VEHICLE PATH OPTIMIZATION OF AGRICULTURAL PRODUCTS COLD CHAIN LOGISTICS BASED ON GREEN EVALUATION
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基于绿色评价的农产品冷链物流车辆路径优化分析

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ABSTRACT
With the development of the economy and society and the improvement of living standards, the demand for fresh products is increasing, and the huge demand has driven the rapid growth of fresh products in China. However, fresh products are prone to spoilage and wear, and higher transportation requirements are put forward to ensure product quality. Based on this, the transportation function of cold chain logistics vehicles on farm products cold chain logistics greatly improves the cold chain transportation efficiency of agricultural products. Aiming at the vehicle path problem of cold chain logistics distribution and under multiple refrigerated trucks, a single distribution center, and multiple commodity types, a path optimization model of cold chain logistics vehicles was established with the optimal evaluation of total distribution cost and distribution vehicles as the objective considering the economy, greenness, and sustainability of vehicles. Then, an evaluation index system of refrigerated trucks consisting of cost index, environmental index and quality index was established, an AHP-TOPSIS (Analytic Hierarchy Process, Technique for Order Preference by Similarity to an Ideal Solution) evaluation model of refrigerated trucks was constructed, and the comprehensive evaluation value of refrigerated trucks was obtained. On the basis of vehicle evaluation results, the corresponding vehicle path optimization model of agricultural cold chain logistics was established, the large-scale neighborhood search SA algorithm was designed to solve an example, and the optimization model was compared with the optimization model without considering vehicle evaluation. The experimental results show that considering the vehicle evaluation factors can effectively reduce the distribution cost, and increasing the vehicle evaluation weight can effectively improve the greenness and sustainability of the distribution fleet.

摘要
随着经济社会的发展和生活水平的提高，人们对生鲜产品的需求量越来越大，巨大的需求量推动了中国生鲜产品的快速增长。然而生鲜产品具有易腐易损性，为了保证产品的品质对运输提出了更高的要求。基于此，冷链物流车辆对农场品冷链物流的运输作用大大提升了农产品冷链运输效率。针对冷链物流配送的车辆路线问题，在多冷藏车、单配送中心、多商品类型的条件下，考虑车辆的经济性、绿色与可持续性，以配送总成本和配送车辆的最优评价为目标，建立冷链物流车辆路线优化模型，建立由成本指标、环境指标和质量指标组成的冷藏车评价指标体系，构建 AHP-TOPSIS 法的冷藏车评价模型，得到了综合考虑的冷藏车评价值。在车辆评价结果的基础上，建立相应的农业冷链物流车辆路线优化模型，设计改进蚁群算法求解算例，并将优化模型与不考虑车辆评价的优化模型进行比较。实验结果验证，考虑车辆评价因素可以有效降低配送成本，增加车辆评价权重可以有效提高配送车队的绿色和可持续性。

INTRODUCTION
The green and low-carbon transformation of logistics industry is an important bridge and channel for the comprehensive green transformation of industrial chain and supply chain. The International Energy Agency (IEA) released a piece of data—transportation carbon emissions accounted for 26% of global carbon emissions in 2020.

According to the research of Green Logistics Branch of CPAG GROUP, the carbon emission of the logistics industry in China reached 880 million tons in 2020, and the carbon emissions of transportation and distribution activities accounted for about 85% of the carbon emissions of logistics industry in China, where loading/unloading and warehousing activities accounted for about 10% and auxiliary logistics activities for about 5%. It is predicted that the carbon emissions of the logistics industry will continue to show an upward trend in a long time. Thus, the low-carbon development of the logistics industry plays a vital role in the implementation of China's double-carbon (peak carbon and carbon neutral) strategy. With the social and economic development and the improvement of living standards, people's demand for fresh products is increasing, which has promoted the rapid growth of fresh products in China *(He M. et al., 2021)*. Fresh products are perishable and vulnerable, and higher requirements are put forward for transportation in order to ensure the quality of products *(Fan H.M. et al., 2018)*. Cold chain logistics has obvious advantages in ensuring product quality and reducing product loss by effectively controlling the temperature. Cold chain logistics has received more attention and development, and meanwhile, it has also put forward new requirements for cold chain logistics enterprises.

According to the statistics of China Mobile Source Environmental Management Annual Report (2021), by 2020, among the 281 million motor vehicles (automobiles) in China, the traditional fuel vehicles were the main force to carry out the traditional agricultural products cold chain distribution and transportation business with the ultra-high data of 98.25%. The data showed that trucks in China emitted 2.073 million tons of carbon monoxide (CO), 5.178 million tons of nitrogen oxides (NOx), 460,000 tons of hydrocarbons (HC), and 58,000 tons of particulate matter (PM), accounting for 29.8%, 84.3%, 26.6%, and 90.9% of the total automobile emissions *(Chen W.Z. et al., 2020)*. High-carbon emission and greenhouse effect are not conducive to environmental development, which is largely attributed to the use of fuel vehicles in quantity. At the same time, for logistics enterprises, the rising oil price and fuel tax expenditure have further squeezed the industry profits under pressure due to changes in the competitive pattern. Under the dual pressures of environmental protection and industrial upgrading, in recent years, the state is actively introducing policies to develop green logistics and vigorously promoting the application of new energy vehicles represented by electric vehicles in the logistics field *(Chen S. et al., 2018)*. For instance, nine departments like the Ministry of Commerce and the Ministry of Transport jointly issued the "Special Action Plan for High-quality Development of Commercial Logistics (2021-2025)", which required to vigorously promote energy-saving and clean energy transportation tools and logistics equipment and guide logistics distribution enterprises to use new energy vehicles or clean energy vehicles. In addition, by 2021, the target, i.e., the proportion of new energy bus stops for logistics distribution vehicles in the key areas of air pollution prevention and control and the national ecological civilization experimental zones was higher than 80%, was put forward in the "New Energy Automobile Industry Development Plan (2021-2035)" issued by the State Council.

STATE OF THE ART

As an important link in cold chain logistics, the distribution of fresh agricultural products plays a vital role in the path programming of distribution vehicles, so it has been widely studied. The existing literature is mainly based on basic model settings, e.g., a single distribution center, the same refrigerated vehicle, a single product, and each customer is served by only one vehicle, with time window constraints *(Shukla M., 2013; Wu H. et al., 2021; Dorigo M. et al., 2006; Pérez-Rodríguez R. et al., 2019)*. In Literature *(Bauernhansl T., 2016; Chiang W.C. et al., 1996; Li B. et al., 2019)*, a heterogeneous fleet was adopted in the model, and in Literature *(LI Z. et al., 2019)*, the model was solved using a threshold algorithm, but the time window constraint was not considered. In Literature, it was verified that a heterogeneous fleet could effectively reduce the distribution cost and improve the capacity utilization rate of distribution vehicles *(Aggarwal D. et al., 2018)*. In Literature, a green vehicle routing problem model of joint distribution was established, in which cold chain logistics enterprises completed the distribution task by considering carbon tax policy and cooperating with each other. It was found that joint distribution could effectively reduce the total cost and carbon emissions compared with single distribution *(Govindan K. et al., 2014)*. In Literature, the vehicle routing problem under multiple distribution centers was considered, and a semi-open joint distribution mode with multiple distribution centers was proposed and solved by designing the ant colony algorithm *(Nwakaire C.M. et al., 2015)*. The conclusion proves that the distribution process in this mode is better than that in case of a single distribution center.

In Literature, carbon emissions were transformed into costs in the path optimization model of cold chain logistics with multiple distribution centers, and the multi-distribution center model was transformed into a single distribution center model by introducing virtual parking lots and solved using an improved genetic algorithm *(Ellabib I. et al., 2007)*. Energy conservation and emission reduction have become a global consensus, and low-carbon technology and low-carbon economy have attracted widespread attention around the world *(Han X. et al., 2019)*. As a major consumer of fuel and carbon emissions, logistics industry, especially cold chain logistics, needs to consume more energy to ensure the quality of products compared with normal temperature logistics *(Zhou X. et al., 2011)*. The environment is more prominently affected by the high energy consumption and high carbon emission characteristics of cold chain logistics, so it is very important to reduce the energy consumption of cold chain logistics and realize green and sustainable development *(Cordeau J-F. et al., 2001)*. With the development of the automobile industry and the response to the low-carbon policy in recent years, in addition to the traditional diesel fuel refrigerated trucks, pure electric refrigerated trucks and refrigerated trucks using mixed fuels, biodiesel, and natural gas have also developed rapidly and are widely used in the cold chain transportation of fresh products.

In cold chain transportation, logistics companies need to make decisions over the use of different vehicle types, and vehicle evaluation mainly provides valuable information for vehicle selection. Vehicle evaluation mainly refers to the establishment of a relevant evaluation system, and the quantitative ranking calculation of vehicle performance and vehicle transportation process indexes by using some evaluation methods. Based on the basic characteristics of green design, in Literature, a comprehensive evaluation system was established for the green design of construction vehicles and the ideas for the green evaluation of engineering vehicles were provided *(Shaw P., 1998)*. In Literature, the drivers' psychological and physiological loads during driving were considered, and the comfort and safety of vehicles were evaluated through heart rate variability *(Mohammed M.A. et al., 2017)*. In Literature, the fuzzy analytic hierarchy process (AHP) was adopted to comprehensively evaluate the performance of armored vehicles *(Venkata N.K. et al., 2013)*.

In Literature, an evaluation index system composed of five aspects—trafficability, dynamic performance, operability, safety, and economy—was established, the TOPSIS method was applied to evaluate the scheme and make fuzzy operation, and the evaluation result of large transport vehicles were acquired *(Liu H. et al., 2014)*.

Through the recent literature research on vehicle path optimization and vehicle evaluation of agricultural cold chain logistics, it is found that vehicle system evaluation has been involved in few literature documents, and the vehicle path optimization of agricultural cold chain logistics is mainly based on a single distribution center and a single vehicle type. In this paper, the economy and sustainability of vehicles were comprehensively considered, and a green vehicle routing problem model with multiple vehicles and commodity types was established under the background of cold chain logistics. Firstly, the vehicle evaluation was performed using the AHP-TOPSIS method, and an evaluation index system of vehicles was constructed from three dimensions, namely, environmental index, cost index, and quality index. Given the vague judgment on complex things, the qualitative evaluation results were quantified by triangular fuzzy numbers, and the comprehensive evaluation model of vehicles was established by combining AHP and TOPSIS methods. The vehicle evaluation value and the total distribution cost were obtained to constitute the objective and establish a model, which was then solved by designing an improved simulated annealing (SA) algorithm. Finally, the effectiveness and feasibility of the models and algorithms established in this paper were verified through a practical example, providing methodological guidance and decision-making support for the distribution process and management.

MATERIALS AND METHODS

In this paper, the vehicle routing problem of a single agricultural products cold chain logistics distribution center with soft time window constraint and capacity restriction was explored. In the model, different types of refrigerated vehicles completed the distribution work of a variety of commodities using the distribution strategy of split delivery. The vehicle distribution route that may exist in multiple distribution centers under the split delivery mode is shown in Fig. 1.

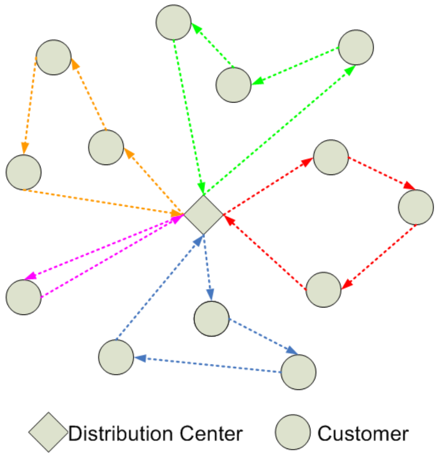

Fig. 1 - Vehicle path network model of agricultural products

The assumptions of the vehicle path optimization model of agricultural products cold chain logistics are as follows:

(1) There is one distribution center, multiple refrigerated vehicles for transportation, and multiple customers in the model.

(2) The distribution center has different quantities and models of refrigerated vehicles, each of which has a certain capacity limit.

(3) The geographical locations of the distribution center and customers are known, the demand of customers is fixed and known, and the distribution center has no demand.

(4) In all distribution processes, the starting point must be the agricultural product distribution center, and the distribution process must end with completing the agricultural product distribution task and returning to the agricultural product distribution center.

(5) Each customer has its own prescribed time window and acceptable time window, and each customer is served by at least one vehicle.

(6) Agricultural products are divided into many types, the storage and transportation temperature conditions of each agricultural product are the same, and the distribution mode of split delivery is adopted.

Mathematical Model

To transform the constrained optimization problem into the unconstrained optimization problem, the penalty function method was used in this paper. A penalty cost was added to this relaxation mechanism, and the solutions violating the capacity and time window constraints were accepted by means of penalty, so as to enhance the diversity of solutions *(LI Z. et al., 2019)*. The penalty coefficient for violating the time window constraint could be set according to the compensation mechanism formulated by the enterprise. Because it was not allowed to violate the capacity constraint in the actual transportation process, the penalty coefficient for violating the capacity constraint should be as large as possible. The sets, parameters, and variables are defined as follows:

Sets: N is a customer set, N={1, 2, 3, ..., n}; V is a node set, $V=\{0\} \cup N$, and 0 represents the distribution center; M is a vehicle set $M=\{1,2,3,...,k\}$.

Parameters: Q is the maximum loading capacity of the vehicle $k(k \in M)$; c_k denotes the fixed cost of each vehicle; c_{ij} is the driving cost generated by a unit distance; q_i is the cargo quantity demanded by the customer $i(i \in N)$; d_{ij} is the Euclidean distance between nodes i and j $(j \in N)$; v is the vehicle velocity; e_i is the earliest service time designated by the customer $i(i \in N)$; l_i is the latest service time designated by the customer i; e_0 and l_0 are the earliest opening time and deadline of the distribution center, respectively; S_i is the service time needed by the customer $i(i \in N)$; α $(\alpha \in N^+)$ represents the penalty coefficient of violating the capacity constraint; $\beta(\beta \in N^+)$ is the penalty coefficient of violating the time window constraint.

Decision variables: x_{ij}^k is the driving variable of the vehicle k, $x_{ij}^k=1$ if the vehicle k drives from the node i to the node j, otherwise, $x_{ij}^k=0$; t_{ki} is the arrival time of the vehicle k at the node i; t_i is the starting service time for the node i; w_{ik} is the waiting time for the vehicle k earlier than e_i; l_{ik} is the delay time of the vehicle k later than l_i; q is the sum of the exceeding part of the total demand of each path from the maximum vehicle load in the solution, $q=\sum_{k=1}^{K}\max\{0,(\sum_{i=1}^{n}q_i x_{jk}-Q)\}\quad(\forall k\in M,\forall i\in N)$; w is the sum of the delayed part of vehicle arrival time from the latest service time in the solution, $w=\sum_{k=1}^{K}l_{ik}(\forall k\in M,i\in V)$.

$$f=c_k\sum_{j=1}^{n}\sum_{k=1}^{K}x_{0j}^{k}+c_{ij}\sum_{i=0}^{n}\sum_{j=0,j\neq i}^{n}\sum_{k=1}^{K}d_{ij}x_{ij}^{k}+\alpha q+\beta_W \tag{1}$$

$$s.t.$$

$$\sum_{j=1}^{n}x_{ij}^{k}=\sum_{i=1}^{n}x_{i0}^{k}\left(\forall k\in M\right) \tag{2}$$

$$\sum_{k=1}^{K}\sum_{j=1,j\neq i}^{n}x_{ij}^{k}=1,\left(\forall i\in V\right) \tag{3}$$

$$\sum_{i=0,i\neq j}^{n}\sum_{j=0}^{n}x_{ij}^{k}\leq 1,(\forall k\in M) \tag{4}$$

$$t_{ij}=\frac{d_{ij}}{v},\left(\forall i,j\in V,i\neq j\right) \tag{5}$$

$$t_i=t_{ik}+w_{ik},(\forall i\in N,\forall k\in M) \tag{6}$$

$$t_{0k}=e_0,\left(\forall k\in M\right) \tag{7}$$

$$w_{ik}=max\{0,(e_i-t_{ik})\},\left(\forall i\in N,\quad \forall k\in M\right) \tag{8}$$

$$l_{ik}=max\{0,(l_i-t_{ik})\},(\forall i\in N,\forall k\in M) \tag{9}$$

$$\sum_{i=1}^{n}q_i x_{ij}^{k}\leq Q,\left(\forall j\in V,i\neq j,\forall k\in M\right) \tag{10}$$

$$l_{0k}=max\{0,\sum_{j=0}^{n}\sum_{i=0,j\neq j}^{n}x_{ij}^{k}(t_i+s_i+t_i j)-l_0)\},\left(\forall k\in M\right) \tag{11}$$

where in Formula (1) is an objective function; Constraint (2) ensures that each vehicle leaves and returns to the distribution center only once; Constraints (3) and (4) ensure that each customer is served by one vehicle only once; Constraint (5) represents the travel time from node i to node j; Constraint (6) indicates the starting service time of the node; Constraint (7) ensures that each vehicle starts service within the opening hours of the distribution center; Constraint (8) represents the waiting time of each vehicle at the node; Constraint (9) represents the delay time of each vehicle at the node; Constraint (10) indicates that the total demand of customer points served by each vehicle cannot exceed the maximum carrying capacity of the vehicle; Constraint (11) indicates the delay time of the vehicle in the distribution center after completing the service.

Vehicle Evaluation Model Based on AHP-TOPSIS

A model integrating TOPSIS and AHP was used to construct an evaluation index system of agricultural product distribution vehicles, and the weight of each index was determined. Refrigerated vehicles were evaluated based on the AHP-TOPSIS method, and the evaluation results were incorporated into the multi-center vehicle path optimization model of cold chain logistics.

In this paper, 6 types of refrigerated vehicles commonly used in distribution centers, namely electric refrigerated trucks, mixed fuel refrigerated trucks, gasoline refrigerated trucks, diesel refrigerated trucks, biodiesel refrigerated trucks, and natural gas refrigerated trucks, were used for the distribution center. The greenness, sustainability, and economy of vehicles were comprehensively considered when evaluating refrigerated vehicles, and a vehicle evaluation index system as seen in Table 1 was established.

Table 1

Vehicle evaluation index system

Objective layer	Level-II indexes	Symbol	Level-III indexes	Symbol
Vehicle evaluation	Cost index	C1	Vehicle cost	C11
			Fuel cost	C12
			Maintenance cost	C13
	Environmental index	C2	Carbon emission	C21
			Vehicle life	C22
			Noise	C23
			Fuel efficiency	C24
			Fuel availability	C25
	Quality index	C3	Safety	C31
			Comfort	C32
			Dynamic performance	C33

The system consists of three dimensions: cost, environment, and quality. In the process of vehicle evaluation, the economy of the vehicle should be considered first, that is, the operating cost of the vehicle, which mainly includes fuel cost, vehicle cost, and maintenance cost. Secondly, the green and sustainability of the vehicle are taken into account. The greenness of the vehicle is mainly reflected in its fuel emission and fuel efficiency. The fuel emission mainly refers to the impact of carbon dioxide and other gases emitted by the vehicle on the environment. The higher the fuel efficiency, the greener the fuel vehicle. Indexes related to vehicle sustainability include vehicle life and fuel availability, in which fuel availability refers to the availability of fuel; meanwhile, the noise pollution of vehicles during operation is considered. Finally, the quality of the vehicle mainly includes the safety and comfort of the vehicle during driving. The safety is evaluated mainly based on the accident rate of the vehicle. The lower the accident rate of the vehicle, the higher the safety. Comfort is evaluated mainly based on the criteria of improving the driving performance and operating performance.

In the establishment of the model, the objective layer, criterion layer, and measure layer are usually used as the hierarchical structure of the AHP method. Firstly, the judgment matrix can be easily constructed according to the hierarchical structure. Each factor with a downward membership (called criterion) is the first factor of the judgment matrix (located in the upper left corner), and the factors subordinate to it are arranged in the first row and the first column in turn, as shown in Formula (12).

$$A=(a_{ij})=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{12}$$

In Formula (12), n refers to the number of factors in the present layer, which are related to one criterion in the previous layer, and a_{ij} indicates the fuzzy scale. Then, the factors in each row of matrix A are continuously multiplied, and an n-order root is extracted, as shown in Formula (13).

$$w_i^* = \sqrt[n]{\prod_{j=1}^{n} a_{ij}}, i=1,2,\cdots,n \tag{13}$$

The weight w_i is solved as per Formula (14).

$$w_i = \frac{w_i^*}{\sum_{i=1}^{n} w_i^*}, i=1,2,\cdots,n \tag{14}$$

Afterward, the indexes in each column of matrix A are summed, as seen in Formula (15).

$$S_j = \sum_{i=1}^{n} a_{ij}, j = 1,2,\cdots,n \tag{15}$$

Then, λ_{max} is solved as seen in Formula (16).

$$\lambda_{max} = \sum_{i=1}^{n} w_i s_i \tag{16}$$

The eigenvalue of the judgment matrix A is solved to get the eigenvector W, which becomes the ranking weight of the attribute after normalization. To avoid weight errors and make the result of judgment matrix more realistic, a consistency test is needed. The specific formula for the consistency index is shown in Formula (17).

$$CI = {\lambda_{max} - n}\big/{n-1} \tag{17}$$

In Formula (17), n is the order of judgment matrix A. Table 2 presents the average random consistency index (CI) value of 1-9-order judgment matrices.

Table 2

Average random consistency index of 1-9-order judgment matrices

Matrix order	1	2	3	4	5	6	7	8	9
CI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46

The TOPSIS method is a method of ranking schemes by taking the “ideal solution” and “negative ideal solution” of multi-objective decision-making problems as standards, which is called the integrated distance evaluation method. The “ideal solution” is an optimal solution envisaged in the standardized original data matrix, while the “negative ideal solution” is the worst scheme. The relative closeness between the best and worst schemes is calculated to rank the evaluation results. The TOPSIS method removes the dimensional effect of different indexes by normalizing and co-trending the original data, which can objectively reflect the real gap between schemes. Firstly, m objectives (finite objectives) and n attributes are set, the evaluation value given by an expert to the attribute j of the objective i is x_{ij}, and then the initial judgment matrix V is:

$$V = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{18}$$

However, because the dimensions may vary from index to index, it is necessary to normalize the initial judgment matrix V to obtain the judgment matrix V' and get the Formula (19).

$$V' = \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1n} \\ x'_{21} & x'_{22} & \cdots & x'_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x'_{i1} & \cdots & x'_{ij} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ x'_{m1} & x'_{m2} & \cdots & x'_{mn} \end{bmatrix} \tag{19}$$

In Formula (19),

$$x'_{ij} = x_{ij}\Big/\sqrt{\sum_{k=1}^{n} x_{ij}^2}, i = 1,2,\cdots,m; j = 1,2,\cdots,n \tag{20}$$

Then, the information weight matrix B of the expert group for attributes is acquired through the AHP method to form the weighted judgment matrix Z, as seen in Formula (21).

$$Z = V^{'}B = \begin{bmatrix} x_{11}^{'} & x_{12}^{'} & \cdots & x_{1n}^{'} \\ x_{21}^{'} & x_{22}^{'} & \cdots & x_{2n}^{'} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i1}^{'} & \cdots & x_{ij}^{'} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^{'} & x_{m2}^{'} & \cdots & x_{mn}^{'} \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{i1} & \cdots & w_{ij} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ f_{i1} & \cdots & f_{ij} & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix} \tag{21}$$

The positive ideal solution f^*_j and negative ideal solution f'_j of the evaluation objective are obtained as per the weighted judgment matrix, as seen in Formula (22).

$$\begin{aligned} f_j^* &= \begin{cases} max(f_{ij}), j \in J^* \\ min(f_{ij}), j \in J^{'} \end{cases}, j = 1,2,...,n \\ f_j^{'} &= \begin{cases} min(f_{ij}), j \in J^* \\ max(f_{ij}), j \in J^{'} \end{cases}, j = 1,2,...,n \end{aligned} \tag{22}$$

In Formula (22), J^* is a benefit-type index and J' is a cost-type index. The Euclidean distance between each objective value and ideal value is solved as seen in Formula (23).

$$\begin{aligned} S_i^* &= \sqrt{\sum_{j=1}^{m}(f_{ij} - f_j^*)^2}, j = 1,2,...,n \\ S_i^{'} &= \sqrt{\sum_{j=1}^{m}(f_{ij} - f_j^{'})^2}, j = 1,2,...,n \end{aligned} \tag{23}$$

Finally, the relative closeness C_i^* of each objective is calculated as seen in Formula (24).

$$C_i^* = \frac{S_i^{'}}{S_i^* + S_i^{'}}, i = 1,2,...,m \tag{24}$$

The objectives are ranked based on the relative closeness C_i^* to form a decision-making basis.

Algorithm Design

In this paper, the large-scale neighborhood SA algorithm was implemented starting from a higher temperature. In the current neighborhood, the bi-directional random search technology based on probability was used, and a better solution in the neighborhood was guaranteed by the Metropolis sampling stability criterion. If the calculated optimal solution was not better than this solution, the random solution would continue to be generated in the neighborhood in the next cycle after annealing. On the other hand, the next larger neighborhood was calculated, and it was repeated with the continuous decrease of temperature until the termination criterion was met. The basic steps of the SAVN algorithm are as follows:

(1) The initial temperature t_0 is determined, and the current temperature is set to $t=t_0$; the neighborhood structure is represented by the set $\{N_k, k=1,2,\ldots,k_{max}\}$, and k=1 is set; an initial solution S_0 is generated; the current solution is set to $S=S_0$ and the historical optimal solution to $S_b=S_0$. (2) Whether the scheme reaches the algorithm termination criterion is judged, if yes, turn to (8), otherwise, the current optimal solution is set to $S_c=S$, and turn to (3). (3) Whether the sampling stability criterion is satisfied if judged, if yes, turn to (6), otherwise, a new solution S^* is randomly generated in the k-th neighborhood structure of S, $s^* \in N_k(s)$, and turn to (5). (4) If $min\{1, exp[-(f(s^*)-f(s))/t]\} \geq randrom[0,1]$, $S=S^*$ is set, and turn to (5), otherwise, turn to (3). (5) If $f(s)<f(S_c)$, $S_c=S$ is set, and turn to (3); otherwise, sc is unchanged, and turn to (3). If $f(s)<f(S_b)$, $S_b=S_c$ is set, and turn to (7); otherwise, $k=(k \; mod \; k_{max})+1$, and turn to (6). (6) Annealing is performed, $t=update(t)$ is set, and turn to (2). (7) The current optimal solution is output.

Before applying the meta-heuristic algorithm, a high-quality feasible solution can be searched using a small-scale heuristic algorithm as the initial solution of the meta-heuristic algorithm. In this paper, the basic steps of the Push-Forward Insertion Heuristic (PFIH) algorithm are described as follows:

(1) k=0 is set, an empty path is newly built, and k=k+1. According to the cost function of seed customers (Formula 16), a customer with the minimum cost is chosen as the seed from all the undistributed customers and inserted into the current path k.

(2) In the presence of any undistributed customer, turn to (3), otherwise, the algorithm is terminated.

(3) If an undistributed customer has feasible insertion points in the current path k, its insertion cost is calculated as per the insertion cost function (Formula 17), the undistributed customer with the minimum insertion cost is selected and inserted into the current path k, and turn to (2); otherwise, any undistributed customer fails to find any feasible insertion point in the current path, and turn to (1).

For the customer i to be inserted into an empty path, the cost function of the seed customer is set as follows:

$$c_i^{(1)} = -\alpha t_{0i} + \beta l_i + \gamma(\frac{|p_i - p_j|}{2\pi} \times t_{0i}) \tag{25}$$

Where p_i is the polar angle of the customer i relative to the station; p_j denotes the polar angle of the last served customer j on the previous vehicle path relative to the station; t_{ij} is the running time of the vehicle k on the path (i,j); l_i stands for the latest service starting time of the customer i. Generally, the three weight factors are set to $\alpha = 0.7, \beta = 0.2, \gamma = 0.1$.

For the customer w to be inserted into the arc (i,j), the insertion cost function consists of four parts: additional path cost, service cost, waiting cost, and subsequent waiting cost variation, as shown in Formula (26):

$$c_i^{(2)} = \left(c_{iw} + c_{uj} - c_{ij}\right) + c_{wait} \times wt_i + c_{serne} \times st_i + c_{wait} \times \sum_{\sigma \in V_j} \left(wt_\sigma^* - wt_\sigma\right) \tag{26}$$

Where c_{ij} is the cost of the path on the arc (i,j); w_t is waiting time; S_t stands for service time; V_j is the set of customer nodes on the current path j and those after j; w^*_t is the new waiting time of subsequent customer nodes after new customers are inserted.

The initial solution obtained by the above method is feasible, but the SAVN algorithm allows the existence of infeasible solutions, which endows the algorithm with a wider search space and increases the possibility of finding a better solution. When setting the objective function, the algorithm increases the penalty value of time window violation, and the penalty value gradually increases with the decrease of temperature, so the algorithm will gradually converge to the feasible solution in the subsequent iteration process.

STASA algorithm replaces the greedy criterion of the state transition algorithm with the Metropolis criterion of the SA algorithm, which can avoid falling into a local optimum and premature convergence very well *(AGGARWAL D. et al., 2018)*. The STASA algorithm can successfully solve combined optimization problems such as the traveling salesman problem and multi-traveling salesman problem. The unified form of the STASA algorithm is as shown in Formula (27):

$$\begin{cases} x_{k+1} = A_k x_k + B_k u_k \\ y_{k+1} = f(x_{k+1}) \end{cases} \tag{27}$$

where $x_k, x_{k+1} \in R^n$ is the new candidate solution generated by the current solution and transform; $A^k, B^k \in R^n$ is a transform operator; $u_k \in R^n$ is the expression of the objective function; $f()$ stands for the objective function. There are three discrete transform operators in the STASA algorithm: exchange, translation, and symmetry, and the calculation formulas are shown in (28)-(30), respectively.

$$x_{k+1} = A_k^{swap}(m_a)x_k \tag{28}$$

$$x_{k+1} = A_k^{shift}(m_b)x_k \tag{29}$$

$$x_{k+1} = A_k^{sym}(m_c)x_k \tag{30}$$

The updating strategy of solutions: During the search process based on the Metropolis criterion, if the new solution is better than the current solution, the new solution is accepted, otherwise, the new solution is accepted at a probability of $P = e^{-(f(\mathcal{X}_{k+1}) - f(\mathcal{X}_k))/T} \geq \eta$, where $\eta \in [0,1]$. With the reduction of temperature $t = t * \gamma$, the probability tends to be 0, and the algorithm gradually reach convergence.

In this paper, the relocation operation was implemented by combining the relocation operator, the generalized exchange operator, and the correlation removal operator and farthest insertion heuristic method in LNS, and the global optimal solution of each iteration was locally searched. Correlation removal operator: One customer is randomly chosen from removed customer points, and the correlation between this customer point and customer points in the distribution scheme is calculated. Distribution schemes are ranked in a descending order according to the correlation, the customer point ranked at $\lceil rand^{D} * nip \rceil$ is removed, $rand \in [0,1]$, and nip is the number of customer points in the distribution scheme. The random factor D can work in a considerably large scope, and the solving effect is favorable. The correlation is calculated via $R(i,j) = \frac{1}{C_y + V_y}$, $C_{ij} = \frac{d_{ij}}{*max\{d_{i1}, d_{i2}, ..., d_{in}\}}$, and d_{ij} is the running distance. If the customers i and j are served by the same vehicle, V_{ij}=1, otherwise, V_{ij}=0.

The farthest insertion heuristic method is adopted to perform the reinsertion operation and find the customer point with the priority to be reinserted and its optimal insertion point.

RESULTS

In the experiment, the Solomon criterion was selected as a CVRPSTW test example to verify whether the algorithm worked. According to the difference between time window and vehicle capacity, the Solomon criterion was divided into series 1(C1, R1, RC1) and series 2(C2, R2, RC2) test example sets. Series 1 had a smaller vehicle capacity and a narrower customer time window, while Series 2 had a larger vehicle capacity and a wider time window, and one vehicle could serve more customers.

Vehicle Evaluation Based on AHP-TOPSIS

Refrigerated vehicles were evaluated based on the established AHP-TOPSIS model, and 4 experts from the field of transportation and logistics were invited to form an evaluation group.

After the original data of AHP was obtained, Matlab2014b was used for programming, and the RI value was 0.520 by looking up the table, so the calculated CR values were 0.009 and 0.000, both of which were less than 0.1. The CI value calculated by the fourth-order judgment matrix was 0.048, and the RI value was 0.890 by looking up the table, so the calculated CR value was 0.054<0.1, that is, the judgment matrix of this paper met the consistency test, and the calculated weights were consistent. The calculated AHP results are listed in Table 3.

Table 3

Weight calculation results of AHP

Objective layer	Level-II index	Symbol	AHP weight	Level-III index	Symbol	AHP weight	Weight
Vehicle evaluation	Cost index	C1	0.2302	Vehicle cost	C11	0.3868	0.0891
				Fuel cost	C12	0.3214	0.0740
				Maintenance cost	C13	0.2918	0.0672
	Environmental index	C2	0.4868	Carbon emission	C21	0.2737	0.1333
				Vehicle life	C22	0.1294	0.0630
				Noise	C23	0.2439	0.1188
				Fuel efficiency	C24	0.1875	0.0913
				Fuel availability	C25	0.1655	0.0806
	Quality index	C3	0.2828	Safety	C31	0.2737	0.0774
				Comfort	C32	0.1294	0.0366
				Dynamic performance	C33	0.2439	0.0690

The TOPSIS method ranks the evaluation objects according to the distance from the positive and negative ideal solutions, so as to evaluate the relative advantages and disadvantages. First, the evaluation indexes are determined and ensured to keep a forward trend (the greater the value, the better), and the results in Table 4 are calculated.

Table 4

Positive ideal solution and negative ideal solution

Item	Positive ideal solution A	Negative ideal solution A-
C11	0.102	0.083
C12	0.111	0.011
C13	0.025	0.01
C21	0.333	0.1
C22	15	15
C23	0.05	0.01
C24	1	0.78
C25	1	0.8
C31	1	1
C32	1	0.8
C33	1	0.8

The positive and negative ideal solutions in Table 4 are intermediate process values when calculating the positive and negative distances (D+ and D-), and their significance is relatively small. The positive ideal solution A+ represents the maximum value of the evaluation index; the negative ideal solution A- denotes the minimum value of the evaluation index.

Table 5

TOPSIS evaluation and calculation results

Item	Positive ideal solution D	Negative ideal solution D-	Relative closeness C	Ranking result
Diesel refrigerated vehicle	0.125	0.067	0.348	3
Gasoline refrigerated vehicle	0.109	0.075	0.407	2
Electric refrigerated vehicle	0.006	0.149	0.962	1
Biodiesel refrigerated vehicle	0.142	0.016	0.099	6
Mixed fuel refrigerated vehicle	0.12	0.04	0.249	5
Natural gas refrigerated vehicle	0.109	0.054	0.331	4

The evaluation indexes of various vehicles were ranked based on AHP, and then the results obtained by the AHP-TOPSIS method are shown in Table 5. The evaluation values of such vehicles were ranked as electric refrigerator > gasoline refrigerator > diesel refrigerated vehicle > natural gas refrigerated vehicle> mixed fuel refrigerated vehicle > biodiesel refrigerated vehicle. The evaluation results of vehicles were taken into account in the multi-center vehicle path optimization model of cold chain logistics to ensure that vehicles with higher evaluation values were given the priority and the quality of the distribution fleet was guaranteed.

Experiment and Comparative Analysis

The evaluation results were multiplied with normal numbers to form the weight of vehicle evaluation, which was then considered into the objective function of the optimization model. By changing the weight of vehicle evaluation, the value of the objective function changed significantly. The greater the weight of vehicle evaluation, the better the greenness and sustainability of the distribution fleet. In this paper, an example in the Solomon Benchmark test set was used to test the algorithm. The examples in the Solomon Benchmark test set could be divided into six categories according to the node position relationship and time scheduling level: R1, R2, C1, C2, RC1, and RC2, and the customer scale of each example was 100. Among them, the node positions in R1 and R2 were randomly generated, and an example R101 with a scale of 100 customers was adopted in this paper.

The fixed cost of vehicles is $P_k = 100$ and the maximum carrying capacity is q_k =4 tons; the path cost of the vehicle k on the arc (i, j) in the time period τ is $c_{ijk}(\tau) = c_{trans} \times distance_{ij}$, where $T0 = 500$, $r = 0.997$, $Ts = 1$, $\text{iter} = 300$, and $\text{maxIterate} = 2100$; Without considering the road congestion, it is assumed that the vehicle is driving at a constant speed of 50 km /h, the average price of agricultural products is 6 yuan /kg, the refrigeration cost of unit product per unit time is 0.5 yuan/(h·kg), the corruption rate during transportation is 0.002, the corruption rate during loading and unloading is 0.003, the penalty coefficient for vehicles arriving in advance is 20 yuan /h, the penalty coefficient for vehicles arriving late is 30 yuan /h, the service time of each customer is 15 min, and the number of vehicles in the distribution fleet is restricted to 10.

In this paper, the large-scale neighborhood search SA algorithm was used to solve the vehicle path optimization model of agricultural products cold chain, and the maximum number of iterations was set to 2100. A satisfactory solution could be obtained by solving the model, that is, 4 electric refrigerated trucks were needed to complete the agricultural product distribution task, and the total cost was 1548.94 yuan.

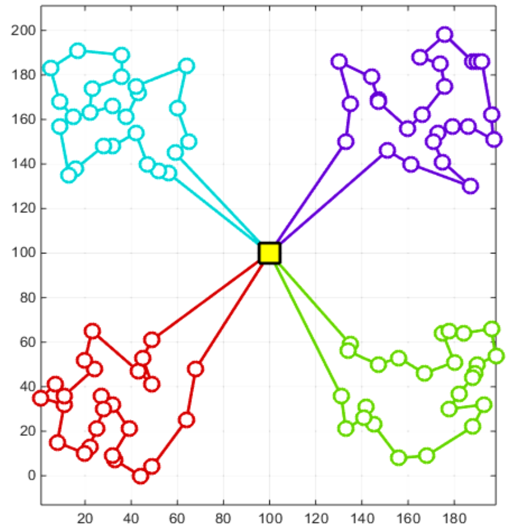

Fig. 2 - Path diagram of the large-scale neighborhood search SA algorithm

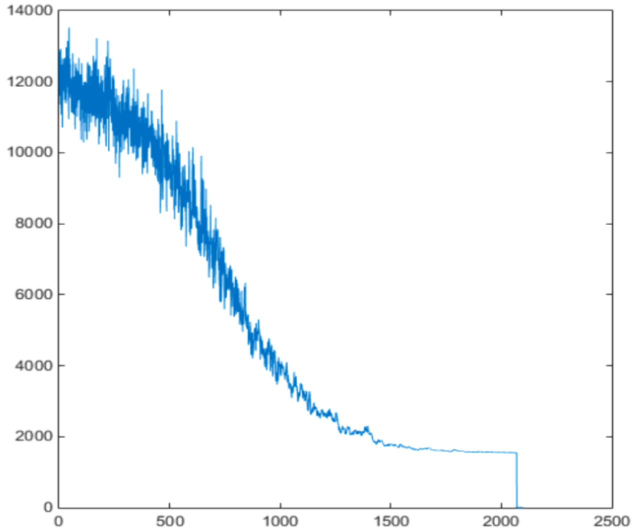

Fig. 3 - Convergence curve of the large-scale neighborhood search SA algorithm

The algorithm spent 413.81 seconds. The path diagram of the large-scale neighborhood search SA method is shown in Fig. 2. The convergence curve of the large-scale neighborhood search SA algorithm is shown in Fig. 3, and the calculation results are listed in Table 3.

To further verify the effectiveness of the large-scale neighborhood search SA algorithm, the model was also solved by designing the traditional SA algorithm in this paper. Under unchanged initial cost and parameters, a total of 5 electric refrigerated vehicles were needed to solve the path optimization model, with a total cost of 1688.6455 yuan and time consumption of 574.48 s. Fig. 4 is the path diagram of the traditional SA algorithm and Fig. 5 displays the convergence curve of the traditional SA algorithm.

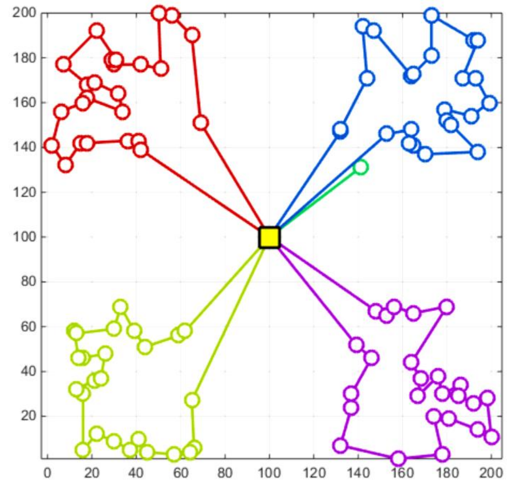

Fig. 4 - Path diagram of the traditional SA algorithm

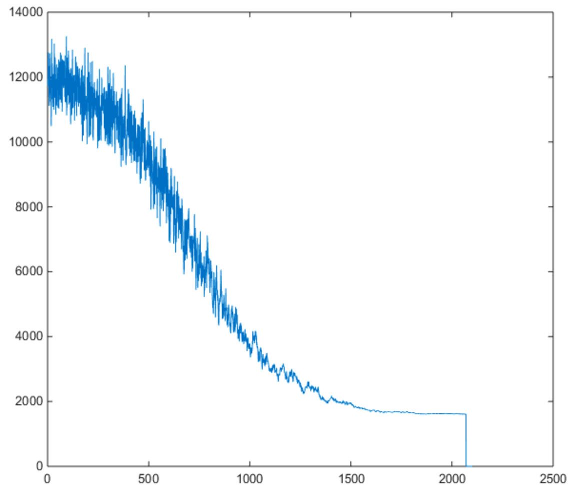

Fig. 5 - Convergence curve of the traditional SA algorithm

As shown in Table 6, compared with the traditional SA algorithm, the large-scale neighborhood search SA algorithm is strongly exploratory and convergent, with a better value of the objective function. The large-scale neighborhood search SA algorithm displays advantages over the traditional SA algorithm in the quantity of refrigerated vehicles, driving distance, total cost, and algorithm time consumption. Therein, the traditional SA algorithm needs 5 electric refrigerated vehicles to complete the agricultural product cold chain transportation task, while the large-scale neighborhood search SA algorithm only requires 4 electric refrigerated vehicles to complete the same task, with the efficiency improved by 20%. The *large-scale neighborhood search SA algorithm* spends 413.81 s in convergence, while the *SA* algorithm embedded with a genetic operator spends 574.48 s, so the algorithm efficiency is improved by 27.96%.

Table 6

Algorithm comparison

Algorithm	Total Cost (RMB)	Total Mileage (Km)	Number of Vehicle	Algorithm Time (s)
Large scale neighborhood search SA algorithm	1548.93	51.631	4	413.81
Traditional SA algorithm	1688.6455	56.288	5	574.48

CONCLUSIONS

Aiming at the route problem of agricultural cold chain vehicles with multiple models and single distribution center, firstly, considering the green, sustainability and economic requirements of refrigerated trucks, as well as the ambiguity, complexity and uncertainty of objective things, the AHP-TOPSIS method was used to evaluate all kinds of refrigerated trucks. Then, an objective function is established based on the assessed value of the vehicle as well as the transportation costs, fixed costs, cargo damage costs, cooling costs and fines incurred during the distribution process. Secondly, the corresponding cold chain logistics vehicle route optimization model is constructed, and the designed genetic algorithm is used to solve the problem, and the route of the batch arriving vehicles is obtained. The model can change the weight of vehicle evaluation, and a larger weight value means that the distribution process is more environmentally friendly and sustainable, and logistics companies can choose the right distribution scheme according to their needs.

The evaluation results of six kinds of refrigerated trucks, such as electric refrigerated trucks, mixed fuel refrigerated trucks, diesel refrigerated trucks, gasoline refrigerated trucks, biodiesel refrigerated trucks and natural gas refrigerated trucks, take into account the cost and green indicators, and provide a reference for cold chain logistics companies to select and integrate distribution vehicles. Taking Daliandili fresh food distribution as an example, the feasibility of the model and algorithm established in this paper is verified. In addition, it has been proven that considering vehicle assessment factors will increase distribution costs to some extent, but it can effectively improve the green and sustainable distribution process. By comparing with the model under the non-divided distribution mode, it is found that the divided distribution mode achieves lower distribution cost than the non-divided distribution mode. This study provides a new way of thinking for multi-vehicle and multi-distribution center cold chain logistics vehicle routing problem, and provides a certain reference for logistics enterprises to make distribution decisions.

REFERENCES

[1] Aggarwal D., Kumar V. (2018). An improved firefly algorithm for the vehicle routing problem with time windows. *International Conference on Advances in Computing, Communications and Informatics (ICACCI)*. pp. 222-229. Bangalore, India;

[2] Bauernhansl T. (2016). Exact method for the vehicle routing problem with mixed line haul and back haul customers, heterogeneous fleet, time window and manufacturing capacity. *Procedia CIRP*, Vol. 41, Issue 06, pp. 573-578. Netherlands;

[3] Chen S., Chen R., Wang G-G, et al. (2018). An adaptive large neighborhood search heuristic for dynamic vehicle routing problems. *Computers & Electrical Engineering*, Vol. 67, pp. 596-607. England;

[4] Cordeau J-F, Laporte G, Mercier A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational Research Society*, Vol. 52, Issue 8, pp. 928-936. England;

[5] Chen W Z, Jiang F, Liu P. (2020). Research on path planning of highly perishable agricultural product based on improved ant colony algorithm (基于改进蚁群算法的易腐农产品配送路径规划研究). *Journal of Hebei Agricultural University*, Vol. 43, Issue 3, pp. 130-135. China;

[6] Chiang W-C, Russell R.A. (1996). Simulated annealing metaheuristics for the vehicle routing problem with time windows. *Annals of Operations Research*, Vol. 63, Issue 1, pp. 3-27. Netherlands;

[7] Dorigo M., Birattari M., Stutzle T. (2006). Ant colony optimization. *IEEE Computational Intelligence Magazine*, Vol. 1, Issue 4, pp. 28-39. England;

[8] Ellabib I., Calamai P., Basir O. (2007). Exchange strategies for multiple ant colony system. *Information Sciences*, Vol. 177, Issue 05, pp. 1248-1264. United States;

[9] Fan H.M., Liu W.Q., Xu Z.L. et al. (2018). Solving VRPSPD problem with a soft time window using hybrid particle swarm algorithm (混合粒子群算法求解带软时间窗的 VRPSPD 问题). *Computer Engineering and Applications*, Vol. 54, Issue 9, pp. 221-229. China;

[10] Govindan K., Jafarian A., Khodaverdi R. (2014). Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*, Vol. 152, Issue 02, pp. 9-28. Netherlands;

[11] Han X., Dong Y., Yue L., et al. (2019). State transition simulated annealing algorithm for discrete-continuous optimization problems. *IEEE Access*, Vol. 7, pp. 44391-44403. United States;

[12] He M., Wei Z., Wu X., et al. (2021). An adaptive variable neighborhood search ant colony algorithm for vehicle routing problem with soft time windows. *IEEE Access*, Vol. 9, pp. 21258 -21266. United States;

[13] Liu H., Liu Y.Z. (2014). A fuzzy TOPSIS-based comprehensive evaluation method of purchasing agents (一种基于模糊 TOPSIS 的采购商综合评价模型). *Statistics & Decision*, Issue 16, pp. 4-6. China;

[14] Li Z., Li W.X., Ju Y.X., et al. (2019). Hybrid ant colony algorithm for solving vehicle routing problem with soft time window (混合蚁群算法求解带软时间窗的车辆路径问题). *Journal of Wuhan University of Technology (Transportation Science & Engineering)*, Vol. 43, Issue 4, pp. 761-766. China;

[15] Li B., Yang X., Xuan H. (2019). A Hybrid Simulated Annealing Heuristic for Multistage Heterogeneous Fleet Scheduling with Fleet Sizing Decisions. *Journal of Advanced Transportation*, Vol. 2019, Issue 10, pp. 1-19. United States;

[16] Mohammed M.A., Gani M.K., Hamed R.I. (2017). Solving vehicle routing problem by using improved genetic algorithm for optimal solution. *Journal of Computational Science*, Vol. 21, pp. 255-262. Netherlands;

[17] Nwakaire C.M., Keirstead J. (2015). Assessing the sustainability of meat transport mode choices in abattoir logistics using the analytic hierarchy process. *ARPN Journal of Engineering and Applied Sciences*, Vol. 10, Issue 20, pp. 9331-9338. Pakistan;

[18] Pérez-Rodríguez R., Hernández-Aguirre A. (2019). A hybrid estimation of distribution algorithm for the vehicle routing problem with time windows. *Computers & Industrial Engineering*, Vol. 130, pp. 75-96. England;

[19] Shukla M. (2013). Agriculture fresh produce supply chain management: a state-of-the-art literature review. *International Journal of Operations & Production Management*, Vol. 33, Issue 2, pp. 114-158. England;

[20] Shaw P. (1998). Using constraint programming and local search methods to solve vehicle routing problems, *International Conference on Principles and Practice of Constraint Programming*, pp. 417-431. Berlin, Heidelberg.

[21] Venkata N.K., Kivelevitch E., Sharma B. (2013). Ant colony optimization technique for solving min-max multi-depot vehicle routing problem. *Swarm and Evolutionary Computation*, Vol. 13, Issue 12, pp. 63-73. Netherlands;

[22] Wu H., Gao Y, Wang W., et al. (2021). A hybrid ant colony algorithm based on multiple strategies for the vehicle routing problem with time windows. *Complex & Intelligent Systems*, pp. 1-18. Saudi Arabia;

[23] Zhou X., Yang C., Gui W. (2011). Initial version of state transition algorithm, *2011 Second International Conference on Digital Manufacturing & Automation*, pp. 644-647. Zhangjiajie, China.