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Bernard J. Jansen
Qingyuan Zhou
Jun Ye *Editors*

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Preface

Cognition has emerged as a new and promising methodology with the development of cognitive-inspired computing, cognitive-inspired interaction, and systems that enable a large class of applications and has developed a great potential to change our life. However, recent advances in artificial intelligence (AI), fog computing, big data, and cognitive computational theory show that multidisciplinary cognitive-inspired computing still struggles with fundamental, long-standing problems, such as computational models and decision-making mechanisms based on the neurobiological processes of the brain, cognitive sciences, and psychology. How to enhance human cognitive performance with machine learning, common sense, natural language processing, etc., are worth exploring.

The 3rd International Conference on Cognitive Based Information Processing and Applications includes data mining, intelligent computing, deep learning, and all other theories, models, and techniques related to artificial intelligence.

The purpose of CIPA2023 is to provide a forum for the presentation and discussion of innovative ideas, cutting-edge research results, and novel techniques, methods, and applications on all aspects of technology and intelligence in intelligent computing.

The conference would not have been a reality without the contributions of the authors. We sincerely thank all the authors for their valuable contributions. We would like to express our appreciation to all Program Committee members for their valuable efforts in the review process that helped us guarantee the highest quality of the selected papers for the conference.

We would like to express our thanks for the strong support of the Publication Chairs, Organizing Chairs, Program Committee Members, and all volunteers.

Our special thanks are also due to the editors of the Springer book series "Lecture Notes on Data Engineering and Communications Technologies" and Ramesh Nath Premnath for his assistance throughout the publication process.

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Contents

Research on Path Optimization of Deep Sea Mining Vehicles Based on Intelligent Algorithms

Xiaodong Jing, Gengjie Zhu, Zepu Song, Laifa Sang, and Jie Liu

Abstract Taking the path planning problem of deep-sea mining vehicles in deep-sea environments as the research object, a path planning model for deep-sea mining vehicles was established based on its characteristics, and corresponding intelligent algorithms were designed to solve the problem. Finally, simulation analysis was conducted on the results, and the simulation results showed that the path planning scheme for deep-sea mining vehicles obtained by the intelligent algorithm is feasible and can better meet the path planning requirements of mining vehicles in deep-sea environments. Therefore, the intelligent algorithm designed in this article can be well applied to the research of deep-sea mining vehicle path optimization and has certain reference value.

Keywords Intelligent algorithms · Shortest path · Multi-objective optimization

1 Introduction

As an important equipment for the development of deep-sea resources in China, deep-sea mining vehicles have great application value and economic value. The path planning problem in deep-sea environments is a very complex dynamic planning problem, involving multiple constraints, including terrain, obstacles, etc. At present, research on the path planning of deep-sea mining vehicles at home and abroad mainly focuses on the seabed terrain and obstacles. Considering the working environment and operational requirements of deep-sea mining vehicles, the seabed terrain can be considered as a special constraint for their path planning problem. Therefore, it is necessary to conduct path optimization research.

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2 Basic Concept of Intelligent Algorithm and Deep-Sea Mining Vehicle Model

2.1 Algorithm Concept

Intelligent algorithm is a method to solve complex problems by imitating the intelligent behavior of organisms in nature. It mainly consists of three parts: search space, search strategy and optimization algorithm.

Search space: Intelligent algorithms need to find the best solution within a certain space, so the search space is a set with a complex structure, rather than a simple set of points. In practical problems, we generally think of a space as a vector in which each element represents an objective function, and the relationship between the elements is a linear combination of the objective functions. Therefore, when conducting intelligent algorithm research, the search space should be divided into different parts in a certain way [1–3].

Search strategy: Intelligent algorithms have a certain search strategy, which is to select or construct a search strategy suitable for the problem characteristics and the objective function according to the problem characteristics. In the traditional search strategy, there are mainly the following: heuristic algorithm based on learning factor, heuristic algorithm based on fuzzy logic and genetic algorithm.

Optimization algorithm: Intelligent algorithms are generally divided into two categories: global optimization algorithm and local optimization algorithm. The global optimization algorithms mainly include particle swarm optimization algorithm, artificial immune system, etc. The local optimization algorithm mainly includes genetic evolution algorithm, simulated annealing and artificial neural network.

2.2 Mine Car Model

Deep-sea mining vehicle is a complex system composed of multiple modules. In order to make its path planning in deep-sea environment more simple and effective, it is necessary to decompose the deep-sea mining vehicle into several modules, and allocate each module to the surrounding seabed environment reasonably [4]. The deep-sea mining vehicle path planning model established in this paper mainly includes deep-sea mining vehicle model and environment model. At the same time, the path planning problem of deep-sea mining vehicle in different environments needs to be considered in the path planning, so the corresponding objective function needs to be established to describe the impact of various environmental factors on the path planning results. The model and the objective function are analyzed below [4–6].

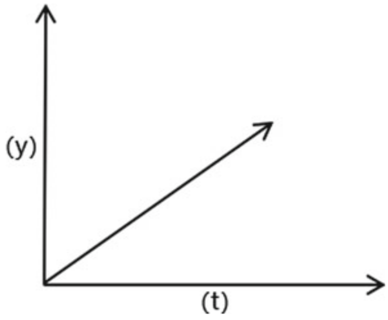

Fig. 1 Movement form of deep-sea mining vehicle

2.2.1 Modeling

When the deep-sea mining vehicle is carrying out mining operations, its movement form is linear movement, as shown in Fig. 1.

In Fig. 1, the horizontal coordinate is time t, and the vertical coordinate is the trajectory y-axis. Let the robot carry out translation motion at the origin of coordinates, and the expression of its motion form is as follows:

$$P = \frac{p}{t}(z\theta - \alpha), \tag{1}$$

where: p—the position of the robot on the z-axis; t—time ($t = 0 \sim T$); θ—the initial angular velocity of the robot on the z-axis; alpha is the static angle.

When $\alpha = 90°$, the maximum angular velocity of the robot is $\theta = 90°$. When $\alpha = 90°$, the maximum angular velocity of the robot is $\theta = 180°$. In order to facilitate the study, we take the initial angular velocity and the maximum angular velocity of the robot as fixed values. In order to improve the accuracy and stability of the algorithm, we set a small step size and a large step size in the process of solving. For the linear motion trajectory, because the deep-sea mining vehicle can carry out translation motion on the z-axis, the gravity influence of the deep-sea mining vehicle on the z-axis can be ignored. But since the deep-sea mining vehicle has an initial angular velocity on the z-axis, its gravity needs to be taken into account. Since gravity has little effect on the initial angular velocity of the robot on the z-axis, its effect is ignored [7, 8].

2.2.2 Environment Model

When the deep-sea mining vehicle is operating, its movement direction and speed will change due to the influence of the deep-sea environment. According to the movement characteristics of deep-sea mining vehicle, its environmental model is divided into the following parts:

(1) Seabed terrain model: Since the deep-sea mining vehicle is running on the seabed, its movement direction and speed will be affected by the seabed terrain. In the submarine terrain model, there are three parameters: depth, slope, and width. Among them, the depth refers to the position of the deep-sea mining vehicle on the seabed; Slope refers to the direction of the deep-sea mining vehicle on the seabed; the width is the length of the deep-sea mining vehicle on the seafloor. In this paper, the three parameters in the submarine terrain model are defined [9, 10].
(2) Mining operation environment model: Since the deep-sea mining vehicle is running on the seabed, it is subject to various influences, such as water flow, ocean currents, etc., so it is necessary to model the mining operation environment. In the mining operation environment, there are two influencing factors: hydrodynamic factor and flow rate factor. Among them, the hydrodynamic factors mainly include two factors: seabed disturbance and ocean current. Flow velocity factors mainly include flow velocity and flow density in the mining environment. The deep-sea mining vehicle will produce different motion forms and speed changes under different operating environments, so it is necessary to model these motion forms and speed changes.

2.2.3 Objective Function

Because the deep-sea mining vehicle has a large space and a small mass, it needs to carry out path planning in three-dimensional space to make it move according to a certain trajectory. In this paper, considering the large mass and long length of deep-sea mining vehicle, the objective function is set as follows:

$$m + \frac{t}{k}, \tag{2}$$

where: m represents the quality of the deep-sea mining vehicle, t represents the time; and k is the length of the deep-sea mining vehicle. In this paper, the path planning problem is transformed into a convex optimization problem with nonlinear and randomness, so that the objective function can be solved more effectively. Since the solution in this paper is carried out under the given trajectory and objective function, it is necessary to consider the influence of marine environmental parameters on the objective function. Because of the randomness and fuzziness of the marine environment parameters, the marine environment parameters are taken as the input of fuzzy rules in the fuzzy control system, so that the objective function can be solved through the fuzzy control system.

3 Intelligent Algorithm for Path Optimization

3.1 Algorithm Introduction

With the continuous development and utilization of marine resources, deep-sea mining technology has also been rapidly developed. Deep-sea mining vehicle is an important part of deep-sea mining technology. In the deep-sea mining process, the path of deep-sea mining vehicle must be optimized in order to ensure that the mining vehicle can complete the whole mining process safely and efficiently. As an optimization method to simulate biological evolution, genetic algorithm (GA) is widely used in path optimization problems because of its advantages such as fast computation speed, strong global search ability and wide search range. Genetic algorithm mainly includes three basic processes: selection, crossover, and variation. Variation is in the evolutionary process of genetic algorithm, through the way of random selection to produce new individuals and make the original individual occupy a certain proportion in the gene space, so as to obtain new individuals. The selection process of genetic algorithm is mainly based on the current environment and current state to calculate the fitness between the individual and the environment in the population. The two basic processes of crossover and mutation are the key steps of genetic algorithm. In the crossover process, the best individuals from the current population and other populations are crossed to produce a new population; in the process of mutation, the poorer individuals in the current population are mutated to produce a new population. Through the above two processes, genetic algorithm can find the optimal solution.

The main steps of the genetic algorithm designed in this paper are shown in Table 1.

Initial population: The deep-sea mining vehicle is set to carry out path planning in a certain area, and an optimal path needs to be found in the area. In this paper, genetic algorithm is used to solve the problem.

Selection operation: In view of the situation that there are multiple feasible solutions in the target region, this paper chooses one of the better solutions as the fitness function of the next selection operation.

Cross-operation: In order to avoid premature phenomenon, cross-operation is carried out between the best and the second-best solutions in the current population,

Table 1 Steps of genetic algorithm in this paper

Step sequence	Name
(1)	Initial population
(2)	Selection operation
(3)	Cross-operation
(4)	Mutation operation
(5)	Termination condition judgment

and cross-operation is carried out between the poor and the second-best solutions in the current individuals to produce new individuals.

Mutation operation: In view of the large gap between the best solution and the second-best solution in the current population, new individuals are generated through mutation operation.

Termination condition judgment: When a better solution and a second-best solution are found, the path optimization is judged according to the two cases respectively. If the path is optimized, it is considered that the current algorithm has obtained the optimal solution. Otherwise, it is considered that the algorithm has not obtained the optimal solution and the second-best solution.

Two basic operations, crossover and mutation, are adopted in this paper. In addition, in the process of path planning, if there is a large gap between a better solution and a second-best solution, the current algorithm is considered to have obtained the optimal solution and the second-best solution. When the path planning problem is NP-hard, genetic algorithm is used to solve it. When a feasible path is found, all nodes connected to the feasible path on the path are set as the new point. When new sites appear, all nodes on the path are considered feasible. Otherwise, it is considered that all nodes on the path are not feasible.

4 Path Optimization Method

4.1 Initialize the Population

When the deep-sea mining vehicle is in a certain area for path planning, it needs to find an optimal path in the area, so that the mining vehicle can consume as little energy and time as possible while completing the entire mining process. Therefore, when initializing the population, it is necessary to enable deep-sea mining vehicles to find an optimal path within the area. The population initialization in this paper adopts the random initialization method, and the specific steps are as follows:

(1) Generate initial population randomly. A set of nodes with the same number is randomly generated on each path node. The collection contains two nodes: the first node contains all nodes on the current path, and the second node contains all nodes generated in the first step. Each node contains a data point numbered 1; each data point contains a data point numbered 1, indicating that the node has two points. The result of initializing the population is a set with random numbers.

(2) Randomly select an individual in the current population as a fitness function. In this paper, an improved adaptive mutation operator is used to select individuals, so that the fitness function of individuals in the population can be evenly distributed as far as possible to avoid prematurity.

According to the characteristics of the path planning problem, this paper selects a better solution as the fitness function of the next selection operation.

(3) Set the population size.
(4) Set parameters such as population size, initial chromosome length and maximum number of iterations, and initialize them. The population size represents the number of chromosomes in the entire population, the initial chromosome length represents the number of genes in the population, and the maximum number of iterations represents how long each individual can run. In this paper, 10 is used as the initial value of population size and number of iterations, and chromosome length is determined by crossover operation in genetic algorithm.
(5) According to the above settings, the initial population is obtained after initialization. In the initial population, an individual is randomly generated as the fitness function of the fitness function, and the individual is used as the fitness function of the next selection operation.
(6) The individual value is substituted into the genetic algorithm for path optimization.

4.2 Selection Operations

This paper mainly considers the following aspects in selecting the fitness function of the operation: First, whether the problem belongs to NP-hard problem, that is, whether the objective function satisfies the extreme value condition. If the problem is NP-hard, then the selection operation is not applicable; the second is whether there are multiple feasible solutions to the problem, then crossover operation can be used; if the problem does not have multiple feasible solutions, then the mutation operation can be used. The third is whether the optimal path of the problem appears in this region. This problem is considered to be NP-hard, and crossover operations are used to solve the problem. Therefore, the fitness function of the selection operation is set as:

$$Wi = \theta, \tag{3}$$

where *Wi* is the ratio of the best solution to the next best solution in the current population. In this paper, the best solution refers to the global optimal solution, and the second-best solution refers to the local optimal solution.

It should be noted that since genetic algorithm is adopted in this paper, the fitness function of selection operation is not unique, but different fitness functions can be selected according to the actual situation. In order to avoid the precocious phenomenon, different fitness functions are selected for cross-operation in this paper. In the mutation operation, in order to avoid the unreasonable mutation rate and unfitness function, this paper adopts two basic operations: crossover and mutation. The crossover operation includes three basic operations: crossover, mutation, and exchange.

4.3 Crossover Operations

Cross-operation is one of the important operations of genetic algorithm, which directly affects the convergence speed and convergence rate of the algorithm. The crossover operation is to randomly select two individuals from the group, exchange their positions with each other, and make the two individuals a certain distance in space, and then make the two individuals close to each other. The selection operation, on the other hand, randomly selects an individual from the population and swaps places with the best individual in the current population. According to the different types of cross-operation, cross-operation can be divided into two ways: random cross-operation and selective cross-operation. The operation of selecting a cross is essentially selecting a cross.

Two basic crossover operations are used in this paper: one is random crossover and the other is selective crossover. Random crossover refers to the random selection of two individuals from the group, and then the two individuals exchange positions with each other; selective crossover is the process of randomly selecting an individual from the group and then switching the two individuals to each other.

(1) Random crossover: This paper adopts the probability-based random combination method, that is, the whole population is divided into several subpopulations, and in each subpopulation, an optimal individual is randomly selected to exchange positions with the worst individual in the current population; the best individual in each subpopulation switches places with the worst individual in the current population. In order to avoid prematurity, each subpopulation was randomly divided into two groups: one group switched places with the best group of the current population; The other group switched places with the worst group in the current population. Since the best individual in each subpopulation may be unique, this can effectively avoid prematurity.
(2) Selection crossover: In the process of selection crossover, this paper adopts a probability-based approach: if there are multiple optimal individuals in the current subpopulation that can form a new population, then the new population is likely to be the only one in the current subpopulation. This can effectively avoid the phenomenon of premature puberty.
(3) Selection crossover: In the process of selection crossover, this paper adopts a probability-based method: randomly select an individual from each subpopulation as a new population; then randomly select the worst individual as the new group.

5 Simulation Analysis

In this paper, MATLAB software is used to simulate the algorithm. First, the initial map is generated in the simulation environment and each node is numbered. Then, the path length, running time, and energy consumption in the objective function are

Table 2 Results of genetic algorithm path optimization

Item	Result
Algorithm run time	100s
Operating energy consumption	20w
Path length	600m
Travel time	103s

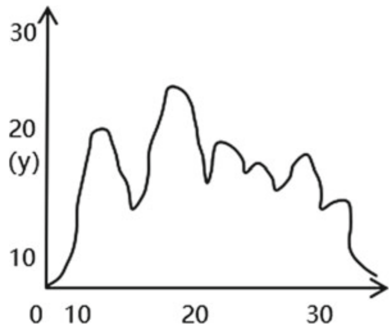

Fig. 2 Final path planning scheme

taken as optimization objectives, and the genetic algorithm is used to optimize the path. The results are shown in Table 2.

According to Table 1, parameters of the algorithm were set, and the final path planning scheme was obtained, as shown in Fig. 2.

As can be seen from Fig. 2, after algorithm initialization, the current environment is simulated. As can be seen from the figure, in the whole path planning process, seven iterations have been passed, and the planned path length is short, which meets the path planning requirements of deep-sea mining vehicles in deep-sea environment. According to the simulation results, combined with the scaling ratio of the environmental model, the total distance of the traditional genetic algorithm in the actual environment is 267.699 km, and the time is 242.372s. The path planning scheme obtained by multi-objective genetic algorithm in this paper has a total distance of 358.991 km and a time of 32.956s.

6 Conclusion

To sum up, the deep-sea mining vehicle path planning is very important, which directly affects the operation effect of the mining vehicle in the deep-sea environment, and the complex deep-sea environment has brought huge challenges to the mining vehicle path planning work, making the past mining vehicle path regulations always fail to meet expectations, and intelligent algorithms can help solve the problem. Therefore, people should fully understand the intelligent algorithm and apply the algorithm to the path planning of mining vehicles, which can effectively improve the efficiency of deep-sea mining.

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Research on Technical Analysis Method of Green Building Based on Genetic Algorithm

Zhaofei Xu and Feifei Jiang

Abstract With the continuous development of China's construction industry, building energy consumption is increasing, and resource and environmental problems are becoming increasingly prominent. In this context, China has put forward the concept of green building. Green building technology refers to the use of environmentally friendly or less harmful energy and resource utilization technology in the design, construction, and operation stage, which has high application value in itself, but there are still some problems, such as inconsistent data types in technical analysis, unintuitive expression of results, and inaccurate analysis of results. In order to solve these problems, this paper studies on the basis of genetic algorithm, mainly introduces the basic concept of genetic algorithm, and then puts forward the green building technology analysis method under the algorithm, hoping to provide reference help.

Keywords Genetic algorithm · Green building technology · Comprehensive evaluation method

1 Introduction

Green building technology has the characteristics of high input, high output, and low pollution, so it is widely used in the construction field. However, in the application process of green building technology, due to the wide variety of green building technologies, there are complex logical relationships among various indicators, and because the green building evaluation system is relatively complex, there are a lot of

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problems in the current green building technology analysis, such as inconsistent data types, unintuitive results, and inaccurate results analysis. To solve these problems, we can try to analyze them through genetic algorithm, and in order to master the specific methods, it is necessary to carry out relevant research.

2 Basic Concepts of Genetic Algorithm

Genetic algorithm is a kind of optimization algorithm which is formed by imitating the process of biological evolution and simulating the process of biological evolution. The core of genetic algorithm is genetic operation, which is composed of various different operations, as shown in Table 1.

Population and chromosome are the two most important operations in genetic algorithm, and their respective characteristics are as follows: First, a group is a collection composed of one or more individuals in the evolutionary process, whose purpose is to pass on the same characteristics, genes (or combination of characteristics), or traits (or combination of traits) to the next generation, that is, to increase the diversity of individuals in the group by passing on the differences between individuals. During evolution, a population does not evolve without some mechanism to facilitate the exchange of individuals within the group. The population is composed of individuals in the population, and the individuals in a population have their own unique genes, so it can be said that the entire population is composed of a subproblem of the genetic algorithm. As shown in Fig. 1, there are three independent subproblems in a population: (1) there is one chromosome in the population; (2) there is one chromosome in the population; and (3) there is one chromosome in the population. In each subproblem, there are three genes, which are: (1) a coding gene; (2) one

Table 1 Operation composition of genetic algorithm

Name	Intro
Colony	The collection of all individuals in a group
Chromosome	Represents a specific gene or set of genes
Mode	It represents differences between individuals
Fitness function	Used to measure differences between individuals in a population
Chromosome coding	Encode the results of genetic manipulation
Genetic operator	It is used to control the replication, exchange, mutation, and selection of chromosomes in the population
Mutation operation	It is used to control the change of differences between individuals in a population and ensure the diversity of individuals in a population so that the population can adapt to environmental changes
Convergence criterion	It is used to control the group to reach the global optimal in the iterative process

chromosome; and (3) a mutant gene. In the genetic algorithm, these three subproblems are all groups composed of individuals, so we call the whole group a group; second, chromosome refers to the DNA segment carrying specific genetic information, which is composed of one or more base sequences in the DNA molecule, each base sequence in the DNA molecule corresponds to a genetic information, that is, the carrier of genetic information. In genetic algorithms, chromosomes can be viewed as the genes of a population. As a gene in an individual population, an individual is made up of a certain number of genes, and each gene can be regarded as a chromosome. And each individual has one or more chromosomes. As the carrier of genetic algorithm, chromosome expresses specific genetic information in a specific way. Since each chromosome is made up of one or more genes, it carries genetic information. For genetic algorithms, the genes on all chromosomes are the same. But the number and quality of genes on different chromosomes differ, so there are differences between different individuals. Formula (1) is an expression of genetic algorithm [1–3].

$$X = \frac{a}{b}\left(\sum_{v}^{e} d/m_{yj}\right), \quad (1)$$

where X is the final result, a and b are populations and chromosomes respectively, e and v are patterns and fitness functions, d is chromosome coding, m, y and j are genetic operators, mutation operations and convergence criteria respectively.

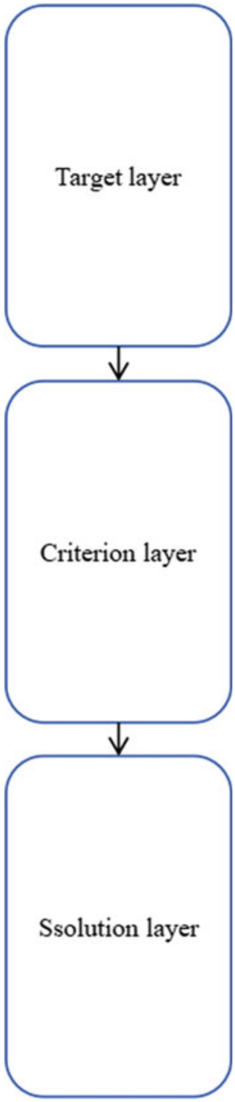
3 Technical Analysis Method of Green Building

3.1 Establish a Comprehensive Evaluation Model of Technology

Firstly, the hierarchical structure model is constructed, and the comprehensive evaluation system of green building technology can be divided into three levels. The first level is to analyze green building technology and determine the main objectives of green building technology; the second level is the establishment of evaluation index system, this level needs to conduct a comprehensive and comprehensive analysis of green building technology, considering the characteristics of green building technology, and it is also necessary to add the degree of impact on the target object in this level; the third level is to build a comprehensive evaluation model, which requires quantitative processing of each evaluation index to facilitate subsequent calculation [4–6]. The architecture model of comprehensive evaluation of green building technology is shown in Fig. 1.

Secondly, according to Fig. 1, the comprehensive evaluation system of green building technology is divided into three levels, namely the target level, the criterion

Fig. 1 Architecture model of comprehensive evaluation of green building technology



level, and the scheme level. The target layer refers to a relatively abstract concept from the perspective of green building technology. The criterion layer is to convert the specific indicators of the target layer into quantifiable digital representation. The solution layer refers to the results obtained after the analysis of the target. From this level, it can be seen that the target level is the most fundamental, the most core and the most critical factor, which determines the weight coefficient of each index in the comprehensive evaluation system of green building technology. Therefore, when constructing the comprehensive evaluation model, it is necessary to set the target layer reasonably. This paper chooses economic index as the target layer. In the second level, in order to effectively reflect the impact of each evaluation index on the target object, the target object should be considered as a whole. Therefore, it is necessary to divide the target object into three different subsystems when constructing the comprehensive evaluation model. Each subsystem is composed of several indexes which are interrelated, influence and restrict each other. For example, economic indicators include three aspects: economic impact, economic environment, and economic benefit, and their components are shown in Table 1. The economic indicators are divided into three sub-indicators: total investment, cost, and fund rate of return; environmental indicators are further divided into: energy consumption per unit area, water consumption per unit area, carbon dioxide emissions per unit area and noise per unit area and other sub-indicators; the benefit index is divided into: investment payback period, investment profit rate, investment profit and tax rate and economic growth rate and other sub-indexes. In order to facilitate the weight coefficient of each sub-index in the subsequent calculation process, the target layer should be reasonably divided when constructing the comprehensive evaluation model, so the genetic algorithm is used to determine the weight coefficient of each subsystem [7–10].

3.2 Determining Indicator Weights

Genetic algorithm is a method to decompose complex problems into different levels and then compare and analyze each factor in each level, so as to determine its relative importance. According to the different degrees of influence of each evaluation index on the target object, the evaluation index can be divided into four categories: low-impact category, high-impact category, and no-impact category. When establishing the comprehensive evaluation model of green building technology, according to the level of each index, AHP method is used to decompose the evaluation index into different levels, and then each factor in each level is compared and analyzed to determine its weight coefficient.

3.3 Construct a Judgment Matrix

The most important step in genetic algorithm is to construct the judgment matrix. When constructing the judgment matrix, the scale method of 1–9 is used to determine the scale size. The relative importance of each factor at the same level to each factor at the next level is compared in pairwise, and the pairwise judgment matrix is constructed. The 1–9 scale method is usually used to determine the relative importance of each factor. In this method, *a*, *b*, and *d* are mainly adopted as the judging criteria, where a represents “importance degree”; *b* stands for “degree of impact

Table 2 Judgment indexes of the judgment matrix

Name	At the level
Green building technology	Ground floor
Building materials and equipment	Second floor
Green building management and technology	Layer 3
Environmental, economic, and social benefits	The fourth floor

on the target"; *d* is for "target impact level." Based on this standard, the judgment indicators in the judgment matrix are shown in Table 2.

3.4 Consistency Test

Consistency testing is to determine the degree of consistency of the relative importance of the elements in one level to the elements in the previous level.

The consistency test is divided into absolute consistency test and relative consistency test. Absolute consistency refers to the consistency test of all judgment matrices, if the root of one side of the judgment matrix P is equal to 1, then the judgment matrix is considered to have satisfactory consistency. When the value of P is less than 0.1, the judgment matrix does not meet the relative consistency test. When P is greater than 0.1, it is considered that the judgment matrix does not meet the absolute consistency test. When P is less than 0.1, it is considered that the judgment matrix does not meet the relative consistency test.

3.5 Calculate Index Weight Coefficients

Genetic algorithm is a decision analysis method which combines qualitative and quantitative analysis. The basic idea is as follows: Firstly, the target of the system is divided into several levels, and the relative weight of each index in the hierarchy is determined according to its importance; Then, pairwise comparison is made for each layer to determine whether the comparison results are basically consistent. If they are not consistent, it indicates that there is a correlation between the two factors, and it is necessary to further determine the degree of correlation between the factors. Finally, according to the judgment results, the importance degree of each index relative to the target is calculated, and it is converted into the corresponding value, and then the weight coefficient of each factor is obtained. It is worth mentioning that in order to ensure the reliability and scientificity of data processing results in actual operation, it is necessary to carry out normalization processing of various indicators.

3.6 Hierarchical Total Sorting

Hierarchical total ranking refers to the ranking of all indicators in the evaluation object according to their importance. Since each evaluation index has different importance to the target object, it should be sorted according to the importance of each evaluation index in the target object. In the comprehensive evaluation of green building technology, the importance order of each evaluation index is: energy saving > water saving > material saving > indoor environmental quality > sound > light > heat. This order is consistent with the importance of energy saving, water saving, material saving, sound, light, and heat in the project. By using the hierarchical total ranking method, the relative weight coefficients of each evaluation index in the target object are obtained, and then the overall ranking is conducted according to the weight coefficients of each index in the target object. Finally, the results are compared with the final results of the technical comprehensive evaluation model, and the optimal solution set of the technical comprehensive evaluation model can be obtained. Among them, the weight coefficient of each index in the comprehensive evaluation model of green building technology is determined on the basis of AHP, which can be realized by MATLAB software.

3.7 Determine the Weight

The determination of the weight coefficient of evaluation indicators is mainly calculated by genetic algorithm, and the whole algorithm is divided into several levels. The specific process is as follows: Firstly, a hierarchical structure model is established, and each level in the index system is divided into three elements: target layer, criterion layer, and indicator layer. The target layer is further divided into four indicators, as shown in Table 3. The standard layer includes four aspects: building structure safety, energy and resource conservation, indoor environmental quality, and operation and maintenance cost. The index layer consists of five indicators, namely energy saving and emission reduction, material saving and resource saving, indoor environmental quality and operation and maintenance cost.

In the process of establishing the hierarchical structure model, indicators are classified according to different influencing factors, and each influencing factor is

Table 3 Target layer indicators

At the level	Index
Target layer	Building performance index
	Building environment index
	Comprehensive evaluation index
	Technical feasibility

divided into several levels according to its importance. When judging the same indicator system, different factors are used and different weights are used. For example, the energy saving and emission reduction part of building performance needs to determine its weight coefficient according to the importance of energy and resource conservation among its influencing factors. Because of the relative importance of each evaluation index in the evaluation system, entropy weight method is needed to determine the weight coefficient of each evaluation index. Entropy weight method is a commonly used subjective weighting method. When calculating the weight coefficient, it is necessary to quantify the opinions of experts, which requires the establishment of a judgment matrix to express the judgment of experts on the relative importance of each evaluation index. According to the established judgment matrix, the corresponding weights are assigned to each evaluation index according to a certain weight ratio. Because the genetic algorithm is used in this paper to determine the weight coefficient of each evaluation index, the established judgment matrix can be solved by MATLAB software during calculation. When genetic algorithm is used in MATLAB to solve the weight coefficient, the fmincon function in MATLAB software can be used to calculate the maximum value of each indicator (the maximum value is defined as the maximum proportion of each factor in all levels). This can not only ensure the consistency of all indexes in calculation but also ensure that the weight coefficient can meet the actual engineering requirements. Then the weight coefficient is assigned to each evaluation object according to a certain proportion.

4 Evaluation Operation

4.1 Calculate the Comprehensive Score of Each Index

As the results of comprehensive evaluation need to be expressed by mathematical methods, it is necessary to use MATLAB software to realize it. This paper uses MATLAB software to realize the comprehensive evaluation process. In MATLAB, the comprehensive score of each index can be obtained by matrix operation, and the comprehensive score of each index can be expressed by matrix multiplication operation.

First, to obtain the initial population: First, the entire evaluation system is divided into multiple levels, and then the evaluation indicators in each level are decomposed, and then each decomposed index is assigned a value.

Second, select the individual: Write the genetic algorithm according to the function selected in MATLAB software, and set the parameter to the initial value.

Third, determine the population size: According to certain coding principles, code the entire population. In chromosomes, each individual has a chromosome length and a gene value, two variables that represent the evolutionary direction of each individual. After each individual is encoded, it is possible to determine the size of the gene value carried by each individual in the population.

Fourth, genetic operations on each individual: In the chromosome, hybridization and mutation operations are carried out according to the set genetic operations, which is the core part of the genetic algorithm.

Fifth, calculate fitness: In order to ensure the optimal solution set for the whole population, it is necessary to compare and select the value of each gene in the chromosome. In this paper, the individual fitness values of each individual offspring will be compared and selected.

Sixth, reproduction: The generation of new offspring individuals through the above genetic operations.

The seventh, termination condition: When the new variation or selection operation is completed, the proportion of all gene values in the current population to the total gene value is added as the new population fitness value, and then the genetic algorithm is used to calculate the entire population, so as to obtain the new individuals that meet the requirements.

The eighth, the output result: After the output result in MATLAB software, the comprehensive score of each index can be output by matrix transformation. In order to compare the advantages and disadvantages of different technical schemes, the comprehensive score between different technical schemes can be compared and analyzed.

4.2 Solution

The evaluation model is a nonlinear programming problem whose objective function is to minimize the objective function. Although the traditional genetic algorithm can obtain the optimal solution, it cannot optimize the nonlinear problem, so it is difficult to get satisfactory results. In this paper, based on genetic algorithm, the nonlinear problem is transformed into a linear problem by increasing individual fitness.

After calculating the weights of each index in the evaluation model, the interval data corresponding to each index is obtained by discretizing the evaluation index data. The weights of all indexes in different intervals are obtained by weighted summation of data in different intervals. Then each evaluation index and the objective function are linearly combined to obtain the comprehensive evaluation value that meets the requirements.

Since each index has its corresponding objective function and constraint conditions, it is necessary to process all indicators before we can get the comprehensive evaluation value. In this paper, the improved genetic algorithm is used to solve the multi-objective problem. The basic idea is to convert each evaluation index into the corresponding fitness function. The fitness function is regarded as the individual fitness function of genetic algorithm, and the optimal solution is obtained by multi-objective genetic algorithm. This method can simultaneously obtain the comprehensive evaluation value of all technology combination schemes under each evaluation index.