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著者	LI Jiacheng
著者別名	李 嘉誠
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遺伝的アルゴリズムの改良に基づくマルチターゲットの運輸問題に関する研究

The Study on Multi-target Transportation Problem Based on Improved Genetic Algorithm

指導教員　李　磊　教授

法政大学大学院理工学研究科応用情報工学専攻
学籍番号　17R9401
リ　カセイ
氏名　李　嘉誠

Abstract

With the rapid development of economic globalization and information technology, rapid changes have taken place in all fields of society. The status of modern logistics industry in the process of the flow of social means of production and commodities has become increasingly prominent, accompanied by profound changes in production and manufacturing, material circulation, commodity transactions and management methods. Logistics cost accounts for a large share of national GDP, which can reflect the quality and scale of a country's national economy, reduce the logistics cost of enterprises, and greatly improve the profit space. Especially under the background of economic globalization, the competition among enterprises is increasingly fierce, and the impact of logistics on the competitiveness of enterprises is increasingly obvious. In the modern e-commerce environment, with the rapid development of science and technology, the space for enterprises to obtain profits from the products themselves has been greatly reduced. In order to reduce costs and improve profits as much as possible, enterprises focus on logistics. In the whole logistics system, transportation is a very important link. Therefore, efforts to reduce the cost of logistics and transportation can greatly reduce the cost of the entire logistics system. This paper starts from the main factors involved in the transportation logistics, optimizes the main factors affecting the logistics, reduces costs and improves profits.

Firstly, this paper discusses and studies the distribution personnel, mainly including the logistics distribution under the limitation of personnel fatigue and the delivery distribution mode under the new mode of personnel allocation - "crowdsourcing logistics". Aiming at the research on the limitation of fatigue, aiming at the maximization of customer satisfaction and the minimization of total cost, this paper constructs a model of path optimization for driver's fatigue driving, and designs a single Partheno-genetic algorithm for the model, which is verified by the distribution case of Japan's otaku. On the research of crowdsourcing delivery, taking the delivery network as the research object, this paper analyzes the distribution process, mode and existing problems of crowdsourcing delivery mode. Based on the purpose of optimizing the distribution network, taking the shortest distribution path and the least time delay as the objective function, the basic optimization model and dynamic optimization model of crowdsourcing distribution path with time window are established, and the rationality of the model is evaluated.

Secondly, from the perspective of vehicle research and analysis, mainly study the two-tier node logistics distribution mode based on heterogeneous vehicles. This paper analyzes the common transportation vehicle selection problem in the existing transportation. Based on the genetic algorithm, taking the transportation cost of the double-layer logistics node of a city's seafood products as the optimization goal, and comprehensively considering the problem of taking delivery vehicle route and vehicle configuration strategy of different routes at the same time, the mathematical model of vehicle scheduling and transportation route problem in the double-layer node transportation route is established. In this paper, MATLAB software is used to solve the model based on traditional genetic algorithm and Partheno-genetic algorithm, and the correctness and effectiveness of the model and Partheno-genetic algorithm are verified.

Then, from the perspective of transportation path mode, the research mainly involves the current hot "multimodal transport" problem. In this paper, the coal transportation in a country is taken as the research object. Under the mode of "iron water combined transportation", how to reasonably distribute the transportation capacity and correctly select the transportation mode can realize the enterprise to control the logistics cost and ensure the maximum profit. At the same time, based on the traditional genetic algorithm mechanism, aiming at the premature and local search ability of the traditional genetic algorithm in solving the logistics transportation path optimization problem are analyzed Due to the shortage of power, a hybrid genetic algorithm is proposed to solve the model.

Finally, the optimization algorithm of logistics distribution is discussed. This paper presents a hybrid genetic algorithm based on information entropy and game theory. First, the initial population is generated by calculating population diversity with information entropy. Combined with parallel genetic algorithm, standard genetic algorithm (SGA), Partheno-genetic algorithm (PGA) and hybrid genetic algorithm (sga-pga) which integrates standard genetic algorithm and Partheno-genetic algorithm (sga-pga) are used to perform evolutionary operations. At the parallel node, information entropy and fitness value of each sub population are used Finally, three programs checking functions Rosenbrock function, Rastrigin function and Schaffer function are introduced to analyze the performance superiority of the algorithm.

Key words: fatigue driving, crowdsourcing distribution, heterogeneous vehicles, multimodal transport, genetic algorithm, information entropy, game theory

Content

1 Introduction

1.1 Research Background and Significance

1.1.1 Research Background

With the development of economic globalization and e-commerce, logistics, as the third source of profit, is becoming more and more important. The concept of logistics was first proposed by Clark, an American scholar, in 1920s, and renamed "logistics" by American Logistics Management Association in 1984[1]. Logistics also changes from the original transportation function to a more comprehensive logistics system centered on information technology and management. Logistics can ensure the normal flow of goods in the whole social system, which can be compared to the social blood transfusion system, supporting the lifeline of the national economy.

Logistics cost accounts for a large share of national GDP, which can reflect the quality and scale of a country's national economy[2]. Reducing the logistics cost of enterprises can greatly improve the profit space. Especially under the background of economic globalization, the competition among enterprises is increasingly fierce, and the impact of logistics on the competitiveness of enterprises is increasingly obvious. E-commerce has become an important battlefield of enterprise competition. Without a good logistics system as support, the products purchased online can not be delivered to consumers in a timely and sound manner, which may cause consumer returns and adverse impact on enterprise reputation. Without the support of logistics, business flow will also become a piece of empty talk. In addition, in the modern e-commerce environment, with the rapid development of science and technology, the space for enterprises to obtain profits from products themselves has been greatly reduced. In order to reduce costs and improve profits as much as possible, enterprises focus on logistics. In the whole logistics system, transportation is a very important link. Therefore, efforts to reduce the cost of logistics and transportation can greatly reduce the cost of the entire logistics system.

As the first link of logistics system, personnel quality research is particularly important. In the logistics, people will have fatigue driving and need to rest. With the increase of the number of cars, there are more and more traffic accidents, which brings great potential safety risks to people's travel. In order to reduce the occurrence of traffic accidents as much as possible, in recent years, the state has issued a lot of relevant policies and achieved remarkable results. However, at this stage, traffic accidents are still one of the main threats to people's lives, such as the lack of road safety awareness, drunk driving, fatigue driving and so on. Among them, fatigue driving accounts for 14% - 20% of the causes of traffic accidents, 43% of the major traffic accidents, and 37% of the traffic accidents on large trucks and highways[3]. Similarly, the situation abroad is not optimistic. According to the NHTSA (National Highway Traffic Safety Administration) survey on drivers' driving conditions, more than 70% of the drivers surveyed have experienced fatigue driving. The NTSB (the National Transportation Safety Board) found that nearly 60% of the 120 traffic accidents related to drivers were related to driver fatigue. In France, 23% of all traffic accidents are caused by driver fatigue. According to a major traffic accident because report released by NRSA (National Road Safety Administration), fatigue driving accounts for more than 15%. After investigating the causes of traffic accidents, Flatley et al found that more than 21.6% of traffic accidents are related to fatigue driving[4]. In addition, the investigation also found that other traffic accidents caused by improper operation and carelessness are also related to fatigue driving to some extent.

With the development of logistics, there are also new changes in the personnel allocation mode, especially the logistics transportation of crowdsourcing mode. Crowdsourcing model is to evaluate the process of open innovation from the perspective of collaboration and make full use of external innovation resources and capabilities through crowdsourcing and collaborative process. The task of crowdsourcing is usually undertaken by individuals, involving tasks that need to be completed by multiple people, or in the form of individual production relying on open source. Crowdsourcing model integrates the collaborative process of mass creation, mass filtering, mass communication and mass evaluation. Compared with individual technology, the process of promoting public participation is more important, and its implementation requires the following four preparations: first, technical preparation: to establish a comprehensive application platform integrating the Internet and mobile Internet, PC and mobile phone; second, business preparation: to establish a business model and service provision suitable for the promotion and application of mobile Internet in combination with the main business; third, customer preparation: to According to the characteristics of the closest terminal customers of mobile Internet, select the target customers and make the customer development plan and marketing plan; then, service preparation: organize the service resources according to the service plan, and explore a new mode of mobile commerce integrating business and service. More and more large enterprises, such as Boeing, DuPont, P & G and Colgate, have joined in the use of "crowdsourcing" mode[5].

Thirdly, the related development of network information technology theory and practice provides theoretical and technical support for crowdsourcing mode. Communication technology makes fundamental changes in organizational mode and business mode. When people contribute individual value to "digital commons", they don't need to spend a lot of cost. After many studies, it is proved that the contribution of network services to national economy is often Compared with the contribution of the physical product sector to the national economy is only a few times or a little more than the cost, a more social and coordinated development path should be chosen between "ecological pessimism" and "scientific and technological optimism" and between "single concentration" and "single dispersion" economic prospects. The emergence of a large number of emerging knowledge exchange products has increased the categories of service products that can be decomposed, whether low value data or high value data. These service products are needed by different people, stingy industry companies and various institutions[6].

After the personnel is more important is the transportation problem, vehicle transportation as the most important part of the logistics system, its path optimization problem has always been the hot spot of scholars in various countries. According to whether it is a single vehicle or multiple vehicles, the path optimization problem can be divided into traveling salesman problem (TSP) and vehicle routing problem (VRP). The traveling salesman problem is that a transport vehicle starts from the distribution center, searches for the optimal access sequence, visits all customers, and finally returns to the distribution center, so as to minimize the total distance (total cost) traveled by the vehicle. Vehicle routing optimization problem refers to the problem that multiple vehicles start from the distribution center and design the optimal routing sequence to complete the transportation of goods between customers and distribution center on the premise of satisfying a series of constraints (distance constraint, time constraint, cost constraint, etc.). TSP problem was first proposed by flood in 1956[7], and then Dantzig and ramser put forward VRP Problem[8] on the basis of TSP problem in 1959. TSP and VRP are the most classical combinatorial optimization problems, which have attracted the research interest of many experts and scholars all the time and become the continuous research hotspot in the field of operational research and combinatorial optimization.

In theoretical research, there are a lot of literatures on VRP with time window cvrptw) and more literatures on VRP with simultaneous delivery (VRPSPD), but there are very few literatures considering both time window and delivery (VRPSPD'tw), and there is no effective algorithm to solve the problem. However, the flow of goods is two-way in enterprise distribution, which usually needs to deliver products to customers, and sometimes also needs to pick up goods from customers. At the same time, in order to meet the requirements of customers, distribution enterprises often need to consider the time window of customers, so as to complete the delivery and pick-up tasks within the specified time[9]. In addition, some scholars consider the location and distribution of distribution network as a whole when they study VRP, which constitutes location routing problem (LRP). However, most of the current research is limited to single level distribution network. However, in enterprise distribution, the process of goods flow usually includes two stages: the distribution stage from the central distribution center to the regional distribution network, and the distribution stage from the regional distribution network to the customer, which is a two-level (2e) distribution problem [10].

In practical application, VRP has been widely used in developed countries, including express delivery industry, air transportation, shuttle route planning, etc. In recent years, with the adjustment and upgrading of China's industrial layout, the rapid development of e-commerce, the transformation of consumption mode, and the increasingly diversified development mode of urban industry and commerce, the rapid development of small batch, multi frequency, time-effective direct distribution, residential distribution and "door-to-door" distribution and other distribution businesses not only effectively promote the economic and social development, but also facilitate the development of the economy and society Diversified needs of residents. However, there are many distribution enterprises in our country with different service levels. The selection of distribution route mainly depends on the driver's experience, lacking the reasonable design of distribution route and the assistance of computer software. The direct result is not only to reduce the enterprise's unitary efficiency and distribution cost, but also to the city's traffic and environment due to the large increase of distribution business and the rapid growth of distribution vehicles It brings problems. Therefore, it is of great practical significance to assist enterprises in optimizing vehicle distribution routes through scientific and reasonable methods[11].

The problem of path optimization involves many interdisciplinary subjects, including management, logistics science, operations research, mathematics, computer application, graph theory and other disciplines. It has also been proved to be NP hard problem, which is relatively difficult to solve. It has a very broad application prospect in real life and can be used to solve the problems of transportation vehicle distribution route in the logistics industry, aircraft scheduling in Airlines, and shuttle route planning. With the development of information technology, optimization theory and method have been widely used in engineering design, economic planning, transportation, social production and other aspects, making it a very active discipline. In recent decades, artificial intelligence technology has injected new vitality into the optimization field. A series of heuristic optimization methods, such as genetic algorithm, simulated annealing, tabu search and so on, have been proposed by simulating natural phenomena or processes and based on bionic principles. These methods have made remarkable achievements in the complex problems which can not be solved or difficult to be solved by classical optimization methods. Swarm intelligence optimization algorithm is generated by simulating the behavior of simple organisms. Biologists found in the study of social insect group behavior that the individual behavior ability of individual insects is very limited and random, but through the cooperation between individuals, the whole group can complete complex tasks, showing a high degree of organization and discipline [12-16].

With the development of international logistics, the problems of transnational transportation and multimodal transportation appear in the path optimization, which is the inevitable result of the development of chain enterprises, and also a means to realize green distribution. Through the sharing of distribution resources, the reasonable allocation of distribution network, and the efficient allocation of distribution tools, the purpose of reducing the waste of distribution resources is achieved. Chain enterprises reorganize the collection, delivery or opposite transportation of small batches of goods in the region, so that they can carry out mixed loading transportation comprehensively. In this way, the original one-way transportation of goods collection or delivery can be changed into two-way mixed load distribution. To a certain extent, the service object can be expanded, the vehicle loading rate can be increased, the empty driving rate can be reduced, and then the traffic volume can be effectively reduced, and the use and emission of energy can be reduced. Therefore, it is extremely important to reasonably plan the transportation route and prepare heterogeneous vehicles to reduce the distribution cost and improve the distribution efficiency[17] .

1.1.2 Research Significance

The purpose of this paper is to help logistics enterprises to plan personnel, vehicles and routes through scientific and reasonable algorithms. On the premise of meeting the constraints, enterprises can reduce transportation costs as much as possible, obtain maximum profits, and ultimately improve customer service satisfaction. This study has important theoretical and practical significance.

(1) Theoretical significance

Personnel, vehicle and path constitute the three elements of logistics distribution. The optimization algorithm of distribution is the equation of reasonable planning. Personnel fatigue and reasonable distribution of personnel, heterogeneous vehicles, multimodal transport and algorithm problems have been major problems for the development of large-scale logistics enterprises. The research based on personnel, vehicles, paths and algorithms is of great significance for the construction of a reasonable logistics distribution network, reducing the logistics burden of enterprises and improving the competitiveness of enterprises.

First of all, this paper considers the fatigue limit of personnel and the path optimization under the problem of personnel allocation. With the automobile becoming a more and more common means of transportation, there are more and more road traffic accidents. There is a large number of statistical evidence that driver fatigue driving is one of the main causes of road traffic accidents [18] [19] [20]. Therefore, it is of great significance to study how to control driver driving behavior in order to avoid fatigue driving.

As for the research of crowdsourcing mode, Professor Martin Weitzman of MIT put forward the idea of "sharing economy" in the 1980s. The concept of crowdsourcing is based on the idea of sharing economy[21]. In order to solve the problems exposed in the traditional logistics system, many businesses have begun to try "crowdsourcing logistics". Crowdsourcing logistics is mainly based on the idea of "crowdsourcing" in the sharing economy. The core idea of crowdsourcing is to share the surplus resources, that is, to match the underutilized surplus resources with the demand by using network technology. Crowdsourcing logistics is to integrate the idle human resources by using network technology and apply them to the demand of logistics distribution, so as to create a new logistics system that meets the cost-effectiveness . Therefore, the traditional logistics enterprises have gradually introduced the "crowdsourcing" mode, outsourcing some logistics and distribution links (especially the last kilometer of distribution) to local public groups, resulting in crowdsourcing logistics[22].

Secondly, vehicle scheduling is the central problem in the field of logistics and transportation. Most of the related problems are very difficult to solve. In order to save the transportation cost, the weight and volume of goods have to be considered in vehicle scheduling[23]. Therefore, the research on vehicle routing optimization with load constraints has profound practical and research significance.

Then there is the research of route optimization, which is based on land transportation or small-scale urban distribution, but less on the research of rail water intermodal transportation. The research of multimodal transport belongs to the field of operational research in management science. How to obtain more social logistics resources and customer needs, make use of the competitive advantages of various modes of multimodal transport, and integrate them at a high level, so that they can cooperate accurately in time and geography, and realize seamless connection on time, so as to reduce logistics costs and improve service quality, is a very complex decision-making problem for multimodal transport carriers. With the logistics regulations with the rapid development of module, it is very challenging to optimize the model and solve the problem, which has become one of the most important and difficult research topics in management science. At present, although there are some progress in this field at home and abroad, most of the research focuses on the modeling and solving of single objective and small-scale problems, and there is still a need to break through in modeling methods and solving algorithms[24].

Finally, this study provides a new algorithm for vehicle routing optimization in logistics industry. Path optimization has always been a research hotspot in the field of operational research and combinatorial optimization. It involves the interdisciplinary intersection of management, logistics science, operational research, mathematics, computer application, graph theory and so on. It has long been proved to be NP hard and difficult to solve. Many scholars put forward precise algorithm and heuristic algorithm to solve this kind of problems[25].

VRP is regarded as a NP hard problem[26], it is difficult to find an optimal solution from a large-scale VRP in an accurate way. Therefore, most scholars will seek an approximate solution as the main research direction in the field of VRP. Now there are two kinds of VRP solution methods, one is the traditional precise optimization algorithm, the other is the modern heuristic optimization algorithm. In the traditional precise optimization algorithm, there are dynamic programming, linear programming, branch and bound method and so on. The branch and bound method is widely used. Scholars such as Gauvin C [27], Errico f [28] and so on have carried out relevant research in this respect. The main purpose of this research is to study how to divide the feasible solution space into subsets in an appropriate way. On the basis of calculating the lower bound of each feasible solution subset, repeat the branch and bound operations to get the final goal. Lefever w et al.[29] are aimed at the single distribution cycle inventory path problem, which is transformed into a convex function optimization problem, and then the exact solution is obtained according to the properties of the convex function. With the development of modern computer technology, the modern heuristic optimization algorithm is a method to construct a mathematical model according to the characteristics of the problem under study, and to obtain an approximate solution in an acceptable time and space range by using computer algorithm. A significant difference between this algorithm and the traditional precise optimization algorithm is that its approximate solution is not accurate, that is to say, the approximate solution obtained by the same method may be different. Modern heuristic optimization algorithm based on natural simulation algorithm is an important way to solve VRP. Among them, there are many researches on VRP solution based on genetic algorithm, such as Zhang Xiaonan[30], Liu Jiali[31], Guo Haixiang[32], etc. The research on genetic algorithm of VRP mainly focuses on two aspects: one is to study the most basic modeling and coding design, and to study how to transform abstract problems into chromosome codes that are easy to calculate; the other is to improve the genetic algorithm itself, so as to avoid premature algorithm, improve the operation speed of the algorithm, and make the optimization result further approach the optimal solution. In the aspect of genetic algorithm improvement, such as Zhang Xiaonan, et al. Embed tabu search algorithm and random algorithm into genetic algorithm, improve the search ability of the algorithm, and greatly avoid the formation of local optimal solution. Liu Jiali et al. combined scanning algorithm, C-W saving algorithm and genetic algorithm to form hybrid genetic algorithm, which improved the performance of the algorithm on the basis of optimizing the initial population. Guo Haixiang and others also improved the genetic algorithm on the basis of scanning algorithm and random way to generate initial solution, so as to keep the population diversity and improve the convergence speed. Hou Yumei et al. [33] designed an adaptive probability that changed dynamically with the next generation of reproduction, aiming at the mutation and crossover probability of genetic algorithm, so as to improve the convergence efficiency under the premise of ensuring the population diversity. In general, the improvement of genetic algorithm focuses on three aspects: initial population construction, mutation and crossover improvement with other advanced algorithms, mutation and crossover probability design. In this study, we also propose algorithms to solve the problems, including genetic algorithm, Partheno-genetic algorithm, hybrid genetic algorithm and genetic hybrid genetic algorithm based on game theory and information entropy.

(2) practical significance

First of all, from the perspective of enterprises, it is conducive to promoting the development of e-commerce and logistics enterprises. Profit maximization has always been the goal of an enterprise. It is also the driving force for an enterprise to improve its working efficiency and seize the market. Efficient distribution system helps enterprises reduce the cost of distribution and get more profits. Low efficiency distribution system can reduce the market competitiveness of enterprises, which may eventually lead to market elimination [34]. The purpose of this paper is to help express companies design the optimal distribution route, optimize the distribution system and reduce the distribution cost.

Secondly, from the perspective of customers, it helps to improve the quality of customers' life. Logistics distribution is closely related to customers' food, clothing, housing and transportation, and residents' lives. Completing the smooth handover of goods from suppliers to customers is the basic need to ensure the normal operation of customers' lives. In the e-commerce environment, if the goods purchased by the customer are not delivered to the customer in time, it may affect the normal life of the customer, cause the customer's dissatisfaction with the e-commerce enterprise and the express delivery enterprise, weaken their intention to purchase the products, and even generate complaints and returns[35], thus adding negative emotions, bringing unnecessary to both the buyer and the seller Trouble.

Finally, from the perspective of urban environment, a good distribution system is conducive to reducing the traffic burden of the city, reducing the noise pollution of the city, as well as exhaust pollution. Segalou pointed out that the emissions of nitrogen oxides and suspended particles generated by the transportation of goods in cities account for 40% and 45% of the total urban transportation emissions. Therefore, by optimizing the distribution route, we can reduce the number of trips, driving mileage, no-load rate, etc. of vehicles on the premise of meeting the needs of customers, and finally ease the traffic congestion, noise pollution and other phenomena, as well as reduce the emission of exhaust gas [36].

The research on path optimization has always been a hot topic in the academic and business circles at home and abroad, and it is also a practical problem urgently needed to be solved in the rapid development of logistics industry. It can be seen from the above that the optimization of the three elements and algorithms of logistics and distribution has both high academic research value and very important practical significance.

1.2 Research content and innovation

1.2.1 Research content

Based on the background of logistics transportation, this paper discusses the related problems of the rapid logistics distribution system in this environment. In the environment of logistics transportation, people, vehicles, path paths and algorithms will affect the quality and efficiency of logistics transportation, so each element can become a research direction. This paper respectively discusses people, vehicles, paths and algorithms. Because the algorithm is involved in people, vehicles and paths, the algorithm will be studied in the research of each element, and the comprehensive discussion of the algorithm will be carried out at the end. It includes the following contents:

The third chapter discusses and studies the distribution personnel, mainly including the logistics distribution under the limitation of personnel fatigue and the delivery distribution mode under the new mode of personnel allocation "crowd sourcing logistics". Aiming at the research on the limitation of fatigue, aiming at the maximization of customer satisfaction and the minimization of total cost, this paper constructs a model of path optimization for driver's fatigue driving, and designs a Partheno-genetic algorithm for the model, which is verified by the distribution case of Japan's otaku.

On the research of crowdsourcing delivery, taking the delivery network as the research object, this paper analyzes the distribution process, mode and existing problems of crowdsourcing delivery mode. Based on the purpose of optimizing the distribution network, taking the shortest distribution path and the least time delay as the objective function, the basic optimization model and dynamic optimization model of crowdsourcing distribution path with time window are established, and the rationality of the model is evaluated.

In the fourth chapter, from the perspective of vehicles, we mainly study the two-tier node logistics distribution model based on heterogeneous vehicles. This paper analyzes the common transportation vehicle selection problem in the existing transportation. Based on the genetic algorithm, taking the transportation cost of the double-layer logistics node of a city's seafood products as the optimization goal, and comprehensively considering the problem of taking delivery vehicle route and vehicle configuration strategy of different routes at the same time, the mathematical model of vehicle scheduling and transportation route problem in the double-layer node transportation route is established. In this paper, MATLAB software is used to solve the model based on traditional genetic algorithm and Partheno-genetic algorithm, and the correctness and effectiveness of the model and Partheno-genetic algorithm are verified.

The fifth chapter studies from the perspective of transport route mode, mainly involving the current hot "multimodal transport" issues. In this paper, the coal transportation in a country is taken as the research object. Under the mode of "iron water combined transportation", how to reasonably distribute the transportation capacity and correctly select the transportation mode can realize the enterprise to control the logistics cost and ensure the maximum profit. At the same time, based on the traditional genetic algorithm mechanism, aiming at the premature and local search ability of the traditional genetic algorithm in solving the logistics transportation path optimization problem are analyzed Due to the shortage of power, a hybrid genetic algorithm is proposed to solve the model.

Chapter six discusses the optimization algorithm of logistics distribution. This paper presents a hybrid genetic algorithm based on information entropy and game theory. First, the initial population is generated by calculating population diversity with information entropy. Combined with parallel genetic algorithm, standard genetic algorithm (SGA), Partheno-genetic algorithm (PGA) and hybrid genetic algorithm (sga-pga) which integrates standard genetic algorithm and Partheno-genetic algorithm (sga-pga) are used to perform evolutionary operations. At the parallel node, information entropy and fitness value of each sub population are used Finally, three programs checking functions Rosenbrock function, Rastrigin function and Schaffer function are introduced to analyze the performance superiority of the algorithm.

1.2.2 Paper innovation

This paper studies the main factors that affect the efficiency and quality of distribution in logistics distribution, including personnel, vehicles, routes and algorithms. Compared with the traditional route optimization problem, the research in this paper is carried out one by one from all angles, summarizes the optimization model of each element in logistics transportation, and adopts appropriate algorithms for optimization.

The main innovations of this paper are as follows: in the background of logistics and distribution, the optimization of vehicle routing with fatigue driving based on genetic algorithm, the research of delivery and distribution network based on crowdsourcing theory, the research of transportation optimization of double-layer logistics nodes based on heterogeneous vehicles, the research of coal logistics network optimization based on multimodal transport and the hybrid genetic algorithm based on information entropy and game theory are respectively carried out Algorithm research. The details are as follows:

(1) In the third chapter, the optimization model of logistics vehicle path is built. The numerical analysis based on the case of logistics and distribution of Japan's asakushi company shows that the solution of the logistics vehicle distribution path optimization with personnel fatigue constraint proposed in this paper, through the solution of genetic algorithm, obtains the minimum distribution cost and the optimal distribution route, which can fully meet the actual needs of the company and customers, improve vehicle utilization, reduce distribution cost and save distribution time. In the problem of crowdsourcing delivery, we use the thought of pairwise constraint and priority constraint for reference. On this basis, we consider the distance from the starting point of crowdsourcing delivery personnel to the starting point of the first order in the distribution route, the distribution time limit of crowdsourcing delivery platform, the limit of the maximum number of orders received at one time and other factors to optimize the order distribution and path of crowdsourcing delivery At the same time, the static model and dynamic model of crowdsourcing delivery are built.

(2) In the fourth chapter, the two-node transportation problem in practice is simplified into a transportation model. Based on heterogeneous vehicles, with the help of genetic algorithm, the real coding of vehicles and routes is carried out to optimize the transportation cost of two-layer logistics nodes of seafood products in a city, and

the cross-mutation operation is used to solve the problem.

(3) In the fifth chapter, with the help of a coal transportation case of an enterprise, the simulation analysis is carried out, and it is found that the hybrid genetic algorithm has good applicability and effectiveness for solving such problems. The results can provide a reference for the formulation of enterprise transportation scheme.

(4) In the sixth chapter, the genetic algorithm is improved by using parallel multi group genetic operation and introducing information entropy to make quantitative analysis of the diversity in the evolution process, so as to ensure the diversity of population genetic. At the same time, combining with the game theory, the game strategy that is most conducive to the diversity and adaptability of the whole population is adopted to achieve strong information entropy changes in the evolution process the purpose of making good individuals and eliminating ineffective individuals.

1.3 Paper structure

This paper consists of seven chapters, the main contents and interrelations of each chapter are as follows:

The first chapter is the introduction, which gives the research background and significance of the topic of logistics vehicle route optimization based on the analysis of various logistics elements, summarizes the important research content of the article, and clarifies the innovation of the research.

Chapter 2 gives a literature review related to this study. Firstly, this paper summarizes the problem of path optimization, and then reviews the existing literature from the aspects of logistics personnel, vehicles, path and algorithm.

Chapter 3, Chapter 4 and Chapter 5 respectively discuss the model establishment and algorithm calculation of typical problems in people, vehicles and paths. The real problems are abstractly simulated into mathematical models, and the problems are solved with various optimization software and heuristic algorithm to find the optimal pre optimized path.

In Chapter 6, inspired by path optimization, a genetic algorithm based on information entropy and game theory is proposed. Three programs checking functions Rosenbrock function, Rastrigin function and Schaffer function are introduced to analyze the performance superiority of the algorithm.

Chapter 7 summarizes the work of this paper and points out the future research direction based on the analysis of the lack of this paper.

2 Literature Review

This chapter first summarizes the characteristics and complexity of path optimization, highlighting the necessity and feasibility of its research. Then, starting with the elements of logistics path optimization, this paper summarizes the current research situation from the aspects of personnel, vehicles, path and algorithm. Through the analysis of the relationship and differences between this paper and existing literature, the necessity of this study is highlighted.

2.1 Overview and complexity of logistics transportation problems

Vehicle logistics path optimization is an important part of modern logistics research. Choosing the right vehicle path can quickly respond to customers' needs, improve customer service quality, enhance customer satisfaction, and reduce operating costs [37]. The classic vehicle routing problem was first proposed by scholars g. Dantzig and J. ramser in 1959 [38], which refers to a group of vehicles from one or more depot points to serve a series of geographically distributed customer points, requiring that the needs of each customer point must be met and only one vehicle can provide services, and the route of each vehicle starts from the depot point, and It ends at the parking lot. Vehicle routing problem is widely used in reality, such as urban garbage collection, parcel distribution, school bus arrangement, newspaper delivery, milk distribution, bank daily capital escort and so on. It has become an important research topic in the field of distribution management. Choosing appropriate vehicle routing can not only improve the quality of distribution services, but also and it can reduce the cost of logistics operation. Foreign scholars have carried out a lot of fruitful research work on vehicle routing and achieved fruitful research results. For example, as early as 1983, Bodin [39], golden and others [40] [41] listed more than 700 documents in their literature review.

The two basic characteristics of modern logistics industry different from traditional logistics are informatization and networking. At present, Japan, the United States and some Western European countries have not only established a relatively perfect logistics network system on the macro level, but also provide network services in the process of enterprise operation. All links are connected with each other to realize the whole process of "door-to-door" service. In the wave of economic globalization, the resources, technology, production and sales of enterprises should be easy to be distributed in the market, so modern logistics services must be networked. The vast service area of modern logistics enterprises determines that the service facilities of enterprises must be networked.

As the main development mode of logistics activities, logistics network has attracted more and more attention. Since the design of logistics network was put forward, it has been considered as one of the key problems in the design of logistics system. In order to build an effective logistics network, it is often necessary to make some relevant decisions, including the system level, the connection between facilities, etc. Specifically, the optimization design of the logistics network needs to determine the number and location of all kinds of facilities needed to undertake the logistics work scientifically and reasonably, and further determine how each facility carries out inventory operation and how much inventory is stored, and where to arrange the delivery of customer orders. The network of logistics facilities forms a structure to carry out logistics operations. Therefore, this network integrates information and transportation capacity, as well as specific work related to order processing, inventory maintenance and material handling.

For vehicle routing optimization, the number of feasible solutions increases with the number of customers. For VRP with only 15 customers, 1012 feasible solutions will be generated [42]. Therefore, there are only a few precise algorithms abroad to solve the modified problem, such as branch pricing method [43], branch pruning method [44], branch pruning method algorithm for one and two commodity flow models [45]. Heuristic algorithm and sub heuristic algorithm are the main algorithms to solve VRPSPD problem. The traditional heuristic algorithm is to solve vrp-spd problem through path construction and improvement. Some classic heuristic algorithms are used to solve VRPSPD problem [46].

2.2 Research on logistics transportation elements

2.2.1 Logistics and transportation optimization based on personnel fatigue limitation and personnel allocation mode

(1) research status of logistics optimization of personnel fatigue limitation

The study of fatigue started in 1880's and has a history of more than 100 years.

Although fatigue is a common phenomenon, it is difficult to define it accurately. Psychologists and physiologists have come up with various definitions.

Bartlett believes that fatigue is a deterioration of function related to continuous activity. This definition reflects the feeling of boredom, annoyance and indifference caused by too long activities and too many spiritual needs [47].

Grandj can defines fatigue as "inability to continue other activities due to constant energy consumption" [48]. Zhou baokuan thinks that fatigue is caused by overuse (over limit) of the body, resulting in decreased function and discomfort of the body. Overuse includes excessive time and intensity [49].

Fatigue driving is a very complex physiological phenomenon, early research mainly from the medical point of view, to study the causes of fatigue driving. So far, the cause of human fatigue is not clear, and there is no common understanding and strict definition of fatigue driving in the world [50] [51].

In the logistics transportation problem, most of the research on the limitation of personnel fatigue is done through the fatigue inspection of drivers, and few of the research on adding the limitation of personnel fatigue to the logistics transportation model. The fatigue monitoring algorithms of drivers are mainly divided into the following categories: detection algorithm based on physiological parameters, detection algorithm based on operation behavior and vehicle behavior, and detection algorithm based on the principle of computer vision [52]. However, there are relatively few active prediction techniques for personnel fatigue.

In 2007, favaretto et al. [53] discussed the vehicle routing problem of personnel fatigue limit.

In 2011, cescina et al. [54] designed a tabu search algorithm to solve the vehicle routing problem with time window and personnel fatigue limitation;

In 2014, belhaiza et al. [55] proposed the vehicle routing problem with multiple time windows, added the fatigue constraint to the model, and recorded the minimum waiting time and the minimum delay time in the route generation process.

(2) research on Logistics Optimization of crowdsourcing distribution

In June 2006, the concept of crowdsourcing was first proposed in Wired magazine. The concept of crowdsourcing was put forward by Jeff Howe. In his opinion, crowdsourcing refers to the way that a company or institution outsources work tasks performed by employees in the past to non-specific (and usually large) mass networks in a free and voluntary manner [56].

Although the concept of crowdsourcing is very new, similar practices have existed for a long time: in 1714, the British government publicly offered a reward to solve the longitude of the earth; this business model has a long history in the eastern civilization, from the ancient "jiehuangbang", "reward wanted" to the modern "prize collection" and so on are the prototype of the "crowdsourcing" model, but the audience has greater limitations [57]. In the Internet era, "crowdsourcing" uses the Internet as the information publishing media, and Internet users all over the world will receive relevant information, and self sponsors are all over the world, so it can also be said that the Internet makes "crowdsourcing" a global concept since its birth [58]. Crowdsourcing mode provides a new way to organize labor force through the Internet. In essence, it is "the public entrustment contract that uses the wisdom, strength and resources of people outside the organization to complete specific tasks of the organization without specific contract awarding objects". The factor that makes crowdsourcing mode reach a new height is the Internet, which uses the Internet online platform to distribute work, find ideas or solutions Solve technical problems and make it possible to seek business wisdom and inspiration for the public. The advantage of crowdsourcing is not only economic efficiency, sometimes the works of customers are more excellent. Customers are the people who participate in the production and are also the people who care about the production and service most, and they understand their own needs most [59].

Thrift (2006) believes that crowdsourcing is a new innovation mode, which can integrate idle social resources and deepen the relationship between consumers and commodities [60].

Wikipedia believes that crowdsourcing is a kind of open system activity initiated by enterprises, which volunteers or amateurs use their free time to put forward ideas or solve problems.

According to bribham (2008), crowdsourcing mode is a problem-solving or production mode in which enterprises publish problems online, and professional or nonprofessional mass groups provide solutions, while crowdsourcers get corresponding rewards, and knowledge achievements belong to enterprises [62].

In 2013, Wal Mart, a retailer, used the idea of crowdsourcing to put forward a distribution method that uses customers who shop in its stores to help deliver packages to customers who shop online. In the same year, DHL was in Stockholm as a pilot, using an app called "my ways" to make ordinary people deliver packages for it. Amazon also uses customers as crowdsourcing objects to deliver "the last kilometer" [63].

Berbeglia et al. Studied static and dynamic on-site receiving and distribution [64] [65]. Recently, a variation of a specific dynamic problem has attracted some attention because it involves the arrival of packages ordered from the Internet in Huitian [66] [67]. ALP M. Arslan et al. Studied a kind of parcel picking and distribution problem based on temporary driver under the concept of crowdsourcing logistics [68].

2.2.2 Research on vehicle based logistics transportation optimization

In 1964, Clarke and Wright first proposed the case of multiple vehicles, defined the problem, and proposed a greedy algorithm for solution, which can be regarded as the first literature to propose vehicle routing problem [69].

Brank et al. Studied the change of order in the process of vehicle delivery and optimized the route of vehicle with the goal of the longest online time of vehicle [70].

Li et al. Proposed a scheduling method for rescheduling backup vehicles according to dynamic customer demand and established the corresponding scheduling mathematical model [71].

Wang Liang, Li Shiqiao, etc. studied the vehicle distribution strategy with random demand in the two-level distribution system, proposed to optimize and integrate the inventory control and transportation decision, and established the corresponding mathematical model [72].

Liu Qing (2013) studied the problem of taking delivery vehicle path at the same time with random demand [73].

Li Kunpeng and Ma Shihua (2008) studied the transportation coordination and scheduling problem in the supply chain led by 3PL under the background of JIT [74].

Most of the literatures are based on the unified vehicle model, aiming at the minimum operating cost or the shortest driving distance, without considering the difference between vehicle loading and transportation cost

2.2.3 Research on Optimization of logistics transportation based on path

Multimodal transport is defined as a modern mode of transport, which is a combination of two or more modes of transport with the means of transport as the carrier [75].

Multimodal transport is based on the development of container transport, and it is a mode of transport organization to achieve the best benefits of cargo transport. One shipment, one billing, one document, one insurance, the carrier of each transportation section and the operator of hub jointly complete the whole process of transportation and transfer of goods. The whole transportation process is arranged as a whole, and different modes of transportation are combined to form a continuous, optimal and comprehensive integrated transportation of goods [76].

Some of them have studied the optimization model and solution algorithm for the design of multimodal transport network of dangerous goods from the tactical level of transport planning, such as Kara and verter [77], erkut and ALP [78], verter and Kara [79], erkut and gzara [80] and Zhao [81]. Other literatures, based on the classic vehicle routing problem, study the transportation path planning of dangerous goods from the operation level of transportation planning, and consider the specific needs of customers when modeling, such as tarantis and kiranoudis [82], androutsopoulos and Zografos [83], Boyer and so on [84]. Other documents, such as Zografos and Samara [85], helander and melachrinoudis [86], giannikos [87], alumur and Kara [88], Boyer, etc., and Zhao and verter [89], have emphasized the importance of the location of the hazardous material recycling and treatment center while planning the transportation route of hazardous materials. From the above literature, it can be found that the current research on the route planning of multimodal transport of dangerous goods is very limited. In the limited research, Xie et al. [90] and Jiang et al. [91] respectively studied the "location and path planning" problem of the combined transport of dangerous goods by public rail from the perspective of multi-commerce flow planning. There are many multimodal transports of non dangerous goods:

Crainic and Rousseau C designed a set of basic modeling framework based on integer nonlinear programming and algorithm design framework based on decomposition and column generation for the design of multimodal transport service network. The research results of this literature laid a good foundation for the follow-up research of multimodal transport service network service design [92].

Kim et al. Discussed the design and application of the express parcel post land air intermodal service network and planned to deal with this problem as a multimodal transport service network design problem with a time window. In this study, two kinds of optimization models are proposed: exact model and approximate model, and a linear programming relaxation algorithm optimized by valid inequalities is designed to obtain the optimal solution of the actual problem, which completes the design of large-scale multimodal transport service network [93].

Zhang et al. Considered the control of CO2 emissions and the improvement of node scale efficiency into the design of multi commodity flow multimodal transport service network and constructed a two-level planning model for this problem. Among them, the upper model uses genetic algorithm to get the optimal topology of nodes layout of multimodal transport service network, while the lower model is dedicated to solving the distribution problem of multi commodity flow in multimodal transport service network [94].

Qu et al. Constructed an integer nonlinear programming model to solve the design problem of multimodal transport service network with transit cost and CO2 emission cost. In this study, the linearization technology is used to linearize the nonlinear part of the objective function to obtain the integer linear programming model equivalent to the original model, so that the problem can be solved accurately by using the mathematical programming software CPLEX [95].

2.2.4 Research on logistics transportation optimization based on Algorithm

The logistics optimization algorithm in this paper is mainly based on genetic algorithm. As an intelligent algorithm to solve NP problem, genetic algorithm has been widely studied.

Davis edited and published the Handbook of genetic algorithms, which covers a large number of application examples of genetic algorithms in engineering technology and scientific calculation [96].

Goldberg in "genetic algorithms for search, optimization and machine learning" proposed to solve optimization problems by combining Pareto theory in economics with genetic algorithm [97].

Bernabe introduced the cellular genetic algorithm with real number coding and studied the performance of solving continuous optimization problems. The results are better than other algorithms [98].

Nagham proposed a new structured population approach for genetic algorithm, based on the custom, behavior and pattern of human community is provided [99]

Tu Chengyuan et al. Proposed to overcome the problem of "premature convergence" by constructing new genetic operators such as restoration, reconstruction and self crossover, namely the so-called Partheno-genetic algorithm [100].

These are more classic genetic algorithms, they have efficient search ability, but there are still inherent disadvantages of genetic algorithm. In order to find a better way to solve NP problem, many scholars have studied hybrid genetic algorithm or improved genetic algorithm.

Li Jia puts forward a new genetic algorithm, namely hybrid genetic algorithm, which is dominated by genetic algorithm, and then integrates tabu search algorithm into it [101].

Zhang Tao and others also put forward a new hybrid genetic algorithm, which still takes the genetic algorithm as the dominant one, and then integrates the 3-opt algorithm into it. This hybrid genetic algorithm not only utilizes the efficient global search ability of the genetic algorithm, but also uses the local search ability of the 3-opt algorithm [102].

Chen Xiangzhou et al embedded a reversal operator into genetic algorithm, which improved the convergence speed of the algorithm in the later stage of operation [103].

Zhang Jing and others introduced the idea of cloning into genetic algorithm [104].

Dai Xiaoming and others introduced the idea of parallel evolution into genetic algorithm [105].

Fang Xia et al. Applied immune algorithm to genetic algorithm to solve VRP Problem [106].

The hybrid algorithm effectively balances the diversity and convergence of the algorithm and embodies the advantages of the multi group algorithm. However, the diversity within the hybrid algorithm is relatively low, and the information exchange between the populations is not reflected. With the emergence of interdisciplinary subjects, scholars introduce information entropy and game theory into genetic algorithm to further optimize the algorithm.

Xue Feng and others used information entropy to generate initial population, increased the diversity of initial population, and provided the basis for subsequent processing [107].

Chen Xiaofeng and others used the concept of information entropy to improve and integrate quantum evolutionary algorithm and immune genetic algorithm and proposed a quantum immune genetic algorithm based on information entropy [108].

Wei Qinfang and others proposed a genetic algorithm for intrusion detection in wireless sensor networks based on information entropy [109].

Myrica rubra and other scholars used the relevant ideas of game theory in strategy optimization for reference and proposed a hybrid optimization mechanism of multiple subgroups and one multiple strategies, which improved the search accuracy and convergence speed, but required the selection of subgroups [110].

The optimization ability of genetic algorithm is reflected in the diversity of population and the convergence speed of the algorithm. Traditional genetic algorithm is easy to fall into local optimum, which has a great relationship with the diversity of individuals in the population. Therefore, it is necessary to keep the diversity of population in each generation to jump out of local optimum. At the same time, genetic algorithm involves genetic and selection operations, whether and how to keep the new genetic population In this paper, the concept of information entropy is introduced to optimize the population diversity, and the game theory is used to optimize the new population generated by genetic operation. Through the comparison of relevant literature, it is found that scholars have launched the research on the combination of information entropy and genetic algorithm, and the combination of game theory and genetic algorithm for algorithm optimization. However, there is no relevant report on the application of information entropy, game theory and genetic algorithm to optimization algorithm.

2.3 Summary

This chapter systematically combs the related background and research status of this paper, including:

(1) the necessity and feasibility of logistics optimization are analyzed. Modern logistics is the product of economic globalization and an important driving force to promote economic globalization. Modern logistics industry is also growing into an important pillar industry of national economy. Developed countries in Europe and America have always attached great importance to basic research in the field of logistics, especially the application of advanced supply chain management ideas to logistics practice, effectively promoting its economic development. Therefore, it is necessary to study the optimization of logistics. At the same time, logistics is related to the interests and development of enterprises. Good methods and methods of logistics distribution play a decisive role in the long-term development of enterprises.

(2) the existing research on the factors of logistics transportation, such as personnel, vehicle, path and algorithm, is discussed respectively. Through the analysis of each factor, it is found that few articles discuss each factor in a paper. Therefore, the research of this paper is necessary to analyze the important factors in each link of logistics transportation to form a system solution.

3 Research on logistics transportation optimization based on personnel factors

The research in this chapter is mainly based on the limitation of personnel fatigue and the mode of personnel allocation.

Under the premise of increasing demand for logistics distribution, the existing logistics distribution develops rapidly. At the same time, with the diversification of customer demand, punctuality becomes an increasingly important indicator for customers to choose logistics distribution. At the same time, because of the different needs of customers, the vehicles equipped by logistics companies are also enriched with the change of customer demand. Considering that long-distance transportation will inevitably lead to driver fatigue, this paper adds a variable to limit driver fatigue driving. Based on the above conditions, this paper optimizes the logistics distribution network.

Since the appearance of online takeout ordering, the proportion of takeout in the catering industry has gradually increased. With the emergence of o2o platforms for takeout, takeout has become a new force in the catering industry. Accordingly, the competition of fast food and beverage industry is more and more fierce. As a service industry, timely, fast and effective distribution of fast food has become a very important factor to improve user experience. Therefore, each o2o platform for takeout chooses to build its own logistics distribution system to improve the distribution service level. However, the self built logistics distribution system not only improves the service level, but also brings about the problem of high distribution cost. At this time, there is crowdsourcing distribution in Yingyun [111].

The professional distribution service level is high, and the distribution cost is also high; the crowdsourcing distribution cost is low, and the distribution service level is correspondingly low. Therefore, how to optimize the crowdsourcing distribution network and improve the service level while reducing the cost has become an urgent problem to be solved in the development of take out o2o platform [112].

3.1 Optimization of Vehicle Routing Problem with Fatigue Driving Based on Genetic Algorithm

3.1.1 Problem Description

A logistics VRP model with a soft time window can generally be described as a distribution center transports goods to demand sites through transport vehicles, the maximum carrying capacity of each transportation vehicle is different, which is responsible for the distribution of finished vehicles. The demand quantity of each demand site is known, and each demand site can only be visited once; each transport mission route can only be borne by a transport vehicle. After the completion of the distribution task, the delivery vehicle must return to the distribution center. All transport vehicles are of different types and only one vehicle of different types is parked in the distribution center. The fixed use fee for each transport vehicle is different for a single transport; the distance from the demand site to the demand site, the distance from the distribution center to the distribution center, and the transportation cost per kilometer are fixed; the transportation speed of the vehicle is fixed, the time constraints of distribution require the distribution center to complete the distribution task within the specified time window, and it takes a certain time to unload the goods when it is delivered to the demand site, penalty is required if the distribution is advanced or postponed. In addition, there is an upper limit for the load of each transport vehicle. If the sum of the weight of the goods carried by the transport vehicle exceeds the maximum load of the delivery vehicle, a certain penalty must be given and a penalty factor for the overweight of per unit weight must be specified. At the same time, the driver is required to drive for more than a certain number of hours. For safety, the driver needs to be forced to rest to ensure that the driver is not fatigue driving. The general logistics distribution process is shown in Figure 3.1:

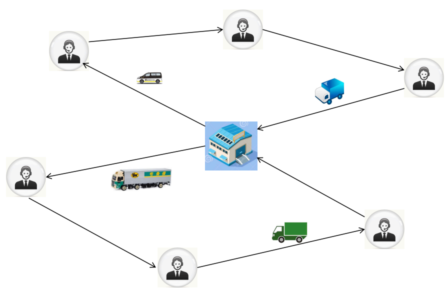


Fig3.1 Logistics distribution process

3.1.2 Model establishment

According to the above problem description, the model for minimizing the total cost of vehicle logistics VRP routes with soft time windows can be described as:

G: number of processor.

g: processor index. g=1,2…, G.

K: number of customer.

k: customer index. k=1,2…, K.

I: vehicle type number.

i: vehicle type index. i=1,2…, I.

H_i: vehicle type number i. number of vehicle belonged to vehicle type i.

h_i: vehicle index belonged to vehicle type i. h_i=1,2…,H_i.

l_{gk}: distance from processor g to customer k.

X_{gk}: if processor g serves customer k, it takes value 1, otherwise, 0, which is the decision variable.

C_{gk}: penalty cost unit time that earlier or later than the time window for customer k.

∂_{gk}: transport cost in each unit distance from g to k.

V_i: fix cost of vehicle type i.

Y_i: used vehicle's number for vehicle type i. Y_i=1,2…,H_i.

$[w_k^1, w_k^2]$: time window of customer k. k=1,2…, K.

TD_{gk}: arrival time from processor g to customer k.

S_{gk}: supply from processor g to customer k.

d_k: customer k's demand.

Cap_g: capacity of processor g.

Cap_i: capacity of vehicle type i.

TS_{gk}: departure time from g to k.

t_{gk}: travel time from g to k.

θ_{gk}: delay time on arc (g, k), which is a random variable.

α_1: penalty cost per unit time that is earlier than the earliest arrival time.

α_2: penalty cost per unit time that is later than the latest arrival time.

M: number of travel lap.

m: lap index.

dt': maximum driving time.

$dt_{m_{h_i}}$: uninterrupted driving time in m'th lap of the travel for vehicle hi.

The model is as follows:

$$min \quad Z = \sum_{g=1}^{G}\sum_{k=1}^{K} l_{gk}X_{gk}\,\partial_{gk} + \sum_{g=1}^{G}\sum_{k=1}^{K} C_{gk}X_{gk} + \sum_{i=1}^{I} V_iY_i$$

s.t:

$d_k = \sum_{g=1}^{G} S_{gk}$ k=1, 2, ..., K. (1)

$\sum_{k=1}^{K} S_{gk} \le Cap_g$ g=1, 2, ..., G (2)

$d_k \le \sum_{i=1}^{I}\sum_{h_i=1}^{H_i} Cap_iY_iX_{gk}$ k=1, 2, ..., K. (3)

$\sum_{g=1}^{G} X_{gk} = 1$ k=1, 2, ..., K. (4)

$Y_i \le H_i$ i=1, 2, ..., I. (5)

$TS_{gk} + (t_{gk} + \theta_{gk}) = TD_{gk}$ k=1, 2, ..., K. (6)

$X_{gk} \in \{0,1\}$ (7)

$$C_{gk} = \begin{cases} \alpha_1(w_k^1 - TD_{gk}) \quad , & w_k^1 > TD_{gk} \\ \alpha_2(TD_{gk} - w_k^2) \quad , & w_k^2 < TD_{gk} \\ 0 \quad , & \text{other} \end{cases} \tag{8}$$

$$t_{gk} = \sum_{m=1}^{M} dt_{m_{h_i}} + \sum_{m=1}^{M-1} wt_{m_{h_i}}, 0 \le dt_{m_{h_i}} \le dt' \tag{9}$$

Constraint description

1. The demand satisfaction for customers.
2. The capacity satisfaction for processors.
3. Vehicles ensure the customers' demand satisfaction.
4. Each customer is exactly visited once by processor.
5. Used vehicles' number for type i is less than the total number of vehicle type i.
6. Ensure time continuity.
7. If one of the g to k is chosen to transport the goods it takes value 1, otherwise, it takes value 0, which is a decision variable.
8. penalty cost that earlier or later than the time window for customer.
9. The total time from g to k which includes the constrained driving time.

3.1.3 Algorithm Design

The Genetic Algorithm simulates the evolutionary laws (survival of the fittest, selecting the superior and eliminating the inferior) of Darwin's biological evolution theory and the computational model of genetic mechanism processes in Mendel's genetics, adopts the adaptive stochastic iteration to find the optimal solution.

The genetic algorithm borrows the principles of simulation genetics and natural selection, and gradually completes the improvement of individual adaptability through mechanisms such as natural selection, inheritance and variation. In a sense, GA is a mathematical simulation of the biological evolution process, which reflects the principle of survival of the fittest in nature. Similarly, GA knows nothing about the nature of the solution problem, starting with a population that represents a possible potential solution set for a problem, each population consisting of a certain number of individuals coded by genes. In fact, each individual is a chromosome characterized entity, the solution to the problem is represented by the chromosome. Choosing the chromosomes based on a fitness value, the genetic algorithm only needs to evaluate every chromosome produced by the algorithm, so that it is able to obtain more reproductive opportunities with strong adaptability. In the calculation process, the string structure is generally encoded in binary, and the values at each position correspond to the corresponding alleles. By compiling a group of chromosomes that are hypothetical solutions and placing them in the "environment" of the problem, the corresponding adaptation function is used for evaluation. According to certain principles, chromosomes that can adapt to this environment are selected for replication, individuals with lower fitness are eliminated, more progeny chromosome groups that can adapt to the environment are produced through the crossover and mutation process, until the most suitable value for the environment is appeared through finally continue through the next round of screening

3.1.3.1 Coding and Decoding

The coding process includes the allocation of the distribution relationship between the logistics nodes and the customers and the routes of vehicles. Firstly, about the distribution relationship between the logistics nodes and the customers, three-layer coding is adopted. Suppose there are n customers and m logistics nodes. At the first layer disrupt the order of n customers at arbitrary; at the second layer disrupt the order of m logistics nodes at arbitrary; at the third layer generate [1, m-1] different numbers between 1 and n-1 as the nodes. Three-layer coding is finished.

Suppose m=10 and n=3, then the first coding example is:

1 5 7 3 4 6 8 9 10 2 | 2 3 1| 2 8

The meaning of the individual is: Disrupt at Position 2 and Position 8 in the first-layer coding, i.e., all the customers are divided into three parts: (1, 5), (7, 3, 4, 6, 8, 9) and (10, 2); in total three nodes are needed, and according to the second-layer coding, they are (2, 3, 1); that means the three groups of customers are served by 2, 3 and 1 logistics nodes respectively.

Then it is the dispatch of transport vehicles. Disrupt vehicles at arbitrary and then dispatch them onto the route from the production factory to logistics nodes and then to customers; the corresponding relations is: vehicles correspond to above-mentioned production factory to No.2, No.3 and No.1 logistics nodes, and then it is from No.2 logistics node to No.1 customer, No.5 customer, and the rest can be done in the same way.

After finishing the distribution at that stage, according to the demand of each node, the product demand of each logistics node can be calculated; meanwhile due to natural number coding, the serial number after coding can be converted into the specific solution of problems.

3.1.3.2 Genetic Operator

The article adopts Parthenon-Genetic Algorithm (called PGA in brief) to realize problem solving. During problem solving use the coding and decoding methods mentioned above. PGA is a genetic method using and choosing gene transposition, gene shifting and gene inversion for offspring reproduction. Therein, gene transposition operator is the process to change the genes at some positions in a chromosome according to certain probability Pe; the position being changed is arbitrary.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{i+1}, \dots, c_{j-1} c_i c_{j+1}, \dots, c_n)$$

Fig.3.2 Single Gene Transposition Operation

Gene shifting operator is to shift the genes in some substrings in a chromosome to the back successively according to certain probability Ps and shift the last gene in the substring to the headmost. In a chromosome, the substring to which the gene shifting is conducted, and its length are chosen arbitrarily.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_i c_{i+1}, \dots, c_{j-1} c_{j+1}, \dots, c_n)$$

Fig.3.3 Single Gene Shifting Operation

Gene inversion operator is to inverse the genes in some substrings in a chromosome according to certain probability P_i successively, and in a chromosome the substrings to which gene inversion is conducted and their length are chosen arbitrarily.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{j-1}, \dots, c_{i+1} c_i c_{j+1}, \dots, c_n)$$

Fig.3.4 Single Point Inversion

Multiple genetic operator is usually used when the chromosome string length 1 is big while single genetic operator is used when 1 is small. On such basis, the article uses the Genetic Algorithms including single gene transposition, single gene shifting and single gene inversion for offspring production to carry out genetic operator operation.

3.1.3.3 choose

Adopt the strategy that elite individuals shall be kept upon the choosing operation; copy the individual with the highest fitness function to the next generation directly. After all the parent generation individuals finish the genetic operator, adopt the mechanism that elite individuals shall be kept again; replace the individuals with the worst fitness function in the new group with the elite individuals before the genetic operator operation and get rid of low-quality individuals to make elite individuals continue.

3.1.3.4 Loop Iteration

Determine if the terminal conditions are reached; stop computing if it satisfies the conditions, and otherwise go on the iterative computation till the terminal conditions are reached.

3.1.4 Example Analysis

Japan's Takkyubin Corporation has an express delivery service in the Tokyo area, as shown in Figure 3.5, Point O indicates the distribution center, and Point A-H indicate the demand site. Coordinated geographical location can only measure the straight distance from the central warehouse to each customer, and the straight distance is not the distance that the vehicle actually travels, the actual driving distance is often greater than the straight distance. In order to make the research data more authentic, this paper first sets the position of each customer by map and GPS as the end point and calculates the distance that the vehicle travels in the absence of various road traffic conditions, then, according to my own field visits and transportation of driving routes and driving distances provided by the driver and makes the information of driving distance from customer i to customer j as shown in Table 1 (unit of measurement: km).

Fig.3.5 Distribution Center and Customer Location Information

Table.3.1 Distance from customer i to customer j

Dij	O	A	B	C	D	E	F	G	H
O	0	7.9	7.5	90.4	76.3	120.9	61.4	64.4	49.2
A	7.9	0	2.9	78	77	116.8	61	61	67.8
B	7.5	2.9	0	80	77.8	115.8	61.9	60.8	67.1
C	90.4	78	80	0	20	120	12	100	105
D	76.3	77	77.8	20	0	116	45.8	120	125
E	120.9	116.8	115.8	120	116	0	115.3	50	53

F	61.4	61	61.9	12	45.8	115.3	0	170	175
G	64.4	61	60.8	100	120	50	170	0	5
H	49.2	67.8	67.1	105	125	53	175	5	0

Based on the actual distance information reflected in the above table, combined with the average speed of 55 km/h delivered by the delivery vehicle, the author calculates the driving time of the vehicle between the customer and the customer, the customer and the distribution center, in order to facilitate the calculation, the time parameter is rounded down. The products provided by Takkyubin Company are ordinary spare and accessory parts, the general transportation vehicles can be used, and there are no special requirements. It is not like the delivery requirements of fresh fruits and vegetables, in terms of delivery time, the spare parts requirements of the Takkyubin company are not very harsh. The customer generally requests the delivery time is basically between 9am and 2pm. If the customer needs to adjust the delivery time, just inform the distribution center in advance so that the distribution center can adjust the delivery plan in time. The customer’s requested delivery time is basically fixed under normal circumstances. However, the customer's demand is different from the delivery time, the demand of the customer is always in a dynamic state, it will change as the customer's demand for its usage changes, distribution center needs to adjust delivery activities at any time for customer orders. The following table shows the Takkyubin customer's demand for delivery time and the demand in a certain day. In order to solve the convenience of the model, this paper sets the expected delivery time and the acceptable delivery time to minutes.

Table. 3.2 The demand and time window request from the customer one day

Customer Number	Customer demand(kg)	Expected delivery time(min)	Acceptable waiting time(min)	Unloading time(min)
A	6000	300-360	0-540	30
B	7000	60-240	0-240	30
C	5000	60-120	0-240	25
D	4000	120-180	0-320	20
E	2000	330-390	0-540	12
F	5000	240-450	0-540	38
G	3000	60-120	30-180	15
H	1000	120-360	60-380	10

This paper also assumes the following data:

(1) There are three types of vehicles in the distribution center, each carrying 10t, 12t, and 15t.

(2) Vehicles start from the distribution center, and the charge per vehicle is 18 yen per kilometer.

(3) The overweight penalty coefficient for each vehicle is W=0.2.

(4) According to the average daily wage of the driver, the penalty factor for arriving early or late to the customer's desired delivery time is calculated to be 0.75 yen per minute.

(5) Driver's continuous driving time should be less than 4 hours.

The above model is an integer nonlinear programming problem. Generally, the vehicle routing problem with soft time windows will be solved with a heuristic algorithm, the case solution of this paper is also a heuristic algorithm that is a genetic algorithm. This paper uses MATLAB tools to solve the model. Parameter settings: the maximum crossover probability of 0.9 and the maximum probability of mutation of 0.1. Each generation population scale is 50, evolutionary results after 50 generations of cycles per generation are shown in Figure 3.6. The minimum fee is 1,2363.9 yuan.

In this paper, the delivery time is set to be 100 minutes, the final optimal solution is as follows. A total of three vehicles are used. The driving route is:

The route for the first vehicle is as follows: 0->D->F>0, and the vehicle is a 10t vehicle;

The route for the second vehicle is as follows: 0->B->G->E->H>0, and the vehicle is a 15t vehicle;

The route for the third vehicle is as follows: 0->C->A->0, and the vehicle is a 12t vehicle;

For a total of 600.3 kilometers, the waiting time for the vehicles earlier than the earliest service time customers expect is a total of 54 minutes, the latest service time later than thecustomer expected is a total of 168 minutes, totaling a total of 1,2363.9 yen.

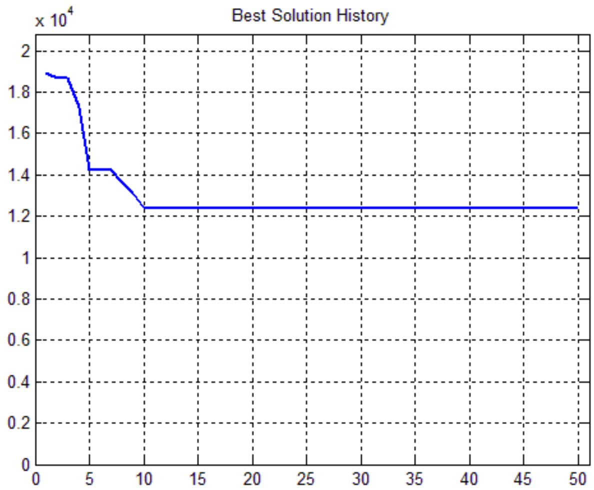


Fig. 3.6 Figure of fitness function changing with genetic algebra

It can be seen from the figure that the algorithm can converge quickly and solve the problem of VRP logistics with soft time windows and proves the validity and correctness of the model and algorithm.

3.2 Research on Optimization of logistics transportation based on crowdsourcing

Crowdsourcing distribution mode is a new distribution mode that introduces the concept of crowdsourcing into the field of logistics. It refers to assigning the distribution tasks that were originally undertaken by the express delivery staff inside the enterprise to the public to complete, so as to realize the socialization and fragmentation of the logistics distribution force. In crowdsourcing distribution, the public, as a free courier, can obtain task information through crowdsourcing distribution platform, select appropriate tasks according to their own time and schedule, carry others' express, and complete the distribution [113].

The crowdsourcing distribution mode in the takeout industry is: the sender issues the distribution demand through the platform and pays the freight to the platform, the platform informs the nearby riders of the order task, the receiver chooses to receive the order freely, and delivers the subject matter to the destination by the time specified by the platform, so as to obtain the income. In the process of distribution, a deposit is generally required, including a small part of the payment upon arrival / collection bill of lading. The carrier needs to pay the consignor the consideration of the goods in advance, and then collect the consideration from the consignee after delivery. The platform collects the platform information fee in the form of price difference for crowdsourcing distribution. If the delivery task of the takeout order generated by the settled merchants of platform a chooses the crowdsourcing distribution mode, platform a is the issuer of the crowdsourcing distribution, and platform a need to pay the related expenses of the crowdsourcing distribution.

Through the analysis of the way of crowdsourcing distribution, it is found that the main problem of crowdsourcing distribution is that no one receives the order. The problem of unattended order receiving mainly refers to the problem that there is no crowdsourcing distribution personnel to respond to the order receiving when there is distribution demand, resulting in the problem of unattended distribution when there is distribution demand. The way to solve the problem of unattended order receiving is to plan the distribution of personnel who have accepted the distribution task.

3.2.1 Problem description

The distribution mode of crowdsourcing take out has the problems of low distribution efficiency and serious distribution overtime. Through the analysis, it can be seen that the main causes of this problem are unreasonable order distribution and distribution route planning. Therefore, how to reasonably distribute orders and plan distribution route is very important. The following aspects need to be considered in order allocation and route planning:

(1) the crowdsourced takeout distributor does not start from the same distribution site, but scattered to different places, with different distribution starting positions. The starting position of the crowdsourced takeout distributor directly affects the length of the path of taking meals of the crowdsourced takeout distributor, and then affects the distribution efficiency and overtime of the crowdsourced takeout. Therefore, in the process of order allocation and distribution route planning, it is necessary to consider the distance from the starting point of the crowdsourcing delivery personnel to the starting point of the order.

(2) the task points in the takeout order are all in pairs and have the requirements of delivery sequence. The delivery personnel of the crowd contracted take out must first arrive at the beginning of the order to complete the meal taking task and then arrive at the end of the order to complete the meal delivering task. In the past, the research on

the delivery path of crowdsourced takeout mostly simplified the delivery process, only optimized the delivery path or separated the delivery path completely. In fact, in the actual delivery process, the delivery path and the delivery path are not separated. Therefore, in order to optimize the delivery route, we should consider the characteristics of delivery order task points existing in pairs and having delivery order requirements and optimize the joint delivery route and delivery route.

(3) take out orders are generated dynamically. A large number of orders can't be predicted in advance, but they are generated in real time during the delivery process of crowdsourcing delivery personnel; at the same time, in the process of order generation, the location and receiving capacity of crowdsourcing delivery personnel are also constantly changing. Therefore, when a new order is generated, the crowdsourcing delivery platform needs to readjust the order distribution and route planning scheme according to the location and receiving ability of the crowdsourcing delivery personnel at that time.

The goal of crowdsourcing delivery optimization is to improve the delivery efficiency of crowdsourcing delivery and reduce the delivery timeout. The key to achieve this goal is to solve the problem of unreasonable order distribution and unreasonable route planning. For the optimization goal of crowdsourcing delivery, the distribution path length can be used to represent the distribution efficiency of crowdsourcing delivery. This is because the shorter the distribution path is, the shorter the required distribution time is, and the higher the distribution efficiency is. Therefore, this paper chooses the two factors of distribution path length and distribution timeout as the optimization goal. The solution to achieve the optimization goal lies in how to reasonably allocate orders and plan distribution routes. In fact, there is the following relationship between the order allocation process and route planning process: the order allocation process directly affects the route planning process, while the route planning process also directly affects the distribution route length and order distribution timeout, while the distribution route length and order As an optimization target, the single delivery time-out reacts to the order allocation process. Therefore, this paper needs to optimize the process of order allocation and route planning to improve the efficiency of distribution and reduce the time-out.

From the perspective of crowdsourcing delivery platform, this paper focuses on solving the problem of order allocation and route planning combination optimization in crowdsourcing delivery process. This paper takes the distribution path length and distribution time-out time as the optimization objective, transforms the distribution time-out time into the time cost of the platform, and at the same time, for the convenience of modeling, transforms the total distribution path length of the completed order into the distribution cost, and constructs the model with the minimum assembly cost of the sum of the distribution cost and time cost as the objective. To sum up, this paper considers the location of the crowdsourcing takeout delivery staff, the path of taking and delivering meals in the process of takeout delivery, aiming at the minimum total cost including delivery cost and time cost, discusses the combination optimization problem of order distribution and route planning, and considers the dynamic generation of orders.

The process of crowdsourcing delivery is a process in which the crowdsourcing delivery clerk completes the task of taking out and delivering meals according to a certain delivery route from the current location. In the crowdsourcing delivery network, there are m crowdsourcing delivery workers, each crowdsourcing delivery worker has a current location point K+; there are n delivery orders, each order has an order starting point and end point as well as a time limit for taking and delivering meals. The problem to be solved in this paper is how to allocate N orders to m crowdsourced takeout distributors and optimize the distribution path of each crowdsourced takeout distributor to minimize the sum of distribution cost and time cost to complete all order

In the process of route optimization, we can use the optimization idea of taking delivery for reference. It can be seen that the task points in a crowdsourcing take out order exist in pairs and have the requirements of delivery sequence, that is, the start and end points of a take out order must be delivered by the same crowdsourcing take out delivery clerk, and the crowdsourcing take out delivery clerk must first visit the starting point of the order to complete the take out task and then visit the end point of the order to complete the delivery task. Most of the previous studies do not consider these characteristics or simplify the processing: one is not considering the order starting point that is the process of taking meal, only optimizing the order end point that is the process of delivering meal; the other is to separate the starting point and the end point of the take out order (that is, the process of taking meal and the process of delivering meal) to simplify the distribution sequence limit of the starting and ending points in the order. In the actual process of crowdsourcing delivery, we need to consider the start and end points of delivery orders and can't distribute them separately. For any order, we only need to ensure the start point of delivery and then the end point of delivery. This is very similar to the problem of pick-up and delivery, and the task points of pick-up and delivery also exist in pairs. Each task has a pick-up point and a delivery point, which is very consistent with the characteristics of the start and end points in take out orders. When optimizing the path, the problem of pick-up and delivery realizes the joint optimization of the pick-up path and delivery path by setting the pairing constraints and priority constraints of the task points, so it can In order to learn from the optimization idea of taking delivery problem and apply it to the planning process of delivery route.

In this paper, in order to minimize the total cost of the sum of the distribution cost and time cost of all orders, we need to consider the factors such as the distance from the location of the delivery staff to the order starting point, the pairing and priority constraints of the delivery order, the distribution time constraints of the delivery platform, and the one-time maximum order quantity constraints The process of order allocation and route planning is combined and optimized. In the process of route planning, the joint optimization of meal taking route and delivery route is realized, and the solution of low efficiency and serious overtime of crowd outsourcing delivery is explored.

3.2.2 Considering the static optimization of the crowd sourcing distribution paths with the time window

3.2.2.1 Model Assumption

In the process of establishing the model, in order to ensure the consistency and solvability of the model, the following reasonable assumptions are made according to the actual situation:

(1) For the distribution time of the crowd sourcing distributor, only the driving time of the vehicle on the route is considered, and the time for taking the meal and the waiting time for delivering the meal are not considered.

(2) The number of crowd sourcing distributors meets the distribution requirements in the system, and the number of orders cannot exceed the maximum one-time order amount of the crowd sourcing distributors in the system.

(3) The distribution speed of the crowd sourcing distributor is constant.

(4) All distribution personnel in the current system are involved in the distribution, and the number of crowd sourcing distributors remains unchanged during the distribution process.

(5) In order to facilitate the description of the model, it is assumed that each crowd sourcing distributor has a virtual end position after completing the distribution, and the distance from the last distribution point to the virtual end point is not included in the distribution path of the crowd sourcing distributor.

3.2.2.2 Model parameter

In order to facilitate the construction of the objective function and constraint conditions, the parameters of the model are set as follows:

N_0: order set {1, 2, ..., n};

i^+: starting point of Order i;

i^-: end point of Order i;

M: set of crowd sourcing distributors {1, 2, ..., m};

k_0^+: K crowd sourcing distributor starting position;

k^-: K crowd sourcing distributor virtual end position;

V_0: starting point of all orders, $V_0 = \{i^+, i^- | i \in N_0\}$;

$x_{u,v}^k$: $x_{u,v}^k$=1 indicates that the K crowd sourcing distributor travels from Point u to Point v, otherwise, it is 0;

$d_{u,v}$: distribution distance from Point u to Point v;

B_u^k: time when the crowd sourcing distributor departs from his starting position to Point u, and it is considered only when the crowd sourcing distributor delivers to the Point u;

T_u: estimated arrival time of point u stipulated by the crowd sourcing takeaway platform;

q: maximum number of orders received by the crowd sourcing distributor;

c_0: unit distribution path parameters;

c_1: unit timeout parameter within the timeout period specified by the platform;

M_0: time to reach the distribution point exceeds the timeout period specified by the platform, and unit timeout time parameter;

v_0: average driving speed of crowd sourcing distributors.

From the perspective of crowdsourcing delivery platform, this paper considers two factors of delivery path length and overtime time in the process of crowdsourcing delivery, and transforms them into cost for quantitative analysis, and solves the crowdsourcing delivery scheme with the goal of minimizing the total cost of the sum of delivery cost and time cost. The specific cost analysis is as follows:

(1) distribution cost

Distribution cost is the product of distribution path length and distribution coefficient of all orders completed by crowdsourcing delivery personnel. The total distribution path length includes the distance between the current location of the crowdsourcing takeout distributor and the first order point in the distribution route and the distance between the order points in the distribution route. The mathematical expression is:

$$\sum_{k\in M}\sum_{v\in V_0}\sum_{u\in V_0} c_0 (x_{k_0^+,v}^{k} d_{k_0^+,v}^{k} + x_{u,v}^{k} d_{u,v}^{k}) \tag{3-1}$$

Among that, $\sum_{k\in M}\sum_{v\in V_0}\sum_{u\in V_0} x_{k_0^+,v}^{k} d_{k_0^+,v}^{k}$ represents the distance from the location of the crowdsourcing take away delivery clerk to the first order in the delivery route; $\sum_{k\in M}\sum_{v\in V_0}\sum_{u\in V_0} x_{u,v}^{k} d_{u,v}^{k}$ Represents the distance between the order points in the distribution line of the crowdsourcing take out distributor.

(2) Time cost

Time cost is the time-out cost caused by the delivery overtime when the delivery staff completes all orders. Each take out order will have a time limit for pick-up and delivery. The time limit of taking out meal is the time interval limit of taking out meal from receiving the order to arriving at the restaurant (order starting point) specified by the crowdsourcing delivery platform, and the time limit of delivering meal is the time interval limit of taking out meal from receiving the order to arriving at the customer point (order ending point) specified by the crowdsourcing delivery platform. On the one hand, the time limit for taking out meals is set in the crowdsourcing delivery platform to standardize the order taking of the crowdsourcing delivery personnel as soon as possible, to minimize the probability of delivery overtime, on the other hand, to prevent the waiting time for taking out which has been prepared by the restaurant from being too long and affecting the customer experience; on the other hand, the time limit for sending out meals is set in the crowdsourcing delivery platform to prevent the waiting time from being too long and reduce the satisfaction of the platform. In the case of overtime delivery, the longer the time of overtime delivery, the greater the overtime cost to the platform, showing a linear relationship between the two; in the case of overtime delivery, the impact of the time of overtime delivery on the platform is not the same, the time of overtime delivery is within 15 minutes, which is generally acceptable to customers, and the unit overtime cost is small Once the time-out exceeds 15 minutes, the customer's dissatisfaction will increase and the unit time-out cost will increase. Time cost is the sum of meal taking overtime cost and meal delivery overtime cost of all orders completed by crowdsourcing delivery personnel, as follows:

$$\sum_{k\in M}\sum_{i\in N_0}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+c_1\max(B_{i^+}^k-T_{i^+},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\} \quad (3\text{-}2)$$

Therein, $\sum_{k\in M}\sum_{i\in N_0}c_1\max(B_{i^+}^k-T_{i^+},0)$ is the meal overtime cost, and the meal overtime coefficient is c_1 ; $\sum_{k\in M}\sum_{i\in N_0}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}$ is the overtime cost of meal delivery, and the overtime coefficient within 15 minutes is c_1, When the timeout time is more than 15 minutes, the timeout coefficient becomes larger.

3.2.2.3 Model building

According to the model parameters in the previous section and the distribution cost and time cost in the objective function, combined with the delivery order pair constraints and priority constraints in the process of crowdsourcing delivery, the one-time maximum order quantity constraints and so on, the outstanding delivery static model is obtained.Objective function:

$$\begin{aligned}\min\sum_{k\in M}\sum_{v\in V_0}\sum_{u\in V_0}c_0(x_{k_0^+,v}^k d_{k_0^+,v}^k+x_{u,v}^k d_{u,v}^k)+\sum_{k\in M}\sum_{i\in N_0}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+c_1\max(B_{i^+}^k-T_{i^+},0)\right.\\ \left.+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}\end{aligned} \quad (3\text{-}3)$$

s.t:

$$\sum_{k\in M}\sum_{v\in V_0}x_{i^+,v}^k=1,\forall i\in N_0 \quad (3\text{-}4)$$

$$\sum_{v\in V_0\cup\{k^-\}}x_{k_0^+,v}^k=1,\forall k\in M \quad (3\text{-}5)$$

$$\sum_{v\in V_0\cup\{k^+\}}x_{v,k^-}^k=1,\forall k\in M \quad (3\text{-}6)$$

$$\sum_{v\in V_0\cup\{k^+\}}x_{v,u}^k-\sum_{v\in V_0\cup\{k^-\}}x_{u,v}^k=0,\forall u\in V_0,\forall k\in M \quad (3\text{-}7)$$

$$\sum_{v\in V_0} x_{i^+,v}^k - \sum_{v\in V_0} x_{v,i^-}^k = 0, \forall i \in N_0, \forall k \in M \tag{3-8}$$

$$\sum_{i\in N_0} x_{i^+,v}^k \le q, \forall k \in M \tag{3-9}$$

$$B_v^k = B_u^k + d_{u,v} / v_0, k \in M, 且 x_{u,v}^k = 1, \forall u \in V_0 \cup \{k_0^+\}, \forall v \in V_0 \cup \{k^-\} \tag{3-10}$$

$$B_{i^+}^k < B_{i^-}^k, \forall i \in N_0, \forall k \in M \tag{3-11}$$

$$B_{k_0^+}^k = 0, \forall k \in M \tag{3-12}$$

$$x_{u,v}^k = 0 \ or \ 1, \forall k \in M, \forall u \in V_0 \cup \{k_0^+\}, \forall v \in V_0 \cup \{k^-\} 且\ u \ne v \tag{3-13}$$

Where:

Equation (3-3) is the objective function, indicating that the system's delivery path and timeout period are the shortest while all current orders are completed.

Equation (3-4) indicates that each order is served once and only once by a crowd sourcing distributor;

The meaning of Equation (3-5) and Equation (3-6) is that each crowd sourcing distributor has a starting point and an end point in his distribution route, i.e., each crowd sourcing distributor starts from his starting point and ends the distribution in the end point after completing the distribution;

Equation (3-7) means that after each crowd sourcing distributor arrives at an order node (not the starting point and the end point of the crowd sourcing distributor), he will definitely leave from that point;

Equation (3-8) indicates that the starting point of an order must be served by the same crowd sourcing distributor;

Equation (3-9) means that each crowd sourcing distributor has a one-time maximum order receiving limit;

Equation (3-10) indicates the time when the crowd sourcing distributor k reaches Point v;

Equation (3-11) means that for a distribution order, the distributor must first access the starting point of the order, and then access the end point of the order;

Equation (3-12) indicates that the crowd sourcing distributor starts from his current position and the starting time is 0;

Equation (3-13) represents a decision variable.

3.2.3 Dynamic distribution model of crowdsourcing takeout

Because take out orders are dynamic and high-frequency, that is, a large number of order information is generated in real-time dynamic in the process of delivery by the delivery personnel of crowdsourcing take out, not all order information can be known in advance like the static model, so it is of great significance to consider the dynamic generation of orders for solving practical problems. In addition to the characteristics of the order task points existing in the static delivery process, such as pairing, distribution priority, time limit, etc., the dynamic delivery process of crowdsourcing delivery also has the following characteristics:

(1) the frequency of dynamic generation of crowdsourcing take out orders is high in the peak period. Because the time of taking out order is usually concentrated in the peak period of dining, it is easy to have the phenomenon of high frequency of taking out order. It can be seen that from 11:00 to 12:00, there are basically 10-20 orders generated dynamically every 3 minutes. It can be seen that the dynamic generation frequency of crowdsourcing take out orders is very high.

(2) in the process of dynamic generation of take out orders, the location and the number of orders that can be received by the delivery staff of crowdsourcing take out are constantly changing. This is because in the process of dynamic generation of orders, crowdsourcing delivery personnel are also on the way to deliver orders. Therefore, at different times of order generation, the distribution location and completed distribution tasks of crowdsourcing delivery personnel naturally change, which leads to the change of the number of orders that can be received.

(3) at the time when a new order is generated, the unfinished distribution tasks of the crowdsourcing delivery personnel cannot be reassigned, but the distribution route can be readjusted, that is, the crowdsourcing delivery platform must decide whether or not to assign orders to the crowdsourcing delivery personnel or which orders to assign based on the task completion of the crowdsourcing delivery personnel at the current time. If a new order is assigned, the platform needs to assign orders to the crowdsourcing delivery personnel Redefining the delivery route of the delivery staff.

There are two ways to solve the dynamic distribution problem: one is to insert new orders in real time; the other is to delay the insertion of new orders. Real time insertion of a new order is to assign the order to the appropriate distributor immediately and optimize the distribution route of the distributor when the new order is generated. The method of real-time insertion of a new order requires high algorithm, and the order demand cannot be too much, otherwise it will affect the quality of the solution. Delay insertion of a new order is to divide the time into multiple time periods and update at the end of each time period the distribution path is to transform the orders generated dynamically in this period of time into the orders generated statically in the next period of time for processing. This method is suitable for dealing with the problems with more dynamic demands in a period of time. As take out orders continue to be generated during the peak period of dining, the delayed insertion method is obviously more reasonable than the real-time insertion method.

In the dynamic delivery scenario of crowdsourcing delivery, the order information is updated every t time. The orders generated in t time period are allocated and optimized as static orders at the end of t time period (the beginning of next time period). At the time of order updating, the position and receiving ability of the delivery staff of crowdsourcing have changed. Therefore, at the time of order updating, the order point that the crowdsourcing delivery clerk is delivering or the next order point to be delivered is defined as the starting point of temporary distribution, and the unfinished order quantity in each crowdsourcing delivery clerk's hand is determined at the same time, so as to determine the order receiving ability of each crowdsourcing delivery clerk at that time. On the premise of defining the location of the temporary distribution starting point and the current maximum order receiving quantity of the crowdsourced takeout delivery personnel, the crowdsourced takeout delivery platform allocates the newly generated orders to the crowdsourced takeout delivery personnel and re optimizes the path of the unfinished orders and newly allocated orders of the crowdsourced takeout delivery personnel so as to minimize the total distribution cost and time cost. The specific refresh diagram is shown in Figure 3-9 below. The orders generated in the 0-t period are refreshed and assigned at time T. at the same time, the orders generated in this time are all generated at time t by default, and the orders generated from time t to time 2T are processed at time 2T, and so on. (R-1) the orders generated from time t to time RT are processed at time RT.

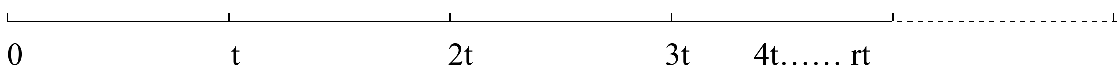


Fig.3.9 Refresh Schematic

3.2.3.1 Model Assumptions

(1) the order information is updated every t time period. The orders generated in each update time interval are generated at the end of the time interval by default.

(2) at the time of updating the order information, the point where the delivery staff is delivering or the next order point to be delivered is defined as the starting point of temporary delivery.

(3) in the period of order dynamic generation, the number of crowdsourcing delivery staff remains unchanged and can meet the order distribution demand generated in this period, that is, the sum of the one-time maximum orders received by all crowdsourcing delivery staff is greater than all the delivery orders generated in this period, so as to ensure that all the new orders can be allocated at this time when the order is updated , there is no case that the order generated at this time is delayed until the next order is updated.

(4) other assumptions refer to the assumption of the static distribution model of crowdsourcing delivery.

3.2.3.2 Model parameter

At the time of the r-th order update, the orders can be divided into the following categories according to the distribution situation of the crowdsourcing takeout distributor: the new orders generated by the r-th refresh and the old orders generated previously. Among them, the old order includes the completed order and the unfinished order, and the unfinished order includes the order which has been taken and the order which has not been taken. Therefore, there may be four types of orders in the system at the time of order update: newly generated orders, old orders that have completed distribution, old orders that have not been taken but not distributed, and old orders that have been taken but not distributed.

The unfinished order set in the old order and the newly generated order set after refreshing are the order sets that have influence on the later update optimization. At the time of order updating, the model needs to re plan the unfinished old order points and the newly generated order points. At the same time, the old order cannot be re allocated, only the distribution path can be adjusted. For unfinished orders, the delivery time of the order has changed when the distribution path is planned again, and the completion degree may also change: for the order that has been taken, only the end point of the order needs to be considered during planning, and for the order that has not been taken, the start and end point of the order still needs to be arranged during planning.

To facilitate the construction of objective functions and constraints, the parameters of the model are set as follows:

N_{new}^{r}:Refresh R, the newly generated order set, i.e. label 4 in Figure 3.9.

N_{w}^{r}:Before r refresh, the system does not complete the order collection of the order fetching task, $N_{w}^{r}=\{i|B_{i^{+}}^{k}>rt, i\in N_{r-1,}k\in M\}$. That is, label 2 in Figure 3.9.

N_{q}^{r}:Before r refresh, the order set in the system that has completed the order fetching task but has not completed the order delivering task, $N_{q}^{r}=\{i|B_{i^{+}}^{k}<rt, B_{i^{-}}^{k}>rt, i\in N_{r-1,}k\in M\}$. That is, label 1 in Figure 3.9.

V_{r}:After r refresh, all unfinished order points in the system.

N_{cr}:The collection of temporary delivery start points is refreshed for R times, $N_{cr}=\{k_{\mathrm{r}}^{+}|k\in M\}$.

Q_{or}^{k}:When refreshing r times, the quantity of unfinished orders of K distributor, excluding the newly generated orders after refreshing r times.

R_{r}^{k}:When refresh r times, the optimization path of k distributor does not include the new order generated by refresh r times, R_{r}^{k}=$\{U_{1}, U_{2}, \ldots U_{z}\}$.

Other parameters are set according to the static model of crowdsourcing delivery.

In this paper, at the time of r order update, on the premise of completing the undelivered task point at the time of R update and the newly generated order task point at the time of R refresh, the dynamic distribution model of crowdsourced takeout is still constructed with the goal of minimizing the total cost of the sum of the R distribution cost and time cost. The specific cost analysis is as follows:

(1) refresh the distribution cost for the r time

The r-th distribution cost is the product of the distribution path length and distribution coefficient of the undelivered task point and the newly generated order task point at the time of r-th update. The total distribution path length includes the distance from the temporary distribution starting point position at the time of R update to the first order point in the distribution route and the distance between the order task points in the distribution route. The mathematical expression is:

$$\sum_{k\in M}\sum_{v\in V_r}\sum_{u\in V_r} c_0(x_{k_r^+,v}^{k} d_{k_r^+,v}^{k} + x_{u,v}^{k} d_{u,v}^{k}) \qquad (3\text{-}14)$$

Therein, V_r represents the collection of all unfinished order points in the system after r refresh, including the undelivered task points at the time of R update and the newly generated order task points after r refresh； k_r^+ represents the location of the temporary distribution starting point of the crowdsourcing takeout distributor K at the R refresh. $\sum_{k\in M}\sum_{v\in V_r}\sum_{u\in V_r} x_{k_r^+,v}^k d_{k_r^+,v}^k$ represents the distance between the location of the temporary delivery starting point at the time of R refresh and the starting point of the first order in the delivery route； $\sum_{k\in M}\sum_{v\in V_r}\sum_{u\in V_r} x_{u,v}^k d_{u,v}^k$ represents the distance between the order task points in the distribution line of the crowdsourcing takeout distributor during the R refresh.

(2) time cost of the r-th refresh

The time cost of the r-th refresh needs to consider the type of unfinished orders: for the new orders generated by the r-th refresh and the old orders that did not take meal during the r-th refresh, the time cost of taking meal, the time cost of sending meal and the serious time cost of sending meal need to be considered; for the orders that have taken meal but not sent meal during the r-th refresh, the time cost of taking meal need not be considered, but the time cost of taking meal needs to be considered The order's delivery overtime cost and delivery serious overtime cost. The details are as follows:

$$\begin{aligned}&\sum_{k\in M}\sum_{i\in N_{new}^r\cup N_w^r}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+c_1\max(B_{i^+}^k-T_{i^+},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}\\&+\sum_{k\in M}\sum_{i\in N_q^r}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}\end{aligned} \quad (3\text{-}15)$$

Therein, $N_{new}^r \cup N_w^r$ represents the collection of newly generated orders in the R refresh and the old orders without meals in the R refresh, N_q^r represents the collection of newly generated orders in the R refresh and the old orders without meals in the R refresh

$$\sum_{k\in M}\sum_{i\in N_{new}^r\cup N_w^r}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+c_1\max(B_{i^+}^k-T_{i^+},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}$$

represents the overtime cost of taking meal, the overtime cost of sending meal and the serious overtime cost of sending meal of the newly generated order and the old order that did not take meal at the time of R refresh;

$\sum_{k\in M}\sum_{i\in N_q^r}\left\{c_1\max(B_{i^-}^k-T_{i^-},0)+M_0\max(B_{i^-}^k-T_{i^-}-15,0)\right\}$ represents the delivery overtime cost and delivery serious overtime cost of the old order that has been taken but not delivered when the R refresh is completed.

3.2.3.3 Model building

Objective function:

$$\min \sum_{k\in M}\sum_{v\in V_r}\sum_{u\in V_r} c_0(x_{k_r^+,v}^k d_{k_r^+,v}^k + x_{u,v}^k d_{u,v}^k) + \sum_{k\in M}\sum_{i\in N_{new}^r\cup N_w^r}\left\{c_1\max(B_{i^-}^k - T_{i^-},0) + c_1\max(B_{i^+}^k - T_{i^+},0)\right.$$
$$\left. + M_0\max(B_{i^-}^k - T_{i^-} - 15,0)\right\} + \sum_{k\in M}\sum_{i\in N_q^r}\left\{c_1\max(B_{i^-}^k - T_{i^-},0) + M_0\max(B_{i^-}^k - T_{i^-} - 15,0)\right\}$$

（3-16）

s.t:

$$\sum_{k\in M}\sum_{v\in V_r} x_{i^+,v}^k = 1, \forall i \in N_{new}^r \quad (3\text{-}17)$$

$$\sum_{v\in V_r\cup\{k_r^-\}} x_{k_r^+,v}^k = 1, \forall k \in M \quad (3\text{-}18)$$

$$\sum_{u\in V_r\cup\{k_r^+\}} x_{u,k^-}^k = 1, \forall k \in M \quad (3\text{-}19)$$

$$\sum_{v\in V_r\cup\{k_r^+\}} x_{v,u}^k - \sum_{v\in V_r\cup\{k^-\}} x_{u,v}^k = 0, \forall u \in V_r, \forall k \in M \quad (3\text{-}20)$$

$$\sum_{v\in V_r} x_{i^+,v}^k - \sum_{v\in V_r} x_{v,i^-}^k = 0, \forall i \in N_{new}^r \cup N_w^r, \forall k \in M \quad (3\text{-}21)$$

$$Q_{or}^k = \sum_{v\in R_r^k}\sum_{i\in\left\{i \mid B_{i^-}^k > rt\right\}} x_{v,i^-}^k, \forall k \in M \quad (3\text{-}22)$$

$$Q_{or}^k + \sum_{v\in V_r}\sum_{i\in N_{new}^r} x_{i^+,v}^k \le q, \forall k \in M \quad (3\text{-}23)$$

$$B_v^k = B_u^k + d_{u,v}/v_0, \forall k \in M, 且 x_{u,v}^k = 1, \forall u \in V_r \cup N_{cr}, \forall v \in V_r \cup \{k^-\} \quad (3\text{-}24)$$

$$B_{i^+}^k < B_{i^-}^k, \forall i \in N_{new}^r \cup N_w^r, \forall k \in M \quad (3\text{-}25)$$

$$B_v^k = rt, \forall k \in M, \forall v \in N_{cr} \quad (3\text{-}26)$$

$$x_{u,v}^k = 0 \ or\ 1, \forall k \in M, \forall u \in V_r \cup N_{cr}, \forall v \in V_r \cup \{k^-\} 且\ u \ne v \quad (3\text{-}27)$$

Equation (3-16) is the objective function, which means that the distribution cost and time cost of the system are the minimum on the premise that all unfinished orders (including the old orders that are not completed before the r-refresh and the new orders that are generated during the r-refresh) are completed at the r-refresh time.

In the constraints, equation (3-17) represents the distribution process of newly generated take out orders when R refreshes, indicating that each newly generated order is served only once by a crowdsourced take out distributor;

Formula (3-18) and formula (3-19) mean that each crowdsourcing delivery clerk has a temporary delivery starting point and a virtual destination in his delivery route, that is, each crowdsourcing delivery clerk starts from his temporary delivery starting point and finishes the delivery from the completion of the delivery to the virtual destination;

Equation (3-20) indicates that each crowdsourcing delivery person will leave from an order node (all unfinished order task points after r refresh) after arriving at it;

Equation (3-21) indicates that the starting point of an order (the old order without taking meal or delivering meal before r refresh and the new order generated during R refresh) must be served by the same crowdsourcing delivery clerk;

Equation (3-22) refers to the quantity of unfinished orders of K distributor in R refresh, excluding the newly generated orders in R refresh;

Equation (3-23) means the limit of the maximum number of orders received at one time by each crowdsourcing delivery clerk during the R refresh, which is used to determine the maximum number of new orders generated by the platform for the crowdsourcing delivery clerk during the R refresh.

Equation (3-24) indicates the time when the crowdsourcing take away delivery delivery clerk K arrives at point v;

Equation (3-25) indicates that for an order (the old order without meal and delivery before r refresh and the new order generated during R refresh), the distributor must visit the starting point of the order first, and then the end point of the order;

Equation (3-26) indicates r refreshes, and the crowd delivery delivery staff starts from their own temporary delivery starting point, which is RT;

Equation (3-27) represents the decision variable.

3.2.4 Model algorithm and solution

Crowdsourcing delivery problem is a combination of order distribution and path optimization. Because the problem of taking out and delivering food is NP hard, this paper adopts integer coding and genetic algorithm to solve it. The process of genetic algorithm is as follows: first, we generate a certain scale of initial population, one chromosome represents a complete distribution scheme, then we select the optimal chromosome in the initial population to enter the next population and select the remaining chromosomes to perform cross variation, so as to generate multiple generations, then we select the excellent individuals to enter the next population to perform cross variation repeatedly Operate differently until the termination conditions are met.

1.Generate initial population

Genetic algorithm is based on the initial population, so the setting of the initial population has a significant impact on the quality of the final solution. The initial population is usually generated randomly, but the delivery problem needs to meet the pairwise and priority constraints of the order when arranging the delivery path, that is, the start and end point of an order must be arranged to the same crowdsourced delivery staff for distribution, and the crowdsourced delivery staff must first complete the catering task at the beginning of the order and then complete the catering task at the end of the order. A large number of invalid solutions may be generated by the random generation method. Therefore, this paper uses the order pair point insertion method to generate the initial solution. The specific steps are as follows:

Step 1: A certain size of order scheduling is generated taking no account of the location of crowdsourced takeaway distributors. This paper uses 1,2,......,n to represent orders, assuming that there are currently 6 orders to be distributed, with a population size of 20, i.e. 20 order arrangements are generated, one of which can be represented as (1 2 3 4 5 6).

Step 2: Insert the location point of the crowdsourcing takeaway distributor in the order scheduling generated in Step 1 and consider the allocation of the orders for the crowdsourced takeaway distributor under the condition that the maximum one-time pick-up quantity of the crowdsourcing takeaway distributor is not exceeded. For example, there are 2 crowdsourcing takeaway distributions of A and B, the starting position of the crowdsourcing takeaway distributor A is inserted into the first place on the chromosome, the crowdsourcing takeaway delivery staff B is inserted behind the belt 4, that is (A 1 2 3 4 B 5 6), which represents assigning orders 1, 2, 3 and 4 to crowdsourcing takeaway deliveryman A, and assigning Orders 5 and 6 to crowdsourcing takeaway deliveryman B.

Step 3: To Arrange the delivery order at the start and end points of the order. The start and end points of order i are expressed in $i^+$and i^- respectively, inserting the start and end points of the order i into the distribution path of the corresponding crowdsourced takeaway distributor in pairs and ensuring that the delivery order of i+ is prior to that of i-. The initial solution is generated until all the start and end points of the orders are inserted into the initial path, e.g. （A 1^+ $2^+2^-3^+$ 4^+1^- 4^- 3^-B 5^+ 6^+ 6^- 5^-）. The distribution path for other chromosomes is also inserted in this way, and if all chromosome orders are slotted in the population are inserted, the initial population is generated.

Step 4: To calculate the target function value for each chromosome. Each chromosome represents a distribution solution that calculates the sum of the distribution and time costs of each distribution solution, i.e. the target function value z. Using 1/z to represent the adaptability of chromosomes, the higher the adaptability represents, the better the individual is, and the smaller the target function value is.

2. Genetic operation

Genetic algorithms generate new populations based on initial populations through three steps: selection, crossover and variation, and in the course of evolution, the relatively good individuals are chosen to be left, passing on the good genes of the previous generation to the next generation. This process enables the children to have a higher degree of adaptation than the parent generation, thus generating better solutions. After several iterations, the most adaptable individual in the last generation of populations can be considered as an approximate optimal solution to the problem.

(1) Selection

In the process of generating the initial population, the adaptive values of each chromosome in the population have been calculated. The most adaptable chromosomes are selected directly into the next generation of populations, and the least adaptable chromosomes are removed from the initial population, and then the chromosomes are selected from the population by roulette for cross-variation. The specific steps for roulette are as follows:

Step1: Calculate the sum $\sum f_i$ of all chromosome adaptations in the initial population;

Step2: Calculate the probability $p_i = f_i / \sum f_i$ that each chromosome is selected;

Step3: Calculate the $q_i = \sum_{j=1}^{i} p_j$ probability of each chromosome being selected cumulatively;

Step4: Randomly generate a number within the section of [0, 1], to which it falls the corresponding chromosome should be chosen.

(2) Cross

Cross operation is conducted aiming to the marshalling sequence of the orders during the generation process of initial population. In the cross process, the children are likely to inherit the good genes of the parent generation to become more adaptable individuals, which is conducive to the evolution of the population in a good direction.

Step1: Randomly match chromosomes selected in the previous initial population in pairs;

Step2: Randomly generate the random number within the section of [0, 1], so that each pair of chromosome corresponds to a random number;

Step3: If the random number generated in step 2 is less than or equal to the cross probability, then the corresponding two chromosomes should perform cross-operation;

Step4: Randomly generate an intersection point, the genes after the intersection of two chromosomes should be exchanged, while paying attention to removing the repeat point of the non-interchange gene, the missing point should be supplemented at the end of the chromosome. The specific cross over process is shown in Figure 3.12 below, and the intersection is 3:

parent1:（1 2 3 |4 5 6） parent 2:（2 5 3 |4 6 1）

child（1 2 3 4 6 1）（2 5 3 4 5 6）

（234615）（234561）

Fig.3.12 The Process of Chromosome Crossover

(3) Variations

The main purpose of the variation operation is to strengthen the local search ability of the algorithm, enhance the diversity of the population and prevent the result of premature convergence. The variation operation is performed on the generation distribution path in the initial population. The steps are as follows:

Step1: Generate random numbers corresponding to each chromosome in the initial population;

Step2: Determine whether it meets the condition of variation, if the random number generated is less than or equal to the probability of variation, then the corresponding chromosome performs the mutation operation;

Step3: Randomly select a mutated order and reinsert the start and end of the order into the delivery path of the original distributor, as follows:

Parent（A 1^+2^+ 2^- 3^+4^+ 1^- 4^- 3^- B 5^+ 6^+ 6^- 5^-）

Select Order 2 and Order 6 to reinsert, the mutated chromosome sits as follows:

Children（A 1^+ 2^+3^+ 4^+ 2^- 1^- 4^- 3^-B 5^+ 6^+ 5^- 6^-）

3.2.5 Instance analysis

This section is based on the actual order data of the M platform to solve the model and analyze the effect, verify the validity of the model, and provide reference suggestions for the development of crowdsourced takeaway distribution.

3.2.5.1 Solution to the Crowdsourced Takeaway Static Distribution Model

(1) Scene and data preparation of crowd-sourced takeaway static distribution

The crowdsourced takeaway static distribution scene is the current moment, all crowdsourced takeaway orders are known to be delivered, without generating new orders in the delivery process of the crowdsourced takeaway delivery personnel , and the number of crowdsourced takeaway distributors and their respective location points are known. Then assign orders and plan distribution routes to crowdsourced takeaway distributers based on the crowdsourced takeaway static distribution model built earlier. This paper studies crowd-sourced takeaway distribution data in an area by selecting the order data generated during the lunch peak hours, and produces 60 orders in the region in 15 minutes from 11:00 to 11:15. The coordinates of the start and end points of the takeaway orders are obtained through the Google API Map, and then the coordinate system is established with a point in the area as the coordinate origin, which converts the coordinates of the order start and end points into the coordinates within the coordinate system. The delivery time limit of the takeaway order is set according to the distance between the starting point (merchant) and the end point of the order by the crowd-sourced takeaway distribution platform, the time limit is generally set to 15 minutes, crowd-sourced takeaway distribution platform generally requires crowdsourced takeaway delivery staff to pick up meals within 15 minutes after receiving the order. The distribution of customer points and merchant points in specific takeaway orders is shown in figure 3.13, and from Figure 3.13, it can be seen that the merchant points in the takeaway order are significantly less than the customer points in the order, because the mechant point of many takeaway orders are the same, with just only 1 in the figure.

Fig.3.13 the diagram of orders' origins and destinations

In this area, the number of crowdsourced takeaway delivery personnel is randomly generated, but the sum of the maximum one-time pick-up of crowdsourced takeaway deliveryman should be guaranteed to be greater than the order volume in the region. Suppose the number of available crowdsourced takeaway distribution staff is 10 people, 10 crowdsourced takeaway distribution points are randomly generated within the distribution area, with the order into a 1:6 ratio relationship, the specific coordinates are shown in Table 3.3.

Table 3.3 the Information for CrowdsourcingOut Workers

Delivery man number	Distributor X coordinates/km	Distribution man Y coordinates/km
1	1.11	5.59
2	3.33	6.69
3	0.89	7.56
4	2.53	7.40
5	2.54	5.94
6	2.11	8.57
7	1.60	5.37
8	3.80	6.17

9	2.97	8.32
10	4.23	7.34

Other parameters of the crowdsourced takeaway static distribution model are set as follows: The delivery speed of crowdsourced takeaway deliveryman is 12km/h (0.2km/min), and the one-time maximum order of the crowdsourced takeaway deliveryman is 8 orders. In terms of time cost, if the crowd-sourced takeaway delivery staff did not complete the task of picking up or delivering meals within the specified time of the order, the crowdsourced takeaway distribution platform will have a certain amount of time penalty costs, the penalty factor C_1 within 15 minutes is set to be 0.5 yuan / minute, the penalty factor M_0 beyond the time limit of 15 minutes is set to be 1 yuan / minute. In terms of distribution costs, unit distribution cost parameter C_0 is according to unit distribution costs of the crowd-sourced takeaway distribution staff, which is determined by adding the depreciation cost of electric vehicles with unit driving distance consumption, assuming that the price of an electric vehicle for a distributor is 7000 yuan, the service life of 2 years, monthly depreciation of 291.7 yuan; The power consumption is 4.5kwh, the electricity price is 0.5 yuan / kwh, the average monthly electricity bill is 58.5 yuan, the monthly cost of electric vehicles is about 350.2 yuan; the distribution time of the takeawy deliveryman is 8 hours per day, thus the unit driving cost of the electrombile is 0.12 Yuan/km. The parameter settings are shown in table 3.4.

Table3.4 Parameter Setting

Parameter settings	Set the value
Delivery speed v_0	12km/h
Maximum one-time pick-up quantity	8
Unit distribution cost factor C_0	0.12 yuan/km
Unit normal timeout cost C_1	0.5 yuan/min
Unit Critical Timeout Cost M_0	1 yuan/min

(2) Solution to the Crowdsourced Takeaway Static Distribution Model

In this paper, the crowdsourced distribution data is optimized, in which the algorithm parameters are set as follows: the initial population size is 200, the number of iterations is 500, the cross probability is 0.9; the probability of variation is 0.1. This paper uses matlab to solve the problem, and the iterative process of the solution is shown in Figure 3.14 below.

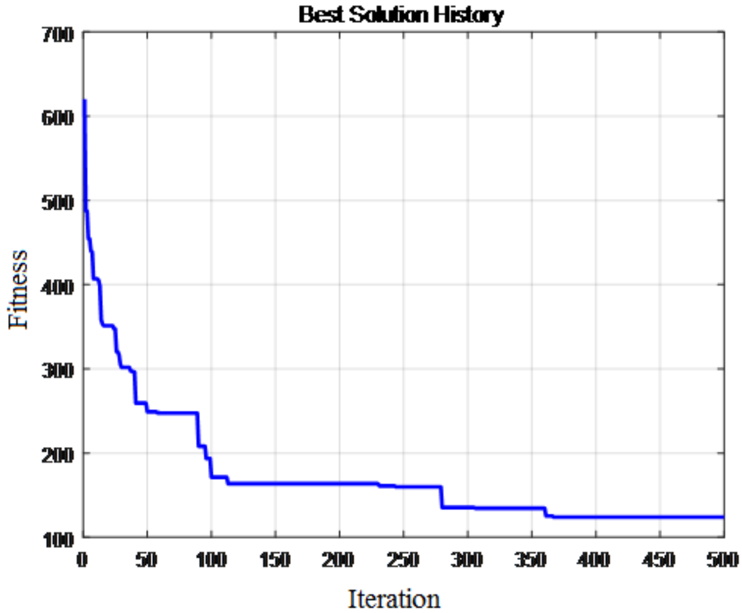


Fig.3.14 The Iterative Process Diagram

According to the iterative process in Figure 3.14, the algorithm iterates 500 times during the solution process, and the optimal solution stabilizes at the 350th time, and the solution effect is good.

The starting point of the order i (restaurant location) is expressed in i^{+} and the end point of the order i (customer point) is expressed in i^{-}, the location point of the No.n crowdsourced takeaway delivery man is used as Kn. By calculation, the target function value is 123.80, the total distribution path length is 97.04km, the total timeout time is 220.19min, and the specific distribution path is as follows:

No.1 crowd sourcing takeaway distributor:

$K1 \rightarrow 22^{+} \rightarrow 30^{+} \rightarrow 43^{+} \rightarrow 2^{+} \rightarrow 2^{-} \rightarrow 40^{+} \rightarrow 43^{-} \rightarrow 15^{+} \rightarrow 15^{-} \rightarrow 22^{-} \rightarrow 40^{-} \rightarrow 30^{-}$;

No.2 crowd sourcing takeaway distributor:

$K2 \rightarrow 26^{+} \rightarrow 17^{+} \rightarrow 50^{+} \rightarrow 7^{+} \rightarrow 41^{+} \rightarrow 31^{+} \rightarrow 17^{-} \rightarrow 31^{-} \rightarrow 26^{-} \rightarrow 7^{-} \rightarrow 41^{-} \rightarrow 50^{-}$;

No.3 crowd sourcing takeaway distributor:

$K3 \rightarrow 28^{+} \rightarrow 24^{+} \rightarrow 14^{+} \rightarrow 54^{+} \rightarrow 56^{+} \rightarrow 24^{-} \rightarrow 14^{-} \rightarrow 54^{-} \rightarrow 28^{-} \rightarrow 56^{-}$;

No.4 crowd sourcing takeaway distributor:

$K4 \rightarrow 57^{+} \rightarrow 45^{+} \rightarrow 5^{+} \rightarrow 51^{+} \rightarrow 5^{-} \rightarrow 45^{-} \rightarrow 38^{+} \rightarrow 47^{+} \rightarrow 57^{-} \rightarrow 51^{-} \rightarrow 47^{-} \rightarrow 38^{-}$;

No.5 crowd sourcing takeaway distributor:

$K5 \rightarrow 59^{+} \rightarrow 10^{+} \rightarrow 34^{+} \rightarrow 8^{+} \rightarrow 33^{+} \rightarrow 59^{-} \rightarrow 33^{-} \rightarrow 37^{+} \rightarrow 34^{-} \rightarrow 8^{-} \rightarrow 37^{-} \rightarrow 10^{-}$;

No.6 crowd sourcing takeaway distributor:

$K6 \rightarrow 1^{+} \rightarrow 3^{+} \rightarrow 36^{+} \rightarrow 13^{+} \rightarrow 27^{+} \rightarrow 60^{+} \rightarrow 3^{-} \rightarrow 52^{+} \rightarrow 32^{+} \rightarrow 52^{-} \rightarrow 13^{-} \rightarrow 1^{-} \rightarrow 32^{-} \rightarrow 27^{-} \rightarrow 36^{-} \rightarrow 60^{-}$;

No.7 crowd sourcing takeaway distributor:

$K7 \to 35^+ \to 35^- \to 29^+ \to 20^+ \to 6^+ \to 9^+ \to 4^+ \to 9^- \to 49^+ \to 29^- \to 20^- \to 6^- \to 4^- \to 49^-$;

No.8 crowd sourcing takeaway distributor:

$K8 \to 44^+ \to 12^+ \to 55^+ \to 25^+ \to 39^+ \to 55^- \to 12^- \to 39^- \to 25^- \to 44^-$;

No.9 crowd sourcing takeaway distributor:

$K9 \to 58^+ \to 21^+ \to 16^+ \to 18^+ \to 53^+ \to 42^+ \to 21^- \to 53^- \to 42^- \to 18^- \to 58^- \to 16^-$;

No.10 crowd sourcing takeaway distributor:

$K10 \to 19^+ \to 48^+ \to 11^+ \to 48^- \to 46^+ \to 23^+ \to 19^- \to 23^- \to 11^- \to 46^-$;

Considering that the final result is approximate solution, in order to avoid a large deviation of single solution, this paper runs the same study 5 times and then analyzes it accordingly. The results of the 5 runs are shown in table 3.5.

Table 3.5 the 5 Times Running Results

Number of operations	Target value/Yuan	Delivery path/km	Time-out/min	Pick-up time-out/min	Delivery time-out/min	Critical timeout/min	severe timeout of picking up meals/min	severe timeout of delivering meals/min
1	106.06	96.33	182.70	67.44	115.25	3.15	0.00	3.15
2	108.96	87.91	181.03	91.03	90.00	7.90	1.09	6.81
3	121.23	92.90	220.14	59.43	160.71	0.01	0.00	0.01
4	123.80	97.04	220.19	79.39	140.80	2.06	0.00	2.06
5	121.85	93.68	212.96	84.64	128.32	4.13	0.00	4.13
Optimal value	106.06	96.33	182.70	67.44	115.25	3.15	0.00	3.15

In summary, the results of 5 operations on the static distribution model of crowdsourced takeaway are selected for the optimal results of the objective function value, and the target function (total cost) of the optimal scheme was 106.06 yuan, the total distribution path was 96.33 km, and the total time-out time was 182.70 minutes. Among them, the timeout period of picking up meals is 67.44 minutes, the timeout period of delivering meals is 115.25 minutes, the serious timeout period of picking up meals is 0 minutes, and the the serious timeout period of delivering meals is 3.15 minutes.

In reality, the crowdsourced takeaway distribution platform only considers the distribution path of crowd-sourced takeaway distribution staff to optimize in the optimization process, and in the order allocation process the time-out situation is not considered, this paper will set the cost coefficient to 0, and compare the result of not considering the overtime costs and the results of taking into account the time-out cost, see table 3.6:

Table 3.6 The ComparisonbetweenThe Results of Considering Overtime Cost and The Results of Not Considering Overtime Cost

--	Objective value/Yuan	Delivery paty/km	Overdue time/min	Overtime of picking up meals/min	Overtime of delivering meals/min	Severe overdue time/min	Severe Overtime of picking up meals /min	Severe Overtime of delivering meals /mim
Taking into accout	106.06	96.33	182.70	67.44	115.25	3.15	0.00	3.15
Not taking into account	9.97	83.087	425.06	186.52	238.54	21.17	22.02	65.36

As can be seen from Table 3.6, the total timeout time is more than half lower than the total timeout time calculated without taking into account the time-out cost, and although the path has increased, the time-out time is essential for takeaway delivery. Therefore, it can be concluded that it should consider time-out costs in crowdsourced takeaway distribution, thus the optimization effect will be better.

3.2.5.2 Solution to the Crowdsourced Takeaway Dynamic Distribution Model

(1) Crowd-sourced takeaway dynamic distribution scene and data preparation

Unlike static distribution scenarios, crowdsourced takeaway dynamic distribution scenarios cannot be known for all crowdsourced takeaway orders to be delivered, and crowdsourced takeaway distributors will have new orders generated during the delivery process, so the platform needs to complete two tasks at the time of order update: One is to assign newly generated orders to crowdsourced takeaway distributors. The second is to optimize the route of the outstanding orders for the previous phase and the newly generated orders for this phase.

This article still selects the area within 15 minutes of the crowdsourced takeaway distribution data to study; the initial state is known to be 25 mass-sourced takeaway orders to be distributed, and the order is updated every 5 minutes, assuming the first update of 20 orders, the second update of 15 orders. The initial location point coordinates of the crowdsourced takeaway distributor remain the same as in the static distribution scene, while the other parameters in the algorithm are left unchanged in this article, and the results of the order update are calculated twice.

(2) Solution to the Crowd-sourced takeaway dynamic distribution model

In this paper, the crowdsourced takeaway dynamic distribution scene is solved using matlab; the result of the solution is as follows:

1)the distribution path of the 25 orders at the initial stage is as follows:

No.1 crowd sourcing takeaway distributor:$K1\to 2^{+}\to 20^{+}\to 5^{+}\to 5^{-}\to 20^{-}\to 2^{-}$；

No.2 crowd sourcing takeaway distributor:$K2\to 8^{+}\to 8^{-}$；

No.3crowd sourcing takeaway distributor:$K3\to 9^{+}\to 3^{+}\to 1^{+}\to 9^{-}\to 1^{-}\to 3^{-}$；

No.4 crowd sourcing takeaway distributor:$K4\to 23^{+}\to 7^{+}\to 23^{-}\to 11^{+}\to 7^{-}\to 11^{-}$；

No.5 crowd sourcing takeaway distributor:$K5\to 18^{+}\to 16^{+}\to 18^{-}\to 16^{-}$；

No.6 crowd sourcing takeaway distributor:$K6\to 21^{+}\to 6^{+}\to 21^{-}\to 25^{+}\to 6^{-}\to 25^{-}$；

No.7 crowd sourcing takeaway distributor:$K7\to 10^{+}\to 4^{+}\to 10^{-}\to 4^{-}$；

No.8 crowd sourcing takeaway distributor::$K8\to 13^{+}\to 13^{-}\to 15^{+}\to 15^{-}$；

No.9 crowd sourcing takeaway distributor:$K9\to 12^{+}\to 19^{+}\to 17^{+}\to 19^{-}\to 17^{-}\to 12^{-}$；

No.10 crowd sourcing takeaway distributor:$K10\to 24^{+}\to 22^{+}\to 14^{+}\to 22^{-}\to 24^{-}\to 14^{-}$；

2) In the second stage, 20 new orders emerge after 5 minutes, when the temporary delivery starting point of each crowd-sourced takeaway distribution operator is marked with(), the order point before the temporary distribution starting point is the distribution task which has been completed in the previous stage , the point after the temporary distribution startpoint is the the unfinished point of the previous stage and the distribution path of the order point newly generated, The distribution path adjustments are as follows:

No.1 crowd sourcing takeaway distributor:

$K1\to$（2^{+}）$\to 20^{+}\to 5^{+}\to 28^{+}\to 2^{-}\to 28^{-}\to 5^{-}\to 20^{-}$；

No.2 crowd sourcing takeaway distributor:

$K2\to 8^{+}\to$（8^{-}）$\to 39^{+}\to 40^{+}\to 29^{+}\to 39^{-}\to 29^{-}\to 40^{-}$；

No.3 crowd sourcing takeaway distributor:

$K3\to$（9^{+}）$\to 35^{+}\to 9^{-}\to 3^{+}\to 35^{-}\to 1^{+}\to 32^{+}\to 30^{+}\to 30^{-}\to 3^{-}\to 32^{-}\to 1^{-}$；

No.4 crowd sourcing takeaway distributor:

$K4\to 23^{+}\to 7^{+}\to$（23^{-}）$\to 26^{+}\to 41^{+}\to 11^{+}\to 26^{-}\to 7^{-}\to 11^{-}\to 41^{-}$；

No.5 crowd sourcing takeaway distributor:

$K5\to$（18^{+}）$\to 16^{+}\to 42^{+}\to 18^{-}\to 42^{-}\to 38^{+}\to 16^{-}\to 38^{-}$；

No.6 crowd sourcing takeaway distributor:

$K6\to$（21^{+}）$\to 21^{-}\to 6^{+}\to 25^{+}\to 44^{+}\to 6^{-}\to 44^{-}\to 25^{-}$；

No.7 crowd sourcing takeaway distributor:

$K7 \to (10^{+}) \to 4^{+} \to 37^{+} \to 27^{+} \to 4^{-} \to 10^{-} \to 37^{-} \to 27^{-}$；

No.8 crowd sourcing takeaway distributor:

$K8 \to (13^{+}) \to 33^{+} \to 15^{+} \to 43^{+} \to 45^{+} \to 45^{-} \to 13^{-} \to 43^{-} \to 15^{-} \to 33^{-}$；

No.9 crowd sourcing takeaway distributor:

$K9 \to 12^{+} \to (19^{+}) \to 17^{+} \to 31^{+} \to 19^{-} \to 12^{-} \to 31^{-} \to 17^{-}$；

No.10 crowd sourcing takeaway distributor:

$K10 \to (24^{+}) \to 36^{+} \to 14^{+} \to 34^{+} \to 22^{+} \to 36^{-} \to 24^{-} \to 22^{-} \to 34^{-} \to 14^{-}$；

(3)At the third stage, the second update produces 10 orders after 5 minutes, when each crowd-sourced takeaway delivery man's temporary delivery starting point ia marked with(), the distribution path adjusted as follows:

No.1 crowd sourcing takeaway distributor:

$K1 \to 2^{+} \to 20^{+} \to (5^{+}) \to 28^{+} \to 54^{+} \to 5^{-} \to 56^{+} \to 20^{-} \to 2^{-} \to 28^{-} \to 54^{-} \to 56^{-}$；

No.2 crowd sourcing takeaway distributor:

$K2 \to 8^{+} \to 8^{-} \to (39^{+}) \to 40^{+} \to 59^{+} \to 29^{+} \to 29^{-} \to 39^{-} \to 59^{-} \to 40^{-}$；

No.3 crowd sourcing takeaway distributor:

$K3 \to 9^{+} \to 35^{+} \to (9^{-}) \to 30^{+} \to 32^{+} \to 3^{+} \to 1^{+} \to 35^{-} \to 32^{-} \to 60^{+} \to 60^{-} \to 30^{-} \to 3^{-} \to 1^{-}$；

No.4 crowd sourcing takeaway distributor:

$K4 \to 23^{+} \to 7^{+} \to 23^{-} \to 26^{+} \to 41^{+} \to (11^{+}) \to 50^{+} \to 7^{-} \to 11^{-} \to 26^{-} \to 41^{-} \to 50^{-}$；

No.5 crowd sourcing takeaway distributor:

$K5 \to 18^{+} \to 16^{+} \to 42^{+} \to (18^{-}) \to 38^{+} \to 42^{-} \to 57^{+} \to 55^{+} \to 55^{-} \to 38^{-} \to 57^{-} \to 16^{-}$；

No.6 crowd sourcing takeaway distributor:

$K6 \to 21^{+} \to 21^{-} \to 6^{+} \to 25^{+} \to (44^{+}) \to 47^{+} \to 58^{+} \to 6^{-} \to 47^{-} \to 25^{-} \to 44^{-} \to 58^{-}$；

No.7 crowd sourcing takeaway distributor:

$K7 \to 10^{+} \to (4^{+}) \to 37^{+} \to 27^{+} \to 53^{+} \to 53^{-} \to 37^{-} \to 10^{-} \to 27^{-} \to 4^{-}$；

No.8 crowd sourcing takeaway distributor:

$K8 \to 13^{+} \to 33^{+} \to (15^{+}) \to 49^{+} \to 45^{+} \to 13^{-} \to 43^{+} \to 52^{+} \to 33^{-} \to 52^{-} \to 43^{-} \to 49^{-} \to 15^{-} \to 45^{-}$；

No.9 crowd sourcing takeaway distributor:

$K9 \to 12^{+} \to 19^{+} \to 17^{+} \to 31^{+} \to (19^{-}) \to 46^{+} \to 12^{-} \to 31^{-} \to 17^{-} \to 46^{-}$；

No.10 crowd sourcing takeaway distributor:

$K10 \to 24^{+} \to 36^{+} \to 14^{+} \to 34^{+} \to 22^{+} \to (36^{-}) \to 48^{+} \to 24^{-} \to 51^{+} \to 22^{-} \to 51^{-} \to 48^{-} \to 34^{-} \to 14^{-}$；

After two updates, the target function value of the total delivery result is 24.80, the total distribution path length is 90.21 km, and the total timeout period is 34.01min. Considering that the final result is approximate solution, this paper runs the same study 5 times and then analyzes it accordingly in order to avoid a large deviation of single solution. The results of the 5 runs are shown in table 3.7.

Table 3.7 the 5 Times Running Results

Number of operations	Target value/meta	Delivery path/km	Time-out/min	Pick-up time-out/min	Delivery time-out/min	Critical timeout/min	severe Pick-up timeout/min	severe deliverytimeout/min
1	25.46	90.34	29.24	5.65	23.59	0.00	0.00	0.00
2	22.12	89.15	22.84	4.96	17.89	0.00	0.00	0.00
3	19.44	84.83	18.52	5.08	13.44	0.00	0.00	0.00
4	20.10	88.62	18.93	10.66	8.27	0.00	0.00	0.00
5	27.43	90.12	33.22	1.51	31.71	0.00	0.00	0.00
Optimal value	19.44	84.83	18.52	5.08	13.44	0.00	0.00	0.00

In summary, the results of 5 operations of the dynamic distribution model take the optimal value, and the target function (total cost) in the optimal scheme is 19.44 yuan, the total distribution path is 84.83 km, the total timeout time is 18.52 minutes, the time-out period of picking up meals is 5.08 minutes, the time-out period of delivering is 13.44 minutes, and the severe time-out period is 0.

3.3 Summary

3.3.1 Summary of optimization of personnel fatigue limit constraints

In this chapter, a logistics vehicle routing optimization model with soft time window constraints is constructed, and a Partheno-genetic algorithm is designed to calculate the optimal solution of the model. The research process and results show that the corresponding algorithm of the modeling and application effectively solves the optimization problem of distribution path selection of this kind of parts logistics.

The numerical analysis based on the case of logistics and distribution of Japan's otaku express company shows that the solution of logistics vehicle distribution path optimization with soft time window proposed in this paper, through the solution of genetic algorithm, obtains the minimum distribution cost and the optimal distribution route, which can fully meet the actual needs of the company and customers, improve vehicle utilization, reduce distribution cost and save distribution time. Therefore, for the automobile logistics and its related enterprises, the research results of this paper can improve the economic benefits of enterprises, reduce energy consumption, and then enhance the core competitiveness of enterprises, to achieve a win-win situation for customers and companies.

3.3.2 Summary of the optimization of take out delivery

In this chapter, based on the pairwise and priority constraints of take delivery problem, considering the distance from the starting point of the delivery staff to the first order starting point in the distribution route, the distribution time limit of the delivery platform, the maximum order quantity limit at one time and other factors, the order distribution problem and path optimization problem of take delivery are combined, At the same time, the static model and dynamic model of crowdsourcing take out distribution are constructed by jointly optimizing the take out route and delivery route. In the static model, considering the location of the crowdsourcing delivery staff, the pairing and priority constraints of the order task points, and the maximum order quantity at one time, the static model of the total cost including the distribution cost and time cost is constructed with the distribution path and overtime time as the optimization objective; in the dynamic model, the delayed insertion method is adopted to consider the crowdsourcing delivery at the order update time The position of the staff and the ability to receive orders are changed. The new orders are allocated, and the distribution path is adjusted. On the premise of completing all new orders and all unfinished old orders, the goal is to minimize the sum of the distribution cost and time cost. At the same time, the unfinished orders of the crowdsourcing delivery staff in the previous stage cannot be reallocated. Finally, genetic algorithm is used to solve the problem.

4 A study on transportation algorithm of bi-level logistics nodes based on Genetic Algorithm

To study common transportation lines and transportation vehicle selection problem, the paper makes mathematical modeling against vehicle scheduling and transportation line in bi-level node transportation line based on genetic algorithm with the optimization objective of bi-level logistics node transportation expense after considering the allocation strategy between the path of vehicle picking up and delivering goods simultaneously and vehicle model with different paths. Applying MATLAB software, the paper solves the model based on traditional genetic algorithm and Partheno-genetic algorithm and verifies the correctness and effectiveness of the model and Partheno-genetic algorithm. It indicates that the model and algorithm proposed in the paper could solve bi-level node transportation problem of multiple vehicle models better.

4.1 Introduction

A fresh food processing company in a city needs to conduct fresh product transportation within the range of the entire city, and the transportation route of fresh products is from the processing factory to the three depots distributed in the city via trucking at first and then from the depot to the 10 customers distributed within the city; see Table 4.1.

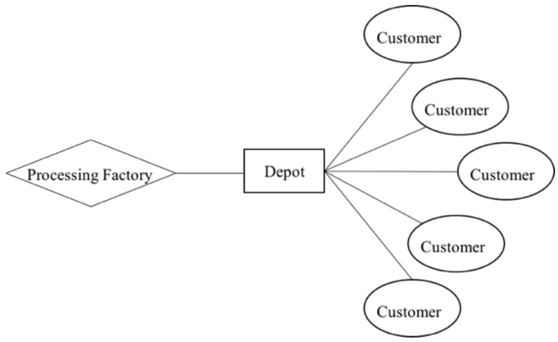


Fig.Two-node transport diagram

Mathematical model:

$$\min Z = \sum_{i=1}^{I}\sum_{h_i=1}^{H_i} V_{h_i} X_{h_i} Y_i + \sum_{g=1}^{G} C_{mg} S_{mg} X_{mg} + \sum_{g=1}^{G}\sum_{k=1}^{K} C_{gk} S_{gk} X_{gk} + \sum_{g=1}^{G}\sum_{k=1}^{K} X_{gk} l_{gk} \quad (4\text{-}1)$$

s.t

$$\sum_{k=1}^{K} S_{kg} = S_{mg} \quad (4\text{-}2)$$

$$\sum_{g=1}^{G}\sum_{k=1}^{K} S_{kg} \le Cap_g \ (g=1,2,\ldots,G) \quad (4\text{-}3)$$

$$\sum_{g=1}^{G} X_{gk} = 1 \quad (4\text{-}4)$$

$$X_{hi} \in \{0,1\} \quad (h_i=1,2,\ldots,H_i.\ i=1,2,\ldots,I.) \quad (4\text{-}5)$$

$$X_{gk} \in \{0,1\} \quad (g=1,2,\ldots,G.\ k=1,2,\ldots,K.) \quad (4\text{-}6)$$

$$Y_i \le H_i \quad (i=1,2,\ldots,I.) \quad (4\text{-}7)$$

$$X_{mg} \in \{0,1\} \quad (g=1,2,\ldots,G.) \quad (4\text{-}8)$$

$d_{kg} \le \sum_{i=1}^{I} \sum_{h_i=1}^{H_i} Cap_i Y_i X_{h_i}$ （4-9）

$d_{kg} = S_{gk}$ (g=1,2,…,G. k=1,2,…,K.) （4-10）

Where:

I : Number of vehicle type；

i : Index of vehicle type , i=1,2…,I；

H_i: Number of the i'th vehicle type；

h_i: Index of vehicle of type i ,h_i=1,2,…,h_i；

V_{h_i}: Fix cost of vehicle h_I,h_i=1,2,…,H_I;

X_{h_i}: If the vehicle h_I is used to be deliver the goods, it take value 1 , otherwise , it takes value 0 ,which is the decision variable,h_i=1,2,…,H_I;

Y_i: Used vehicle type his number; M: producer; G: Number of depot; g : index of depot , g=1,2,…,G;

C_{mg}: Unit freight of good from m to g. (m=1,2,…,M. g=1,2,…,G) ;

S_{mg}: Freight volume from m to g. (m=1,2,…,M. g=1,2,…,G);

X_{mg}: If one of the m to g is chosen to transport the goods it take value 1, otherwise , it takes value 0, which is the decision variable , (m=1,2,…,M. g=1,2,…,G);

K: Number of customer; k : Index of customer, k=1,2,…,K;

X_{gk}:If vehicle pass one of g to k,it take value 1,otherwise ,it takes value 0, which is the decision variable. (g=1,2,…,G .k=1,2,…,K);

l_{gk}:Distance between depot g and customer k. (g=1,2,…,G. k=1,2,…,K);

d_{kg}: Demand of customer k for depot g;

S_{gk}: supply of depot g to customer k;

Cap_i: Capacity of vehicle type i.

4.2 Mathematical model

Genetic Algorithm seeks the optimal solution through adaptive random iterations by simulating the evolutionary laws of Darwin Evolution (survival of the fittest, survival of the fittest) and the genetic mechanism of Mendel genetics.

Genetic Algorithm uses the principles of simulation genetics and natural selection, and through the mechanisms of natural selection, heredity and mutation, the improvement of individual adaptability is gradually accomplished. In a sense, GA is a mathematical simulation of the process of biological evolution, which embodies the principle of survival of the fittest in nature. Similarly, GA knows nothing about the nature of the problem, starting with a population that represents a potential solution to a problem, and each population is made up of a certain number of individuals encoded by the gene. In fact, each individual is a chromosome with a characteristic entity, the solution of the problem is expressed by chromosomes. The selection of chromosomes based on an adaptive value. The Genetic Algorithm only needs to evaluate each chromosome produced by the algorithm and promote the adaptive ability to obtain more breeding opportunities. In the process of calculation, the coding string structure is generally binary, and the value of each position corresponds to the corresponding allele. By compiling a group of chromosomes that are hypothetical solutions and placing it in the "environment" of the problem, the corresponding adaptive function is evaluated. According to certain principles, select the chromosomes that can adapt to this environment to replicate, eliminate the less adaptive individuals, and then through the intersection, mutation process to produce the offspring chromosome group, which is more able to adapt to the environment, and finally continue to use the next round to screen, until the most suitable value for the environment appears.

4.2.1 Coding and Decoding

The coding process includes the allocation of the distribution relationship between the logistics nodes and the customers and the routes of vehicles. Firstly, about the distribution relationship between the logistics nodes and the customers, three-layer coding is adopted. Suppose there are n customers and m logistics nodes. At the first layer disrupt the order of n customers at arbitrary; at the second layer disrupt the order of m logistics nodes at arbitrary; at the third layer generate [1, m-1] different numbers between 1 and n-1 as the nodes. Three-layer coding is finished.

Suppose m=10 and n=5, then the first coding example is:

1 5 7 3 4 6 8 9 10 2 | 2 3 1 | 2 8

The meaning of the individual is: Disrupt at Position 2 and Position 8 in the first-layer coding, i.e., all the customers are divided into three parts: (1,5), (7,3,4,6,8,9) and (10,2); in total three nodes are needed, and according to the second-layer coding, they are (2,3,1); that means the three groups of customers are served by 2, 3 and 1 logistics nodes respectively.

Then it is the dispatch of transport vehicles. Disrupt vehicles at arbitrary and then dispatch them onto the route from the production factory to logistics nodes and then to customers; the corresponding relations is: vehicles correspond to above-mentioned production factory to No.2, No.3 and No.1 logistics nodes, and then it is from No.2 logistics node to No.1 customer, No.5 customer, and the rest can be done in the same way.

After finishing the distribution at that stage, according to the demand of each node, the product demand of each logistics node can be calculated; meanwhile due to natural number coding, the serial number after coding can be converted into the specific solution of problems.

4.2.2 Genetic Operator

The article adopts Parthenon-Genetic Algorithm (called PGA in brief) to realize problem solving. During problem solving use the coding and decoding methods mentioned above. PGA is a genetic method using and choosing gene transposition, gene shifting and gene inversion for offspring reproduction. Therein, gene transposition operator is the process to change the genes at some positions in a chromosome according to certain probability Pe; the position being changed is arbitrary. Gene transposition can be divided into single gene transposition and multiple gene transposition. Single gene transposition is to change the positions of a pair of genes (two genes) only at one time; multiple gene transposition is for a given positive integer Ue, to choose an arbitrary number i (1≤i≤Ue) and change i pairs of genes at a time. Single gene transposition is also called mutation operator; due to the coding method is natural number coding and repeated number is not allowed, the transposition adopts the method to change the position of a gene and the position of the other gene with the same number. The operation is shown in Figure 4.2.

$$A = (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B = (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{i+1}, \dots, c_{j-1} c_i c_{j+1}, \dots, c_n)$$

Fig.4.2 Single Gene Transposition Operation

Gene shifting operator is to shift the genes in some substrings in a chromosome to the back successively according to certain probability Ps and shift the last gene in the substring to the headmost. In a chromosome, the substring to which the gene shifting is conducted, and its length are chosen arbitrarily. Gene shifting can be divided into single gene shifting and multiple gene shifting. Single gene shifting means to choose only a substring in a chromosome to conduct gene shifting while multiple gene shifting is for a given positive integer in advance, to choose an arbitrary number j (1≤j≤Uj) and then to choose j substrings in a chromosome to conduct gene shifting. Shifting operation must satisfy a condition that it shall not lead to the overflow of the new parent node's volume; the single gene shifting operation is in Figure 4.3.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_i c_{i+1}, \dots, c_{j-1} c_{j+1}, \dots, c_n)$$

Fig.4.3 Single Gene Shifting Operation

Gene inversion operator is to inverse the genes in some substrings in a chromosome according to certain probability Pi successively, and in a chromosome the substrings to which gene inversion is conducted and their length are chosen arbitrarily. Gene inversion can be divided into single gene inversion and multiple gene inversion. Single point inversion means to choose only a substring in a chromosome to conduct gene inversion while multiple gene inversion is for a given positive integer in advance, to choose an arbitrary number j (1≤j≤Uj) and then to choose j substrings in a chromosome to conduct gene inversion. Inversion operator does not need to judge the overflow situation of the parent node's volume; the operation is in Figure 4.4.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{j-1}, \dots, c_{i+1} c_i c_{j+1}, \dots, c_n)$$

Fig.4.4 Single Point Inversion

Multiple genetic operator is usually used when the chromosome string length 1 is big while single genetic operator is used when 1 is small. On such basis, the article uses the genetic algorithms including single gene transposition, single gene shifting and single gene inversion for offspring production to carry out genetic operator operation.

4.2.3 Choose

Adopt the strategy that elite individuals shall be kept upon the choosing operation; copy the individual with the highest fitness function to the next generation directly. After all the parent generation individuals finish the genetic operator, adopt the mechanism that elite individuals shall be kept again; replace the individuals with the worst fitness function in the new group with the elite individuals before the genetic operator operation and get rid of low-quality individuals to make elite individuals continue.

4.2.4 Loop Iteration

Determine if the terminal conditions are reached; stop computing if it satisfies the conditions, and otherwise go on the iterative computation till the terminal conditions are reached.

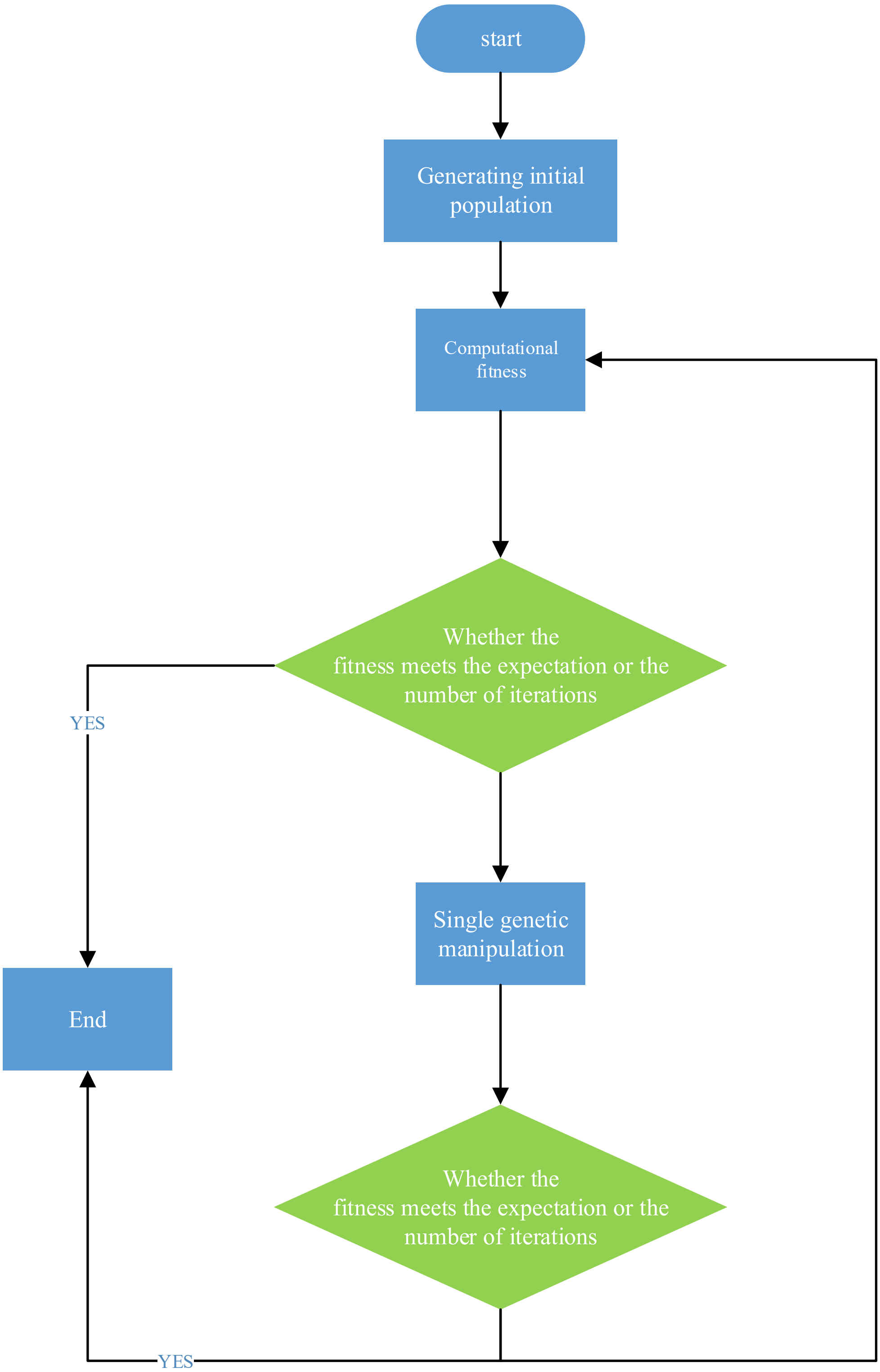


Fig. 4.5 Algorithm flow chart

4.3 Example

A fresh food processing company in a city needs to conduct fresh product transportation within the range of the entire city, and the transportation route of fresh products is from the processing factory to the four depots distributed in the city via trucking at first and then from the depot to the 10 customers distributed within the city; see Table 4.1.

The company has 25 trucks in total, among which there are 4 trucks whose maximum carrying capacity is 3t, and the freight is 1.8/km; there are 12 trucks whose maximum carrying capacity is 6t and the freight is 2/km; there are 9 trucks whose maximum carrying capacity is 8t and the freight is 2.4/km; they are responsible for the straight-line transportation of 25 routes respectively.

Table 4.1 Position Information

No.	Category	Relative Position	
		x Coordinate	y Coordinate
Processing	Processing Factory	50	50
Depot1	Depot	47	71
Depot2		34	37
Depot 3		63	64
Depot 4		56	70
Depot 5		57	28
Customer 1	Customer	42	80
Customer 2		13	11
Customer 3		34	95
Customer 4		62	56
Customer 5		28	76
Customer 6		69	84
Customer 7		11	37
Customer 8		21	22
Customer 9		63	90
Customer 10		24	79
Customer 11		32	42
Customer 12		96	76
Customer 13		41	79
Customer 14		66	28
Customer 15		54	56
Customer 16		17	11
Customer 17		12	74

Customer 18		83	58
Customer 19		46	28
Customer 20		44	16

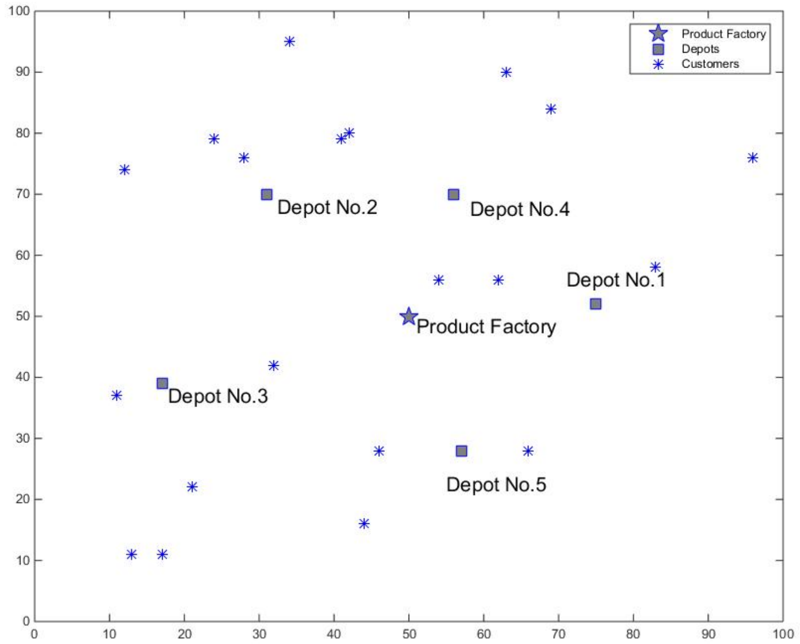


Fig.4.5 Factory Location Diagram

Use straight-line distance to simulate the distance between the processing factory, the depot and customers; do not take into consideration of the influence of traffic jams and traffic lights etc.

The production of the processing factory proceeds based on customers' orders at each month, i.e., the processing factory is capable of satisfying customers' needs and the capacity of the depot can satisfy product transfer need. Customers' demand data is shown in Table 4.2.

Table 4.2 Data on customers' Demand

No	Quantity Required(t)	No	Quantity Required(t)
Customer 1	16	Customer 11	28
Customer 2	15	Customer 12	26
Customer 3	18	Customer 13	13
Customer 4	27	Customer 14	19
Customer 5	26	Customer 15	10
Customer 6	19	Customer 16	10
Customer 7	28	Customer 17	28

Customer 8	12	Customer 18	16
Customer 9	19	Customer 19	19
Customer 10	15	Customer 20	26

Goal: Optimal vehicle distribution route and route-matching vehicles.

Take advantage of MATLAB program to realize the Genetic Algorithm of above-mentioned problem. Parameter Setting: the maximum crossover probability is 0.9 and the maximum mutation probability is 0.1. The population size of each generation is 200, and the evolution result after a cycle of 200 generations is shown by Figure 6 and Figure 7. The minimum expenses is 10434.

Comparing traditional genetic algorithm and single genetic algorithm, it is seen Partheno-genetic algorithm converges at 42th generation, but traditional genetic algorithm reaches convergence after 100 generations. It proves the effectiveness of Partheno-genetic algorithm.

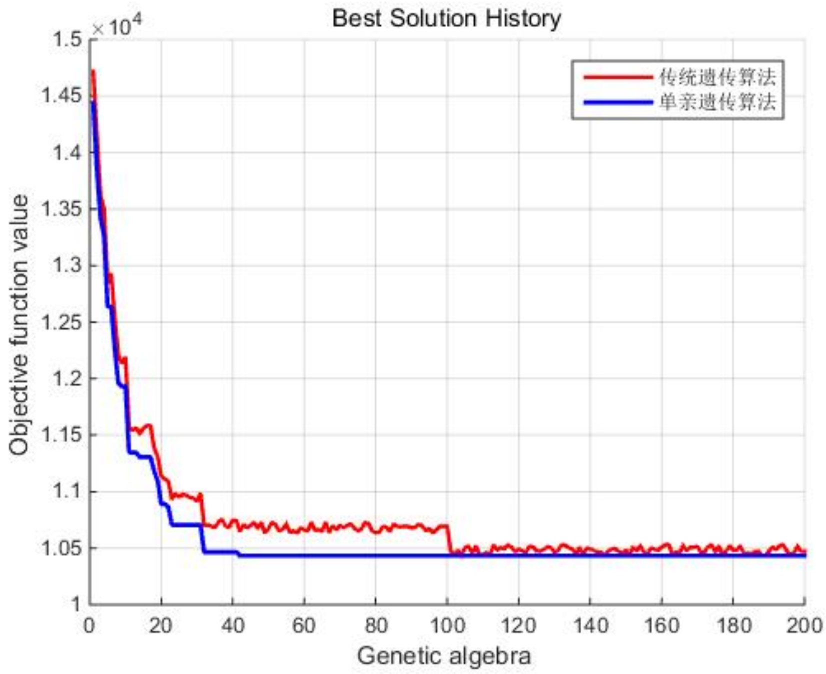


Fig.4.6 Diagram of the Fitness Function Changing with the Genetic Algebra

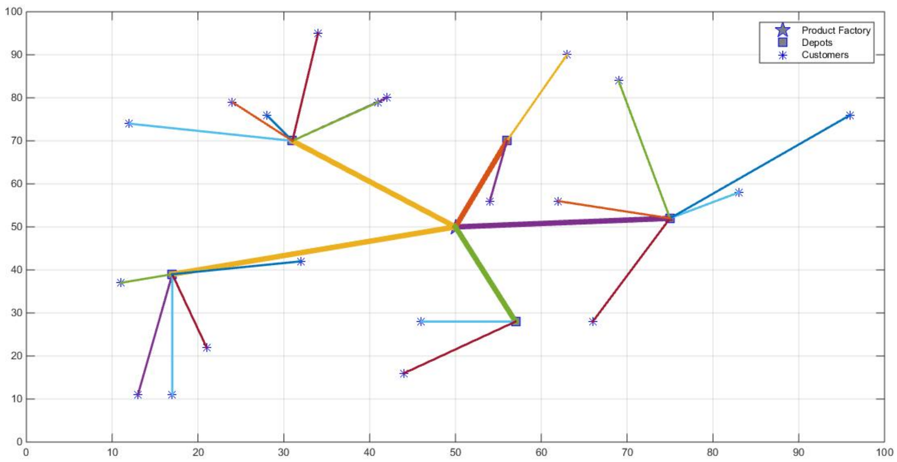


Fig.4.7 Vehicle Dispatch Diagram

Table 4.3 Table on the Vehicle Dispatch from depot to customers

Depot No.	Customer No
Depot1	6 18 14 12 4
Depot 2	1 13 17 3 5 10
Depot 3	2 7 16 8 11
Depot4	9 15
Depot5	19 20

Vehicles are numbered 1, 21, 8, 22, 19, 7, 16, 14, 5, 3, 24, 25, 11, 17, 18, 10, 20, 9, 23, 6, 15, 12, 4, 13,and 2, responsible for the vehicle transportation from the processing factory to three depots and then from depot 1, depot 2, depot 3, depot 4 and depot 5 to respective customers; the numbering of customers is done in the same way mentioned above. Therein, 1-4 mean 3t vehicles; 5-16 mean 6t vehicles and others are 8t vehicles.

From the figure, it can be known that the algorithm has advantages as follows: it can effectively solve the dispatch of different vehicles during transportation, and the distribution of vehicles for different routes has a big influence on the overall freight; the algorithm converges fast. For the transportation line and vehicle dispatch problems based on genetic algorithm, the model and problem-solving algorithm used in this article are quite effective.

4.4 Conclusion

The article simplifies the problem of dual-node transportation to a transportation model; based on genetic algorithm, taking the optimization of the transportation expenses of the bi-level logistics node of the sea food in a city as the optimization goal, conduct real number encoding to vehicles and the routes and use crossover and mutation operations for problem solving; the result demonstrates the method adopted by the problem can excellently settle the problem of dual-node transportation and it is effective.

5 Research on Optimization of logistics transportation based on path elements

5.1 Mathematical Model for Optimization of Coal Logistics Transportation

With the development of social economy, different levels and scopes of social logistics are gradually formed, such as regional logistics, international logistics, etc. Meanwhile, perfect logistics network system is required to support. The development of enterprise globalization requires the formation of a global logistics network system. The development of e-commerce technology also needs the support of timely, accurate and simple logistics network system. Therefore, logistics must be networked to meet the requirements of the development of the times. In this case, it is very urgent and important to study the structure design and optimization of logistics network. Logistics network refers to the network mode with specific organizational structure formed by planning, designing and implementing the logistics functions, logistics resources, logistics information and other elements in a certain market area according to the principles of logistics integration. The goal is to improve the mobility of logistics system and realize the overall optimization of logistics cost.

At present, the development of multimodal transport has become the mainstream of the development of transport modes in various countries, especially in the context of economic globalization, the establishment of an efficient and low-cost long-distance multimodal transport network is of great significance to promote trade exchanges and save commodity costs. This paper will take the transportation of bulk cargo coal as an example to analyze multimodal transport [114].

Traditional coal logistics system structure: after the raw coal from the coal mine mouth is transported out, the finished coal is generated through the washing and processing process, and then flows to the user through various transportation modes (mainly railway transportation, waterway transportation, highway transportation and pipeline transportation) [115]. At the beginning of the establishment of coal transportation and marketing company, in order to achieve unified management and marketing, a series of small-scale coal preparation plants and coal generating stations were rapidly established in a short period of time to carry out coal washing, processing and shipping management. In the traditional structure of coal logistics system, there are a large number of coal preparation plants and coal generating stations that play a role of bridge, which makes the relationship between upstream coal mines and downstream coal preparation plants and coal generating stations extremely unstable, unable to form a long-term partnership, increasing transaction costs.

With the increasingly profound understanding of logistics in coal enterprises, some coal transportation and marketing workers and scholars have seen the important strategic significance of logistics for the development of coal enterprises, and the research on coal logistics is more and more comprehensive, more and more comprehensive, more and more systematic. For example, the relationship between the two organizations of coal transportation, i.e. the carrier and the shipper, is essentially a long-term contractual relationship between the enterprise and the market, which can not be managed simply according to the market regulations. The enterprise should change the existing market governance mode, focus on the governance of the network organization, follow the principle of cooperation first and the overall interests of the network as the best, and deal with various problems Question.

The difference between coal transportation and ordinary transportation is that the coal transportation volume is large and long, but the route is relatively fixed. Compared with ordinary transportation, the timeliness requirements are not too high, so it is necessary to find a long-distance and large loading way. For example, railway and water transportation are the best choices. As one of the three characteristics of coal transportation in the world, "iron water intermodal transport" has become an important means to effectively utilize the railway and waterway resources to achieve seamless connection and reasonable transportation of coal transportation resources. In the face of the continuous adjustment of railway freight and shipping price, it is of great significance for energy group to reduce logistics cost how to reasonably allocate transportation capacity, correctly select transportation mode and optimize logistics network.

5.1.1 Problem description

Transportation not only considers the logistics costs in the coal logistics network, but also considers how to maximize the group's overall benefits on the basis of saving logistics costs. Based on the actual operation of a transportation group, this article has established a coal transportation model with multiple production sites, multiple demand sites, and multiple transportation modes. At the same time, taking into account the proportion of the Group’s shareholdings in the subsidiaries, The Group's overall interests are ultimately determined by making decisions on the production volume of coal mines owned by the Group, the transportation volume of shipping companies, the choice of coal transportation methods, and the method and quantity of coal purchased by power plants.

The realization of the optimization of the structure of the coal logistics network is the primary goal of the coal logistics network design. Therefore, the following factors that may affect the coal logistics network structure should be considered, including:

- Quantity and price of coal commodity;
- Coal production sites and geographical distribution of power plants;
- The amount of coal required by power plants;
- The maximum capacity limit for railways and ports;
- Transportation costs of transport modes;
- The fixed cost of the operation of links;

5.1.2 Model Assumptions and Model Symbols

The model adopts the transport mode of “rail-water intermodal transport”, which not only protects the rational allocation and utilization of natural resources, protects the natural environment, but also saves costs and increases corporate profits.

The following assumptions can be made through the description of coal logistics network problems:

1) The coal purchased from the power plants studied by the model comes from coal mines inside and outside the Group, and the output can fully meet the needs of the power plant;

2) Coal transportation methods include nonstop railway transportation and rail-sea intermodal transport.

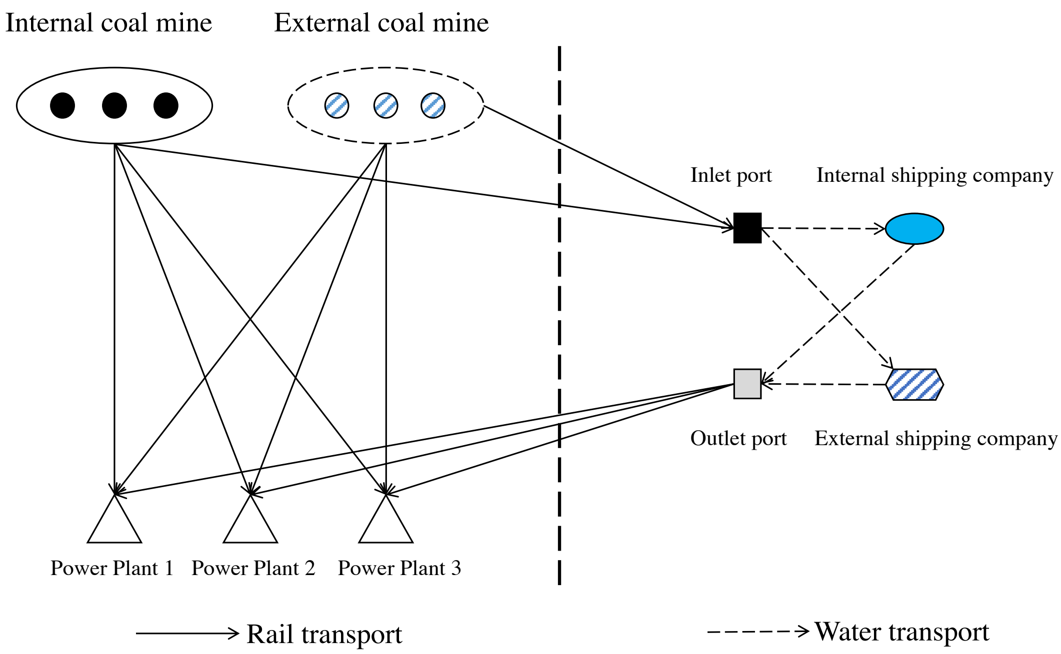
3) In the transportation process, when coal passes through individual railway sections, the capacity is limited, and the throughput of the port is limited;

4) When rail-sea intermodal transport is selected as the mode of transportation, the sea cargo is divided into two alternative modes: the shipping company within Group and the shipping company outside Group;

5) The shipping capacity of group-owned shipping companies and external shipping companies is not limited.

6) In the rail-water intermodal transportation, the transshipment cost between railway and waterway is not counted, and there is no transportation process between power plant and water outlet.

The roadmap for the mode of transportation is as follows:



Transportation route map

Based on the above assumptions, an optimization model for coal logistics transportation is established. The relevant mathematical symbols are defined as follows:

i: represents coal mine, when $\mathrm{i} = 1,2, \ldots \mathrm{k}, \mathrm{k}+1, \ldots, \mathrm{I}$ ($\mathrm{i} = 1,2, \ldots \mathrm{k}-1$, it represents coal mines within the Group, when $\mathrm{i} = \mathrm{k}, \mathrm{k}+1, \ldots, \mathrm{I}$, it represents coal mines outside the Group);

j: represents the power plants within the Group, $\mathrm{j} = 1,2, \ldots, \mathrm{J}$;

α_j: indicates the power generation efficiency(power generation efficiency refers to how much electricity can be generated with 1 ton of standard coal) of the power plant jwithin the Group, $\mathrm{j} = 1,2, \ldots, \mathrm{J}$;

a: represents the inlet port, $\mathrm{a} = 1,2, \ldots, \mathrm{A}$;

b: represents the outlet port, $\mathrm{b} = 1,2, \ldots, \mathrm{B}$;

l: represents the transportation mode,($\mathrm{l} = 1$ represents the transportation mode of the nonstop railways, $\mathrm{l} = 2$ represents the mode of transportation of railways and shipping companies within the Group, $\mathrm{l} = 3$ represents the mode of transportation of railways and shipping companies outside the Group);

Q_i: represents the annual production of coal in coal mine i;

D_j: represents the annual demand of coal on power plant j;

x_{ijl}:indicates the traffic volume of coal from the coal mine i to the power plantj via the mode of transport j;

In it:

When $l=1$, x_{ij1} represents transport volume of coal from coal mine i to power plant j via the nonstop railway mode;

When $l=2$, x_{ij2}^{ab} represents transport volume of coal from coal mine i to power plant j via railway and the water route in the transportation mode of the Shipping Conpany within Group from the inlet port a to the port of expert b;

When $l=3$, x_{ij3}^{ab} represents transport volume of coal from coal mine i to power plant j via railway and the water route in the transportation mode of the Shipping Conpany outside Group from the inlet port a to the port of expert b;

M_{ij} : represents the maximum transport volumes of coal from coal mine i to power plant j;

M_a : represents the maximum throughputs of the inlet port a of coal from the coal mine i to the power plant j via shipping;

M_b : represents the maximum throughputs of the outlet port b of coal from the coal mine i to the power plant j via shipping;

c_{ij} : represents the unit transportation cost(yuan/(t*km)) of railway from coal mine i to power plant j via the transportation mode of nonstop railway;

c_i^a : represents the unit transportation cost(yuan/(t*km)) of railway from coal mine i to inlet port a;(The location of all power plants is considered to be the location of the outlet port b, so there is no c_i^b);

c_1^{ab} : represents the unit transportation cost(yuan/ton * nautical miles) of when choosing rail-water intermodal transport and using the water transportation of internal shipping company from inlet port a to outlet port b;

L_{ij} : represents the transportation distance(km) of the railway line from the coal mine i to the power plant j via the transportation mode of nonstop railway;

L_i^a : represents the transportation distance(km) of the railway line from the coal mine i to the inlet port a via the rail-water intermodal transport;

L_{ab} : represents the water transport distance(nautical miles) from the inlet port a to the outlet port b;

c_a^1 : represents the unit operating cost of the port in the process of the transfer inlet port a(yuan/ton);

c_b^1 : represents the unit operating cost of the port in the process of the transfer of outlet port b(yuan/ton);

p_a^1 : represents the unit service cost of the port in the process of the transfer of inlet port a(yuan/ton);

p_b^2 : represents the unit service cost of the port in the process of the transfer of outlet port b(yuan/ton);

c_i^3 : represent the mine-mouth coal costs in coal mine i;

p_i^3 : represent the mine-mouth coal prices in coal mine i;

p_1^{ab} : represents the unit transportation price of the internal shipping company's water transportation from the inlet port a to the outlet port b(yuan /(ton * nautical miles));

p_2^{ab} : represents the unit transportation price of the external shipping company's water transportation from the inlet inlet port a to the outlet port b(yuan/(ton * nautical miles));

p_j : represents the electricity price per kWh of the plant j;

F_a^1 : represents the fixed cost of operation of the inlet port a;

F_b^2 : represents the fixed cost of operation of the outlet port b;

F_i^3 : represents the fixed cost of coal mine i operation($i = 1,2, \dots k-1$);

F_j^4 : represents the fixed costs of the operation of the power plant j;

F^5 : represents the fixed costs of the operation of the Group's shipping companies;

R_i^1 : represents the proportion of shares of the group in the coal mine i($i = 1,2, \dots k-1$);

R_j^2 : represents the proportion of the company's shares in power plant j;

R_a^3 : represents the proportion of the group's share in the inlet port a;

R_b^4 : represents the proportion of the group's share in the outlet port b;

R^5 : represents the proportion of the company's shares in the shipping company;

Note: The annual production volume of coal mines, the annual demand of power plants, the throughput of ports, and the rail transportation are in tons.

5.1.3 Modeling

With the goal of maximizing the profit of a coal group, the model carries out optimizing and solving, and the objective function and constraints are as follows:

(1) Profit of coal mines i within the group:

$$W_i = \left(p_i^3 - c_i^3\right) \sum_{j=1}^{J} \sum_{l=1}^{3} x_{ijl} - F_i^3$$

$$x_{ij2} = \sum_{a=1}^{A} \sum_{b=1}^{B} x_{ij2}^{ab}$$

$$x_{ij3} = \sum_{a=1}^{A} \sum_{b=1}^{B} x_{ij3}^{ab}$$

(2) The profit of power plant j:

$$W_j = \alpha_j p_j \sum_{i=1}^{I} \sum_{l=1}^{3} x_{ijl} - C_j^1 - C_j^2 - C_j^3 - C_j^4 - F_j^4$$

Therein:

(1) Railway transportation costs C_j^1 paid by power plant j:

$$C_j^1 = \sum_{i=1}^{I} (x_{ij1} L_{ij} c_{ij}) + \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{i=1}^{I} (x_{ij2}^{ab} c_i^a L_i^a) + \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{i=1}^{I} (x_{ij3}^{ab} c_i^a L_i^a)$$

(2) the cost C_j^2 of the coal purchased by the power plant j:

$$C_j^2 = \sum_{i=1}^{I} \sum_{l=1}^{3} (p_i^3 x_{ijl})$$

(3) C_j^3 transportation costs C_j^3 of the external shipping company paid by the power plant j:

$$C_j^3 = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{i=1}^{I} (p_2^{ab} L_{ab} x_{ij3}^{ab})$$

(4) The transportation costs C_j^4 of the internal shipping company paid by the power plant j:

$$C_j^4 = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{i=1}^{I} (p_1^{ab} L_{ab} x_{ij2}^{ab})$$

(5) Transshipment profits of inlet port a:

$$W_a = (p_a^1 - c_a^1) \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{b=1}^{B} \left(x_{ij2}^{ab} + x_{ij3}^{ab}\right) - F_a^1$$

(6) Transshipment profits of outlet port b:

$$W_b = (p_b^2 - c_b^2) \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{a=1}^{A} \left(x_{ij2}^{ab} + x_{ij3}^{ab}\right) - F_b^2$$

(7) Freight revenue of internal shipping companies:

$$W_s = \sum_{a=1}^{A} \sum_{b=1}^{B} \left[\left(p_1^{ab} - c_1^{ab}\right)\left(\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ij2}^{ab}\right) L_{ab}\right] - F^5$$

Objective function:

$$W = Max\left(\sum_{i=1}^{k} R_i^1 W_i + \sum_{j=1}^{J} R_j^2 W_j + \sum_{a=1}^{A} R_a^3 W_a + \sum_{b=1}^{B} R_b^4 W_b + R^5 W_s\right)$$

The objective function represents the total profit of the group.

Subject to:

(1) The minimum coal demand to meet the power plant j:

$$\sum_{i=1}^{I} Q_i \geq \sum_{j=1}^{J} D_j$$

It means that the demand of power plants can be met.

(2) The maximum capacity of the selected route for rail transport:

$$x_{ij1} \leq M_{ij}$$

It means that the demand for coal transportation in railway transportation cannot exceed the maximum capacity of railway transportation.

(3) The maximum throughput of inlet port a cannot be exceeded:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{b=1}^{B} (x_{ij2}^{ab} + x_{ij3}^{ab}) \leq M_a$$

It means that in the rail-water intermodal transportation, the amount of coal transported into the port should not exceed the maximum throughput of the port.

(4) The maximum throughput of outlet port b cannot be exceeded:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{a=1}^{A}\left(x_{ij2}^{ab}+x_{ij3}^{ab}\right)\leq M_b$$

It means that the coal transportation through the outlet port cannot exceed the maximum throughput of the port in the rail-water intermodal transportation.

(5) The proportion of the company's shares in each company:

$$0\leq\left(R_i^1,R_j^2,R_a^3,R_b^4,R^5\right)\leq 1$$

In it:

W: represents the total profit of the company;

W_i: represents the profit of the coal mine i within the group;

W_j: represents the profit of the Group's power plant j;

W_a: represents the profit of the inlet port a;

W_b: represents the profit of the outlet port b;

W_s: represents the profit of the shipping company;

C_j^1: represents the railway transportation costs paid by the power plant j;

C_j^2: represents the cost of the coal purchased by the power plant j;

C_j^3: represents the transportation costs of the external shipping company paid by the power plant j;

C_j^4: represents the transportation costs of the internal shipping company paid by the power plant j;

5.2 Hybrid Genetic Algorithm for Coal Transportation Optimization Model

The traditional standard genetic algorithm is based on the Bionics Principles to optimize and solve, and it can exert the superiority of the parental individual very well. However, for the requirement of the initial population in number, it is easy to “premature convergence” when the parental individual is the same. Therefore, based on the traditional genetic algorithm, this paper further optimizes the optimized individuals in the offspring, and adopts partheno-genetic operations to update the offspring individuals with poor target values. This can not only retain the good individuals in the offspring, but also further optimize the fitness of offspring.

5.2.1 Standard Genetic Algorithm.

Genetic algorithm has the advantages of robustness, globality, and implicit parallelism, which make it widely used. The design of genetic algorithms mainly includes the following aspects:

(1) Solution encoding and decoding.

The structure of many application problems is complex, but it can be translated into simple bit strings. The process of transforming a problem structure into a bit string is called coding; conversely, the process of transforming a bit string form into the original problem structure is called decoding. The bit string in the above process is usually called a chromosome(individual).

(2) Determination of initial population and size.

The initial population is generally selected at random or it is generated by some heuristic method. The initial population was randomly selected and iterated through genetic manipulations to traverse all states, thus allowing the optimal solution to survive in the evolution of genetic algorithms.

(3) Determination of fitness function.

In order to reflect the adaptability of chromosomes, a function that can measure each chromosome in the problem is introduced, called the fitness function.

(4) Genetic operators.

When searching for the optimal solution, the genetic algorithm searches the solution space through the extension of the genetic operator. Operators of basic genetic algorithms include selection(replication) operators, crossover operators, and mutation operators.

5.2.2 Parthenon-Genetic Algorithm

The genetic operators of Parthenon-Genetic Algorithm(PGA) are selective, gene recombination and gene mutation, among which the selection operator is basically the same as the operator of traditional genetic algorithm. The genetic operations of the parthenon-genetic algorithm are all performed on one chromosome. Compared with the traditional genetic algorithm, the offspring individual of the Parthenon-genetic algorithm inherits most of the genetic characteristics of the parental individual, and there is no phenomenon of premature convergence. Even if all individuals in the population are the same, genetic operations can be performed and it is easy to handle constraints that constrain the optimization problem.

Partheno-genetic algorithm is a genetic method that uses selection, gene transposition, gene shifting, and gene inversion to propagate offspring. Among them, the operator of gene transposition is a process of exchanging genes at certain positions in a chromosome with a certain probability Pe, and the positions of the exchanged genes are random. Gene transposition can be divided into single-point transposition and multi-point transposition. Single-point transposition only exchanges one pair(two) genes at a time; The multi-point transposition takes a random number i(1≤i≤Ue) to exchange i pairs of genes at a time for a predetermined positive integer Ue. Single-point transposition is also called mutation operator. Since the encoding method is natural number encoding, duplicate numbers are not allowed. The method of transposition is to change one gene position while changing another gene position with the same sequence number. The operation process is shown in Figure 1.

$$\text{A}= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$\text{B}= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{i+1}, \dots, c_{j-1} c_i c_{j+1}, \dots, c_n)$$

Fig.1 The operation of single-point transposition

The operator of gene shifting shifts the genes in some substrings of a chromosome backwards, with a certain probability Ps, and shifts the last gene of the substring to the frontmost position. The substring and its length of the gene shifting on a chromosome are randomly selected. Gene shifting can be divided into single point shifting and multi-point shifting. Single-point shifting is to take only one substring in a chromosome to perform a operation of gene shifting; Multi-point shifting is to take a random number j(1 ≤ j ≤ Us), and take j sub-strings in one chromosome to perform a operation of gene shifting for a predetermined positive integer. The shifting operation must satisfy a constraint that the shift operation cannot cause the capacity of the new parental node to overflow. The operation of single-point shifting is shown in Figure 2.

$$\text{A}= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$\text{B}= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_i c_{i+1}, \dots, c_{j-1} c_{j+1}, \dots, c_n)$$

Fig.2 The operation of single point shifting

The operator of gene inversion reverses the genes in some substrings of a chromosome, with a certain probability Pi, and the substrings and lengths of the gene inversion in one chromosome are randomly selected. Gene inversion can be divided into single-point inversion and multi-point inversion. Single-point inversion is to take only one substring in a chromosome to perform gene inversion; The multi-point inversion is to take a random number j(1≤j≤Uj) and take j sub-strings in one chromosome to perform a gene inversion operation for a predetermined positive integer Uj. The inversion operator does not need to determine the capacity overflow of the parental node. The operation is shown in Figure 3.

$$A= (c_1, c_2, c_3, \dots, c_{i-1} c_i c_{i+1}, \dots, c_{j-1} c_j c_{j+1}, \dots, c_n)$$

$$\Downarrow$$

$$B= (c_1, c_2, c_3, \dots, c_{i-1} c_j c_{j-1}, \dots, c_{i+1} c_i c_{j+1}, \dots, c_n)$$

Fig.3 The operation of single-point inversion

Multi-point genetic operators are generally used when the chromosome length l is large, while single-point genetic operators are generally used when the chromosome length is small.

5.2.3 Hybrid Genetic Algorithm

The hybrid genetic algorithm mainly performs the mixing on the processing of genetic operators. This not only retains the traditional bionic genetic operation, that is, the generation of offspring is through the parent's cross-compilation, but also in the offspring of good individuals to perform further Parthenon-genetic operations, to avoid falling into premature convergence.

(1) Encoding and decoding. The encoding process is a process of using numbers to express the traffic volume of each route, Due to the need to solve the specific traffic volume for each route, binary encoding is used. This article uses 10-bit binary encoding, 12 lines, that is, 120-bit binary encoding. After the encoding is completed, according to the total demand of each power plant, binary-to-decimal values are manipulated to distribute the proportion of traffic on the line. In other words, the traffic volume on each route can be counted, and the corresponding fees and profits can be obtained.

(2) Determination of initial population and size. Traditional genetic algorithms tend to fall into a local optimum when the population size is small, but the introduction of a

Parthenon-genetic in traditional operation can effectively avoid this problem. Therefore, the number of populations in this paper is set to 60.

(3) Fitness function. With the objective of maximizing the profit of the Group company, this paper optimizes the transportation routes and traffic volume. At the same time, considering the constraint conditions, when dealing with the constraint problem, this article quantifies the violation of the constraint, and quantifies the combination of the penalty function and the objective function into a fitness function.

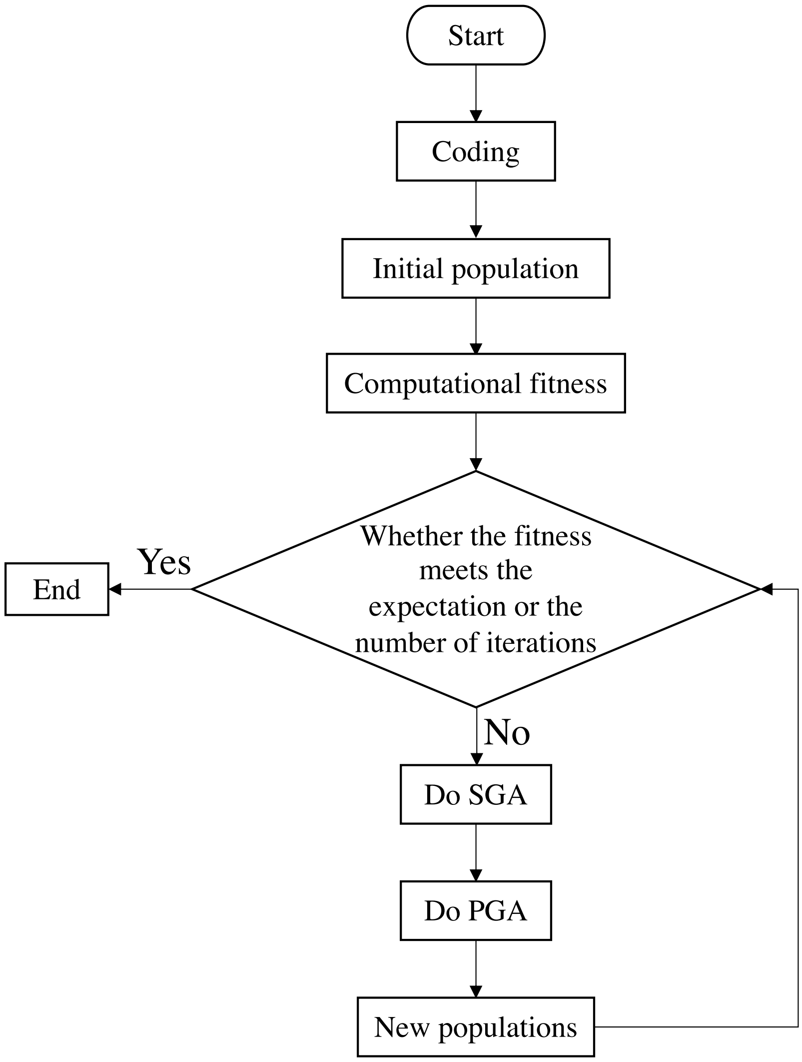
(4) Selection. The selection in this article uses an elite retention strategy. Adopting this strategy in the traditional algorithm is easy to lose the diversity of the population, but it can be well avoided by combining Parthenon-genetic operation, and the operation is simple, and the diversity of the population is not lost.

(5) Genetic operators. In genetic manipulation, the first is the traditional crossover of individuals in a population to generate offspring and offspring mutation operations, and then combine the offspring population with the parental population to form a new population. Based on the limit of population size, populations with better fitness are selected to form new offspring populations. Next, according to the Parthenon-genetic strategy, after excellent individuals transpose, shift, and invert non-excellent individuals in the offspring population, new individuals are created to replace and update the population.

The algorithm is coded as follows:

```
Initial population
   For each h in population, compute Fitness (h)
       While (iter<maxiter)
           do SGA(do crossover, do mutation, do selection)
           do PGA(do transpose, do shift, do invert)
       update population
       End
   For each h in population, compute Fitness (h)
Return best Fitness
```

The algorithm flowchart is as follows:



5.3 Model Solving and Data Analysis

5.3.1 Preparation of Examples and Data

As China's main energy source, the coal industry is an important basic industry that is related to the sustained, stable, and healthy development of Chinese economy. With the acceleration of the construction of large-scale coal bases in China, large-scale coal enterprise groups have developed rapidly, and large-scale modern coal capacity has been continuously released. Driven by market demand, in general, the production of coal has maintained rapid growth. In 2017, the coal output of large-scale and above coal enterprises reached 3.445 billion tons, a year-on-year increase of 3.2%.

Because coal occupies a dominant position in production and consumption structure of China's energy sources, the imbalance of geographical distribution and industrial layout of China's coal results in a large amount of coal flowing from west to east and from north to south within the Chinese territory, thus meeting the demand for coal in various regions and industries. Therefore, the transport link plays a very important role in the coal circulation process, has become the key to achieving the balance between supply and demand of coal, and is one of the main factors affecting the balance of the coal market.

(1) Coal mines and power plants.

The three coal mines of a coal industry group in China were selected, which are located in Shanxi(M1), Shaanxi(M2) and western Inner Mongolia(M3). Two coal mines outside the group were selected, located in Henan(M4) and Shanxi(M5) respectively. The power plants were selected as Yangluo Power Plant(E1)(Wuhan, Hubei), Qinbei Power Plant(E2)v(Jiyuan, Henan) and Yingkou Power Plant(E3)(Yingkou, Liaoning). As an inland power plant, Yangluo Power Plant can directly transport coal from coal mines to power plants via railways and can also use rail-sea transport. At the same time, Yangluo Power Plant can also enter the inland river through the coastal ports to transport coal by means of sea-to-river transport. As Qinbei Power Plant is located near Shanxi Province and Shaanxi Province where coal reserves are relatively large, its main mode of transportation is nonstop railway. Yingkou Power Plant is a coastal power plant. After the coal was first transported by railway or highway to a coastal port, it used coastal vessels to transport the coal to the power plant. Its electricity-coal industry mainly relies on domestic railway-sea transport.

Shanxi's coal is mainly transported through Daqin (R1), Zhangtang (R2), Taijiao (R3), Jiaoliu (R4) and Hantan (R5), mainly to Beijing, Tianjin, Hebei, East China and coastal ports; Shanxi's coal is mainly transported through Xikang (R6), Xiangyu (R7), Hantan, Longhai (R8) and Jiaoliu Railway, mainly to Beijing, Tianjin, Hebei, East China and coastal ports; Mongolia's coal is mainly transported through Beijing, Tianjin, East China and the coastal ports. Bao (R9), Da Zhun (R10), Hu Da (R11), Da Qin, Hudong (R12), Ji Bao (R13) and Bao Cao (R14) are mainly transported to Beijing, Tianjin, Hebei, Northeast and coastal ports. In addition, Jing Guang (R15), Meng Bao (R16), Hou Yue (R17) and Shuo Huang (R18) railways are mostly used for coal transportation, including Qinhuangdao Port (P1) and Yingkou Port (P2), Caofeidian Port (P3), Huanghua Port (P4), Taicang Port (P5).This model assumes that the specific route from the coal mine to the power plant is as follows:(The entire route is fixed, and it uses the model to select the route and the amount of traffic on this route).

Table 1. Transport routes in model

	M1	M2	M3	M4	M5
E1	R3-R4-R5	R6-R7-R5	R9-R10-R11-R1-P1-P5	R15	
E2	R3-R4	R6-R7-R5		R15-R4	R17
E3	R1-P1-P2 R1-R2-P3-P2		R12-R13-R14-P3-P2		R18-P4-P2

A total of five coal mines were selected, of which three were coal mines within the group and the other two were coal mines outside the group.

Table 2.Data for coal mines

	Coals within the Group			Coals outside the Group	
Coal origin i	M1	M2	M3	M4	M5
Annual output Q_i	4900000	4000000	3000000	1800000	2800000
Mine-mouth coal prices P_i^3	680	624	590	696	660
Mine-mouth coal costs C_i^3	510	518	460	540	522
Stock's proportion R_i^1	50%	30%	70%	45%	65%

The annual output Q_i of coal mines is in tons, and the mine-mouth coal price and mine-mouth coal cost is in yuan. The difference value represents the profit earned by coal mine that sells a ton of coal. The profit of a coal mine W_i consists of the difference between the total profit of selling coal and the fixed cost of a coal mine. Next, i=1,2,3,4,5 represent Shanxi Coal Mine, Shanxi Coal Mine and Coal Mine of West of Inner Mongolia in the Group, Henan Coal Mine and Shanxi Coal Mine outside the Group.

Table 3.Data for power plant

Power plant j	E1	E2	E3
Annual demand D_j	2890000	7930000	5000000
Electricity price P_j	1.3	1.1	0.9

Fixed cost F_j^4	870000	930000	1250000
generating efficiency α_j	2300	2280	2150
stock's proportion R_j^2	75%	60%	100%

The annual demand D_j for power plants is in tons, Electricity prices and fixed costs are in yuan, and Power plant profit $W_j = \alpha_j p_j \sum_{i=1}^{I} \sum_{l=1}^{3} x_{ijl} - C_j^1 - C_j^2 - C_j^3 - C_j^4 - F_j^4$ is divided into two parts: income and fees. The source of revenue for the power plant and the fees charged by the users charged. The fees include the railway transportation cost of the power plant, the cost of purchasing the coal, the transportation cost of the shipping company, and the fixed cost(not directly related to electricity production, including material costs, wages, depreciation, maintenance, etc.).

(2) Data for nonstop railway

Table 4. Maximum capacity of railway lines from coal mines to power plants(unit: ton)

j \ i	M	M2	M3	M4	M5
E1	2780000	1916000	1340000	1220000	1257000
E2	2300000	1290000	1650000	1426465	2880000
E3	2902700	1483000	3147000	2810000	1390600

Since the number of power plants involved in the model is only three, the maximum traffic volume of railway lines has been reduced.

$$\textit{The maximum traffic volume of railway in the model} = \frac{\textit{The maximum traffic volume of railway}}{\textit{Coal demand of all power plants in the group}} * \textit{Coal demand for power plants in the model}$$

Table 5.Unit transportation cost of railways from coal mines to power plants through the transportation of nonstop railway(Unit: yuan/(tons*km));

j \ i	M1	M2	M3	M4	M5
E1	0.98	0.88	—	1.17	—
E2	1.03	0.92	—	1.10	0.78
E3	—	—	—	—	—

Note: "—" means non- railway nonstop routes, so there is no value(the same below).

Table 6. Transportation distance of railways from coal mines to power plants through the transportation of nonstop railway(unit: km)

i j	M1	M2	M3	M4	M5
E1	1500	884	—	632	—
E2	623	478	—	236	231
E3	—	—	—	—	—

The ports of $a = 1,2,3$ entry represent Qinhuangdao Port, Caofeidian Port and Huanghua Port respectively. The ports of $b = 1,2$ export represent Yingkou Port and Taicang Port respectively. The maximum throughput was reduced in proportion based on the total demand of the all power plants in the Group and the total demand of three power plants studied in models.

Table 7.Maximum throughput of inlet port(units: tons)

a	P1	P3	P4
M_a	8000000	2250000	4000000

Table 8.Maximum throughput of inlet port(units: tons)

b	P2	P5
M_b	5800000	1800000

Table 9.Unit transportation costs for railroads from coal mines to ports of entry via rail-water intermodal transport

(Unit: yuan/ton*km)

i a	M1	M2	M3	M4	M5
P1	1.21	—	1.02	—	—
P3	1.08	—	0.98	—	—
P4	—	—	—	—	1.1

Table 10.Transportation distances of railway lines from coal mines to ports of entry via rail-water intermodal transport (unit: km)

i a	M1	M2	M3	M4	M5
P1	644	—	1123	—	—

P3	688	—	1075	—	—
P4	—	—	—	—	598

Table 11.Unit shipping price of water transportation from the inlet port to the outlet port by an internal shipping company(Yuan/(Ton*Nautical miles))

b \ a	P1	P3	P4
P2	0.34	0.27	0.32
P5	0.28	0.36	0.26

Table 12.Unit shipping price of water transportation from the inlet port to the outlet port by an external shipping company(Yuan/(Ton*Nautical miles))

b \ a	P1	P3	P4
P2	0.31	0.33	0.29
P5	0.38	0.34	0.27

Table 13.Data of shipping company

Fixed costs F_5	stock's proportion R_5
880000	100%

Table 14.Data of the outlet port

a	C_a^1	P_b^1	F_a^1	R_a^3
P1	23.5	28	850000	50%
P3	20.5	31	680000	100%
P4	21.6	27.6	730000	30%

Table 15.Data of the outlet port

b	C_b^1	P_b^2	F_b^2	R_b^4
P2	27	32	720000	60%
P5	35	40.5	540000	80%

5.3.2 Parameter settings

According to the above model and optimization method, in the process of using Matlab-R2016b to solve the algorithm, the crossover probability Pm = 0.9, the mutation probability Pm = 0.1, the population size is taken as 60, and the genetic algebraicity is 100, to write a program for algorithm solving.

5.3.3 Results of the test.

Figure 4, Figure 5, and Figure 6 respectively show the changing curves of the function values of the fitness with the genetic algebra in the standard genetic algorithm, partheno-genetic algorithm, and the hybrid genetic algorithm. As can be seen from the figure, the fitness function is negative in the initial population. This shows that under the initial conditions, the constraint condition is not satisfied, and as the genetic operation progresses, the fitness function gradually increases, the penalty terms of the constraint condition gradually increase, and the profit value gradually increases. Finally, they gradually converge to a certain value, indicating the effectiveness and convergence of the algorithm.

In the three genetic algorithms, the standard genetic algorithm starts to converge at the 36th algebra, the partheno-genetic algorithm starts to converge at the 32nd algebra, and the hybrid genetic algorithm converges at the 12th algebra, indicating that the hybrid genetic algorithm has a good advantage in solving the transportation problem, and its convergence speed is very fast. Table 16, Table 17 and Table 18 show the actual route traffic volume obtained by the three genetic algorithms. Table 19 shows the profit value. It can be shown from Table 19 that the hybrid genetic algorithm can find the optimal solution better. The comprehensive results show that the hybrid genetic algorithm has a good applicability in solving such transportation problems.

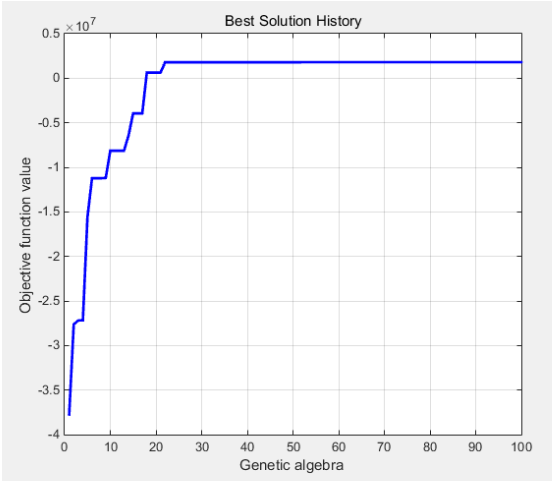


Fig.6 Standard Genetic Algorithm changing curve of total profit with the genetic algebra

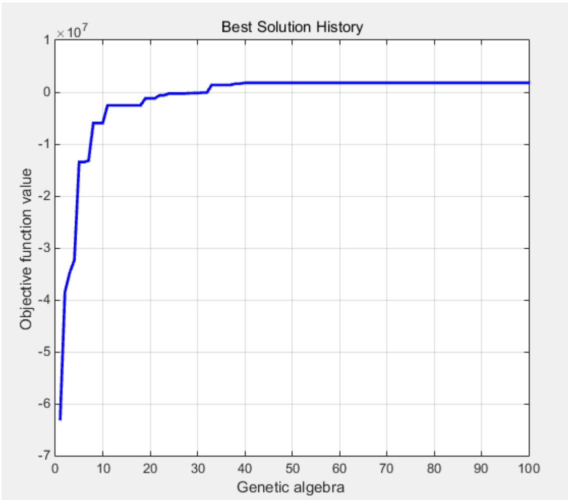


Fig.7 Partheno-Genetic Algorithm changing curve of total profit with the genetic algebra

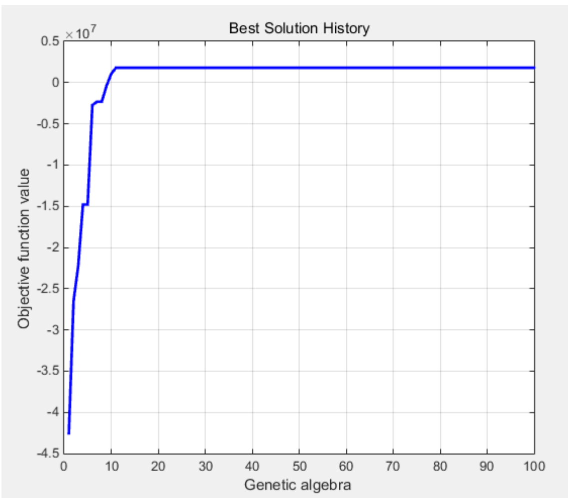


Fig.8 Hybrid Genetic Algorithm changing curve of total profit with the genetic

algebra

Among the three genetic algorithms, standard genetic algorithm began to converge in 36 generations, partheno-genetic in 32 generations, and hybrid genetic algorithm in 12 generations. It shows that hybrid genetic algorithm has a good advantage in solving this transportation problem and the convergence speed is fast.

Standard genetic algorithm optimizes quickly before the 10th generation, the optimization rate decreases gradually after the 10th generation. partheno-genetic algorithm optimizes quickly before the 10th generation, the optimization result is better than standard genetic algorithm. But after the 10th generation, the optimization rate decreases more than standard genetic algorithm, the optimization effect is not obvious. Hybrid genetic algorithm completely overcomes the previous optimization effect, with the genetic algebra. The problem of increasing and decreasing optimization speed has reached the optimal solution in about 10 generations, and the optimization effect is better than the former two methods, which shows that the hybrid genetic algorithm has better optimization performance.

Table 16.Standard Genetic Algorithm Model Transport Lines and Volumes

(/ten thousand tons)	M1	M2	M3	M4 (outside the group)	M5(outside the group)
E1	35	102	97	54	—
E2	229	197	—	191	176
E3	148 106	—	122	—	124

Table 17. Partheno-Genetic Algorithm _Model Transport Lines and Volume

(/ten thousand tons)	M1	M2	M3	M4 (outside the group)	M5(outside the group)
E1	93	72	68	57	—
E2	142	224	—	239	188
E3	113 166	—	110	—	111

Table 18.Hybrid Genetic Algorithm_Model Transport Lines and Volumes

(/ten thousand tons)	M1	M2	M3	M4 (outside the group)	M5(outside the group)
E1	23	15	129	22	—
E2	199	185	—	224	184
E3	122 163	—	103	—	112

Table 19. Three Genetic Algorithms_Model Transport Lines and Volumes

Genetic Algorithm	Standard Genetic Algorithm	Partheno-Genetic Algorithm	Hybrid Genetic Algorithm
Total profit(ten thousand yuan)	165	150	180

Table 16, table 17 and table 18 show the actual line traffic volume obtained by the three genetic algorithms, and table 19 shows the profit value. It can be seen from table 19 that the hybrid genetic algorithm can better find the optimal solution.

From the above table, it can be seen that the difference of coal quantity between railway transportation and intermodal transport is not nearly equal, which indicates that waterway transportation plays a very important role in heavy cargo transportation. At the same time, many railway lines bear very few transportation tasks, and the cost of railway construction is high. Therefore, it is particularly important to plan railway construction reasonably, and at the same time, to develop multimodal transport. Under the international background of intermodal transport, waterway transport will undertake more and more transportation tasks, and transport costs and time will be better optimized. The optimization results can provide good guidance for coal transport enterprises to formulate transport strategies.

The results show that the hybrid genetic algorithm has good applicability and validity in solving such transportation problems.

5.4 Conclusion

Combining with the coal transportation problem of a group company, this paper establishes a mathematical model for profit maximization. Based on the traditional genetic algorithm, this paper combines the constraint conditions, and adopts the operating mode of genetic operator mixed with Partheno-genetic algorithm to carry out the model solving, which not only avoids premature problems, it also improves the speed of convergence and the ability to find global optimums. Through the simulation analysis of the actual data, compared with the traditional genetic algorithm and the Partheno-genetic algorithm, the hybrid genetic algorithm has excellent applicability and effectiveness for solving such problems. The result of the solution can provide a reference for the company to develop a transportation scheme, and this solution can be used in more complex transportation problems to further optimize the algorithm.

6 Research on Optimization of logistics transportation based on algorithm elements

Logistics optimization problem has been proved to be NP problem [117]. In this chapter, the genetic algorithm will be improved to study the algorithm suitable for logistics optimization.

6.1 Introduction

6.1.1 Genetic Algorithm

The genetic algorithm refers to a computational model of biological evolutionary process that simulates natural selection and genetic mechanism of Darwin's biological evolution theory; it is also a method to search for optimal solutions by simulating natural evolutionary process[118]. The genetic algorithm starts from a population representing a potential solution set of problems. After the production of first generation of population, better approximate solutions will be generated through evolution of generations in accordance with the principle of survival of the fittest. While in each generation, individuals are selected in light of their fitness in problem domain, and genetic operators of natural genetics are relied on for crossover and mutation, which generates populations representing new solution sets. Luckily, this process will enable populations, same as later generations of populations evolving naturally, to be more adaptable to environment than previous ones. The optimal individual in the last generation of population can be used as approximate optimal solution of a problem after being decoded.

6.1.2 Information Entropy

Proposed by Clausius, a German physicist as the concept of thermodynamics in the 1860s,information entropy was originally used to describe energy conversion amount and conversion direction. In 1854, Clausius defined the state function-entropy of the reversible thermodynamic system, with mathematical expression as follows:

$$ds = \frac{dQ}{dT}$$

That is the micro-increment of entropy is equal to the ratio of heat absorption to temperature of reversible elementary process from X0 state to X.

The information entropy is an important concept in information theory. In 1948, C.

E. Shannon, the American scientist published the famous paper A Mathematical Theory of Communication, which laid the theoretical foundation of information theory[119]. According to this theory, entropy describes the degree of uncertainty of random variables, while in general, information entropy is used to measure information or the degree of uncertainty in selection.

The determined amount of general information measure of information entropy should be the average information amount provided when each symbol is issued by information source X. It is the statistical average in information source probability space of information number of different symbols that may be issued by information source X, and this average is information entropy H(X):

$$H(x) = -\sum_{x \in X} P(x) LnP(x) \tag{1}$$

Wherein, X refers to all solutions.

In addition, the information entropy calculation can be used to analyze the degree of wide distribution of individuals in population. It is known to all that the more complicated the population diversity, the higher the corresponding entropy value, or vice versa, which is conducive to preventing populations from falling into local optimization cycle.

6.1.3 Game Theory

Game theory, also known as game theory, is a theory to study the decision-making when the behavior of decision-makers has direct interaction and the equilibrium problem of such decision-making [120]. Game theory originated in the beginning of the 20th century. The theory of game and economic behavior, written by von Neumann and Morgan Stein in 1994, laid the theoretical foundation of game theory [19]. Since the 1950s, Nash, zeerten, hesani and others have made game theory mature and practical. In the past 20 years, game theory, as a tool to analyze and solve conflicts and cooperation, has been widely used in the fields of Economics [121], complex network [122], power system [123], transportation [124] and path planning [125].

The typical problem of game theory research is that two or more participants (called players) make their own decisions in some antagonistic or competitive situation, so that one of them can get the most favorable results. The so-called game is a set of rules, which stipulates all the methods and regulations that the whole game (or competition, competition, struggle) should follow from the beginning to the end, including the players, strategies, the outcome after selecting strategies, etc. The elements of game include participants, strategies, utility functions, etc.

Participant: The decision-maker involved in the game is called participant, also known as the player, and represented by $Y_i(i=1,2\ldots,n)$generally.

Strategy: It refers to action S adopted by each participant.

Utility function F: It is a function of set S and is used to measure profit of participants in the game, providing important basis for participants to make rational decisions.

6.2 Application of Information Entropy and Game Theory in Genetic Algorithm

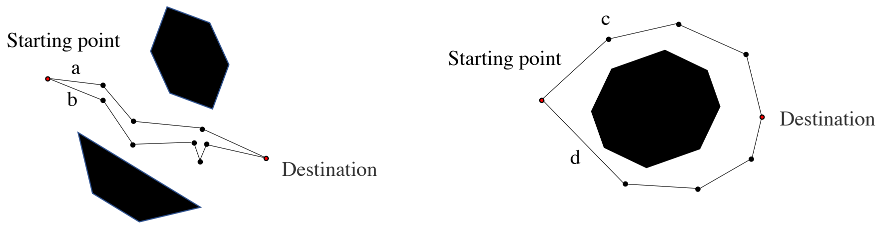
6.2.1 Application of Information Entropy in Population

（1）Calculation of information entropy based on fitness function

In genetic algorithm, the fitness function value of each individual can be calculated, and function distribution of each function value is obtained through statistical analysis, calculating probability P(x) that different solutions are obtained thereby. Then degree of population diversity represented by information entropy can be calculated by formula (1).

（2）Calculation of entropy based on coding

In the process of using the genetic algorithm to optimize a route, calculating the information entropy based on solely on the fitness function cannot accurately reflect the degree of diversity of the population. Typically, issues are encountered in the VRP problem. In Figure 2(a), paths a and b are basically the same and can be considered similar, but if the fitness function is based on the length of each path, the two fitness function values will greatly differ. For paths c and d in Fig. 2(b), in a fitness function with the path length as the main criterion, the difference in the resulting values for these two paths may not be large. However, based on individual habits, these two paths may vary greatly. Thus, the fitness function value is not suitable as a measure of the path-based population diversity.



(1) Similar Path (2) dissimilar paths

Fig. 2 Path optimization diagram

Therefore, a metric of population diversity called the encoding information entropy can be obtained based on the differences in coding.

Let the population consist of N chromosomes of length L. First, the degree of coding similarity for L positions in N chromosomes is determined. Then, chromosomes with similarity values higher than 90% are classified into one class. Next, according to the probability of each class P(x), formula (1) is used to calculate the information entropy. To ensure the accuracy of the information entropy values, the coding information entropy is used to determine the population diversity.

(3) Initialize the Population Using the Information Entropy

To uniformly distribute the initial population in the solution space, avoid a centralized distribution in the local region of the solution space, and increase the diversity of the initial population, the population can be initialized by calculating the information entropy.

The process of using the information entropy to generate an initial population is as follows.

- Step 1: Set the critical entropy value $\boldsymbol{S_0}$.
- Step 2: Randomly generate the first chromosome in the chromosome domain.
- Step 3: Generate a chromosome each time in the same way and calculate the entropy value S of the chromosome and the existing individual. If $\boldsymbol{S > S_0}$, then accept the chromosome; otherwise, reject the chromosome. In this case, regenerate a new chromosome, and calculate the entropy value S until the condition of $\boldsymbol{S > S_0}$ is met.
- Step 4: Repeat Step until the number of chromosomes reaches the specified initial population.

(4) Setting the Information Entropy Threshold S_0

The execution process of genetic algorithms is similar to a system evolution process. At the beginning of the algorithm, the internal diversity of the population is high, and the algorithm has a wide search space. As the population multiplies from generation to generation, some individuals with large adaptation values and their descendants account for the majority of the population. As a result, the population diversity decreases, the algorithm search space shrinks, and the population tends to be stable. The process of population evolution in the genetic algorithm is consistent with the phylogenetic process; therefore, the entropy threshold $\boldsymbol{S_0}$ value needs to be gradually reduced according to the evolution of the population. The method of changing $\boldsymbol{S_0}$ used in this paper is as follows:

$$\boldsymbol{S_0}(\mathrm{K}) = \boldsymbol{S_0}(\mathrm{K}-1) * \gamma \qquad \mathrm{K} = 1,2..., \mathrm{n} \qquad (2)$$

where K represents evolutionary algebra and γ is the threshold reduction factor.

6.2.2 Parallel Algorithm

To perform game calculations with the standard genetic algorithm, partheno-genetic algorithm, and standard partheno-genetic hybrid algorithm, three groups of populations must be generated. A coarse-grained model, also known as a distributed model or an island model, can be constructed, which is a type of parallel genetic algorithm.

However, this approach divides a group into several subgroups according to the number of nodes. The algorithm is independently run for each child's generation in parallel based on the respective nodes. During each evolutionary generation time step, each subgroup will exchange individual information. This process can identify and maintain the best individuals, enriches the diversity of the population and prevents early convergence.

6.2.3 Application of Game Theory in Genetic Operation Mode

Genetic theory can be optimized using game theory. Specifically, classical game theory is based on classical game theory and individual rationality, and the purpose of each participant is to maximize their own income function. This paper assumes that the group population is a participant who emphasizes collective rationality and that the two parties reach a cooperative agreement to maximize the benefit of the entire population. The game at this time is a complete information cooperation game.

In addition, this paper introduces information entropy to evaluate the diversity of populations in the evolution process, calculates the value of information entropy through formula (1), and combines the strategy set to make game choices for individuals. The game theory and element mapping relationships in this algorithm are as follows.

Table 1 Element mapping relations for game theory and the hybrid optimization algorithm

Element	Game Theory	Optimization
Participant	A decision-making body in a game whose purpose is to maximize the level of utility by choosing actions	Refers to the subgroup that participates in independent optimization in the hybrid optimization algorithm. All individuals in the subgroup act as a subject for policy selection.
Strategy	In the game, each participant has an optional action plan given the available information.	The sub-population strategy is determined by the entropy value when the subgroup is optimized.
Income	The result of the game is called income. The payoff of each player at the end of a game is related not only to the strategy chosen by the player but also to the set of strategies selected by all players.	The degree of the solution for each subgroup at parallel nodes based on the fitness value and information entropy.

6.2.3.1 Game Model in the Algorithm

We define three subgroups, pop1, pop2 and pop3, participating in independent optimization and three strategies, strategy1, strategy2 and strategy3. Then, for participants N={1,2,3}, each subgroup i∈N is the decision-making subject in the game problem, and it is assumed that all three subgroups have collective rationality. The purpose of the game is to maximize the global benefit. Each subgroup has a separate strategy, pop_i, yielding the strategy set Si={ strategy1, strategy2, strategy3}. The game result is represented by (q1, q2, q3), where q1, q2, and q3 correspond to the fitness values of pop1, pop2 and pop3, respectively, considering the adaptation of the best individual in the group. The degree value is determined by equation (3).

$$q_i = best(pop_i) \tag{3}$$

6.2.3.2 Solving the Game Model

The income of the three subgroups is recorded as P= (P1, P2, P_3), and the income of subgroup i is P_i. This value depends not only on the strategy of each subgroup but also the strategies of other subgroups as function of the combination of strategies.

Classical game theory is based on personal rationality. The objective of each participant is to maximize their own income function. This paper assumes that the three subgroups are participants who emphasize collective rationality and that the three parties reach a cooperative agreement to maximize P* for the entire population. That is, each individual implements a single strategy but shares the optimal solution of the combination of strategies, namely, P*=best(P).

Under these assumptions, when the subpopulations are searched in parallel, the population strategy at the nodes is updated according to formula (4):

$$X_i^{t+1} = X_i^t + \delta x_i^{t+1}(P^*) \quad (4)$$

where X_i^t represents the position at node t of subgroup i and $\delta x_i^{t+1}(P^*)$ is the strategy for subgroup updating based on the following three modes.

(1) Cooperation Mode

When the population is optimized to the Kth (K = 1, 2,..., n) generation, the entropy values Q_1, Q_2, and Q_3 of the three populations are calculated according to the following formula.

$$\max (Q_1, Q_2, Q_3) < \boldsymbol{S_0}$$

At this time, cooperative mode begins. Moreover, the three populations are merged into one population, and according to the fitness function value f of the individuals in the population, the individuals with function values less than the media value are eliminated, and the remaining are retained and evenly distributed among the three populations. These populations are used to regenerate the population in the same manner as discussed for the initial population.

The cooperative mode is a multi-group self-coordination mechanism. By synergizing with other populations, the performance of at least one population is improved, and the diversity and convergence of the algorithm are balanced.

(2) Competition Mode

When the population is optimized to the Kth (K = 1, 2,..., n) generation, the entropy values Q_1, Q_2, and Q_3 of the three populations are calculated according to the following formula.

$$\min (Q_1, Q_2, Q_3) > \boldsymbol{S_0}$$

At this time, competition mode begins. The maximum fitness value Fmax of each population is calculated, and the largest function value Fmax is obtained. The individual represented by the function value is copied into the other two populations, and the individuals with the smallest function values are excluded.

Competition mode yields excellent populations in the algorithm and improves the convergence.

(3) Coordination Mode

Coordination mode is divided into two situations.

1) The population is optimized to the Kth (K = 1, 2,..., n) generation, and the entropy values Q_1, Q_2, and Q_3 of the three populations are calculated. When the entropy Q of two of the populations is greater than the critical entropy $\boldsymbol{S_0}$, the information entropy of one population is lower than the critical entropy $\boldsymbol{S_0}$. At this time, each of the two populations with information entropy values that meet the threshold requirement account for 1/4 of the population used to obtain the best fitness function. In this case, the information entropy is less than the critical threshold $\boldsymbol{S_0}$ in the population, and the population excludes individuals whose fitness function value is less than the median.

2) The population is optimized to the Kth (K = 1, 2,..., n) generation, and the entropy values Q_1, Q_2, and Q_3 of the three populations are calculated. When the entropy Q of two of the populations is less than the critical entropy $\boldsymbol{S_0}$, the information entropy of one population is greater than the critical entropy $\boldsymbol{S_0}$. At this time, from the population with an information entropy that satisfies the threshold requirement, the individuals with fitness values larger than the median are retained, and other individuals are excluded.

In general, coordination mode is used to improve the diversity of the algorithm and reduce the possibility of local populations being trapped.

6.3 Improved Genetic Algorithm Based on Information Entropy and Game Theory

Based on the above analysis, the steps used to develop the hybrid genetic algorithm in this paper based on information entropy and game theory are as follows.

(1) First, determine the coding method according to the relevant requirements. Then, complete the initialization of the three populations based on the population information entropy in the search space. Next, set the search boundary and initialize the maximum iteration number MaxDT and the parallel optimization threshold MaxJT. Finally, initialize the global optimal solution fbest.

(2) Implement the parallel genetic algorithm for the three populations according

to the standard genetic algorithm, partheno-genetic algorithm and hybrid genetic algorithm methods. Record the fitness value of each population i.

(3) Calculate the global maximum return P* and the population information entropy according to the payment utility rule; then, obtain the population updating strategy $\delta x_i^{t+1}(P^*)$.

(4) Update the population according to the population updating strategy determined in (3).

(5) Determine whether the global maximum return P* is better than the global optimal fbest and whether to update fbest.

(6) Evolve the MaxJT generation according to the free strategy for the updated population.

(7) Determine whether the maximum number of iterations M is reached. If so, the process proceeds to step (5); otherwise, the process proceeds to step (2).

(8) Output the results.

The flow chart of this process is shown in Figure 4.

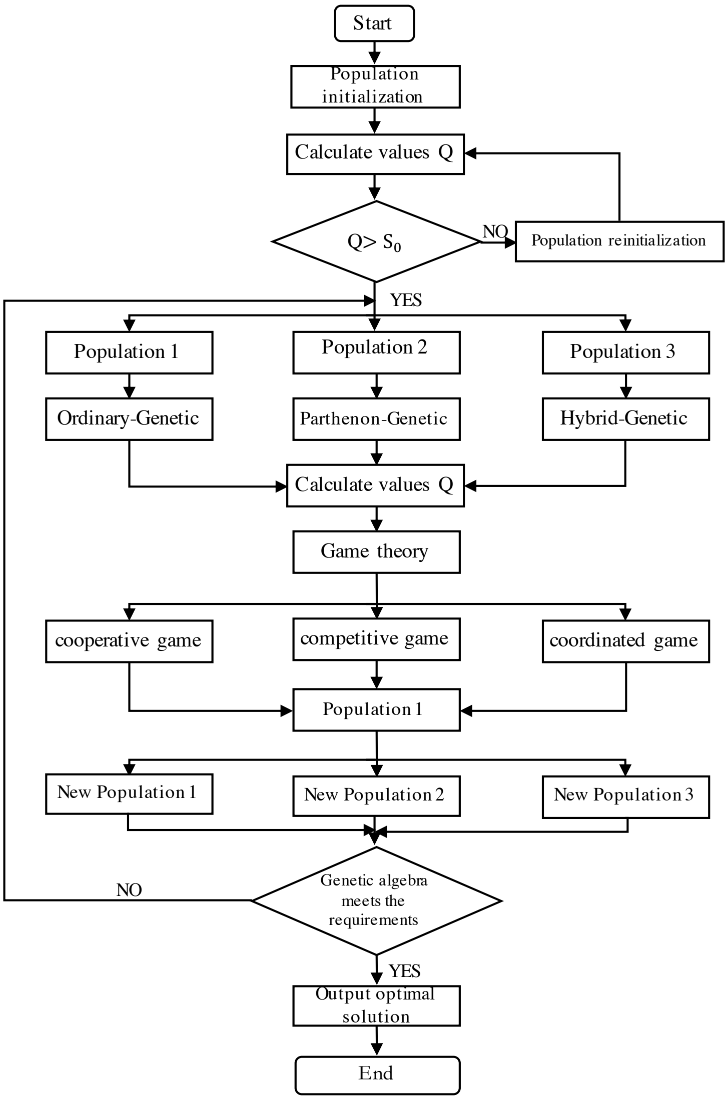


Fig.4 Flow chart of the hybrid genetic algorithm for an information entropy game

6.4 Simulation Experiment

In this section, the hybrid optimization algorithm is tested based on the information entropy and game theory process developed in the previous sections. Three simulation functions, namely, the Rosenbrock function, Rastrigin function and Schaffer function, are used in the numerical simulation experiments. SGA, PGA and SGA-PGA are selected as the reference algorithms to verify the rationality and effectiveness of the proposed algorithm.

Table 2 Standard test functions and parameter values

Function name	Function expression	Dimension	Search area
Rosenbrock function	$f(X)=\sum_{i=1}^{n}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2]$	10/20/30	$[-4, 4]^n$
Rastrigin function	$f(X)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	10/20/30	$[-5.12, 5.12]^n$
Schaffer function	$f(X)=\frac{\sin^2\sqrt{x_1^2+x_2^2}+0.5}{[1+0.001(x_1^2+x_2^2)]^2}-0.5$	10/20/30	$[-5.12, 5.12]^n$

To examine the scalability of the algorithm, different variable dimensions are used for each function test, including 10, 20 and 30 dimensions. When performing simulation experiments, the common parameters are set as follows: 100 chromosomes, 300 generations of genetic algebra, a crossover probability of 0.8, a probability of variation of 0.1, an information entropy threshold S_0 of 0.7, and a threshold reduction factor γ of 0.99. All the optimization algorithms were implemented in the MATLAB R2014b environment.

To measure the convergence accuracy, robustness and convergence speed of different optimization algorithms, the optimal value, average optimal value, worst value and standard deviation of each function were determined from 50 independent runs as the final evaluation indexes. The average optimal fitness curve was plotted with the number of iterations as the abscissa and the average optimal value of each function as the ordinate. The average optimal fitness value characterizes the accuracy that the algorithm can achieve for a given number of iterations, reflecting the convergence speed of the algorithm.

(1) Rosenbrock Function

$$f(X)=\sum_{i=1}^{n}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2] \tag{5}$$

The test function takes a minimum value of 0 at (1, 1,..., 1), and a three-dimensional diagram of the test function is shown in Figure 5.

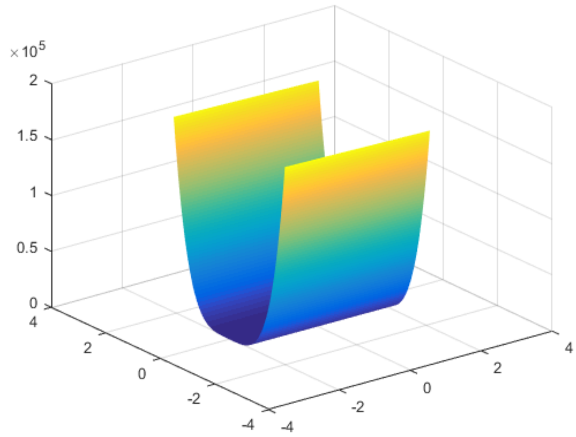


Fig.5 3D diagram of the Rosenbrock function

As shown in Figure 5, the Rosenbrock function is a unimodal function. The function is very simple in regions farm from the most advantageous area, but the areas near the most advantageous area is banana shaped, with strong correlation between variables and gradient information. Thus, it is often difficult to optimize the search direction of the algorithm and find the extreme values of the function. Selecting this test function can test the optimization ability of the algorithm.

Table 3 Results for the Rosenbrock function under different optimization algorithms

Algorithm	Dimension	Theoretical optimum	Optimal Value	Worst value	Average optimal value	Standard deviation
SGA	10	0	1.21E-03	3.58E-01	1.68E-02	1.24E + 00
	20	0	1.93E-02	4.79E-01	2.75E-01	1.86E + 00
	30	0	2.65E-01	7.43E+01	3.77E + 00	3.27E+00
PGA	10	0	1.29E-03	2.75E-02	1.60E-02	6.43E-02
	20	0	1.69E-02	4.08E-01	2.32E-01	9.58E-01
	30	0	3.84E-01	1.12E+01	4.37E + 00	1.42E + 00
SGA-PGA	10	0	5.84E-04	1.63E-02	8.20E-03	2.66E-02
	20	0	2.85E-03	8.42E-02	3.03E-02	6.51E-02
	30	0	2.99E-02	7.93E-01	3.55E-01	9.86E-01
Improved genetic algorithm	10	0	6.43E-06	1.31E-03	6.89E-04	1.54E-03
	20	0	5.88E-04	1.67E-02	6.45E-03	2.08E-03
	30	0	2.49E-03	7.29E-02	3.63E-02	2.84E-01

For n=20, the average optimal fitness value of the Rosenbrock function changes with the number of iterations, as shown in Figure 6.

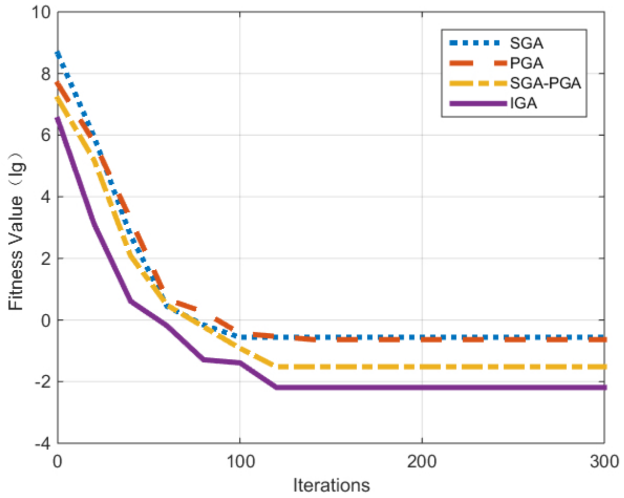


Fig. 6 Curve of the average optimal fitness value of the Rosenbrock function with the iteration number

(2) Rastrigin Function

$$f(X) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10] \quad (6)$$

The Rastrigin test function takes the minimum value of 0 at (0, 0,..., 0), and a three-dimensional diagram of the test function is shown in Figure 7.

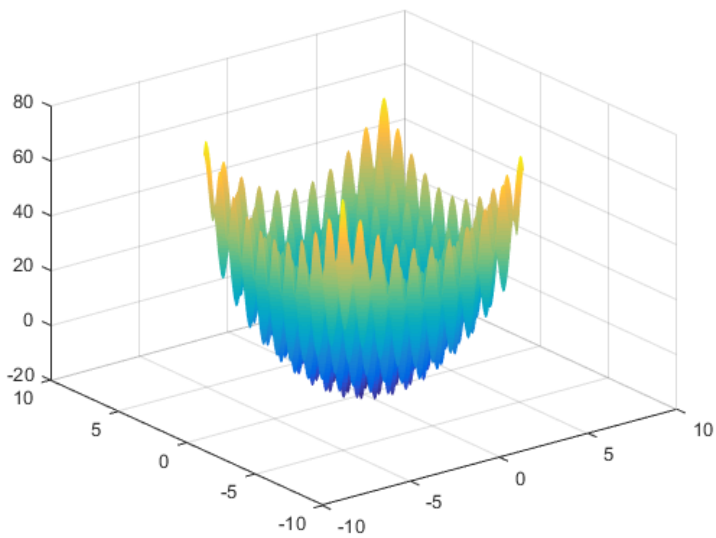


Fig.7 3D diagram of the Rastrigin function

Figure 7 shows that the test function contains a plurality of extreme points. As a result, the algorithm easily falls to local optima when the minimum value of the test function is obtained, so the function can be used to verify the optimization ability of the algorithm.

Table 4 Results for the Rosenbrock function under different optimization algorithms

Algorithm	Dimension	Theoretical optimum	Optimal value	Worst value	Average optimal value	Standard deviation
SGA	10	0	1.24E-03	1.26E-02	3.05E-03	1.24E + 00
	20	0	7.02E-03	2.04E-01	4.59E-02	1.86E + 00
	30	0	7.55E + 00	1.25E + 03	1.05E+00	3.27E+00
PGA	10	0	2.21E-03	1.63E-02	2.39E-02	6.43E-01
	20	0	5.44E-03	5.03E-01	1.27E-01	9.58E-01
	30	0	7.78E-02	2.82E+00	5.98E-01	1.42E + 00
SGA-PGA	10	0	9.12E-04	1.05E-02	6.73E-03	2.66E-01
	20	0	1.32E-03	3.19E-02	1.59E-02	6.51E-01
	30	0	2.17E-02	9.57E-01	8.24E-02	9.86E-01
Improved genetic algorithm	10	0	1.03E-06	4.35E-04	8.65E-05	1.54E-02
	20	0	1.46E-04	1.27E-02	1.03E-03	2.08E-01
	30	0	2.10E-03	2.23E-02	1.03E-02	2.84E-01

For n=20, the average fitness value of the Rastrigin function varies with the number of iterations, as shown in Figure 8.

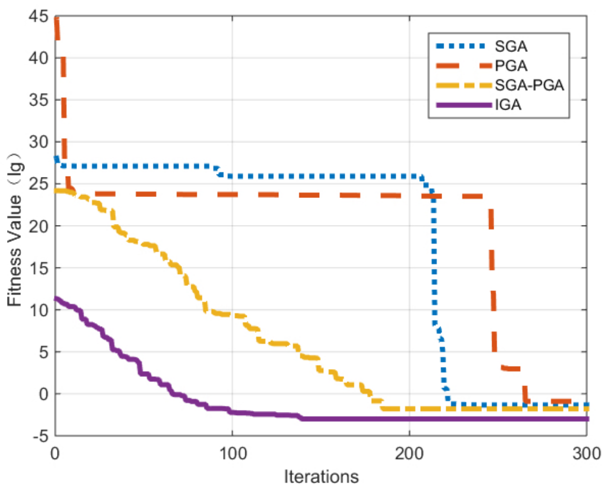


Fig. 8 The average optimal fitness value of the Rastrigin function varies with the number of iterations

(3) Schaffer Function

The mathematical expression of the Schaffer function is shown in equation (7).

$$f(X) = \frac{\sin^2\sqrt{x_1^2+x_2^2}+0.5}{[1+0.001(x_1^2+x_2^2)]^2} - 0.5 \qquad (7)$$

The test function takes a minimum value of 0 at (0,0), and a three-dimensional diagram of the test function is shown in Figure 9.

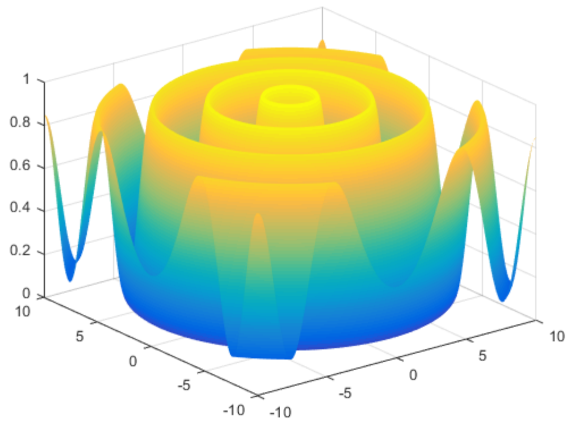


Fig.9 3D diagram of the Schaffer function

Figure 9 shows that there are multiple extreme points in the test function and that there is oscillation between the extreme points; therefore, the test function can be selected to verify the optimization ability of the algorithm.

Table 5 Results for the Rosenbrock function under different optimization algorithms

Algorithm	Dimension	Theoretical optimum	Optimal value	Worst value	Average optimal value	Standard deviation
SGA	10	0	3.86E-07	1.78E-03	6.22E-05	1.24E-02
	20	0	4.08E-05	1.26E-02	3.82E-04	1.86E + 00
	30	0	2.59E-04	6.19E-01	1.28E-02	3.27E+00
PGA	10	0	8.95E-07	4.46E-03	1.80E-04	6.43E-02
	20	0	7.89E-05	4.44E-03	3.72E-04	9.58E-01
	30	0	1.43E-03	9.34E-02	1.40E-02	1.42E + 00
SGA-PGA	10	0	0	7.81E-07	4.24E-05	2.66E-02
	20	0	0	3.39E-04	9.38E-05	6.51E-02
	30	0	0	1.76E-03	4.60E-03	9.86E-01
Improved genetic algorithm	10	0	0	2.77E-07	6.53E-06	1.54E-03
	20	0	0	6.80E-05	8.56E-06	2.08E-03
	30	0	0	2.98E-04	4.75E-05	2.84E-01

For n=20, the average fitness value of the Schaffer function varies with the number of iterations, as shown in Figure 10.

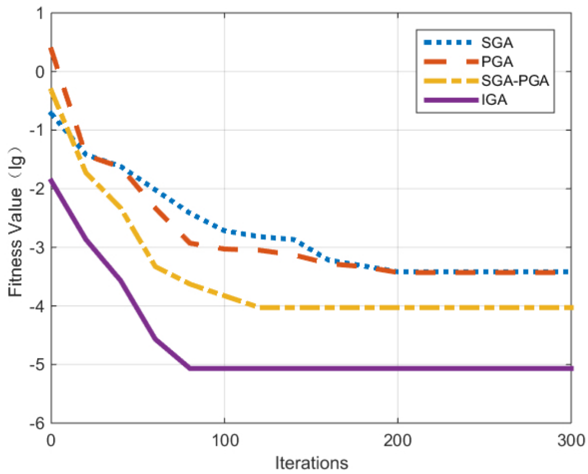


Fig.10 The average optimal fitness value of the Schaffer function varies with the number of iterations

By comparing the test function optimization results in Table 3, Table 4 and Table 5 with the fitness value curves in Figure 6, Figure 8 and Figure 10, we find that the algorithm developed in this paper has a strong optimization ability. In the optimization of each of the above three functions, the dimension of the function has a significant influence on the obtained optimal value. As the dimension increases, the optimal value of each algorithm also changes. For the Rosenbrock function, the variable dimension has a considerable influence on each algorithm. For low-dimensional functions, the algorithm can achieve global optimization with other algorithms, but for high-dimensional functions, the algorithm still yields good results. Furthermore, the information entropy game genetic algorithm has the best optimization effect based on the convergence tests with the three test functions, and the convergence speed is faster than that of the SGA optimization, PGA optimization and SGA-PGA optimization methods. For the Rosenbrock and Schaffer functions, in the process of function optimization, the SGA optimization method achieves local optimization quickly due to a premature convergence phenomenon. Although the SGA-PGA optimization algorithm has a fast search speed and overcomes local optima, the convergence speed and convergence accuracy are lower than those of the information entropy game genetic algorithm. Additionally, the information entropy game genetic algorithm also achieves local optimization in the search process. However, due to the introduction of information entropy, the optimization algorithm can quickly avoid local optima and find the global solution in the feasible domain. The optimal value indicates that the information entropy game genetic algorithm has good global and local search abilities.

In the comparison of algorithm stability, the experiments in this paper are repeated

50 times. In addition to the strong search ability of the proposed algorithm, the stability of the algorithm is another indicator of performance. Based on the 50 repetitions, the variance of the experimental results was determined to assess the fluctuations in the optimal value obtained by the algorithm. Although the Rosenbrock and Schaffer functions yielded unstable results for most algorithms, the proposed method displayed good stability.

For the function value of the initial population, the information entropy game genetic algorithm yielded a better fitness function can be obtained using traditional genetic score methods, indicating that the method based on information entropy can increase population diversity and optimize the initial population. Additionally, the information entropy game genetic algorithm uses parallel genetic operations; therefore, the efficiency of algorithm optimization can far exceed that of traditional genetic methods. Thus, with the proposed algorithm, the optimal value is found earlier, and the information entropy-based population game operations are associated with genetic nodes, thus avoiding the main disadvantage of the traditional genetic algorithm, which easily falls to local optima.

Based on comprehensive analysis of the above experimental results, the information entropy game genetic algorithm can be applied to complex nonlinear and high-dimensional functions with multiple extreme points and obtain high-precision global optimal values with low computational costs. Notably, the proposed algorithm not only has fast convergence speed but also has better global and local optimization performance than traditional methods.

6.5 Conclusion

In this paper, the genetic algorithm is improved, and multi-group genetic operations are performed in parallel. Information entropy is introduced to quantitatively analyse the diversity in the evolution process and ensure diversity in population genetics. Additionally, combined with game theory, various types of evolutionary processes occur. The changes in group information entropy using the game strategy that is most conducive to the diversity and adaptability of the whole group are considered to strengthen good individuals and eliminate invalid individuals. Three test functions are introduced to assess the validity and convergence of commonly used test algorithms. Based on the Rosenbrock, Rastrigin and Schaffer functions and a coding test, the results show that the proposed improved hybrid genetic algorithm has a considerable advantage over traditional genetic score-based methods in initializing the population and obtaining high fitness values, rapid convergence, and a high optimization speed.

7 Summary and Prospect of the whole work

7.1 Work summary

This paper mainly analyzes the main factors that affect the efficiency and quality of logistics transportation and the competition of enterprises. Starting from each factor, it analyzes the principle, optimization model, optimization method and results of each factor. The general situation is as follows:

(1) the third chapter analyzes how to solve the problem of logistics distribution and improve customer satisfaction from the aspects of fatigue limitation and crowdsourcing transportation. In this paper, the goal is to minimize the total cost, and at the same time, the variable that limits the driver's fatigue driving is added to the model. Then, Partheno-genetic algorithm is designed for the model, and the algorithm is verified by the distribution case of Japan's asakushi company. The numerical results of an example show that the logistics distribution path optimization scheme based on Partheno-genetic algorithm can meet the customer's demand for goods and time, control the driver fatigue and improve the economic benefits of the enterprise. This study provides a new solution for improving the distribution problem.

At the same time, from the perspective of crowdsourcing delivery platform, this paper focuses on solving the combination optimization problem of order distribution and route planning. Under certain assumptions, considering the location, overtime time and pairwise constraints of the delivery staff, the process of order allocation and route planning is combined and optimized with the goal of minimizing the total cost of the sum of the delivery cost and time cost of all orders, and the joint optimization of the delivery route and the delivery route is realized in the process of route planning. At the same time, the research is carried out In the case of order dynamic generation, considering the dynamic generation frequency of take out order is high, the change of delivery personnel's ability to receive order and the condition that order can't be re allocated after order allocation, the dynamic distribution model of take out by crowdsourcing is built on the basis of static model. Through the construction of static distribution model and dynamic distribution model of crowdsourcing takeout, this paper explores the solution to the low efficiency and serious overtime of crowdsourcing takeout distribution.

(2) in the fourth chapter, based on the genetic algorithm, taking the transportation cost of the double-layer logistics node of a city's seafood products as the optimization

objective, the vehicle routing and the vehicle configuration strategy of different routes are considered comprehensively, and the vehicle scheduling and transportation route problems in the double-layer node transportation route are modeled. Matlab software is used to solve the problem based on the traditional genetic algorithm and the Partheno-genetic algorithm. The correctness and effectiveness of the model and the Partheno-algorithm are verified. It shows that the model and algorithm proposed in this paper can solve the problem of multi vehicle double-layer node transportation well.

(3) the fifth chapter takes coal as an example to discuss the optimization of the transportation path of multimodal transport. Coal is the main energy in the world, and the distribution of coal and industrial layout in different parts of the world are unbalanced, that is to say, the coal production area, reserve area and consumption area are distributed in a dislocation space, so it is particularly important to have a good coal logistics network. Based on the mechanism of traditional genetic algorithm, this paper proposes a hybrid genetic algorithm which combines Partheno-genetic algorithm and traditional genetic algorithm to optimize the route, aiming at the shortcomings of premature and insufficient local search ability of traditional genetic algorithm in solving the problem of logistics transportation route optimization. The experimental results show that the hybrid genetic algorithm is better than this kind of transportation problem Usability.

(4) in Chapter 6, a hybrid genetic algorithm based on information entropy and game theory is proposed. First, the initial population is generated by calculating population diversity with information entropy. Combined with parallel genetic algorithm, standard genetic algorithm (SGA), Partheno-genetic algorithm (PGA) and hybrid genetic algorithm (sga-pga) which integrates standard genetic algorithm and Partheno-genetic algorithm (sga-pga) are used to perform evolutionary operations. At the parallel node, information entropy and fitness value of each sub population are used Finally, three programs checking functions Rosenbrock function, Rastrigin function and Schaffer function are introduced to analyze the performance superiority of the algorithm. The results show that, compared with the traditional genetic algorithm, the algorithm has good optimization ability and accuracy, and has high convergence rate and stability.

7.2 Future outlook

(1) the research knowledge of this paper starts from various angles alone. The

model only integrates one or several factors and does not integrate all the factors that affect the logistics and transportation into the model for discussion, so there is not enough complexity to fully meet the actual situation. In order to be more in line with the reality of logistics problems, we can integrate the various factors in this paper and establish a comprehensive model for research and analysis.

(2) considering the location, overtime and order pair constraints of the delivery staff, the paper optimizes the order distribution and route planning, and realizes the joint optimization of the delivery route and the delivery route in the process of route planning. At the same time, it constructs the dynamic of the delivery of the crowdsourcing considering the dynamic generation of the order Distribution model. Although the static and dynamic distribution model of crowdsourced takeout has certain practical significance, some practical factors are ignored in the process of model construction, and there are certain deficiencies in the application process. In the future, when studying the problem of crowdsourced takeout distribution, several conditions can be considered:

1) deeply explore the characteristics of crowdsourcing delivery staff.

2) consider the actual distribution road.

3) consider the change of distribution speed caused by road conditions in different periods.

(3) in terms of algorithm, we can add AI technology of artificial intelligence to make comprehensive analysis. With the progress and development of science and technology, the rapid development of intelligent transportation, logistics transportation is more inclined to unmanned transportation and distribution, so the research in this paper can provide theoretical guidance for the follow-up intelligent logistics transportation, but for the transportation mode in the era of robot, this paper is not applicable, and can be studied and discussed on the basis of this paper.

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