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Research Article

E-Commerce Logistics Path Optimization Based on a Hybrid Genetic Algorithm

Dong Yang[1,2] and Peijian Wu[2]

[1]*School of Management Science and Engineering, Dongbei University of Finance and Economics, Dalian, Liaoning 116025, China*
[2]*School of Business Administration, Anhui University of Finance and Economics, Bengbu, Anhui 233030, China*

Correspondence should be addressed to Peijian Wu; 120100001@aufe.edu.cn

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Based on the problem of e-commerce logistics and distribution network optimization, this paper summarizes the solution ideas and solutions proposed by domestic and foreign scholars and designs a method to optimize the B2C e-commerce logistics and distribution network by taking into account the special traffic conditions in the city. The logistics network optimization model is established and solved by combining various methods. Taking into account the new target requirements constantly proposed in the modern logistics environment, the vehicle path problem under the generalized objective function is studied, and the multidimensional impact maximization problem in this type of problem is proposed and modeled. The problem follows from the path planning for emergency material delivery. Given locations, roads, and multiple classes of supplies in a map, each road allows vehicles to deliver each class of supplies with a certain probability. The goal of the problem is how to select a finite number of locations in the map as centers of supplies so that the number of locations that can be effectively covered by vehicle paths from them is maximized with the desired probability. For the first time, we used a hybrid genetic algorithm to optimize the e-commerce logistics path, and the optimized results are more reasonable than other algorithms.

1. Introduction

With the vigorous development of information science and Internet technology, the world has entered the era of the fourth industrial revolution represented by industrial intelligence [1]. A series of new service industries represented by e-commerce has completely changed people's lifestyles and consumption concepts and is still improving people's quality of life by continuously enhancing their service capabilities [2]. Compared with the traditional service model, this new service model based on information technology contains several elements: product, information platform, logistics, and consumer [3, 4]. Among them, as a necessary link for networked consumption to return to the entity, logistics service plays an important role, crossing the time and geographical barriers of consumption activities for service providers and consumers in [5]. Therefore, the quality of logistics directly determines the profit of service providers and the satisfaction of consumers. Under the premise of constant product quality and total consumption, the efficiency of logistics services directly restricts the development of new service industries [6].

Logistics is the process of the physical flow of services from providers to consumers, which requires the organic combination of basic functions such as storage, packaging, handling, transmission, distribution, loading and unloading, and information processing [7]. Among them, logistics cost is the monetary representation of various labor expended in the spatial movement or time possession of the service entity and is the sum of human, material, and financial resources expended in the logistics process [8]. The logistics industry, known as the largest industry in the 21st century, has been facing the problem of how to reduce logistics costs and improve economic efficiency [9]. It takes the domestic logistics industry as an example; on the one hand, logistics enterprises have the characteristics of many types, wide range, and a large number: logistics types involving passenger transport, food, drugs, etc.; service types involving intracity express, long-distance highway transport, air transport, etc.; in terms of quantity, according to the China Federation of Logistics and Purchasing statistics, there are 495 a-class logistics enterprises; the five a-class indicators are consistent, flexibility, flexibility, safety, environmental protection, etc. According to the statistics of the China Federation of Logistics and Purchasing, there are 495 A-grade logistics enterprises [10]. On the other hand, compared with developed countries, domestic logistics enterprises are still in the stage of rough economic growth, with the characteristics of "many, small, scattered, chaotic and poor." Besides, logistics enterprises in developing countries are gradually moving toward consolidation [11]. Therefore, in the face of fierce industry competition, logistics companies must improve their competitiveness to achieve long-term healthy development. Among them, the degree of optimization of the transportation path directly affects the transportation cost and various indicators in SA. Thus, the vehicle path problem comes into being [12].

In terms of theoretical contributions and solution algorithms, current research on the vehicle path problem is mainly focused on the study of exact and heuristic algorithms. As shown in Figure 1, the vehicle path problem and its large number of extended problems and subproblems are NP-hard, so the exact algorithm will not be able to meet the running time requirement as the problem size increases, and thus does not have practical application value [13, 14]. Although the heuristic algorithm can solve the vehicle path problem in polynomial time, its computational results are uncertain and cannot be guaranteed to have the desired performance for all instances of the problem [15]. The approximation algorithm can solve the vehicle path problem in polynomial time while limiting the ratio of the computational result of the optimal solution from a theoretical perspective, so this type of algorithm is the most desirable algorithm in both theoretical and practical applications [16]. When applied to a practical logistics environment, the approximation algorithm can be heuristically improved to make its computational results closer to the optimal solution [17].

In this paper, we take the modern logistics industry as the application object, establish a mathematical model for vehicle path problems according to the actual logistics environment, and design the approximation algorithm with the specific nature of the model. First, the overall logistics environment is stratified according to the intercity, intracity, and terminal area: among them, the intercity logistics environment targets the transportation environment on one-dimensional loads such as air routes, railroads, and long-distance highways. The intracity logistics environment considers a two-stage logistics structure with originating stations, transit stations, and logistics business points; the terminal area logistics environment is centered on logistics business points, and the goods are finally dispatched to the final customers around it, and the distance between the nodes in this region is close so that it can be simplified as the European distance [18]. Then, based on the above layers of logistics environment and their characteristics, the one-dimensional vehicle path problem between cities, the two-stage vehicle path problem within cities, and the Euclidean plane vehicle path problem in the terminal area are proposed and modeled, respectively. The result of using a hybrid genetic algorithm to e-commerce coordination path is more reasonable than other algorithms. Also, the multidimensional impact maximization problem is studied, which is a vehicle path problem in the logistics environment under the generalized objective function. Finally, combinatorial optimization properties of each problem are analyzed, and then an approximation algorithm is designed.

2. Study on the Optimization of an Urban Cooperative Distribution Network Based on Customer Selection

2.1. Development of MCCSVRP Model for Collaborative Urban Distribution. There are multiple distribution centers of expressing enterprises within the city. Accepting goods from truck transportation, the distribution center of the enterprise is responsible for packing, loading, distribution to different areas of the township, rural franchise service stations, and then the township customers can pick up and send goods in the service stations closer. Distribution center vehicles are loaded and driven to the unloading location to unload while picking up the township self-pickup points gathered by the need to transport the return cargo to other cities [19]. Courier enterprises can exchange distribution tasks through the way of the formation of a cooperative distribution alliance. It reduced the cost of distribution and, at the same time, improved customer satisfaction in townships, as shown in Figure 2.

Thus, the collaborative urban distribution network optimization problem can be positioned as a class of closed collaborative multicenter vehicle path optimization problems with simultaneous delivery and pickup mixed loading characteristics. Before building the model, some reasonable assumptions need to be made for the problem under study. Without considering the influence of terrain and traffic, the distance between the nodes is a straight line distance; the goods that start from urban distribution centers and are transported to rural service stations are served by vehicles with a large vehicle model, and the goods that belong to the transfer between urban distribution centers are served by vehicles with a small vehicle model, and the vehicle attributes are known. Without considering the heterogeneity of goods, the average size of goods is demanded by customers at a certain time. It is a linear function of the volume of goods in the distribution center; without considering the dynamics of demand, the average monthly volume of goods in the demand node is set as a predetermined value in a certain time and is stable in a certain time [20]. The cost is borne by the distribution center. For the transfer of goods picked up on the return trip, the transportation cost and cargo handling cost delivered from the distribution center to the cooperative distribution center are borne by the cooperative distribution center. The number of vehicles owned by each distribution center can always meet the distribution requirements, and vehicle models of all distribution centers are the same without considering the heterogeneity of vehicles [21].

2.2. Urban MCCSVRP Problems Solving Based on Genetic Algorithm. Genetic Algorithm (GA) is a highly parallel and stochastic adaptive global optimization algorithm based on the "survival of the fittest" strategy. As shown in Figure 3, it represents a set of feasible solutions to a problem as a computer-operable "chromosome" code; each chromosome is called an individual, and multiple individuals are defined to form a set of primitive populations. Through the genetic laws of the population (including selection, crossover, and mutation), iterative evolution continues from generation to generation until certain performance indicators and convergence conditions are met to find the optimal individual with the highest value of the fitness function (the optimal or satisfactory solution to the problem). Compared with other optimization methods, GA can directly search the objective function value as the fitness value, which has the characteristics of strong global search capability, flexible search process, and fast convergence [22]. Therefore, it has been widely used in all researches related to vehicle path problems. Based on the GA algorithm structure, the GA algorithm flow framework is designed to solve the MCCSVRP problem for the special nature of the MCCSVRP problem.

The goal of the urban distribution MCCSVRP problem is to design a reasonably cooperative vehicle distribution network so that the total cost of the whole network is minimized, and here the total cost includes the following three components. Relative to the original distribution scheme, if there is a cooperation between distribution centers, distribution center h receives goods that distribution center i needs to deliver to rural service station j and goods that distribution center h recovers from rural service station J that need to be transferred to distribution center i, where the total cost of transferring goods between distribution centers is Z_1, and Z_1 consists of three parts, which are the operating cost of the trolley, the fixed usage cost, and the processing cost of transferring goods by the distribution center.

$$Z_1 = \frac{\sum (g(d_{hi}) + g(v_{mk}))}{\sum_{i \in I} (c \times L_{hi} + \mu_{mk})} + \left(d_{hi} \times c_i^f\right). \quad (1)$$

The final cost of goods handling for all distribution centers as Z_2 can be expressed as follows:

$$Z_2 = \frac{\sum \sum_{j \in J} r_{ij}}{\sum_{i \in I} q_{ij} \times c_i^f}. \quad (2)$$

When the distribution center delivers and picks up goods from the township service station, the sum of the vehicle transportation cost and the fixed usage cost of the large vehicle, Z_3, can be expressed as follows:

$$Z_3 = \frac{\sum \sum_{j \in J} \left(L_{ij} \times x_{ij}^k \times c^{bk}\right)}{\sum_{i \in I} \left(NK_{ij} \times c_i^f\right)}. \quad (3)$$

Then the total objective function of the problem is as follows:

$$\max Z = \frac{(Z_1 + Z_2)}{Z_3}. \quad (4)$$

Constraints on the solution to this problem:

$$y_i^k = \left(\sum_{j \in J}^{i=0} x_{ij}\right)^k, \quad i \in I, \quad (5)$$

$$\sum_{u \in I \cup J} (x_i + x_u + x_k) - r_{ij}^k \geq 0, \quad i \in I. \quad (6)$$

3. Genetic Algorithm Based Analysis of Benefits Distribution of Logistics Path Cotransportation

Numerical experiments use arithmetic examples constructed based on the basic problem, under which each distribution center delivers goods strictly for the township demand point it serves. The maximum loading capacity of the large vehicle is 550 pieces, the maximum distance traveled is 3 0 km, and the unit transportation cost is 5 yuan/km. The maximum loading capacity of the small car is 300 pieces, and the unit transportation cost of the small car is 1.2 yuan/km due to mutual transfer within the city and short distance, without considering the maximum travel of the small car. The initial distribution scheme is constructed based on the basic problem, which is constructed by determining the location of the distribution center and the demand points. The shortest domain search algorithm is used to select and connect the different points to form a specific vehicle path. The parameters of the algorithm GA proposed in this paper are set as the chromosome population size of 100, the maximum number of iteration steps set by the algorithm is 200, the number of iteration steps for chromosome anisotropy check is 5, the probability of chromosome crossover is 0.8, and the probability of variation is 0.25. The initial solution is directly used as an initial solution when the logistics collaborative optimization scheme is used. Through the experiment, the optimal individual of the optimization problem when not synergistic is obtained appears in the 53rd generation, and the optimal result is 6522.11. The output optimal individual result is shown in Figure 4.

The genetic algorithm uses the code of the decision variable bai as the object of operation and can directly operate on structural objects such as sets, sequences, matrices, trees, and graphs. The genetic algorithm directly uses the objective function value as the search information. It only uses the fitness function value to measure the individual's goodness and does not involve the process of

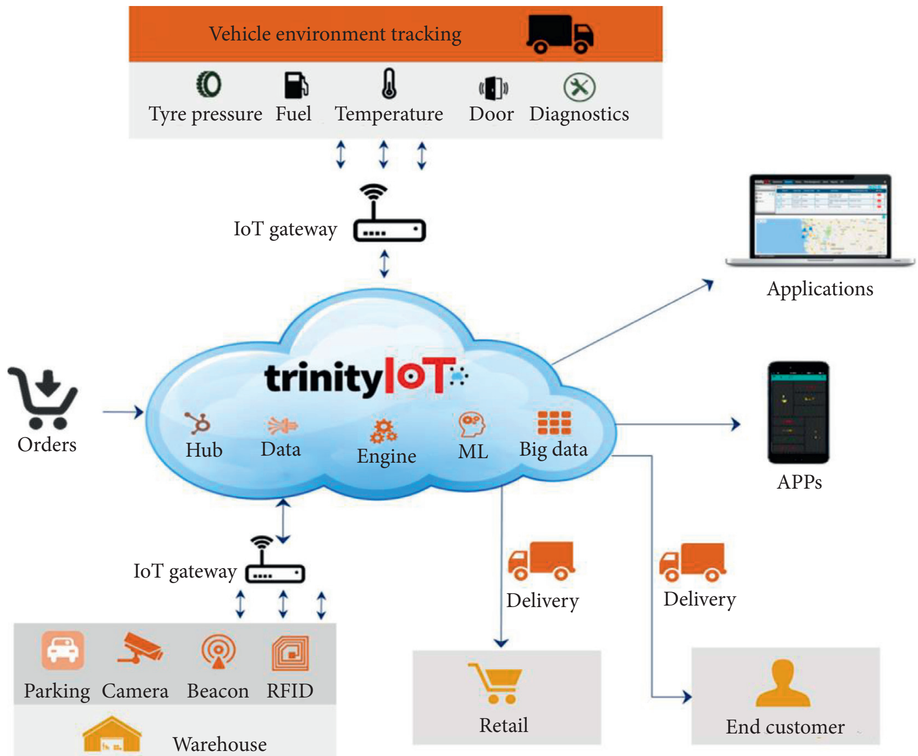

FIGURE 1: Interface diagram of logistics route optimization software.

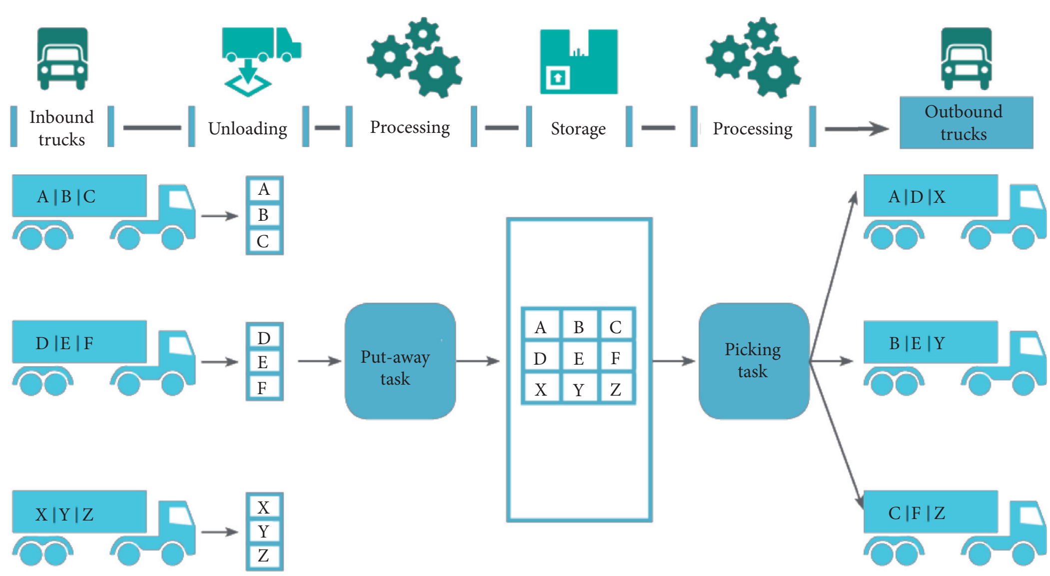

FIGURE 2: Schematic diagram of urban e-commerce logistics cooperative distribution model.

deriving and differentiation of the objective function value. Because many objective functions are difficult to derive, even there is no derivative, so this also makes the genetic algorithm show a high degree of superiority. As shown in Figure 5, we can see that the noncooptimized solution reduces the service of DC 1 by 1 distribution vehicle compared with the initial state, which reduces the total cost by 9.15%; DC 2 still uses the service of 3 distribution vehicles, which reduces the total cost by 0.9%; DC 3 also uses the service of 3 distribution vehicles, which reduces the total cost by 0.57%. The total cost of the combined network is reduced by 4.13%. This demonstrates the effectiveness of the noncoordinated optimization solution.

Compared with the initial solution, DC2 reduces the service of 2 distribution vehicles and the sum of distribution cost and cargo handling cost by 54.8%; compared with the noncooptimized solution, it reduces the service of 2 distribution vehicles and the sum of distribution cost and cargo

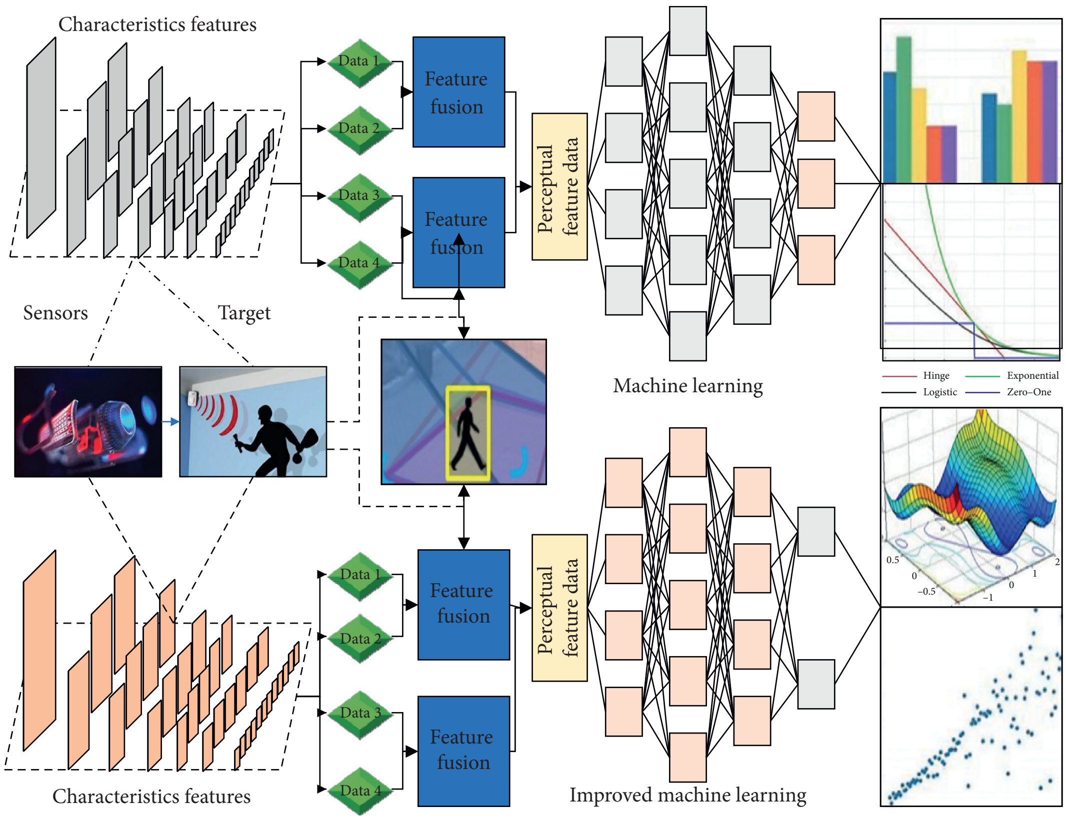

Figure 3: Flow chart of the genetic algorithm for solving the MCCSVRR problem.

handling cost by 54.3%. The total cost of DC2 is reduced by 46.3% and 45.9%, respectively, because DC2 has to bear the cost of cargo transfer 197.3 in the synergistic solution. DC3 uses the same number of vehicles for service compared to the initial solution. The sum of distribution cost and cargo handling costs increased by 26.1% and 26.9% compared with the initial state and the noncooptimized solution, respectively; the total cost of DC3 increased by 38.5% and 39.3% because DC3 still needs to bear the cargo forwarding cost of 212.15 in the cooptimized solution. The total network cost of the e-commerce logistics cooperative distribution solution is 6117.98, which is 10.1% and 6.2% lower than the initial distribution solution and the noncooperative distribution solution, respectively.

4. Analysis of e-Commerce Logistics Path Optimization Results by Terminal-Oriented Regional Genetic Algorithm

4.1. One-Dimensional Vehicle Path Optimization Analyses in the Inner City. The top-level logistics environment in the modern logistics industry is the intercity logistics environment. In the map of this type of environment, the stations for receiving and sending goods are airports, railroad stations, or coach stations, etc. In each city, and the roads between stations are air routes, railroads or highways, etc. Based on the one-dimensional characteristics of the above roads in general, this chapter models the map as a one-dimensional space and thus presents the one-dimensional vehicle path problem between cities. The problem is referred to as the one-dimensional vehicle path problem, and its objective is to find a set of vehicle paths with the shortest total length so that the demand at each station is served within a specified time window, thus minimizing the transportation cost based on the completion of logistics tasks. One-dimensional vehicle paths are not only NP-hard problems but also do not exist for polynomial-time approximation schemes [23]. To solve the problem, this chapter designs an asymptotic polynomial-time approximation scheme, which has polynomial-time complexity and whose approximation ratio approaches infinitely between 1 with the asymptotic condition. Therefore, under the asymptotic condition, this algorithm is the best algorithm available for solving the one-dimensional vehicle path problem. Metaheuristic algorithms mainly refer to a general-purpose heuristic algorithm. The optimization mechanism of this type of algorithm does not rely too much on the organizational structure information of the algorithm and can be widely used in combination optimization of functions and function calculations.

This study presents an asymptotic polynomial-time approximation scheme for solving the one-dimensional vehicle path problem with multiple stations and time windows. The algorithm takes as input the set of originating stations, the set of customers, the set of one-dimensional roads, and the vehicle loading capacity. Then, three phases, rounding, partitioning, and solving, are used to solve the problem. Among them, the rounding stage includes two

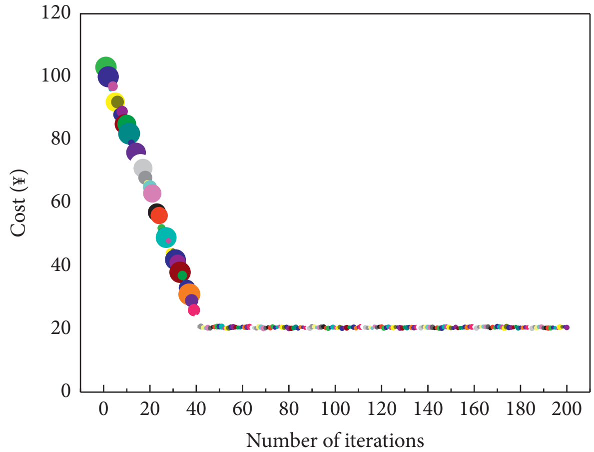

Figure 4: Iterative optimization process of genetic algorithm in collaborative optimization of logistics path.

stages: demand rounding and location rounding; the partitioning stage includes two stages: station partitioning and interstation partitioning; the solution stage includes two stages: instance solving both sides and intermediate instance solving [24]. Finally, the algorithm outputs the approximate solution of the instance in polynomial time.

As shown in Figure 6, it compares the total path lengths of each problem instance, which are represented in it as triangular dotted lines, circular dotted lines, and square dotted lines, respectively. The x-axis is the number of the problem instance, and the y-axis is the total path length. First, it can be seen from the comparison of the three curves that the total path length tends to increase as the number of time windows for problem instances increases. Then, the decreasing trend of each curve shows that the total length of the path gradually decreases as the number of originating stations increases. Finally, when the number of origination points is the same, the total path length gets shorter as the number of customers on more and more time windows converges to zero. This indicates that the fewer the customers on a single time window, the smaller the impact of that time window on the total route length.

4.2. Two-Stage Vehicle Path Optimization Analyses in Inner Cities. The service mode of phased delivery has been commonly adopted in the modern logistics environment for the following three reasons. From the site point of view, different types of sites have different characteristics and use, large sites with large storage capacity and strong service capacity, small sites are widely distributed and flexible scheduling, the phased planning can improve site management and efficiency. For example, large domestic logistics enterprises have set up logistics sites in the airport so that the first time after the arrival of goods to count, check, and sorting operations, to establish the basis for the subsequent efficient delivery. From the perspective of vehicles, large sites have a large loading capacity, and small sites can shuttle vehicles between various narrow roads. Domestic Gulangyu Island on many streets not only winding narrow and up and down, very unfavorable to the vehicle, but some roads can also even only allow the passage of manual board; foreign such as Italy and France and other ancient streets for protection does not allow large vehicles to drive. It can be seen that the phased vehicle has become a necessary condition for the completion of logistics services. Besides, logistics companies have set up a wide range of logistics business points in the city. They are not only large and geographically dispersed so that the goods can quickly reach the final customer around the business point in the subsequent delivery. In summary, phased logistics can take advantage of the above features to improve service efficiency and reduce transportation costs [25].

The instances come with one originating station and two transit stations with a different number of customers and different demand for different instances; the edge length between two nodes is their Euclidean distance; for the first stage, the number of available vehicles per originating station is 4 and the vehicle capacity is 15000; for the second stage and the adaptive stage, the number of available vehicles per originating station or transit station is 3 and the vehicle loading capacity is 60000. In terms of experimental parameters, when solving the set of instances 1, there is no delay in the solution time for the algorithm within the outer loop number of 50, and the improvement of the result when the inner loop number is greater than s is already very small, so the outer and inner loop numbers are set to 50 and 5, respectively. In terms of search steps, adding all neighboring nodes of each customer node 2 does not reduce the solution speed of the algorithm when constructing from. In solving the set of instances 2 and 3, for the above reasons, the number of outer loops is set to 15, the number of inner loops to 20, and the search step size to 0.1. The number of neighboring clients from it is 21.

It compares the lower bound on the optimal solution and the total length of feasible solutions for the adaptive two-stage vehicle path problem in different transit stations with the total length of feasible solutions for the classical two-stage vehicle path problem, which are represented as triangular dotted lines, circular dotted lines, and square dotted lines in Figure 7. The x-axis indicates the number of instances and the y-axis indicates the total length of the path. It

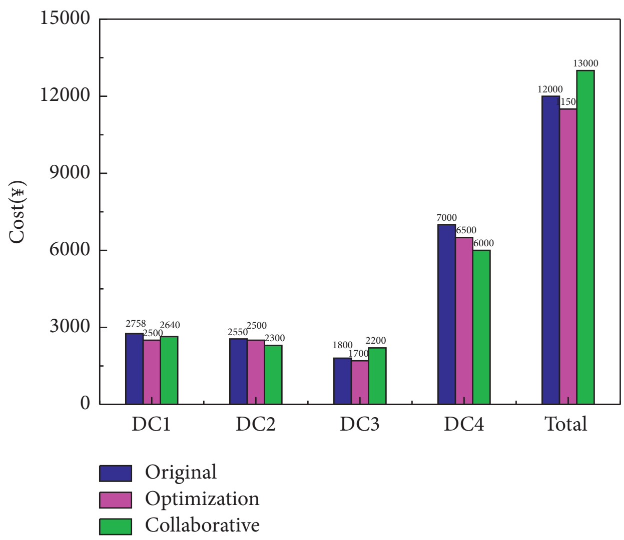

Figure 5: Cost comparison of each path optimization scheme.

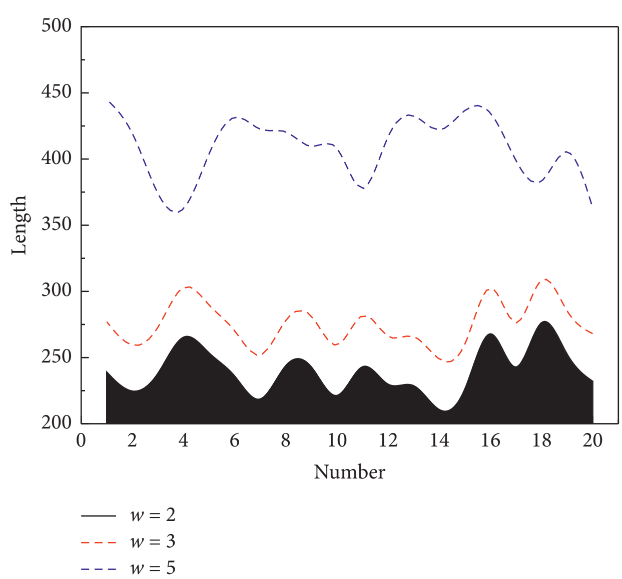

Figure 6: Comparison of path lengths of optimization algorithms.

can be seen that this shows that the use of adaptive paths can improve the optimal solution of the two-stage vehicle path problem.

4.3. Europlanar Vehicle Path Optimization Analyses for Terminal Areas. The terminal area dispatches goods from the logistics business point to the final customer. From the practical application point of view, the logistics business point is close to the surrounding customers, so the road length in the map can be simplified to the Euclidean distance; from the computational theory point of view, even if the map is restricted to the Euclidean plane, the vehicle path problem is still NP-hard. Therefore, this chapter studies the Euclidean plane vehicle path problems in the terminal area, specifically, three types of problems are studied step by step in-depth: traveler problems with time windows, vehicle path problems with time windows, and vehicle path problems with multiple stops and time windows [26].

We assume that the time for the computer to execute each basic operation of the algorithm is a fixed unit of time, so how many basic operations there are represents how many units of time it will take. Obviously, for different machine environments, the exact unit time is different, but how many basic operations (that is, how many time units it takes) for the algorithm is the same in the order of magnitude, so the influence of the machine environment can be ignored.

The above problems is related in terms of mathematical models in a step-by-step extension. In terms of solution algorithms, a polynomial-time approximation scheme is first proposed for the traveler problem with time windows, which provide the key mathematical tools and theoretical support for the design of approximation algorithms for the latter two problems. On this basis, the proposed polynomial-time approximation scheme is proposed for the latter two problems. The theoretical analysis of the performance of the above algorithms and experimental results shows that they are efficient in both computational theory and practical applications [27].

In practical applications, the classical vehicle path problem on the European plane needs to be extended. For example, in the European plane vehicle path problem with multiple stations, vehicles depart from different business points to serve customers. For example, in the logistics environment of multiple business points in Shenzhen, unified planning of vehicle paths from each business point can shorten the path length and save transportation costs from a global perspective. The time window of the European-style plane vehicle path problem also has practical application value. For example, logistics companies provide customers with optional time windows in their courier services, and customers can choose one for receiving goods. How to solve the vehicle path with the shortest total length on the basis that all customers receive the goods within the specified time window is a combinatorial optimization problem with theoretical significance and practical application value.

The computational results of the approximate algorithm and the comparison algorithm are compared in Figure 8, where the x-axis is the number of problem instances and the y-axis is the total length of the path. First, it is easy to see that the approximate algorithm outperforms the comparison algorithm in terms of computation results on each instance. Second, it can be concluded from the rising trend of each curve that an increasing number of time windows significantly increases the total length of the path of the approximate solution. Besides, the fewer the number of clients on a given time window, the less it affects the approximate solution.

The last class of experiments runs on a genetic algorithm model with multiple material types, where “mixed” means that the probabilities on each edge are different for different material types. As shown in Figure 9, it presents the results of the experiments running the hybrid cascade model for two types of materials, where the probabilities are set to (0.1, 0.2), (0.1, 0.3),

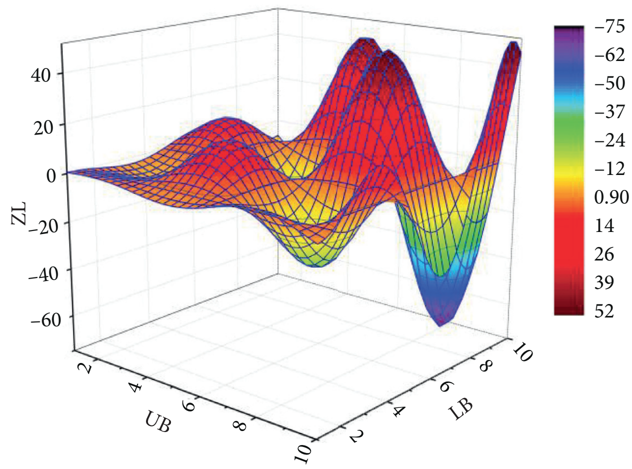

Figure 7: Comparison of approximate and optimal solutions for the two-stage vehicle paths under the session.

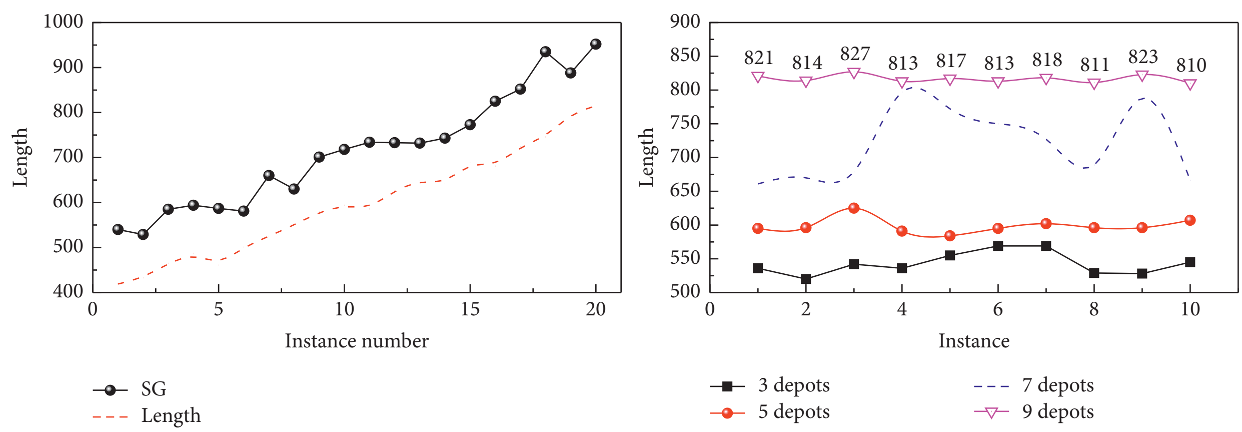

Figure 8: Effect of the values of the genetic algorithm parameters on the computational results in the approximation scheme.

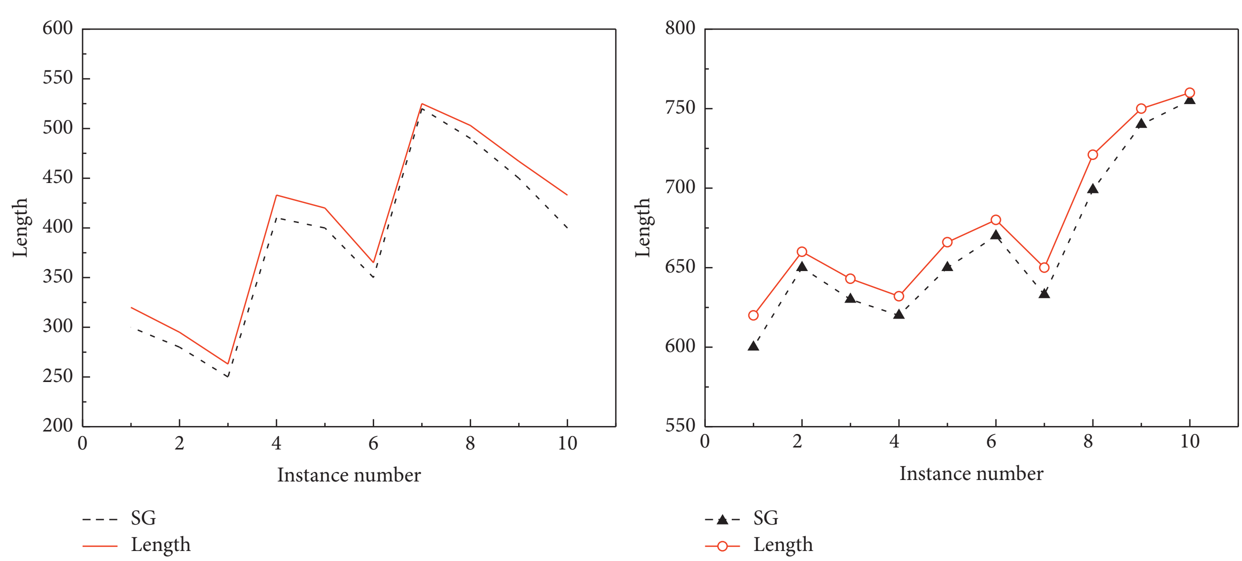

Figure 9: Comparison of predicted and actual values of e-commerce path optimization by genetic algorithm.

and (0.1, 0.5), respectively. It can be seen that when the probability of the delivery model is fixed at 0.1 for one type of material and increases for another type of material, the number of nodes effectively covered increases in the end. In this paper, experimental results are given for a mixed cascade model running on three types of supplies, where the settings of the impact probabilities are (0.1, 0.3, 0.5) and (0.2, 0.3, 0.4), respectively. The final number of nodes effectively covered is 200 and 450, respectively. This result indicates that the smallest probability determines the number of nodes covered under the condition that the number of material types is the same. The experimental results of the hybrid cascade model with 5 types of materials and their probabilities of (0.2, 0.4, 0.5, 0.6, 0.8) can be seen that the number of nodes covered on the hybrid cascade model is still acceptable when the number of material types reaches 5.

5. Conclusion

In this paper, for the modern logistics industry, the whole logistics environment is stratified according to intercity, intracity and terminal area, and the mathematical model of the vehicle path problem is established, the combinatorial optimization property of the model is proved, and the approximation algorithm for solving the corresponding model is designed, respectively, with the characteristics of each logistics environment. First, an integer linear programming model is developed for the problem and extended to any stage. Then, the lower bound of the optimal solution on this model is proposed and proved, which is better than the optimal solution of the linear relaxation model of the problem. Finally, a gradient descent algorithm is designed based on the lower bound of the optimal solution. For the logistics environment in the terminal area, three types of Euclidean planar vehicle path problems are proposed. Traveler problems with time windows are in a hierarchically extended relationship in terms of mathematical models and approximation algorithms. The time window constraint is introduced to the Euclidean plane traveler problem, and the structure of the path is analyzed with the nature of the traveler problem to design a polynomial-time approximation scheme for solving this problem. For complex and multioptimization objectives in real logistics environments, the vehicle path problem under the corresponding generalized objective function is modeled, while other classical combinatorial optimization problems are incorporated so that effective mathematical tools can be introduced to design the solution algorithm.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] A. Victor and M. R. Ghalib, "Detection of skin cancer cells-A review," *Research Journal of Pharmacy and Technology*, vol. 10, no. 11, pp. 4093–4098, 2017.

[2] M. N. Sudra and S. Selvarajan, "Hybrid approach towards feature selection for breast tumor classification from screening mammograms," *International Journal of Biomedical Engineering and Technology*, vol. 29, no. 4, pp. 309–326, 2019.

[3] M. Worker and A. Thakare, "Classification of stages of lung cancer using genetic candidate group search approach," *IOSR Journal of Computer Engineering*, vol. 18, no. 5, pp. 7–13, 2016.

[4] L. Yang and Z. Xu, "Feature extraction by PCA and diagnosis of breast tumors using SVM with DE-based parameter tuning," *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 3, pp. 591–601, 2019.

[5] Y.-K. Chan, M.-J. Chang, Y.-W. Hung et al., "Tissue section image-based liver scar detection," *Journal of Medical and Biological Engineering*, vol. 38, no. 6, pp. 857–866, 2018.

[6] R. V. Paul, S. Sannakki, and V. S. Rajpurohit, "A survey on classification of liver diseases using image processing and data mining techniques," *International Journal of Computer Sciences and Engineering*, vol. 5, no. 3, pp. 29–34, 2017.

[7] T. Liu, W. Zhang, P. McLean, M. Ueland, S. L. Forbes, and S. W. Su, "Electronic nose-based odor classification using genetic algorithms and fuzzy support vector machines," *International Journal of Fuzzy Systems*, vol. 20, no. 4, pp. 1309–1320, 2018.

[8] A. Das, P. Das, S. S. Panda, and S. Sabut, "Adaptive fuzzy clustering-based texture analysis for classifying liver cancer in abdominal CT images," *International Journal of Computational Biology and Drug Design*, vol. 11, no. 3, pp. 192–208, 2018.

[9] J. Ralph, A. Singh, and H. S. Bhadauria, "Computer assisted classification framework for prediction of acute lymphoblastic and acute megaloblastic leukemia," *Biocybernetics and Biomedical Engineering*, vol. 37, no. 4, pp. 637–654, 2017.

[10] M. Allan and M. Nandhini, "A study on optimization techniques in feature selection for medical image analysis," *International Journal of Computer Science and Engineering (IJCSE)*, vol. 9, no. 3, pp. 75–82, 2017.

[11] R. Manda, M. J. Walsh, and R. Bhargava, "Selecting optimal features from Fourier transform infrared spectroscopy for discrete-frequency imaging," *Analyst*, vol. 143, no. 5, pp. 1147–1156, 2018.

[12] P. Kaur, G. Singh, and P. Kaur, "An intelligent validation system for diagnostic and prognosis of ultrasound fetal growth analysis using neuro-fuzzy based on genetic algorithm," *Egyptian Informatics Journal*, vol. 20, no. 1, pp. 55–87, 2019.

[13] C. Wang, Z. Li, N. Dey et al., "Histogram of oriented gradient based plantar pressure image feature extraction and classification employing fuzzy support vector machine," *Journal of Medical Imaging and Health Informatics*, vol. 8, no. 4, pp. 842–854, 2018.

[14] N. Nanda, P. Kakkar, and S. Nagpal, "Computer-Aided segmentation of liver lesions in CT scans using cascaded convolutional neural networks and genetically optimised classifier," *Arabian Journal for Science and Engineering*, vol. 44, no. 4, pp. 4049–4062, 2019.

[15] I. Anguish and A. V. A. Kumar, "Improving medical diagnosis performance using hybrid feature selection via relief and entropy based genetic search (RF-EGA) approach: application to breast cancer prediction," *Cluster Computing*, vol. 22, no. 3, pp. 6899–6906, 2019.

[16] C. Salem, D. Azar, and S. Tokajian, "Image processing and genetic algorithm-based approach for the detection of melanoma in patients," *Methods of Information in Medicine*, vol. 57, pp. 74–80, 2018.

[17] S. L. Aarhus and S. Prabu, "Tri-texture feature extraction and region growing-level set segmentation in breast cancer diagnosis," *International Journal of Biomedical Engineering and Technology*, vol. 26, no. 3-4, pp. 279–303, 2018.

[18] A. Lakshmi, T. Arivoli, and M. Pallikonda Rajasekaran, "A novel M-ACA-based tumor segmentation and DAPP feature extraction with PPCSO-PKC-based MRI classification," *Arabian Journal for Science and Engineering*, vol. 43, no. 12, pp. 7095–7111, 2018.

[19] S. Ronald and S. Asadi, "An evolutionary deep belief network extreme learning-based for breast cancer diagnosis," *Soft Computing*, vol. 23, no. 24, pp. 13139–13159, 2019.

[20] R. D. L. Thomaz, P. C. Carneiro, J. E. Bonin, T. A. A. Macedo, A. C. Patrocinio, and A. B. Soares, "Novel Mahalanobis-based feature selection improves one-class classification of early hepatocellular carcinoma," *Medical & Biological Engineering & Computing*, vol. 56, no. 5, pp. 817–832, 2018.

[21] G. Seth and B. S. Saini, "Computer aided diagnosis system for abdomen diseases in computed tomography images," *Biocybernetics and Biomedical Engineering*, vol. 36, no. 1, pp. 42–55, 2016.

[22] H. Chroma, S. Abdulkareem, and T. Herawan, "Evolutionary Neural Network model for West Texas Intermediate crude oil price prediction," *Applied Energy*, vol. 142, pp. 266–273, 2015.

[23] C. Laing and T. Schlick, "Computational approaches to RNA structure prediction, analysis, and design," *Current Opinion in Structural Biology*, vol. 21, no. 3, pp. 306–318, 2011.

[24] H. Oh, S. Lee, and a C. Bovik, "Stereoscopic 3D visual discomfort prediction: a dynamic accommodation and vergence interaction model," *IEEE Transactions on Image Processing*, vol. 25, no. 2, pp. 615–629, 2015.

[25] W. Wang, M. Carr, W. Xu, and K. Kobbacy, "A model for residual life prediction based on Brownian motion with an adaptive drift," *Microelectronics Reliability*, vol. 51, no. 2, pp. 285–293, 2011.

[26] N. Gordon, "A genetic algorithm approach for SMEs bankruptcy prediction: empirical evidence from Italy," *Expert Systems with Applications*, vol. 41, no. 14, pp. 6433–6445, 2014.

[27] G. Baum and M. Blangiardo, "Hierarchical layered model for the prediction of football results," *Journal of Applied Statistics*, vol. 37, no. 2, pp. 253–264, 2010.