An electric vehicle routing model with charging stations consideration for sustainable logistics

Yan Li
Chongqing Changan Minsheng APLL Logistics Co., Ltd, Chongqing, China,
and School of Management Science and Real Estate, Chongqing University, Chongqing, China
2514691564@qq.com

Ming K. Lim
Adam Smith Business School, University of Glasgow, Glasgow, United Kingdom
ming.lim@glasgow.ac.uk

Weiqing Xiong[*]
College of Mechanical Engineering, Chongqing University of Technology, Chongqing, China
wq.xiong@cqut.edu.cn

Xingjun Huang[*]
Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong, China
xingjun.huang@polyu.edu.hk

Yuhe Shi
School of Management Science and Real Estate, Chongqing University, Chongqing, China
shiyuhe@cqu.edu.cn

Songyi Wang
Department of Statistics and Data Science, Southern University of Science and Technology, Shenzhen, China,
and Peng Cheng Laboratory, Shenzhen, Guangdong, China
wsy196973@163.com

[*]Corresponding author: Weiqing Xiong and Xingjun Huang

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Abstract

Purpose-Recently, electric vehicles are widely used in the cold chain logistics sector to reduce the effects of the excessive energy consumption, so as to support environmental friendliness.

Considering the limited battery capacity of electric vehicles, it is vital to optimize battery charging during the distribution process.

Design/methodology/approach- This study establishes an electric vehicle routing model for cold chain logistics with charging stations, which will integrate multiple distribution centers to achieve sustainable logistics. The suggested optimization model aimed at minimizing the overall cost of cold chain logistics, which incorporates fixed, damage, refrigeration, penalty, queuing, energy, and carbon emission costs. In addition, the proposed model takes into accounts of factors such as time-varying speed, time-varying electricity price, energy consumption, and queuing at the charging station. In the proposed model, a hybrid crow search algorithm (CSA), which combines opposition-based learning (OBL) and taboo search (TS), is developed for optimization purposes. To evaluate the model, algorithm and model experiments are conducted based on a real case in Chongqing, China.

Findings- The result of algorithm experiments illustrate that hybrid CSA is effective in terms of both solution quality and speed compared to genetic algorithm (GA) and particle swarm optimization (PSO). In addition, the model experiments highlight that the benefit of joint distribution over individual distribution in reducing costs and carbon emissions.

Originality/value-In prior studies, many scholars have conducted related research on the subject of cold chain logistics vehicle routing problem and electric vehicle routing problem separately, but few have merged above two subjects. In response, this study innovatively designs an electric vehicle routing model for cold chain logistics with consideration of time-varying speeds, time-varying electricity prices, energy consumption and queues at charging stations to make it consistent with the real world.

Research implications-The optimization model of cold chain logistics routes based on electric vehicle provides a reference for managers to develop distribution plan, which contributions to the development of sustainable logistics.

Keywords: electric vehicle routing; cold chain logistics; carbon emission; crow search algorithm

1. Introduction

The logistics sector has been expanding rapidly in recent years, but the greenhouse effect caused by excessive carbon emissions has become a significant obstacle to its long-term sustainability (Osman et al., 2022). According to data from the International Energy Agency (IEA), the transportation industry accounts for 24% of the carbon emissions caused by fuel consumption, with three quarters attributed to road transportation (Zhao et al., 2022). Therefore, it is crucial to consider the carbon emissions produced by road transportation. In this context, cold chain logistics, as an important component of road transportation, should also be paid attention to (Shi et al., 2022b). Cold chain logistics produces more carbon emissions than normal logistics because it requires more fuel to keep a cold environment (Chen, J. et al., 2021). As the market for cold chain logistics grows, its pollution on the environment will become increasingly severe (Liu et al., 2022). Therefore, it becomes crucial to figure out how to lower carbon emissions in the transportation industry, especially in the field of cold chain logistics.

In response, scholars have suggested using electric vehicles as a viable way to cut carbon emissions in the transportation sector (Li, Y. et al., 2020b). According to the IEA, there were more than 10 million electric vehicles on the road worldwide in 2020, representing a 41% increase from 2019 (Li, J. et al., 2022). This trend indicates that electric vehicles are becoming more and more popular. In practice, major companies such as DHL, UPS, and Walmart have applied electric vehicles in their urban distribution system to achieve sustainable development (Lin et al., 2021). Electric vehicles offer many benefits over conventional fuel-powered vehicles, such as producing less noise pollution, having cheaper operation cost, and emitting lower carbon emission (Huang et al., 2021). However, due to the limited battery capacity, electric vehicles are subject to many restrictions, including short operating distance, long charging time, and limited charging stations, all of which have negative impacts on the use of electric vehicles in the logistics industry (Attar et al., 2022). The optimization of electric vehicle routing is an effective approach to tackle the aforementioned challenges (Bac and Erdem, 2021). Therefore, it is important to design electric vehicle routing rationally to encourage the adoption of electric vehicles.

Currently, there is a lack of research that combines cold chain logistics with electric vehicle routing problems, and this study is intended to bridge this gap. This study proposes an electric vehicle routing model for cold chain logistics based on charging stations, which aims at minimizing the overall cost, including fixed, damage, refrigeration, penalty, queuing, energy, and carbon emission costs. The contributions of this study are as follows. In theory, (1) An innovative optimization model is proposed. To reflect real-world conditions, the proposed model considers cargo damage, refrigeration, time-varying speeds, time-varying electricity prices and queues at charging stations. (2) An innovative hybrid algorithm is designed. To improve solution quality, an original hybrid crow search algorithm (CSA) based on opposition-based learning (OBL) and taboo search (TS) is designed to solve the constructed model, which simulates the scenario of considering multiple distribution centers and charging stations. In practice, the suggested model integrates the information related to multiple distribution centers and customers to design the optimal routes to promote sustainable logistics.

The remaining sections of this study are organized as follows: Section 2 reviews relevant literature from three perspectives: the vehicle routing problem of cold chain logistics, the electric vehicle routing problem, and solutions to the electric vehicle routing problem. An electric vehicle routing model is proposed in Section 3, followed by the design of a hybrid crow search algorithm in Section 4. The effectiveness of the proposed model based on a real case is explored in Section 5. Finally, Section 6 discusses the main findings, limitations, and future research directions.

2. Literature review

To gain a comprehensive understanding of research in related fields, this section conducts a literature review from two aspects, namely, cold chain logistics vehicle routing problem, and electric vehicle routing problem.

2.1 Cold chain logistics vehicle routing problem

Numerous scholars have studied in-depth research on the issue of cold chain logistics vehicle routing problem (Shi et al., 2022b; Stellingwerf et al., 2021), with most aiming to minimize total cost (Chen, J. et al., 2021; Wang, M. et al., 2021). For example, Liu et al. (2020) designed a green vehicle routing model for cold chain logistics based on joint distribution with the goal of reducing overall cost. Due to the unique characteristics of products and transportation equipment involved in cold chain logistics, the composition of distribution cost is more complex than that of ordinary logistics, including three different cost categories related to transportation, product quality, and environmental pollution (Al Theeb et al., 2020; Wang, Y. et al., 2021).

The energy cost is the largest component of transportation cost and is mainly influenced by driving distance (Zheng et al., 2021). Initially, the energy cost was obtained by setting the energy cost per unit distance. For instance, Liu et al. (2020) used this approach to formulate the energy cost when calculating the transportation cost. However, their research ignored the impact of additional variables such as load and speed. In response, Li, Y. et al. (2019) and Qi and Hu (2020) proposed an energy consumption formula that includes load and travel distance when constructing the cold chain logistics vehicle routing models. This study suggests a more realistic approach to calculating energy consumption that considers the joint effects of load, speed, and distance. Another component of transportation cost is fixed cost (Shi et al., 2022a). Leng et al. (2020a) defined fixed cost as the rent for warehouses and vehicles, while the definition of fixed cost in Qin et al. (2019) included driver wages, vehicle depreciation cost, and road maintenance cost. Although many studies consider different fixed costs, the number of vehicles used for distribution is the only factor that affects the total fixed cost, regardless of other factors (Li, Y. et al., 2020a; Li, Y. et al., 2022). In conclusion, this study categorizes transportation costs into energy cost and fixed cost.

The perishable nature of cold chain products makes it necessary to consider the cost associated with product quality in the distribution process (Bai et al., 2022; Fahmy and Gaafar, 2022). To address the issue of reducing product loss, scholars have introduced the concept of damage cost into the objective function of cold chain logistics vehicle routing problems (Wang, Y. et al., 2021; Zhao et al., 2020). Qi and Hu (2020) used a constant value to represent the cargo damage rate when calculating damage cost in cold chain logistics. This study proposes to use an exponential function to represent the cargo damage rate of cold chain product to make it more realistic. Additionally, it is important to focus on the paths that generate the cargo damage when calculating the cargo damage cost (Qiu et al., 2020). Wang, M. et al. (2021) identified two mtion during transportation, and air exchange with the outside world during unloading. In addition, cold chain logistics needs to maintain the low temperature throughout the whole process to ensure the product quality, resulting in refrigeration cost (Wang et al., 2018). Regarding the two ways of generating cargo damage, Li, Y. et al. (2019) divided the refrigeration cost into refrigeration cost during transportation and refrigeration cost during unloading. Currently, this approach is widely used in refrigeration cost calculation for cold chain logistics vehicle routing problem (Guo et al., 2022). In summary, the costs associated with product quality in cold chain logistics includes cargo damage cost and refrigeration cost.

The high energy consumption of cold chain logistics results in an increased environmental degradation (Leng et al., 2020b; Liu et al., 2022). As a result, the research of cold chain logistics considering carbon emission has attracted a lot of attention (Zhang et al., 2021; Zhang et al., 2019). Yao, Q. et al. (2022) developed a vehicle routing model for fresh food, where carbon emission is reflected in the objective function through a sub-cost, and the results showed that considering carbon emission cost in the objective function effectively reduced carbon emission. By analyzing existing research, it is found that many scholars convert carbon emission into carbon emission cost when studying cold chain logistics vehicle routing problems (Li, L. et al., 2019). Li, K. et al. (2022) and Hu et al. (2021) adopted above approach, where the environment cost was obtained through the unit price and carbon emission determined based on emission factor. At present, this method for calculating carbon emission cost has become the research mainstream (Chen et al., 2019; Wu et al., 2022). Although considering carbon emission cost in the objective function reduces carbon emission, it does not address the carbon emission at the source (Li, Y. et al., 2020b). In response, scholars began to explore the application of clean energy in the area of cold chain logistics.

2.2 Electric vehicle routing problem

This section reviews the literature of electric vehicle routing problem from two aspects: feature and solution.

2.2.1 Feature of electric vehicle routing problem

Due to the benefits of high energy efficiency, less noise, and low carbon emission, the electric vehicles are becoming more and more popular in the logistics industry, which has sparked research into the topic of electric vehicle routing problem (Abid et al., 2022; Erdelic and Caric, 2022). The electric vehicles may need to detour to charging station for power replenishment during distribution process because of battery capacity restrictions, which makes electric vehicle routing problem more challenging than conventional vehicle routing problem (Zhang et al., 2018). Conrad and Figliozzi (2011) proposed the first vehicle routing optimization model that considers electricity supplementation. However, the charging in their research was performed at the customer's point, which differs from the actual situation (Li, Y. et al., 2020b). As a result, scholars began to explore the electric vehicle routing problem issue with regard to charging stations. Yang et al. (2021) created an electric vehicle routing model considering charging stations with the aim of lowering the total cost while taking the backhaul and time window limitations into account. With technological advancements, the battery swap strategy has emerged as an alternative method for replenishing electricity (Sayarshad et al., 2020). Compared to charging stations, the battery swap stations perform a similar function to regular gas stations in that batteries can be changed quickly (Kucukoglu et al., 2021). Chen, Y. et al. (2021) investigated the location routing problem of battery swap stations, aiming to minimize the construction and distribution costs. However, the battery swap strategy presents a challenge in that all electric vehicles must use the same type battery, which is currently difficult to achieve (Liang and Zhang, 2018). Therefore, this study focuses on the electric vehicle routing problem considering charging stations.

It is crucial to think about the charging strategy for electric vehicle routing problem that involve charging stations. Scholars have divided charging strategies into partial and full charging (Kucukoglu et al., 2021), and a full charging strategy is selected in this study to reduce the travelling distance caused by frequent access to charging stations (Li, Y. et al., 2020b). Hof et al. (2017) also adopted a full charging way in their electric vehicle routing model, but with a fixed charging time. This study improves upon their approach by determining the charging time based on the remaining electricity at arrival to the charging station. At present, the objective function of electric vehicle routing problem includes minimum energy consumption (Zhang et al., 2018), shortest running distance (Zhu et al., 2020), shortest operating time (Erdem and Koc, 2019), and lowest total cost (Wang, Mengtong et al., 2021). This study involves some factors including time, cost and carbon emissions. Therefore, a medium is needed to bring these factors together. In this context, total cost is the best option. However, the presence of charging time increases customers' waiting time (Zuo et al., 2019). As a result, research on the electric vehicle routing problem with time window limitations is important (Ren et al., 2021; Tas, 2021). Li, H. et al. (2020) developed an electric vehicle routing model that considers time window as constraint, requiring that the distribution service should be finished within the time window. However, it is impossible for any delivery task to follow the time required by the customer in a real environment. Therefore, time constraint is translated into penalty cost to enhance distribution flexibility in this study.

Many cities have implemented time-varying electricity prices to balance electricity consumption in each time period (Capitan et al., 2021). As a result, the topic of electric vehicle routing problem under time-varying electricity prices has become a research hotspot (Ham and Park, 2021; Li, Y. et al., 2020b; Lin et al., 2021). Lin et al. (2021) constructed an electric vehicle routing model that considers time-varying electricity prices, and the results showed that electric vehicles can function as energy storage systems, storing energy when electricity prices are low and injecting it into the grid when prices are high, which facilitates cost recovery. However, their model only considered one distribution center. With the development of sharing economy concept, collaboration among multiple distribution centers becomes a future direction (Hou et al., 2021). Hence, this study proposes an electric vehicle routing problem considering multiple distribution centers under time-varying electricity prices. Deng et al. (2022) built an electric vehicle routing model integrating price-responsive charging decisions, and the findings illustrated that the time-varying electricity prices had the potential for reducing cost. However, their research did not consider two crucial factors: firstly, limited charging facilities may trigger queues at charging stations (Li, Y. et al., 2020b), and secondly, realistic traffic congestion should be accounted in the model (Chen, J. et al., 2021). To address the aforementioned shortcomings, this study introduces the queuing cost at charging stations and time-varying speeds. Notably, to the best of our knowledge, carbon emission from electric vehicles has not been considered in any of the research mentioned above. It is true that electric vehicles do not produce carbon emission, but the production of electricity does (Li, Y. et al., 2020b). Therefore, the carbon emission should be considered when optimizing the electric vehicle routing problem.

2.2.2 Solution of electric vehicle routing problem

Initially, exact algorithms were used to solve the electric vehicle routing problem, which can find the optimal solution, including algorithms such as Branch and Price (Bahrami et al., 2020; Lee, 2021), Branch and Price and Cut (Duman et al., 2022; Lam et al., 2022), and Mixed Integer Programming (Yao, C. et al., 2022; Zhou et al., 2021). For example, Lam et al. (2022) used the Branch and Price and Cut to solve the electric vehicle routing problem with charging stations, while Yao, C. et al. (2022) explored the joint distribution routing problem for electric vehicles by Mixed Integer Programming. Usually, exact algorithms are suitable for solving small-scale optimization problems. However, as the problem size expands, the solution time of exact algorithm climbs exponentially, making it challenging to find solutions (Qin et al., 2021). As a result, scholars have begun to explore the use of heuristic algorithms. Building on a column algorithm, Duman et al. (2022) offered two branch-and-price-and-cut approaches: exact method and heuristic method, and the results demonstrate that the heuristic method performs better for larger instances. Heuristic algorithms optimize the solution by continuously perturbing the current solution until finding a satisfactory one (Ye et al., 2022). Extensive research has been carried out by scholars on heuristic algorithms. For instance, Jia et al. (2022) proposed a bi-level ant colony optimization approach for the capacitated electric vehicle routing problem, while Karakatic (2021) developed a two-layer genetic algorithm to solve the capacitated electric vehicle routing problem considering multi distribution centers and time windows. Literature reveals that heuristic algorithms used for resolving the electric vehicle routing problem include genetic algorithm (Karakatic, 2021; Moazzeni et al., 2022), ant colony algorithm (Leite et al., 2022; Mao et al., 2020), and particle swarm optimization (Yang et al., 2022; Zhen et al., 2020). However, there is currently a lack of discussion on the application of novel heuristic algorithms in the field of electric vehicle routing problems.

To address engineering practice problems, scholars have created various unique heuristic algorithms in recent years, such as the crow search algorithm (Askarzadeh, 2016), the mayfly algorithm (Zervoudakis and Tsafarakis, 2020), and the whale optimization algorithm (Mirjalili and Lewis, 2016). The crow search algorithm (CSA) is a new population intelligence algorithm inspired by crows' foraging behavior created in 2016 (Askarzadeh, 2016). Askarzadeh (2016) utilized CSA to solve six engineering problems, compared results with genetic algorithm and particle swarm optimization, and found that CSA produced better solutions. Additionally, CSA demonstrated an advantage over other algorithms by requiring fewer tuning parameters. Since the creation of CSA, scholars have applied to a wide range of engineering practices, including electricity resource scheduling (Tang et al., 2021), medical image processing (Vineeth et al., 2021), and wind power prediction (Li et al., 2021). However, few scholars have applied CSA in the field of electric vehicle routing problems. Although CSA offers many benefits, such as simple parameter tuning, its slow convergence speed and low convergence accuracy are still considered shortcomings, and scholars have suggested improving CSA to address these issues (Xu et al., 2022). Therefore, hybrid heuristic algorithms that combine different algorithms are proposed to improve performance, which can be parallel or inseparable in parts (Ramachandran et al., 2022; Tang et al., 2021). Khalilpourazari and Pasandideh (2020) created a hybrid CSA by combining the sine cosine algorithm with CSA, demonstrating that this hybrid approach outperformed both the standard CSA and the sine cosine algorithm. Building on these ideas, this study proposes a novel hybrid heuristic algorithm based on CSA by combining opposition-based learning (OBL) and taboo search (TS). Using OBL to construct an initial population can increase the population diversity, which enhances the solving ability (Houssein et al., 2021). After CSA completes the memory update, TS is used to prevent falling into a local optimum, thus improving the convergence accuracy (Li, Y. et al., 2019). As far as we know, this approach is a brand new attempt to utilize the strengths of OBL and TS.

This study is located at the intersection of cold chain logistics vehicle routing problem and electric vehicle routing problem. Through the previous analysis, the features of this study are marked in Table A1 (Appendix). Compared with previous studies, the constructed model has the following innovations: (1) The proposed model fully considers the characteristics of electric vehicles and cold chain logistics, as well as introduces environmental issue. (2) Relevant factors are incorporated into the model based on the actual situation, such as cargo damage, refrigeration, time-varying speed, time-varying electricity price, energy consumption, queuing at the charging station, and limited charging stations availability. (3) A hybrid CSA is created to enhance the solution performance by integrating the OBL and TS.

3. Modeling approach

The purpose of this section is to present the suggested electric vehicle routing model for cold chain logistics. Section 3.1 introduces the model description and Section 3.2 formulates the model.

3.1 Model description

The proposed electric vehicle routing problem involves multiple distribution centers and customers, with the objective of minimizing overall cost. The electric vehicles must return to the distribution center eventually and they should visit a charging station if there is not enough power to complete the distribution. The basic assumptions of the suggested model are as follows: (1) The distribution centers have sufficient quantities of the same commodities demanded by customers, and the same type of electric vehicles are available. (2) The maximum load capacity of electric vehicles should not be exceeded, and distribution should meet the time requirements. (3) Customer information (location, demand, time window, and service time), distribution centers locations, and charging stations locations are all known. (4) Customer demand for commodities cannot be divided, requiring each customer to receive delivery from only one electric vehicle. (5) The electric vehicle must be charged when the battery drops below 10% of total electricity, and it fully charges after each trip to the charging station. Figure I depicts the distribution routes of electric vehicles. There are three routes: (1) Route 1: D1-C6-C4-C1-D1; (2) Route 2: D2-C2-C3-C5-C8-S3-C12-D2; and (3) Route 3: D3-C11-C10-C9-S2-C7-D3. Route 1 does not require visiting charging stations, while Routes 2 and 3 do.

Figure I. **Diagram of electric vehicle distribution routes.**

3.2 Model formulation

This section creates an electric vehicle routing model that considers features of cold chain logistics and electric vehicles, and it includes cost analysis and model setting.

3.2.1 Cost analysis

This part analyzes the costs that make up the objective function, which includes fixed, damage, refrigeration, penalty, queuing, energy, and carbon emission costs. The parameters and variables involved in the proposed model are shown in Table A2 in the Appendix A.

(1) Fixed cost. The fixed cost consists of driver cost and vehicle cost during transportation, and the fixed cost changes depending on how many electric vehicles are participating, as shown in Equation (1).

$$C_1 = \sum_{e\epsilon E} F_r \cdot m_e + \sum_{e\epsilon E} F_l \cdot m_e \tag{1}$$

(2) Damage cost. The damage cost is divided into two categories: the cost resulting from time accumulation during transportation and the cost resulting from heat entering the vehicle during unloading. The formula for calculating damage cost is shown in Equation (2).

$$C_2 = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} n_i^e \cdot F_c \cdot \left(q_i\left(1 - K_1 \cdot e^{-\theta\left(t_i^e - t_0^e\right)}\right) + Q_i\left(1 - K_2 \cdot e^{-\theta \cdot t_s^i}\right)\right) \tag{2}$$

(3) Refrigeration cost. The refrigeration cost is incurred to maintain a cold environment for distribution, which is broken down into refrigeration cost during transportation and refrigeration cost during uploading, as shown in Equation (3).

$$C_3 = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} \left(x_{ij}^e \cdot F_a \cdot t_{ij}^e + n_i^e \cdot F_b \cdot t_s^i\right) \tag{3}$$

(4) Penalty cost. Cold chain logistics normally has strict time restrictions, so distributions that do not meet the customers' required time can result in penalty cost, as shown in Equation (4).

$$C_4 = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} \left(F_e \cdot max\{ET_i - t_i^e, 0\} + F_l \cdot max\{t_i^e - LT_i, 0\}\right) \tag{4}$$

(5) Queuing cost. The electric vehicles may have to wait in line at charging stations due to a lack of available charging stations. Equation (5) displays the queuing cost.

$$C_5 = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} F_w \cdot z_h^e \cdot TQ \tag{5}$$

(6) Energy cost. The energy cost is split into two parts: the cost incurred at the charging station when a rapid charging strategy is used, as shown in Equation (6); and the cost generated at the distribution center when a slow charging strategy is adopted, as shown in Equation (7). Therefore, the energy cost is calculated as in Equation (8).

$$C_{61} = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} z_h^e \cdot P_f \cdot \int_{t_s^e}^{t_s^e+t_{cf}} (S_t + S_v) d_t \tag{6}$$

$$C_{62} = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} z_d^e \cdot P_s \cdot \int_{t_r^e}^{t_r^e+t_w} S_t d_t \tag{7}$$

$$C_6 = \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} \left(z_h^e \cdot P_f \cdot \int_{t_s^e}^{t_s^e+t_{cf}} (S_t + S_v) d_t + z_d^e \cdot P_s \cdot \int_{t_r^e}^{t_r^e+t_w} S_t d_t \right) \tag{8}$$

(7) Carbon emission cost. The carbon emission generated by electric vehicles is changed into the carbon emission produced by the process of producing electricity. Equation (9) calculates the electricity consumed in the time period $t_a \sim t_b$. Hence, the carbon emission cost is determined, as shown in Equation (10).

$$W = \varphi \int_{t_a}^{t_b} \left[\frac{1}{2} c_r S c_d v(t)^2 + \mu\left(m_k + Q_j\right) g + \delta\left(m_k + Q_j\right) a \right] v(t) dt \tag{9}$$

$$C_7 = F_i \cdot \sum_{i,j\in C\cup D\cup V} \xi \cdot \varphi \int_{t_a}^{t_b} \left[\frac{1}{2} c_r S c_d v(t)^2 + \mu\left(m_k + Q_j\right) g + \delta\left(m_k + Q_j\right) a \right] v(t) dt \tag{10}$$

3.2.2 Model setting

Based on above analysis, the overall cost minimization is the goal of the electric vehicle routing problem, and it is expressed as Equation (11).

$$C_{min} = \begin{pmatrix} \sum_{e\epsilon E} F_r \cdot m_e + \sum_{e\epsilon E} F_l \cdot m_e + \\ \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} n_i^e \cdot F_c \cdot \left(q_i \left(1 - K_1 \cdot e^{-\theta(t_i^e - t_0^e)} \right) + Q_i \left(1 - K_2 \cdot e^{-\theta \cdot t_s^i} \right) \right) + \\ \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} (x_{ij}^e \cdot F_a \cdot t_{ij}^e + n_i^e \cdot F_b \cdot t_s^i) + \\ \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} (F_e \cdot max\{ET_i - t_i^e, 0\} + F_l \cdot max\{t_i^e - LT_i, 0\}) + \\ \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} F_w \cdot z_h^e \cdot TQ + \\ \sum_{e\epsilon E} \sum_{c\in C} \sum_{d\in D} \sum_{v\in V} \left(z_h^e \cdot P_f \cdot \int_{t_s^e}^{t_s^e+t_{cf}} (S_t + S_v) d_t + z_d^e \cdot P_s \cdot \int_{t_r^e}^{t_r^e+t_w} S_t d_t \right) + \\ F_i \cdot \sum_{i,j\in C\cup D\cup V} \xi \cdot \varphi \int_{t_a}^{t_b} \left[\frac{1}{2} c_r S c_d v(t)^2 + \mu\left(m_k + Q_j\right) g + \delta\left(m_k + Q_j\right) a \right] v(t) dt \end{pmatrix} \tag{11}$$

Constraints：

$$\sum_{i\in C\cup D\epsilon V} \sum_{e\in E} x_{ij}^e = 1, \forall j \in C, \forall e \in E \tag{12}$$

$$\sum_{i\in D} x_{ij}^e = \sum_{i\in D} x_{ji}^e = 0, \forall j \in D, \forall e \in E \tag{13}$$

$$\sum_{i\in D}\sum_{j\in C}x_{ij}^{e}=\sum_{i\in D}\sum_{j\in C}x_{ji}^{e}\leq 1,\forall e\in E \tag{14}$$

$$\sum_{i\in D\cup C\epsilon V}n_i^e\cdot q_i\leq Q,\ \forall e\in E \tag{15}$$

$$q_j=q_i-\int_{t_i+t_s}^{t_j}P_l dt\geq 0.1W,\ \ \forall i\in C \tag{16}$$

$$q_j=W-\int_{t_0}^{t_j}P_l\, dt\geq 0.1W,\ \ \forall i\in D \tag{17}$$

$$q_j=W-\int_{t_i+t_w}^{t_j}P_l\, dt\geq 0.1W,\ \ \forall i\in V \tag{18}$$

$$ET_j\leq\left(t_j=t_i+t_s+d_{ij}/v_{ij}\right)\leq LT_j,\ \ \forall i\in C \tag{19}$$

$$ET_j\leq\left(t_j=t_0+d_{ij}/v_{ij}\right)\leq LT_j,\ \ \forall i\in D \tag{20}$$

$$ET_j\leq\left(t_j=t_i+t_c+t_w+d_{ij}/v_{ij}\right)\leq LT_j,\forall i\in V \tag{21}$$

Equation (12)-(14) are routes constraints: Equation (12) indicates that a customer can only be delivered by one vehicle; Equation (13) represents no road connecting two distribution centers, indicating that the vehicle should back to the distribution center that is leaving; and Equation (14) states that the vehicle must travel to the distribution center after service is completed. Equation (15) shows that the load capacity cannot exceed its maximum carrying capacity. Three types of remaining electricity q_j from node i to customer point j are shown in Equation (16)-(18), t_i denotes the time of arrival at node i, t_j denotes the time of arrival at node j, t_s denotes the service time at node i, t_w denotes the time to replenish power at charging station, P_l denotes the driving power from node i to node j. Equation (19)-(21) show that the time t_j from node i to customer point j must fall within the time window $\left(ET_j,LT_j\right)$, t_0 denotes the time of starting distribution, t_c represents the waiting time at the charging station, d_{ij} represents the distance between node i to customer point j, v_{ij} is the speed from node i to customer point j.

4. Algorithm design

This study uses the crow search algorithm (CSA) to solve the developed model. Section

4.1 introduces the standard CSA, and a hybrid CSA is designed in Section 4.2.

4.1 Standard crow search algorithm

The CSA was created according to the crows' predatory nature with the following characteristics: in nature, crows will hide extra food and will rediscover it when needed. In addition, crows will also observe where other crows are hiding food and then go there to steal it when they leave. Therefore, crows use their experience to constantly move location to obstruct other crows' judgment to secure their food. There are M crows in the crow population, and location vector of the crow i is $s_i^{iter}(i = 1,2,\dots,M; iter = 1,2,\dots,iter_{max})$, in which $iter_{max}$ represents the maximum number of iterations. The location vector of crow i is represented as in Equation (22), where d denotes the dimensionality of the variable.

$$s_i^{iter} = \left[s_{i,1}^{iter}, s_{i,2}^{iter}, \dots, s_{i,d}^{iter}\right] \tag{22}$$

Each crow in the population has the optimal hiding place m_i^{iter}. At the same time, it also looks for the hiding place of crow m_j^{iter}. At a certain iteration, the crow j plans to reach the hiding place. At this time, the crow i will follow crow j to its hiding place. There are two scenarios may occur depending on the awareness probability AP_j^{iter}.

Scenario 1: When crow j is unaware that it is being followed, crow i will move closer to the hiding place of crow j. In this instance, the location of crow i at the next moment is calculated as in Equation (23), where r represents a random number between 0 and 1, and fd_j^{iter} represents the flight distance of crow i in the iteration.

$$s_i^{iter+1} = s_i^{iter} + r \times fd_j^{iter} \times \left(m_j^{iter} - s_i^{iter}\right) \tag{23}$$

Figure II. illustrates the effect of flight distance fd_j^{iter} on the crow location. If fd_j^{iter} takes a small value, it leads to a local search, that is, finding the optimal value near s_i^{iter}. As shown in Figure II(a), when $fd_j^{iter} < 1$, the location of crow i at the next moment s_i^{iter+1} is between s_i^{iter} and m_j^{iter}. If fd_j^{iter} takes a large value, it leads to a global search, that is, finding the optimal value far from s_i^{iter}. As shown in Figure II(b), when $fd_j^{iter} > 1$, the location of crow i at the next moment s_i^{iter+1} is on the extension of s_i^{iter} and m_j^{iter}.

Figure II. **Location of crow i at the next moment.**

Scenario 2: When crow j knows that it is being followed, crow j will make random flights to avoid crow i from finding its hiding place. Combining the above two scenarios, the location of crow i is updated as in Equation (24).

$$s_i^{iter+1} = \begin{cases} s_i^{iter} + r \times fd_j^{iter} \times \left(m_j^{iter} - s_i^{iter}\right),\ r \geq AP_j^{iter} \\ s_{rand},\ r < AP_j^{iter} \end{cases} \tag{24}$$

The value of the awareness probability (AP) affects the solution performance. The CSA will search for the optimal solution in the global range when increasing the AP value. Furthermore, when decreasing the AP value, the CSA will search exactly in the vicinity of the current solution to improve the convergence efficiency.

4.2 Hybrid crow search algorithm

Although the CSA has many advantages, it still has problems such as slow convergence speed and insufficient convergence accuracy. A hybrid CSA is designed in this study, which combines opposition-based learning (OBL), taboo search (TS), and CSA. In the proposed approach, the OBL increases the population diversity to expand search range, which can effectively avoid the algorithm from settling for a local optimum and find the global optimum solution. In addition, the TS enhances the CSA's local search capability. The solution steps of the hybrid CSA are as follows, and Figure III depicts its flow.

Figure III. **Solution steps of the hybrid CSA.**

Step 1. Initialize the parameters. Setting parameters, including crows number *N*, flying distance *F*, awareness probability *AP*, forbidden length, and maximum number of iterations.

Step 2. Initialize the location and memory of crows. In a *d*-dimensional search space, there are *N* crows that are randomly dispersed. Each crow represents a solution to the problem, and *d* represents the number of decision variables. The crow population can be expressed as Equation (25).

$$Crows = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nd} \end{bmatrix} \quad (25)$$

Initialize the memory of crows. The crows have no memory at first, assuming that they hide food in the initial location, and their memory can be expressed as Equation (26).

$$Memory = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1d} \\ m_{21} & m_{22} & \cdots & m_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ m_{N1} & m_{N2} & \cdots & m_{Nd} \end{bmatrix} \quad (26)$$

Step 3. Reverse construction of initialized populations. The randomly generated population from Step 2 is used to generate an opposition population with the same size according to Equations (27) and (28). The details are as follows:

The size of the crow population is M, the dimension of the problem is D, the variables of each dimension take values in the range $\left[x_d^{min}, x_d^{max}\right]$, the population can be expressed as $X = \{X_i, i = 1,2,\ldots,M\}$, X_i can be expressed as $X_i = \{X_{id}, d = 1,2,\ldots,D\}$, and the expression of population individual X_{id} is shown in Equation (27).

$$X_{id} = x_d^{min} + rand(0,1) \times \left(x_d^{max} - x_d^{min}\right) \quad (27)$$

The opposition population $OX = \{OX_i, i = 1,2,\ldots,M\}$ can be calculated from the population X, OX_i can be expressed as $OX_i = \{OX_{id}, d = 1,2,\ldots,D\}$, the expression for the opposition population individual OX_i is shown in Equation (28).

$$OX_{id} = x_d^{min} + x_d^{max} - X_{id} \quad (28)$$

Finally, individuals in the original population and individuals in the opposition population are merged.

Step 4: Calculate the fitness values of all individuals. All individuals in the original population and opposition population are calculated the values of the fitness function, and select the best individuals in both populations to form a new initial population.

Step 5: Generate a new location. To find the hiding place of crow j, crow i will follow crow j, and a new location of crow i is generated according to Equations (23) and (24).

Step 6: Check the feasibility of the new crow location. The crow i will go to the new location if it is feasible; otherwise, it will remain the original location.

Step 7: Calculate the fitness value of the new location. If the fitness function value of the new location of crow i is better than the fitness function value of the memory location, crow i will reach the new location and update its memory, otherwise, it will stay at the original location， as shown in Equation (29).

$$m_i^{iter+1} = \begin{cases} x_i^{iter+1}, f\left(x_i^{iter+1}\right) \; is \; better \; than \; f\left(m_i^{iter}\right) \\ m_i^{iter}, \; f\left(x_i^{iter+1}\right) \; is \; worse \; than \; f\left(m_i^{iter}\right) \end{cases} \tag{29}$$

Step 8: Start the taboo search. The optimal solution obtained in **Step 7** is used as the initial solution for the taboo search, and an empty taboo table is created.

Step 9: Calculate the fitness value of the neighborhood solution. The neighborhood solution is generated by interpolation, inverse order and reciprocity operations, and the fitness function value is derived to obtain the neighborhood optimal solution.

Step 10: Judge whether the neighborhood optimal solution is in the taboo table. If it appears in the taboo table, determine whether the amnesty requirement is satisfied, if yes, proceed to step 11; if not, go back to **Step 9** to continue seeking the best solution; if it is not in the taboo table, go to **Step 11**.

Step 11: Update the forbidden table and record the new optimal solution.

Step 12: Check to determine if the termination condition is met; if so, end the search and output the optimal solution; if not, go back to **Step 2** and repeat the process until the maximum number of iterations is reached.

5. Computational experiments

The proposed model is applied to a real case to plan the distribution routes of Company H from Chongqing, China. The aim of using Company H to carry out case study is to demonstrate that the suggested model is valuable across the board and not only for Company H. Over time, Company H has relied on work experience to develop its distribution routes. However, this approach is no longer appropriate as the volume of business increased. In addition, the distribution centers of Company H perform tasks independently, which causes a lot of waste. Facing the above challenges, the proposed model automatically optimizes the distribution routes from the global optimum perspective. Around the urban area of Chongqing, Company H has three distribution centers A, B, and C, and delivers a total of forty-five customers, which have been presented in Figure IV. The customer information, including location, demand, service time window, and service time, is shown in Table A3 in Appendix A. Table A4 displays the locations of distribution centers and charging stations. Furthermore, the model parameters are set according to the Table A5. The computational experiments are carried out from two aspects: algorithm experiments and model experiments. The experimental environment is Intel(R) Core(TM) i5-7Y54 CPU @ 1.20GHz 1.61 GHz, running memory is 8GB, and running software is MATLAB 2018a.

Figure IV. **Location of distributions, customers, and charging stations.**

5.1 Algorithm experiments

In the algorithm experiments, the optimal parameters of the CSA are explored in Section 5.1.1, and the effectiveness of the designed algorithm is demonstrated in Section 5.1.2.

5.1.1 Parameter setting

The value of flying distance F and awareness probability AP have a significant impact on the effectiveness of the CSA. Therefore, choosing appropriate values for these parameters can improve the search efficiency and overall performance. According to the research of Askarzadeh (2016), there are twenty five possible combinations of F and AP. Specifically, F takes values in the range of 0.5, 1, 1.5, 2, and 2.5, while AP takes values in the range of 0.1, 0.15, 0.2, and 0.25. The number of crow is 50, and the maximum number of iterations is 300. The forbidden length of the taboo search is set to 5. The results of different parameters combinations are shown in Table I. Table I indicates that the combination of F=2 and AP=0.15 in the optimal solution with the lowest overall cost of 3425.79 RMB. In all subsequent experiments, the parameters of CSA are set to F=2 and AP=0.15.

Table I. **Results of different parameters combinations.**

5.1.2 Algorithm comparison

To prove the hybrid CSA proposed in this paper is superior, it is compared with three other algorithms: standard CSA, genetic algorithm (GA), and particle swarm optimization (PSO). Combing the researches of Li, Y. et al. (2022) and Li, Y. et al. (2019), as well as experimental experience, the following parameters are set: All four algorithms have the same population size of G=50 and maximum iteration count of 300. CSA and hybrid CSA parameters: F=2, AP=0.15; GA parameters: crossover probability Pc=0.54 and the variance probability Pm=0.05; PSO parameters: learning factor $C1$=2, learning factor $C2$=2, and inertia factor is 0.7. The optimal solution, number of iterations and algorithm running time under different algorithms are recorded in Table II. Figure V shows the convergence function curves of proposed four algorithms when finding the optimal solution. As can be seen from Figure V and Table II, GA, PSO, CSA, and hybrid CSA, have approximately the same number of iterations, 97, 103, 95, and 98, respectively. The hybrid CSA algorithm has the shortest running time (72.8 seconds) and the lowest cost (3425.79 RMB) for the optimal solution. It can be seen that the hybrid CSA is better than the standard GA, PSO, and CSA.

Table II. **Results of GA, PSO, CSA, and hybrid CSA.**

Figure V. **Fitness convergence curves of GA, PSO, CSA and hybrid CSA.**

5.2 Model experiments

This section demonstrates the validity of the proposed model from two perspectives: different distribution modes and different battery capacities.

5.2.1 Results of different distribution modes

This section provides a comparison of how individual distribution and joint distribution affect the distribution process. Table III and Figure VI are obtained by solving the individual distribution and joint distribution separately using the hybrid CSA. The distribution routes of the individual distribution are given in Figure VI(a)(b)(c), while the distribution routes of the joint distribution are displayed in Figure VI(d). As shown in Table III, the overall cost is decreased from 4865.38 to 3425.79 RMB when the joint distribution is performed. To get a clear picture of the variation within the overall cost, Table IV lists every sub-cost that contributes to the overall cost.

Table III. **Results of individual distribution and joint distribution.**

Table IV. **Costs of individual distribution and joint distribution, Unit: RMB.**

Figure VI. **Distribution routes of individual distribution and joint distribution.**

Table IV shows that all sub-cost drop when the joint distribution mode is adopted, with the exception of the penalty cost C_4. The reasons for the above results are as follows: according to Equation (1), the fixed cost C_1 of joint distribution is lower than individual distribution since fewer vehicles are used. However, fewer vehicles indicate that more customers will be delivered by each vehicle, which means that the customer's delivery time requirement are not properly met, leading to an increase in the penalty cost C_4. It can be learned from Figure VI that changing the distribution order can shorten the distance, which decreases the overall distribution time. As a result, the damage cost C_2 and the refrigeration cost C_3 are reduced when the joint distribution is used. From Table III, the adoption of joint distribution reduces the numbers of vehicles visiting the charging station, which cuts the queuing cost C_5. The shorter operating distance causes lower electricity consumption, so the energy cost C_6 is reduced. Similarly, the carbon emission cost C_7 is decreased because fewer carbon emission is produced. Based on above analysis, the joint distribution model has favorable effects on cost savings and carbon emission reduction.

5.2.2 Results of different battery capacities

This section explores the effect of different battery capacities on the distribution routes. The battery capacities W are set to 20kwh, 40kwh, 60kwh, 80kwh, and 100kwh, and the results of different battery capacities are shown in Tables V, VI and Figure VII. The following conclusions can be obtained from Table V. As the battery capacity increases: (1) The distance travelled by the vehicle is reduced from 1243.02 km to 1050.22 km. One of the main reasons for above result is the reduction in the number of visiting charging stations from 32 to 0, which results in a significant reduction in the ineffective distance. Figure VII shows the distribution routes when the battery capacities are 20 kwh and 100 kwh. (2) The initial 923.39 kg of carbon emission is decreased to 643.19 kg. The quantity of electricity consumed affects carbon emissions, which depends on the running distance. As a result, cutting operational distance lessens the carbon emission of distribution process. (3) The overall cost drops steadily from 4155.56 RMB to 3263.40 RMB. To explore the reasons for the cost reduction, Table VI is obtained.

Table V. **Results of different battery capacities.**

Table VI. **Costs of different battery capacities, Unit: RMB.**

Figure VII. **Distribution routes of W=20kwh and W=100kwh.**

There are three main conclusions emerge from Table 6. As the battery capacity increases: (1) The energy cost keeps decreasing. This study divides the energy cost C_6 into two categories, charging at charging stations C_{61}, and charging at distribution centers C_{62}. The C_{61} keeps decreasing, which is due to the decreasing number of charging at charging stations. The C_{62} keeps increasing means that the charging at distribution centers gradually increases. However, the cumulative cost effect of C_{61} and C_{62} keeps decreasing because charging at charging stations requires a service fee. (2) The distribution time keeps reducing. As the number of charges at charging stations decreases, it leads to lower queuing cost C_5. The fewer queuing save the total distribution time, so the damage cost C_2, and refrigeration cost C_3 gradually decrease. However, there seems to be no pattern in the penalty cost C_4 change, which is due to the fact that the distribution time is the only one influencing factor, while the distribution order is the most important factor affecting penalty cost. (3) The trend of overall cost variation keeps decreasing. The largest part of the cost change is the charging cost C_6, which results in a smaller change in overall cost as the number of accesses to charging at charging stations less and less. As the battery capacity continues to increase, the change in overall cost will no longer be significant. This section provides an important reference for companies to choose the right battery capacity of electric vehicles.

6. Conclusion

This study provides an electric vehicle routing optimization model for cold chain logistics to achieve the lowest overall cost, which includes fixed, damage, refrigeration, penalty, queuing, energy, and carbon emission costs. Regarding the actual situation, the suggested model considers some factors such as multiple distribution centers, time-varying speed, time-varying electricity price, and energy consumption. In addition, this study transforms the carbon emissions of electric vehicles into the electricity generation process. To solve the proposed model, a hybrid crow search algorithm (CSA) is created based on opposition-based learning (OBL) and taboo search (TS). The computational experiments are conducted from two aspects, algorithm and model, through a real case. In the algorithm experiments: Firstly, the optimal parameters of the hybrid CSA are determined, specifically, the lowest overall cost is obtained when the flying distance F=2 and the awareness probability AP=0.15; Secondly, the hybrid CSA is compared with genetic algorithm (GA), particle swarm optimization (PSO), and standard CSA, and the results show that the hybrid CSA has the shortest solution time and the best solution. In the model experiments: Firstly, the effects of individual distribution and joint distribution on the routes are compared. The findings demonstrate that the joint distribution model reduces cost and carbon emission, which improves the efficiency of the entire distribution process. Secondly, the impact of different battery capacity on the routes is explored. According to the statement, cost and carbon emission continue to decline as battery capacity rises. Therefore, the battery capacity issue is an important obstacle to the application of electric vehicle in distribution. In addition, this study provides an important reference for companies to choose the right battery capacity electric vehicle.

Both theoretical and practical contributions are made through this study. The theoretical contributions are twofold. The first is to enrich the vehicle routing optimization model. An innovative electric vehicle routing model for cold chain logistics is developed, which fully considers the characteristics of both cold chain product and electric vehicle. The second is to improve the performance of the solution approach for vehicle routing problem. To increase the solution efficiency, this study creatively suggests a hybrid CSA, which uses OBL and TS to optimize standard CSA. This study also makes contributions to the practice sector. Excellent companies should consider environmental benefits along with economic benefits. Using electric vehicles with the joint distribution mode can both cut cost and carbon emission associated with the distribution process. The optimization model proposed in this study can help companies plan reasonable distribution routes to achieve sustainable development. In addition, there are some limitations in this study. Firstly, the impact of electricity prices and customer waiting time on distribution plan deserves to be explored in future research. Secondly, this study only sets one objective function, and the vehicle routing model with multi objective functions is worth being studied. Lastly, the dynamic vehicle routing problem deserves in-depth study with consideration of market environment uncertainty.

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