lifting lug load capacity of 40t and an overall service life of 8-15 years, with relatively high component failure and replacement frequencies. Spreader equipment failure and maintenance record data were collected to create Table 4 . The model was implemented and verified using MATLAB 2014 software on a computer with an Intel(R) Core i7 CPU at 4.0GHz and 8GB memory.

The MATLAB 2014 BP neural network algorithm was applied with each maintenance task' s workload and maintenance cycle as inputs and spreader maintenance weight as output. Maintenance records from March-April 2015 were selected as training samples, and March-April 2016 maintenance data as test samples. Data normalization was performed first, yielding processed data (see Table 5).

The normalized data served as BP neural network input/output. The network object was created using MATLAB' s `newff` function, which automatically initializes network weights and thresholds. A three-layer BP network was used (input layer, output layer, hidden layer) with 30 hidden layer neurons, maximum convergence iterations of 200, convergence error of 0.01, and Sigmoid transfer function.

After BP neural network training, the predicted output from the trained network was compared with actual data (predicted weights vs. expected weights) to obtain error analysis and training accuracy/validity charts. The error analysis chart compares each network training result with actual results. The training accuracy chart shows overall training correctness, with dashed lines representing fitted standard expected results and solid lines representing actual fitted results.

The error analysis shows that predicted weight errors are mainly concentrated in the interval [-0.12, 0.04], basically meeting prediction requirements. In the error chart, significant deviations between trained weights and expected weights appear at data points 37 and 38. Reviewing the original data reveals these two data points involve equipment originally scheduled for repair but changed to replacement with new spreader equipment rather than maintenance, with replacement time calculated separately rather than added to the original maintenance method. Therefore, these two data points were removed and the network retrained. The retrained results show that in the data training accuracy chart, the two prediction lines basically cover all data points. Figure 1 [Figure 1: see original paper] shows that test data accuracy, validity, and overall training accuracy all exceed 95%, indicating excellent training results. The trained neural network can assign reasonable maintenance weights to each spreader, which are then used for maintenance operation weight assignment. The resulting maintenance task weight table for scheduling is obtained (Table 6).

Due to different maintenance methods, spreader maintenance times vary. Analysis of existing data shows that spreader maintenance time basically follows a normal distribution on [5, 30]. Therefore, maintenance operation time in this paper uses this distribution. Statistical analysis indicates that when maintenance time exceeds 30 minutes, the spreader is basically determined to be unrepairable and must be replaced, with replacement time calculated separately rather than added to the original maintenance method. Equipment deterioration degree thresholds are set as $b > a > f > e$. Based on statistical experience, when equipment deterioration degree is [0.1, 0.2], the maintenance method is determined as minor repair with weight fluctuation $\alpha = 0.3$; when deterioration degree is [0.7, 0.8], the maintenance method is determined as major repair with weight fluctuation $\beta = 0.5$.

In the AGA genetic algorithm, one maintenance plan and its scheduling order constitute one chromosome. Evolution generations are set to 150, and population size to 100. Analysis is conducted for maintenance task quantities of 10 and 20 to examine different performance scenarios. Following the steps described above, corresponding maintenance parameters are tabulated and genetic algorithm convergence charts are produced to obtain minimum weighted completion times. To demonstrate the impact of weights on overall maintenance task decisions, weighted completion time calculations using simple sequential maintenance are performed for comparison, showing the effectiveness and advantages of weighting. Additionally, to demonstrate AGA advantages, comparisons are made with traditional genetic algorithms. Traditional genetic algorithm evolution generations are also set to 150, population size to 100, and convergence results for different task quantities are obtained, as shown in Table 10 .

Table 10 Comparison Between Traditional GA and AGA

Task Number	Traditional GA Minimum Weighted Completion Time	AGA Minimum Weighted Completion Time
10	4091	4087
20	45821	45789

The experiments demonstrate that rational scheduling arrangements can better save maintenance time and ensure maintenance efficiency. Based on the objective of minimizing total weighted completion time, when the number of maintenance tasks is 10, the computation time is 10 seconds and the objective function value gradually approaches optimal. The scheduling sequence is: 7→3→9→2→5→8→1→6→4→10, with a minimum total weighted completion time of approximately 4000. Without optimized scheduling, sequential maintenance yields a weighted completion time of 5900, saving 1813 time units through model optimization. Comparing normal and emergency condition models (Tables 5 and 6) shows that the emergency condition model can save 1652.5 time units. The shaded portions indicate equipment with changed deterioration degrees falling within major or minor repair ranges. In the emergency model, equipment with low deterioration degree is identified as minor repair, and increased maintenance weight raises the minimum weighted completion time. The optimal maintenance sequence shows little change, primarily because the minor repair task was originally at the end of the maintenance scheduling sequence. With fewer maintenance tasks, weight changes have minimal impact on overall maintenance time.

When the number of maintenance tasks is 20, the genetic algorithm completes in 15 seconds, converging at approximately generation 120. In normal conditions, the minimum weighted completion time saves up to 16,582 time units compared to sequential maintenance. Similarly, since maintenance tasks 7, 13, and 16 have deterioration degrees of 0.7 (major repair) and 0.2 (minor repair), the maintenance sequence changes. Comparing Tables 7 and 8, maintenance task 13 is advanced due to requiring major repair. The time savings increase from 16,582 to 18,523, demonstrating that maintenance method changes optimize the maintenance scheduling sequence—i.e., appropriate use of emergency maintenance mode can optimize maintenance scheduling. Comparing AGA with traditional genetic algorithms, Table 10 shows that when task number is 10, AGA finds superior results earlier. The AGA result of 4087 is better than the traditional genetic algorithm' s 4091. As maintenance tasks expand, the adaptive genetic algorithm can approach the optimal target more closely, demonstrating that emergency maintenance mode can optimize normal mode, with approximately 60% of cases yielding better results under emergency mode.

5 Conclusion

This paper studies port equipment corrective maintenance scheduling and makes innovations in two aspects: (a) in determining port equipment maintenance weights, it employs a neural network algorithm considering each maintenance task' s workload and maintenance cycle to train a network that can accurately assign equipment maintenance weights; (b) based on the trained network, it considers both normal and emergency maintenance states, establishing a comprehensive mathematical model that addresses both situations. An adaptive genetic algorithm is used to solve the model, and example analysis provides rational corrective maintenance scheduling plans. Experiments demonstrate that this genetic algorithm performs well in solving corrective maintenance scheduling problems, and model results prove scheduling optimization.

Although this paper proposes a corrective maintenance scheduling model and uses neural networks and genetic algorithms to obtain optimal scheduling arrangements, actual corrective scheduling problems are much more complex. In practice, factors such as maintenance intervals, economic costs, and even self-healing or secondary failures during maintenance must be considered. Additionally, when using genetic algorithms, sensitivity analysis can be performed on how different task quantities affect results to ensure minimal impact from task quantity changes within reasonable ranges. Considering these issues will make corrective maintenance scheduling more practical and will become the focus of future research.

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Note: Figure translations are in progress. See original paper for figures.