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Marine Cold Chain Transportation Monitoring and Route Scheduling Optimization Based on IoV-BDS

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ABSTRACT Recently, the research of the internet of vessels system is a hotspot in the marine engineering area. In this article, the Internet of Vessels based on Beidou satellite navigation system (IoV-BDS) architecture is proposed for marine cold chain transportation monitoring and scheduling. An improved communication method using Beidou short-message communication (SMC) is designed to ensure the reliability of ship-shore data transmission. Additionally, based on the IoV-BDS, we proposed a novel route scheduling optimization model which considers the key costs for marine cold chain transportation, such as fuel, catches damage, and refrigeration energy consumption, and designed a speed selection mechanism. Furthermore, an improved ant colony optimization (IACO) algorithm was utilized to optimize the whole fleet transportation routes, which takes advantage of the A-star algorithm to speed up the convergence of ant colony algorithm (ACO), a novel state transition rule was used to prevent falling into a locally optimal solution. The applicability of IoV-BDS was verified by the shipboard data acquisition and Beidou SMC experiments. The performance evaluation and analysis of route optimization schemes were presented by simulations and comparison with other schemes. The results demonstrated the benefit of our proposed schemes, in terms of solution quality and convergence of the algorithm.

INDEX TERMS IoV, Beidou SMC, cold chain, route optimization, refrigerator ship.

I. INTRODUCTION

With the development of information technology and the popularization of mobile terminals, modern society is gradually entering the ‘‘Internet of Things (IoT) era’’. The IoT has become an important tool in all walks of life [1]–[3]. Aiming at the specific characteristics and application scenarios of vessels, a new technological revolution, Internet of Vessels (IoV), is constructed based on the IoT framework.

The IoV is defined as a network of smart interconnected vessels and the shore facilities, which contains a series of digital entities [4]. Based on the wireless communication technology and global positioning system, the ship intelligent service could use electronic sensing devices to exchange information on the Internet, and realize the extraction, monitoring, and utilization information of each sensor node.

Nowadays, as one of the most important transportation modes, the waterway has to undertake more than 80% of the world's trade transportation. However, there are still imperative problems in navigation safety, energy-saving, and transport efficiency due to the lack of basic communication methods. Thus, marine transportation based on the IoV arouses great interests to researchers over the last decade [5], [6].

As the IoV system is essential for marine cold chain transportation monitoring and route scheduling optimization. The following requirements should be met: reliable communication, real-time monitoring, route scheduling optimization, reducing transportation cost. Aim at the application scenarios, the monitoring data of ships need to be transmitted to shore-based center, and then used to calculate and generate optimal scheduling information for each ship. In addition, the shore-based center should monitor the cold chain transportation process in real-time.

To achieve our objectives, this article proposes the Internet of Vessels based on Beidou satellite navigation system (IoV-BDS) architecture. An improved communication method utilizing Beidou short-message communication

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(SMC) is designed to ensure reliable ship-shore data transmission and efficient use of bandwidth. We focus on constructing a ship route optimization model and an optimal speed selection mechanism to minimize transportation costs. The model takes into account the main cost of marine cold chain transportation and several necessary constraints. An improved ant colony optimization (IACO) algorithm is employed to solve the model, which uses the A-star algorithm to accelerate the convergence of ACO.

The subsequent sections of this article are organized as follows. The related works are presented in section 2. In section 3, the IoV-BDS architecture is proposed and an improved communication method is introduced. In section 4, the cost structure of ship cold chain transportation is analyzed, and then the mathematical model is established, in addition, the optimal speed selection mechanism is designed. Section 5 proposes an improved ant colony algorithm to solve the model. Section 6 and section 7 gives the experiments, simulations, and analysis for our schemes. Finally, Section 8 concludes our work and mentions future work.

II. RELATED WORK

In this section, we present the related work of the IoV-BDS technology and route scheduling optimization in recent years. We also give the properties of our schemes, which differ from previous work at the end of the section.

A. RESEARCH ON MARITIME COMMUNICATION BASED ON IOV-BDS

The IoV system makes it possible to realize the intelligent navigation of ships, which will play a greater role in the guarantee of ship safety navigation than before [7]. Moreover, with the help of the IoV system, managers could get the accurate and complete real-time movement of the ships and predict the potential traffic problems, therefore, they can make reasonable plans and project emergencies to prevent disasters and reduce property loss [8]–[10]. Another typical application of IoV is for traffic flow prediction, with the help of the IoV system, it can analyze the dynamic laws of the ships and the changes in the relationship between the traffic speed and the traffic density. Recently, several advanced models are proposed for predicting the traffic flow [11], [12]. With the development of the IoV system. These implementations are bound to result in the rapid rising data quantity in the existing network of ships, consequently, the data transmission of the network has also proposed some requirements on real-time and accuracy.

In the last few years, several technologies can realize ship-shore communications, including Automatic Identification System (AIS), mobile communication network (GPRS, WCDMA, 3G, and 4G), INMARSAT system, and BDS. AIS and mobile communication networks apply only to an inland river or offshore [13], [14]. INMARSAT system can carry out seamless communication in the world [15], [16], but its high communication cost brings great resistance to cost-saving seaborne transportation. BDS is capable of providing positioning and navigation, two-way communication, and precise timing service anytime and anywhere within the coverage area [17], these functions make BDS not only work as GPS but also work as an INMARSAT system to realize maritime communication [18]. Existing studies have evaluated the progress and performance of BDS [19]–[21] and applied to many scenarios, such as precise positioning [22], [21], fire warning [23], smart grid [24], emergency rescue [25], [26], environment monitoring [27], [28].

Relevant works [29]–[31] are introduced for maritime communication based on BDS. The paper [29] put forward a scheme of monitoring oil spill in all-weather and whole process through using Beidou satellite positioning communication mode. The work in [30] studied the application of the Beidou system and RFID temperature tag in marine cold chain logistics, the real-time monitoring of the transportation process has been realized successfully. In work [31], a shipboard terminal was designed and implemented, which integrates data acquisition, processing, transmission, and reception. The data collected by the sensors were regularly transmitted to the shore-based center by the Beidou SMC module. The shore-based computing center pushed the results back to the ship, which provides security for the safe and stable navigation of the ship. All these works show extensive applicability of BDS technology on maritime communication. Although Beidou SMC [32] has the limitations of communication frequency and length, it is enough to meet the requirement of a small amount of data transmission in marine cold chain transportation, and the communication cost is low, which is more suitable for our work comparing with other IoV communication technologies.

One data packet capacity of an off-the-shelf terminal with one Beidou ID card is no more than 77 bytes [33]. Besides, data packets are transmitted may be lost randomly due to unreliable signal channel caused by weather condition, signal interference and terminal performance. Some authors proposed several solutions in their work [34], [35]. The work in [34] presented an Adaptive Hybrid Error Correction (AHEC) protocol, which combines the advantages of selective ARQ and Front Error Correction (FEC). The authors in work [35] used a Chinese segmentation algorithm to cut Beidou short message into the dictionary index code, and get the final message by compressed algorithm. The methodologies in these works can be used for reference to improve the packet delivery rate and compression performance in the Beidou SMC.

In our work, marine refrigerator ships equipped with Beidou terminals can send monitoring data (ship position, temperature, etc.) or receive scheduling information to or from the shore-based center. Thus, how to improve communication reliability and bandwidth utilization are critical problems for data transmission based on Beidou SMC.

B. RESEARCH ON ROUTE SCHEDULING OPTIMIZATION

Vehicle Route Problem (VRP) is important for marine refrigerator ship transportation Scheduling. The classical VRP can be applied to various transport modes, but it often needs to be adapted according to the specific scenarios, which is especially true for ship route problems.

As explained earlier, we focus on a route scheduling problem for a fleet of refrigerator ships in marine cold chain transportation, and catches generally are transported directly from the fishery distribution center to ports. This transport mode is similar to a full truckload operation [36]. Generally, the catches volume is smaller than the load capacity of the ship, and the delivery time window of the port is controlled.

It was found that the direct objective for the ship route scheduling is to minimize the transportation cost [37]. It is worth noting that due to the perishable nature of the catch, most ports propose time windows for the delivery of catch to improve service levels, and require ships to transport the catch to the designated location within a specified time to avoid the penalty cost. Besides, costs associated with perishable products, such as refrigeration and damage cost should be considered for cold chain transportation. Some works [38]–[40] have investigated these issues, authors all modeled the distribution activities of cargos under the constraints of the fuzzy time window. The work in [38], [39] considered a VRP of cold chain logistics, which is similar to ours. Costs connect to perishable products are incorporated into the optimization model, and constraints on the time window of the port and load capacity of the ship are considered to meet actual scenarios.

For marine transportation, it should not be ignored that the fuel cost accounts for a proportion of operating costs with the increase of fuel price [41]. Some scholars have focused on fuel consumption model of ship. In work [42], authors found the empirical relationship for fuel consumption per nautical mile, which is applicable to the speed interval of 14 to 20 knots (kn), and the fuel emission can be reduced by optimizing the route speed. The work [43] showed that quadratic function can well estimate the relationship between fuel consumption per unit distance and speed. Normally, the relationship between fuel consumption and sailing speed is described as a non-linear function, which is defined in the actual speed range of the ship. The fuel consumption or sailing cost in a given distance is strongly dependent on speed. Therefore, we describe a sub-problem of the marine cold chain transportation route optimization, which is to minimize total cost by adjusting speed along a fixed ship route.

As a variant of VRP problem, our work is an inherently non-deterministic polynomial (NP-hard) problem, which need to be addressed by heuristic algorithms, such as particle swarm optimization algorithm [44]–[46], genetic algorithm [47], [48], artificial bee colony algorithm [49], [50], fruit fly optimization algorithm [51], [52], tabu search algorithm [53], [54], simulated annealing algorithm [55], [56], The ant colony optimization (ACO) algorithm was first proposed by Dorigo *et al.* [57], it has shown good performance in solving problems such as task assignment and route optimization. The advantages of ACO in real applications have also been demonstrated [58]–[60].

Authors in work [58] proposed a method combining IACO algorithm and tabu search to solve low carbon freshness vehicle route problem for cold chain distribution. In work [59], an IACO algorithm based on the multi-population and co-evolution strategy, and pheromone updating and diffusion mechanism was proposed to balance the convergence speed and solution diversity. Based on the ACO algorithm, combined with the concept of genetic algorithm, authors in work [60] realized the effective route planning of ships in the cross-ocean voyage. In these works, the ACO algorithm shows several advantages, such as positive feedback and strong robustness, but lacking the pheromone in the initial stage may lead to the convergence speed slower. Therefore, we intend to use A-star algorithm to improve this drawback.

Some properties of this article which differ from the previous ones are summarized as follows:

(1) The IoV-BDS architecture is proposed for marine cold chain transportation monitoring and scheduling.

(2) An improved communication method with good scalability and transmission reliability is designed.

(3) A novel route optimization mathematical model is established, which considers costs of cold chain transportation and speed selection mechanism with realistic constraints. The improved ant colony optimization (IACO) algorithm is proposed to solve the model, which takes advantages of A-star algorithm to speed up the convergence.

III. COMMUNICATION ARCHITECTURE AND METHOD

A. IOV-BDS ARCHITECTURE

The IoV-BDS architecture, as could be seen in Figure 1, which is mainly composed of two parts: the shipboard data acquisition system and the shore-based monitoring and scheduling center. Beidou SMC module realizes two-way communication between ship and shore. The shipboard monitoring data are transmitted to Beidou command terminal by Beidou SMC module, and IoV gateway is responsible for reception and protocol conversion of data, and used to connect with enterprise cloud platform by Message Queue Telemetry Transfer (MQTT). The enterprise managers can access the cloud platform through the browser to realize refrigerator ship monitoring, data statistical analysis and fleet scheduling management.

1) SHIPBOARD DATA ACQUISITION SYSTEM

The data acquisition system is depicted in Figure 2, utilizing the Shipboard Local Area Network (SLAN).

As presented in Figure 2, temperature recorder, working condition monitor, wireless Access Point (AP) and Digital Video Record (DVR) firstly are connected to the Power Over Ethernet (POE) switch using a Category 6 cable (CAT-6), and then access the Industrial Personal Computer (IPC). The acquired data are stored in the local database to meet the requirements of the shipboard management, and the key monitoring data (temperature, geographic position, etc.) for marine cold chain transportation are transmitted to the

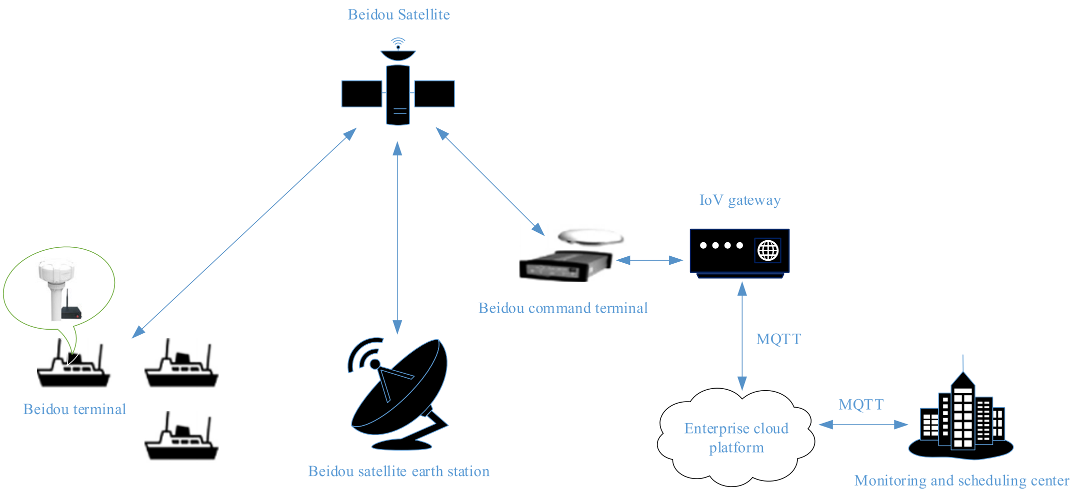

FIGURE 1. **"IoV-BDS" architecture.**

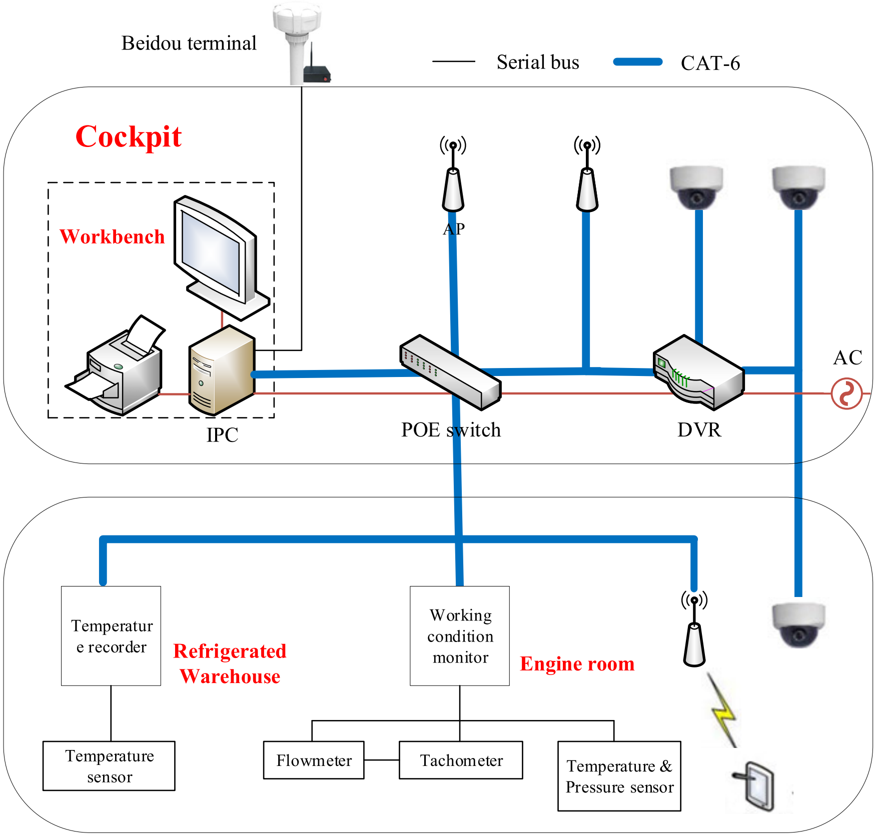

FIGURE 2. **Shipboard data acquisition system.**

shore-based center by the Beidou terminal connected to IPC. The terminal has the functions of Radio Determination Satellite Service (RDSS) and Radio Navigation Satellite System (RNSS), which can not only send and receive Beidou SMC but also receive and analyze the RNSS positioning data.

The PT100 sensor is selected for temperature measurement of the refrigerated warehouse, the upper and lower thresholds of temperature could be set at the IPC, and an alarm be given when it exceeds the threshold value. Electromagnetic flowmeter is employed to monitor cumulative fuel consumption, and speed of the main engine could be measured using electromagnetic pulse tachometer. Temperature and pressure of fuel are collected by a temperature sensor and pressure sensor respectively. Sensor data are acquired in real-time by temperature recorder and working condition monitor, and uploaded to IPC using the Modbus Transmission Control Protocol (TCP). Surveillance cameras are installed in the engine room, cockpit and other important areas to guarantee the safety of production and responsibility tracing. The DVR is employed as the core of video monitoring, and the shot images of the cameras are constantly output to the video monitor of the bridge. The wireless APs are placed in the cockpit and warehouse to achieve the WiFi coverage of the SLAN, and the staff completes the data control and confirmation of the ex-warehouse using the iPad when the catches are transferred.

2) SHORE-BASED MONITORING AND SCHEDULING CENTER

The shore-based monitoring and scheduling center consists of Beidou command terminal, IoV gateway, cloud platform, and monitoring and scheduling center. The Beidou command terminal connects to the IoV gateway by the serial bus. The IoV gateway receives and parses the short message, and translates monitoring data into JavaScript Object Notation (JSON) format. Then, monitoring data are uploaded to the cloud platform by MQTT protocol. The shore-based monitoring and scheduling center gets monitoring data and ships' routes from the cloud platform, and carry out remote management and scheduling of marine cold chain transportation.

B. DATA PROCESSING AND TRANSMISSION SYSTEM

In our work, sensor data such as temperature of the refrigerated warehouse, position and speed of refrigerator ship and fuel consumption are transmitted to the shore-based center utilizing Beidou SMC technology. For sensor data, we design an encoding method and introduce a packet structure to improve bandwidth utilization and communication reliability.

1) DATA ENCODING

Due to the BCD encoding has better channel utilization than the ASCII encoding, and messages are encoded with BCD to further reduce the overall data size. The monitoring data content are mainly divided into two parts: ship information and catches information. The data encoding are as follows:

1. Ship information

- Refrigerator ship number: It is numbered based on the number of refrigerator ships and occupy 0.5 bytes.
- Time: Identifying the specific time of data acquisition. Including year, month, day, hour, minute and second, which is represented by one byte respectively, with a total of 6 bytes.
- Fuel consumption: It accurate to 0.001 tons based on the electromagnetic flowmeter reading and occupy 3 bytes.
- Geographical position: The longitude and latitude of location of refrigerator ship shall be represented by 0.5 bytes (range), 1.5 bytes (degree), 1 byte (minute) and 1 byte (second), with a total of 8 bytes.
- Speed: It accurate to 0.01 knots and occupy 2 bytes.

2. Catches information

- Refrigerated warehouse number: It is numbered based on the number of refrigerated warehouses and occupy 1 byte, and there are 24 refrigerated warehouses in one refrigerator ship.
- Species and grade of catches: High 8 bits represent species (1 byte) and low 4 bits represent grade (0.5 bytes), with a total of 1.5 bytes.
- Refrigerated warehouse temperature: The temperature is a signed number and accurate to one-tenth of a degree, and occupy 2 bytes.
- Remaining catches: Ensuring that the remaining catches volume meet the requirement of the next port, and occupy 1.5 bytes.

Data encoding example are as shown in Table 1, total monitoring data of one refrigerator ship occupy $144 + 19.5 = 163.5$ bytes.

2) PACKET STRUCTURE

One data packet capacity of an off-the-shelf terminal with one Beidou ID card is no more than 77 bytes, which can't meet the requirement amount of monitoring data transmitted (165.5 bytes) once. Accordingly, we divide the long packet into subpackets according to Beidou standard, namely, we "unpack" the encoded monitoring data at the sending end, and add the corresponding "unpacking control" to identify the uniqueness of each subpacket. At the receiving end, the "unpacking control" are removed from each subpacket, and the data are merged according to the information of "unpacking control" to correctly and orderly restore original message.

Furthermore, Forward Error Correction technology is used to improve the reliability of Beidou SMC transmission, which is adopted for recovering lost subpacket by redundant check packet.

As depicted in Figure 3, at first monitoring data transmitted are divided into three subpackets. 3 bytes of "unpacking control" information is added to the header of each subpacket, and the remaining 74 bytes of each subpacket is used for monitoring data. The 'FF' is used to make up to 74 bytes for redundancy calculation when the length of monitoring data of the last subpacket is less than 74 bytes. Then, XOR operation is performed on the data of 74 bytes of each subpacket to get a redundant check packet, it with "unpacking control" information and is sent together with three subpackets in front. As long as the receiver successfully receives any three packets in the FEC block, it can successfully recover the complete monitoring information.

IV. ROUTE OPTIMIZATION MODEL

A. DESCRIPTION OF PROBLEM

The route optimization problem in the marine cold chain logistics can be described as follows. A fishery distribution center can provide services for multiple ports. Given refrigerator ships of the same type, it starts from the distribution center, stops at each port, and returns to distribution

TABLE 1. Code example of monitoring data with improved communication method.

Information type	Domain	Information content	Code	Bytes
Ship information 19.5bytes	Ship number	Refrigerator ship 1	0001	0.5
	Time	2020/4/18 11:44:50	0010 0000 0000 0100…0101 0000	1(year)+1(month)+1(day)+1(hour)+1(minute)+1(second)=6
	Fuel consumption (ton)	175.135	0001 0111 0101 0001 0011 0101	3
	Longitude	"1" stand for "E" "2" stand for "W"	0001	0.5
		117°10′11″	0001 0001 0111 0001…0001 0001	1.5(degree)+1(minute)+1(second)=3.5
	Latitude	"1" stand for "N" "2" stand for "S"	0001	0.5
		34°21′32″	0000 0011 0100 0010…0011 0010	1.5(degree)+1(minute)+1(second)=3.5
	Speed (kn)	20.11	0010 0000 0001 0001	2
Catches information 6x24=144bytes	Warehouse number	Warehouse 1	0000 0001	1
	Species and grade of catches	"11" stand for "squid" "3" stand for "small"	0001 0001 0010	1.5
	Temperature (°C)	"2" stand for "below zero" -23.2	0010 0010 0011 0010	2
	Remaining catches (ton)	410	0100 0001 0000	1.5

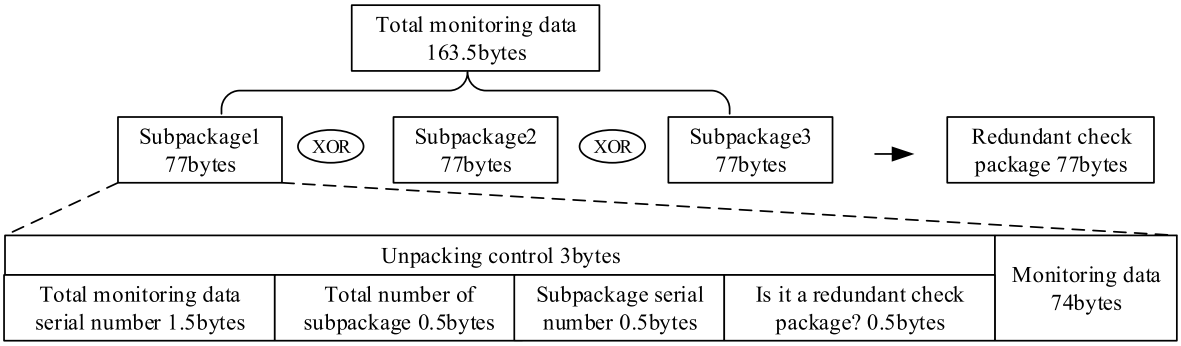

FIGURE 3. Packet structure with improved communication method.

center after completing all distribution tasks. The location and catches volume unloaded of each port are known, and each port is reached by only one refrigerator ship. At the same time, there is a soft time window constraint of each port, the port cannot be served until its expected time arrives. A specific penalty cost should be given for early or late arrivals of ships to improve port satisfaction.

According to the characteristics of the marine cold chain logistics, the route optimization model is constructed with the constraints of soft time windows and ship load capacity, to minimize the comprehensive cost. Because the selection of ship speed has a certain impact on fuel consumption and cost structure, we design an optimal speed selection mechanism for each leg.

Since the problem is route scheduling optimization, we explain some of the notations as follows. Let G = (N, E) be a fully directed graph, denoting the distribution network of the marine cold chain logistics. Specifically, $N = \{0, 1, 2, \ldots, n\}$ is a set of all nodes, where 0 represents the distribution center and 1, 2, …, n represent the ports. $E = \{(i,j)|i,j \in N, i \neq j\}$ is the set of edges, representing the section of routes that the refrigerator ships travel.

B. SYMBOL DESCRIPTION

Descriptions about symbols in the model are explained as in Table 2.

C. COST ANALYSIS AND ESTABLISHMENT OF THE MODEL

1) COST ANALYSIS

The comprehensive cost of marine cold chain logistics consists of the following parts:

- Ship operating costs including port charge, shipping fee, and fuel cost.
- Damage cost caused by catches partially damage during transportation.
- Refrigeration cost to keep a low-temperature storage environment.

TABLE 2. Symbols and descriptions in the model.

Symbol	Descriptions
x_{ij}^k	Binary variable, if refrigerator ship k goes to port j after servicing port i, $x_{ij}^k = 1$, otherwise $x_{ij}^k = 0$
y_i^k	Binary variable, if port j is serviced by refrigerator ship k, $y_i^k = 1$, otherwise $y_i^k = 0$
K	Number of ships available in distribution center
t_{ij}^k	Time of ship k sails between port i and port j
t_i^k	Arrival time of ship k at port i
t_0^k	Departure time of ship k from the distribution center
d_{ij}	Distance from port i to port j (nm)
v_{ij}^k	Speed of ship k from port i to port j (kn)
s_i	Service time at port i (h)
p_H	Unit price of HFO (RMB/ton)
p_M	Unit price of MDO (RMB/ton)
q_i	Volume unloaded of port i (ton)
p	Unit price of catches (RMB/ton)
Q_v	Full load capacity of ship (ton)
λ_1	Waiting cost per unit time (RMB/h)
λ_2	Delay cost per unit time (RMB/h)
(e_i, l_i)	Expected time window of port i
(E_i, L_i)	Acceptable time window of port i
w_i^k	Waiting time of ship k at port j (h)

- Penalty cost due to arrive without the specified time window.

The above costs are explained in detail as below.

a: OPERATING COSTS

Port charge: It refers to the various expenses incurred by refrigerator ships during unloading the cargo at the port. Based on work [61], to simplify the model, we regard that the port charge has an approximate linear relationship with the amount of cargo. let a_i denotes port charge of the port i. Total port charge can be formulated as follow:

$$C_{11} = \sum_{i=1}^{n} a_i \tag{1}$$

Shipping fee: It refers to maintenance cost, crew salary, marine material cost, and lubricating oil cost of the refrigerator ship during the operation period, which can be regarded as positively related to the total shipping time. f_k is the shipping fee unit time of the refrigerator ship k, and total shipping fee can be formulated as follow:

$$C_{12} = f_k\Big(\sum_{k=1}^{K}\sum_{i,j=0}^{n} x_{ij}^k t_{ij}^k + \sum_{k=1}^{K}\sum_{j=1}^{n} y_j^k (w_j^k + T_j)\Big) \tag{2}$$

Fuel cost: In a realistic scenario, the fuel consumption in marine cold chain logistics mainly induces two sources. The first one is the Heavy Fuel Oil (HFO) consumption generated by the ship's main engine during the driving, while the second one is the Marine Diesel Oil (MDO) consumption generated by auxiliary engine during berthing.

When refrigerator ship provides distribution service for port j, the classic HFO consumption model during the driving proposed by work [62] is shown in formula (3), the consumption of DMO have an absolute liner correlation with ship berthing time at port, which can be expressed by fuel consumption coefficient of the auxiliary engine in formula (3).

$$\begin{aligned} &G_H = t_{ij}^k g_e P_e \Big/ 10^6, \quad G_M = \varphi(w_j^k + s_j) \\ &P_e = \frac{(\Delta_{ij}^k)^{2/3}(v_{ij}^k)^3}{\mathbb{C}}, \quad t_{ij}^k = \frac{d_{ij}}{v_{ij}^k} \end{aligned} \tag{3}$$

where G_H is HFO consumption (ton), G_M is DMO consumption (ton), g_e is HFO consumption rate of the main engine ($g/KW \cdot h$), P_e is main engine power (KW), Δ_{ij}^k is displacement of the refrigerator ship k from i to j (ton), $\mathbb{C}$ is admiralty coefficient of the refrigerator ship, and φ is DMO consumption coefficient of the auxiliary engine (ton/h).

Generally, the values of parameters g_e, Δ_{ij}^k, and $\mathbb{C}$ are fixed when ship sails along the arc (i, j), value of HFO consumption mainly rely on ship speed of this leg. After obtaining the fuel consumption, the total fuel cost of the refrigerator ship in transportation is computed as:

$$\begin{aligned} C_{13} = C_{131} + C_{132} = &\sum_{k=1}^{K}\sum_{i,j=0}^{n} x_{ij}^k p_H \frac{g_e(\Delta_{ij}^k)^{2/3}(v_{ij}^k)^2 d_{ij}}{10^6\mathbb{C}} \\ &+ \sum_{i=1}^{K}\sum_{j=1}^{n} y_{jk} p_M \varphi(w_j^k + s_j) \end{aligned} \tag{4}$$

where C_{13} is total fuel cost in the transportation (RMB), C_{131} is HFO cost during the driving (RMB), C_{132} is DMO cost during the berthing (RMB). The operating cost is computed as $C_1 = C_{11} + C_{12} + C_{13}$.

b: DAMAGE COST

The freshness of fishery catches is influenced by storage temperature, delivery time and their own characteristics. Marine cold chain logistics can provide a stable environment for the catches in the process of transportation. Consequently, the freshness attenuation coefficient of the catches can be considered as constant. According to the traditional Time-Temperature-Tolerance (T.T.T.) theory and the special scenario of cold chain transportation [33], freshness attenuation function of the catches is as follow:

$$\psi(t) = \psi_0 e^{-\phi t} \tag{5}$$

where ϕ denotes the freshness attenuation coefficient, $\psi(t)$ is the freshness of catches at time t. ψ_0 is the freshness of catches when ship departs from the distribution center, initialized to 1.

Damage cost is computed as follow:

$$C_2 = \sum_{k=1}^{K} \sum_{i=1}^{n} y_i^k p q_i (1 - e^{-\phi(t_i^k - t_0^k + w_i^k)}) \tag{6}$$

c: REFRIGERATION COST

In the process of transportation, HFO is consumed by ship generators to generate electricity for refrigerators. To simplify the mathematical model, we regard the fuel consumption cost caused by refrigerators as the refrigeration cost. With the decrease of catches in delivery process, the empty refrigerated warehouse can close the refrigerators to save energy. Therefore, we define that the refrigeration cost per unit time is positively correlated with the remaining catches in refrigerated warehouses. The total refrigeration cost is computed as follow:

$$C_3 = \sum_{k=1}^{K} \sum_{i=1}^{n} y_i^k \frac{q_i}{Q_v} \partial (t_i^k - t_0^k + w_i^k + s_i) \tag{7}$$

where ∂ is the refrigeration cost per unit time at a certain temperature when the refrigerator ship is fully loaded. Q_{in} are the remaining catches in refrigerated warehouses.

d: PENALTY COST

Penalty cost is caused by the arrival time of ship without the time window of the port, when the ship arrives at the port before the expected time or after the expected time.

The penalty cost of port i is computed as follows:

$$C_4(i) = \begin{cases} M & t_i^k < E_i \\ \lambda_1 (e_i - t_i^k) & E_i < t_i^k \leq e_i \\ 1 & t_i^k \in (e_i, l_i) \\ \lambda_2 (t_i^k - l_i) & L_i > t_i^k \geq l_i \\ M & t_i^k > L_i \end{cases} \tag{8}$$

Thus, the total penalty cost is computed as follow:

$$C_4 = \sum_{k=1}^{K} \sum_{i=1}^{n} (\lambda_1 \max \left(e_i - t_i^k, 0\right) + \lambda_2 \max \left(t_i^k - l_i, 0\right)) \tag{9}$$

2) ESTABLISHMENT OF THE MODEL

Based on the above considerations, the marine cold chain transportation route optimization model is established as follow:

$$Min\ C = C_1 + C_2 + C_3 + C_4 \tag{10}$$

$$\text{subject to: } \sum_{j=1}^{n} x_{ij}^k = \sum_{j=1}^{n} x_{ji}^k \leq 1, \quad i = 0,\ \forall k \in K \tag{11}$$

$$\sum_{j=1}^{n} q_j y_j^k \leq Q_v, \quad \forall k \in K \tag{12}$$

$$\sum_{k=1}^{K} y_j^k = \begin{cases} K, & j = 0 \\ 1, & j = 1, 2, \ldots, n \end{cases} \tag{13}$$

$$t_j^k = t_i^k + w_i^k + s_i + t_{ij}^k, \quad \forall i,\ j \in N, i \neq j,\ \forall k \in K \tag{14}$$

$$E_i \leq t_i^k \leq L_i, \quad \forall i \in N,\ \forall k \in K \tag{15}$$

$$w_i^k = \max \left(e_i - t_i^k, 0\right), \quad \forall i \in N,\ \forall k \in K \tag{16}$$

Formula (11) shows that refrigerator ships firstly start from the distribution center, and lastly return to the distribution center in a distribution round. Formula (12) ensures that no refrigerator ship surpasses its load capacity. In addition, formula (13) indicates that the distribution center has m refrigerator ships, and each port is only for one refrigerator ship berthing. The time windows constraints are defined by formula (14) - (16).

D. SPEED SELECTION MECHANISM

We optimize the total cost of the whole route by selecting the optimal speed on each leg.

The function relationship between speed and fuel consumption of the refrigerator ship is shown in formula (3), which can provide a proper estimate on fuel cost of the arc (i, j) when the ship sails normally.

The load capacity of ship and soft time window of port must be considered when refrigerator ship sails along arc (i, j). As known in section 4-subsection C, $C_{12}^{i\to j}$, $C_{132}^{i\to j}$, $C_2^{i\to j}$, $C_3^{i\to j}$, and $C_4^{i\to j}$ are time-related costs, having a certain correlation with sailing time along the arc (i, j), $C_{131}^{i\to j}$ represents a speed-related cost approximated by formula (3), $C_{11}^{i\to j}$ is a constant. For instance, we suppose that ship sails along arc (i, j) with a higher speed, $C_{131}^{i\to j}$ will increase. Meanwhile, the sailing time along arc (i, j) will reduce, consequently, $C_{12}^{i\to j}$, $C_2^{i\to j}$, and $C_3^{i\to j}$ will decrease. Here, $C_{132}^{i\to j}$ will increase with the berthing time at the port j. Furthermore, the ship may arrive at the port j before the expected time, $C_4^{i\to j}$ will be a waiting cost. Thus, we can obtain the minimum value of total cost by adjusting the speed value within the given speed interval.

We assume that ship k has completed the delivery service at port i and will select the next port j for service, Q_{in} denotes the remaining catches in the ship, and the current time is T_{now}. $open$ denotes an unserved port set. $[v_{\min}, v_{\max}]$ denotes a given speed interval of ship, $[v_{ij\min}, v_{ij\max}]$ denotes a speed interval of arc (i, j), $[v_{ij\min}, v_{ij\max}] \subset [v_{\min}, v_{\max}]$. We construct the X by formula (17), it represents a set of ports, and the remaining catches in the ship could meet requirement of any ports in X.

$$X = \left\{ j | Q_{in} + q_j \leq Q_v, j \in open \right\} \tag{17}$$

A speed selection mechanism for arc (i, j) is described as follows:

V. IMPROVED ANT COLONY ALGORITHM

The ACO algorithm is widely used in route optimization problems due to its advantages such as positive feedback and strong robustness. However, the pheromone on the initial

```
Optimal Speed Selection Mechanism
Input: $X$, $T_{now}$, and initialization parameters.
Output: the minimum cost and corresponding speed of serving these port.
if $X = 0$ then Return to fishing ground, $k + 1 \to k$
else
    for all port $j \in X$ do
        if $T_{now} < E_j$ then
            $E_j - T_{now} \leq \frac{d_{ij}}{v} \leq L_j - T_{now}$; Obtain $[v_{ij\min}, v_{ij\max}]$
            if $v_{ij\min} \geq v_{\max}$ or $v_{ij\max} \leq v_{\min}$ then Delete $j$ from $X$
            else if $v_{ij\min} \leq v_{\min}$ and $v_{ij\max} \geq v_{\max}$ then
                $v_{ij\min} \to v_{\min}, v_{ij\max} \to v_{\max}$
            else if $v_{ij\min} \leq v_{\min}$ and $v_{\min} \leq v_{ij\max} \leq v_{\max}$ then $v_{ij\min} \to v_{\min}$
            else if $v_{\min} \leq v_{ij\min} \leq v_{\max}$ and $v_{ij\max} \geq v_{\max}$ then $v_{ij\max} \to v_{\max}$
            end if
        end if
        if $E_j < T_{now} < L_j$ then
            $\frac{d_{ij}}{v} \leq L_j - T_{now}$; Obtain $[v_{ij\min}, v_{ij\max}]$; $v_{ij\max} \to v_{\max}$
            if $v_{ij\min} \geq v_{\max}$ then Delete $j$ from $X$
            else if $v_{ij\min} \leq v_{\min}$ then $v_{ij\min} \to v_{\min}$
            end if
        end if
        if $T_{now} > L_j$ then Delete $j$ from $X$
        end if
    end for
    Update $X$ and $[v_{ij\min}, v_{ij\max}]$
    if $X = 0$ then Return to fishing ground, $k + 1 \to k$
    else
        for all port $j \in X$ do
            for all $[v_{ij\min}, v_{ij\max}]$ do
                Calculate $C^{i \to j}(v)$ defined in the $[v_{ij\min}, v_{ij\max}]$
            end for
        end for
    end if
end if
```

route is unspecified; the blindness of search in this stage leads to the convergence slower. Therefore, we combine A-star algorithm [63] and ACO algorithm to accelerate the solution efficiency. The A-star algorithm has a fast globally search capability and does not traverse the entire search space in the optimizing process, instead, it advances in the most promising direction according to the selected heuristic function. The A-star algorithm is utilized to perform the initial pheromone distribution on the route, and the ACO algorithm take full advantage of the positive feedback to find the best route, which can form the complementary advantages. Furthermore, a novel state transition rules is utilized to avoid the local optimal and improve the solution diversity.

A. INITIAL PHEROMONE SETTINGS

The heuristic function of the A-star algorithm is expressed as follow:

$$f(j) = g(j) + h(j), \quad j \in open_A \tag{18}$$

where $open_A$ represents an unserved port-set. $f(j)$ is the heuristic function of port j, $g(j)$ is the actual cost from the current port i to next port j, which computed as formula (19). $h(j)$ is the estimated cost from next port j to the fishery distribution center, which computed as formula (20).

$$g(j) = T_{now} + \frac{d_{ij}}{v_{ij\max}}, \quad j \in open_A \tag{19}$$

$$h(j) = \frac{d_{j0}}{v_{j0\max}}, \quad j \in open_A \tag{20}$$

We define the position of the fishery distribution center as D, and all ports are in the $open_A$ set. The heuristic function is called to start searching from D. A speed selection mechanism is implemented as described above, and obtains the speed interval $[v_{ij\min}, v_{ij\max}]$ of each leg. The port with the smallest value of $f(j)$ is placed in $S[k]$, at same time, is removed from the $open_A$ set, used as the starting port for next leg. The above steps are executed repeatedly with the constraint of load capacity. Here, the sequence of elements in the $S[k]$ is the sequence of ports visited by refrigerator ship k, representing the route of ship k. The generated route set S is the initial solution. The initial pheromone assigned to this route set S is expressed as $\tau_{R_{best}} = \mu\tau_{ij}(0)(\mu > 1)$. The pheromone assigned to other routes without the set S is defined as $\tau_{ij}(0)$.

$\tau_{ij}(0)$ denotes the initial concentration of pheromone which is expressed as $\tau_{ij}(0) = Q/C_{A-star}$, Q here refers a constant related to the quantity of pheromone released by ants and C_{A-star} is totally cost obtained by A-star algorithm. The A-star algorithm can be described as follows:

B. STATE TRANSITION RULES

Ants select the next port j from current port i through the state transition rule. In the traditional ACO algorithm, the state transition rule is expressed as equation (21)

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum\limits_{s \in open_k} \tau_{is}^{\alpha}\eta_{is}^{\beta}} & j \in open_k \\ 0 & otherwise \end{cases} \tag{21}$$

where p_{ij}^{k} defines the probability of ant k transfers from port i to port j. τ_{ij} is the pheromone amount on arc (i, j). $\eta_{ij} = 1/C_{ij}$ is the heuristic factor of arc (i, j), which is expressed by the inverse of the cost on arc (i, j). Both α and β are parameters supporting regulation, which express the weight of accumulated pheromones and heuristic factor on the route

```
A-Star Algorithm
Input: Initialize the variables
$open_A = \{1, \dots n\}, k = 1, S[k] = \emptyset, Q_{in} = 0, D \to a, X = 0$
Output: Initial solution
1.  while $open_A > 0$ do
2.      for all port $j \in open_A$ do
3.          if $Q_{in} + q_j > Q_v$ then place $j$ in $X$
4.          end if
5.      end for
6.      if $X = 0$ then Return to fishing ground, $k + 1 \to k$
7.      else
8.          for all port $j \in X$ do
9.              run optimal speed selection mechanism
                (line 4 - line 20)
10.         end for
11.         if $X = 0$ then Return to fishing ground,
                $k + 1 \to k$
12.         else
13.             for all port $j \in X$ do
14.                 calculate the heuristic function $f(j)$
15.             end for
16.             select the port $j$ with the smallest heuristic
                value as next service port, place this port
                in $S[k]$ and remove from $open_A$ set,
                $Q_{in} = Q_{in} + q_j, j \to a$;
17.         end if
18.     end if
19. end while
```

of ant motion. $open_k$ represents a set of ports that ant k hasn't visit yet.

In order to prevent the algorithm from falling into local optimization and premature stagnation, a pre-set parameter q_0 between [0, 1] is introduced. When the ant k selects the next port, the algorithm will produce a random number q_1 of [0, 1], which is compared with q_0 to select the next port. The specific selection method is shown in formula (22)

$$p_{ij}^k = \begin{cases} \arg\max\limits_{j\in open_k} [\tau_{ij}^{\alpha}\eta_{ij}^{\beta}] & q_1 \le q_0 \\ \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum\limits_{s\in open_k} \tau_{is}^{\alpha}\eta_{is}^{\beta}} & q_1 > q_0, j \in open_k \\ 0 & q_1 > q_0, otherwise \end{cases} \tag{22}$$

When $q_1 \le q_0$, the port with minimum cost is directly selected to be the next port; when $q_1 \ge q_0$, the state transition probability is selected based on the roulette. The q_0 has a great influence on the final solution if q_0 is set as a fixed value, it should be adjusted in equation (23) to improve solution efficiency.

As shown in equation (23), q_0^l is the value of q_0 in the l iteration, C_{best}^l is the total cost on the optimal route of the l iteration, ζ belongs to (0, 1). $\left(C_{best}^l - C_{best}^{l-1}\right) \Big/ C_{best}^{l-1}$ is used to adjust q_0 dynamically. When the optimal solution of the current iteration is less than the optimal solution of previous iteration, a better route is found. Thus, the value of q_0 will become bigger, and the probability to search current area will become bigger, and vice versa. In order to avoid trapping into the local optimal, due to the same results from several continuous iterations, a maximum stagnation number $num_{\max}$ should be set. When the number of continuous stagnations exceed $num_{\max}$, the value of q_0 will decrease, the ants will reduce the search probability of the current area, and strengthen search in other areas.

$$q_0^{l+1} = \begin{cases} q_0^l\left(1 - \dfrac{C_{best}^l - C_{best}^{l-1}}{C_{best}^{l-1}}\right) & C_{best}^l \ne C_{best}^{l-1} \\ q_0^l & C_{best}^l = C_{best}^{l-1}, num \le num_{\max} \\ \zeta q_0^l & C_{best}^l = C_{best}^{l-1}, num > num_{\max} \end{cases} \tag{23}$$

C. PHEROMONE UPDATE RULES

In the process of calculation, to avoid premature convergence operation and lead to the result that is not for the global optimal solution, all route pheromone values are required to be within the prescribed scope. We define the parameter τ_{ij} with the interval $[\tau_{\min}, \tau_{\max}]$, if $\tau_{ij}(t) \ge \tau_{\max}$, $\tau_{ij}(t) \to \tau_{\max}$; if $\tau_{ij}(t) \le \tau_{\min}$, $\tau_{ij}(t) \to \tau_{\min}$. In this way, it can avoid the pheromone in a certain route too large or too small.

After finishing one cycle, the pheromone of the optimal solution route will be updated, expressed as follow:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{best}, \Delta\tau_{ij}^{best} = \frac{Q}{C_{best}} \tag{24}$$

where C_{best} is the total cost on the optimal route in current iteration. ρ denotes the pheromone evaporation rate, $(1-\rho)$ represents the value of pheromone residual rate.

$$\tau_{\max} = \frac{\sigma}{1-\rho} \times \frac{1}{C_{best}}, \tau_{\min} = \frac{\tau_{\max}}{5} \tag{25}$$

$\tau_{\min}$ and $\tau_{\max}$ can be obtained by expression (22), the σ is obtained by experiments. Here, $\sigma = n/20$. n is the number of ports.

D. IMPLEMENTATION OF THE IACO ALGORITHM

The steps of the IACO algorithm are described as follows.

VI. EXPERIMENTS

In our work, we carried out experiments on the refrigerator ships from Zhoushan Ningtai Ocean Fisheries Co., LTD, which provides cold chain transportation service for ports in the Bohai Bay. The Beidou terminals equipped on the ships can send monitoring data or receive scheduling information to or from the shore-based center. The feasibility of our scheme is demonstrated by following experiments.

IACO Algorithm

Input: Maximum number of iterations $iter_{\max}$, the transportation map G, the number of ants m.

Output: The optimal transportation route.

```
Execute **A-star algorithm**, the initial pheromone distribution on the route obtained by A-star algorithm.
while $l \leq iter_{\max}$ do
    for all ant $i \in m$ do
        while $open > 0$ do
            for all port $j \in open$ do
                if $Q_{in} + q_j > Q$ then place $j$ in $X$
                end if
            end for
            Execute **optimal speed selection mechanism** Select next port according to equation (22).
            Update $open$ set and load etc.
        end while
        Calculate the total cost obtained by ant.
    end for
    Update parameter $q_0$ according to equation (23).
    Update the pheromones according to equation (24).
    $l + 1 \rightarrow l$
end while
```


(a) (b)

FIGURE 4. Shipborne devices (a): Temperature recorder (b): Beidou terminal.

A. TEMPERATURE MONITORING EXPERIMENT

During marine cold chain transportation, the temperature data of the refrigerated warehouse were collected by the temperature recorder (in Figure 4(a)) every 10 minutes, and transmitted to the shore-based center by the Beidou SMC module (in Figure 4(b)). In Figure 5, we sampled the temperature data of four refrigerated warehouses and a food supplies warehouse during one day.

It can be seen from Figure 5, the temperature of refrigerated warehouses was approximately −25 °C during one day, which can provide a suitable and stable storage condition for the catches. The temperature of food supply warehouse was about −18 °C, it can meet daily diet needs of the crew.

B. BEIDOU SMC EXPERIMENT

In order to better illustrate the advantage of the improved communication method for Beidou SMC, we compared our method with the original method. The original communication method is shown in Table 3 and Figure 6.

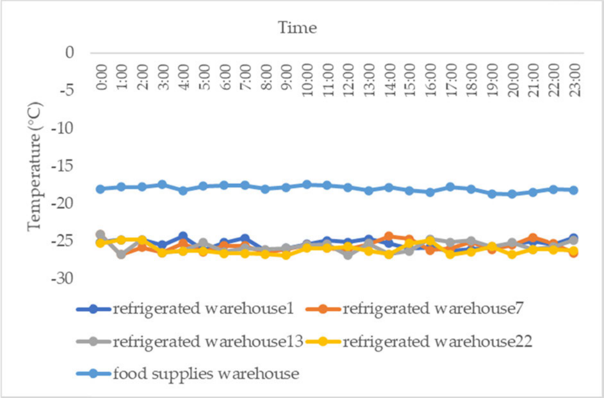

FIGURE 5. Temperature monitoring of the warehouses during one day.

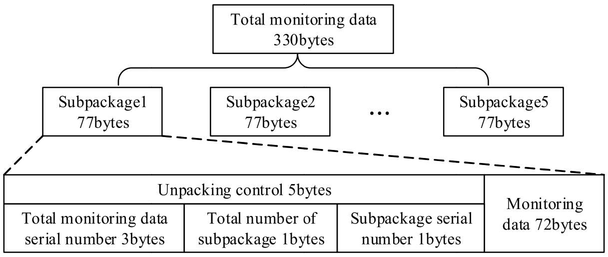

FIGURE 6. Packet structure with original communication method.

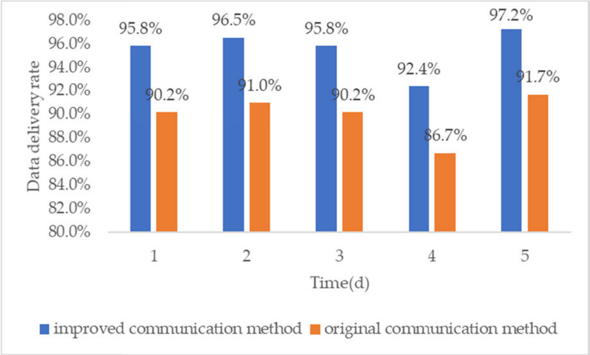

FIGURE 7. Comparison of packet delivery rate.

As can be seen from Table 3. The length of total monitoring data is 288 + 42 = 330 bytes, Obviously, The data length (163.5 bytes) with our improved method is much smaller than that with the original method, and the compression ratio is close to 50%, indicating the efficient bandwidth utilization of our improved method.

In Figure 6, monitoring data with the original method are divided into 5 subpackets, 5 bytes of ''unpacking control'' information are added to the header of each subpacket, and the remaining 72 bytes of each subpacket is used for monitoring data. Once any one of the five subpackets transmission fails, it needs to be retransmitted; in this case our improved method can recovery the lost subpacket.

In order to test the reliability of the improved communication method, we calculated the packet delivery rate of the improved method and the original method during five days. As depicted in Figure 7, it is clear that packet delivery

TABLE 3. Code example of monitoring data with original method.

Information type	Domain	Information content	Code	Bytes
Ship information 42 bytes	Ship number	Refrigerator ship 1	01	2
	Time	2020/4/18 11:44:50	20200418114450	14
	Fuel consumption (ton)	175.135	175135	6
	Longitude	117°10′11″E	1171011E	8
	Latitude	34°21′32″N	0342132N	8
	Speed (kn)	20.11	2011	4
Catches information 12x24=288 bytes	Warehouse number	Warehouse 1	01	2
	Species and grade of catches	“11” stand for “squid” “3” stand for “small”	113	3
	Temperature (°C)	-23.2	-232	4
	Remaining catches (ton)	410	410	3

TABLE 4. The set of parameters of algorithms.

Parameters	Ants (m)	Maximum iterations ($iter_{\max}$)	Pheromone factor (α)	Heuristics factor (β)	volatility coefficient (ρ)	Pheromone amount (Q)	μ	q_0^1	ζ	$num_{\max}$
ACO	30	100	3	1	0.3	300	N/A	N/A	N/A	N/A
IACO	30	100	3	1	0.3	300	1.7	0.5	0.95	5

rate of the improved method was higher than that of the original method, which shows that the FEC technology effectively improves the reliability of Beidou SMC transmission. Therefore, our scheme can provide reliable ship-shore communication and meet the monitoring requirement of the IoV system. However, the packet delivery rate on the fourth day was obviously lower than that on other days, it may be caused by the severe marine weather.

VII. SIMULATION AND ANALYSIS

Simulation experiments were carried out with the standard test data and practical example to test the performance of the IACO algorithm for the ship route optimization. The basic ACO algorithm is selected to compare the optimization performance with the proposed IACO algorithm. We implement the proposed IACO and basic ACO algorithm using MATLAB2016a, running on a desktop with Intel Core i5-6200U, CPU 2.3GHz with Windows10.

The selection of parameters in algorithms has a great influence on the results. Therefore, we implement a large number of tests to get the reasonable initial values of the parameters. The values of the parameters selected may result in the optimal solution and the reasonable running time. The obtained initial values of the parameters are shown in Table 4.

We suppose that refrigerator ships start transportation at 04:00 a.m. The parameters in simulations are listed in Table 5, which are obtained mainly according to the operation of Zhoushan Ningtai Ocean Fisheries Co., LTD..

TABLE 5. Parameters and the value in the computation example.

Parameter	Implication	Value
p_H	Unit price of HFO (RMB/ton)	1200
p_M	Unit price of DMO (RMB/ton)	2200
p	Unit price of catches (RMB/ton)	5000
Q_v	Load capacity (ton)	500
λ_1	Waiting cost per unit time (RMB/h)	1000
λ_2	Delay cost per unit time (RMB/h)	3000
ϕ	Freshness attenuation coefficient	0.0014
∂	Refrigeration cost per unit time (RMB/h)	2400
φ	DMO consumption coefficient (ton/h)	0.054
Δ	Full load displacement(ton)	805
□	Admiralty Coefficient	400
f	Shipping fee per unit time (RMB/h)	650
$[V_{\min}, V_{\max}]$	Speed interval (kn)	[10,15]

A. CLASSICAL DATASET TEST

1) DATA SELECTION

Without loss of generality, we took three classical datasets (Solomon benchmark datasets R201, C201, and RC201), 100 nodes in each dataset, to test the performance of the IACO algorithm for the route optimization problem. Among them, the node locations of C201 data are relatively concentrated, while those of R201 data are relatively scattered, and those of RC201 data are uniform. Meanwhile, datasets R2, C2 and RC2 have wide time windows, which are in accord with delivery time requirements of ports.

According to actually marine cold chain logistics scenarios, the format of classical datasets should be adjusted properly in experiments as follows. (1) Adjustment of time window: we suppose that the hard time window of the classical dataset is [a, d]. We adjust [a, d] to [a, b, c, d], where the values of a, b, c, and d form an arithmetic sequence. For instance, the time window of a port is [161, 171], the updated time window is [161, 164.33, 167.67, 171]. (2) Converting kilometers into nautical miles: one nautical mile equals 1.8 kilometers, namely, the distance between two nodes (i, j) is defined as $d_{ij} = 1.8\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$.

TABLE 6. Results obtained using ACO and IACO.

Datasets	IACO			ACO		
	Optimal solution (RMB)	Average solution (RMB)	Average convergence algebra	Optimal solution (RMB)	Average solution (RMB)	Average convergence algebra
R201	1756240.79	1791794.63	57.7	1779888.75	1795895.72	82
C201	7113930.77	7292232.37	31.50	7220631.40	7306641.90	53.6
RC201	2227866.48	2333965.82	59.4	2290212.31	2370335.44	76

TABLE 7. Statistics of stability and reliability.

Datasets	Critical value (RMB)	IACO		ACO	
		Success rate (%)	Standard Deviation	Success rate (%)	Standard Deviation
R201	1796000	30	11493.83	100	20792.78
C201	7307000	40	19609.83	100	52203.23
RC201	2371000	40	25918.45	100	50033.32

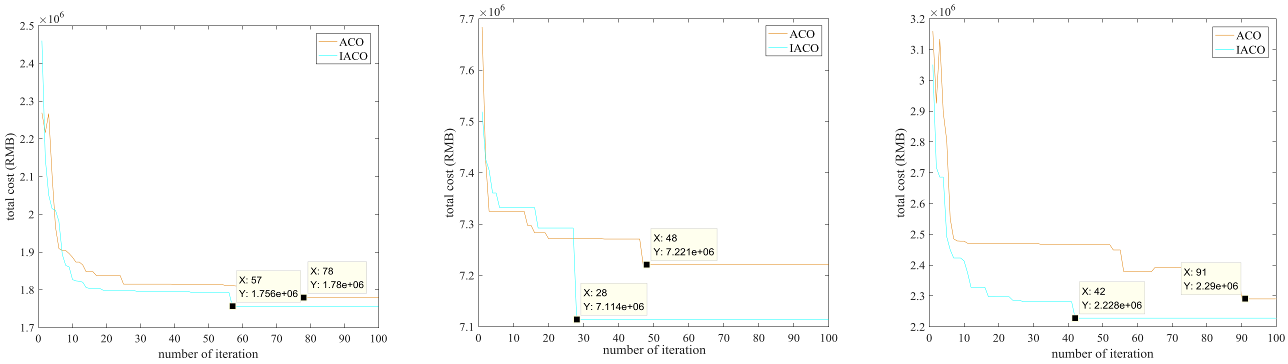

FIGURE 8. Convergence comparison for R101(left), C101(middle), and RC101(right).

2) RESULTS AND ANALYSIS

The basic ACO algorithm and the IACO algorithm are used to solve the datasets 30 times. The results obtained by ACO and IACO are shown in Table 6. It shows that the optimal solution and the average solution obtained by IACO are better than those obtained by ACO. Specifically, for the three datasets, the optimal solutions of IACO algorithm are 1.34%, 1.50%, and 2.80% less than those of the ACO algorithm respectively, and the average solutions of IACO algorithm are 2.3%, 2.0%, and 1.6% less than those of the ACO algorithm respectively. In terms of the convergence rate, the average convergence algebra of IACO is less than that of ACO.

The reliability of the algorithm is based on the success rate, which is defined as the ratio of the number of the optimal solution reaching the predefined critical value, and the number of simulations [39]. The stability of the algorithm is based on the standard deviation of the results. As shown in Table 7, in terms of stability, the standard deviations of the results of IACO are less than that of ACO; in terms of reliability, the success rates of IACO for solving the three datasets are all 100%, which are significantly higher than that of ACO. The results demonstrate that IACO algorithm have better stability and reliability than ACO.

Figure 8 shows the convergence process of the basic ACO algorithm and the IACO algorithm to solve the datasets C101, R101, and RC101. With the increase of the number of iterations, the total costs for both algorithms decrease, but the IACO algorithm gets the lower results with the less number of iterations.

B. SIMULATION EXAMPLES

1) DATA SELECTION

Our improved model and algorithm for solving the route scheduling problem was verified through practical marine cold chain transportation application. In our work, Zhoushan Ningtai Ocean Fisheries Co., LTD., which provides the marine cold chain distribution service for 14 ports in the Bohai Bay, is taken as the subject of case study. The fleet of company normally fish near a fishing ground (38°43′ 22″ N, 119°52′ 21″ E) in the Bohai Sea. This location of the fishing ground is regarded as distribution center. The basic information of ports are shown in Table 8, which according to the practical application of Zhoushan Ningtai Ocean Fisheries Co., LTD..

2) RESULTS

The IACO algorithm run 30 times, the best result is obtained in the case that 4 refrigerator ships are used to perform the delivery task with a total cost of 270642.2RMB. The optimal scheduling information obtained are shown in Table 9, which can be transmitted from the shore-based center to the refrigerator ships.

TABLE 8. Port information.

Number	Port	Location	Time window (h)		Demand (ton)	Service time (h)	Port charge (RMB)
			(e_i, l_i)	(E_i, L_i)			
1	Weihai	37°30′21″N,122°08′58″E	[18.5,24.5]	[17.5,25.5]	140	3	3060
2	Yantai	37°32′34″N,121°25′50″E	[22,29]	[21,30]	150	3	3280
3	Penglai	37°49′55″N,120°43′58″E	[15,22]	[14,23]	120	2.75	2610
4	Longkou	37°38′27″N,120°17′22″E	[14.5,21.5]	[13,23]	160	3.5	3510
5	Bohai Bz Terminal	38°14′35″N,119°41′58″E	[8.5,12.5]	[7,14]	70	1	1520
6	Bz 34 Terminal	38°06′59″N,119°33′00″E	[10,14.5]	[8.5,16]	80	1	1700
7	Bz 25-1 Terminal	38°13′59″N,119°08′53″E	[8,12]	[7,13]	80	1.25	1750
8	Dongying	38°05′13″N,118°59′16″E	[9,14]	[8,15]	140	3	3100
9	CaoFeiDian Terminal	38°46′18″N,118°42′17″E	[12,18]	[10,20]	110	2.5	2400
10	Caofeidian 11 Terminal	38°56′03″N,118°27′49″E	[16,22]	[15,23]	60	1	1290
11	Tianjin	39°02′00″N,117°40′58″E	[15,23]	[14,24]	150	3	3210
12	Jingtang	39°13′00″N,119°00′59″E	[10.5,16.5]	[9,18]	200	4	4340
13	Qinhuangdao32 terminal	37°07′00″N,119°12′11″E	[8.5,11.5]	[7.5,12.5]	60	1	1320
14	Lushun	38°48′00″N,121°14′59″E	[9,13]	[8,14]	120	2.5	2610

TABLE 9. Optimal scheduling information obtained by IACO.

Number of ships	Transportation route (port $\xrightarrow{\text{speed (kn)}}$ port)	Volume (ton)	Departure time
1	$0 \xrightarrow{10} 13 \xrightarrow{10.5} 12 \xrightarrow{11} 10 \xrightarrow{12.6} 11 \xrightarrow{10} 0$	470	4:00 a.m.
2	$0 \xrightarrow{11.2} 7 \xrightarrow{11.4} 6 \xrightarrow{15} 5 \xrightarrow{13.3} 9 \xrightarrow{10} 0$	340	4:00 a.m.
3	$0 \xrightarrow{12.1} 14 \xrightarrow{12.5} 1 \xrightarrow{12.6} 2 \xrightarrow{10} 0$	410	4:00 a.m.
4	$0 \xrightarrow{11.2} 8 \xrightarrow{12.8} 4 \xrightarrow{15} 3 \xrightarrow{10} 0$	420	4:00 a.m.

TABLE 10. Adjust main controlling parameters and simulated results.

(α, β, ρ)	(2, 1, 0.3)	(2, 2, 0.4)	(2, 3, 0.5)	(3, 1, 0.3)	(3, 2, 0.4)	(3, 3, 0.5)	(4, 1, 0.3)	(4, 2, 0.4)	(4, 3, 0.5)
K	4	4	4	4	4	4	4	4	4
Optimal solution (RMB)	270642.2	270642.2	270642.2	270642.2	270642.2	270642.2	272763.7	271280.9	272763.7
Relative gap (%)	0	0	0	0	0	0	0.78	0.24	0.78

As can be seen from Table 9, the refrigerator ship 1, carried 470 tons of catches, departed at 4:00 a.m. and served Qinhuangdao32 terminal, Jingtang, Caofeidian 11 Terminal, and Tianjin in turn, the speed of each leg is 10, 10.5, 11, and 12.6 kn respectively. The refrigerator ship 2, carried 340 tons of catches, departed at 4:00 a.m. and served Bz 25-1 Terminal, Bz 34 Terminal, Bohai Bz Terminal, and CaoFeiDian Terminal in turn, the speed of each leg is 11.2, 11.4, 15, and 13.3 kn respectively. The refrigerator ship 3, carried 410 tons of catches, departed at 4:00 a.m. and served Lushun, Weihai, and Yantai in turn, the speed of each leg is 12.1, 12.5, and 12.6 kn respectively. The refrigerator ship 4, carried 420 tons of catches, departed at 4:00 a.m. and served Dongying, Longkou, and Penglai in turn, the speed of each leg is 11.2, 12.8, and 15 kn respectively. After delivery, the refrigerator ships return to the distribution center with 10 kn in the Bohai Sea. Figure 9 shows the optimal transportation routes obtained by IACO algorithm.

As can be seen from the results, the IACO can effectively assign these ships to serve 14 ports, and obtain the proper assignment result. Thus, The IACO algorithm shows the effectiveness in solving ship route optimization problem.

3) ANALYSIS

a: THE INFLUENCES OF DIFFERENT PARAMETERS ON THE STABILITY PERFORMANCE OF IACO

In order to further investigate the influence of main controlling parameters on the solution performance, we adjusted the values of α, β, and ρ parameters. The simulated results are shown in Table 10, in which K is the number of ships. Obviously, it can be seen that the most of the solving results of the IACO algorithm with different parameters can reach the best-known solution (270642.2 RMB), and the relative gap between the optimal solution and 270642.2 is controlled within 0.78%, it shows that adjustment of values of α, β, and ρ have no significant impact on the total cost. It suggests a good stability of IACO for solving ship route optimization in marine cold chain transportation.

b: COMPARISON WITH DIFFERENT ALGORITHMS

We compare the IACO algorithm with the basic ACO algorithm for the practical marine cold chain transportation application, to verify the optimization performance. The control parameters are set as shown in Table 5. The experiments are implemented with 30 consecutive runs. Table 11 presents the average and optimal solutions of IACO (270642.2 and

TABLE 11. Results obtained by ACO and IACO.

Algorithms	Optimal solution (RMB)	Average solution (RMB)	Average convergence algebra	Standard deviation	Average running time (s)
ACO	272763.7	273525.9	50.65	781.99	20.57
IACO	270642.2	270854.4	27.93	652.98	42.95

TABLE 12. Comparison on cost structure and HFO consumption between two models.

Model	Operating costs (RMB)			Damage cost (RMB)	Refrigeration cost (RMB)	Penalty cost (RMB)	Total cost (RMB)	HFO consumption (ton)	Average speed (kn)
	Port charge	Fuel cost	Shipping fee						
1	35700	31922.0	74298.2	12978.3	111485.9	4257.8	**270642.2**	24.41	11.74
2	35700	25396.2	94826.7	13666.7	116365.0	2323.9	288278.5	17.08	10
2	35700	30143.7	93470.7	12964.4	111407.9	1933.7	**285620.4**	20.67	11
2	35700	36678.6	98968.6	12447.4	107757.5	2284.0	293836.1	25.26	12
2	35700	43411.0	87176.0	12813.8	110327.5	6292.9	295721.2	32.06	13
2	35700	49999.3	87449.2	12605.3	108856.7	6185.9	300796.3	37.18	14
2	35700	62783.8	104618.1	12509.0	108197.1	3980.8	**327788.6**	46.13	15

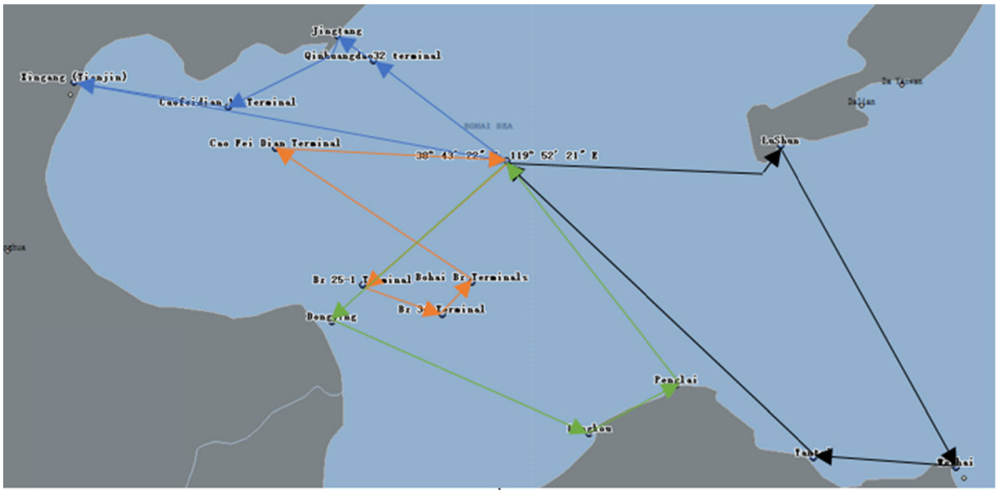

FIGURE 9. Optimal transportation routes obtained by IACO.

304918.3 RMB respectively), which are lower than that of ACO (307880.1 and 305680.1 RMB respectively), indicating that the former outperformed the basic ACO. As to the speed of convergence, the average convergence algebra using IACO is smaller than that using ACO. The standard deviation of the optimal solutions of IACO are smaller than that of ACO, showing the stability IACO for the practical marine cold chain transportation application.

From the experiment results, we can see that runtime of the IACO algorithm is more than that of the basic ACO algorithm. The time complexity of the IACO algorithm is $O(iter_{\max} \cdot n^2 \cdot m)$, where $iter_{\max}$ represents maximum iterations, n and m represent number of port and ant respectively. Thus, the longer runtime by IACO may be caused by the extra runtime generated by A-star algorithm and improved state transition rules. Although the IACO algorithm uses more time to solve ship route optimization, the duration of tens of seconds has little influence on practical marine cold chain transportation application. Comparing with the basic ACO algorithm, the IACO algorithm can escape the local minimum value and improve the global search ability, and can effectively improve the optimization performance for the practical marine route optimization problem.

In Figure 10, during 1–6 iterations, the solutions of IACO decrease rapidly, and then drop gradually until 24th iteration, after that, it is stable. The IACO algorithm convergence rate and optimization results are superior to those of the basic ACO algorithm obviously.

c: EFFICIENCY ANALYSIS OF SPEED SELECTION MECHANISM

In this part, we mainly analyzed the speed selection mechanism from cost structure and fuel consumption aspects, and its impact on the marine route optimization application.

We compare two models (Model 1 and Model 2), with and without speed selection mechanism respectively. We only consider HFO consumption, which speed can cause a great influence on, as can be seen from formula (3). In Model 2, ship speed is constant. To analysis performance of the two models, we operated the model 2 by the ship speed with

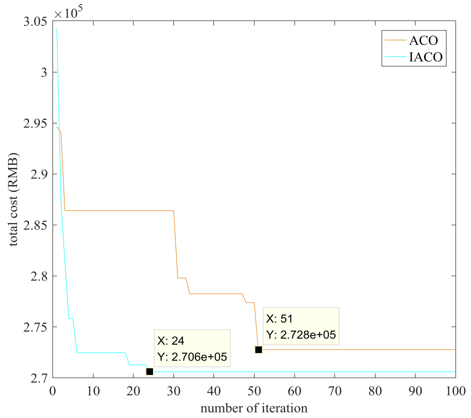

FIGURE 10. Performance evaluation of IACA and ACO.

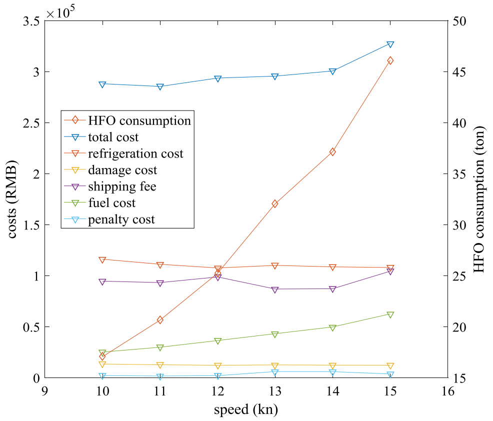

FIGURE 11. Effects of different speed on costs and HFO consumption in model 2.

10, 11, 12, 13, 14, and 15 kn respectively. Each model run 20 times independently by the IACO algorithm, the best results are shown in Table 12. Figure 11 describes the costs and HFO consumption varying with the ship speed. As to Model 2, it can be seen that speed selection has a certain impact on all costs except port charge, with the increase of speed selected, the HFO consumption and fuel cost increases, and but other costs do not show a regular change.

The reason maybe that the transport routes generated by speed selection mechanism maybe different each time, thus, the different transport distances may result in the different costs change, such as damage cost and refrigeration cost.

The total cost using Model 1 is 5.53% less than that using Model 2 with a speed of 12 kn, which is the least among the total cost using Model 2 with different speeds. It indicates that the Model 1 can achieve a better total cost by adjusting the speed of each leg. In a word, as to the total cost, the Model 1 with speed selection mechanism has better optimize performance. Therefore, it is efficient to the marine cold chain route optimization application.

VIII. CONCLUSION

In this article, the IoV-BDS architecture is proposed for marine cold chain transportation monitoring and scheduling optimization. The crews can obtain the ship navigation status and catches information in real-time; at the same time, the shore-based center can remotely monitor and schedule refrigerator ships. An improved communication method is designed, to improve communication reliability and bandwidth utilization of Beidou SMC. The stability and the reliability of our schemes are verified by experiments of temperature monitoring and the packet delivery rate of Beidou SMC, which can meet the requirements of ship-shore communication and marine cold chain transportation monitoring.

We establish a mathematics model under the real application scenario in terms of cost minimization, with a comprehensive consideration of operating costs, damage cost, refrigeration cost, and penalty cost. Moreover, an optimal speed selection mechanism is designed to further reduce the total cost by adjusting the speed of each leg. The improved ant colony optimization (IACO) algorithm is proposed to solve the model, which takes advantages of ACO algorithm and A-star algorithm to improve the convergence efficiency. Moreover, we design a novel state transition rule to avoid the local optimal.

We carry out the simulations and experiments with Solomon benchmark datasets and practical marine cold chain transportation scenery, respectively. The analysis and results show the better performance of IACO algorithm, in terms of optimization effectiveness, convergence efficiency, and stability.

For future work, we will further research the model for the practical scenarios, and improve the IACO algorithm efficiency. Some costs composition will be further investigated and modelled, such as port charge. In addition, complex marine weather scenarios will be considered in the route optimization problem.

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