Optimization of Distribution Routes in Agricultural Product Supply Chain Decision Management Based on Improved ALNS Algorithm

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Abstract—The transportation of fresh agricultural products is not conducted along a sufficiently precise route, resulting in an extended transportation time for vehicles and a consequent deterioration in product freshness. Therefore, the study proposes an agricultural product transportation path optimization model based on an optimized adaptive large neighborhood search algorithm. The Solomon standard test case is used for the experiment, and the algorithm before and after optimization is compared. From the results, the optimized method was effective for the distribution model C201, R201, and CR201 sets after conducting case analysis. The total cost of the R201 transportation set was the lowest, while C101 had the highest total cost. The lowest vehicle cost consumption was R201 at 600, and the highest was C101 at 2220. The C101 algorithm took 145 s to calculate, and R201 took 199 s. All values of CR201 were average, with high fault tolerance. The proposed method was used to address the optimal operator solution. The C201 example took 244 s to calculate 2350 objective function values. The R201 example took 239 s to obtain 657 objective function values. The CR201 example took 233 s to obtain 764 objective function values. This indicates that the designed method has a significant effect on optimizing the distribution path of agricultural products. Compared with the unimproved algorithm, it has more accurate search ability and lower transportation costs. This algorithm provides path optimization ideas for the agricultural product transportation industry.

Keywords—ALNS; agricultural products; path optimization; cold chain transportation; supply chain

I. Introduction

In a rapidly developing society, the demand for fresh agricultural and related products among urban residents is increasing day by day. In recent years, the e-commerce industry has developed rapidly. Online ordering of fresh agricultural and related products has become one of the main consumption channels that is widely popular among consumers [1]. The distribution task of agricultural products in urban areas is also increasing due to low distribution efficiency, which greatly affects the industrial development. As fresh agricultural and related products themselves have short freshness and shelf life, they are prone to deterioration over time. Once the freshness is too low, they lose their nutritional value and appearance as products for sale. Therefore, how to ensure product freshness during transportation is the main issue that needs to be urgently addressed in the logistics of the entire supply chain. This poses a challenge to the timeliness of logistics transportation and the cold chain level of transport vehicles [2]. The competition for Fresh Agricultural Products (FAP) to stand out is the entire supply chain. The circulation mode of FAP refers to the transfer mode from the place of origin to the dining table, including various elements involved in the circulation of agricultural products [3]. For the supply chain, it is crucial to increase agricultural product enterprises, production and suppliers of raw materials in the middle and upper reaches, such as vegetables, seedlings and pigs. In addition to being responsible for sowing, picking, breeding, slaughtering and packaging FAP, enterprises must also directly supply raw processed agricultural products to wholesale or retail companies [4, 5]. The supply chain has drawbacks such as high loss, untimely delivery and lack of trust. The reason for this is that certain fresh ingredients that require strict time and storage conditions have increased cold chain transportation pressures and transportation costs.

More and more scholars have noticed that the transformation of agricultural supply chains requires strong technical support. Yu and Rehman proposed an evolutionary game model on the basis of the relationship between agricultural product suppliers and urban residents. This model applied evolutionary game theory to analyze the financing game model. The results indicated that the model could effectively improve the operational capability of agricultural product platforms [6]. Fu et al. introduced contract and trust mechanisms to control the uncertainty. Therefore, a digital system coupling relationship between blockchain and FAP supply chain was proposed. The results indicated that the blockchain-based digital system could help the agricultural supply chain achieve significant industrial transformation [7]. Syofya et al. proposed a value-added approach through transparent methods and supply chain management among commercial actors to address the impact of the Clincy coffee agricultural supply chain on the agricultural economic added value in Chambe Province. The results showed that this method effectively increased the yield of coffee agricultural products [8]. Mukherjee et al. established a decentralized, data-immutable, smart contract supply chain, transparency, and shared database for blockchain technology in complex multi-electronic supply chain. The results indicated that the supply chain provided deep significance for potential practitioners [9]. Luckstead et al. discussed the impact of the pandemic on workers in the food supply chain accepting important job decisions. The study analyzed the attitudes of low-skilled workers towards the processing plant industry during the epidemic. The results showed that gender, current agricultural workers, and information about COVID-19 and agricultural workers affected respondents' answers [10].

The optimization of supply chain transportation paths cannot be achieved without search algorithms. Prymachenko et al. proposed a method for evaluating multi-modal transportation in transportation enterprises based on the multi-modal transportation route network model. The results indicated that this method could minimize the supply cost [11]. Chang et al. found that there were problems with the route planning of freight buses in urban distribution systems. Therefore, a mixed integer linear programming model was established, and an Adaptive Large Neighborhood Search (ALNS) was developed. The results showed that the correlation of the mathematical model and the model effectiveness was demonstrated through numerical experiments [12]. Hu et al. found that fast online route decisions must be made to fulfill offline retail service commitments. Therefore, a vehicle path optimization method combining an open architecture ALNS algorithm was proposed. The results indicated that this method could achieve offline training of neural network models to generate almost immediate solutions online [13]. Relying on the two levels and multiple centers in the urban logistics joint distribution system, Li et al. analyzed the two-level joint delivery path. An ALNS algorithm was proposed to solve models with multiple deletion and insertion operators. The ALNS algorithm was faster and more effective [14]. Nikzad et al. established a two-stage stochastic mathematical model for asset protection routing under wildfires. This model used the ALNS algorithm to determine routing decisions. The results showed that numerical analysis confirmed the effectiveness [15].

In summary, domestic and foreign researchers have also introduced the ALNS algorithm for the optimization of transportation paths in agricultural supply chains, but few scholars have improved and applied the ALNS algorithm. In response to this issue, a FAP distribution path optimization model is constructed for supply chain decision-making, aiming to improve transportation efficiency. The innovation lies in the ALNS algorithm, which is adapted from the Solomon standard test case for experimental testing. This algorithm fully meets the characteristics of fresh time limit requirements during agricultural product transportation, which benefits to optimize the delivery efficiency of fresh agricultural and sideline product distribution enterprises.

II. Methods and Materials

Aiming at optimizing the distribution path of agricultural product supply chain, an improved ALNS is designed. Firstly, the transportation vehicle routing problem is introduced, and the freshness calculation of agricultural products at each stage of transportation is explained. Secondly, the operational framework of the ALSN algorithm and the transportation process and cost of cold chain vehicles are introduced. Finally, an improved ALSN algorithm model framework is proposed.

A. *Distribution Cost of Agricultural Product Supply Chain Ground on Improved ALNS Algorithm*

The urban transportation stage of the fresh agricultural and sideline product supply chain, which is the transportation stage of delivering goods from the supply location to the consumer's ordering location [16]. During transportation, agricultural products have the characteristics of high storage difficulty, high distribution cost, freshness requirements, and irreversibility, as well as high timeliness requirements [17]. In accordance with the features of agricultural products, the supply chain distribution path problem is reasonably optimized. Vehicle path refers to the transportation path optimized by the logistics distribution center that meets the delivery requirements under certain dispatching conditions [18]. When planning the vehicle routing problem, it is necessary to cover constraints such as customer needs, location selection of logistics centers, number of transportation vehicles dispatched on different routes, and characteristics of agricultural products. The vehicle routing problem is displayed in Fig. 1.

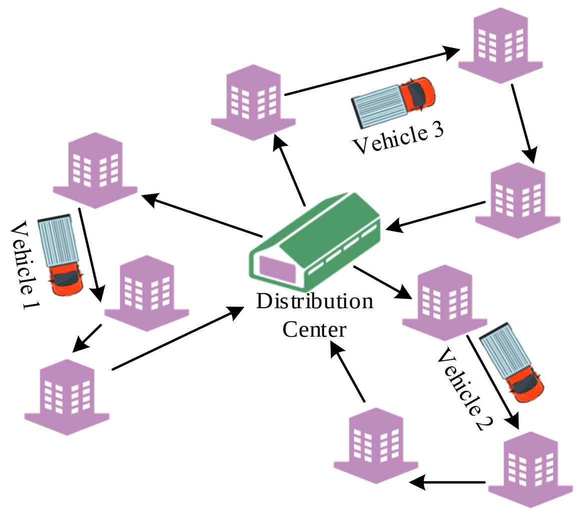

Fig. 1. Sketch map of vehicle routing problem.

Due to their strict freshness requirements, FAP lose their selling and purchasing value once they exceed the optimal freshness period. However, any fresh or similar product has the freshness loss during transportation, so freshness requirements must be an important constraint in planning and optimizing delivery routes. At present, many transportation enterprises and scholars in related fields have attached great importance to the freshness changes during the transportation of agricultural and sideline products. Various prediction algorithms have been proposed, among which linear decreasing functions can be used to represent the freshness reduction. Combining the decreasing functions, transport vehicles depart at time A, the vehicle arrived at time B, and the freshness at random time $t\left(A \le t \le B\right)$ is shown in Eq. (1).

$$\theta\left(t\right)=1-\frac{t-A}{B-A} \tag{1}$$

In Eq. (1), θ signifies the freshness at time t. The maximum freshness time limit T of the product after transportation time $t\left(0 \le t \le T\right)$ is shown in Eq. (2).

$$\theta\left(t\right)=1-\frac{t^2}{T^2} \tag{2}$$

In Eq. (2), $1-\frac{t^2}{T^2}$ represents the freshness factor of a monotonic continuous decreasing function. The freshness changes during the transportation after time *t* are shown in Eq. (3).

$$\theta(t)=\theta_0 e^{-\mu t} \tag{3}$$

In Eq. (3), θ_0 is the product freshness just picked. μt signifies the decreasing freshness index of FAP. To ensure that agricultural products can exhibit clear changes under the common constraints of time and preservation costs, a three parameter Weil function is used for prediction. The freshness variation of agricultural products constructed by the three parameter Weil function is shown in Eq. (4).

$$\theta(t)=\theta_0^{(\mu-f(r))\cdot t} \tag{4}$$

In Eq. (4), μ is the decay rate during transportation calculated by the three parameter Weil function. $f(r)$ represents the cost of preservation investment. FAP is also divided into different categories. To predict the freshness changes of different products, the Arrhenius function is used to construct the freshness changes, as shown in Eq. (5).

$$\theta(t)=\begin{cases}\theta_0-\mu t & if\ \gamma=0\\ \theta_0\cdot\exp(-\mu t) & if\ \gamma=1\end{cases} \tag{5}$$

In Eq. (5), γ represents the reaction level of FAP. In addition to the inherent freshness characteristics, transportation efficiency is also affected by the traffic congestion in different regions, the number of residents traveling at different time points, and license plate restrictions. Search models can effectively improve uncertainty factors. ALNS is an algorithm based on large-scale neighborhood search. The solution process of this algorithm is to first calculate the global optimal solution, then move and insert this optimal solution to iteratively calculate and obtain more domain optimal solutions near the optimal solution range [19]. The optimal solution for insertion and removal in this algorithm can represent the planned consumer ordering location in the transportation path. When different transportation routes pass through this location, the nearby better route is searched again and closely associated with the nearest transportation point. The removal and insertion processes of the ALNS algorithm are shown in Fig. 2.

The ALNS algorithm is affected by the weight values of the insertion and removal operators during the iterative calculation process, resulting in the inability to select the optimal path reasonably when there are too many paths to select. Therefore, it is necessary to determine in advance the effectiveness and necessity of the optimal solution calculation for the operators to be removed and inserted, and make adjustments when the optimization conditions are met. The ALNS algorithm must continuously eliminate bad paths and paths with constant distances by adaptively adjusting the adjustable values, which can continuously improve the accuracy of the algorithm's prediction. The ALNS algorithm has been discovered and used by logistics companies for transportation path optimization problems due to its advantages such as wide applicability and large macro search range. The flowchart of the ALNS algorithm is shown in Fig. 3.

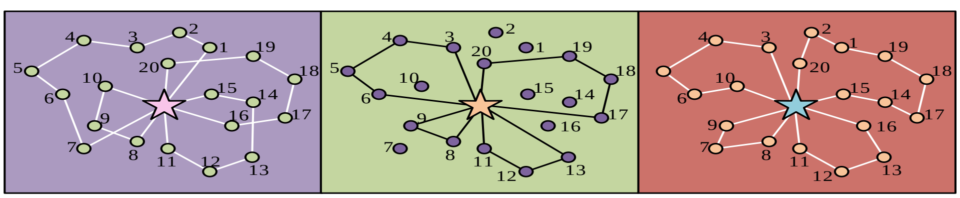

Fig. 2. Process diagram of ALNS algorithm's removal and insertion operations.

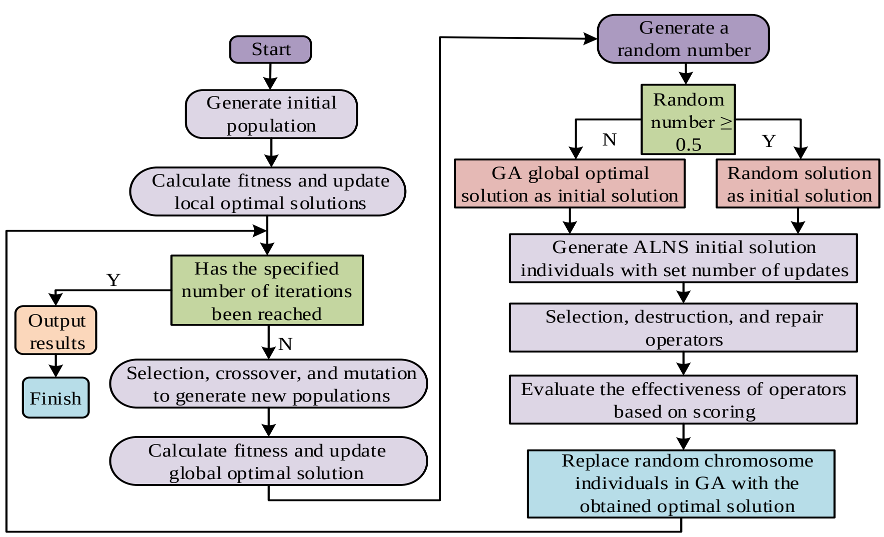

Fig. 3. ALNS algorithm flowchart.

B. Construction of Distribution Route Optimization Model for Agricultural Product Supply Chain Decision Management

The ALNS algorithm optimizes the transportation path, but the transportation mode also has an important impact on the quality of agricultural products. Cold chain transport vehicles can maintain freshness through refrigeration, which is consistent with the principle of refrigeration in refrigerators, ensuring the freshness of agricultural products to the greatest extent possible and reducing the spoilage rate. However, cold chain transportation requires a large amount of energy to cool, resulting in high costs and carbon emissions, which leads to high-cost consumption for logistics enterprises. Therefore, the unit time fuel consumption of the refrigeration unit of the cold chain truck is predicted, as shown in Eq. (6).

$$f_c(g) = R_0 + \frac{R_* - R_0}{Q_{\max}} g \tag{6}$$

In Eq. (6), f_c represents the fuel consumption rate. R_0 is the fuel consumption per unit time when the vehicle is unloaded, and R_* is the fuel consumption at full load. g is the maximum load of the cold chain truck. The fuel consumption of the refrigeration unit generator is displayed in Eq. (7).

$$F(g_{ij}) = \left(R_0 + \frac{R_* - R_0}{Q_{\max}} g_{ij} \right) T_{ijk} \tag{7}$$

In Equation (7), T_{ijk} represents the total time traveled. (i, j) represents the path traveled. $F(g_{ij})$ signifies the fuel consumption of the refrigeration unit generator in the cold chain vehicle. In light of the considerable variation in the loads of different cold chain vehicles and the marked differences in the fuel consumption of refrigeration units at different times of year, the calculation method of fuel consumption is subjected to rigorous and comprehensive analysis. Numbers 1 to 4 represent prefabricated cold, in delivery, loading and unloading, and returning after completion. Cold chain truck transportation is shown in Fig. 4.

Cold chain vehicles need to be placed in the logistics center's cold storage for full refrigeration before the delivery task departs. It can effectively avoid the aggravation of agricultural product spoilage caused by filling effects [20]. The research assumes that the time required for a single cold chain vehicle to enter the warehouse for refrigeration is T_p. Moreover, the fuel consumption calculation of the unloaded cold chain vehicle refrigeration unit at this time is shown in Eq. (8).

$$F_1 = \sum_{k=1}^{K} R_0 Z_k T_p \tag{8}$$

In Eq. (8), F_1 is the fuel consumption of the refrigeration unit. After the final stage of service, the delivery unit needs to be shut down to save energy. At this time, the cold chain truck is in an unloaded state. The fuel consumption calculation for the journey back to the logistics center is shown in Eq. (9).

$$F_2 = \sum i, j \in N, i \neq j \sum_{k=1}^{K} X_{ijk} f_c(g_{ij})(T_{ijk} - T_{j0k}) \tag{9}$$

In Eq. (9), F_2 represents the fuel consumption of the cold chain vehicle when the refrigeration unit is turned off and unloaded. Therefore, it can be inferred that the economic cost of refrigeration fuel is calculated, as shown in Eq. (10).

$$C_{21} = P_2(F_1 + F_2) \tag{10}$$

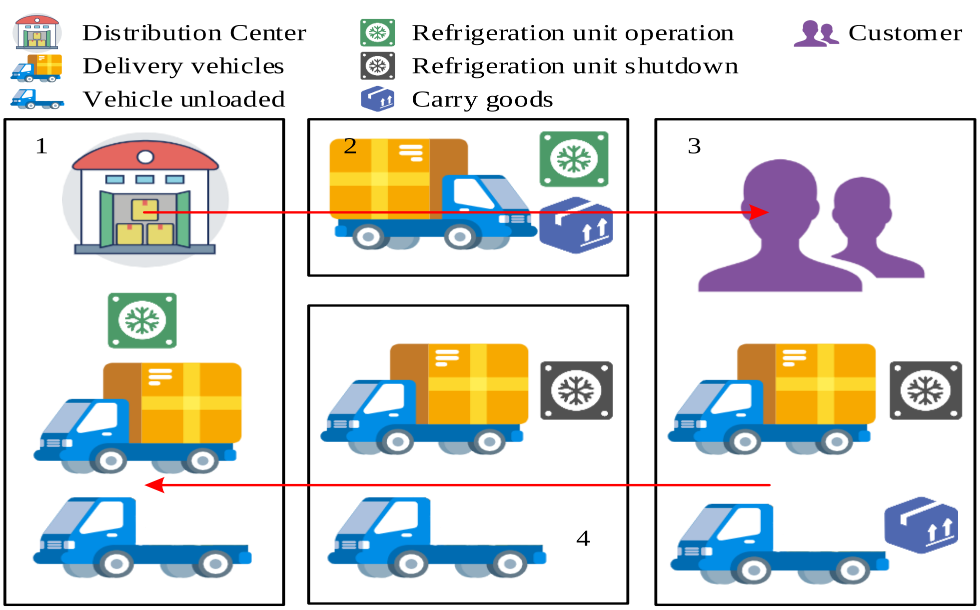

Fig. 4. Cold chain vehicle delivery process diagram.

In Eq. (10), C_{21} represents the economic cost of refrigeration fuel. The fuel consumption and carbon dioxide emissions of delivery vehicles during the delivery process are calculated, as shown in Eq. (11).

$$fuel = \chi \left(\begin{array}{l} FeNeVe\dfrac{d}{v} + \eta\beta d\left(v\right)^2 + \\ \eta\alpha d\left(G_d + G_i\right) \end{array} \right) \tag{11}$$

In Eq. (11), $fuel$ represents the fuel consumption of the delivery vehicle. v represents the return speed. d represents the distance between the location of the last delivery task and the logistics center. Fe represents the friction index. Ne represents the engine speed of the cold chain vehicle. Ve represents the carbon emissions of cold chain vehicles. G_d represents the weight of the cold chain vehicle during the return journey. G_i represents the cold chain vehicle load. The research takes into account the distribution costs generated during the distribution process. The final constructed agricultural product distribution path optimization model is shown in Eq. (12).

$$\begin{aligned} \min Z = {} & c_p \sum_{k\in K}\sum_{j\in V'} x_{0jk} + \\ & c_t\left(\sum_{i\in V'} a_i + \sum_{i\in V'} w_i + \sum_{k\in K}\sum_{(i,j)\in A} x_{ijk}t_{ij}\right) \\ & + c_f \sum_{k\in K}\sum_{(i,j)\in A} x_{ijk} f_{ij} + c_e \sum_{k\in K}\sum_{(i,j)\in A} x_{ijk} e_{ij} \end{aligned} \tag{12}$$

In Eq. (12), c_p represents the cost of dispatching. c_t represents the cost of transportation labor. a_i signifies the time when the delivery vehicle arrives at customer i. w_i signifies the waiting time before the vehicle starts transportation. x_{ijk} represents the transportation vehicle k traveling from node i to customer j. c_f represents the fuel consumption cost. c_e represents the carbon emissions cost. To ensure that the freshness of agricultural products received by consumers exceeds the expected requirements, the calculation is shown in Eq. (13).

$$\theta_i \geq \theta_r, \quad \forall i \in V' \tag{13}$$

In Eq. (13), θ_i represents that the agricultural products are within the freshness expected by consumer i. θ_r represents the minimum freshness that consumers can accept. The waiting time for the delivery vehicle of agricultural products to consumers is shown in Eq. (14).

$$w_i = b_i - a_i, \quad \forall i \in V' \tag{14}$$

In Eq. (14), w_i represents the waiting time before the delivery vehicle starts transportation. b_i represents the time when consumer i started being served. The time for the consumer to confirm receipt, the delivery vehicle to leave the delivery point, and proceed to the next service point is displayed in Eq. (15).

$$\tau_i = b_i + s_i, \quad \forall i \in V' \tag{15}$$

In Eq. (15), τ_i signifies the time when the delivery vehicle leaves after completing the task. s_i represents the time when consumers accept agricultural products. The calculation results of the model constructed represent the set of distribution paths for cold chain vehicles. Meanwhile, the study enhances the ALNS algorithm by incorporating insertion and removal operators, specifically the ordering consumer. The improved ALNS algorithm is shown in Fig. 5.

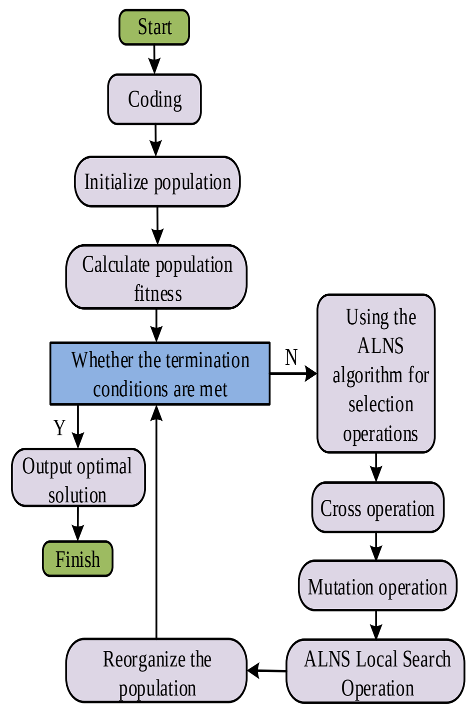

Fig. 5. Optimized ALNS algorithm.

The distribution of agricultural products exhibits regional characteristics, with a greater concentration observed in urban residential areas. The service distance for consumers in close proximity to one another is approximately equivalent [21,22]. The transportation path needs to meet various delivery conditions of the waybill, ensuring smooth driving, less congested road sections, and less freshness loss. Therefore, based on the density of distribution tasks, the supply chain hub is established. The distribution hub combined with the distribution path optimized by ALNS can ensure the freshness of agricultural products reaching consumers. Cold chain vehicles can also minimize consumption. The red dots represent the points at which consumers are required to complete delivery tasks when placing orders. The black five-pointed stars represent the points at which supply chain hubs are constructed. The overview of distribution tasks and hub construction is shown in Fig. 6.

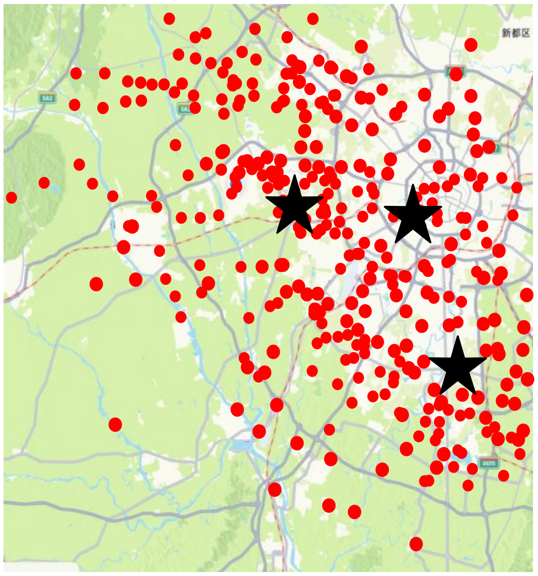

Fig. 6. Overview of distribution tasks and hub construction.

III. Results

To display the effectiveness of the improved ALSN in optimizing the transportation path of agricultural products, a set of case studies were conducted. Firstly, a standard test case was constructed to compare the driving paths of cold chain vehicles. Next, C201, R201, and CR201 were used to conduct case studies to further validate the freshness and total cost of agricultural products. Finally, the path results before and after ALSN algorithm optimization were compared.

A. Effectiveness of Distribution Route Optimization in Agricultural Product Supply Chain Decision Management

Due to the high demand for freshness in agricultural products, a cold chain distribution route model for agricultural products was constructed. Relevant experimental data required for the model was supplemented. The Solomon standard test case was used to conduct numerical experiments on the adapted ALNS algorithm. The experiment adopted Windows 10, 64 bit operating system, and the processor uses Intel® Xeon® Platinum 8124 M, with 64 CB memory. The experiment was conducted using Solomon standard test cases adapted and downloaded from the website neo.lcc.uma.exe/vrp/solution methods/. An example of a set of 100 consumers was analyzed. Class C refers to densely distributed consumption points, Class R refers to dispersed consumption points, and CR refers to consumption points with cross distribution. The experiment mainly focused on C201, R201 and CR201 sets for example analysis. Therefore, the distribution path scheme of the six cold chain vehicles presents two states, as shown in Fig. 7.

From Fig. 7(a), before the optimization of the distribution path, the path was relatively chaotic and cumbersome. Six cold chain vehicles crossed the central hub significantly, resulting in high transportation costs and low efficiency. Fig. 7(b) shows the optimized distribution route. The transportation of each cold chain truck was in an orderly manner. Among them, vehicles 3 and 4 had a wider service range due to their larger capacity, while vehicle 5 had a narrower time window constraint and presented a narrow and short driving path due to its urgent service demand at consumer points. The cost of six vehicles and the freshness delivered to consumers are displayed in Table I.

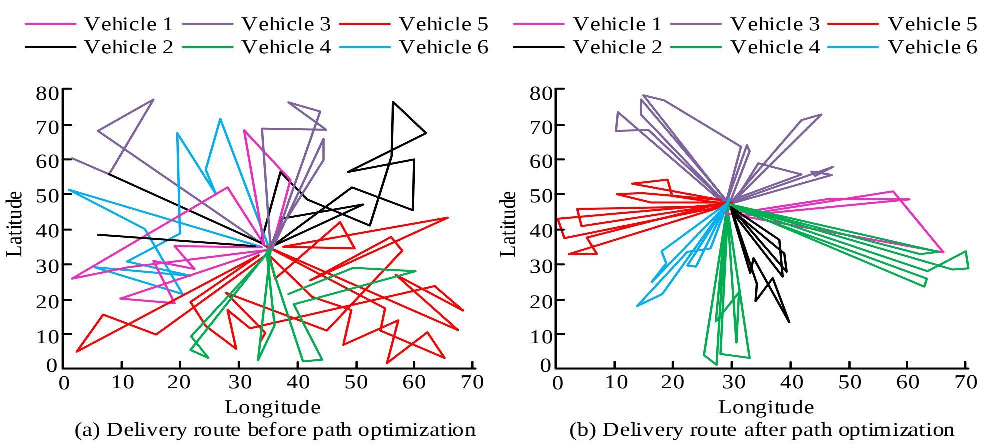

Fig. 7. Delivery path plan for cold chain vehicles.

TABLE I. THE CORRELATION EVALUATION COEFFICIENTS OF THE EXPERIMENT AND THE CALCULATED RESULTS

Example number	Total cost	Vehicle cost	Labor costs	Fuel cost	Low carbon cost	Average freshness	Medium speed driving ratio	Algorithm running time
CR101	1457	1540	23	35	8	90.96%	19.26%	153 s
CR201	764	700	26	31	7	82.86%	21.17%	195 s
R101	1676	1600	25	33	8	92.55%	22.19%	149 s
R201	657	600	24	27	6	80.81%	20.72%	199 s
C101	2533	2220	106	40	9	80.86%	21.66%	145 s
C201	2350	2200	103	39	8	81.17%	19.31%	194 s

From Table I, in order to evaluate more objective and accurate path optimization examples, the agricultural products delivered to consumers were all delivered with average freshness and moderate transportation speed. The lowest total cost for R201 transport set was 657. The highest total cost of C101 was 2533, with the lowest vehicle cost consumption of R201 at 600 and the highest consumption of C101 at 2220. The minimum running time of the algorithm was C101, taking 145 s, and the maximum time was R201, with a total time of 199 s. All values of CR201 were average values, and the optimized delivery path was within this average value, with high fault tolerance, which could meet consumers' requirements for freshness of agricultural products, and the cost was also within a reasonable range. The ALNS algorithm used the following parameters when calculating the substitution example: maximum number of customers removed 15 (N), weight response coefficient 0.9 (ρ), weight score σ 1 (50), weight score σ 2 (20), weight score σ 3 (5), weight score σ 4 (0), and initial annealing temperature 5000 (Te). The numerical variation of the global optimal solution with specific values is shown in Fig. 8.

In Fig. 8, C201 showed a downward trend before 200 iterations, dropping from 3500 to around 2500. After 200 iterations, the value remained constant at 2400, with small fluctuations. The overall trend of R201 values was roughly consistent with C201, with a decrease from the highest value of 2300 before 250 iterations to 1600. After 250 iterations, the values fluctuated around 1600. CR201 showed significant fluctuations before 450 iterations, with values dropping from 1200 to 700, but the overall change was flat. This indicated that as the iteration increases, the optimal solution converged, and the weights of the three sets of examples decreased. Operators were quickly stacked in the early stage, which maximized the probability of obtaining the global optimal solution.

B. Analysis of Factors Influencing Delivery Routes based on Improved ALNS Algorithm

In order to further analyze the ALNS algorithm, it was necessary to compare the weights of the insertion and removal operators in the actual optimization effects during solving. The study mainly analyzed the Worst Removal (WOR), Wait-time Related Removal operator (WRR), Regret Insertion operator (REI). The calculation example was validated to obtain the updated weight values and their adaptability as the number of iterations increased. The iteration is shown in Fig. 9.

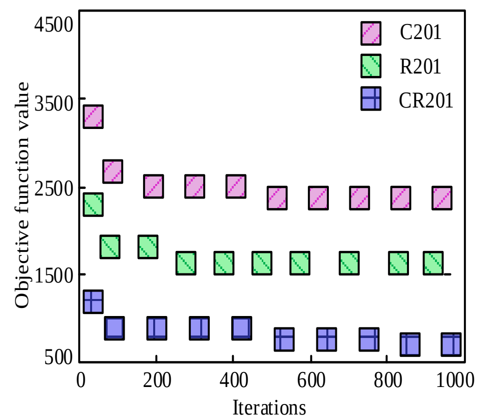

Fig. 8. Objective function iteration diagram.

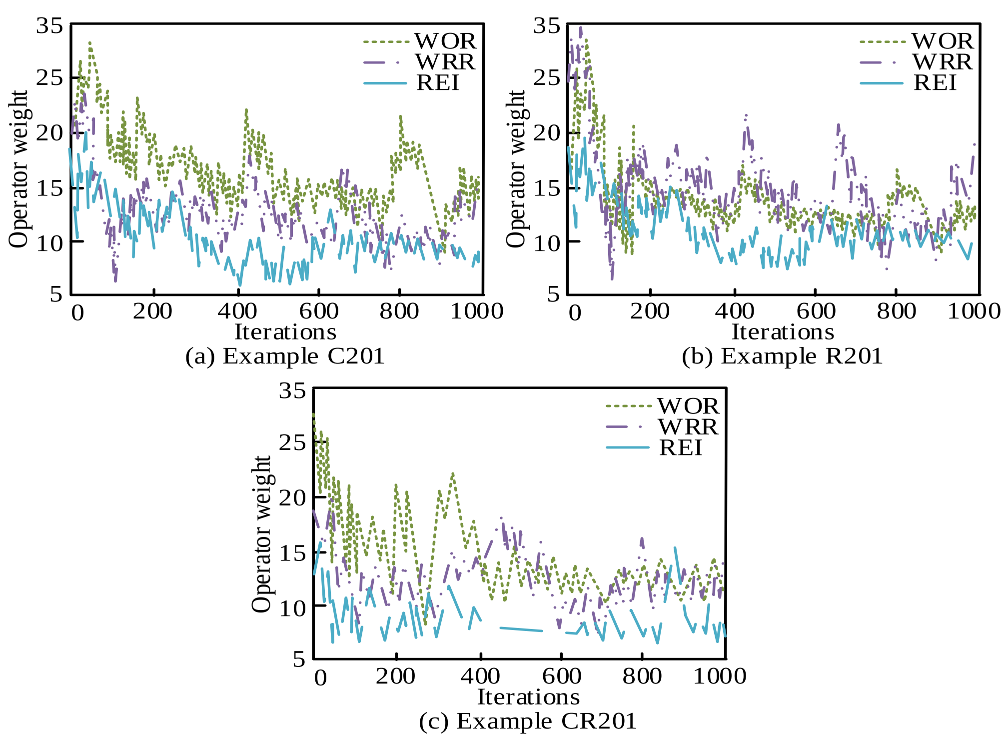

Fig. 9. Operator weights and usage iterations graph.

As shown in Fig. 9(a), the WOR operator had a higher iteration weight in example C201, which was much higher than WRR and REI. It had significant changes in the overall curve, with the highest weight value of 33 and the lowest weight value of 11. The WRR operator was in the middle, with a minimum weight value of 6 and a maximum weight value of 24. The weight values of the REI operator were the highest at 17 and the lowest at 7. In Fig. 9(b), the WRR operator had the highest weight of 35 and the lowest weight of 7. The overall curve position and most of the values were higher than the other two operators, which indicated that WRR had the highest proportion of weights. The WOR operator was the median curve, with a maximum weight of 34 and a minimum weight of 8. The maximum weight value of the REI operator curve was 19, and the minimum was 7. In Fig. 9(c), in the CR201 example, the weight values of the WOR operator were relatively stable in the later stage, with a maximum of 26 and a minimum of 9. The overall fluctuation of the WRR operator curve was uniform, with a maximum of 19 and a minimum of 7. The weight value curve of the REI operator had the smallest variation, with a maximum value of 17 and a minimum value of 6. This demonstrated that the improved algorithm yielded more accurate results. The running results before and after improvement is displayed in Fig. 10.

In Fig. 10, the purple color represented the unimproved ALNS algorithm. Among them, C201 took 194 s to calculate 2495 objective function values, R201 took 199 s to calculate 699 objective function values, and CR201 took 195 s to calculate 768 results. The green color represented the improved ALNS algorithm. Among them, C201 took 244 s to calculate 2350 objective function values, and R201 took 239 s to calculate 657 objective function values. The CR201 example took 233 s to attain 764 objective function values. This indicated that the improved ALNS algorithm had higher efficiency and less time consumption in the same number of iterations. The decay rate also affected the delivery quality of agricultural products. Based on a decay rate of 0.01, the study incorporated the rates of each stage of agricultural products into the improved ALNS algorithm for optimal solution calculation, as shown in Fig. 11.

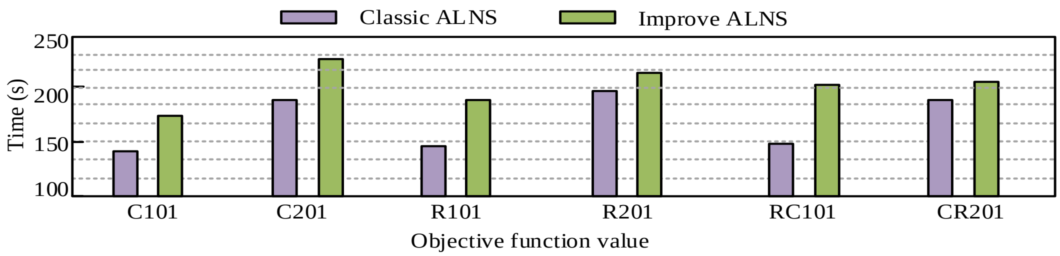

Fig. 10. Comparison of running results before and after algorithm improvement.

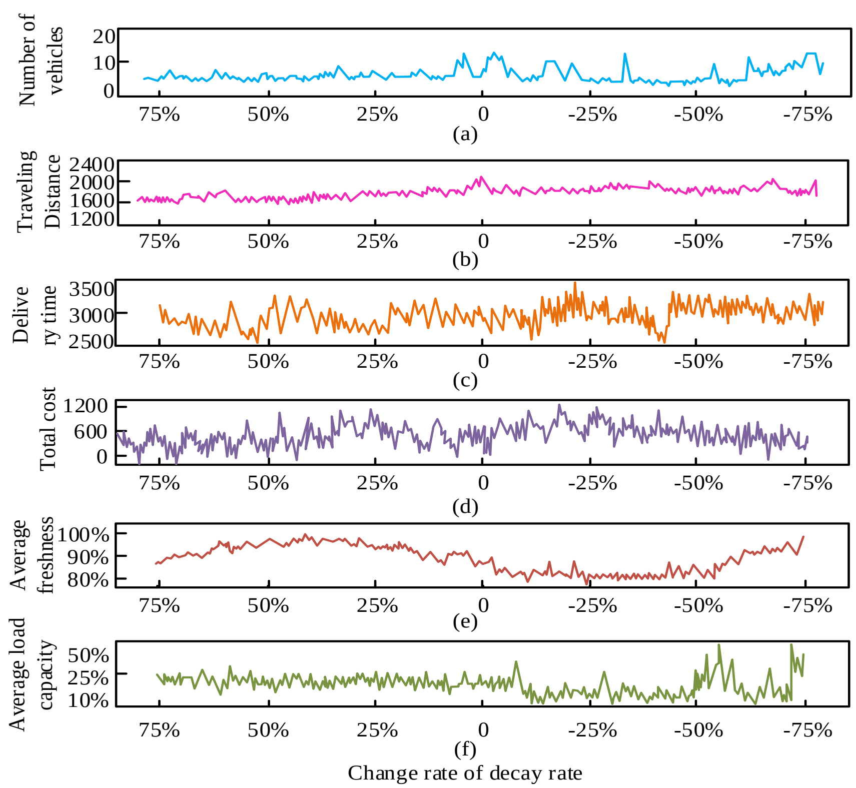

Fig. 11. Analysis of the calculation results of decay rate.

Fig. 11(a) shows the number of transportation vehicles for agricultural products. At a decay rate of 75%, the maximum number of transport vehicles reached 11. In Fig. 11(b), the driving distance was the lowest at a speed of -75%, only 1510 km. In Fig. 11(c), the delivery time was the highest at a 25% decay rate, reaching 3043 minutes, and the lowest at a 50% rate, reaching 2478 minutes. The total cost in Fig. 11(d) was directly proportional to the change in decay rate. In Fig. 11(e), when the decay rate was -75%, the freshness was as high as 91.89%. When the rate was 25%, the freshness remained the lowest at 81.55%. In Fig. 11(f), when the decay rate was -75%, the freshness was as high as 91.89%. When the rate was 25%, the freshness remained the lowest at 81.55%. From this, in practical application, the optimized path for delivering agricultural products was faster and more efficient, with the lowest cost and the best freshness.

IV. Discussion

As the demand for fresh produce delivery increases, consumers have demands for delivery times and product freshness. Therefore, the study proposes an improved ALNS algorithm for optimizing the cold chain distribution path of agricultural products, taking into account product characteristics comprehensively. The results showed that after analyzing the optimized distribution models C201, R201, and CR201, the total cost of the R201 transportation set was the lowest at 657 and the highest at 2533. The lowest vehicle cost consumption was 600 for R201 and 2220 for C101. The minimum runtime of the algorithm was C101, taking 145 s. Moreover, the maximum runtime was R201, with a total runtime of 199 s. All values of CR201 were average, with high fault tolerance. The improved ALNS algorithm was used to solve the operator optimal solution, and the C201 case took 244 s to calculate 2350 objective function values. The R201 example took 239 s to obtain 657 objective function values. The CR201 example took 233 s to obtain 764 objective function values. The study optimized the delivery path by combining the ALNS algorithm to ensure that the average freshness of agricultural products was above 80%. The lowest loss cost was achieved when the spoilage rate was between -25% and -75%. The higher the decay rate, the more cold chain vehicles were used, and the lower the decay rate, the shorter the driving distance. When the delivery time was at a decay rate of 25%, it took the most time, reaching 3043 minutes. Moreover, the lowest consumption was at a rate of 50%, 2478 minutes. The improved ALNS algorithm proposed in the study has significant advantages in optimizing the cold chain distribution path of agricultural products and can provide a reference for path optimization in the agricultural product distribution industry. Nevertheless, research is predominantly grounded in historical empirical data, which limits its practical applicability. In the future, there is the potential for greater use of real-time data in research.

V. Conclusion

The research proposes an improved ALNS algorithm for optimizing the cold chain distribution path of agricultural products. By combining the ALNS algorithm to optimize the distribution path, the average freshness of agricultural products was ensured to be above 80%, and the lowest loss cost was achieved when the decay rate was between -25% and -75%. Ni C et al. also obtained similar data for the verification calculation of the freshness of cold chain vehicles, which proved that the higher the decay rate, the more cold chain vehicles were used, the lower the decay rate, and the shorter the driving distance [23]. When the decay rate was -75%, the freshness reached 91.89%. Moreover, when the rate was 25%, the freshness remained the lowest at 81.55%. Wofuru Nyenke O et al. also obtained similar data on freshness preservation under different decay rates, proving the effectiveness of the research experiment [24]. When the delivery time was at a decay rate of 25%, it took the most time, reaching 3043 minutes. Moreover, the lowest consumption was at a rate of 50%, 2478 minutes. Bao H et al. also obtained similar data in their experiment on the effect of cold chain truck delivery time on the spoilage rate of agricultural products [25]. This indicates that the improved ALNS algorithm proposed in the study has significant advantages in optimizing the cold chain distribution path of agricultural products and can provide a reference for path optimization in the agricultural product distribution industry.

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