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Deployment Strategy of Shore-Based Cooperative Units for the Internet of Inland Vessels

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Abstract: Aiming at the communication network optimization problem of the Internet of Inland Vessels, this work presented a network model and deployment strategy with shore-based cooperative units as network nodes. Firstly, the system architecture and communication mode of the Internet of Inland Vessels were analyzed. The three-layer model of service, data, and transmission of ship–shore communication was established to calculate the ship–shore communication data volume of the system. Then, considering the comprehensiveness of the signal coverage of the base station, a coverage model of two-layer heterogeneous network communication was established. Furthermore, an optimization model of shore-based cooperative unit deployment was established with power consumption, cost, and data transmission rate as the objectives. The multi-objective optimization model was solved by the genetic algorithm. Finally, the proposed deployment strategy was verified through simulation cases. The simulation results showed that the proposed deployment strategy could reduce the deployment cost of shore-based cooperative units based on meeting the communication demand and deploy regional shore-based cooperative units.

Keywords: Internet of Vessels; communication networking; communication demand calculation; base station deployment; inland water transportation

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1. Introduction

Mobile communication technology, computer technology, and the Internet of Things are developing rapidly. Relevant researchers have proposed the Internet of Vessels, combining mobile self-organizing networks with inland river traffic scenarios [1], that is, ships are connected through the network to achieve efficient interconnection between people and ships, ships and ships, cargo and shore with the purpose of refined shipping management, comprehensive industry services, and humanized travel experience. The Internet of Vessels supports instant communication between ships and channel infrastructure, ports, locks, etc., which can improve traffic efficiency and the speed of obtaining ship information as well as reduce traffic accidents. Inland shipping has a large capacity, small footprint, low energy consumption, and low pollution. It is one of the main transportation systems of bulk commodities in China, with irreplaceable cost advantages [2]. Building an efficient inland riverboat network is the basic work of optimizing the inland river shipping system, which is of great significance for the development of inland river shipping, transportation, and environmental protection.

In recent years, researchers and research institutions both at home and abroad have studied the definition, structure, and operating mode of ship networking. Ship networking is defined as a network that connects ships to shore facilities through numeric entities [3]. The authors in [4] define the Internet of Vessels as a novel transportation ecosystem. It is suitable for maritime transportation by integrating emerging technologies related to the Internet of Things such as cloud computing, edge computing, and satellite communications. At present, the ship networking systems that have been built and put into operation include e-Navigation [5] led by the International Maritime Organization, the Waterway-Information-Network [6] led by the United States, the Ship-Area-Network [7] led by South Korea, and the River Information Services (RIS) [8] led by Europe, which have promoted inland shipping. China has also strengthened the construction of its inland-shipping information management system with great progress. At present, inland-shipping information management systems based on AIS, the BeiDou positioning system, RFID, and other technologies have been built in some waters such as the Yangtze River, the Pearl River, and the Beijing-Hangzhou Canal. Furthermore, certain social and economic benefits have been achieved.

At present, the networking methods of ship networking can be divided into three types: ship-based self-networking [9], satellite networking [10], and ground-base station networking [11]. Ship-based self-networking and satellite networking are mainly used in marine scenarios and are less restricted because they do not require the support of shore-based base stations. Ground-base station networking is mainly used in coastal and inland river scenarios. On-board communication units and shore-based coordination units form network communication nodes, and shore-based coordination units can be used as a communication relay or directly provide calling services to ships. Ship-to-ship communication alone is not enough to maintain the stability of communication due to the mobility of ships and the need for real-time information acquisition. Therefore, the introduction of shore-based collaborative units to assist in network construction can enhance the robustness and robustness of the network.

Currently, the methods for ship–shore data transmission mainly include very high frequency (VHF) systems, the automatic identification system (AIS), mobile network communication, and satellite communication [12]. Although the AIS system significantly enhances navigational safety, its narrow communication bandwidth and inability to conduct point-to-point communication are inherent in its technical principles. Shore-based mobile communication networks, relying on architectures such as cellular networks and wireless local area networks, facilitate maritime communication in nearshore and inland waterways, offering services to vessels within a certain range, and possessing advantages of security, stability, and high bandwidth [13].

Regarding the coverage issue in inland waterway communication, Wang [14] analyzed the equipment status of AIS ship stations in inland waterway navigation areas, identified characteristics of communication coverage blind spots for AIS shore-based systems, and proposed solutions such as deploying small AIS receiving stations to address this problem. To tackle the issue of 4G mobile network signal blind spots in inland waterways leading to potential signal interruptions for vessels at critical moments, the utilization of both the 4G mobile network and BeiDou short message communication methods was suggested [15]. Furthermore, a 4G signal strength detection module and communication mode switching algorithm were designed to ensure continuous communication for vessels navigating inland waterways. In response to the intelligent navigation requirements for vessels in the Yangtze River waterway, Wang [16] proposed a solution that integrated 4G and satellite communication technologies to achieve integrated ship–shore data fusion communication for direct navigation between rivers and seas. The SeaFi project [17] employs WiFi technology to transfer large-scale data from ships to shore or vice versa, aiming to address data transmission challenges in ship–shore communication. By establishing an unmanned surface vehicle platform, integrating devices including WiFi communication and satellite-based global positioning system (GPS) signals, a network with a land-based control center was constructed. With the rapid growth of communication service demands, wireless communication networks are evolving toward heterogeneity, which aids in addressing complex communication scenarios, achieving resource sharing among different networks, managing interference, and enhancing the system capacity. However, resource allocation issues in heterogeneous networks have concurrently become critical technical challenges in resource management.

In dense HetNets, spectrum resource allocation is one of the most significant challenges. This issue involves partitioning a segment of spectrum resources into multiple smallest resource units such as subcarriers or physical resource blocks and then allocating these resources to users in the system to meet their rate requirements while minimizing the interference as much as possible. Palanisamy [18] proposed a strategy to reduce interference including power control and channel allocation. However, further research is needed on how to reduce the time complexity while ensuring performance. Fan [19] proposed a distributed iterative algorithm that maximizes the overall efficiency of all base stations/access points while guaranteeing terminal quality of service, which is applicable to various heterogeneous network scenarios. In heterogeneous networks, users can choose different levels of base stations for access compared to traditional single networks. The selection of access points is an important issue; for example, in 4G mobile communication networks, the signal reception strength is typically defined as the criterion for user access to base stations. Kazmi [20] studied the access selection problem of users at different hierarchical base stations in heterogeneous networks and proposed an access strategy, but this strategy overlooks resource allocation issues and considers limited factors. Therefore, to achieve optimal overall system performance, both spectrum resource allocation and user access issues should be considered together.

Regarding the allocation of communication resources in maritime traffic systems, Long et al. [21] proposed a ship wireless communication resource allocation method based on the ant colony algorithm to maximize the communication capacity as the objective function and used the ant colony algorithm to find its optimal solution. Jiang [22], based on the two indicators of throughput and fairness, established a slot resource allocation optimization model to achieve precise slot resource allocation in ship wireless communication networks. Yao proposed a channel allocation method for maritime communication systems based on throughput and load balancing. Yang [23] optimized a water communication network resource allocation strategy with the objectives of minimizing energy consumption and delay, solved it through convex optimization, and the simulation results showed that the scheme could achieve a good balance between energy consumption and delay. Wang [24] introduced new communication technology into maritime ship communication systems and proposed a channel resource allocation scheme for system interference control to increase the number of devices in the network.

A reasonable deployment of shore-based collaborative units can improve the network performance of ship networking and reduce construction costs. At present, more studies have focused on the deployment of mid-road side units instead of the deployment strategy of shore-based collaborative units in the Internet of Things. The deployment strategy of roadside units in highway scenarios has been studied to establish optimization goals for communication energy loss and network connectivity [25]. The deployment strategy of roadside units has also discussed to improve the positioning accuracy of vehicles [26]. A deployment strategy was proposed to minimize the number of roadside units and ensure the quality of traffic service [27]. The needs of ship–shore communication services and the Internet of Vehicles are quite different due to the special navigation methods of inland river ships. Therefore, the rational deployment of shore-based collaborative units is of great significance to the needs of the intelligent navigation business of inland ships.

2. Ship–Shore Communication Needs of Internet of Inland Vessels

2.1. System Architecture and Operating Mode of the Internet of Inland Vessels

The Internet of Inland Vessels aims to achieve efficient collaboration between ships, shore facilities, and related management departments. The system realizes real-time information sharing among ships, ports, docks, and other shore infrastructure through information technology, communication technology, and computing technology. Figure 1 shows the system architecture of the Internet of Inland Vessels.

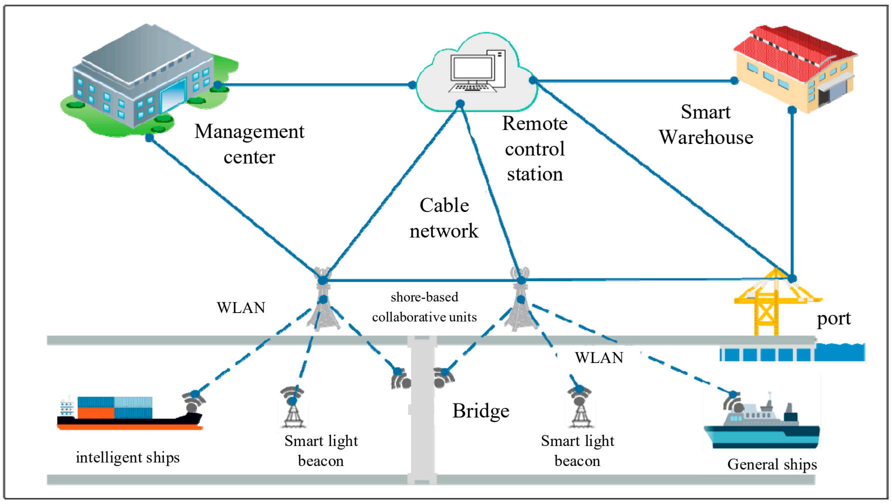

Figure 1. Collaborative architecture of the Internet of Inland Vessels.

The information support of shore-based collaborative units in the Internet of Inland Vessels includes basic information about the navigable environment and related information (e.g., shore-based perception, remote decision-making, and remote control for intelligent ships). Basic navigational environment information includes the types of navigable water areas, meteorological and hydrological conditions, regional traffic flow status, maritime management information, ports and terminals, and other berthing information. Shore-based perception information includes shore-based video, radar, smart bayonet and other perceived water target information, shore-based infrastructure status information, etc. Remote decision-making and remote control instructions come from remote control stations and serve the remote control and autonomous navigation of intelligent ships.

2.2. Communication Service Model and Communication Demand Calculation

Shore-based collaborative units provide traffic safety, traffic efficiency, and information service services for sailing ships in the Internet of Inland Vessels. The traffic safety business can ensure the safety of personnel and cargo on board such as navigation safety early warning, navigation scene reproduction, and remote driving instruction verification. Traffic efficiency services aim to improve the transportation network and reduce transportation time. The improved transportation system can plan a reasonable driving route for ships and increase the capacity of the transportation network (e.g., route planning and speed optimization). The information service business provides users with convenient and fast services such as perception enhancement and the broadcasting of the navigable environment [28].

A three-layer model is established from the business layer, data layer, and transport layer (Figure 2) to analyze the information service mechanism of the shore-based collaborative units. The business generation and data transmission performance of shore-based collaborative units in the system are described from the business generation, data packet rules, and the underlying transmission process. The business layer describes the rules generated by the ship–shore communication service in the model. Considerations include traffic flow characteristics, business type, and business arrival characteristics (i.e., business arrival time, and business duration). The data layer describes the transmission frequency of the data packets and the length of each data packet when each ship performs each service. The transport layer describes the transmission process of the data air interface including the data retransmission rate, packet loss rate, effective data ratio, and signaling ratio.

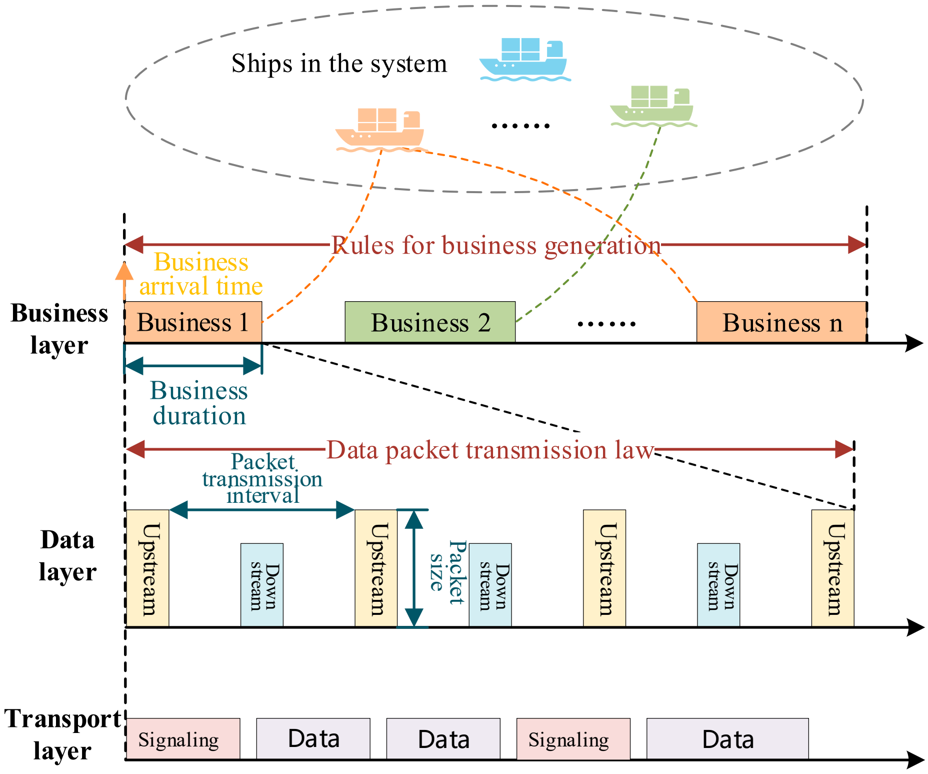

Figure 2. Three-layer business model.

For the business layer, the randomness of ship–shore communication services is large, and the number of services generated in the system has a greater correlation with the arrival process of the ship. Ship traffic flow, business types, and businesses generated in a single ship are synthesized to represent the arrival process model of businesses in the system. The characteristics of ship traffic flow are described through the traffic flow density. Assuming that the density of ships is ρ ship/km in a certain section of a channel with a length of S km, $n_s = S{\cdot}\rho$ is the number of ships in that section of the channel. For each ship, the OFF/ON model is used to describe the arrival characteristics of various services; the ON/OFF state duration of some services is described by exponential distribution. The arrival time and duration of each business are as follows: the start time of the ON stage is the arrival time of a certain business, and the duration of the ON stage is that of the business.

The data layer is analyzed by selecting some services in traffic safety, traffic efficiency, and information services. Combined with the ship's intelligent navigation specifications, data packet rules are defined for each business (Table 1 for details).

Table 1. Business types and names.

Business Type	Business Name	Communication Method
Traffic safety	Navigation safety warning	Upstream and downstream
	Reconstruction of sailing scenes	Upstream
	Remote driving command verification	Upstream and downstream
Traffic efficiency	Route planning	Downstream
	Speed optimization	Downstream
Information service	Traffic flow status broadcast	Downstream
	Perception enhancement	Downstream

In the transport layer, according to different communication methods, we can choose to use the TCP/IP protocol, DDS protocol, and MQTT protocol to encapsulate and transmit data. Lappl bytes is the amount of data in the application layer of the shipping service per unit time; η is the effective data rate of the system. The amount of data is as follows after encapsulation.

$$L_{DLL} = \frac{L_{appl}}{\eta} \tag{1}$$

Signaling refers to messages or instructions used to control and manage a communication system in wireless communication. Signaling needs to be transmitted between different links in a communication network, and each link needs to be analyzed and processed. A series of operations and controls are formed through interaction to ensure that the user information can be transmitted effectively and reliably.

Assuming that R_{sig} is the signaling ratio in the network is, the total amount of information and data required to be transmitted in the system per unit time is

$$I_{total} = \frac{L_{DLL}}{1 - R_{sig}} \tag{2}$$

Re-transmissions and packet losses are mainly affected by the congestion of the communication network and the communication environment. Assuming that P_{retr} is the probability of data packet re-transmissions in a certain scenario and δ is the maximum number of allowed data packet re-transmissions, the data-packet loss rate is

$$\eta_{lost} = P_{retr}^{\delta+1} + P_{retr}^{\delta+2} + P_{retr}^{\delta+3} + \cdots = \frac{P_{retr}^{\delta+1}}{1 - P_{retr}} \tag{3}$$

The average number of transmissions per data packet is

$$F_{RLL} = 1 + P_{retr} + P_{retr}^{2} + \cdots + P_{retr}^{\delta} = \frac{1 - P_{retr}^{\delta+1}}{1 - P_{retr}} \tag{4}$$

After considering the re-transmission rate, the total amount of data transmitted by the system per unit time (i.e., the system throughput) is

$$Q_{sys} = I_{total} \cdot F_{RLL} \tag{5}$$

3. Deployment Strategy of Shore-Based Collaborative Units

3.1. Problem Description

For a channel with a length of S, shore-based collaborative units include a mobile communication base station and a WiFi base station. A two-layer heterogeneous communication network is carried out in the area to ensure signal coverage and meet the communication needs of inland riverboat networking. The deployment strategy is analyzed from the type of the base station and the configuration of the base station.

The type of the base station is defined from the communication technology used by the base station and the operating frequency band such as a 4G base station with an operating frequency band of 1.9 GHz and a WiFi5 base station with an operating frequency band of 5 GHz, if there are a total of M types of base stations to choose from including m_1 types of mobile communication base stations and m_2 types of WiFi base stations ($M = m_1 + m_2$).

The configuration of base stations should consider the total bandwidth, transmission power, tower/pole height (the antenna hanging height is consistent with the tower/pole height), and antenna type. For each type of base station, there are k_1, k_2, k_3, and k_4 options for its configuration factors. Therefore, each type of base station has $K = k_1{\cdot}k_2{\cdot}k_3{\cdot}k_4$ configurations.

The selection matrix for available base-station types and configurations is

$$A = (a_{km})_{K\times M} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m1} & \cdots & a_{1M} \\ a_{21} & a_{22} & \cdots & a_{2m1} & \cdots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ a_{K1} & a_{K2} & \cdots & a_{Km1} & \cdots & a_{KM} \end{bmatrix} \tag{6}$$

where a_{km} is a variable of 0–1, indicating the selection of the communication base station; a_{km} = 1 indicates that the first type of configuration is selected; a_{km} = 0 indicates no selection. Due to the need to build a two-layer heterogeneous network based on mobile communication and WiFi,

$$\begin{aligned} \sum_{m=0}^{m_1} \sum_{k=0}^{K} a_{km} = 1 \\ \sum_{m=m_1}^{M} \sum_{k=0}^{K} a_{km} = 1 \end{aligned} \tag{7}$$

When the first configuration of the mth type is selected, P_{km} is the transmission power of the base station and B_{km} is the bandwidth. According to the signal-coverage link budget and the corresponding propagation model [16], the coverage radius r of the base station can be obtained.

The maximum allowable spacing d_s between the network sites of the same layer can be obtained according to the length of the overlapping coverage band, the signal coverage radius, the width of the channel, and the vertical distance from the base station to the edge of the channel (Figure 3).

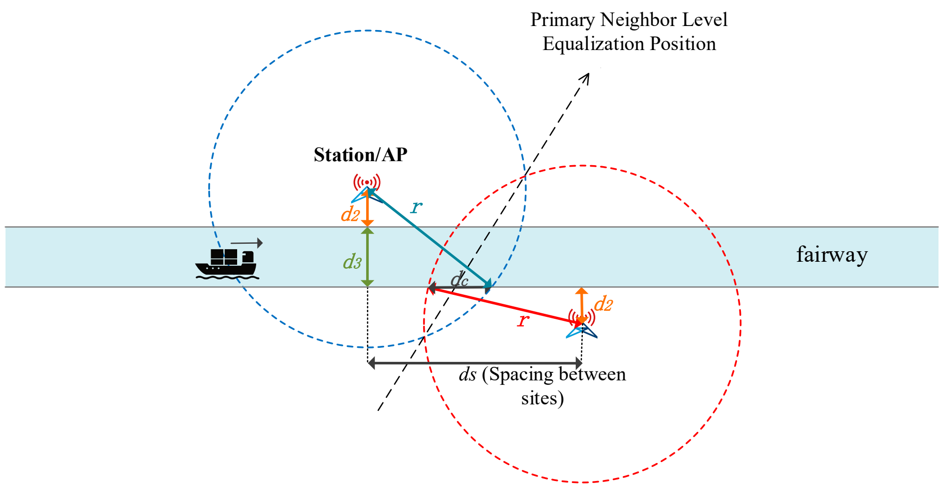

Figure 3. Overlapping coverage belt.

d_1 represents the length of the overlapping coverage belt; d_2 represents the distance between the base station and the edge of the channel; d_3 represents the width of the channel; r_{km} represents the signal coverage radius of the base station. The following relationship exists between the above parameters.

$$d_s = \sqrt{r^2 - (d_2 + d_3)^2} + \sqrt{r^2 - d_2^2} - d_1 \tag{8}$$

Therefore, the corresponding number of deployed base stations is

$$n_{km} = \lceil S/d_r \rceil \tag{9}$$

where $\lceil\rceil$ means that the value in the symbol is rounded up to an integer.

3.2. Deployment Principles and Planning Objectives

Base-station planning considers the data transmission rate of the ship and shore, the power consumption of the base station, and the deployment cost. The data transmission rate of a base station refers to the number of bits transmitted by the base station per unit time. The maximum data transmission rate of a single base station is related to the bandwidth of the base station and its spectral efficiency. Spectral efficiency is an index used in wireless communication to evaluate the efficiency of radio-channel resource utilization and is mainly related to the modulation and coding method of base stations (i.e., the types of base stations).

η_m is the spectral efficiency of type-m base stations. The maximum data transmission rate of a single base station can be calculated by spectral efficiency $\times$ bandwidth, namely $\eta_m \cdot B_{km}$. Therefore, the maximum data transmission rate that the system can provide is

$$f_1(A) = \sum_{m=1}^{M} \sum_{k=1}^{K} a_{km} \cdot n_{km} \cdot \eta_m \cdot B_{km} \tag{10}$$

The planning of the data transmission rate of the base station is generally related to communication service requirements in the region. According to the calculation of the communication requirements in Section 2.2, the maximum throughput $Q_{sys.max}$ in the system can be obtained. Therefore, the objective function is $f_1(A) \geq Q_{sys.max}$.

The power consumption of a base station refers to the energy consumption required by the base station to maintain normal operation, which increases with increased transmission power. Therefore, the transmission power of the base station can reflect the power consumption of the system. The objective function of the total system power consumption can be equivalently defined by

$$f_2(A) = \sum_{m=1}^{M} \sum_{k=1}^{K} a_{km} \cdot P_{km} \cdot n_{km} \tag{11}$$

The costs of station deployment account for most of the investment in wireless network construction. Therefore, the costs of station deployment should be reduced as much as possible under the premise of ensuring network quality. Assuming that the construction costs of the same type of station are the same, the construction cost of the communication base station is related to the type, configuration, and number of base stations. When the k^{th} configuration of the m^{th} type is selected, C_{km} is the construction cost of a single site of the base station. The objective function of the total system cost can be defined by

$$f_3(A) = \sum_{m=1}^{M} \sum_{k=1}^{K} a_{km} \cdot n_{km} \cdot \mathrm{c}_{km} \tag{12}$$

An optimization model is established, and its objective function and constraints are

$$\begin{gathered} max\ f_1(A) \\ min\ f_2(A) \\ min\ f_3(A) \end{gathered} \tag{13}$$

$$\begin{gathered} st1 : f_1 \geq Q_{sys.max} \\ st2 : f_2 \leq P_{max} \\ st3 : f_3 \leq c_{budget} \\ st4 : R_{km} \geq R_{min} \end{gathered} \tag{14}$$

where c_{budget} represents the budget cost of the system communication planning; P_{max} represents the maximum power allowed by the system; $st1$ indicates that the transmission rate supported by the system is greater than the total throughput required for ship-shore communication services; $st2$ indicates that the total transmission power of the base station in the system does not exceed the maximum allowable power; $st3$ shows that the total cost of base station planning does not exceed the budget value; $st4$ shows the edge rate of the base station not lower than the specified minimum value.

3.3. Model Solving Based on the Genetic Algorithm

In light of the multi-objective optimization problem proposed in the previous section, the Pareto optimal solution set was obtained by the multi-objective genetic algorithm. Single optimal solutions were screened to obtain the final planning plan of the base station. The steps are as follows.

(1) Genetic coding. The solution space of the above-mentioned base station planning should be a $K \times M$-order matrix, which corresponds to the configuration selection of each type of base station. Turn the solution space into $1 \times M$ $K+1$ binary strings, and the value in each solution space string represents a certain type of base station. Select its $1^{st}\_K^{th}$ type of base-station configurations, and 0 means that this type of base station is not selected. Then, $K+1$ binary strings undergo binary coding.

(2) Target evaluation. Individual binary encoding is decoded to obtain a subset of corresponding base-station selections. Then, calculate the indicators corresponding to the subset. If the constraints are not met, the negative correlation factor of the individual is set to reduce the probability that the individual passes on to the next generation.

(3) Congestion calculation. Part of the solution is resolved in the area with the dense solution set to ensure the diversity of the population (Equation (15)).

$$I_i = \sum_{j=1}^{m} \frac{\left|f_j^{i+1} - f_j^{i-1}\right|}{\left|f_j^1 - f_j^m\right|} \tag{15}$$

where f_j^{i+1} and f_j^{i-1} represent the value of the j^{th} objective functions of the $i+1^{th}$ and $i-1^{th}$ points, respectively.

(4) Population update. The previous solution is used as the optimal solution set for the iteration after individuals are sorted by crowding. If the number of iterations is reached, the optimal solution set is output. Otherwise, the latter solution will be cross-mutated to produce a new dominant solution.

(5) Crossovers and mutations. Random crossovers are performed for the latter $1-a\%$ solution. Then, variation is performed with the single-point machine (Figure 4).

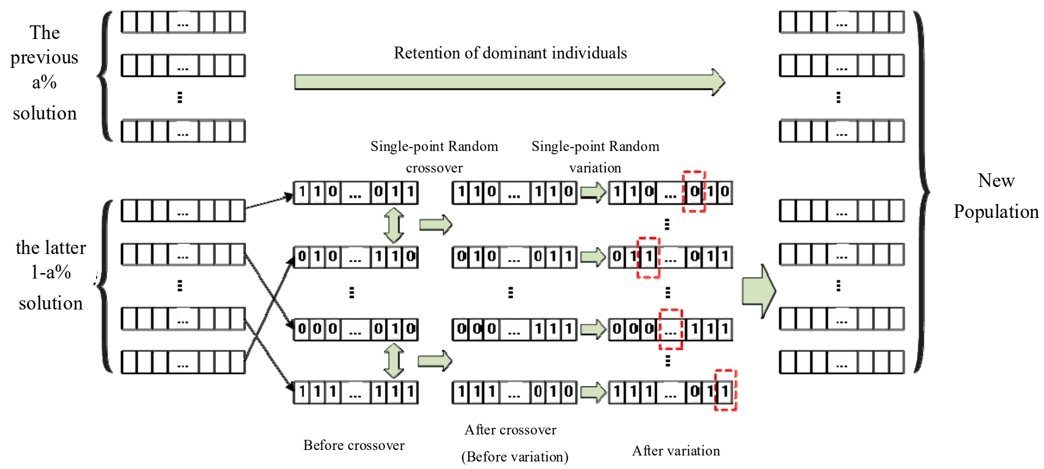

Figure 4. Crossover and mutation process.

(6) Single optimal solution screening. The Pareto solution set should be decoded to convert into corresponding base-station planning. Then, screen the single optimal solutions, and determine the final planning of base stations according to Equation (16).

$$A^* = \operatorname{argmin}\left\{\frac{f_1\left(A_j^*\right)}{f_{1\max}} + \frac{f_2\left(A_j^*\right)}{f_{2\min}} - \frac{f_3\left(A_j^*\right)}{f_{3\min}}\right\}, j = 1, 2, \ldots, J \tag{16}$$

where J is the number of Pareto optimal solution sets; f_{1max} is the maximum value of objective function f_1 in the Pareto optimal solution sets; f_{2min} is the minimum value of objective function f_2; f_{3min} is the minimum value of objective function f_3.

4. Case Study

4.1. Calculations of Communication Requirements

The traffic flow density is 10 ships/km in a channel with a length of 10 km. According to the business model in Section 2.2, relevant computing software was used to calculate the data throughput of system communication (Table 2) [20]. η is 0.87; R_{sig} is 0.1; P_{retr} is 0.01.

Table 2. Simulation parameter settings.

Business	Packet Generation Description	Transmission Direction	Packet Size (B)	Frequency (Hz)
Navigation safety warning	The ship's end detects complicated navigation and sends the ship's status and early warning information to the shore end.	Upstream	200	10
	Conduct safety monitoring at the shore end and return the results.	Downstream	50	10
Reconstruction of sailing scenes	Bridge-perspective video	Upstream	$U(1.25 \times 10^4, 2 \times 10^4)$	30
	Cabin-perspective video	Upstream	$U(1.25 \times 10^4, 2 \times 10^4)$	30
Remote driving command verification	Remote driving instructions issued at the shore-end	Downstream	100	10
	The ship-end performs command verification and returns the result.	Upstream	10	10
Route planning	The shore-end system performs route planning based on various factors and sends the planning results to the ship-end.	Downstream	500	1
Speed optimization	The shore-end system optimizes the speed according to various factors and sends the results to the ship-end.	Downstream	50	1
Perception enhancement	The shore-end sends navigation-area traffic information, channel conditions, and meteorological information to the ship-end.	Downstream	500	10
	The shore-end sends video information of the navigation area to the ship-end.	Downstream	$U(1.25 \times 10^4, 2 \times 10^4)$	30

According to the simulation results of the total communication data throughput of the system (Figure 5), the probability density function (PDF) and cumulative distribution function (CDF) of the system throughput can be obtained (Figure 6). The system communication data throughput of the channel is mainly concentrated at 5.7×10^8 bps in the above-given scenario. If the 6.3×10^8 bps communication bandwidth is provided for this channel, the communication needs of the system can be met.

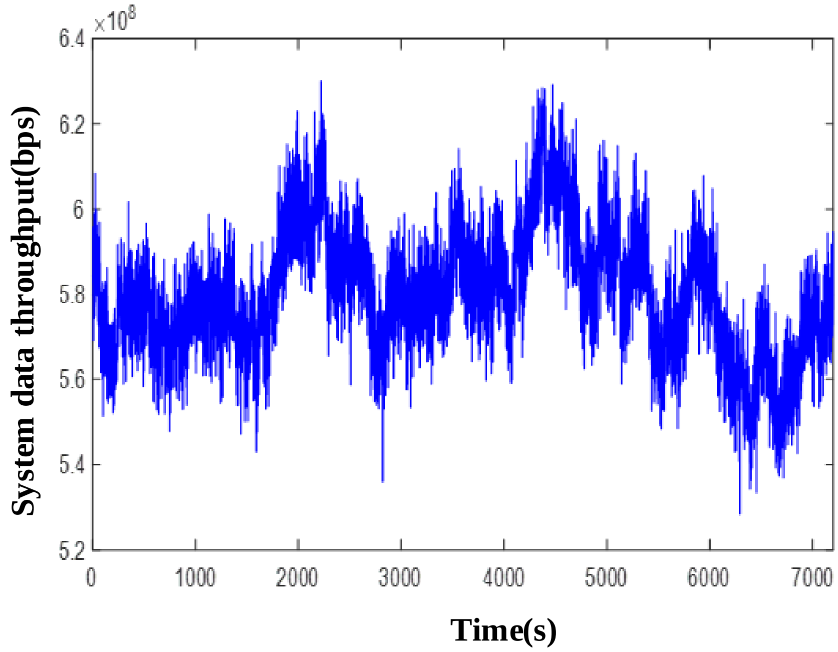

Figure 5. System communication throughput.

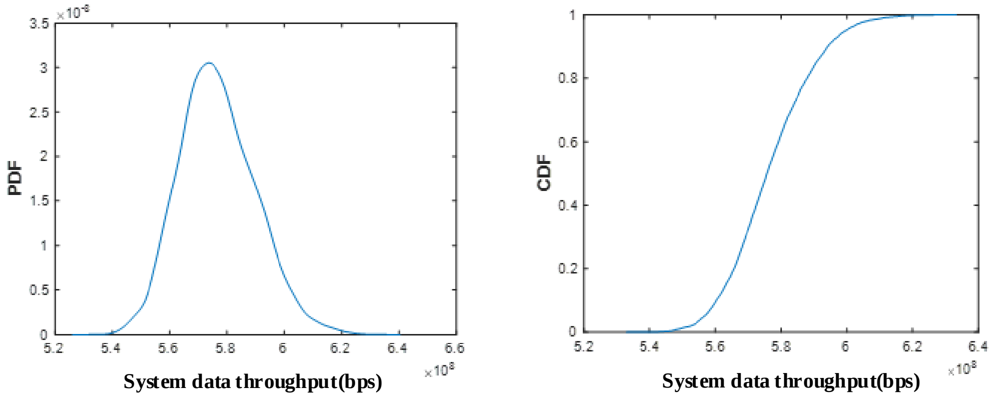

Figure 6. PDF and CDF curves of the system data throughput.

4.2. Deployment Strategy Examples

The density of ships is 10 ships/km and the average speed is 12 knots in a channel with a length of 10 km and a width of 70 m. The terminal has different requirements for signal reception sensitivity and transmission quality due to the different operating frequency bands and transmission technologies of mobile networks and WiFi. The signal reception sensitivity of ship communication equipment for mobile networks is −100 dBm; the signal reception sensitivity for WiFi networks is −80 dBm [29]; the vertical distance between the deployment location of the base station and the edge of the channel is 50 m; the length of the same frequency signal overlap switching band is 16.5 m.

For the above scenarios, suitable mobile base stations and WiFi base stations were selected to cover heterogeneous two-layer communication networks. According to the deployment method above-mentioned, the planning and selection of base stations were considered from the following two aspects.

Types of base stations: Following the M type (M = 9) of base stations (Table 3) should be considered to plan the communication coverage of autonomous transportation systems on inland rivers.

Table 3. Types of base stations for selection.

Type Number	Base Station Type		Spectral Efficiency (bps/Hz)
	Communication Technology	Operating Frequency Band (GHz)	
1	4G	1.9	3
2	4G	2.3	3
3	4G	2.5	3
4	5G	2.6	5
5	5G	3.5	5
6	5G	4.9	5
7	WiFi5	5	3.5
8	WiFi6	2.4	4.8
9	WiFi6	5	4.8

Base-station configuration: M types (M = 9) of base stations have $K = k_1 \cdot k_2 \cdot k_3 \cdot k_4 = 5 \times 5 \times 5 \times 5$ configurations separately. Taking into account the differences between mobile communication technology and WiFi technology, Tables 4 and 5 list the types of available configurations.

Table 4. Available configurations of mobile communication base stations.

Base-Station Configuration Considerations	Optional Types				
Total bandwidth (MHz)	20	40	60	80	100
Transmit power (W)	40	45	50	55	60
Tower height (m)	30	35	40	45	50
Antenna type	9 dBi direction	11 dBi direction	13 dBi direction	17 dBi direction	20 dBi direction

Table 5. Available configurations for WiFi base stations.

Base-Station Configuration Considerations	Optional Types				
Total bandwidth (MHz)	20	40	60	80	100
Transmit power (W)	50	100	120	150	200
Upright height (m)	16	18	20	22	25
Antenna type	10 dBi direction	12 dBi direction	14 dBi direction	16 dBi direction	18 dBi direction

There are a total of 625 combinations for each type of base station based on the total bandwidth, transmission power, base-station height, and antenna type.

Signals in the low-frequency band propagate farther and cover a wider area with stronger penetrability in the case of the same bandwidth. Therefore, they are subject to more demand and competition. For bandwidth resources of the same size, the price of the higher frequency band is usually lower than that of the lower frequency band. Moreover, antenna prices are affected by the communication frequency band and communication technology. Even if the same type of configuration combination is selected for different types of base stations, the price corresponding to a single station is different.

The transmission power of ships can be adjusted adaptively, so the downlink can be considered when making the link coverage budget. According to the link coverage budget equation and the corresponding propagation model of various types of base stations, the base-station coverage radius of the k^{th} configuration in the m^{th} type can be obtained. Then, the deployment spacing can be obtained.

The genetic algorithm in the above was used to solve and screen for a single optimal solution (Table 6).

Table 6. Solutions of base-station planning.

Base Station Type	Base-Station Configuration			
	Bandwidth	**Transmit Power**	**Tower/Upright Height**	**Antenna Type**
1.9 GHz 4G	40 MHz	47 dBm	35 m	11 dBi directional antenna
2.4 GHz WiFi6	60 MHz	23 dBm	20 m	18 dBi directional antenna

According to the obtained type and configuration of base stations, three mobile communication base stations in Table 4 need to be deployed, and the deployment distance of the base stations is about 3378 m. Eight WiFi base stations (Table 5) should be deployed, with a deployment spacing of about 1371 m.

4.3. Algorithm Performance Analysis

The present study employed a genetic algorithm-based improved heuristic algorithm to address the ship–shore communication base station planning problem. In comparison to commonly used particle swarm optimization [30] and deep reinforcement learning (DRL) [31] methods, the proposed algorithm demonstrated a faster convergence speed. The convergence speed of the algorithm is directly related to the population size, as evidenced in Figure 7, where with an increase in the number of ships in the system, the convergence time of the algorithm also increased. However, the algorithm proposed in this study exhibited a significantly faster convergence speed compared to other algorithms. This advantage stems from the algorithm's inherent memory feature, wherein the genetic information retains the position and velocity information of the optimal solution from the current iteration. Consequently, it follows the trajectory of the current optimal solution during the search update process, leading to faster convergence speed. As depicted in Figure 8, the proposed algorithm surpassed particle swarm optimization and other algorithms in terms of accuracy, making it more suitable for meeting the low latency requirements of safety-related services in inland waterway vessel networking.

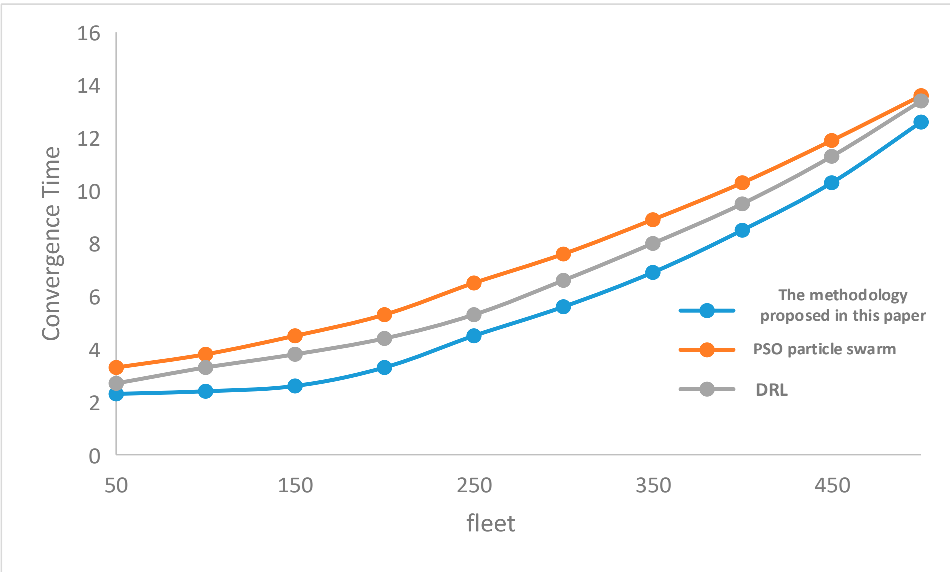

Figure 7. Comparison of the convergence time of different algorithms.

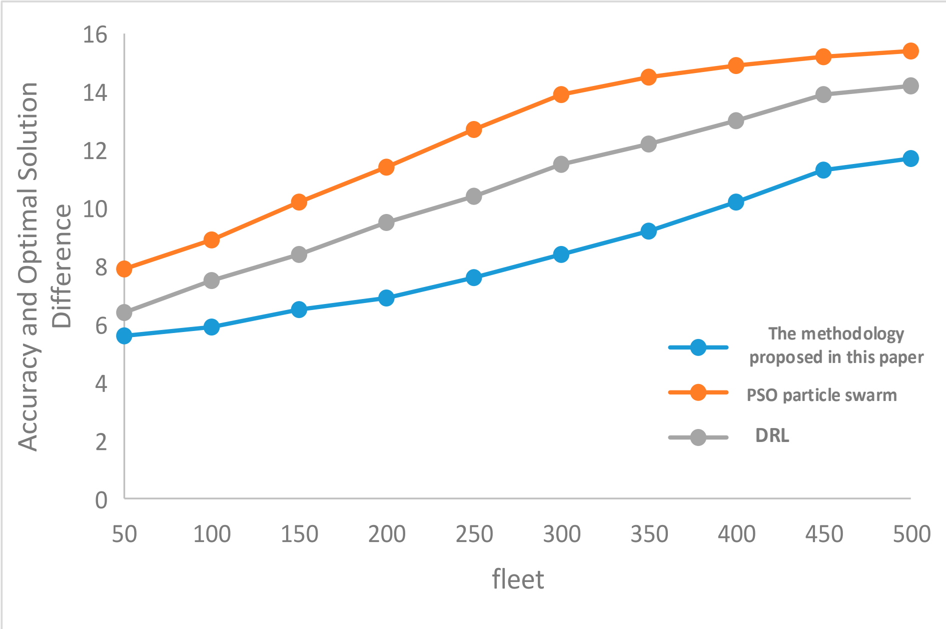

Figure 8. Comparison of the accuracy and optimal solution difference of different algorithms.

5. Conclusions

The work explained the architecture and business model of the inland riverboat networking system, with the functions and scenarios of the ship–shore communication service as well as the communication requirements analyzed. Modeling was performed from the system-service arrival process, the data-packet generation rules of each service, and the transmission process to calculate the amount of ship-to-shore communication data of the system. Then, a coverage model of two-layer heterogeneous network communications was established from the comprehensiveness of the base-station signal coverage.

Considering the types and configurations of deployed base stations, a multi-objective optimization model was established with the goals of power consumption, cost, and data transmission rate. The multi-objective optimization model was solved by the genetic algorithm. Finally, the proposed deployment strategy was verified through simulation cases. The simulation results showed that the proposed deployment strategy could deploy regional shore-based collaborative units. The deployment costs of shore-based collaborative units were reduced when the communication needs were satisfied.

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