



DESIGN AND IMPLEMENTATION OF VEHICLE SCHEDULING OPTIMIZATION FOR SMART LOGISTICS PLATFORM POWERED BY HADOOP BIG DATA

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Abstract. E-commerce has become the mainstream consumption mode for people, and with the continuous increase of online shopping business volume, controlling logistics costs has become an urgent problem to be solved. In order to solve the challenges in vehicle scheduling and achieve a scientific and reasonable vehicle scheduling scheme, this research is based on Hadoop Big data platform, introduces the concept of time axis, and builds a vehicle scheduling model based on Hadoop intelligent platform. Based on quantum genetic algorithm and combined with MapReduce model, a quantum improved genetic algorithm is constructed to solve vehicle scheduling optimization problems. The results show that the traditional quantum genetic algorithm converges after 20 iterations, achieving an optimal value of 575 and taking 360 seconds. The improved quantum genetic algorithm converged after 10 iterations and achieved an optimal value of 675, taking 200 seconds. Compared with quantum genetic algorithm, the improved quantum genetic algorithm reduces the time spent by 44.4%. Selecting customer data from a certain logistics company for testing, the improved algorithm shortens the delivery time and achieves the design of the optimal path scheduling plan. This study optimized transportation routes and resource scheduling, reduced transportation costs, and played an important role in optimizing vehicle scheduling in the logistics industry.

Key words: Hadoop big data; vehicle scheduling; quantum genetic algorithm; MapReduce model; path planning cost

1. Introduction. The logistics industry is a crucial part of modern socio-economic activities, involving the flow, storage, and distribution of goods. With the advancement of globalization and the rise of e-commerce, the logistics industry has rapidly developed and has had a profound impact on economic development and social life [1]. However, vehicle scheduling faces many challenges, requiring a balance and optimization between limited resources and complex requirements. Vehicle scheduling needs to consider the transportation needs and time windows of goods, and in addition, the delivery and delivery times of goods also need to be accurately controlled to meet customer expectations and ensure the smooth supply chain. Secondly, urban traffic congestion is becoming increasingly severe, bringing difficulties to vehicle scheduling. Reasonable planning of vehicle routes and avoiding congested areas is crucial for improving transportation efficiency and reducing time costs [2]. Therefore, through scientific and reasonable vehicle scheduling schemes, logistics enterprises can improve transportation efficiency and service quality, reduce costs and risks. The optimization of vehicle scheduling models plays an important role in improving scheduling efficiency and enhancing enterprise competitiveness. Under this background, this research builds a vehicle scheduling model based on Hadoop Big data platform. Based on quantum genetic algorithm and combined with MapReduce model for improvement, a quantum improved genetic algorithm is constructed.

The study has been divided up into four sections. The first section focuses on the study done by domestic and foreign academics on the VS problem in the logistics sector and the practical use of QGA. The development of the VS model and quantum-improved genetic algorithm constitutes the second half. The third section provides an example along with the performance testing of the quantum-improved genetic algorithm. The article's faults are discussed in the fourth and final section.

2. Related works. The logistics sector has grown as a result of people's increasing material needs, and domestic and international academics have focused their research on the VS problem in logistics distribution. The standard VS issue can only address static issues; it cannot address the dynamic issues that emerge throughout the distribution process. Some academics have proposed solutions to the dispatching problem for automobiles

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under various dynamic demands. Luo et al. propose a bespoke labelling algorithm based on a mixed integer programming model in order to solve the problem of cost control and route optimization in the logistics distribution process. A large amount of distribution data from a company is selected and the proposed method is solved for two different problems. The method can effectively solve problems with different objectives, reduce distribution costs, improve distribution efficiency and provide decision makers with better decision solutions [3]. Yami et al. have proposed a multi-product production routing problem model for the vehicle transportation problem in order to help decision makers develop better production plans. The model takes into account issues such as cost and product demand in the production process and greatly reduces the cost consumption in the production and transportation process. Through a study of a company's actual case, it was verified that the method can reduce production costs, improve resource utilization and play an important role in production planning [4]. Midaoui et al. found that the healthcare sector was facing distribution difficulties, especially as the logistics of supplying medicines to individual hospital pharmacies accounted for a large part of the budget. To address this problem, a new intelligent logistics approach was proposed based on the multi-warehouse vehicle routing problem. The method uses a clustering approach to provide suitable locations for new pharmacies and uses a genetic algorithm to route the vehicles. The method is able to solve equipment and drug distribution problems faster and can provide a better drug pick-up system for the healthcare sector [5]. Andrade-Michel et al. propose an accurate constraint planning model in order to solve the vehicle scheduling problem by integrating driver information and the VS problem. The model combines the reliability of the driver and the importance of the journey, and is able to take into account the multiple aspects of the problems present in VS. Through the scheduling of vehicles in different scenarios, it is demonstrated that the method can effectively reduce trip coverage and improve delivery efficiency, thereby enhancing customer satisfaction [6].

To address the problems in logistics distribution, some scholars have made studies based on QGA. Lin et al. constructed an intelligent dispatching model based on enhanced QGA in order to adopt a truth coding system with vehicle departure time as the variable objective optimization. The model targets the minimum waiting time for customers and the maximum benefit for logistics companies by reducing the departure interval and increasing the on-board rate appropriately. The actual distribution routes were selected for empirical analysis, and the results showed that the method can meet the requirements of various aspects with high applicability and intelligence [7]. Ning et al. proposed an improved QGA based on dual-chain coding for the VS problem under low-carbon emission constraints. The study constructed a mathematical model with the objectives of minimum distribution time and minimum carbon emission, based on which an improved QGA using improved dual-chain QGA. Examples were selected for experiments and the model performance was analyzed using analysis of variance (ANOVA). The results showed that the model reduced carbon emissions in the dispatch process and achieved the objective of model optimization [8]. D Li et al. found that remote monitoring for automatic detection of arrhythmia is a challenging task. Based on this, a fast patient specific arrhythmia diagnosis classifier scheme is proposed by combining wavelet adaptive threshold denoising with quantum genetic algorithm based on least squares dual support vector machines. The results show that the proposed method has a detection accuracy of 98%, and compared to other representative existing technical methods, it consumes less CPU running time [9]. Y Yang et al. found that the current meta heuristic algorithm is slower in solving TSP problems. To solve this problem, a multi-scale adaptive quantum free particle optimization algorithm is proposed based on the inspiration of wave functions in quantum theory. The experimental results show that this algorithm has a faster search time compared to the ant colony optimization algorithm [10].

In summary, vehicle scheduling has always been a key issue in the logistics and distribution industry. In vehicle scheduling problems, many scholars only consider a single factor that exists in the distribution problem, while neglecting the dynamic needs of customers in the distribution network and not comprehensively considering the diversified problems that exist in the distribution process. This study takes into account the dynamic demand problem in distribution and improves the quantum genetic algorithm to achieve the goal of path optimization. It has certain reference value in the research of dynamic demand distribution.

3. VS Model and Improved QGA Construction. The optimization and enhancement of VS affects the rate of logistics and the development of logistics companies. To solve the problem of VS optimisation in dynamic situations, this chapter is divided into two parts for research. The first part is the construction of a Hadoop-based smart platform VS model and the second part is the construction of an improved QGA. The

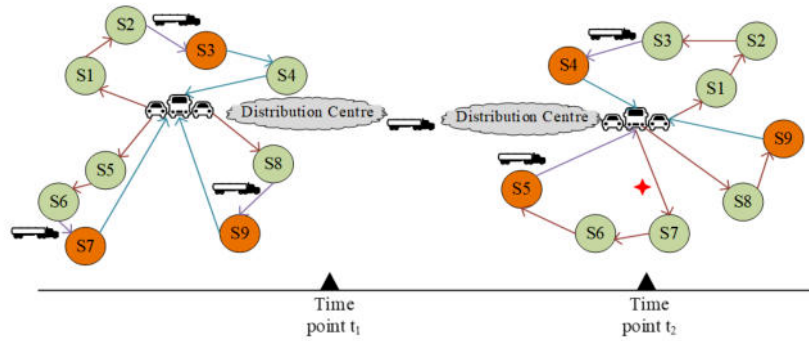


Fig. 3.1: Schematic diagram of dynamic demand distribution

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3.1. Hadoop-based Smart Platform VS Model Construction. The Hadoop wisdom platform has powerful cloud computing capabilities, with the advantages of high performance, scalability and low cost, which can meet the needs of enterprises for data processing and analysis [11]. In the smart platform delivery mode, the influencing factors in vehicle scheduling status exhibit dynamic changes, including the time required by customers, real-time delivery status, and current vehicle status. In vehicle scheduling, there are different influencing factors that can lead to a decrease in delivery efficiency, and time is an important factor affecting the scheduling status of vehicles. Considering the criticality of time in vehicle scheduling, the concept of timeline is introduced to determine a clear scheduling cycle, which facilitates the collection of dynamic demand information [12]. A schematic diagram of dynamic demand distribution is shown in Figure 3.1. In Figure 3.1, the red stars represent dynamic customers, the orange and red lines represent as well as the distribution routes that have been travelled, the light blue lines represent routes that have not yet been travelled and the purple lines represent routes that are being travelled. The orange circle indicates the most critical node in the logistics status being distributed under the condition of time. In the case of this node, the distribution task cannot be changed. The Smart Platform will identify the location of the critical node, vehicle information and customer information and generate a new dispatch plan. Setting the whole distribution network as A , vehicles are needed to complete the task at the moment, and the number of vehicles is calculated by the equation shown in equation 3.1.

$$m = \left\lceil \sum_{i \in w(t)} q_i / Q \right\rceil \quad (3.1)$$

In equation 3.1, w_{ut} denotes the set of static customers with unfinished distribution tasks and dynamic customers with new requests. q_i denotes the demand of the i th customer at the moment of i . Q denotes the maximum volume of the vehicle. The minimum function of distribution cost is shown in equation 3.2.

$$\min Z = Fm + \sum_{i, j \in w_{upo}(t)} \sum_{k=1}^m C_{ij} X_{ijk} \quad (3.2)$$

In equation 3.2, F denotes the vehicle fixed cost that has the minimum value in the total cost of distribution at the moment. $W_{upo}(t)$ denotes the set of all critical points, static customers who do not complete their tasks, dynamic customers who propose new demands and distribution centre points at the moment of t . C_{ij} denotes

the target cost of distribution distance, distribution time and distribution cost from customer i to customer j in the distribution route. The relationship between the total vehicle distribution tasks and vehicle load limits is shown in equation 3.3.

$$\sum_{i \in w_u(t)} q_i y_{ik} \leq Q - Q_{jk}(t), j \in W_{uo}(t), k = 1, 2, \dots, m \quad (3.3)$$

In equation 3.3, y_{ij} indicates that the distribution task of customer i is completed by vehicle k , $Q_{jk}(t)$ indicates the weight of the vehicle already loaded when it departs from the j th customer. The customer's requirements for the distribution vehicle are shown in equation 3.4.

$$\sum_{k=1} y_{ik} = 1, i \in W_u(t) \quad (3.4)$$

Equation 3.4 indicates that Customer i accepts only one vehicle to complete the task. The number of departing vehicles is shown in equation 3.5.

$$\sum_{i \in W_{po}(t)} y_{ik} = m \quad (3.5)$$

In equation 3.5, m denotes a vehicle departing from a key node and distribution centre. The relationship between customers and vehicles is shown in equation 3.6.

$$\begin{cases} \sum_{i \in W_u(t)} x_{ijk} = y_{jk}, j = W_u(t), k = 1, 2, \dots, m \\ \sum_{i \in W_u(t)} x_{ijk} = y_{jk}, i = W_u(t), k = 1, 2, \dots, m \end{cases} \quad (3.6)$$

In equation 3.6, x_{ijk} indicates that the vehicle entering the distribution network from the customer k , the vehicle driving from customer i to customer j and the initial distribution vehicle should be the same vehicle. The relationship between the variables is shown in equation 3.7.

$$\begin{cases} y_{ij}(y_{ik} - 1) = 0, i = 1, 2, \dots, m & k = 1, 2, \dots, m \\ x_{ijk}(x_{ijk} - 1) = 0, i = 1, 2, \dots, m & j = 1, 2, \dots, m \end{cases} \quad (3.7)$$

Equation 3.7 represents the relationship between the distribution tasks of customer i and the vehicles distributed between the two customers. The dynamic scheduling problem is more complex than static scheduling because of the uncertainty of information in the dynamic vehicle scheduling process [13]. In dynamic vehicle scheduling, there is uncertainty in information, and customer needs vary at different times. In order to establish a complexity criterion for the dynamic vehicle scheduling process, the equation is shown in equation 3.8 based on the ratio of dynamic customers in the distribution network

$$rs = 1 - \frac{n_t}{n}, 0 \leq rs \leq 1 \quad (3.8)$$

In equation 3.8, rs denotes the complexity rate of distribution, n_t denotes the number of dynamic customers and n denotes the total number of customers. The higher the percentage of dynamic customers in the distribution process, the more complex the distribution task is. When rs takes the value of 0, it means that all the customers in the distribution task are dynamic customers and the distribution task is complex. When the value of rs is 1, it means that all the customers in the distribution task are static customers, and the scheduling problem at this time is a static scheduling problem. In order to express the influence of dynamic information on the complexity of distribution, the complexity ratio is introduced, and the equation is shown in equation 3.9.

$$re = \frac{\sum_{i=1}^{n_t} t_i / T}{n} \quad (3.9)$$

In equation 3.9, T denotes the total distribution time and t_i denotes the time when dynamic information is generated. The above model introduces the concept of time axis, which is used to keep track of the current distribution task when dynamic information arises. The dynamic demand scheduling problem is transformed into a static scheduling problem to reduce the complexity of distribution scheduling and achieve global optimization.

3.2. VS Model based on improved QGA. Genetic algorithm is based on the principle of nature's law of superiority and inferiority, and is often used to solve multi-pole optimization and combinatorial optimization problems to achieve the purpose of global search for optimal solutions [14]. Apply genetic algorithm to vehicle scheduling to find the optimal path solution. Quantum genetic algorithm is based on genetic algorithm, introducing a quantum vector table into the chromosome encoding process, using quantum bits and quantum superposition as calculation rules. Using quantum gate rotation technology to enhance the global optimization ability of the algorithm. Quantum algorithms are solved for transformations of quantum states, and the introduction of quantum actions can increase the computational rate [15]. The quantum equation ion is shown in equation 3.10.

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle \quad (3.10)$$

In equation 3.10, α and β denote the probability of generation relative to the state, both of which are complex numbers. α and β satisfy the normalized case as shown in equation 3.11.

$$|\alpha|^2 + |\beta|^2 = 1 \quad (3.11)$$

In equation 3.11, $|\alpha|^2$ denotes the probability that the state is 0 and $|\beta|^2$ denotes the probability that the state is 1. The quantum algorithm uses either binary or decimal for calculation. A novel form of quantum bit encoding is introduced to represent chromosomes, and the equation is shown in equation 3.12.

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \\ \beta_1 & \beta_2 & \dots & \beta_m \end{bmatrix} \quad (3.12)$$

A chromosome with m quanta is represented in equation 3.12, and equation 3.12 can describe a superposition of any linear form. Assume that there exists a chromosome of length 2 and that the chromosome is shown in equation 3.13.

$$\begin{bmatrix} \frac{1}{\sqrt{2}}|\frac{1}{\sqrt{2}}\rangle \\ \frac{1}{\sqrt{2}}|\frac{1}{\sqrt{2}}\rangle \end{bmatrix} \quad (3.13)$$

Equation 3.13 represents the chromosomal state represented by equation (12) and the state of the quantum position is represented as shown in equation 3.14.

$$\frac{1}{2} |00\rangle - \frac{1}{2} |01\rangle + \frac{1}{2} |10\rangle - \frac{1}{2} |11\rangle \quad (3.14)$$

In equation 3.14, $|00\rangle$, $|01\rangle$, $|10\rangle$ and $|11\rangle$ are four quantum bits, all of which occur with a probability of 25%. The description using the quantum bit state approach allows a single chromosome to exhibit multiple state overlays, increasing the population diversity of the algorithm [16]. A quantum chromosome is represented by a three-dimensional quantum bit matrix of $n \times n \times 2$ for a scheduling problem with n customers. where the order of service is represented by the horizontal coordinate and the customer delivery service number is represented by the vertical coordinate. Assuming that the order of customer delivery is randomly generated within the $[0,1]$ interval, after obtaining a two-dimensional matrix of $m * m$, the search adjustment function is used to make each row and column of the matrix contain only one digit 1. Assuming that there are five customer delivery demands, the matrix representation is shown in equation 3.15.

$$\begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad (3.15)$$

In equation 3.15, the customer delivery sequence is 2-1-4-3-5 and the service is completed using the same vehicle. If the delivery demand cannot be met at this time, consider adding new quantum chromosomes, and

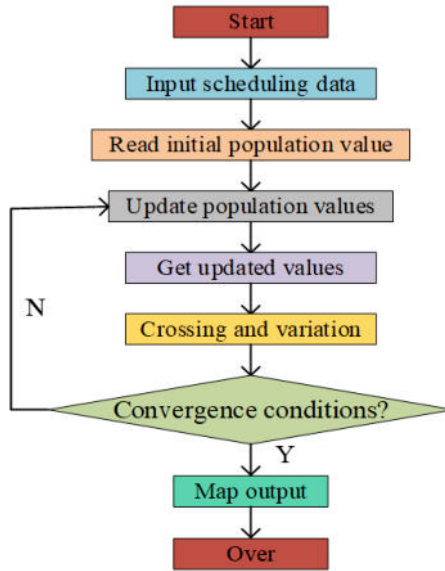


Fig. 3.2: Map function flowchart

the special group will also be converted into an integer population. Quantum gates can convert states between algorithms, and the representation of quantum gates is shown in equation 3.16.

$$\begin{bmatrix} \alpha_{m,n}^{t+1} \\ \beta_{m,n}^{t+1} \end{bmatrix} = U(\delta\theta) \begin{bmatrix} \alpha_{m,n}^t \\ \beta_{m,n}^t \end{bmatrix} = \begin{bmatrix} \cos(\delta\theta) & -\sin(\delta\theta) \\ \sin(\delta\theta) & \cos(\delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_{m,n}^t \\ \beta_{m,n}^t \end{bmatrix} \quad (3.16)$$

In equation 3.16, $\delta=s(\alpha\beta)$ denotes the direction of rotation and θ denotes the angle of rotation. the equation satisfies the condition $UU' = 1$. using quantum gates can improve the convergence efficiency of the algorithm. After the quantum gate is updated, the chromosomes are decoded and the corresponding fitness values are calculated. Due to the coexistence of disorder and order in vehicle path scheduling, the encoding structure is chosen as a real number encoding structure. MapReduce is a widely used open-source software framework for parallel processing of large datasets, MapReduce computing is divided into two phases, Map phase and Reduce phase. The combination of QGA and Map and Reduce can enhance the parallelization of algorithms [17]. In the Map session, what is obtained by the computation is the solution space string record in the VS data. Assuming the existence of i_n clients, the intermediate key-value pairs obtained after computation are shown in equation (17).

$$key = 'n' + 'm', value = \sum_m^n ('n' + 'm') \quad (3.17)$$

In equation 3.17, n indicates the number of customers and m indicates the dispatched vehicles. The variables are expressed in character form to facilitate the calculation of the data in the function. The flow chart of the Map function is shown in Figure 3.2.

In Figure 3.2, first input the scheduling data and obtain the initial population value. Update the population values through quantum gates to obtain the updated values. Then cross and reorganize the data. If it meets the requirements, it will be output. If it does not meet the requirements, it will continue to update the population values. In the Reduce function, the key and value values in equation 3.17 are combined to obtain the sequence $(key : value_1, value_2, \dots, value_n)$, which is passed to the Reduce function for processing. the Reduce function normalizes the sequence to obtain the set $(P_{c1}, P_{m1}, P_{c2}, P_{m2}, \dots, P_{ci}, P_{mj})$ which can be derived from the optimized population [18]. the computational flow of the Reduce function is shown in Figure 3.3.

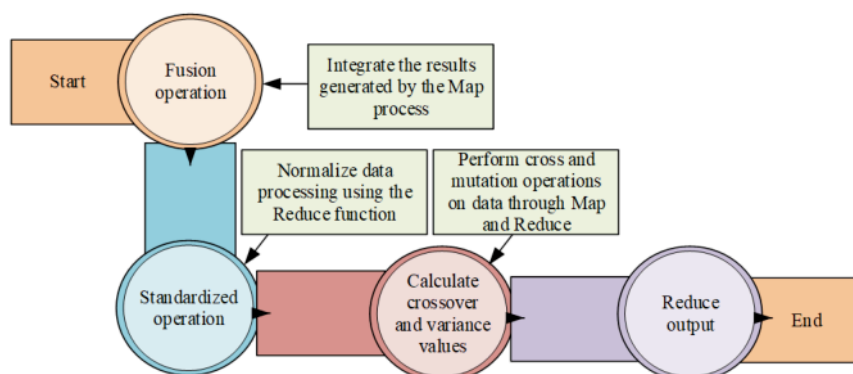


Fig. 3.3: Reduce function calculation flowchart

In Figure 3.3, the key and value values are first combined to obtain the sequence ($key : value_1, value_2 \dots value_n$). Then use the Reduce function for standardized data processing to obtain the standardized results. By using Map and Reduce to perform cross and mutation operations on the data, cross values and variance values can be calculated. Finally, output the results to obtain the optimized population.

HDFS is a database on the Hadoop platform in which all parameters are stored [19]. According to the above, improving QGA first requires setting a MapReduce parameter. In the Map function operation, the various types of data stored in the HDFS system, including vehicle information, customer demand information, vehicle location and other data, are obtained and initialized. All genetic population individuals in the Map are encoded and processed. After processing, the initial population is randomly selected and the number of populations is calculated. The calculated information is stored in the HDFS system and output to the Reduce function as value. During the computation of the Reduce function, the data in the HDFS system is first read, the population is optimized by quantum gates, and crossover and mutation operations are applied to obtain the optimal individuals [20]. The flow chart of the improved QGA is shown in Figure 3.4.

4. Algorithm Performance Testing and Example Analysis. The first part of this chapter is devoted to performance testing of the improved QGA and analyzing the performance differences between the improved QGA and the original QGA. The second part selects dynamic customer requirements and static customer requirements information to analyze the application of the improved QGA in real-world situations.

4.1. Algorithm Performance Testing. In order to test the performance advantages and disadvantages of the QGA and the improved QGA, this experimental environment used an Intel(R) Core (TM) i3 processor, CentOS7 as the operating system and Tomcat 7.0 as the web server. the QGA and the improved QGA were compared and the convergence process of the two was analyzed. The comparison graph is shown in Figure 4.1.

Figure 4.1.a shows a comparison of the convergence times of the two algorithms, and Figure 4.1.b shows a comparison of the optimal values obtained by the two algorithms. The traditional quantum genetic algorithm converges after 20 iterations, achieving an optimal value of 575 and taking 360 seconds. The improved quantum genetic algorithm converged after 10 iterations and achieved an optimal value of 675, taking 200 seconds. Compared with quantum genetic algorithm, the improved quantum genetic algorithm reduces the time spent by 44.4%. The enhanced QGA performs better during convergence and converges more effectively. The 0/1 backpack problem can be solved via combinatorial optimization, which is the process of identifying the best solution. The backpack's maximum loaded weight is 1000 pounds, and it can hold 30 items. Figure 4.2 depicts the algorithm solution diagram. From Figure 4.2, it can be seen that the convergence effect of the improved quantum genetic algorithm is better than that of the quantum genetic algorithm. The maximum value obtained by the improved quantum genetic algorithm is 2840, while the maximum value obtained by the quantum genetic algorithm is 2690. The improved quantum genetic algorithm performs better than quantum genetic algorithm

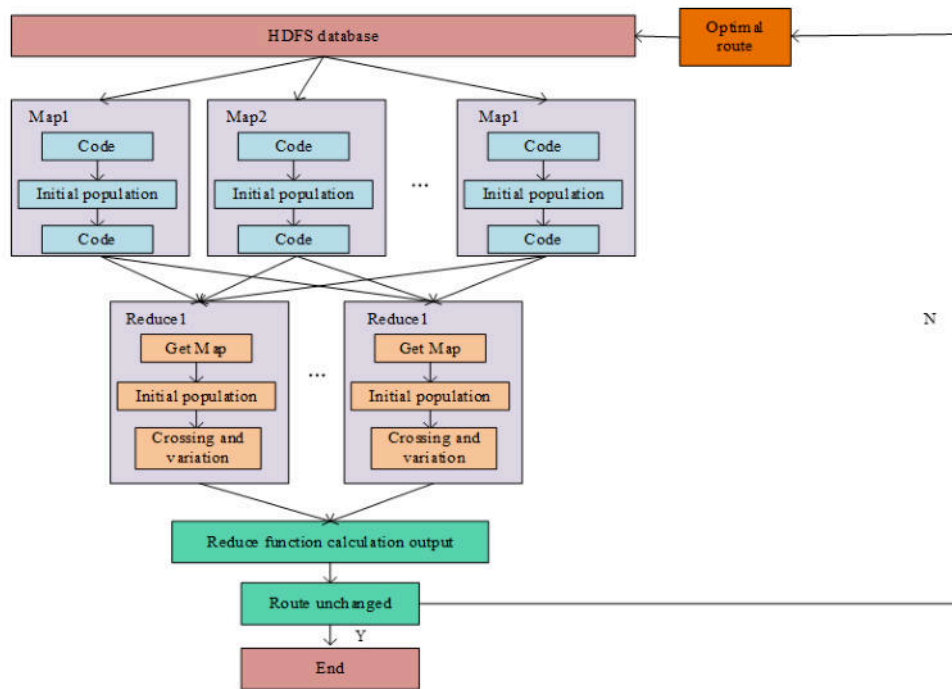


Fig. 3.4: Flow chart of improved quantum genetic algorithm for MapReduce

in solving optimal solution problems. In the transportation process, the transportation speed is affected by the real-time road conditions, and the two algorithms are used to predict the traffic flow in the transportation process, and the prediction results are shown in Figure 4.3.

Figure 4.3.a shows the prediction graph of the quantum improved genetic algorithm, and Figure 4.3.b shows the prediction graph of the original QGA. The comparison of the two plots shows that the prediction results of the quantum improved genetic algorithm match the actual results, indicating that the improved QGA has a better path finding ability for path design and can achieve good path planning for VS. The comparison graph of the planning accuracy of the two algorithms is shown in Figure 4.4. In Figure 4.4, the experimental accuracy of the improved quantum genetic algorithm has improved with the increase of experimental times, with an average experimental accuracy of 98.25%. The experimental accuracy of traditional quantum genetic algorithms will also improve with the increase of experimental times, but the improvement is small, with an average experimental accuracy of 93.88%. Compared with the traditional quantum genetic algorithm, the experimental accuracy of the improved quantum genetic algorithm has increased by 4.37%.

4.2. VS Example Analysis. A random group of customers in different cities of a logistics company is selected, and the range of city distribution intervals is a square with a side length taken as 80km. 26 static request customers are selected, each with a demand of no more than 2.5km³. the volume of the distribution vehicle is 7m³ and the vehicle travels a maximum of 120km at a time. the information table for static customers is shown in Table 4.1.

Table 4.1 contains a total of 26 static customers' coordinate locations and their demand. The distribution problem for static customers is solved using QGA and modified QGA to obtain different scheduling schemes. The scheduling schemes are shown in Figure 4.5.

The QGA dispatching plan for static client demand is shown in Figure 9(a). The data shows that there are four vehicles that have been dispatched, four main dispatch routes, and a delivery time of 310.8 minutes.

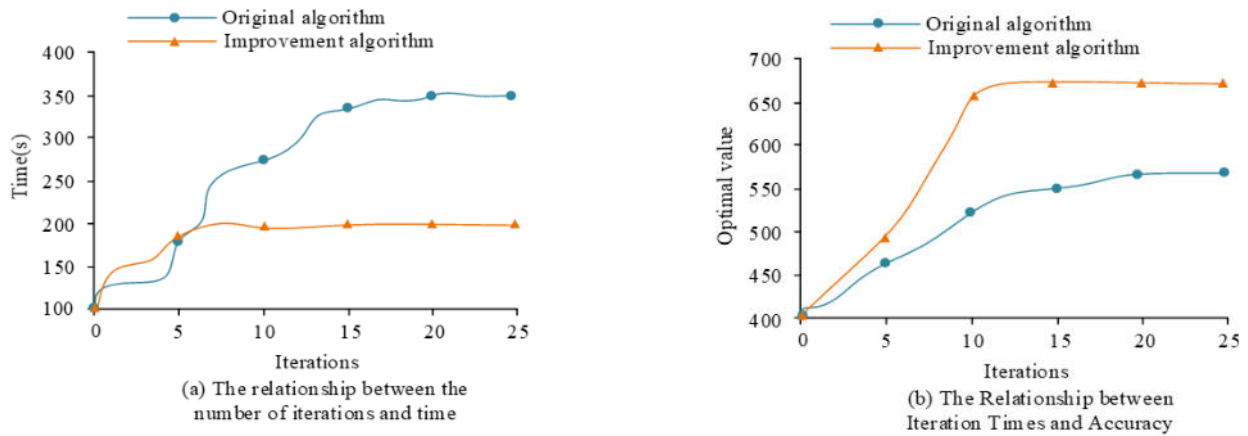


Fig. 4.1: Comparison of convergence results

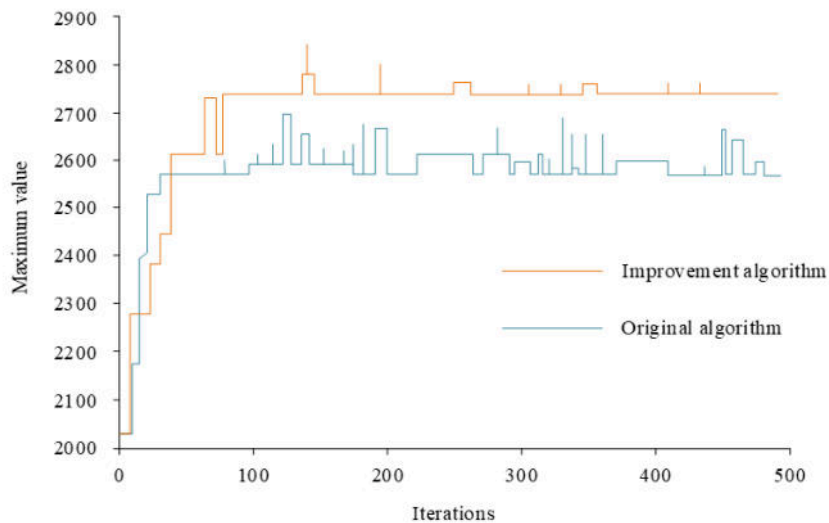


Fig. 4.2: Schematic diagram of two algorithms for solving

The dispatch routes contain route duplications, which is a poor route optimization option and wastes delivery resources. The enhanced QGA scheduling plan for static customer demand is shown in Figure 9(b). The figure shows that there are 4 dispatching vehicles, 4 main dispatching routes, no dispatching routes duplicate each other, the routes are straightforward and quick, and the delivery time is 252.5 minutes. Delivery times are slashed thanks to the enhanced algorithm, which also produces the best route dispatching scheme design. Table 4.2 displays the information table for the fourteen dynamic consumers that were chosen.

In the VS process, the dynamic customer demand changes with time. Based on the improved QGA solving static customer demand scheduling scheme, dynamic demand nodes are added and the improved QGA is used for the scheduling scheme design. The dynamic customer scheduling scheme is shown in Figure 4.6. There are four cars with the same static client demand, as shown in Figure 10. The delivery time for Vehicle 1 is

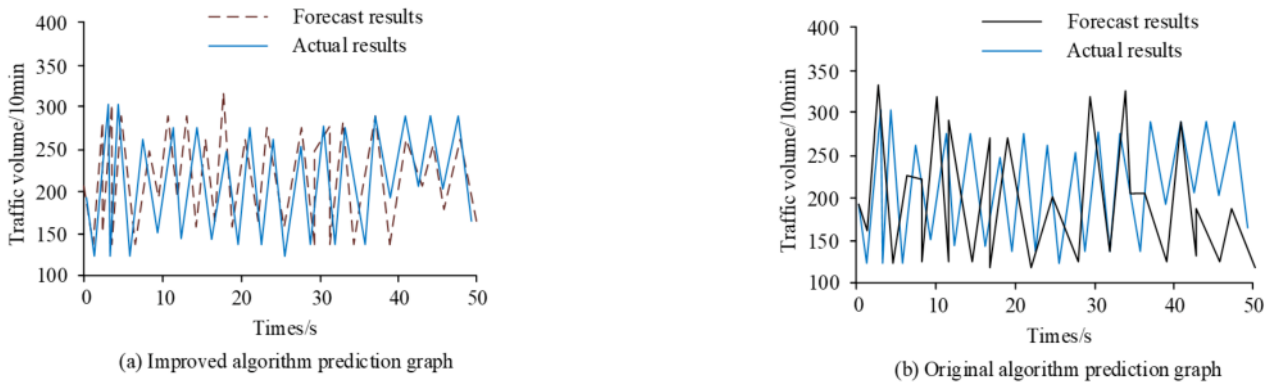


Fig. 4.3: Traffic flow prediction chart

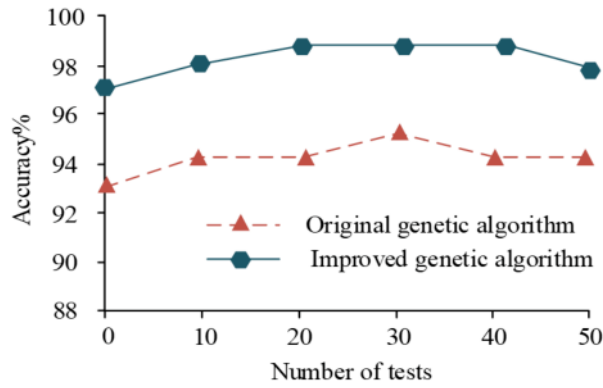
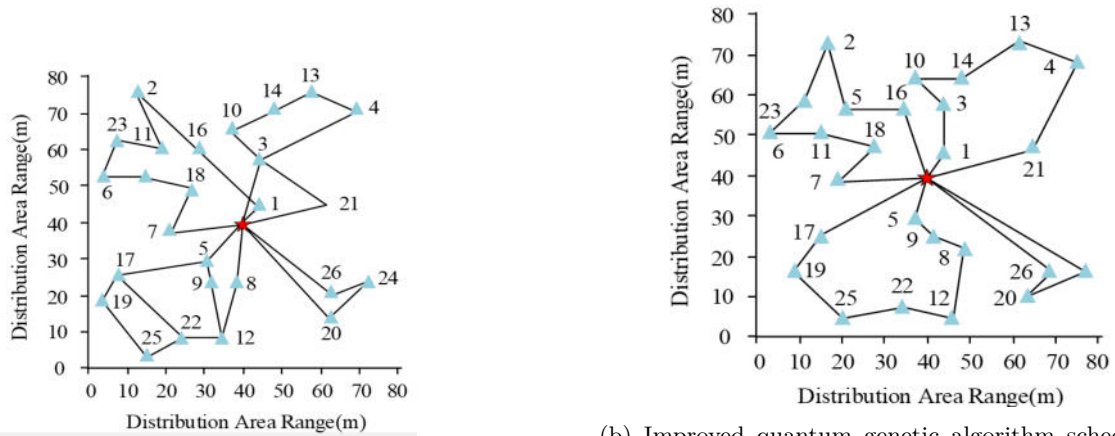


Fig. 4.4: Comparison of path planning accuracy

Table 4.1: Static Demand Customer Information Table

Customer number	Position coordinates	Requirement	Customer number	Position coordinates	Requirement
No.1	(45,40)	1.55	No.14	(48,65)	2.20
No.2	(75,20)	0.50	No.15	(26,35)	1.85
No.3	(56,43)	0.85	No.16	(35,55)	1.55
No.4	(62,70)	2.00	No.17	(15,20)	1.40
No.5	(21,55)	2.00	No.18	(27,45)	1.30
No.6	(5,50)	0.50	No.19	(8,16)	0.75
No.7	(26,35)	0.25	No.20	(14,60)	0.70
No.8	(42,20)	0.20	No.21	(60,45)	0.35
No.9	(35,25)	0.35	No.22	(35,5)	0.70
No.10	(60,42)	0.85	No.23	(10,60)	1.85
No.11	(45,16)	1.00	No.24	(18,70)	2.00
No.12	(38,5)	1.50	No.25	(20,3)	1.00
No.13	(72,60)	0.75	No.26	(16,65)	1.00



(a) Quantum genetic algorithm scheduling diagram

(b) Improved quantum genetic algorithm scheduling diagram

Fig. 4.5: Static customer scheduling scheme diagram

Table 4.2: Dynamic Demand Customer Information Table

Customer number	Position coordinates	Requirement	Customer number	Position coordinates	Requirement
A	(6,25)	2.30	H	(56,70)	1.30
B	(30,10)	0.50	I	(15,55)	1.80
C	(25,43)	0.85	J	(28,58)	1.50
D	(32,40)	1.75	K	(3,30)	1.50
E	(12,55)	2.00	L	(27,32)	1.70
F	(25,60)	0.85	M	(20,10)	1.00
G	(16,8)	0.30	N	(5,60)	2.00

65.8 minutes, with a dispatch route distance of 71.5 km. The delivery time for Vehicle 2 is 56.5 minutes, with a dispatch route distance of 61.5 km. The delivery time for Vehicle 3 is 70.5 minutes, with a dispatch route distance of 75.2 km. The delivery time for Vehicle 4 is 45.5 minutes, with a dispatch route distance of 42.6 kilometers. The enhanced Not only is the revised QGA appropriate for dynamic customer demand dispatching, but it is also ideal for static customer demand dispatching. With the goal to ensure that the distribution route in the solution is the best path and that the distribution takes the least amount of time, the upgraded QGA is able to deliver VS solutions extremely fast in response to new customer requests on the smart logistics platform. When tackling the VS problem of the smart platform, the upgraded QGA has good global optimal solution search performance, which can significantly increase the effectiveness of the distribution service of the smart platform.

5. Conclusion. With the development of Big data and e-commerce, customers’ demand for logistics distribution has increased, and vehicle scheduling is an important link in the logistics distribution network. This research is based on Hadoop Big data platform, introduces the concept of time axis, determines a clear scheduling cycle, and builds a vehicle scheduling model that meets dynamic demand. Combine quantum genetic algorithm with MapReduce model to construct quantum improved genetic algorithm. The algorithm testing results show that the quantum genetic algorithm converges after 20 iterations, achieving an optimal value of 575, taking 360 seconds, and a success rate of 46.8%. The improved quantum genetic algorithm converged after 10 iterations, achieving an optimal value of 650, taking 200 seconds, and a success rate of 75.5%. Compared with quantum genetic algorithm, the improved quantum genetic algorithm has a success rate increase of 61.3% and a time reduction of 44.4%. Two algorithms were used to predict traffic flow, and the improved algorithm matched

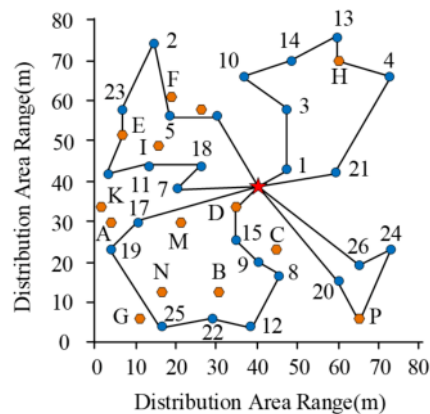


Fig. 4.6: Improved quantum genetic algorithm scheduling diagram

the actual results. Repeat the prediction experiment, and the average experimental accuracy of the improved quantum genetic algorithm is 97.85%. The average experimental accuracy of the traditional quantum genetic algorithm is 90.88%. The experimental accuracy of the improved quantum genetic algorithm is 7.7% higher than that of the traditional quantum genetic algorithm. Selecting customer data from a logistics company for testing, the improved quantum genetic algorithm can effectively plan delivery routes for both static and dynamic customer needs. Compared with the test results of the quantum genetic algorithm, the improved algorithm has shortened the delivery time and can quickly provide a vehicle scheduling plan, making the delivery route in the plan the optimal path and minimizing the delivery time consumption, achieving the design of the optimal path scheduling plan. At the same time, it provides users with faster delivery services, increasing the core competitiveness of the enterprise. There are also shortcomings in this study. The scheduling problem of vehicles only considers the needs of customers and does not consider the impact of other factors on vehicle scheduling. In future research, multiple influencing factors should be considered to improve the scheduling model.

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