An intelligent green scheduling system for sustainable cold chain logistics

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Abstract

This study proposes an intelligent green scheduling system for cold chain logistics (IGSS-CCL) to support the integration and coordination of resources. Post-COVID-19, the traditional cold product market is rapidly converting to retail stores and e-commerce portals owing to social distancing restrictions, which creates a requirement and opportunities for the development of cold chain logistics. However, urban governance requirements, such as pandemic prevention, traffic restriction, energy conservation, and emissions reduction, have added challenges to this development. Therefore, it is vital to design a cold chain logistics scheduling system that considers the economic, safety, and environmental factors. The proposed system includes three parts: (1) the framework structure of the cold chain logistics intelligent scheduling system; (2) a multi-objective scheduling optimization model to allow for efficient and dynamic coordination between the distribution, demand, and external environment; and (3) a two-stage optimization algorithm based on Dijkstra's algorithm and a non-dominated sorting genetic algorithm to support intelligent scheduling operations. Numerical experiments were conducted to analyze the performance of the proposed system and demonstrate its application. The results highlight that multi-objective tactical optimization in the IGSS-CCL is conducive to saving resources, protecting the environment, and promoting the sustainable development of cold chain logistics, which remains ahead of the traditional single-objective optimization method. Managers can use the suggested IGSS-CCL as a decision-support tool to control and supervise the scheduling operations of cold chain logistics.

Keywords: intelligent green scheduling system; cold chain logistics; multi-objective; carbon emission; two-stage optimization algorithm

1. Introduction

Cold chain logistics is an important link for agricultural products to follow the "farm to fork" structure (Esmizadeh et al., 2021a). In 2020, with the global outbreak of COVID-19, cold chain logistics provided people with an important guarantee of emergency supplies during a critical period (Jiang et al., 2021). Due to the post-COVID-19 market, pandemic prevention measures, such as traffic control and home isolation, promoted the active development of the "home-bound economy" such as online shopping (Chen et al., 2020; Fei et al., 2020). The traditional cold product market is rapidly converting into stores and e-commerce portals (De and Singh, 2021), with orders for online cold products having skyrocketed and the demand for cold chain distribution in terminal retail stores, such as fresh food convenience stores and supermarkets, is increasing. Retail stores need to meet the product supply of both online and offline channels, which is a new development opportunity for cold chain logistics. However, COVID-19 has been imported through cold chain logistics many times, which highlights the importance of food safety traceability issues to cold chain logistics scheduling (Han and Liu, 2021). Simultaneously, pandemic prevention measures such as street blockades and traffic control directly affect the state of road traffic (Liu et al., 2020a). According to the actual road conditions, arranging scheduling activities to ensure the quality and efficiency of cold chain distribution is a problem that must be considered in cold chain logistics scheduling.

Nowadays, the discussion on carbon emission targets in countries around the world is more intense than ever before because emission levels have reached a new record (Nguyen et al., 2021), as confirmed in the 26th United Nations Climate Change Conference (COP26) held in Glasgow, UK in 2021. Prior to this, more than 61 carbon pricing mechanisms were introduced by countries, including carbon taxes, total volume control, and trading systems (Hasan et al., 2021; World-Bank, 2020). Cold chain logistics is a high-carbon emissions business that contains a large number of road transportation tasks (Zhang et al., 2019). Under the constraints of various carbon regulations, it is a momentous problem that cannot be ignored for cold chain logistics scheduling in the future to pursue effective ways to reduce emissions and comply with restrictions by incorporating carbon emissions into operational decisions. Furthermore, in the face of urban development with increasingly serious traffic congestion and environmental pollution, London and Singapore have implemented management strategies such as traffic congestion charging and urban area traffic restriction (Ros-McDonnell et al., 2018). Other cities around the world have also explored methods and measures to ease congestion and reduce emissions. In this context, reducing the number and frequency of vehicles used, especially the frequency of large distribution vehicles, is a key concern for cold chain logistics scheduling.

To meet the demand for sustainable development, this study aims to develop an intelligent green scheduling system for cold chain logistics (IGSS-CCL), which not only integrates the resources of distribution, demand, and external environment in cold chain logistics to achieve efficient scheduling, but also capture the requirements of urban governance, such as cold product safety traceability, actual traffic restrictions, congestion alleviation, and emissions reduction. The main contributions of this study are as follows:

1) The IGSS-CCL system framework is designed based on method application research, which can provide integrated scheduling services with safe, green, intelligent and collaborative functions for cold chain logistics.
2) This study constructs a multi-objective scheduling decision model to support the IGSS-CCL. The

model disposes of the operation cost, number of vehicles used and carbon emissions as the optimization objectives, so that managers can flexibly respond to different management requirements. The model also specifically accounts for the multi-route decision affected by road traffic conditions and the impact of three-level time windows on system decisions, which is first proposed for the IGSS-CCL.

3) The two-stage optimization algorithm provided in this study, based on Dijkstra's algorithm and the third-generation non-dominated sorting genetic algorithm (NSGA-III), is useful for researchers to further examine similar problems.

The remaining parts of this study are organized as follows. In **Section 2**, we review the literatures relevant for intelligent logistics scheduling and cold chain logistics scheduling. The applied problem and system framework is introduced in **Section 3**. **Section 4** presents the constructed mathematical optimization model for IGSS-CCL. In **Section 5**, an optimization algorithm including two stages is designed. **Section 6** displays the experimental design and results analysis. Finally, **Section 7** contains concluding remarks.

2. Literature Review

This study relates to the literatures on intelligent logistics scheduling and method analysis of cold chain logistics scheduling.

2.1. Intelligent logistics scheduling

Intelligent logistics refers to improving the intelligence and automation level of logistics services using the Internet of Things (IoT), big data, and other intelligent technologies (Fan et al., 2020; Liu et al., 2020b). In intelligent logistics systems, the key link has always been logistics scheduling, which is also the main link for intelligent technology.

Advanced hardware equipment, including autonomous vehicles (AVs) and unmanned aerial vehicles (UAVs) provide opportunities for the realization of intelligent logistics scheduling (Carlsson and Song, 2018; Chowdhury et al., 2021). Since Amazon was a pioneer in successfully applying automated robots to fulfilment centers, the use of AVs and UAVs in logistics operations began to receive rapid promotion and widespread attention (Bogue, 2016). To investigate the impact of AVs on highway congestion, Mirzaeian et al. (2021) developed a queuing model for a multilane highway and analyzed the different effects of the designated-lane policy and integrated policy. Boysen et al. (2018) and Yu et al. (2020) introduced scheduling procedures for an efficient truck-based AVs delivery. Another concept similar to AVs or self-driving vehicles is UAVs (also known as drones). Many studies have conducted analyses on the application of UAVs in last-mile logistics scheduling (Agatz et al., 2018; Perera et al., 2020; Quang Minh et al., 2018). They conducted modeling research on a new variant of the traveling salesman problem (TSP), and verified the advantages of using UAVs in logistics scheduling, such as their high efficiency and low cost. However, owing to the limitations of endurance, capacity, and external distribution environment, it is still impossible to complete large-scale, multi-batch cold product scheduling tasks in urban logistics using UAVs and AVs.

In addition to hardware equipment, some advanced methods and technologies have been applied to intelligent logistics scheduling. Wang et al. (2020) proposed a dynamically coordinated intelligent dispatch system to shorten the waiting time for customers to pick up goods and to improve the operating efficiency of the dispatch system. Li et al. (2019a) studied the optimal route problem for intelligent port logistics based on cloud computing technology. Tsang et al. (2018) presented an IoT-based route planning system that includes a passive packaging modeling module, route planning module, and IoT monitoring module. Attention also need to be given towards research on intelligent logistics systems from the perspective of logistics scheduling security and system supervision (Li et al., 2019b; Su and Fan, 2020).

Different from hardware applications, this study mainly focuses on how to improve the operational efficiency of cold chain logistics scheduling from the method application. As mentioned above, few studies have discussed the real-time interaction and dynamic coordination among various elements in logistics scheduling from a system perspective, especially how to identify external disturbance factors through the intelligent scheduling system to output economic, safe, and environmentally friendly scheduling plans. This study analyzes the logistics scheduling problem from a systematic perspective based on method application, and an IGSS-CCL is designed in this study.

2.2. Cold chain logistics scheduling

The vehicle scheduling problem for cold chain logistics operations and its related variants has become one of the most important and interesting issues for researchers in this field (Awad et al., 2021). This section provides a brief review on the main features of existing cold chain logistics scheduling models and the methods used from three aspects: optimization objective, problem characteristics, and solution approach to multi-objective problems, with special attention paid to papers that considered location and route problems individually or as a whole.

Optimization objective

Optimizing the operating cost of a cold chain scheduling plan is a general setting in traditional single-objective formulations. For example, Zheng et al. (2020) developed a mixed-integer linear programming (MILP) model to minimize the total cost, which solved the docking truck scheduling problem involving refrigerated and frozen products in cold chain logistics. Al Theeb et al. (2020) addressed the integrated scheduling problem including inventory allocation and vehicle routing and constructed a MILP model to optimize transportation and inventory costs. Given that the operation process of cold chain logistics should be maintained at a specific temperature, it is considered energy-intensive and has a significant emission footprint (Awad et al., 2021). Therefore, reducing the impact of carbon emissions on cold chain logistics has become a hot topic in current research. Many studies have considered the cost of carbon emissions in the cost function (Babagolzadeh et al., 2020; Hsiao et al., 2017; Leng et al., 2020a; Leng et al., 2020b; Li et al., 2020b; Li et al., 2019c; Wang et al., 2018; Zhang et al., 2019), which did not individually optimize the carbon emissions of the systems.

In addition to the economic effects, scholars have begun to explore the multi-objective optimization problem in cold chain logistics scheduling, considering the perishability of cold products and the complexity of the distribution environment. Stellingwerf et al. (2021) proposed a quality-driven vehicle routing problem for fresh food logistics and minimized product decay, carbon emissions, cost, and maximum decay as the objective function. Wang et al. (2021c) worked on reducing the total cost and the number of refrigerated trucks in fresh product logistics networks. Bortolini et al. (2016) solved the optimization problem of fresh food distribution networks by considering the cost, delivery time and carbon footprint as objectives. Esmizadeh et al. (2021b) and Golestani et al. (2021) studied the hub location problem for optimizing the total cost and product quality based on Bortolini et al. (2016). For the low-carbon location-routing problem for cold chain logistics, Leng et al. (2020b) considered minimizing the total cost and total quality decay, and Leng et al. (2020a) considered minimizing the total cost and waiting time. As an extension, Qiu et al. (2020) considered minimizing the total cost, greenhouse gas emissions, average waiting time and total quality decay. Liu et al. (2021) proposed an integrated model for the location-inventory-routing problem of perishable products to optimize the cost, carbon emissions, and product freshness. Similarly, Li and Zhou (2021) , Zhao et al. (2020) optimized the logistics cost, carbon emissions and customer satisfaction in the cold chain logistics scheduling problem. El Mokrini and Aouam (2022) jointly optimized network design and logistics outsourcing in healthcare by minimizing the total supply chain cost and perceived risk.

The operating cost in the existing cold chain logistics scheduling research is a concern for both enterprises and scholars. And carbon emission is an essential factor in cold chain logistics scheduling optimization because of the environmental impact in cold supply chain. Furthermore, given the special nature of cold products, optimizing product freshness or quality decay has received considerable attention in many studies. However, the use of vehicles has a clear impact on both cost and carbon emissions, and existing research with multi-objective optimization has rarely analyzed the number of vehicles used. Especially in the post-COVID-19 era, it is of great practical significance to reduce the contact of vehicles, personnel, and products in the cold chain logistics scheduling process, whether from the perspective of pandemic prevention or congestion alleviation and emission reduction. Hence, this study proposes a multi-objective mathematical model that includes the number of vehicles used, operating cost, and carbon emissions as optimization objectives to support the IGSS-CCL in flexibly outputting scheduling schemes under different optimization objectives.

Problem characteristics

The scheduling plan is one of the main activities of cold chain management. In addition to related studies focusing on separately solving vehicle routing problems (Wang et al., 2021c; Zhao et al., 2020) and facility location or hub location problems (Esmizadeh et al., 2021b; Golestani et al., 2021; Li and Zhou, 2021), the location routing problem (LRP) of cold chain logistics has gradually become a research hotspot (Leng et al., 2020a; Leng et al., 2020b; Qiu et al., 2020; Wang et al., 2018). Some studies have even considered inventory plans in cold chain scheduling optimization (Al Theeb et al., 2020; Ghomi and Asgarian, 2019; Li et al., 2020a; Liu et al., 2021). However, in the aforementioned studies, the straight-line distance between nodes was used as the basic data for scheduling optimization problems. Few studies have considered actual roads, and no research has focused on the possible multiple alternative routes between two nodes. Liu et al. (2021), Esmizadeh et al. (2021b) constructed optimization models for different traffic scenarios, however, none of these studies considered actual road conditions. Management measures, such as street blockades and traffic control, affect the state of road traffic. Arranging scheduling activities according to actual road conditions to ensure the quality and efficiency of distribution is a problem that must be considered in cold chain logistics scheduling. Therefore, this study specifically consider multi-route decisions influenced by road traffic conditions in the proposed open LRP model.

Product perishability plays an important role in cold chain applications. Quality loss of cold products is a key issue that has been discussed in detail. Wang et al. (2021c) calculated the quality loss cost in the cost function. Stellingwerf et al. (2021), Leng et al. (2020b) analyzed the quality decay that occurs during the transportation process and nodes. Bortolini et al. (2016), Golestani et al. (2021) quantified the correlation between quality level and transportation time. Liu et al. (2021), Esmizadeh et al. (2021b), Li and Zhou (2021) described the product freshness (or customer satisfaction) metric as a monotonic continuous decreasing function over time. In the case of quality variation, existing studies have focused on modeling quality decay over time. They calculated the quality loss based on the time at which the vehicle left the distribution center. However, the quality loss that occurs within a predefined time window for cold products is accepted by customers (Liu et al., 2021; Zhao et al., 2020). In addition, the quality decay of some cold products changes in a "0-1" relationship, and cold products can no longer be used once the expiration date is exceeded. Therefore, the time starting point for the quality loss calculation should be the first time that the maximum time acceptance is exceeded. This study introduces a three-level time window to quantify the penalty cost (including sales loss or quality loss). This is a more general method than the one that calculates the quality loss of one or one type of cold product.

Compared to ambient transport, cold chain logistics requires stricter temperature control to maintain the quality of cold products, in addition to investing in refrigerated fleets Hsu et al. (2007). Hsiao et al. (2017),Wang et al. (2017), Li et al. (2019c), Leng et al. (2020b) calculated the cost of fuel consumption for transportation in the total cost. Stellingwerf et al. (2018), Stellingwerf et al. (2021) combined the analysis of fuel consumption for motive power and temperature control. However, they ignored the effect of the time window on the fuel consumption. Based on the limitation of the time window, this study considers the part that increases against the time window in the proposed fuel consumption index, which is mainly used for temperature control.

Solution approach for multi-objective problem

Currently, there are two types of numerical approaches for dealing with multi-objective problem (MOP): classical numerical methods and intelligent optimization algorithms (Karimi et al., 2022). In classical methods, a MOP is transformed into a single-objective problem (SOP), and then an exact or optimization algorithm is used to solve the problem. For example, Stellingwerf et al. (2021) solved models with different single objectives using an exact method, optimizing one objective with the other objectives as constraints. Esmizadeh et al. (2021b) solved the SOP using a genetic algorithm after a weighting treatment. Golestani et al. (2021) used the ε-Constraint method to solve the proposed bi-objective model and transform the problem into a solvable SOP. El Mokrini and Aouam (2022) modeled the objective function as a weighted sum of the normalized total cost and perceived risk and solved it using exact coding. The drawback of applying this approach is the need to determine the importance of each objective in advance by using a priori method (Cui et al., 2017).

To maintain the individual characteristics of multiple objectives, an increasing number of studies have used intelligent optimization algorithms to obtain a trade-off solution for the MOP. Based on the work of Srinivas and Deb (1994) on obtaining Pareto frontiers for multi-objective problems using the non-dominated ranking genetic algorithm (NSGA), research on intelligent optimization algorithms with Pareto-dominated methods has proliferated. Leng et al. (2020b) proposed a multi-objective hyper heuristic to obtain Pareto solutions. Leng et al. (2020a), Qiu et al. (2020) designed an optimization framework by combining multiple multi-objective evolutionary algorithms. Zhao et al. (2020) introduced an ant colony algorithm with a multi-objective heuristic function to solve the MOP. Li and Zhou (2021) adopted the NSGA-II proposed in Deb et al. (2000) and designed the program using double-layer composite coding. Wang et al. (2021c) developed a hybrid heuristic algorithm combining k-means clustering, tabu search and NSGA-II to efficiently solve the proposed cold chain logistics scheduling problem. Deb and Jain (2014); Jain and Deb (2014) proposed a reference point-based NSGA-II for MOP (called NSGA-III). Wang et al. (2021a), Wu et al. (2020) used NSGA-III to solve multi-objective optimization problems in logistics networks. As an extension of NSGA-II, NSGA-III has a significant advantage in addressing MOPs with more than two objectives (Gu and Wang, 2020).

Based on the above analysis, a multi-objective open LRP model with multiple features is constructed for the IGSS-CCL to more closely match the actual scheduling environment of cold chain logistics, which innovatively considers the scenarios of three-level time windows and multi-route selection under actual road traffic conditions. The comprehensive impact of multi-level time windows on the scheduling system, including scheduling efficiency, quality loss and fuel consumption, is analyzed in this study. A hybrid heuristic algorithm combining Dijkstra's algorithm and NSGA-III is designed for the proposed complex model. The exact method is introduced to reduce the computational complexity in large-scale logistics networks and improve the initial solution quality of the intelligent optimization algorithm (Wang et al., 2020). The intelligent optimization algorithm is used to obtain Pareto solutions of the MOP and provide managers with a trade-off analysis between different objectives to support decision-making at the strategic or tactical level.

3. Framework Design

A schematic diagram of the framework for the IGSS-CCL presented in this study is shown in **Fig. 1**. The IGSS-CCL can be divided into two parts: the digital system and operation process. The data center plays a key role in the digital system. Its main function is to collect data and information from the business support departments and operation departments in cold chain logistics to complete calculation and analysis, then outputting a "tactical plan", that is, a cold product scheduling plan, which provides guidance for the actual operation of cold chain logistics.

As shown in **Fig.1**, there are two channels of information related to the business support departments. On the one hand, there is information about management services from the internal system of the enterprise. It is necessary to understand road traffic conditions, weather, and other third-party information to obtain a scheme that meets actual scheduling requirements. These factors directly affect the efficiency of cold product scheduling. The information on the operation departments comes from retail stores (RSs) and distribution centers (DCs), including information about orders, cargo, vehicles, and DC operations. Delivery vehicles carrying cargo and drivers realize information interaction between the RSs and DCs through IoT technology, mobile communication devices (such as mobile phones), and positioning systems (such as BDS and GPS) to achieve the association and intercommunication between staff, vehicles, cargo and depots, which is an effective measure to launch intelligent scheduling and real-time monitoring. The digital system plays a decision-making and supporting role in the operational process. The operational process can share and provide feedback information to the digital system, which will help find problems and better arrange the next scheduling task.

Compared with the traditional manual operation method, IGSS-CCL has some special functions, as shown below:

The first is safe and efficient. The data center provides early warning and identifies possible disturbing factors, such as traffic congestion, traffic control, and street blockades. According to the actual road traffic conditions, the data center outputs a reasonable scheduling plan to avoid the risk of cold chain interruption caused by the above factors, so as to guarantee product quality and delivery efficiency. In addition, the full traceability of cold product is a new requirement in cold chain logistics scheduling for pandemic prevention. Through information sharing and feedback between the operational process and the digital system in IGSS-CCL, the scheduling progress can be grasped in real time, thus meeting the requirement of traceability of cold product transportation. For example, visualization technology is introduced to display the scheduling progress in real time, and scheduling plans can be changed or even suspended in time to deal with unexpected emergencies such as cold products carrying viruses (Han and Liu, 2021). IGSS-CCL can also provide support for virus traceability in pandemic prevention work, and reduce the transmission risk of COVID-19 among DCs, RSs and consumers.

The second is intelligence and collaboration. In the post-COVID-19 era, the traditional offline consumer market has changed (De and Singh, 2021). In the face of massive data related to delivery orders, the data center in IGSS-CCL obtains an intelligent scheduling plan for collaborative operation by integrating various elements in the system (staff, vehicles, cargo, DCs, RSs and roads) to guarantee the smooth flow of people, logistics and information between DCs and RSs. For example, the data center and the vehicles are connected through the IoT technology to realize the function of real-time monitoring and regulation of the temperature inside the refrigerated vehicle.

In actual applications, the digital system in IGSS-CCL should provide decisions and support for the specific operational process. The data from the business support and operation departments are collected in the data center, which requires a mathematical model to process the data and then output a scheduling plan. The scheduling plan should be able to meet the operational requirements of delivering cold products in DCs to the RSs. Two key issues must be addressed. First, DCs should be selected to participate in the scheduling work, and which RSs should be served by the selected DCs. Second, how to make vehicle dispatch plans in DCs and how to choose the actual travel route of the vehicle to each RS. Therefore, it is indispensable to construct an optimization model to support the scheduling decision of IGSS-CCL.

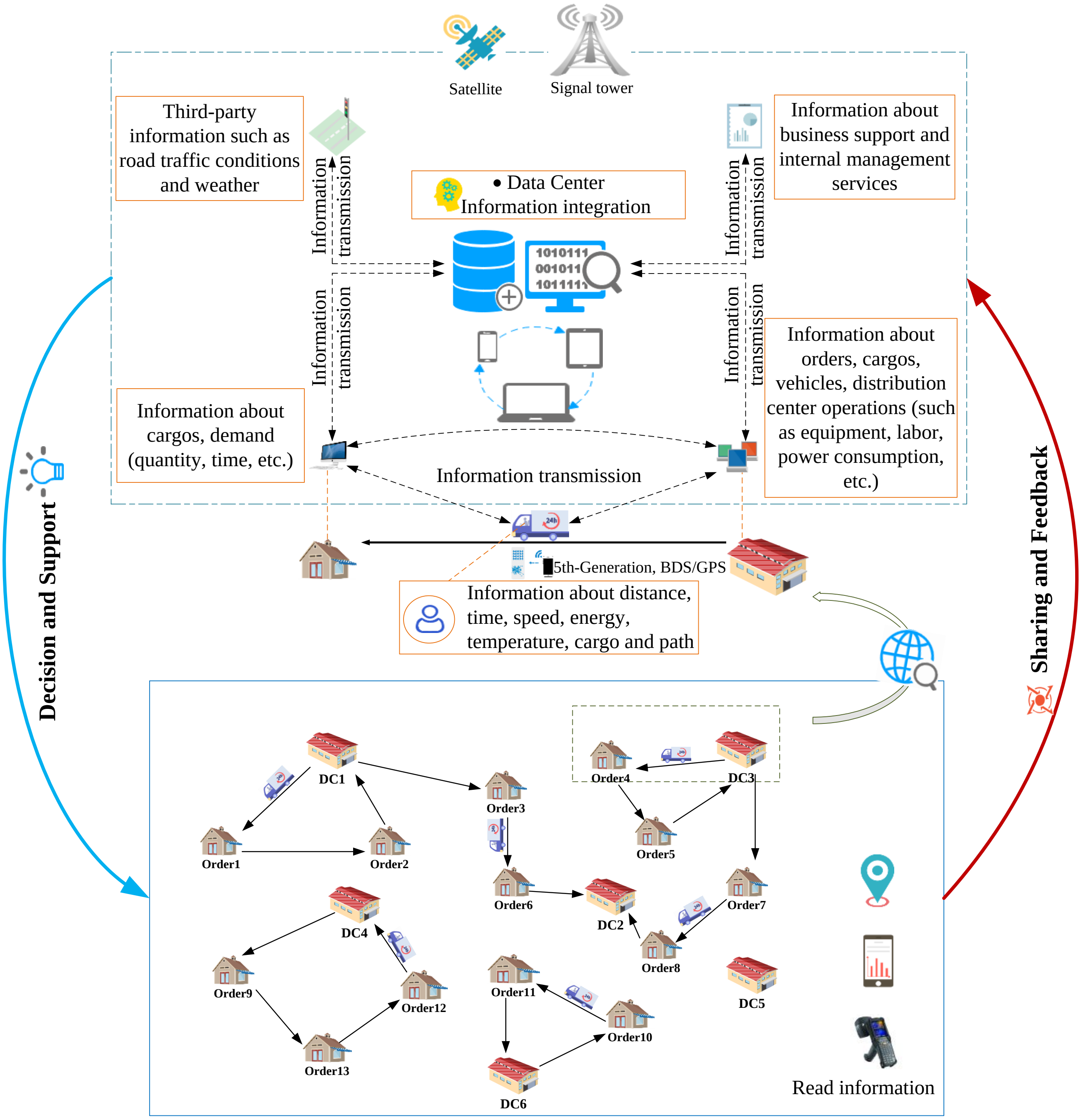


Fig.1. A schematic diagram of the framework for the IGSS-CCL

4. Modeling Approach

The main purpose of this section is to present an optimization model for the open multi-objective LRP with multi-route decision and time windows (MOLRP-MRDTW) in IGSS-CCL. The model aims to capture the trade-off between operating cost, the number of vehicles used, and carbon emissions.

4.1 Model description

The MOLRP-MRDTW optimization model seeks to determine the optimal configuration of the system to deliver cold products to RSs on time. The data center in IGSS-CCL formulates a scheduling plan after the information of orders, time windows, cargo inventory, vehicles, roads and other information are collected. Let $G=(L,A,K_m)$ be a directed graph. Where $L=D\cup R$ represents the set of network nodes. $D=\{1,2,...,m\}$ is the set of m DCs, and $R=\{1,2,...,n\}$ is the set of n RSs. The arc set A is defined as $A=\{(i,j):i,j\in L, i\neq j\}$. Each arc $(i,j)\in A$ corresponds to a travel distance and traffic state (unblocked, congested, prohibited or restricted). $K_m=\{1,2,...,k\}$ represents a set of vehicles in a DC $m\in D$. For a scheduling activity, there are h DCs in set D will be selected to serve n RSs. In addition, what needs to be determined are the RSs served by each DC, the vehicle dispatch plans, and the vehicle routes. Since the m DCs are all operating normally, the vehicles can return to the nearest DC after completing the delivery task. The final scheduling plan is shown in **Fig.2.**

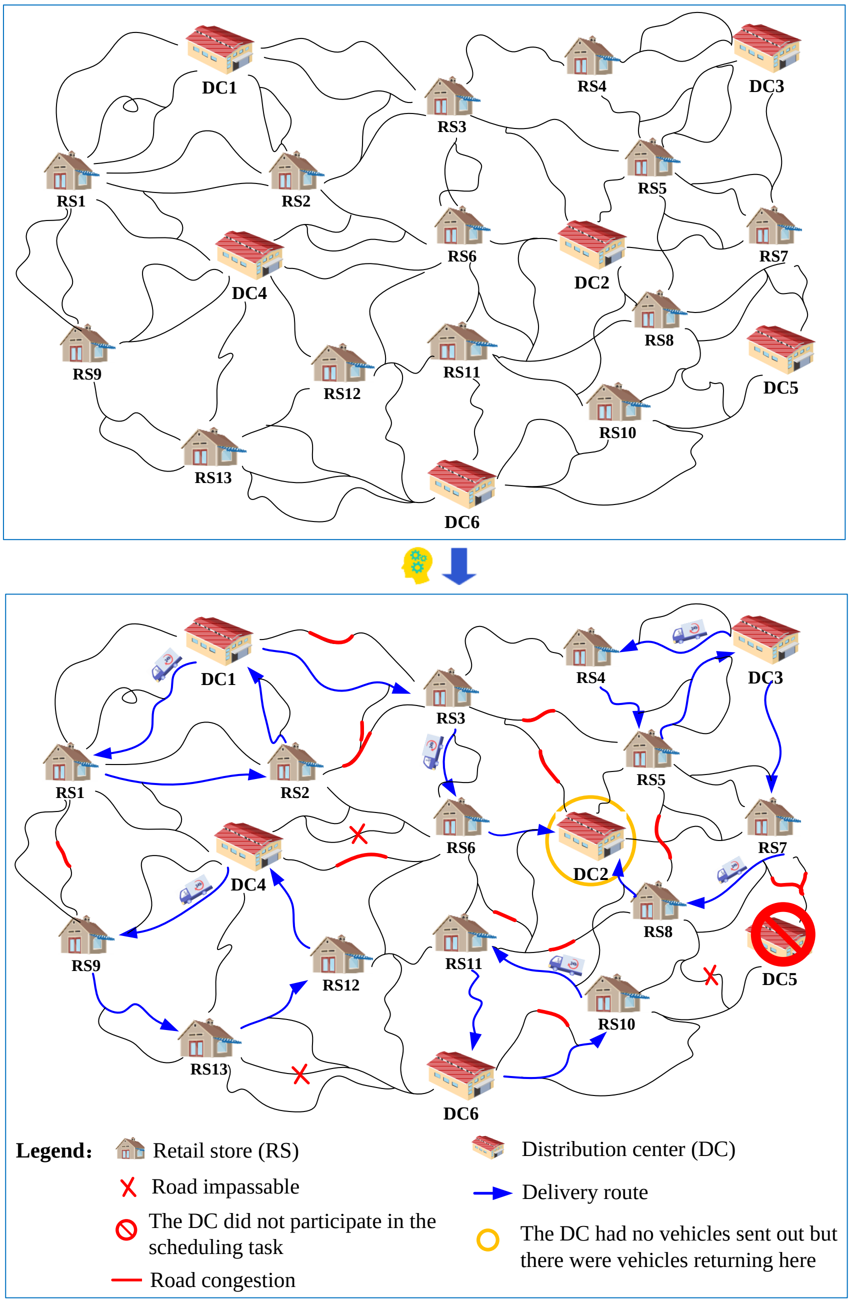


Fig.2. Schematic diagram of scheduling plan

4.2 Model formulation

Cold products generate additional energy consumption during storage and transportation compared to normal-temperature product transportation. In our modeling, we comprehensively consider the cost and carbon emissions caused by energy consumption in the cold chain operational process, as well as cost, number of vehicles used, and carbon emissions are taken as model optimization objectives to aid in the realization of congestion alleviation, carbon emissions reduction, and green development. In particular, considering the impact of road traffic status (unblocked, congested, prohibited, or restricted) on delivery time, constraints on multi-route selection are constructed instead of considering only the Euclidean distance or one route. Moreover, the time windows of the RSs affect the deployment of system resources. Therefore, the impact of the three-level time window constraint on the scheduling plan is analyzed in the model. It was assumed that the demand of each RS is non-negative and less than the maximum loading capacity of the vehicle and maximum inventory of the DC. Split delivery is not allowed for each order. Each vehicle is sent out only once in each period. The notations used to develop the mathematical model are summarized in Appendix A.

4.2.1. Analysis of the number of vehicles used

There are several reasons for taking the number of vehicles used as the optimization function. First, the purpose is to increase the vehicle loading rate, which is conducive to reduce the number of vehicles used in each period of operation in the short term, and it will help enterprises to cut down the number of their own vehicles in the long term, so as to the vehicle fixed costs and labor costs can be decreased, especially in the context of COVID-19 restricting staffs' mobility and leading to financial pressure on the supply chain (Aday and Aday, 2020). Second, what an important way to coordinate the relationship between urban logistics and congestion alleviation, emission reduction, and safety is to effectively controlling the flow of vehicles in central urban areas (Ambrosini and Routhier, 2004). Optimizing the number of vehicles used in cold chain distribution will play a positive role in urban traffic, carbon emissions and travel safety of urban residents. Third, cold chain logistics may become a potential route of COVID-19 transmission (Pang et al., 2020). It is necessary to minimize the number of vehicles used for distribution to help control the spread of the virus and cold chain tracking.

The number of vehicles used N_K in each period is the sum of vehicles sent out by each DC, it can be expressed as:

$$N_K = \sum_{m \in D} \sum_{k \in K_m} o_m u_{mk} \tag{1}$$

4.2.2. Analysis of cost

The cost function of the MOLRP-MRDTW model proposed in this paper includes operating costs of DCs, transportation costs, and penalty costs for violating the time windows.

Operating costs of DCs

The operating costs of DCs include fixed costs such as equipment maintenance, depreciation expenses, and employee salaries, as well as inventory holding costs, electricity costs, and pandemic prevention costs related to demand, which can be presented as follows:

$$C_D = \sum_{m \in D} o_m \left[C_{mf} + \sum_{k \in K_m} \sum_{i \in R} u_{mk} q_i y_i^{mk} \left(C_{mh} + C_{me} E_{ms} / Q_m + C_{mp} \right) \right] \tag{2}$$

Transportation costs

The main consideration about transportation are fuel costs. Note that fuel is used both for driving and for keeping the temperature of the refrigerated vehicle at the right level to maintain cold product quality. Based on the "Greenhouse gas emission accounting method for land transport enterprises" issued by the National Development and Reform Commission of People's Republic of China (China, 2015), the fuel consumption and travel distance of vehicles are positively correlated. The fuel consumption of the vehicle on the arc (i, j) can be approximated calculated as follows:

$$FC_{ij} = OC \times D_e \times d_{ij} \times 10^{-5} \tag{3}$$

The temperature inside the refrigerated vehicle affects the cold product quality during the scheduling process. According to the analysis of Stellingwerf et al. (2018) and Zhang et al. (2018), the heat H_W entering through the vehicle wall when the vehicle is driving and the heat H_D entering through the door when the vehicle is opened affect the temperature inside the vehicle, and the cooling system that controls the temperature inside the vehicle consumes fuel. The total amount of fuel used to control the temperature is directly proportional to the heat entering the vehicle, which can be expressed as follows:

$$FC_{tc} = \left(H_W/1000 + H_D/3.6\times10^6\right)/\left(\eta_e \times COP \times EC_d\right) \tag{4}$$

Where H_W is calculated as $H_W = h_{mk} S_{mk} \Delta T\left(t_{ij} + \max\left\{ET_j - t_j^{mk}, 0\right\}\right)$, $\max\left\{ET_j - t_j^{mk}, 0\right\}$ shows the waiting time when the vehicle arrives at the RS before the earliest service time. The cooling system works normally to maintain the interior temperature while the vehicle is waiting. Similarly, the heat H_D can be calculated as $H_D = V_{mk} HC_a \Delta T_{mk}^i$.

The total fuel consumption in cold chain transportation is formulated as the sum of fuel consumption for vehicle travel, temperature control while the vehicle is driving, and temperature control when the doors are opened:

$$\begin{aligned}
FC &= \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in L} o_m u_{mk} x_{ij}^{mk}\left(FC_{ij} + FC_{tc}\right) \\
&= \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in L} o_m u_{mk} x_{ij}^{mk}\left[\begin{array}{l} OC \times D_e \times d_{ij} \times 10^{-5} \\ + h_{mk} S_{mk} \Delta T\left(t_{ij} + \max\left\{ET_j - t_j^{mk}, 0\right\}\right)/\left(1000 \times \eta_e \times COP \times EC_d\right)\end{array}\right] \\
&\quad + \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in R} o_m u_{mk} x_{ij}^{mk} V_{mk} HC_a \Delta T_{mk}^j/\left(3.6\times10^6 \times \eta_e \times COP \times EC_d\right)
\end{aligned} \tag{5}$$

In addition, there are vehicle maintenance, depreciation costs, and the salary of drivers, which is related to the mileage driven by the vehicle. The total transportation costs are presented as follows:

$$C_T = C_f FC + \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in R} o_m u_{mk} x_{ij}^{mk} C_{kf} d_{ij} \tag{6}$$

Penalty costs

When the goods cannot be delivered within the time windows of the RSs, additional costs will be incurred. Quality loss occurring before the latest tolerable service time LT_i' for cold products is acceptable to the customer (Zhao et al., 2020). Therefore, if the vehicle arrives at RS i before LT_i', waiting costs are incurred only when $t_i^{mk} < ET_i$ and $LT_i < t_i^{mk} \le LT_i'$. If the time to reach RS i exceeds the maximum time acceptance, that is, $t_i^{mk} > LT_i'$, there are a certain percentage of lost sales costs or quality loss costs (considering different cold products) in addition to the waiting costs. In urban distribution of cold products such as vegetables and fruits, if $t_i^{mk} > LT_i'$, the normal sale is affected, then the lost sales costs are calculated. The loss ratio is determined by the delayed arrival time and the saleable time in each period. For fresh milk, and even for medical supplies such as blood and vaccines, there is a "0-1" relationship between the product quality. There is no consideration of a portion of the quality loss, and once the expiration date is exceeded, the cold products are no longer usable. If $t_i^{mk} > LT_i'$, the retail store will reject the products, which is then directly calculated as the quality loss costs, where $t_w = t_i^{mk} - LT_i'$. We regard the additional costs of violating the time windows as the penalty costs, which are calculated by adding the waiting costs and the lost sales costs (or quality loss costs).

$$C_P = \begin{cases} C_{w1} \sum_{i \in R} \left(ET_i - t_i^{mk} \right), & t_i^{mk} < ET_i \\ 0 \;, & ET_i \le t_i^{mk} \le LT_i \\ C_{w2} \sum_{i \in R} \left(t_i^{mk} - LT_i \right), & LT_i < t_i^{mk} \le LT_i' \\ C_{w2} \sum_{i \in R} \left(LT_i' - LT_i \right) + C_l \sum_{i \in R} \left(q_i \left(t_i^{mk} - LT_i' \right) \big/ t_w \right), & t_i^{mk} > LT_i' \end{cases} \tag{7}$$

In summary, the total costs are expressed as the sum of the sub-costs:

$$C = C_D + C_T + C_P \tag{8}$$

4.2.3. Analysis of carbon emissions

Carbon dioxide emission reduction has become an urgent global issue for the development of a low-carbon economy (Lu et al., 2017). What's more, transportation and storage are the main driving forces of environmental issues in logistics (Fichtinger et al., 2015). Compared with normal-temperature products, more energy has been consumed in the operation of cold chain logistics to maintain the low-temperature storage and transportation of cold products, which results in more carbon emissions. Hence, in addition to the carbon emissions generated by transportation, the MOLRP-MRDTW model covers the carbon emissions caused by the fuel consumption used to control the temperature inside the vehicle. Especially in special scenarios where time windows are considered, the additional waiting time leads to increase of fuel consumption for temperature control. And the portion of carbon emissions generated by using electricity in the DCs are also calculated in the model.

In summary, the carbon emissions of the MOLRP-MRDTW model comprehensively includes two aspects. One is carbon emissions from fuel consumption (including transportation and temperature control), and the other is the carbon emissions implied by the use of electricity in the DCs. Carbon emissions from fuel consumption are modelled as follows (China, 2015).

$$E_f = NCV \times FC \times CC \times OF \times 44/12 \tag{9}$$

The carbon emissions implied by the use of electricity are modelled as follows:

$$E_e = AD \times EF_e = \sum_{k\in K_m}\sum_{i\in R} u_{mk} q_i y_i^{mk} \, EF_e E_{ms} / Q_m \tag{10}$$

The total carbon emissions of the cold chain logistics scheduling system in a unit period are formulated as follows:

$$\begin{aligned}
E_{CO_2} &= \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in L} o_m u_{mk} x_{ij}^{mk} E_f + \sum_{m\in D} o_m E_e \\
&= NCV \times CC \times OF \times (44/12) \\
&\times \left[\begin{array}{l} \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in L} o_m u_{mk} x_{ij}^{mk} \left[\begin{array}{l} OC \times D_e \times d_{ij} \times 10^{-5} \\ + h_{mk} S_{mk} \Delta T \left(t_{ij} + \max\left\{ET_j - t_j^{mk}, 0\right\}\right) \Big/ \left(1000 \times \eta_e \times COP \times EC_d\right) \end{array}\right] \\ + \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L}\sum_{j\in R} o_m u_{mk} x_{ij}^{mk} V_{mk} HC_a \Delta T_{mk}^{j} \Big/ \left(3.6 \times 10^6 \times \eta_e \times COP \times EC_d\right) \end{array}\right] \\
&+ EF_e \times \sum_{m\in D}\sum_{k\in K_m}\sum_{i\in R} o_m u_{mk} q_i y_i^{mk} E_{ms} / Q_m
\end{aligned} \tag{11}$$

4.2.4. MOLRP-MRDTW Model Setting

For the MOLRP-MRDTW model of cold chain logistics scheduling system, this study considers the three objective functions of minimizing the number of vehicles used, cost, and carbon emissions, which have been defined in function (1), (8) and (11) respectively in terms of the model parameters and variables.

$$\min N_k \tag{12}$$

$$\min C \tag{13}$$

$$\min E_{CO_2} \tag{14}$$

Constraints and their explanation are discussed as follows:

$s.t.$

$$\sum_{j\in R} x_{ij}^{mk} - o_m \le 0 \qquad \forall i \in D, m \in D, k \in K_m \tag{15}$$

$$\sum_{k\in K_m} x_{ij}^{mk} = 0 \qquad \forall i \in D, j \in D, m \in D \tag{16}$$

$$\sum_{k\in K_m}\sum_{i\in R} o_m u_{mk} q_i y_i^{mk} \le Q_m \qquad \forall m \in D \tag{17}$$

Constraints (15)-(17) associate with the services provided by the DCs. Constraint (15) specifies that the vehicles cannot be sent out from the unopened DCs. Constraint (16) forbids routes between the DCs. Constraint (17) indicates that the total demand of RSs allocated to the DC is not greater than the maximum storage capacity of the DC.

$$\sum_{j\in R} x_{ij}^{mk} \le 1 \qquad \forall k \in K_m, m \in D, i \in D \tag{18}$$

$$\sum_{i\in L} x_{in}^{mk} = \sum_{j\in L} x_{nj}^{mk} \qquad \forall n \in R, k \in K_m, m \in D \tag{19}$$

$$\sum_{i\in R} x_{mi}^{mk} = \sum_{n\in D}\sum_{j\in R} x_{jn}^{mk} \qquad \forall k \in K_m, m \in D \tag{20}$$

$$\sum_{i\in L}\sum_{j\in R} x_{ij}^{mk} q_j \le Q_k \qquad \forall k \in K_m, m \in D \tag{21}$$

Constraints (18)-(21) are restrictions on vehicle service. Constraint (18) forces the model to use a new vehicle when a new route from the DC is started. Constraint (19) ensures that if a node is served by a vehicle, it should leave from the same node to ensure the continuity of the route. Constraint (20) denotes that the vehicle departs from a DC and returns to any DC in the system after completing the delivery task. Constraint (21) limits the maximum total demand of nodes in each route, which cannot exceed the maximum load capacity of the refrigerated vehicle.

$$\sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L} x_{ij}^{mk} \le 1 \qquad \forall j \in R \tag{22}$$

$$\sum_{m\in D}\sum_{k\in K_m}\sum_{i\in L} q_{ij}^{mk} - \sum_{m\in D}\sum_{k\in K_m}\sum_{n\in L} q_{jn}^{mk} = q_j \qquad \forall j \in R \tag{23}$$

$$M\sum_{i\in R} x_{mi}^{mk} - \sum_{i\in R}\sum_{j\in L} x_{ij}^{mk} \ge 0 \qquad \forall k \in K_m, m \in D \tag{24}$$

$$t_i^{mk} = \sum_{n\in L} x_{ni}^{mk}\left(t_n^{mk} + q_n t_u + t_{ni} + \max\left\{ET_n - t_n^{mk}, 0\right\}\right) \qquad \forall m \in D, k \in K_m, i \in R \tag{25}$$

Constraints (22)-(25) are proposed to guarantee the demands of RSs. Constraint (22) enforces that there is only one vehicle serves for each RS and each RS is assigned to only one DC. Constraint (23) confirms that the demand of each RS will be met, which also means the products' flow on a route will be decreased after visiting a RS by its demand. Constraint (24) ensures that the RS is accessed by the vehicle which departs from the DC. Constraint (25) states that the time to arrive at the RS is affected by waiting time, unloading time and driving time.

$$t_{ij} = \min\left(t_{ij}^1, \ldots, t_{ij}^n\right) = \min\left(d_{ij}^1/v + t_{ij}^{1'}, \ldots, d_{ij}^n/v + t_{ij}^{n'}\right) \qquad \forall i \in L, j \in L \tag{26}$$

$$d_{ij} = \begin{cases} \left(t_{ij} - t_{ij}^{n'}\right)v & t_{ij}^{n'} \text{ is unique}, \ \forall i \in L, j \in L \\ \left[\min\left(t_{ij} - t_{ij}^{n'}\right)\right]v & \text{there are multiple } t_{ij}^{n'}, \ \forall i \in L, j \in L \end{cases} \tag{27}$$

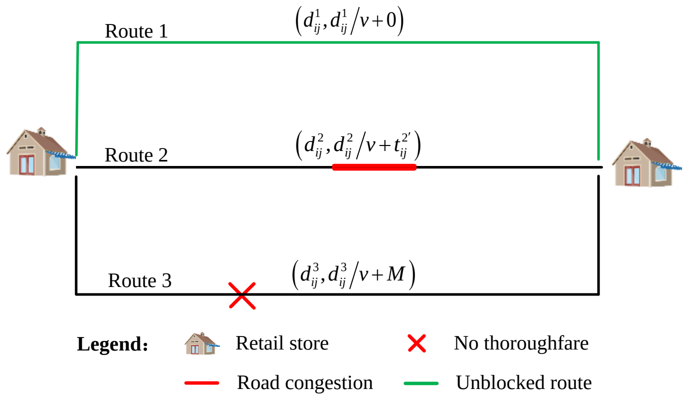


Fig.3. A schematic diagram of route selection

Constraints (26) and (27) relate to route selection. Different from the existing researches, there may be multiple routes to choose between the two nodes in our research. As shown in **Fig. 3**, there are different travel distance and time on different routes. At the same time, road traffic status (unblocked, congested, prohibited or restricted) may bring about additional time, thereby increasing the travel time of the route. Since the routes with prohibited or restricted sections are disconnected, we assume that the additional time brought by prohibited or restricted sections is *M*. Considering the timeliness of cold products distribution, the principle of route selection is to preferentially select routes with less travel time. If there are multiple routes with the same travel time, the route with the shorter travel distance gets the priority.

$$q_{ij}^{mk}, t_i^{mk}, t_{ij}, d_{ij}, \left(t_{ij} - t_{ij}^{n'}\right) > 0 \tag{28}$$

$$o_m, u_{mk}, x_{ij}^{mk} = \{0,1\} \quad \forall m \in D, k \in K_m, i \in L, j \in L \tag{29}$$

$$y_i^{mk} = \{0,1\} \quad \forall m \in D, k \in K_m, i \in R \tag{30}$$

Constraints (28)-(30) limit the values of variables.

5. Algorithm Design

To solve the proposed MOLRP-MRDTW model in an efficient computational time, a hybrid heuristic algorithm is proposed to obtain a high-quality scheduling plan for IGSS-CCL. We introduce a two-stage optimization algorithm (TSOA) based on Dijkstra's algorithm and the NSGA-III. The calculation process of the TSOA designed in this study is shown in **Fig. 4.**

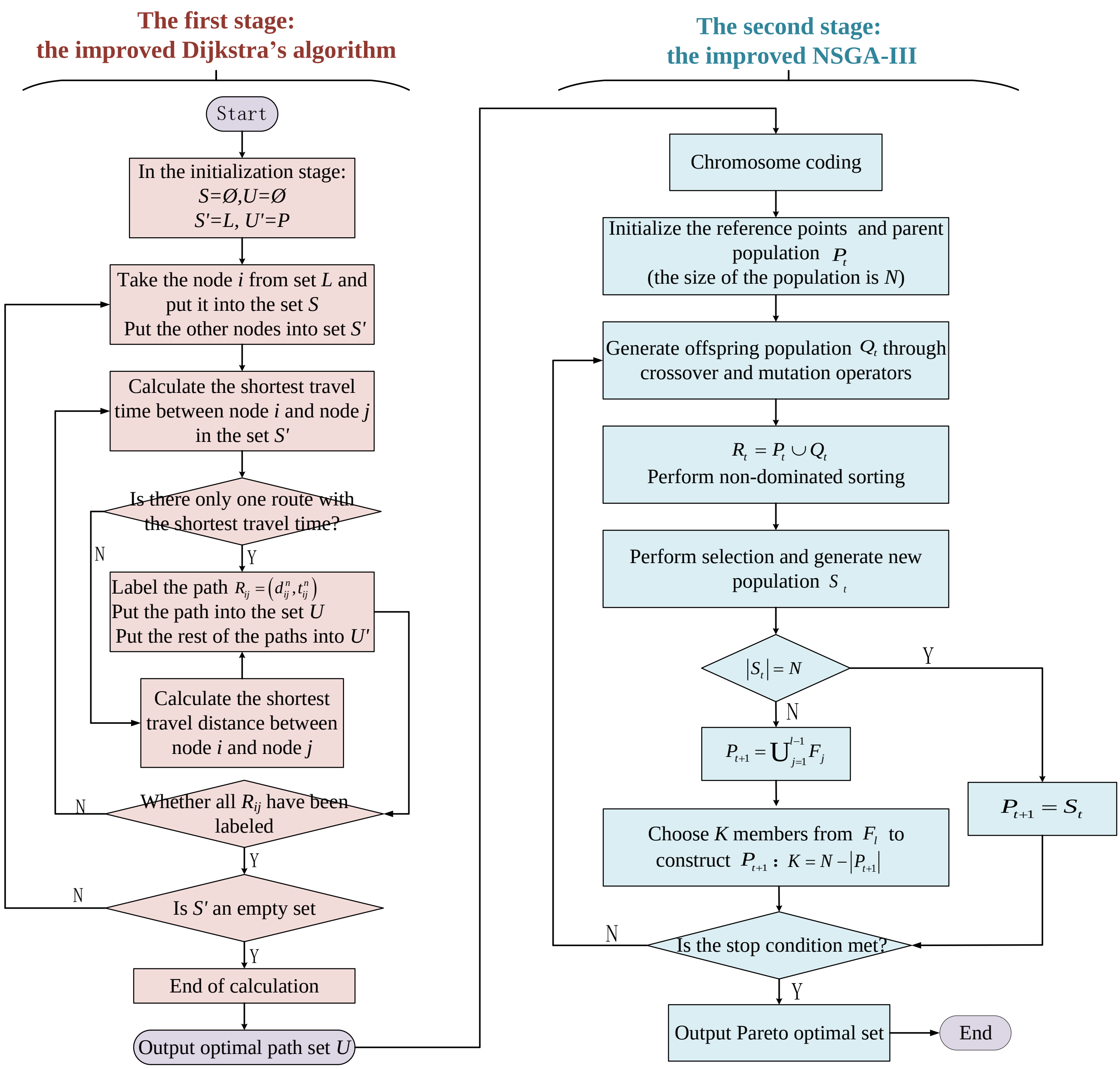


Fig.4. The two-stage optimization algorithm

5.1 The first stage: the improved Dijkstra's algorithm

The improved Dijkstra's algorithm is designed to find the optimal routes between nodes in the network, and then form the optimal route network. Dijkstra's algorithm is a classic algorithm used to solve the shortest path problem in the network (Wang et al., 2020). The basic principle of Dijkstra's algorithm to solve the shortest path problem is to start from one node and gradually explore the shortest path to other nodes through labelling (Dijkstra, 1959). However, the nodes are not connected to each other in the shortest path network calculated by Dijkstra's algorithm, that is, it is only the shortest path from the starting node to all nodes in the network. Such a result cannot be used as the initial network in our second-stage optimization. For this study, what is more important to get the optimal route between each node in a complex multi-route network. Moreover, additional travel time may result from road traffic conditions. When selecting the optimal path, we should consider the travel distance and put the travel time in the first place. Given that the complexity of path selection in this study, the improved Dijkstra's algorithm is designed using the optimal strategy and algorithmic logic of Dijkstra's algorithm. The algorithm traverses all routes from the starting node to the remaining nodes every time to find the optimal routes based on the optimization principle until it is extended to all nodes. The basic principle of the algorithm is shown in **Fig. 5.**

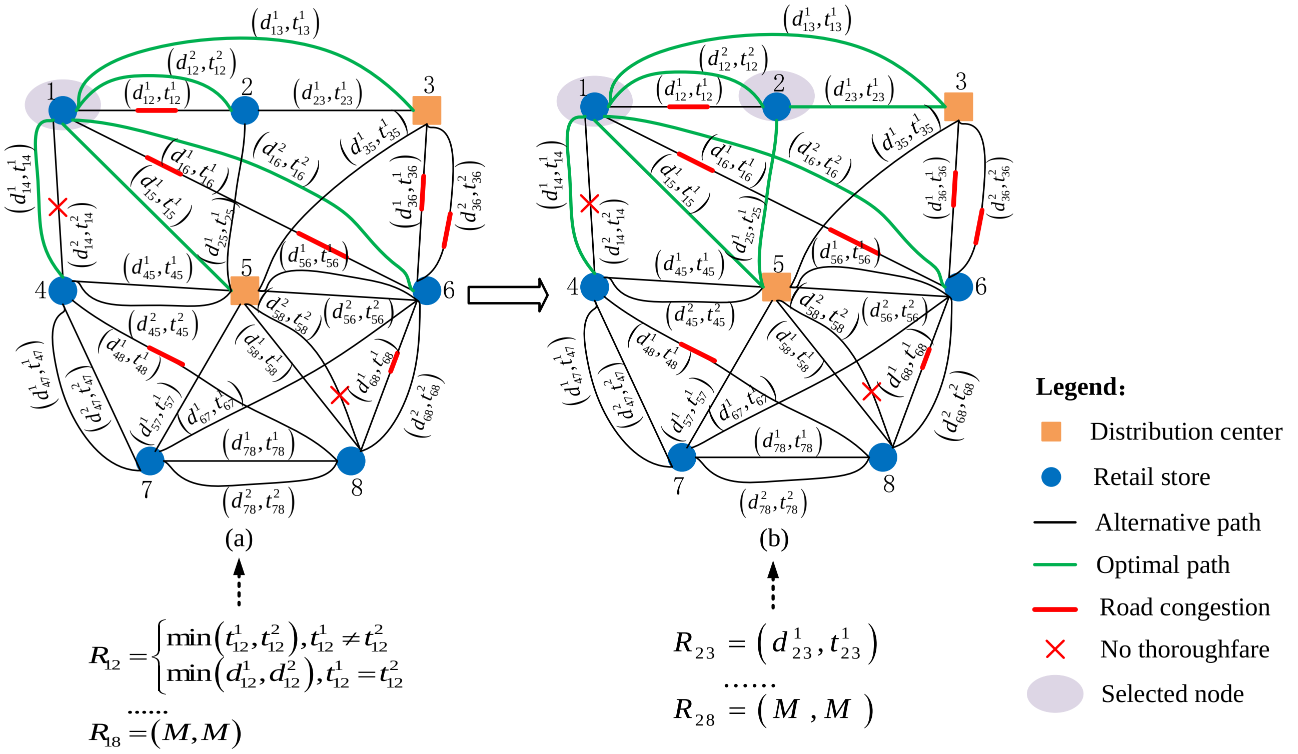


Fig.5. The basic principle of the improved Dijkstra's algorithm

The basic steps of finding the optimal route network in a complex network by the improved Dijkstra's algorithm are presented as follows:

Step 1: All nodes on the network, including DCs and RSs, are numbered sequentially and regarded as a set L. Set S and set S' are constructed, where $S \cup S' = L$. In addition, all routes on the network are part of the set P, and each route has two attribute values $\left(d_{ij}^i, t_{ij}^i\right)$, which represent the travel distance and travel time of the route respectively, where $t_{ij}^i = d_{ij}^i / v + t_{ij}^{n'}$. If there is no connected route between two nodes, the virtual attribute values (M, M) are set, where M is an infinite number. Set U and set U' are constructed, where $U \cup U' = P$. In the initial state, $S' = L$, $U' = P$, set S and set U are empty.

Step 2: Pick any node i in the set L and add it to the set S. By default, the point with the smallest number is selected in turn. As the network shown in **Fig.5 a**, where $L = \{1, 2, ..., 8\}$, node 1 is selected to enter the set $S = \{1\}$, and $S' = \{2, 3, ..., 8\}$. And then, the optimal route between the node 1 and all nodes in the set S' are searched. The optimization principle is the basis of the whole algorithm, which is described in detail as Eq. (31). The shortest travel time between nodes should be calculated at first. If there are multiple routes with the same travel time, the shortest travel distance will be further calculated.

$$R_{ij}=\begin{cases}\min\left(t_{ij}^1,t_{ij}^2,...,t_{ij}^m\right), t_{ij}^1\neq t_{ij}^2\neq ...\neq t_{ij}^m\\ \min\left(d_{ij}^1,d_{ij}^2,...,d_{ij}^m\right), \text{there are multiple minimum } t_{ij}^n \text{ values}\\ j=i+1,...,i+m-1\end{cases} \tag{31}$$

Step 3: According to the optimization principle, the obtained optimal route between node i and node j is labeled as $R_{ij}=\left(d_{ij}^n,t_{ij}^n\right)$, where $j\in S'$. And the route with $\left(d_{ij}^n,t_{ij}^n\right)$ is moved from set P to set U in turn, that is $U=\left\{\left(d_{i(i+1)}^n,t_{i(i+1)}^n\right),\left(d_{i(i+2)}^n,t_{i(i+2)}^n\right),...,\left(d_{i(i+m-1)}^n,t_{i(i+m-1)}^n\right)\right\}$. For example, there are two routes $\left(d_{12}^1,t_{12}^1\right)$, $\left(d_{12}^2,t_{12}^2\right)$ between node 1 and node 2, where $t_{12}^1>t_{12}^2$. So the optimal route between node 1 and node 2 is $R_{12}=\left(d_{12}^2,t_{12}^2\right)$. R_{12} is moved to the set U. Searching the optimal routes from node 1 to other nodes in turn can obtain $U=\left\{\left(d_{12}^2,t_{12}^2\right),\left(d_{13}^1,t_{13}^1\right),\left(d_{14}^1,t_{14}^1\right),\left(d_{15}^1,t_{15}^1\right),\left(d_{16}^2,t_{16}^2\right)\right\}$, where $R_{17}=R_{18}=\left(M,M\right)$ are the virtual attribute value.

Step 4: Continue to take node $i+1$ from the set L and add them to the set S. As shown in **Fig.5 b**, node 2 is selected after node 1 to enter the set $S=\{1,2\}$, and $S'=\{3,4,...,8\}$. The optimal routes between node 2 and all nodes in the set S' are searched sequentially, where $R_{23}=\left(d_{23}^1,t_{23}^1\right)$, $R_{25}=\left(d_{25}^1,t_{25}^1\right)$. Repeat steps 2 and 3 until $S=L$, that is, the optimal routes between all nodes on the network are calculated. Finally, the optimal route set U of the network is obtained, which will be used as the initial state of the next stage operation.

5.2 The second stage: the improved NSGA-III

There is an optimal route network after the running of the first stage algorithm. We presented the second stage algorithm, the improved NSGA-III, to further find the specific scheduling plan for the IGSS-CCL. The MOLRP-MRDTW model is a variant of the vehicle routing problem, so it is also an NP-hard problem (Schiffer et al., 2019). When solving MOPs with three or more objectives, the NSGA-III based on the non-dominated sorting and reference point methods is effective to ensure the convergence and diversity of the algorithm (Deb and Jain, 2014). The improved NSGA-III uses a double-layer structure real coding. Different from the simulated binary crossover and polynomial mutation strategies used in the standard NSGA-III, the improved NSGA-III selects both arithmetic crossover operator and Gaussian mutation operator for genetic operations to improve the local search performance for the focal region. In addition, the NSGA-III with a fixed mutation rate does not always find a final solution to the optimization problem (Yi et al., 2018). The adaptive strategy in the improved NSGA-III enhances its performance by adjusting the mutation rate.

The basic steps of searching the optimal scheduling plan by the improved NSGA-III are presented as follows:

Step 1: Chromosomes coding and decoding. In the algorithm, the chromosome is divided into two gene segments, and the double-layer structure real coding is introduced to encode the gene segments. The first level gene segment $G1$ is an array with a length of m, where m is the number of DCs participating in the scheduling task. And the second level gene segment $G2$ is an array with a length of $n+k-1$, where n is the number of RSs, and k is the number of available vehicles owned by all DCs participating in the scheduling task. Both arrays are composed of real numbers between 0.0 and 1.0. For instance, there are 4 candidate DCs, 2 of which are involved in the scheduling task, and each DC has 2 vehicles. There are 6 RSs waiting for service. A decoding sequence is formed after roulette decoding for $G1$ and random key decoding for $G2$. An example of chromosome coding and decoding is shown in **Fig. 6**.

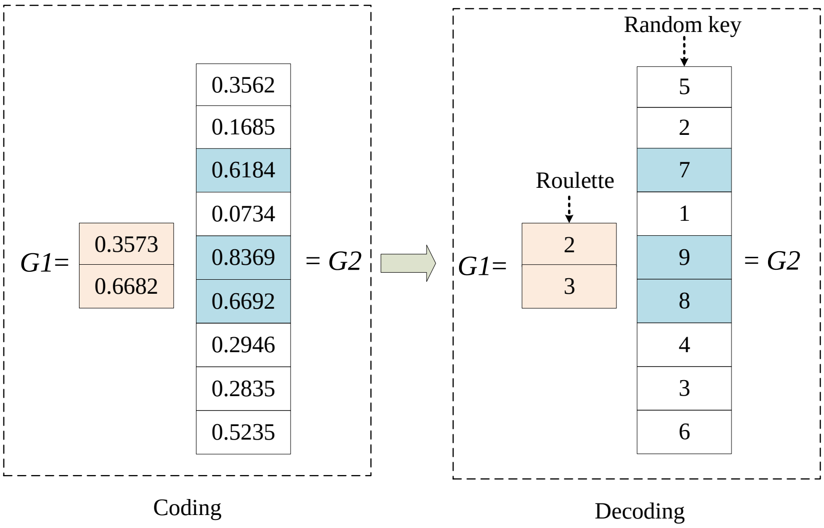


Fig.6. An example of the chromosome structure

Step 2: Initialize the parent population P_t with N individuals. The quality of the parent population directly affects the execution efficiency of the algorithm iteration, so the generation and population size of the parent population work on the quality of the Pareto solution set to a certain extent. The parent population in the standard NSGA-III is randomly generated, and no other screening restrictions are imposed. Therefore, we add screening conditions based on randomly generating the parent population. The individuals that cannot meet the conditions are eliminated before iteration by restricting the overall satisfaction level of the parent population and the loading capacity of delivery vehicles, which contributes to maintain the diversity and quality of the parent population.

Step 3: Design genetic operators. Genetic operators act on the generation process of offspring chromosomes. In standard NSGA-III, simulated binary crossover and polynomial mutation operators with fixed crossover and mutation rates are used to generate new individuals. We adopt arithmetic crossover (Ali and Tawhid, 2017) and Gaussian mutation (Sun and Gao, 2019) to perform on the individuals of the parent population, so that the offspring population Q_t is more adaptable to the environment. Actually, the NSGA-III with fixed mutation rate may lead to unsatisfactory results for some complex problems (Yi et al., 2018). As a result, we introduce an adaptive mutation strategy in the NSGA-III to improve algorithm's performance. The update rule of mutation probability p_m is shown in Eq. (32).

$$p_m = r + (g-1)\times(1-r)/(g_m - 1) \tag{32}$$

Where g and g_m are the current generation and maximum generation, respectively. And $r = I/50$ is the fixed real number, I is the dimension of the problem, $I = 3$ in this study.

Step 4: Non-dominant sorting. The parent population P_t and the offspring population Q_t generated by genetic operation are combined to get a new population R_t. The size of R_t is $2N$.

According to the rule of non-dominated sorting, the individuals in R_t are divided into several different non-dominated layers ($F_1, F_2, ..., F_n$).

Step 5: Perform the individual selection mechanism to construct a new population P_{t+1} for the next iteration. Research on related algorithms shows that the elite preservation strategy and reference points introduced in NSGA-III as the selection instrument can effectively increase population diversity and local search ability when solving problems with more than two objectives (Chen et al., 2017; Tavana et al., 2016). Therefore, TSOA follows the selection mechanism based on the elite preservation strategy and reference points in NSGA-III. Algorithm 1 describes a simplified calculation procedure including selection, normalizing the objectives, associating reference points, and niche-preserving operation. For detailed calculation procedure, please refer to the original paper (Deb and Jain, 2014).

Algorithm 1 The Individual Selection of NSGA-III

Input. H processed reference points Z^r, $(F_1, F_2, ..., F_n) = Non-dominated\ sort(R_t)$
for $t = 1$ to $MaxIt$ **do**
  $S_t = \varnothing,\ i = 1$
  repeat
    $S_t = S_t \cup F_i$ and $i = i + 1$
  until $|S_t| \geq N$
  Last front to be included: $F_l = F_i$
  If $|S_t| = N$ **then**
    $P_{t+1} = S_t$, break
  else
    $P_{t+1} = \bigcup_{j=1}^{l-1} F_j$
    Points to be chosen from F_l: $K = N - |P_{t+1}|$, K is the number of members selected.
    Normalize objectives F^n and create reference set Z^r : $Normalize(F^n, S_t, Z^r)$
    Associate each member s of S_t with a reference point: $[\pi(s), d(s)] = Associate(S_t, Z^r)$
    Where $\pi(s)$ is the closest reference point of s, $d(s)$ is the distance between s and $\pi(s)$.
    Compute niche count ρ_j of reference point $j \in Z^r$
    Choose K members from F_l to construct P_{t+1}: $Niching(K, \rho_j, \pi, d, Z^r, F_l, P_{t+1})$
  end if
end

6. Experimental Design and Result Analysis

To ensure the fairness of the numerical analysis and algorithm solving environment, MATLAB R2018a is used to complete all the experiments. The running environment is Intel® Core™ i7-8550U CPU@ 1.80GHz 1.99 GHz.

6.1. Algorithm experiment

This section evaluates the performance of the designed TSOA through experiments on instances with different sizes. Since MOLRP-MRDTW model is defined for IGSS-CCL for the first time, there are no calculation examples that can be directly called. Therefore, this study generated four test data sets with reference to Wang et al. (2018) and Al Theeb et al. (2020) , including 2 tiny, 2 small, 2 medium, and 2 large instances. The instance sizes are shown in **Table 1**. The TSOA and standard NSGA-III were used to solve four groups of test instances in the same experimental environment. Because the function of multi-route selection cannot be realized in the standard NSGA-III, the results of the first stage in TSOA were called at running. The parameters set in the calculation were as follows: the initial population was 80, and the maximum number of iterations was 500 (Leng et al., 2020b). The performance of the two algorithms is summarized in **Table 2**.

Table 1 The data of instances used in experiments.

Instance	T	S	M	L
Number of candidate DCs	3	5	8	10
Number of RSs	20	50	100	200
Vehicles available in each DC	5	5	10	10
Load capacity of vehicles (kg)	2000	2000	2000	2000

We mainly compare the performance of the algorithms from two aspects: the base metrics and the comprehensive performance metrics. Where the base metrics includes the number of solutions (N_{sol}), the running time (RT) and the optimization values of the objective functions. The hypervolume (HV)(Ishibuchi et al., 2017; Tian et al., 2017; Zitzler and Thiele, 1999) and coverage of two sets (ζ) (Zitzler and Thiele, 1999) are introduced as comprehensive performance metrics.

Table 2 Summary results of the TSOA and standard NSGA-III on different sized instances.

Instance	TSOA			NSGA-III		
	N_{sol}	RT (s)	HV	N_{sol}	RT (s)	HV
T	14	185.67	4.88E-01	11	135.02	3.65E-01
S	42	198.21	4.60E-01	36	145.44	2.83E-01
M	49	207.58	4.14E-01	46	155.87	1.92E-01
L	65	231.98	4.09E-01	58	179.77	1.46E-01
Average	42.5	205.86	0.44275	37.75	154.03	0.24
t-test	-	-	-	4.61	115.08	6.53
p-value	-	-	-	1.92E-02	1.45E-06	7.31E-03

Table 2 displays the number of solutions, running time, and HV values of the two algorithms for solving different sized instances. Two-sample t-test was performed to compare the mean values of two groups (TSOA vs. NSGA-III) (Shi et al., 2022; Wang et al., 2021b). The p-values were all less than 0.05 according to the statistical analysis of the two sets of results, which confirms that the results are significantly irrelevant. Therefore, the relative effectiveness of the proposed algorithm can be validated by comparing the solution results of the data sets. First, in terms of solutions acquisition, it is apparent that TSOA was able to obtain more solutions than NSGA-III for each instance. Second, comparing the running time of the two algorithms objectively, TSOA took longer to search for results, but the average time difference between the two algorithms was less than 60s. The reason is that the standard NSGA-III directly invoked the results of the first stage in the TSOA. And an adaptive

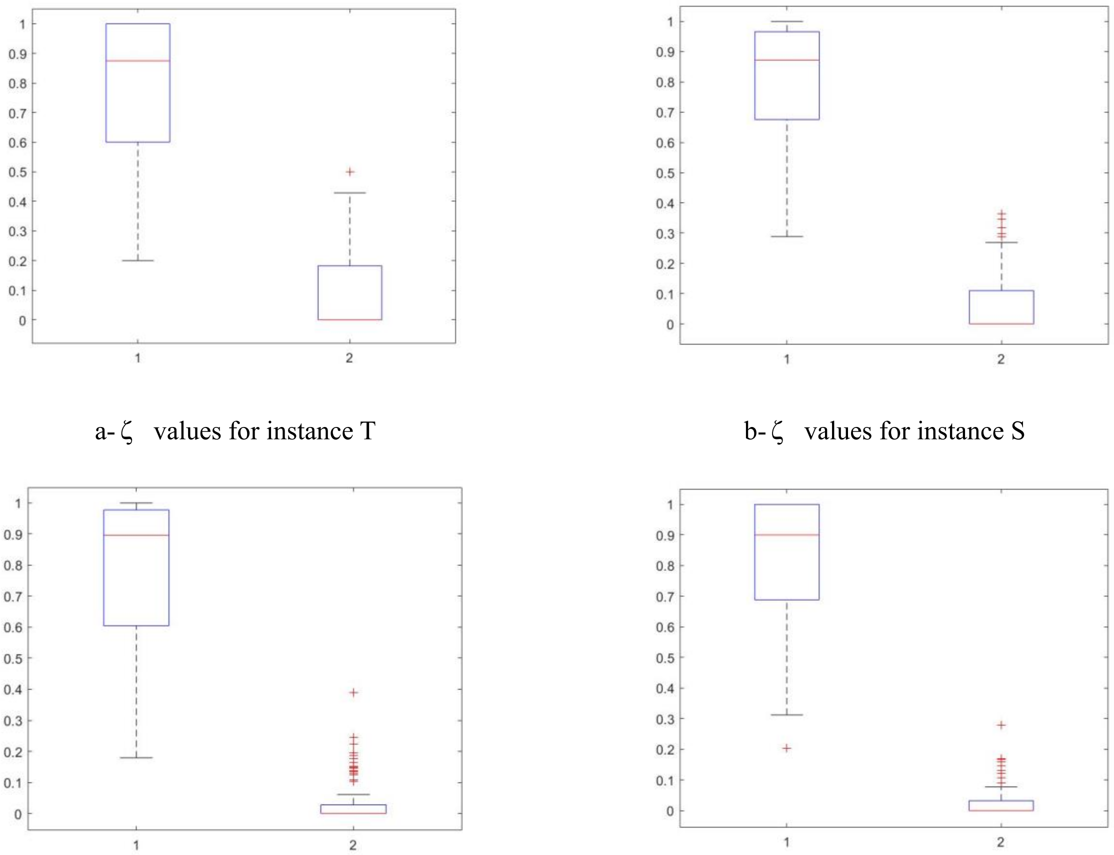
mutation strategy was used in the TSOA, which increases the running time of the algorithm. Third, the HV values of TSOA were greater than that of NSGA-III (the maximum difference reaches 2.63E-01), indicating that TSOA has a better convergence and distribution of an approximate Pareto front than standard NSGA-III. In conclusion, when there is no significant difference in running time, this study focuses on the contribution of the TSOA to the optimal Pareto solutions. In addition, a Pareto solution that has the largest HV value in each group of experiments and is superior to other solutions in at least two dimensions was selected to compare the optimization effects of the algorithms. The corresponding comparison results are shown in **Table 3**.

Table 3 The comparison of optimization values of TSOA and NSGA-III.

Instance	TSOA			NSGA-III			Optimization value		
	$a\min C$	$a\min N_k$	$a\min E_{CO_2}$	$b\min C$	$b\min N_k$	$b\min E_{CO_2}$	C	N_k	E_{CO_2}
T	8417.83	4	230.93	8747.17	4	300.56	329.34	0	69.63
S	24877.74	9	612.38	25590.61	10	672.93	712.87	1	60.55
M	49630.63	22	1247.81	51130.24	23	1322.28	1499.61	1	74.47
L	119750	34	2738.06	141229.2	35	2925.68	21479.2	1	187.61
Average	-						6005.26	1	98.07

Since the optimization functions of the MOLRP-MRDTW model are to minimize cost, the number of vehicles used and carbon emissions, small objective function values are expected. In **Table 3**, the optimization value refers to the difference between the results of TSOA and NSGA-III (C :cost, N_k :the number of vehicle used, E_{CO_2} : carbon emission). The results show that the TSOA has more advantages than the standard NSGA-III, which is mainly reflected in two aspects. The first is that the objective functions values obtained by the TSOA($a\min C$, $a\min N_k$, $a\min E_{CO_2}$) were better than the standard NSGA-III($b\min C$, $b\min N_k$, $b\min E_{CO_2}$), that is, the optimization values of C, N_k and E_{CO_2} were all greater than or equal to zero. The second is that the optimization values of C, N_k and E_{CO_2} all gradually increased with the expansion of instances size by comparing the optimization values of the four groups of instances, where C increased from CNY 329.34 to CNY 21479.2, and E_{CO_2} increased from 60.55kg to 187.61kg. The larger the instance size, the more obvious the optimization effect of the TSOA.

Fig. 7 depicts the direct comparison of ζ values on different sized instances to illustrate the dominance of the outcomes of one algorithm over the outcomes of another. As shown in **Fig. 7**, $\zeta_1\left(X^{TSOA}, X^{NSGA-III}\right)$ was significantly larger than $\zeta_2\left(X^{NSGA-III}, X^{TSOA}\right)$ in the different instances (where X^{TSOA} and $X^{NSGA-III}$ represent the sets of solutions obtained by TSOA and NSGA-III, respectively). The mean values of $\zeta_1\left(X^{TSOA}, X^{NSGA-III}\right)$ were 0.7788, 0.7923, 0.7796, and 0.8080, respectively. And the mean values of $\zeta_2\left(X^{NSGA-III}, X^{TSOA}\right)$ were 0.0931, 0.0589, 0.0361, and 0.0272, respectively. The results show that the optimal solutions found by TSOA largely dominates the optimal solutions found by NSGA-III.



a- ζ values for instance T

b- ζ values for instance S

c- ζ values for instance M

d- ζ values for instance L

Fig.7. $\zeta_1\left(X^{TSOA}, X^{NSGA-III}\right)$ vs. $\zeta_2\left(X^{NSGA-III}, X^{TSOA}\right)$ for different size instances.

In a word, from the analysis of the base metrics and comprehensive performance metrics, the overall performance of the TSOA is better than that of the standard NSGA-III when solving the MOLRP-MRDTW model for IGSS-CCL proposed in this study.

6.2. Case study

6.2.1 Description of the case study

The proposed IGSS-CCL was applied to a real-world case study for the scheduling operation of cold chain logistics in Company S from Chongqing (a provincial administrative region in China). With the development of the online shopping mode, the demand for the cold chain distribution of Company S shows a rapid upward trend. However, in the scheduling process, the scheduling plans were formulated based on the work experience of the managers, and they arranged as many vehicles as possible to meet the time windows requirement of stores. New operational requirements, such as pandemic prevention, energy conservation, and emission reduction, make it more difficult to perform scheduling work using traditional methods. Facing a real-time and dynamic distribution environment and demand, Company S is unable to quickly output an intelligent green scheduling plan that balances the relationship among costs, vehicle frequency, energy conservation and emission reduction.

The purpose of the case study using Company S is to prove that the proposed method has a more general value, not just for Company S. There are five distribution centers belonging to Company S around the urban area of Chongqing, China. Vehicles depart from the DCs at 22:00-00:00 to deliver goods to the RSs. The demand points in the urban area include 71 retail stores. The distribution of the logistics network points composed of the locations of the DCs and RSs is presented in **Fig. 8**.

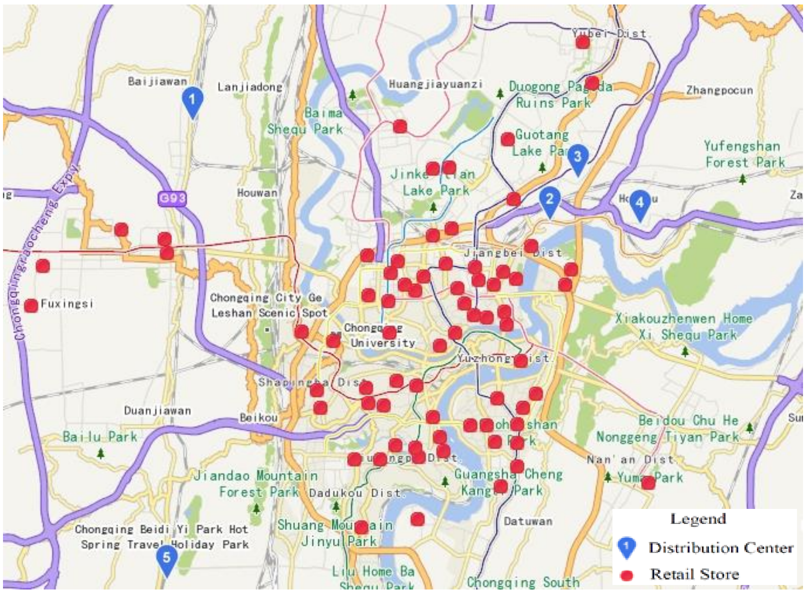


Fig.8. The logistics network points for the case study.

The model constructed for IGSS-CCL in this study is a general model that is not limited to any special statistical distribution. Hence, in accordance with (Berk and Gurler, 2008; Yin et al., 2016), the daily demand data of RSs for cold products were generated using a Poisson distribution. Here, the vehicle speed was considered as a fixed parameter of 40 km/h, which conforms to the majority of road speed standards in the case study. Other parameters used to calculate fuel consumption and carbon emissions were taken from previous studies (China, 2015; Reddy et al., 2021; Stellingwerf et al., 2018; Tassou et al., 2009; Tso et al., 2002).

6.2.2 Results of the case study

Based on the aforementioned values, **Fig. 9** depicts the distribution of the solutions for the case study in Company S within the X-vehicle used, Y-cost, and Z-carbon emission Cartesian space. The result is a Pareto solution set composed of 42 solutions, that is, 42 different scheduling schemes are provided for Company S through IGSS-CCL.

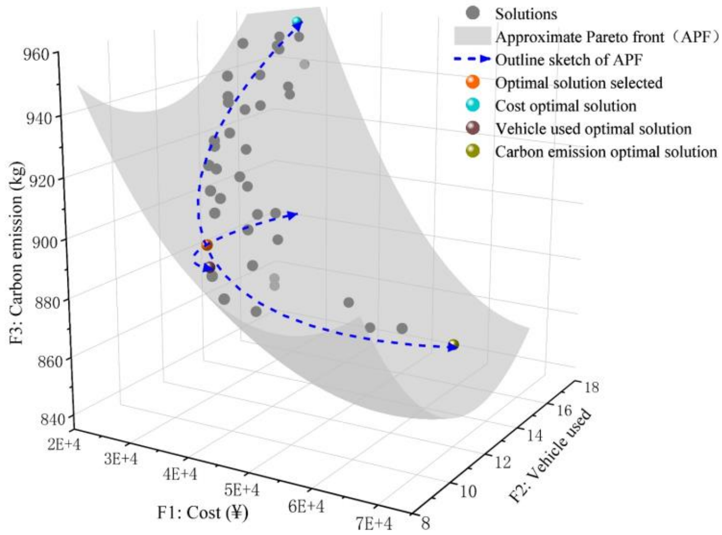


Fig.9. The general view of optimal solutions

The Pareto solution set includes all non-dominated solutions of the MOLRP-MRDTW. As the solutions in the Pareto solution set are all feasible, the final scheduling plan must be selected within this set using an arbitrary method (Bortolini et al., 2016; Lu et al., 2012). For this purpose, a rule that can be expressed as Eq. (33) is introduced to converge to such a final solution.

$$\min G_n = \left(C_n / C^*\right) \times \left(N_n / N^*\right) \times \left(E_n / E^*\right) \tag{33}$$

where n is the index of the n-th solution on the Pareto frontier, and C^*, N^*, E^* are the single-objective optimal solutions for the cost, number of vehicles used and carbon emissions, respectively. The solution with a minimum G_n value is the scheduling plan selected for IGSS-CCL. To verify the superiority of the MOLRP-MRDTW model for IGSS-CCL, which has three objective functions, the solution was compared with the results obtained by single-objective optimization. When one objective function is used, other objective functions become indicators rather than objectives. The tri-objective, optimal cost, vehicles used, and carbon emissions scenarios were investigated and the corresponding optimization results are shown in **Table 4**, highlighting the values and optimization ratio of the objective functions.

Table 4 Optimization results of tri-objective and single-objective.

Item	Objective functions and optimization ratio						
	Tri-objective (cost, vehicle and carbon emissions)	Single-objective (cost)	Δvs. Tri-objective	Single-objective (vehicle)	Δvs. Tri-objective	Single-objective (carbon emissions)	Δvs. Tri-objective
Cost(¥)	40044.46	26400.1	-34.07%	261182.70	552.23%	126681.82	216.35%
vehicles used	9	19	111.11%	8	-11.11%	11	22.22%
Carbon emissions(kg)	901.69	1046.4	16.05%	1160.88	28.74%	830.80	-7.86%

The results in **Table 4** highlights a specific scheduling plan that best balances costs, vehicles used, and carbon emissions by using the three objective functions for optimization in IGSS-CCL. Optimizing only one of the objective functions leads to a significant deterioration of the other two. The main conclusions are as follows.

1) The cost optimization determines a relative increase in the number of vehicles used and carbon emissions; namely, the number of vehicles used globally worsens by approximately 111.11%, whereas carbon emissions increase by 16.05%. The cost of the tri-objective solution is 34.07% higher than that of the single-objective optimal solution. The reason is that the system will arrange as many vehicles as possible to meet distribution requirements on account of the limitation of time windows when optimizing only by cost, to reduce the penalty costs and eventually achieve the goal of optimizing costs.
2) The number of vehicles used for the tri-objective is similar to that of the single-objective optimal solution, with only an increase of 11.11% (from 8 to 9 vehicles). In contrast, the costs of the single-objective (vehicle) optimization increase by 552.23% compared to its optimal value in the tri-objective optimization, and the carbon emissions increase by 28.74% compared to its optimal value in the tri-objective optimization. The system will choose to violate the time windows to reduce the use of vehicles when optimizing only the number of vehicles used, which results in a sharp increase in costs. The waiting time caused by violating the time windows also leads to an increase in carbon emissions.
3) The carbon emissions of the optimal solution of the single-objective (carbon emissions) optimization are only 7.86% better than those of the tri-objective solution. However, the costs and number of vehicles used increased by 216.35% and 22.22%, respectively, compared to the tri-objective optimization. Fuel is used to maintain the normal operation of vehicles and the temperature in vehicles, and fuel consumption is the main source of carbon emissions. Consequently, the optimization of carbon emissions is conducive to reducing the number of vehicles used in system scheduling to a certain extent (compared with the single objective(cost) optimization). The costs are also reduced, which refers to the part caused by violating the time windows (compared with the single objective(vehicle) optimization).

This section provides a method to select the final scheduling plan for Company S, as shown in Eq. (33). However, the optimal solutions in the Pareto solution set are all feasible, and there is no dominant relationship among the solutions. The choice of a specific scheduling plan depends on the decision maker's preference for the objective functions.

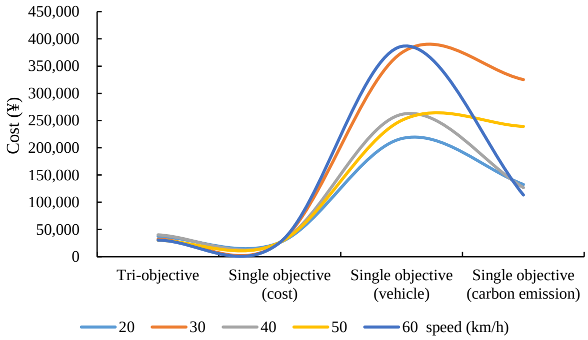
6.3 Sensitivity analysis

To illustrate the stability, economy and greenness of the IGSS-CCL proposed in this study, this section attempts to analyze the impact of different parameter changes on key performance indicators (costs, vehicles used, and carbon emissions). Sensitivity analyses were conducted with changes in vehicle speed, unit penalty cost, and controllable cost of the DC. The solutions of the tri-objective optimization are selected from the Pareto solution sets according to Eq. (33).

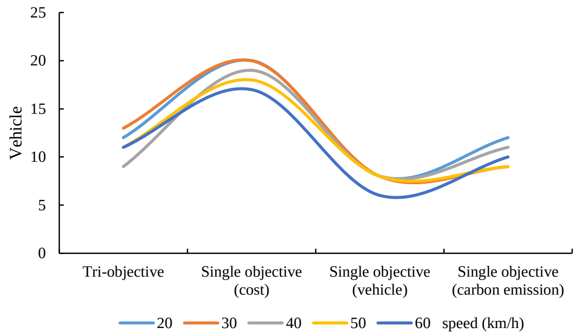
6.3.1 Impact of changes in vehicle speed

This section examines the effects of an increase in vehicle speed on the costs, number of vehicles used and carbon emissions of the solutions.

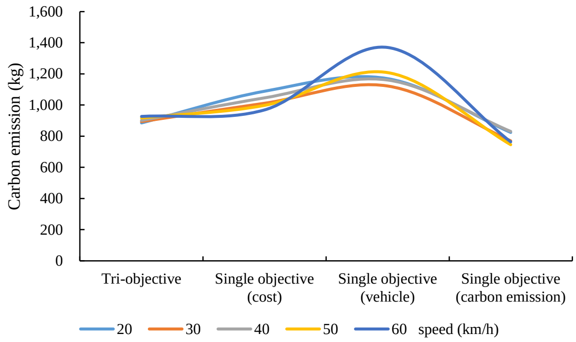
Fig.10 reveals a comparison of the trends of tri-objective and single-objective optimization results at different vehicle speeds. As the vehicle speed changed, the comparative change trends of the costs, vehicles used, and carbon emissions under different objective functions were consistent. For instance, from the optimization results of costs (**Fig. 10 a**), the single-objective (vehicle) has the largest value, followed by the single-objective (carbon emission), and the cost of the tri-objective are only higher than that of the single-objective (cost). The shapes of the five curves with different speeds are similar, which proves that the comparison trend of costs between the tri-objective and single-objective (cost), single-objective (vehicle), and single-objective (carbon emission) does not change even if the vehicle speed changes. The same behavior occurs considering the comparison results of the number of vehicles used (**Fig. 10 b**) and carbon emissions (**Fig. 10 c**); the five curves with different vehicle speeds have the same change trend, and the increase in vehicle speed does not transform the advantages of vehicles used and carbon emissions in the tri-objective optimization compared with the single-objective results. In short, the experimental results indicate that the superiority of the tri-objective optimization for IGSS-CCL has no other trends owing to changes in vehicle speed, which illustrates that the results are stable and reliable.



a-Cost



b-Vehicle used

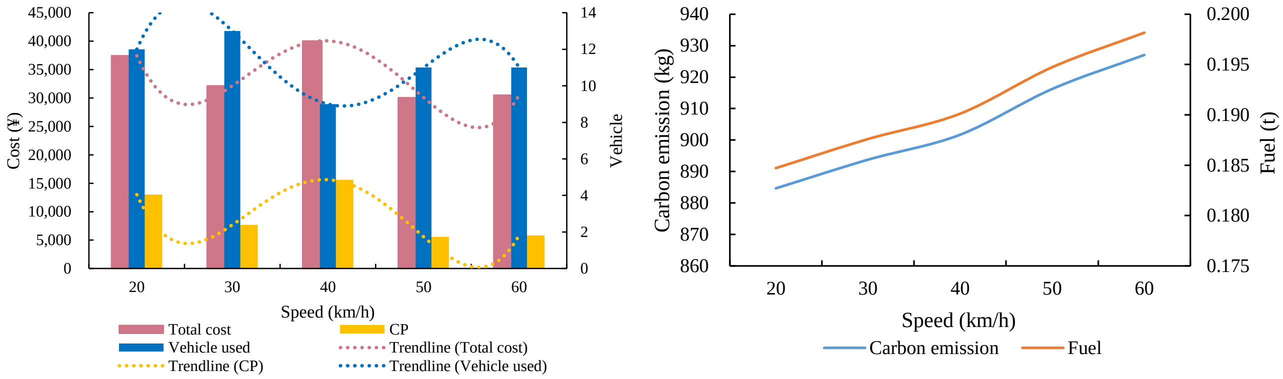


c- Carbon emission

Fig.10. Results comparison of tri-objective and single-objective optimization at different vehicle speeds.

As for the results of the tri-objective optimization, the trend of the objective functions with an increase in vehicle speed is shown in **Fig. 11**. **Fig. 11 a** demonstrates that there are no stable increasing or decreasing trends in the curves of costs and vehicles used, which means that the increase in vehicle speed has an insignificant impact on the costs and number of vehicles used. However, it is obvious that the change curves of the total costs and penalty costs have the same shape, and they change in the opposite direction from the vehicle used curve. For example, as the vehicle speed changed from 30 km/h to 40 km/h, the penalty costs increased by 103.06% and the total costs increased by 24.58%.

Conversely, the number of vehicles used at this speed decreased by 30.77%. The calculation results indicate that the main factor affecting the number of vehicles used is not the vehicle speed but the time windows when considering the time windows in the model. It is also explained that the smaller the number of vehicles used, the higher the penalty costs, which in turn causes the increase of the total costs. However, as shown in **Fig. 11 b**, the fuel used and carbon emissions in the scheduling process have the same changing trend; that is, they increase with increasing vehicle speed. When the vehicle speed increased from 20 km/h to 60 km/h, the fuel consumption increased by 7.3% and carbon emissions increased by 4.8%. This is not surprising because fuel consumption is the major source of carbon emissions in cold chain scheduling, as shown in Eq. (9).



a-The impact on costs and vehicles used b- The impact on carbon emissions

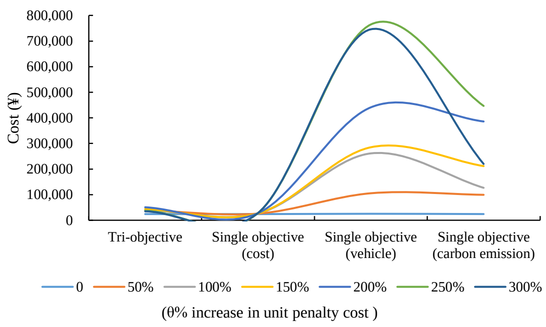
Fig.11. The impact of vehicle speed on the objective functions

The analysis results manifest that the method of increasing vehicle speed cannot be used to achieve the purpose of reducing the number of vehicles used. A higher vehicle speed means more carbon emissions, and the number of vehicles used does not change significantly under the constraints of the time windows. Moreover, high vehicle speeds are in inconformity to regulations of urban traffic management, which poses potential safety risks. At a speed that meets the transportation regulations, the IGSS-CCL is capable of generating a scheduling plan that optimally balances the requirements of economy, safety, and greenness.

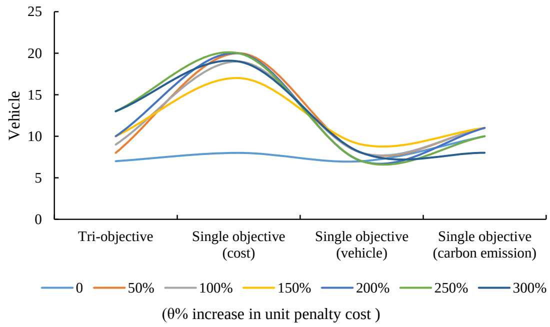
6.3.2 Impact of changes in unit penalty cost

This section analyzes the impact of changes in penalty costs on the costs, vehicles used, and carbon emissions. The unit penalty cost ranged from 0 to 300% in increments of 50%.

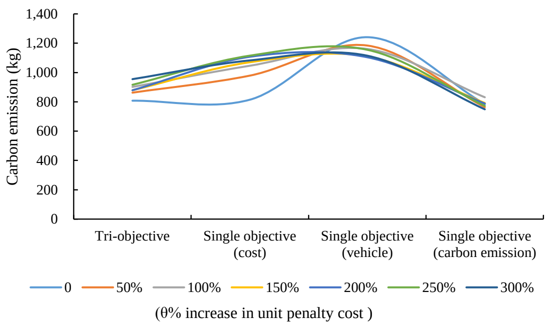
Fig. 12 depicts the comparison trends of the costs (**a**), vehicle used (**b**), and carbon emissions (**c**) of the tri-objective, single-objective (cost), single-objective (vehicle), and single-objective (carbon emission) when the unit penalty cost is set to different values. There are similarly shaped costs, vehicle used and carbon emissions curves even if the unit penalty cost changes, and these results correspond to the results in **Fig. 10**, where the values are different, but the trend is the same. The results reveal that the change in the unit penalty cost does not convert the relative position of the tri-objective and single-objective optimization results; that is, the superiority of the tri-objective optimization for the IGSS-CCL is still prominent. Therefore, the stability and reliability of the results were verified.



a- Cost



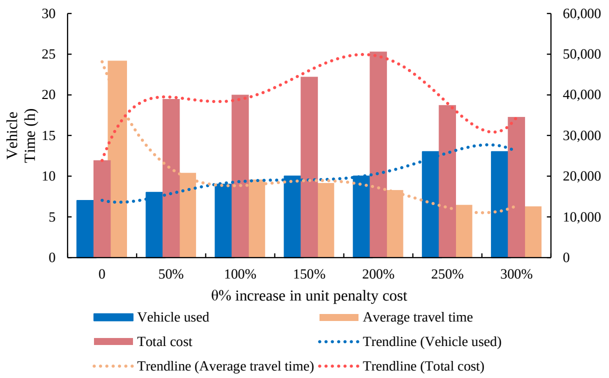
b- Vehicle used



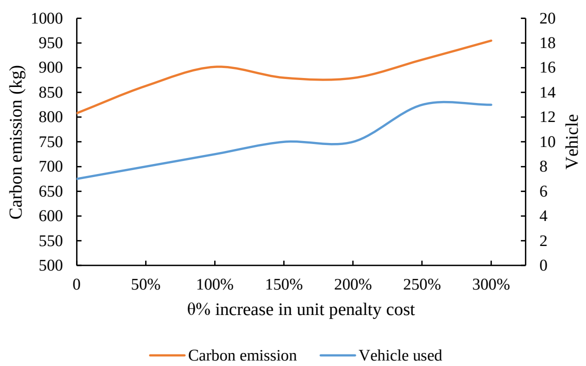
c- Carbon emission

Fig.12. Results comparison of tri-objective and single objective optimization at different unit penalty cost.

Fig. 13 displays the detailed trend of the three-objective optimization results as the unit penalty cost increases. **Fig. 13 a** indicates that when the increase ratio of the unit penalty cost is 0 – 200%, the total costs show a steady increasing trend. However, when the ratio exceeded 200%, the total costs decreased significantly because the number of vehicles used at this ratio increased remarkably (an increase of 30%). To balance the impact of the penalty costs on the total costs, as the unit penalty cost increases, the number of vehicles used increases from 7 to 13, which is an increase of 85.71%. It is worth noting that the system obtains a scheduling scheme with low costs and fewer vehicles when the unit penalty cost is 0. However, the average travel time of each path in the scheme at this time is as long as 24.19 hours, which is completely contrary to the requirements of cold product distribution. In addition, carbon emissions are related to fuel consumption, so there is the same increasing trend between carbon emissions and the number of vehicles used with the increase in unit penalty cost, with an increase of 18.16%, as shown in **Fig. 13 b**.



a-The impact on costs and vehicles used



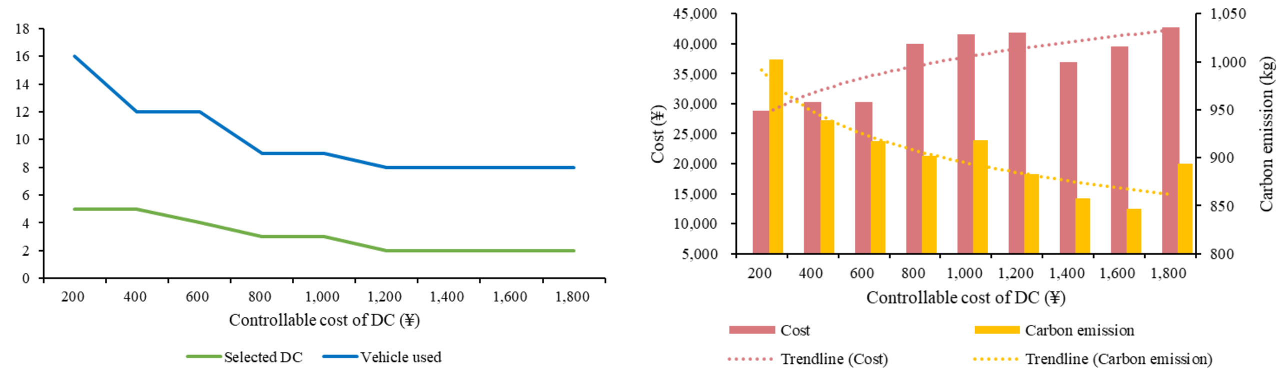
b- The impact on carbon emissions and vehicles used

Fig.13. The impact of unit penalty cost on the objective functions

In general, the data results clarify that as the unit penalty cost increases, the system catches the requirements of time windows by increasing the number of vehicles used, thereby controlling the total costs. An increase in the number of vehicles used leads to more carbon emissions. Considering the costs, vehicles used, carbon emissions, and average travel time of the route comprehensively, there will be a better effect if the ratio of the unit penalty cost is set to 50% – 150%. If managers want to violate the time windows less, they can set the unit penalty cost ratio to 250% – 300%, but at the costs of using more vehicles and increasing carbon emissions.

6.3.3 Impact of changes in controllable cost of DC

This section illustrates the effect of a change in the controllable cost of DC (DC_{cc}) on the results, as shown in **Fig. 14**. As shown in **Fig. 14 a**, the larger the value of DC_{cc}, the fewer DCs and vehicles are used. However, the number of DCs and vehicles used did not continue to decrease during $DC_{cc} \geq 1200$. The benefits of reducing the number of DCs and vehicles cannot compensate for the penalties caused by violating time windows. As fewer vehicles are used, the change in penalty costs for violating time windows drive the change in total costs. **Fig.14 b** indicates that the total costs increased by 48% as the DC_{cc} increased from 200 to 1800. In addition, the carbon emissions of the system tended to decrease by 15% when the DC_{cc} increased. The reason is that changes in the vehicles used affect the fuel consumption, which in turn leads to changes in carbon emissions.



a-The impact on the use of DCs and vehicles b- The impact on cost and carbon emission

Fig.14. The impact of controllable cost of DC on the objective functions

7. Conclusions and Managerial Insights

The scheduling activity of cold chain logistics is a complex system engineering, which is energy-intensive and has operational requirements of safety, efficiency, intelligence, and cooperation. Ensuring the supply of cold products, on the premise of matching the sustainable development requirements of urban governance, such as pandemic prevention, congestion alleviation and emissions reduction, is an important issue for both enterprises and governments.

This study developed the system framework of IGSS-CCL and then focused on the mathematical model and algorithms that provide scheduling decisions for the actual implementation of IGSS-CCL. A MOLRP-MRDTW optimization model was constructed, and the optimization objectives included cost, number of vehicles used and carbon emissions. To make the scheduling system more flexible, this study innovatively considers the scenario of a multi-route decision and three-level time windows. Moreover, this study designed a two-stage optimization algorithm that combines the advantages of

Dijkstra's algorithm and NSGA-III to solve the proposed problem in efficient computational time. Test instances of various sizes were used to analyze the solution performance of the TSOA. The results indicated that the TSOA had better convergence and distribution than the standard NSGA-III.

Finally, the proposed framework was implemented in a real-world case to analyze the green, safety, economic and collaborative utility of IGSS-CCL. Computational experiments demonstrated that if only one objective is optimized, the values of the other two will increase sharply. Compared with the corresponding single-objective configurations, multi-objective tactical network planning was more conducive to cost saving, vehicle control and environmental protection. The potential benefits of multi-objective optimization for IGSS-CCL have been reported many times in experimental results. The changes in the key parameters did not affect the superiority of the multi-objective optimization, which can be manifested in the results of the sensitivity analysis.

Based on sensitivity analysis, the following insights were gained:

1) Setting multi-level time window constraints can effectively quantify the delivery time demands of retail stores and the time requirements of cold product quality, thus enhancing the economic and environmental benefits of cold product scheduling. The allocation of sufficient DCs and vehicles can adequately meet the time window requirements of retail stores, but this leads to idle or wasted resources. The use of fewer DCs and vehicles increases the probability of violating time windows, which results in a loss of quality and sales. When facing the above decision challenges, reasonably satisfying the time window constraints is the essence of the decision. This is where information sharing among cold chain members is particularly critical. If the cold chain logistics enterprises can fully understand the delivery time demands of the downstream cold chain members before the delivery task is started, the multi-level time windows are set to constrain delivery time according to the attributes of the delivered products and match different penalty coefficients for different levels of time window violations. They can scientifically quantify the penalty costs caused by delivery delays.
2) Reducing controllable costs in the system, such as DC fixed costs, not only downgrades the total operating costs, but also promotes the overall optimization effect of scheduling plans. The problem faced by the cold chain members is how to dominate the controllable costs in the system. Cold chain logistics enterprises should actively introduce emerging technologies to upgrade cold chain logistics transportation equipment, continuously optimize the existing intelligent technology and infrastructure layout, to avoid the difficulties caused by information asymmetry between various elements in the scheduling system, and effectively control unnecessary resource idleness or waste. Intelligent and green transformation and upgrading of cold chain facilities are the main trends in the future development of cold chain logistics (China, 2021a). The development and application of technologies, such as IoT, big data, and artificial intelligence, have provided opportunities to overcome the obstacles involved.

In addition, this study identified that increasing vehicle speed to achieve the purpose of reducing the probability of time window violation, reducing penalty costs, or improving delivery efficiency is not a sensible approach. The IGSS-CCL can output the optimal balance of economic, safe, and green scheduling at a speed that complies with traffic regulations. In cold chain logistics operations, the proposed IGSS-CCL can be introduced as a decision support tool for managers to control and supervise the cold product scheduling process. Cold chain members can set different objective function weight values according to their actual needs to select a satisfactory scheduling solution among the set of solutions with the Pareto nature.

1) Under urban governance requirements, such as pandemic prevention, congestion alleviation, and emission reduction, cold chain members with large batch and multi-frequency distribution tasks may face disturbing factors, such as restrictions on the number of delivery staff and traffic. Managers using IGSS-CCL can choose a scheduling plan that uses fewer vehicles to address possible congestion charges or disturbances from traffic restrictions. Furthermore, with the reduction in delivery vehicles, the number of delivery staff will also decrease. This result is also in conformity with the principles for pandemic prevention and control, which contribute to limiting the spread of viruses.
2) In the management of energy-intensive industries with carbon emission control, cold chain members with carbon quota restrictions may face constraints of limited carbon emissions or high emission costs. Managers using IGSS-CCL can select a green scheduling plan with lower carbon emissions by carefully setting appropriate carbon emission weights with economic and environmental benefits in mind. The Chinese government has clearly stated that carbon emissions will reach their peak by 2030 and carbon neutrality will be achieved by 2060 (China, 2021b). If a carbon trading or carbon tax system is applied to the cold chain logistics industry in the future, the IGSS-CCL proposed in this study can assist cold chain members in forming scientific industry development proposals, which can contribute to the achievement of national environmental goals without significantly harming the economic benefits of each cold chain member.

There remain numerous challenges in the process of realizing intelligent green scheduling. In the future, this study could be extended in several ways. Revising the scheduling scheme when the vehicle breaks down or other disturbance factors occur after the scheduling plan has been implemented would be an interesting area for future research. This study considers the uncertainties in supply and demand affected by the external environment or internal factors as a natural extension. Intelligent scheduling decisions under disturbances could be a future research direction.

CRediT authorship contribution statement

Yuhe Shi: Conceptualization, Methodology, Software, Writing - Original Draft. **Yun Lin:** Resources, Supervision, Funding acquisition, Writing - Review & Editing. **Ming K. Lim:** Methodology, Validation, Writing - Review & Editing. **Ming-Lang Tseng:** Validation, Writing - Review & Editing. **Changlu Tan:** Investigation. **Yan Li:** Visualization.

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Appendix A. Model parameter

The notations used in the paper to develop the mathematical model are summarized in **Table A.1**, including sets, parameters and variables. Parameters value related to vehicle is shown in **Table A.2**.

Table A.1 Summary of the notations.

Symbol	Definition	Unit
Sets		
D	Set of candidate DCs, $D=\{1,2,...,m\}$	-
R	Set of retail stores (orders), $R=\{1,2,...,n\}$	-
L	Set of all notes, $L{=}D\cup R$	-
K_m	Set of vehicles in the DC m, $K_m=\{1,2,...,k\}$	-
Parameters		
$\left[ET_i, LT_i, LT_i'\right]$	The service time window of retail stores i, ET_i is the earliest service time, LT_i is the latest service time, and LT_i' is the latest tolerable service time	h
C_{mf}	Unit fixed cost of the DC m in each period (day)	¥/day
C_{mh}	Unit inventory holding cost in the DC m	¥/kg
C_{me}	Unit electricity cost of the DC m	¥/ kWh
C_{mp}	Unit pandemic prevention cost of cargo in the DC m	¥/kg
C_f	Unit cost of fuel	¥/L
C_{kf}	Unit distance cost of vehicle k	¥/km
C_{w1}	Unit waiting cost of driver when the vehicle arrives at store before the earliest service time	¥/h
C_{w2}	Unit waiting cost of consignee when the vehicle arrives at store after the latest service time	¥/h
C_l	Unit lost cost of cargo when the vehicle arrives at store after the latest tolerable service time	¥/kg
E_{ms}	Net electricity purchased by the DC m in each period	kWh/day
Q_m	Inventory of cargoes in the DC m in each period	kg
Q_k	Maximum load capacity of the vehicle	kg
d_{ij}^n	Travel distance of the road n between retail stores i and j	km
t_{ij}^n	Travel time of the road n between retail stores i and j	h
v	Speed of the vehicles	km/h
$t_{ij}^{n'}$	The additional time brought by the road traffic status between the retail store i and j. If the road is clear, $t_{ij}^{n'}=0$. If the road is prohibited, $t_{ij}^{n'}=M$	h
M	An infinite number	-
η_e	Energy conversion efficiency for chemical to refrigeration	-
COP	Coefficient of performance	-
EC_d	Energy content of the fuel	kWh/L
V_T	Speed of the air temperature increase	K/s
q_i	Demand of retail store i	kg
t_u	Unit time required to unload cargoes	h/kg
t_w	Saleable time of the cargoes in each period	h
T_0	Optimal temperature in the refrigerated vehicles	K

h_{mk}	Heat transfer coefficient of the vehicle k	-
S_{mk}	Surface area of vehicle k, S_{out}, S_{in} is the outer and the inner surface area of vehicle, respectively, $S_{mk}=\sqrt{S_{out}S_{in}}$	m^2
ΔT	Difference in average air temperature between inside and outside vehicle	K
V_{mk}	Volume of the vehicle k	m^3
HC_a	Volumetric heat capacity of air at constant pressure	J /m^3·K
ΔT_{mk}^i	the difference between the temperature inside vehicle k and the optimal temperature when the service at node i ends, V_T is the speed of the air temperature increase (K/s), $\Delta T_{mk}^i = V_T q_i t_u$	K
NCV	Average low calorific value of the fuel	GJ/t
CC	Unit calorific value carbon content of the fuel	tC/GJ
FC	Fuel consumption	t
OF	Carbon oxidation rate of the fuel	-
OC	Fuel volume of the vehicle in per 100 kilometers	L/100km
D_e	Density of the fuel	t/m^3
EF_e	Average carbon emission factor of power supply	tCO_2/MWh
Intermediate variables		
q_{ij}^{mk}	Load carried by the vehicle k sent from the DC m on arc (i, j)	kg
t_i^{mk}	Time when vehicle k arrives at customer i	h
d_{ij}	Actual travel distance between retail stores i and j	km
t_{ij}	Actual travel time between retail stores i and j	h
Decision variables		
x_{ij}^{mk}	1 if arc (i, j) is crossed with vehicle k in the DC m, 0 otherwise	-
o_m	1 if the DC is selected to open, 0 otherwise	-
u_{mk}	1 if the vehicle k in the DC m is used, 0 otherwise	-
y_i^{mk}	1 if the vehicle k serves retail store i, 0 otherwise	-

Table A.2 Parameters value related to vehicle.

Notation	Value	Notation	Value
S_{out}	36.9 m^2	η_e	30%
S_{in}	31 m^2	COP	1
V_{mk}	10.47 m^3	EC_d	8.8 kWh/L
Q_k	1485kg	V_T	0.0027 K/s
h_{mk}	0.7 W/m^2·K	OC	20.2 L/100km
HC_a	1400 J /m3·K	D_e	0.84 t/m^3
NCV	43.33 GJ/t	OF	98%
CC	20.2x10^{-3} tC/GJ	EF_e	0.61 tCO_2/MWh

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