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Coastal Shuttle Tanker Scheduling Model Considering Inventory Cost and System Reliability

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ABSTRACT The near-sea off-shore oil extraction and transportation system use heterogeneous fleets to transfer crude oil from the floating production storage and offloading to the land-based oil storage port. Based on the characteristics of this system, the short sea inventory routing problem is investigated considering the shuttle tanker fleet and inventory management. In order to minimize the total operation cost and maximize the system reliability, a semi-continuous model for the shuttle tanker scheduling problem is established. The model optimizes the tanker scheduling plan and the design of the tanker fleet. To solve the complex model, this article proposes an improved non-dominated sorting genetic algorithm with differential evolution operator to solve the optimization of the multi-objective model. This research also uses public vessel operation data to test the modeling and optimizing efficiency. The Pareto Fronts associated with the total operation cost and the system reliability from the optimization outcome is analyzed to provide scheduling priority advice. The results indicate that proposed optimization algorithms are effective, and the operation could be optimized with the proposed model and algorithm.

INDEX TERMS Maritime inventory routing problem, non-dominated sorting genetic algorithm (NSGA-II), off-shore oil transportation, semi-continuous model, shuttle tanker, system reliability.

I. INTRODUCTION

With the increasing demand for energy, the off-shore fossil energy transportation system plays an increasingly important role in ensuring energy production and supply. The structure of the traditional off-shore fossil energy transportation network is relatively simple and the production and operation mode [1]. Therefore, related enterprises have relatively low requirements for water transportation services. In practice, the business decision-making departments of various enterprises (referred to as decision-makers) often rely on work experience and simple economic evaluation methods to set up water transportation systems and manage the configuration and scheduling of tanker fleet [2]. The design of the water transportation system often only emphasizes meeting the transportation needs on time, and have less consideration of the cost control and coordination between production and transportation systems [3]. However, with the continuous upgrading of off-shore fossil energy transportation system, the transportation organization of related energy products has shown a trend of becoming more complex [4]. This trend leads to that the previous simple approach has become insufficient to cope with the complex needs of transportation services for modern fossil energy production and marketing systems. Therefore, it is necessary to make targeted optimization research for such systems.

The off-shore oil extraction and transportation system is currently undergoing a revolution in storage and transportation. The traditional production model with the drilling platform as the core has been rapidly transformed. The new production model gradually adopts the floating production storage and offloading (FPSO)-based system [5], which integrating off-shore crude oil extraction, storage, and initial processing of crude oil [6]. The off-shore oil collection and transportation system include drilling platform, FPSO, unloading port, and special oil tankers (referred to as shuttle tankers). The details are shown in Fig. 1. Crude oil is first extracted from the drilling platform and then transported

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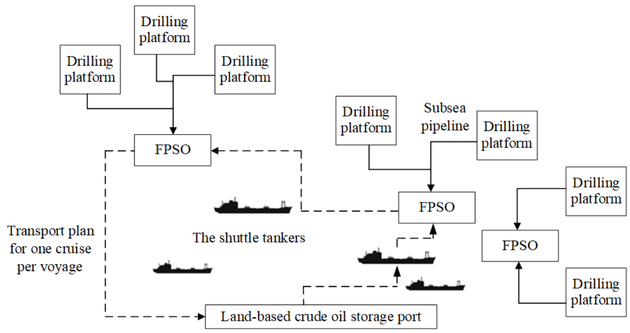

FIGURE 1. A diagram of the off-shore crude oil collection and transportation system.

to the FPSO through pipelines. The so-called FPSO is a comprehensive off-shore floating oil and gas treatment facility that can process and store crude oil simultaneously and integrate personnel residence, production, processing, and command [7]. The off-shore FPSO is generally connected to several drilling platforms. The shuttle tankers frequently transfer the extracted crude oil between sea and land before the oil inventories of the FPSO reach their limits. Under normal circumstances, the storage capacity of FPSO cargo tanks can reach 50,000 to 300,000 tons, which can fully realize the short-term and temporary storage of large amounts of crude oil at sea.

The introduction of FPSO has significantly improved the crude oil storage capacity of off-shore oil extraction and transportation system. On the one hand, it provides the necessary buffering for the crude oil storage; on the other hand, it is possible to use large ships to transport crude oil, which provides the economic benefits of large-scale tanker applications. Therefore, the oil companies (referred to as decision-makers) can consider the changes of FPSO's inventory for controlling and optimizing the off-shore crude oil production system through dispatching and adjusting shuttle tankers in a timely manner.

At the same time, the characteristics of FPSO also bring new challenges for decision-makers to optimize the off-shore oil extraction and transportation system. Due to the different storage capacity, crude oil extraction rates of various FPSOs [8], it is necessary to comprehensively consider the factors such as the type, number, storage capacity of the tanker for the rational design and dispatch of the fleet [9]. These characteristics of the system make the design of the shuttle tanker fleet more complicated. The crude oil produced in Chinese off-shore are waxy and have the physical property of high pour point and high viscosity, which require heating to prevent the crude oil from forming the gel [10]. Therefore, energy consumption is a significant factor in the operation cost for crude oil transfer and processing. Since the FPSOs are collecting crude oil from the oil platform, the oil stock quantity is continually changing, affecting the storage cost of crude oil [11]. The tanker for FPSO operates within a short distance and with high frequency making the transportation system vulnerable for the uncertainty of maritime transportation, such as weather conditions and port occupancy [12]. As a result, the strictly designed plan could not be carried with high accuracy, which leads to potential delay or deviation of the scheduling plan [13]. Since the halt of the oil production platform is not acceptable, the process is sensitive to the uncertainty from the transportation system [4]. The reliability related to the inventory control for the supply chain is essential for the successful function of the system [14]. Therefore the off-shore oil transportation should consider taking the remaining oil storage capacity as the indicator of the system reliability.

Based on the above background, this article will take the Chinese off-shore fossil energy transportation system as the research object. This study considers two significant factors for the optimization purpose. The first one is the operation cost, which consists of the transportation cost and oil storage cost. Usually, the storage costs are directly proportional to the quantity of related crude oil in stock [9]. The second factor is the reliability associated with the effect of transportation uncertainty on the oil storage capability level. This is because during the transportation of fossil energy, the transportation system often encounters some unexpected situations, which delay the system operation and affects the reliability of the transportation system [15]. In practice, Industries had to balance multiple conflicting performance criteria to determine optimal scheduling [16]. The economical operation cost and inventory management are the common optimizing objective for the operation system [17]. Thus, this study proposes the multi-objective optimization problem for the maritime inventory routing problem (MIRP).

The contributions of this research include the following: firstly, this study enriching the research of MIRP, since many assumptions for MIRP do not apply to the short-distance off-shore transportation system involved in this article. Secondly, the spillover effects of inventory management are taken into consideration. Specifically, this article will consider two simulation objectives in tanker scheduling modeling. The first one is the inventory cost of related products, which is the cost paid to maintain the stability of the chemical and physical properties of the crude oil; the second one is the impact of inventory changes on system reliability. Lastly, this article proposes the short sea inventory routing problem(SSIRP) model considering the dual objective of the transportation system, and an improved evolution algorithm based on the differential evolution idea. By comparing with the traditional non-dominated sorting genetic algorithm (NSGA-II), the effectiveness of the model and algorithm is evaluated. The optimization outcome is analyzed with the Pareto fronts to demonstrate the scheduling characteristics under different system reliability preferences.

The paper is organized as follows: Section 2 reviews the related literature. Section 3 describes the significant issues related to the MIRP problem. In section 4, the semi-continuous model of MIRP is designed, and the mathematical model is established. The algorithm to solve the MIRP model is designed in section 5. In section 6, several case studies are conducted to analyze the computational efficiency and the practical applicability of the model and the algorithm. Finally, Section 7 concludes the paper.

II. LITERATURE REVIEW

The inventory routing problem (IRP) aims to improve supply chain efficiency. The proposal of IRP can be traced back to the 1980s by Bell *et al.* [18]. It is described as a combination of vehicle routing issues and inventory management issues in the distribution network between the upstream and downstream nodes of the supply chain. In IRP, suppliers must deliver products to many dispersed customers in the region, while ensuring service quality. IRP provides a comprehensive logistics solution through the collaborative optimization of inventory management, vehicle routing, and delivery planning at the same time [19]. Through IRP, suppliers can save on distribution and production costs because they can coordinate shipments to different customers; customers can also reduce the difficulty of inventory management [19]. Dror and Levyd [20] believed that IRP involves a group of customers, each with different product requirements. The goal of IRP is to minimize distribution costs while ensuring that customers are not out of stock at all times. Campbell and Savelsbergh [21] believe that inventory control and vehicle routing are traditionally handled separately, and their integration will have a huge impact on the overall system performance. Dror and Ball [22] believe that IRP is an allocation problem, given the conditions of the central supplier, optimizing its annual delivery costs while ensuring that there is no shortage of customer goods at any time. Cepeda *et al.* [23] pointed out that IRP is a modification of the vehicle routing problem (VRP), integrating two components of supply chain management, namely customer inventory control and vehicle routing. Custódio and Oliveira [24] believe that the IRP is different from the traditional routing problem because it uses the concept of the demand rate of items, formulates a comprehensive strategy for inventory replenishment, and optimizes the replenishment cycle and the route used in the delivery process.

At the same time, with the economic development, IRP gradually began to be proposed in various fields, such as in the area of vehicle routing problem with satellite facilities [25], onshore crude oil truck transportation [26], periodic pick-up of automotive raw materials [27], optimal shipping routes and shipment sizes on freight networks by trading off transportation, inventory, and production set-up costs [28], inbound inventory routing problem with storage constrains [29], the field of fresh food transportation [30], the periodic inventory routing problem at a supermarket chain [31], the alternative distribution strategies for delivering to a retailer's regional depots from a food manufacturer [32],cement transportation [33], and livestock transportation [34].

In response to the peculiar phenomena in the maritime transportation system, scholars continue to develop new IRP theories and propose a special type of problem, called the Maritime inventory routing problem (MIRP). IRP assumes that in each planning cycle, the inventory of each transportation node is only related to the amount of operation and is not related to the time factor in transportation. This assumption is feasible for transportation systems with relatively short planning periods (e.g., urban logistics systems use 8-hour planning periods and aviation logistics systems use 24-hour planning periods). However, it is not feasible for the maritime transportation system, which has a relatively long transportation distance, which takes a lot of time. Therefore, in MIRP, the inventory level of each node is related to time in addition to the amount of operation. For example, in the off-shore oil extraction and transportation system, the setting of the fleet transportation plan must take full account of the changes in crude oil inventories at relevant transportation nodes. In the past 20 years, MIRP has gradually become a hot spot in maritime research, and scholars have gradually reached consensus on the definition and modeling methods of MIRP. According to Christiansen [35], MIRP is defined as a compound planning problem, where the decision-maker not only needs to consider ship scheduling and route optimization simultaneously but also must consider the inventory control of the transportation node. Christiansen [35] further pointed out that the basic MIRP mainly solves the problem of long-distance water transportation of single category products.

For general MIRP, the inventory storage cost is usually not considered [36]. Zhang *et al.* [37] assume that in the MIRP of a single product, the objective function does not include inventory costs. Diz *et al.* [38] set the production/consumption rate and other parameters to change with time in the MIRP for crude oil transportation but does not consider the changes in inventory costs caused by those parameters. Feng and Chang [39], Cheung and Chen [40], and Li *et al.* [41] set the inventory cost to be constant or not considered. Uchida *et al.* [42] and Papageorgiou *et al.* [43] assume that companies have production and consumption locations at the beginning and end of the route to control inventory, so the effect of changing inventory cost is not considered in the objective function. However, for the short sea inventory routing problem (SSIRP), the waxy crude oil, which is the primary oil type, require constant heating up to 80-90° for the transportation and processing [44]. Since the system operation has high frequency, energy consumption becomes significant. Several studies have discussed adopting the energy recycle technology for improving energy efficiency [45]. Since the storage cost is a significant part of the operation cost, it is necessary to include the storage cost into the optimization.

Oil inventory affects not only the operating cost of the system but also the reliability of the system. The maritime operation is heavily influenced by the uncertainty factors, such as poor weather, the breakdown of shuttle tankers, and the port congestion issue [46]. The uncertainty factor could delay the operation and cause the deviation of the pre-determined plan. Therefore, the decision-maker often adjust the operation plan according to the uncertainty factors [47]. For floating production storage and offloading (FPSO), the unpredictable weather condition and vessel availability are the main reason for operation delay, and the decision-maker often leave some storage capability as the buffer for the unexpected delay [48]. However, in practice, if the system encounters the sever operation delay, the storage capacity could be full, and crude oil production needs to be halted [49]. This kind of the halted is not acceptable because the opportunity cost is extremely high for crude oil production of the multiple oil platforms in the network, and the possible equipment damage could decrease the platform performance [49]. Thus, the FPSO systems have relatively strict requirements of the storage capability level control to handle the uncertainty factors of the operation.

For the solution of the multi-objective model, evolutionary algorithm is an effective and popular algorithm. Evolutionary algorithms are stochastic search methods that mimic the natural biological evolution [50], which is a global optimization method with wide applicability to large-scale problems. So far, there have been many kinds of evolutionary algorithms, such as genetic algorithms, memetic algorithms, particle swarm, ant-colony systems, and shuffled frog leaping [50]. Li and Li [51] used a genetic algorithm for an on-line optimization of the PID parameters. To improve the efficiency of the evolutionary algorithm, the evolution operator could be modified with ideas such as differential evolution. Differential evolution originally was proposed for continuous optimization [52]. Mingyong and Erbao [52] firstly used the differential evolution algorithm in the vehicle routing problem with simultaneous pickups and deliveries and time windows. Tsai *et al*. [53] optimized task scheduling and resource allocation with an improved differential evolution algorithm. Those multi-objective models and algorithms have a wide application in many domains. A he multi-objective evolutionary algorithm based on decomposition (MOEA/D) was proposed to solve the hybrid flowshop lot-streaming scheduling problem [54]. Bekele and Nicklow [55] developed an automatic calibration routine using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which is an effective and efficient multi-objective search technique for the Soil and Water Assessment Tool. Besides that, decomposition based multi-objective evolutionary algorithms proved to be promising in dealing with complicated Pareto set shapes [56]. Deb and Karthik developed a modified NSGA-II for the dynamic multi-objective optimization and decision-making in hydro-thermal power scheduling [57].

Through the literature analysis, it can be concluded that current studies of MIRP focus on the long-distance maritime transportation, and the study of MIRP related to research related to near-sea oil transportation system are quite limited. Also, the characteristics of the FPSO indicates that the storage cost of heating crude oil and the control of oil storage capability for system reliability are important for the optimization of the transportation system. Therefore, this article proposes a special type of MIRP, in which the spillover effects of inventory management are considered.

III. PROBLEM DESCRIPTION

For the new generation crude oil production system based on floating production storage and offloading (FPSO), there are the four issues need to be taken into consideration for short sea inventory routing problem(SSIRP):

(1) Heterogeneous tanker fleet. On the one hand, due to the differences and complexity in the production and storage capacity of each FPSO, using the same type of oil tanker to form a fleet could be a problem for the system efficiency. The reasonable approach should be to determine the composition of the fleet according to the transportation needs of the FPSO system. On the other hand, in practice, the tankers of the shuttle fleet come from a wide range of sources, and a unified setting for the fleet is not realistic. The model setting of heterogeneous fleets is used by other studies to extend the original VRP to meeting the logistical applications of tanker fleet with an unequal capacity [58]. Therefore, in this article, it is assumed that the decision-maker can select a suitable type and number of tankers to perform multi-voyage transportation tasks.

$$\text{Reliability} = \max_{i \in I^-} \left\{ \frac{\text{Oil Storge quantity of FPSO } i \text{ at each operation period}}{\text{Storge capacity of FPSO } i} \right\}$$

(2) Continuous growth of oil inventory. It can be seen from the literature review that stopping the oil production of offshore platforms is not acceptable. Thus, the oil inventory of each FPSO increases continuously. Due to the limited capacity of the FPSO cargo tank, once fully loaded, all the mining platforms connected to it will be shut down, which will cause huge and unnecessary economic losses. Therefore, this article requires that each shuttle tanker dock and operate before the FPSO is fully loaded. In this way, for each FPSO, there is a corresponding transport hard time window.

(3) Introduce inventory maintenance costs. Unlike ordinary commodities, storage of oil products usually requires higher storage costs. After crude oil is extracted from the off-shore drilling platform, it is sent to the FPSO through pipelines for initial processing, and then stored in the FPSO cargo tank for temporary storage. To prevent the solidification of crude oil, FPSO needs to continuously heat the cargo tanks, resulting in higher costs associated with crude oil inventory level, which is called inventory maintenance costs in this article. Generally speaking, such costs are not included in the total operating cost of the transportation system. However, in the FPSO transportation system, since the manager of the fleet itself is the decision-maker of the production system, the inventory maintenance cost of the FPSO becomes a sensitive and influential factor that cannot be ignored. Therefore, for SSIRP, the decision-maker not only need to consider the design and scheduling of the fleet but also need to control both the inventory cost and transportation system operation cost.

(4) Introduce system reliability goals. In reality, offshore oil collection and transportation are often affected by

uncertain factors such as weather, sudden failure of port facilities, and human negligence.

Such uncertain factors often lead to the pre-established tanker scheduling scheme not being accurately carried out. In order to cope with this situation, when setting up a fleet scheduling plan, decision makers need to carefully set and maintain the FPSO cargo tank inventory at an appropriate level, without emphasizing the full use of inventory capacity. To reserve enough buffer for the storage capacity to deal with the unplanned shutdown caused by uncertain factors, and improve the system's ability to resist risks. Therefore, the system control of the inventory capacity level is included in the optimization model framework, and the following index ratios are used to evaluate the reliability of the off-shore crude oil collection and transportation system:

Among them, I^- represents the set consisting of all FPSOs. If Reliability is close to 1, it indicates that the crude oil inventory level of each FPSO is relatively high during the planning period. Thus, the system's ability to respond to unexpected situations is relatively limited, and the probability of an unplanned production shutdown is greater. However, at this time, the storage capacity utilization rate in the system is high, and the system operating cost is low. On the contrary, if reliability is close to 0, it indicates that the system has sufficient inventory buffer to deal with various risks, but at this time, the inventory utilization rate is low, which may lead to an increase in operating costs. Therefore, how to balance the relationship between system operation cost and optimization of reliability becomes a significant problem to be solved in this research.

IV. MODEL CONSTRUCTION

Based on the problem description, the SSIRP discussed in this research can be described as follows.

Given: the length of the known plan period; the crude oil growth rate and storage capacity of each FPSO; the crude oil reserves at the beginning of each FPSO plan; the available fleet; and the data of each ship (alternative speed, tank Capacity, rent, etc.).

Assumptions: 1) During the planning period, the basic unit of the transportation task for the shuttle tanker is the voyage. The so-called voyage refers to the process of an oil tanker leaving the port, docking several FPSOs to extract crude oil, and finally returning to the port to unload the oil. 2) Each FPSO can only be docked once by a shuttle tanker during each sub-plan period. 3) The shuttle tanker extracts all oil storage of a certain FPSO when docking it. 4) The berthing time is included in the sailing time. 5) Since ship leasing can be carried out in the transportation market, there are a sufficient number of various types of tankers for decision-makers to form a fleet. 6) The operating efficiency of each shuttle tanker is the same.

Decision making: With the dual objectives of minimum z_2 and minimum operating costs, the decision-maker needs to optimize the design of the shuttle tanker fleet and the scheduling plan of each tanker within the planning period.

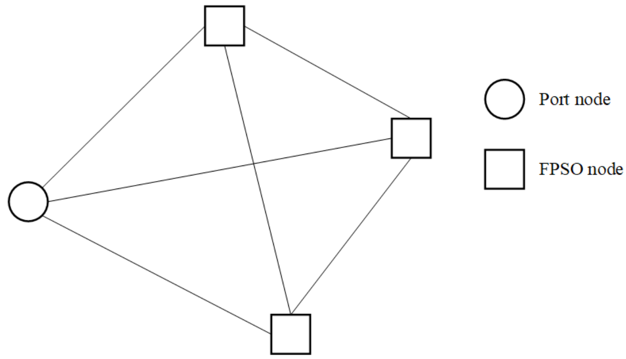

FIGURE 2. A network frame of near sea oil transportation system.

The main challenges for solving short sea inventory routing problem(SSIRP) are: how to describe reliability scientifically and reasonably on the premise of considering the efficiency of the model solution. The key to defining this parameter lies in describing the influence of time factors on relevant decision variables.

If discrete-time modeling ideas are used, MIRP can be defined as an integer programming that can be solved by the modern algorithm of integer programming. But the disadvantages are that this framework cannot accurately describe the relationship between variables and time, and the model structure based on this framework is complicated. If the discrete-time unit is improperly designed, it is easy to encounter the "combination explosion" problem, making solving the model difficult. If the continuous modeling approach is adopted, MIRP can be defined as the mixed-integer programming. This approach can reduce the complexity of the model and provide suitable descriptions of the change of decision variables associated with the time dimension. But the disadvantages are that complex nonlinear relationships are required for the model, and it is necessary to apply complex linearization techniques for effective solutions. Therefore, it is not suitable for modeling multi-objective planning problems.

In view of this, this chapter will use a semi-continuous model structure to construct a mathematical model for solving SSIRP and facilitate the subsequent algorithm design. In the following section, this article will first introduce the basic design ideas of the semi-continuous model and present the definition of related transportation networks and variables, and then give the expression of the model.

A. SEMI-CONTINUOUS MODEL DESIGN

The basic design ideas of the semi-continuous model are as follows: First, split the planning period into several equal-sized interval periods, called the "sub-planning period." Secondly, in each sub-planning period, use continuous modeling ideas to describe the relationship between decision variables; between sub-planning periods, discrete modeling ideas are used to characterize the relationship between variables.

To conveniently describe the semi-continuous concept in the model, this study will adopt special settings for the

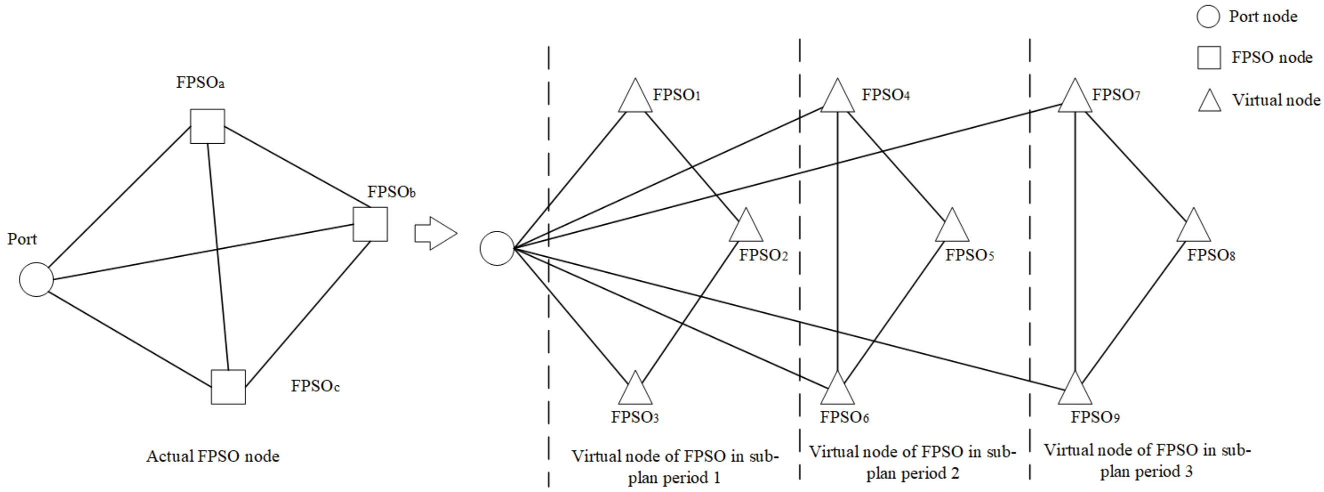

FIGURE 3. The network of FPSO transportation path.

transportation network. Fig. 2 shows a schematic diagram of an off-shore oil collection and transportation system network. Let the $G^{in} = \{I, E\}$ means the transportation network involved in the off-shore oil collection and transportation system. Let $I = \{p\} \cup I^{-}$ denote a collection of transportation nodes, the elements of which are denoted as i or j. Among them, {p} indicates a set composed of port nodes; I^{-} indicates a set composed of floating production storage and offloading (FPSO) nodes; E represents a collection of waterway sections for tankers.

To construct the semi-continuous model, this study makes the following adjustments to the network:

Step 1: Setting virtual nodes for each FPSO with an equal number based on the number of sub-planning periods. For example, if the number of sub-planning periods is n, then set n virtual nodes for each FPSO, delete the original FPSO nodes, and only keep the virtual nodes.

Step 2: Setting the docking time windows for each virtual node of each FPSO according to the start and end times of n sub-planning periods. For example, if the length of the planning period is four weeks, two sub-planning periods of 2 weeks (respectively from 0 to14 days, from 15 to 28 days) are set. Then two virtual nodes i_1 and i_2 should be set for each FPSO node i, and their docking time windows are set to from 0 to14 days and 15 to 28 days respectively. It can be seen from this that the purpose of introducing virtual FPSO nodes in this chapter is to describe FPSO nodes in different sub-plan periods.

Step 3: Adding virtual waterways to connect all virtual nodes and ports. Set the sailing time for the virtual waterway section (as shown in Fig. 3). With the different types of nodes at the ends of the waterway section, the rules for setting the sailing distance are also different. In Fig 3, virtual nodes of each FPSO are added for each sub-plan period. For example, for the sub-plan period 1, virtual FPSO nodes (FPSO1, FPSO2, and FPSO3) are created for the actual FPSO nodes (FPSOa, FPSOb, and FPSOc, respectively. The virtual nodes for other sub-plan periods are created with a similar method. FPSO1, FPSO4, FPSO7 are the virtual nodes of FPSOa in the sub-plan period 1, 2, and 3. Therefore, assuming only one waterway movement occurred in one sub-plan period, the actual transportation path of Port- FPSOa - FPSOc - FPSOb is transformed into a virtual path of Port - FPSO1 - FPSO6 - FPSO8 across three sub-plan periods as shown in Fig 4.

Specifically: 1) For the waterway section between the port node and the virtual node, the navigation distance is set as the navigation distance between the port node and the corresponding FPSO node. For example, in the above example, the navigation distance between port node 0 and the path between i_1 is set to the navigation distance between 0 and the FPSO node i. 2) For the virtual nodes set for the same FPSO node, the passage distance between them is set to 0. For example, in the above example, both the virtual node i_1 and i_2 are obtained from the FPSO node i, so for the waterway section between i_1 and i_2, the sailing distance will be set to 0. 3) Between the virtual nodes set for different FPSO nodes, the distance between the waterway sections is set to the distance between the corresponding FPSO nodes. For example, for the virtual node i_1 set for the FPSO node i and the virtual node m_1 set for the FPSO node m, the sailing distance of the waterway section between them is set as the distance between the FPSO node i and the node m.

Thus, this study has obtained a transportation network consisting of virtual nodes, port nodes, and several virtual waterway sections. In this transportation network, the virtual waterway sections all have corresponding lengths, and each virtual node also has a corresponding access time window. Let $G^{exp} := (I, E)$ indicates the expanded transportation network, where I represent the set of nodes and E represents the waterway section set.

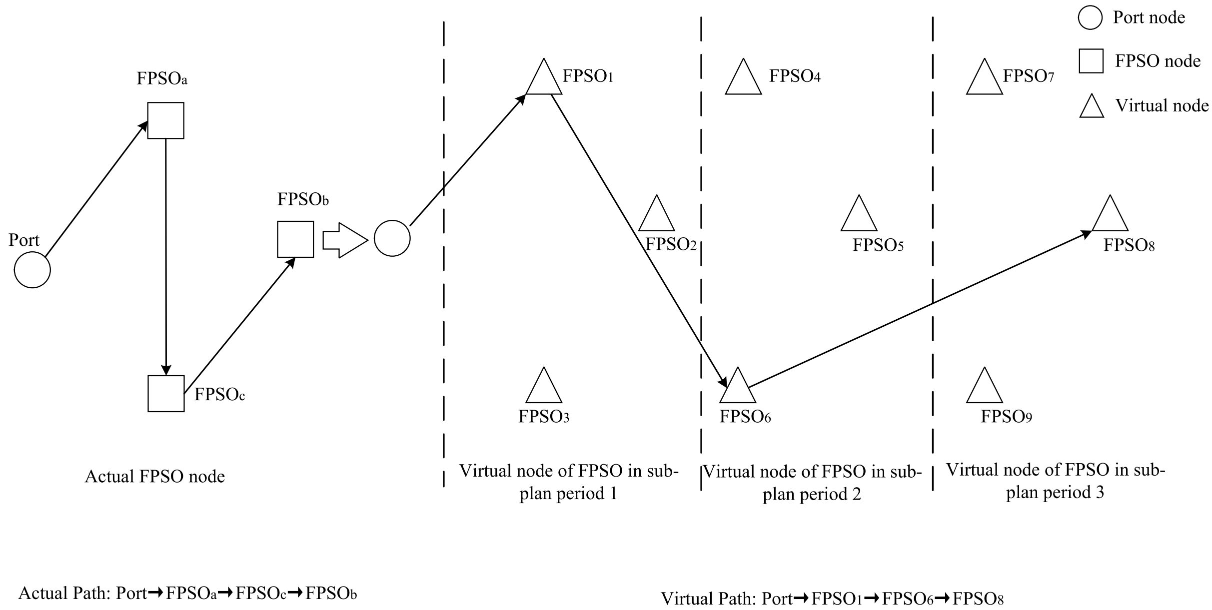

FIGURE 4. The tramp ship operating path.

However, the semi-continuous model is designed based on the assumption of the sub-plan period. The sub-plan period means that the whole scheduling could be divided into smaller scheduling periods and the voyage tasks of the tramp ship are scheduled and organized for these relatively short periods. Although it is the common practice of the scheduling of FPSO tramp ship, this assumption of the sub-plan period reduces the universal adaptivity of the model and causes the model to be not suitable for other types of scheduling. What's more, some parameters of the scheduling are simplified and set as constants, such as the tramp ship speeds, the oil production rate of each FPSO platform, and the cost of the vessel renting. In practice, those parameters could be adjusted under certain situations. For example, the oil production rate of the oil platform could be decreased to prevent the oil inventory from exceeding the FPSO storage capacity.

B. MODEL FORMULATION

For the convenience of readers, the symbols such as sets, parameters, and variables commonly used in this section are described as follows(see Table 1).

1) CONSTRAINT GROUP 1: RESTRICTIONS ON FPSO TRANSPORTATION TIME WINDOW

During the fixed operating period (referred to as the "planning period"), the inventory control in the FPSO i can be constrained by introducing a hard time window. In other words, when the shuttle tanker is docked at each FPSO, it is necessary to satisfy the constraints in constraint group 1. The (1) and (2) indicate that the docking FPSO should meet its time window. Equation (3) and (4) suggest that the time when the virtual node of the FPSO i is docked during the sub-plan period l, should be located in the time window of the sub-plan period l. t_i^{up} and t_i^{lo} represent the upper and lower bounds of the docking time window of FPSO i during the plan period. t_l^{st} indicates the start time of the sub-plan period l and t_l^{ed} indicates the end time of the n-th sub-plan period.

$$\min_{l\in L} t_{i,l} \geq t_i^{lo} \quad \forall i \in I^- \tag{1}$$

$$\min_{l\in L} t_{i,l} \leq t_i^{up} \quad \forall i \in I^- \tag{2}$$

$$t_{i,l} \geq t_l^{st} \quad \forall i \in I^-,\ l \in SP \tag{3}$$

$$t_{i,l} \leq t_l^{ed} \quad \forall i \in I^-,\ l \in SP \tag{4}$$

2) CONSTRAINT GROUP 2: CONSTRAINTS FOR ENSURING THE FEASIBILITY OF EACH VOYAGE

Constraint group 2 provides the constraints that all feasible voyages k should meet. Equation (5) and (6) indicate that the mathematical description of the voyage needs to meet the definition in this article. Equation (7) indicates the continuity of the waterway sections during the voyage. Equation (8) is used to ensure that each FPSO is docked only once during the sub-plan. This article assumes that the FPSO's oil storage capability during the planned period is much smaller than the tanker's capacity. Equation (9) requires that the FPSO in the set I^- must be docked once during the planning period to ensure the continuous production of the drilling platform. Equation (10) is the constraint on decision variables x_{iljmk}.

This article introduces the concept of "voyage" based on G^{exp}. The so-called "voyage" refers to the navigation plan of a tanker on multiple waterway sections according to the existing speed setting plan, and the starting point and endpoint of each voyage are the ports. During the planning period, the set of all voyages performed by the shuttle tanker q is called the single-ship scheduling plan of the shuttle tanker q

TABLE 1. **The symbols such as sets, parameters and variables.**

Set	
I	The set of FPSO virtual nodes and port nodes, whose elements are marked as i or j
I^-	The set of FPSO virtual nodes, whose elements are marked as i or j
K	The set of shuttle tanker voyages whose elements are denoted as k
Q	A collection of selectable shuttle tankers, the elements of which are denoted by q
SP	The set of sub-planned periods, whose elements are denoted as l or m
Parameters and variables	
x_{iljmk}	Variable of $(0-1)$, if the voyage k contains the virtual node of the FPSO i (generated for the sub-plan period l) to the virtual node of the FPSO number j (generated for the sub-plan period m), the variable is set to 1, otherwise 0.
y_{kq}	Variable of $(0-1)$, if voyage k is executed by shuttle tanker v, the variable is set to 1, otherwise set to 0.
$t_{i,l}$	The moment when the virtual node of FPSO i (generated for sub-plan period l) is berthed during the planning period.
t_l^{st}	The start time of plan period l
t_l^{ed}	The end time of plan period l
t^{ed}	The end time of last plan period
t_{ilk}^{in}	The initial moment when the virtual node of FPSO i (generated for sub-plan period l) is berthed at the voyage k during the planning period.
$t_i^{*,op}$	The operation time required to berth the virtual node of the FPSO i. Asterisk '*' represents the time duration.
t_{ij}^*	Time required for tanker from transportation node i to j
c_q^{fix}	The fixed cost of using the tanker q
FD_i	The production rate of FPSO i
$CF_{i,l}^{in}$	The storage capacity of the FPSO i (generated for sub-plan period l) at the beginning of the sub-plan period l.
CT_q	Capacity of tanker q

and is recorded as K_q. Obviously, there is $K_q \subseteq K$. Similarly, the set of single-ship scheduling plans of all tankers in the fleet during the planning period is called the fleet scheduling plan and is denoted as K_q^F, with $K_q \subseteq K_q^F \subseteq K$. For any element k in K, the constraints in constraint group 2 must be satisfied.

$$\sum_{j\in I^-}\sum_{l,m\in SP} x_{iljmk} = 1 \quad i = p, l = o, \ \forall k \in K \tag{5}$$

$$\sum_{i\in I^-}\sum_{l\in SP} x_{iljmk} = 1 \quad j = p, m = o, \ \forall k \in K \tag{6}$$

$$\sum_{i\in I^-}\sum_{l\in SP} x_{iljmk} = \sum_{i'\in I^-}\sum_{l'\in SP} x_{i'l'j'm'k'} \quad \forall j = i' \in I^-, \ k \in K, \ m = l' \in SP \tag{7}$$

$$\sum_{j\in I^-}\sum_{k\in K}\sum_{l,m\in SP} x_{iljmk} + \sum_{l'\in SP}\sum_{k\in K} x_{i'l'j'm'k'} \le 1 \quad j' = p, m' = o, \forall i \in I^- \tag{8}$$

$$\sum_{j\in I}\sum_{k\in K}\sum_{l,m\in SP} x_{iljmk} \ge 1 \quad \forall i \in I^- \tag{9}$$

$$x_{iljmk} \in \{0, 1\} \quad \forall i, j \in I, \ k \in K, l, \ m \in SP \tag{10}$$

3) CONSTRAINT GROUP 3: CONSTRAINTS FOR VOYAGE AND SHUTTLE TANKER MATCHING

This article uses constraint group 3 to match the voyage in K with the shuttle tanker. Equation (11) requires that each voyage can only be performed by one shuttle tanker. Equation (12) is the constraint on decision variables y_{kq}.

$$\sum_{q\in Q} y_{kq} \le 1 \quad \forall k \in K \tag{11}$$

$$y_{kq} \in \{0, 1\} \quad \forall k \in K, \ q \in Q \tag{12}$$

4) CONSTRAINT GROUP 4: CONSTRAINTS ON TANKER DOCKING TIME

To ensure that a tanker can execute every voyage scheduled for it (i.e., no time conflict occurs between the voyages within the single-ship operation plan), several critical time nodes in each voyage must satisfy the constraint group 4. Equation (13) ensures the continuity of the docking time at different transport nodes during the voyage. Equation (14) is used to ensure no time conflict when the same tanker performs different voyages during the planning period. Equation (15) is used to calculate the unloading time at the port when the tanker performs voyage k. Equation (16) requires that the end time of each voyage should not exceed the planned period. Equation (17) is used to ensure that the crude oil loaded by the shuttle tanker in each voyage cannot exceed its capacity. Equation (18) and (19) are used to calculate the $CF_{i,l}^{in}$ in different sub-plan periods. Through the above two formulas, for virtual nodes of different sub-plan periods generated by the same FPSO, inventory can be linked to each other.

In practice, the unloading speed of the shuttle tanker berthing FPSO can reach thousands of tons per hour, or even more than 10,000 tons/hour; therefore the unloading time is very short. To simplify the problem, this article does not consider the situation of tankers waiting in line at FPSO for unloading.

Let M denote a very large positive number. $t^{*,u}$ represents the time required to unload a unit of crude oil at a port. This article assumes that the unloading time at the port is linearly related to the amount of unloaded oil. $t_{p,k}^{*,op}$ represents the unloading time at the port when the shuttle tanker performs voyage k, which is function of vessel oil storage capacity. PD_i represents the oil production of FPSO i during unit time. CF_i^{in} represents the oil storage capacity of FPSO i at the beginning of the plan period. t_0, represents the beginning time of the whole plan period.

$$t_{ilk}^{in} + t_i^{*,op} + t_{ij} \le t_{jmk}^{in} + M\left(1 - x_{iljmk}\right) \quad \forall i \in I, j \in I^-, k \in K, l, m \in SP \tag{13}$$

$$t_{ilk}^{in} + t_i^{*,op} + t_{i0} + t_{p,k}^{*,op} \le t_{(i,l)k'}^{in} + M\left(3 - x_{iljmk} - y_{kq} - y_{k'q}\right) \quad j = p, m = o, \ \forall i \in I^-, \ k < k' \in K, \ q \in Q, \ l \in SP \tag{14}$$

$$t_{p,k}^{*,op} = \sum_{i\in I^-}\sum_{j\in I^-}\sum_{l,m\in SP}\left[\left(t_{ilk}^{in} - t_{ed}\right)PD_i + x_{iljmk}CF_{i,l}^{in}\right]/t^u \quad \forall k \in K \tag{15}$$

$$t_{ilk}^{in} + t_i^{*,op} + t_{i0} \le t_l^{ed} + M\left(1 - x_{iljmk}\right) \quad j=p,\quad m=o,\ \forall i \in I^-,\ k\in K,\ l \in SP \tag{16}$$

$$\sum_{i\in I^-}\sum_{j\in I^-}\sum_{l,m\in SP}\left[\left(t_{ilk}^{in} - t^{ed}\right)PD_i + x_{iljmk}CF_{i,l}^{in}\right] \le \sum_{q\in Q} CT_q y_{kq} \quad \forall k \in K \tag{17}$$

$$FC_{i,l}^{in} = \left(t_l^{ed} - t_{l-1}^{ed}\right)PD_i + CF_{i,l-1}^{in} - \max\left\{\sum_{k\in K}\left(t_{ilk}^{in} - t_{l-1}^{ed}\right)PD_i, p\right\} - CF_{i,l-1}^{in}\sum_{j\in I}\sum_{k\in K}\sum_{m\in SP} x_{iljmk} \quad \forall i \in I^-, l \in SP\backslash\{1\} \tag{18}$$

$$FC_{i,1}^{in} = t_1^{ed}PD_i + CF_{i,l}^{in} - \max\left\{\sum_{k\in K} t_{ilk}^{in}PD_i, p\right\} - CF_{i,l}^{in}\sum_{j\in I}\sum_{k\in K}\sum_{m\in SP} x_{iljmk} \quad \forall i \in I^-, l \in \{1\} \tag{19}$$

5) CONSTRAINT GROUP 5: CONSTRAINTS ON RELATIONSHIPS BETWEEN t_{ilk}^{in} AND $t_{i,l}$

During the planning period, when a certain FPSO has never been berthed, or when a certain FPSO has not been berthed in voyage k, the values of t_{ilk}^{in} and $t_{i,l}$ will be meaningless. Therefore, this article uses constraint group 5 to control their values. Equation (20) and (21) together constitute the constraint on the t_{ilk}^{in}. When voyage k does not berth the FPSO i, let $t_{ilk}^{in} = 0$. Equation (22) to (25) are used to describe the relationship between t_{ilk}^{in} and $t_{i,l}$. When the voyage k is FPSO i, (22) and (23) could let $t_{i,l} = t_{ilk}^{in}$; otherwise, (24) and (25) could let $t_{i,l} = 0$.

$$t_{ilk}^{in} \le M\sum_{j\in I}\sum_{m\in SP} x_{iljmk} \quad \forall i \in I^-,\ k \in K,\ l \in SP \tag{20}$$

$$t_{ilk}^{in} \ge 0 \quad \forall i \in I^-,\ k \in K,\ l \in SP \tag{21}$$

$$t_{i,l} \le t_{ilk}^{in} \quad \forall i \in I^-,\ k \in K,\ l \in SP \tag{22}$$

$$t_{i,l} \ge t_{ilk}^{in} - M\left(1 - \sum_{j\in I}\sum_{m\in SP} x_{iljmk}\right) \quad \forall i \in I^-,\ k \in K,\ l \in SP \tag{23}$$

$$t_{i,l} \ge 0 \quad \forall i \in I^-,\ l \in SP \tag{24}$$

$$t_{i,l} \le M\sum_{j\in I}\sum_{m\in SP} x_{iljmk} \quad \forall i \in I^-,\ k \in K,\ l \in SP \tag{25}$$

The short sea inventory routing problem optimization model (SSIRPM) of SSIRP is expressed as follows:

Based on the above constraints and definitions, this article gives a mathematical description of SSIRP: Under the premise that the Q, I, T and other information are known, and the system is required not to stop production within the planned period, the collaborative model optimization K_q^F and z_2. In other words, the goal of SSIRP is to minimize the system's operating costs and maximize its operational reliability during the planning period, and determine the fleet's scheduling plan based on each FPSO's transportation time window information.

$$\min : z_1 = \sum_{i\in I, j\in I, k\in K, l,m\in SP, s\in S, q\in Q} c_v t_{ijs} x_{iljmk} y_{kq} + \sum_{q\in Q}\left(\min\left\{\sum_{k\in K} y_{kq}, 1\right\} \times c_q^{fix}\right) + \sum_{i\in I^-} c_{Inv}^i\left(b_{i,|L|}\right) + \sum_{i\in I^-, l\in SP} c_{Inv}^i\left[\left(t_{ilk}^{in} - t_l^{ed}\right)PD_i + \sum_{j\in I^-, m\in SP, s\in S} x_{iljmk}CF_{i,l}^{in}\right] \tag{26}$$

$$\min : z_2 = \max_{i\in I^-, l\in SP}\left\{b_{i,|L|}/CF_i^{up}, \left[\left(t_{ilk}^{in} - t_l^{ed}\right)PD_i + \sum_{j\in I^-, m\in SP, s\in S} x_{iljmk}CF_{i,l}^{in}\right]/CF_i^{up}\right\} \tag{27}$$

s.t. (1)-(25)

where, CF_i^{up} represents the upper limit of the oil storage capacity of the FPSO i; c_q^{fix} represents the fixed cost of using the tanker q during the planning period; $c_{Inv}^i(\cdot)$ represents the function between the FPSO i and the inventory cost.

SSIRPM contains a total of 2 objective functions, which are (26) and (27). Specifically, (26) is used to require the minimum operating cost of the shuttle tanker fleet during the planned period. The first term on the right side of the equation is used to describe the operating cost of each tanker (mainly the fuel cost of the tanker). The second term is used to describe the fixed operating cost of the tanker (mainly the rental cost or depreciation of the tanker). The sum of items 3 and 4 reflects the inventory costs incurred at the FPSO during the plan period.

Equation (27) is used to require the oil storage capability level of each FPSO at all times (that is, the ratio of the amount of oil stored in the FPSO cargo tank to its capacity) to be the smallest. In (27), the first term in braces is used to calculate the maximum oil storage capability level of each FPSO at the end of the planning period. The second term is used to calculate the maximum oil storage capability level of the virtual nodes generated by each FPSO when they are docked. It should be noted that the amount of oil stored in the FPSO cargo tank increases linearly with time, and only decreases when the tanker is docked and unloaded. Therefore, for the entire planning period, the extreme value of the FPSO cargo tank oil storage rate will only appear when the shuttle tanker is at berth or when the whole planning period ends.

V. ALGORITHM DESIGN

The short sea inventory routing problem optimization model (SSIRPM) is a large-scale multi-objective mixed

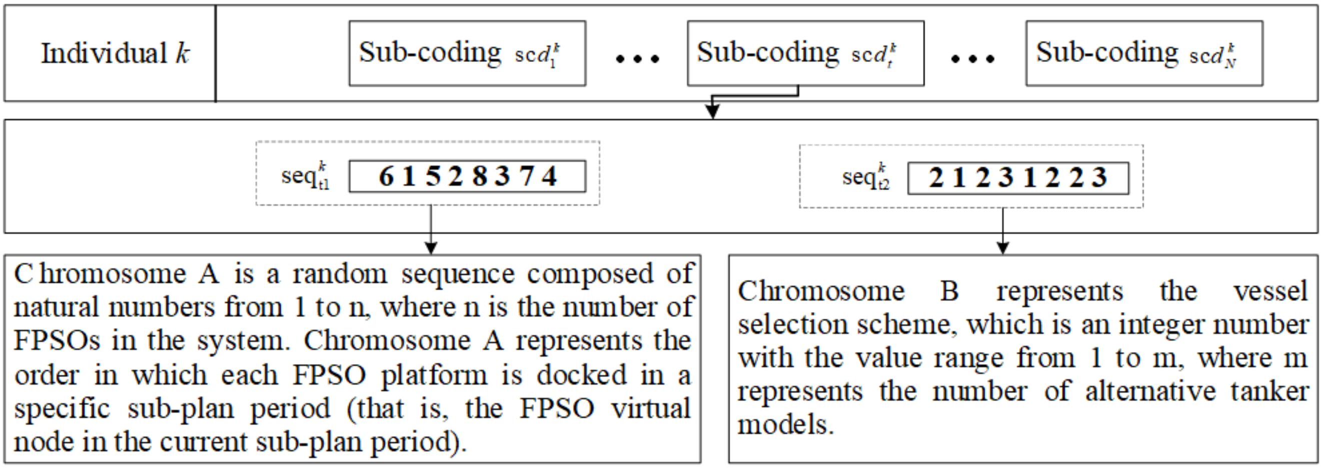

FIGURE 5. The code design for Chromosome A and B.

integer programming, and its original problem MIRP has significant NP characteristics, which makes it difficult to solve accurately. The Genetic algorithm (GA) is suitable for solving complex multi-objective mode with high efficiency [59]. Therefore, this article adopts the more popular multi-objective evolutionary algorithm NSGA-II to solve SSIRPM. To improve the efficiency of the algorithm, this article incorporates the idea of "differential evolution" into the NSGA-II. Specifically, the following work was conducted:

1) An efficient coding method is designed. On the one hand, this method can fully describe the scheduling scheme of ships in each cycle. On the other hand, it can also significantly reduce the formation probability of infeasible solutions and reduce the decoding calculation time.

2) According to the characteristics of SSIRPM, targeted differential evolution operators and mutation operators are proposed.

A. GENETIC CODING DESIGN

Reasonable coding design can effectively compress the search space of the algorithm, improve the exploration performance of the algorithm on the Pareto front, and is essential to ensure the effective solution of the problem. This chapter proposes a coding method for SSIRPM based on the architectural features of semi-continuous models. This method can compress the code length to the greatest extent and reduce the design difficulty of related genetic operators (crossover operator, mutation operator).

The coding design scheme is as follows:

Our individual codes are composed of several sub-coding strings, and the number of sub-coding strings is equal to the number of sub-planned periods. For example, if two sub-planning periods are set for the planning period, the genetic code will contain two sub-coding strings. Each sub-coding string corresponds to the scheduling plan of the fleet in the corresponding sub-cycle. Each sub-coding string is composed of 2 chromosomes (chromosome A, B) with equal-length. The number of genes contained in each chromosome is the same as the number of floating production storage and offloading (FPSO) in the off-shore crude oil collection and transportation system, but the structure and meaning are different. Fig. 5 shows a specific chromosome case.

Among them, chromosome A is a random sequence composed of natural numbers from 1 to n, where n is the number of FPSOs in the system. Chromosome A represents the order in which each FPSO platform is docked in a specific sub-plan period (that is, the FPSO virtual node in the current sub-plan period). Chromosome B represents the vessel selection scheme, which is an integer number with the value range from 1 to m, where m represents the number of alternative tanker models. For example, if the number of alternative ship types is 3, the value range of the B chromosome gene is 1-3. In this way, the combination of chromosome A, B can determine the vessel scheduling plan for each sub-plan period.

The decoding process of the sub-code string is briefly described as follows:

First of all, the process starts from reading the gene on chromosome B, and each reading of a gene point means the activation of an oil tanker. The trajectory of the tanker in the sub-cycle is determined by the genes on chromosome A. For example, if chromosome B determines that tanker v needs to perform a transportation task, then the order of performing tasks needs to be determined based on chromosome A.

The specific decoding method is:

Tanker v needs to start from a known initial position (a certain node in the transportation network) and dock the relevant FPSO virtual nodes and load crude oil according to the sequence of genes on chromosome A. For every FPSO virtual node docked in tanker v, two conditions need to be judged: 1) Whether tanker v has enough capacity to transport all crude oil of the next FPSO virtual node; 2) Whether the berthing and loading of the next FPSO node can be completed before the final time set by the sub-period. If the first condition is not met, the tanker v needs to return to the port to unload the oil, and then re-determine the feasibility of

FPSO node berthing according to the sequence of genes on chromosome A. If the second condition is not met, it means that tanker v can no longer perform transportation tasks within the planned period. In this case, it is necessary to read the next gene point of chromosome B and obtain a new tanker to perform subsequent tasks (if there are still FPSOs that have not been visited). The above process is repeated to ensure that all FPSO virtual nodes in the sub-period are visited.

It should be particularly emphasized that the gene code in chromosome B does not use the tanker number (but the ship type indicator). The purpose is mainly to compress the number of feasible solutions of chromosome B, so as to compress the search space of the algorithm. Of course, this design method also makes it difficult to estimate the required fleet size and fleet operating costs. For example, if n-type ships are used 10 times in sub-period 1 and n-type ships are used 10 times in sub-period 2, it is not correct to directly assume that the total number of n-type ships to be used in 2 cycles is 20. Because if time permits, certain n-type ship can complete multiple missions in the plan period. This problem will be solved when constructing the fitness function below.

Considering that the decoding process of chromosomes A and B is complicated, this article provides corresponding decoding pseudocode for better understanding.

The decoding process of the sub-code string will be divided into 2 stages.

First, introducing a status judgment function to judge the possible FPSO situation when the tanker visits the next FPSO according to the gene sequence on chromosome A. The main state parameters that the function needs to input include: the remaining capacity of the current tanker v (Cap_v^{left}), the speed parameter of the tanker v ($Speed_v$), and the current position of the tanker v (ID_Now), the operating time (Time_passed) of tanker v in the current sub-cycle, and the number of the FPSO to be docked (ID_Next).

This function will return 4 status parameters 1-4, the specific meanings are:

Status 1 stands for the situation: "When the tanker v calls the FPSO with ID_Next, the visiting time exceeds the end time of the relevant sub-cycle."

Status 2 stands for the situation: "When the tanker v calls the FPSO with ID_Next, the total capacity of the tanker is less than the current stock in the FPSO."

Status 3 stands for the situation: "When the tanker v calls the FPSO with ID_Next, the tanker's current capacity is less than the current stock in the FPSO."

Status 4 stands for the situation: "When the tanker v can call the FPSO with ID_Next, the offloading operations completed normally."

The pseudo-code of the status judgment function Status_Decide () is as follows(see **Algorithm 1**):

Thus, the decoding function SubSectionDecode() of the sub-coding string can be further constructed. The inputs to this function are chromosome A (denoted as array GeneA[]), chromosome B (denoted as array GeneB[]), $Speed_v$, $Stock_i^{Max}$, $rate_i^{Pro}$, and $Stock_i^{Int}$. The output is: a two-dimensional array ShipRoute[][] used to represent the tanker assignment and navigation trajectory, and a one-dimensional array StockWEnd[] used to represent the inventory information of each FPSO virtual node in the ending period of the sub-plan. Since we use a compact coding design of chromosome to reduce the calculation time for the evolution process, the rules for the decoding process are complex and hard to explain. Therefore, this article uses the pseudo code to demonstrate the heuristic function. The specific pseudo code of the function is as follows (see **Algorithm 2**):

Algorithm 1 The Pseudo-Code of the Status Judgment Function

Step1: Time2Add (Estimated using time) = Dis [ID_Now, ID_Next]/ $Speed_v$
Step2: If Time_passed + Time2Add > SubTime_Total Then Return 1
Step3: Cap2Reduce (Estimated oil extraction)
= Max ($Stock_i^{Max}$, $Stock_i^{Max}$ + $rate_i^{Pro}$ Time_passed + $rate_i^{Pro}$ Time2Add))
Step4: If Cap2Reduce > Cap_V then Return 2
Step5: If Cap2Reduce > Cap_left then Return 3
Step6: Return 4

B. CROSSOVER AND MUTATION OPERATORS

The crossover operator and mutation operator of the algorithm are designed based on the subsections of both chromosomes A and B, section by section, correspondingly. For example, for two chromosome A of the parents, subsection 1 of the father crosses with subsection 1 of the mother. Thus the subsection 1 of the child is generated from the crossover result. In terms of crossover operators: chromosome A uses the integer crossover operator given by Surry *et al.* [60]; for chromosome B, it uses a two-point crossover operator. In terms of mutation operators, chromosome A uses mutations of exchanging two randomly selected gene points. Chromosome B adopts the method of randomly extracting two gene points to perform random value updates.

C. CONSTRUCTION OF FITNESS FUNCTION

The fitness function of the algorithm is mainly used to calculate the following important indicators: the first one is the sum of the operation and inventory maintenance costs of the shuttle tanker fleet during the plan period; the second is the fluctuation of the oil storage rate of each FPSO during the plan period; the third is the penalty cost for avoiding the full loading of the FPSO caused by the ship scheduling scheme (note that this study assumes that the cargo tank of the FPSO cannot be fully loaded).

For the first indicator, by decoding the genetic code, the scheduling plan of the tanker fleet is obtained to calculate the operating cost of the ship during the planning period (mainly including the cost of fuel oil) and the cost of crude

Algorithm 2 The Specific Pseudo Code of the Decoding Function

```
Step1: GeneA_Index = 0
GeneB_index = 0
ID_This = 0
Step2: v = GeneB [GeneB_index]
Speed_now = Speed_v
Cap_left_now = Cap_v^tol
Time_passed = 0,
Step3: ID_Next = GeneA [GeneA_Index];
Stock_init_now = Stock^Int_ID_Next
Pro_Rate _now = rate^Pro_ID_Next
Stock_Max_now = Stock^Int_ID_Next
Step4: result = Status_Decide (ID_This, ID_Next, Time_passed, Speed_now,
Cap_left_now, Stock_init_now, Pro_Rate_now, Stock_Max_now);
Step5: If result = 1 or result = 2 Then
        GeneB_index + = 1
        Time_passed =0
Go to Step2
Else If result = 3 Then
        Time_passed + = dis [ID_This, 0] / Speed_now
ShipRoute [GeneB_index].Add(0);
        ID_This = 0
        Go to Step3;
Else If Result = 4 Then
        Time_passed + = dis [ID_This, ID_Next] / Speed_now
        StockWEnd [ID_Next] = (SubTime_Total-Time_passed) Pro_Rate_now
        Track [GeneB_index].Add(ID_Next);
        ID_This = ID_Next
GeneA_Index + = 1
Go to Step6
End If
Step6: If GeneA_Index larger than the total number of FPSO Then
        Return
Else
        Go to Step 3
End If
```

oil maintenance in each sub-cycle and the fleet maintenance expenditure (mainly including the fixed rental of oil tankers). For the second indicator, (27) can be directly applied to calculate the index for evaluating the reliability of system operation during the planning period. For the third indicator, based on the tanker's scheduling plan and the crude oil production rate of each FPSO, it is evaluated whether the tanker's scheduling plan may cause the FPSO to fully fill up. If so, the duration of the FPSO full-filling status and the relevant system losses are calculated accordingly. After the loss is multiplied by a large positive number, it is included in the total system operation cost as the penalty cost.

D. DIFFERENTIAL EVOLUTION ALGORITHM OPERATOR

Differential Evolution Algorithm (DE) is a new evolutionary computing technology. It was proposed by Storn *et al.* in 1995 [61]. DE is a random algorithm that simulates biological evolution. Through repeated iterations, DE can keep those individuals who adapt to the environment. Compared with the traditional evolutionary algorithm, DE retains a population-based global search strategy and only has differences in crossover and mutation operators. The direction of the search is guided by "group intelligence" generated by mutual cooperation and competition among individuals within the group.

The basic idea of the algorithm is: starting from a randomly generated initial population. A new individual is generated by summing the vector difference between any 2 individuals in the population and the vector of the third individual. Then the new individual is compared with the corresponding individual in the contemporary population. If the fitness of the new individual is better than that of the current individual, the new individual will replace the old individual in the next generation, otherwise the old individual will be preserved. By constantly evolving, the search is guided towards the optimal solution.

Overall, the calculation process of NSGA-II and DE is basically similar, the main difference is the design of crossover and mutation operators. As shown in Fig. 6, in simple terms, DE actually uses the difference operators 1 and 2 to integrate the crossover and mutation operators, thereby achieving the synchronous operation of the crossover and mutation of genetic individuals. This approach improves the mutation rate of the code, and thus improves the algorithm search efficiency.

Difference operators 1 and 2 are similar in nature. The only difference is the processing methods of creating a new individual in the initial stage. As shown in Fig. 7, the difference operator 1 uses "subtraction", and the difference operator 2 uses "addition". Similar to the crossover and mutation operators, the difference operator 1 is also designed based on the sub-coding string. The specific operation can be further divided into two sub-processes: the generation process of differential gene and the adjustment process of the initial gene. As shown in Fig. 7, ID1 and ID2 are the two child coding strings at the corresponding positions of the parent. Among them, Gene1A, Gene1B, Gene2A, and Gene2B represent chromosome A and chromosome B contained in ID1 and ID2, respectively.

1) THE GENERATION PROCESS OF GENE DIFFERENCE

As shown in Fig. 8, the process of generating the gene difference between ID1 and ID2 is shown as follows: First, subtract the ID1 and ID2 to obtain the transitional sub-coding string and record it as ID1-ID2. Then, for each gene X in the transitional sub-coding string, the positive remainder method is used to obtain the replace gene X:

$$X' = L + (X + U - L) \bmod (U - L)$$

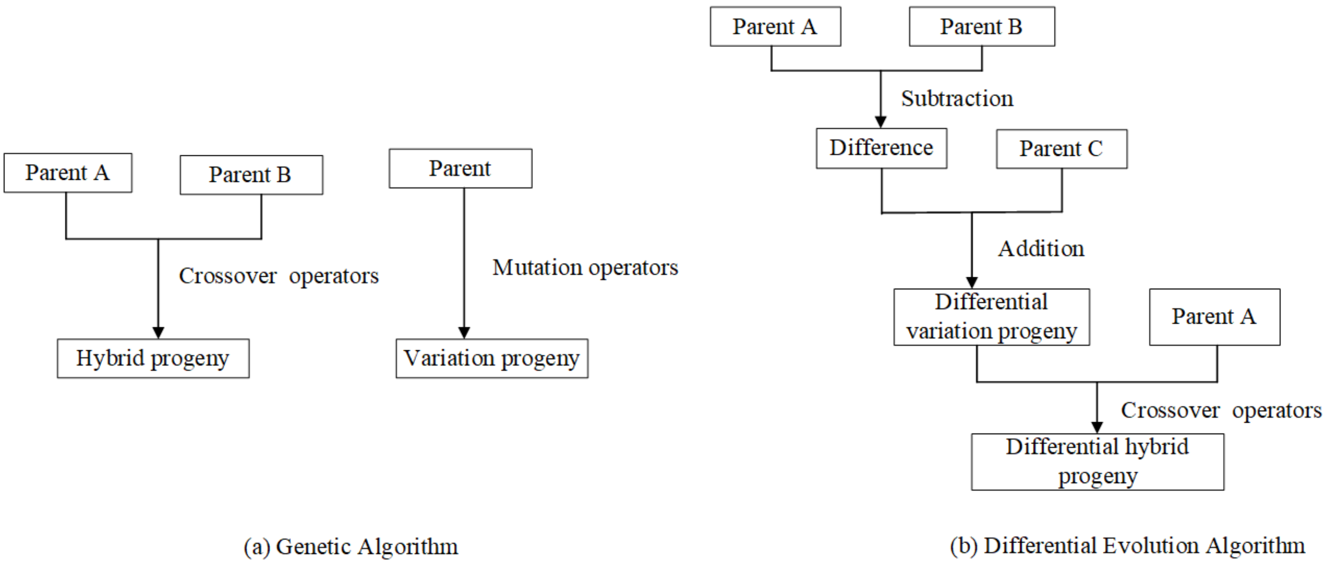

FIGURE 6. The difference between NSGA-II and DE.

	Chromosome A					Chromosome B				
ID1:	1	3	2	5	4	1	2	0	3	1
ID2:	3	4	5	2	1	1	0	3	2	2
ID1-ID2:	-2	-1	-3	3	3	0	2	-3	1	-1

FIGURE 7. The DE operator.

	Chromosome A					Chromosome B				
To be modified:	-2	-1	-3	3	3	0	2	-3	1	-1
To take positive reminder:	3	4	2	3	3	2	3	0	1	3

FIGURE 8. DE generation process.

where, U and L are the upper and lower boundary of the corresponding gene value. For example, in Fig. 8, for the first gene point in the chromosome A in ID1-ID2, the upper boundary is 5 and the lower boundary is 1. The differential initial sub-coding string X is 3 through the above equation, noted as IDO.

2) THE ADJUSTMENT AND REPAIR OF IDO

In practice, chromosome A of IDO usually does not meet the genetic coding settings introduced in Section 5.1, which requires further adjustment and repair. The specific process is as follows:

Step 1: Read the gene points of chromosome A following the order from left to right, and delete the duplicated genes to obtain a temporary gene segment TA. In Fig. 8, the chromosome A of ID1-ID2 after adjustment is 3-4-2-3-3, then the repeated fragment 3-3 is deleted to obtain TA, which is 3-4-2.

Step 2: Randomly read the information from chromosome A of the parent coding string to obtain the reference chromosome PTA.

Step 3: Compare PTA and TA, delete genes that appeared in TA from PTA, and obtain repair fragment SA. In Fig. 8, PTA is 1-3-2-5-4 and TA is 3-4-2. Since TA contains genes 2, 3 and 4, these genes were deleted from PTA to obtain SA (1-5).

Step 4: Combine TA and SA to obtain the repaired chromosome A. TA is 3-4-2 and SA is 1-5, then the chromosome A obtained after repair is 3-4-2-1-5.

After the above steps, the sub-coded string that meets the requirements and undergoes differentiation can be obtained. Repeat the above steps separately for each sub-period to obtain the sub-coding string corresponding to each sub-period, and finally obtain a brand-new individual code.

It should be noted that the calculation process of the difference operator 2 and the difference operator 1 are almost the same. The only difference is that in the differential generation of ID1 and ID2, "addition" is used to create a transitional sub-coding string, and its correction and adjustment process is exactly the same as that of differential operator 1, which will not be repeated in this article.

VI. COMPUTATIONAL EXPERIMENT

A. THE COMPARATION OF THE ALGORITHM EFFICIENCY

This article uses the public information of an oil company as a reference. The data contains information such as tanker type, speed parameters, etc. The geographic location of the port and FPSO, the crude oil growth rate of the FPSO, the crude oil inventory of the FPSO at the beginning of the planned period,

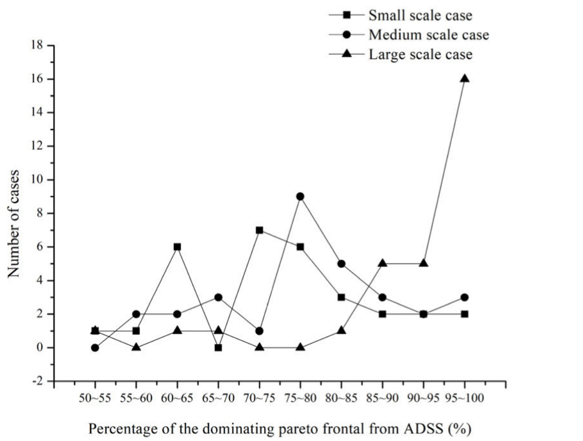

FIGURE 9. The comparison of the percentage of dominating Pareto fronts.

and the capacity of the FPSO cargo tank are randomly generated based on actual data. Then, the NSGA-II and the algorithm proposed in this article are used to solve the six sets of data mentioned above. The relevant algorithm is programmed with C#.net. Different from the traditional single-objective optimization problem, for the multi-objective optimization problem, the main method of comparing the efficiency of the algorithm is to observe the advantages and disadvantages of the Pareto front obtained by each algorithm.

In order to assess the scalability of the model and algorithm, three sets of the case with different scales are used. For the actual situation, there are about 10 FPSOs in the Chinese near-sea oil production platform in the Bohai sea. For other production areas, such as the south china sea, more FPSOs are deployed to cover the larger oil production area. Three different scale settings with different FPSO numbers are adopted to represent the small, medium, and large scales of the case. The small-scale case has 10 FPSO in the test setting, the middle-scale case has 20 FPSO, and the large-scale case of the case has 30 FPSO.Since the number of different FPSO setting are similar to the actual situation of the Chinese off-shore oil production system, the settings of three cases are representative of the different scales of the practical case.

The percentage of Pareto-optimal solutions obtained from the ADSS algorithm, which dominated the related Pareto-optimal solution obtained from the NSGA-II algorithm, are calculated with different scale settings. The larger the percentage is, the more effective the ADSS algorithm will be. In Fig.9, the gray line keeps rising and peaks at 16 cases in 95% to 100% category, which means that the ADSS algorithm is almost always better than the NSGA-II algorithm in the large-scale setting. The line of medium-scale peaks around the category of 75% to 80%, and the line of small-scale probably peaks around the category from the 65% - 75%. Therefore, the ADSS performs better in the large-scale setting. While ADSS algorithm performance of the small and medium scale settings are weaker than the large-scale setting, and the difference between them are not significant. Thus the

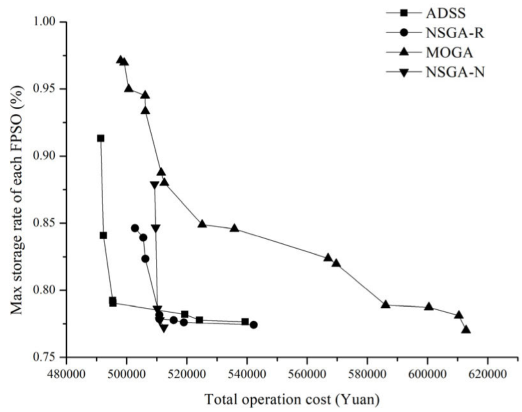

FIGURE 10. The Pareto fronts for different algorithms.

ADSS algorithm is more suitable for the large scale problem. The computation result is demonstrated in Fig 9.

To assess the algorithm effectiveness, several algorithms including ADSS, NSGA-II with roulette wheel selection (NSGA-R), MOGA with elitism operator, and NSGA-II with neighborhood-based crossover (NSGA-N), are tested with the same cases. The Pareto fronts obtained with those algorithms are compared to analyze algorithm effectiveness, as shown in Fig 10. Although the MOGA algorithm provides more Pareto optimal solution, the solutions are further generally dominated by the Pareto front of other algorithms. Therefore, the ADSS algorithm is more effective in finding the optimal solution; however, could not provide more local optimal solutions. For the NSGA-II with the different evolutionary operators, three types of NSGA-II generally provide about the same amount of the Pareto optimal solution. However, the Pareto front from the ADSS dominates the other two types of the NSGA-II, demonstrating that the differential operator is better than the other NSGA-II operators. Therefore, the algorithm proposed by this study is suitable for solving the SSIRP.

For the detail of the algorithm comparing, this study conducted two test schemes with 10 and 20 FPSOs, respectively, each scheme contains three different sets of data. For the same set of data, NSGA-II and the algorithm proposed in this article are used to solve the optimization problem, and two different Pareto fronts are obtained. The quality of the solution is judged by analyzing their position in the Pareto front. In terms of parameter settings, the basic parameters of NSGA-II are set as follows: the initial computation population is 100; the crossover uses the binary tournament mechanism; the mutation probability is 15%; the maximum number of iterations is 16000. Regarding the algorithm proposed in this article, the parameter settings are: the initial computation population is also 100, the selection of evolutionary individuals also uses the binary tournament mechanism, with a maximum iteration number of 16,000. It should be noted that to avoid the impact of the initial population on different algorithms, the initial population of the two algorithms will adopt the same initial population during the efficiency comparison process.

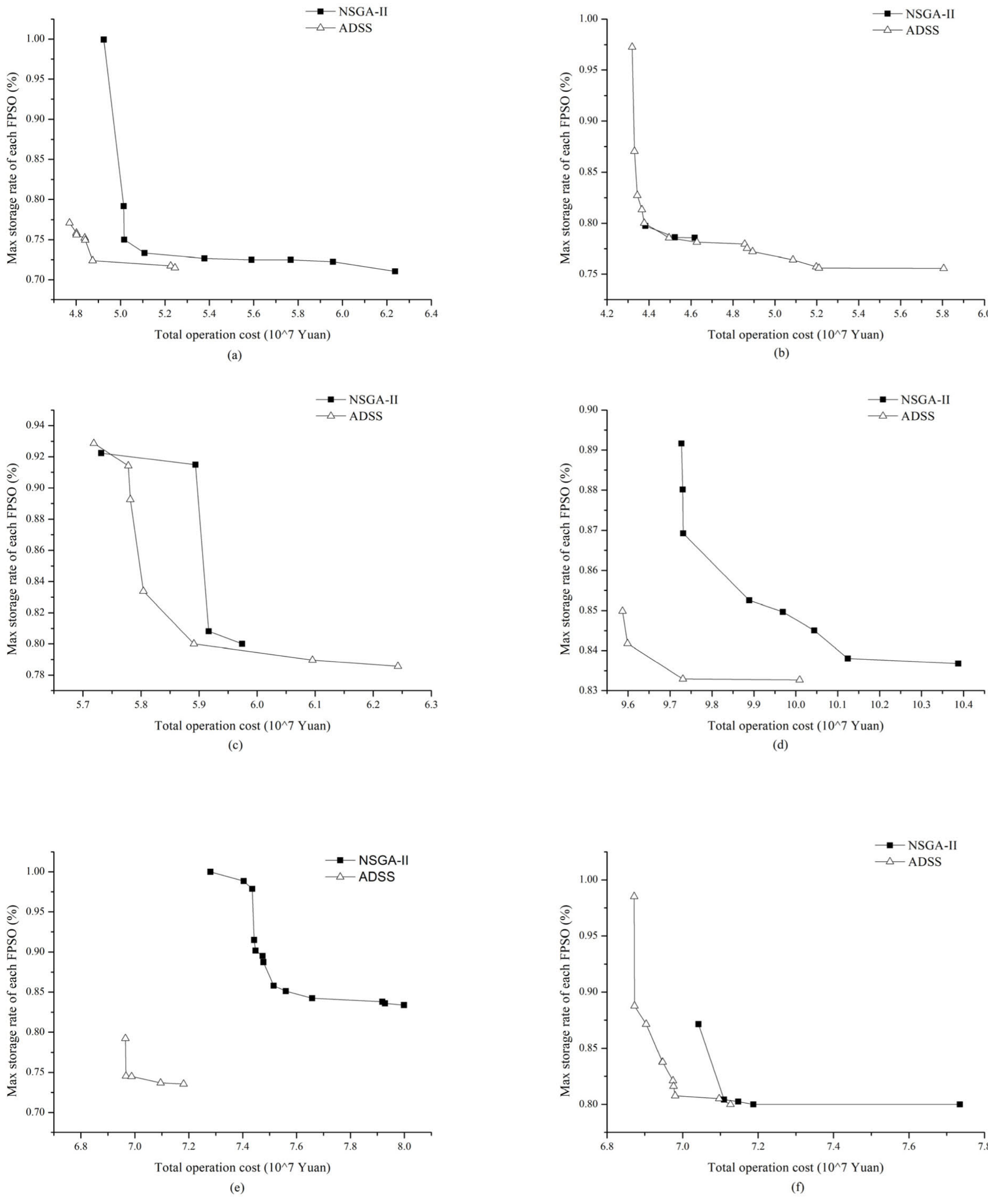

FIGURE 11. **Pareto frontiers for different calculation cases.**

Fig. 11(a)-Fig. 11(f) show the Pareto fronts in the above six sets of calculation cases. Among them, there are two sets of calculation results under different scheme settings, which represent the different computation difficulty. The first group is the calculation results given in Fig. 11(a)-Fig. 11(c), they are all for calculation cases with 10 FPSO; the second group is the calculation results given in Fig. 11(d)-Fig. 11(f), they are for the calculation cases with 20 FPSO. In the two sets of calculation cases, the Pareto front edge depicted by the blue polyline is obtained by the traditional NSGA-II,

TABLE 2. Parameters of different types of shuttle tankers.

Tanker type	Transportation capacity ($\times 10^4$ m^3)	Monthly rent ($\times 10^4$ Yuan)	Speed setting1 (knot)	Speed setting2 (knot)	Fuel cost ($\times 10^3$ Yuan /n mile)
A	6	415.80	22	20	0.33
B	12	535.92	19	17	0.55
C	17	752.64	18	16	0.65
D	18	793.80	18	16	0.67
E	22	882.00	18	16	0.68

and the Pareto front edge depicted by the yellow polyline is obtained by the algorithm proposed in this study (referred to as "ADSS" in the Fig. 11).

By analyzing the Pareto frontiers in Fig. 11, it can be found that for both cases, the solution quality of the ADSS algorithm is significantly better than that of NSGA-II. For example, in Fig. 11(e), the ADSS algorithm gives a better Pareto front solution. In Fig. 11(b), although the NSGA-II and ADSS give the similar Pareto front, the ADSS algorithm offers more Pareto optimal solutions and more Pareto front information. The above results show that the ADSS algorithm provides more advantages than the traditional NSGA-II algorithm in Pareto frontier search capabilities. Therefore, introducing differential evolution operators does improve the effectiveness of ADSS.

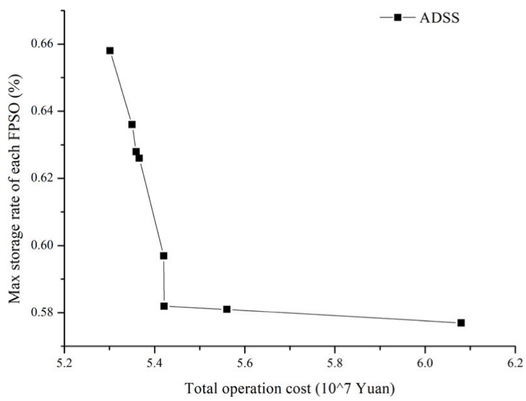

FIGURE 12. Pareto frontal distribution of the actual case.

B. PRACTICAL CASE ANALYSIS

In this section, through the analysis of the Pareto front, the differences between the optimal fleet design and scheduling scheme under different risk preferences will be discussed.

Due to the prosperity of the ship leasing market, a large amount of ship information is open for public access. Therefore, you can directly query the FPSO tanker information required in this article on the relevant websites (for example, http://fpso.com/ and http://www.cosl.com.cn/col/col42951/index.html) information such as the amount of oil, the speed of crude oil production, and the capacity, speed, operating costs, and rent of each shuttle tanker. Based on the above information, this article randomly generates information such as the location of each FPSO to design a calculation case. The sailing distance between each FPSO is uniformly and randomly generated with the Euclidean distance as the minimum value and the distance satisfying the triangle inequality as the maximum value. This is because navigation on the sea is not exactly a straight line, and sometimes it is necessary to consider the actual situation of the fairway and ocean currents. In terms of alternative fleet types, this study mainly exams five types of ships, and each type of tanker has a sufficient number of tankers for operation. The parameters, such as transportation capacity, monthly rent, alternative speed, and fuel cost for different types of tankers, are shown in Table 2 below.

The basic process of the experiment is as follows: based on the above data, the algorithm proposed in this article is used to solve the model to obtain a set of Pareto optimal solutions; Then, three representative solutions were selected from this set of solutions. The first type of solution (referred to as "I solution") has the lowest operating cost and the highest operational risk. The second type of solution (referred to as "II solution") has a balanced operation cost and risk. The third type of solution (referred to as "III solution") has the highest operating cost and the lowest operational risk.

Fig. 12 shows the Pareto front calculated by the algorithm. It can be seen from Fig. 12 that the algorithm has found a total of 8 Pareto optimal solutions. In these solutions, the FPSO oil storage rate is between 58% and 66% at all times, and the system operating cost during the planned period (one month) is between 53 million and 61 million. Table 3 to Table 5 provide detailed information about the fleet, ship utilization rate, voyage information, ship mileage, and so on. Among them, the so-called ship utilization rate refers to the ratio of the operating duration of the tanker to the duration of the whole planned period, which can be used to reflect whether the relevant tanker is fully utilized during the plan period.

Table 3 shows the fleet design and tanker scheduling plan corresponding to the I solution. For this scheme, the fleet consists of two smaller B-type tankers and two larger E-type tankers. Therefore, in this scenario, it takes only four oil tankers to handle the one-month crude oil transportation task. Judging from the voyages performed by each tanker, the average tanker needs to complete four voyages. Among them, I2 tanker carried out the least number of voyages during the planning period, but has docked with more than 2 FPSOs

TABLE 3. Fleet operation plan (corresponding to solution I).

ID	Ship type	Ship utilization rate	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Distance (n mile)	Ship operating cost ($\times 10^4$ Yuan)
I1	E	87.2%	0-8-2-5-0	0-10-2-0	0-4-1-0	0-3-6-7-0		11301	769.10
I2	E	84.1%	0-3-6-7-0	0-7-6-0	0-9-1-0			10896	741.53
I3	B	78.7%	0-4-9-0	0-9-5-0	0-10-4-0	0-8-0	0-5-0	10761	594.69
I4	B	49.6%	0-1-3-0	0-8-0	0-2-0	0-10-0		6785	374.96

TABLE 4. Fleet operation plan (corresponding to solution II).

ID	Ship type	Ship utilization rate	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Voyage 7	Distance (n mile)	Ship operating cost ($\times 10^4$ Yuan)
II1	B	74.1%	0-2-0	0-5-0	0-8-0	0-2-0	0-8-4-0	0-5-3-0	0-8-0	10131	689.47
II2	E	79.2%	0-7-4-0	0-1-6-3-0	0-1-4-10-0					10265	698.59
II3	E	90.8%	0-9-6-3-0	0-7-9-0	0-10-4-0					11770	650.45
II4	B	72.4%	0-1-3-0	0-8-0	0-2-0	0-10-0	0-10-0			9898	547.00

TABLE 5. Fleet operation plan (corresponding to solution III).

ID	Ship type	Ship utilization rate	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Distance (n mile)	Ship operating cost ($\times 10^4$ Yuan)
III1	E	79.5%	0-4-9-1-0	0-4-7-6-0	0-1-5-0				10300	700.97
III2	B	83.7%	0-10-0	0-8-0	0-6-0	0-9-0	0-8-0	0-3-0	11452	632.87
III3	B	70.7%	0-3-0	0-5-1-0	0-9-7-0				9673	534.56
III4	B	78.5%	0-5-0	0-2-0	0-3-0	0-4-2-0	0-10-0	0-8-0	10738	593.42
III5	B	77.8%	0-7-0	0-10-0	0-2-0	0-6-0			10646	588.33

during each voyage. On the contrary, I3 tanker carried out the most voyages, but only docked with one FPSO during some of the voyages. For solution I, the total distance traveled by tankers is 39,943 nautical miles, and the average utilization rate of ships is 74.9%. Thus, various types of tankers have been relatively fully utilized. If this plan is implemented, the maximum oil storage capacity of each FPSO can be controlled below 64.1% during the planning period, and the total cost of system operation is 533.2226 million yuan.

Table 4 gives the fleet design and tanker scheduling plan corresponding to the II solution. In this scheme, the operating fleet is also composed of 4 tankers, including 2 smaller B-type tankers and 2 large-capacity E-type tankers. Similar to solution I, the number of voyages performed by large tankers is relatively small, but the number of FPSOs anchored within the voyage is relatively large. Small tankers, on the other hand, perform more voyages, but the number of FPSOs anchored within the voyage is smaller. In this scheme, the average utilization rate of the tanker is 79.1%, and the total distance traveled by ship is 42064 nautical miles. The implementation of this plan can ensure that the oil storage capacity of each FPSO at all times is less than 60.7%, and the total cost of system operation is 54.764 million yuan.

Table 5 shows the fleet design and tanker scheduling plan corresponding to solution III. The implementation of this plan requires the configuration of 5 tankers, including four small ships (B-type tankers) and one large tanker (E-type tankers). These tankers carried out 22 voyages, and the total cost of the system operation was 60,758,300 yuan. Compared with the II solution, although the operating cost of the fleet has increased by about 10.94%, the maximum oil storage capacity at each moment of the FPSO has only dropped to 58.54%. In other words, the stable capacity level only decreased by less than two percentage points compared to the II solution. In addition, the total distance in tanker operations has increased significantly. Under this scheme, the total distance traveled by each tanker reached 52,809 nautical miles, which was much higher than that of the II solution.

From the comprehensive analysis of the three solutions, it can be seen that, under different FPSO oil storage capacity level control preferences, there are some significant trends in the fleet structure and the design of ship scheduling schemes (see Fig. 13). In terms of fleet structure, with the increase in FPSO inventory capacity level control

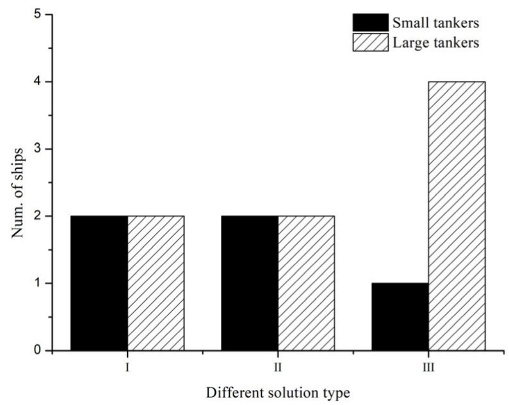

FIGURE 13. Changes in fleet composition by cases.

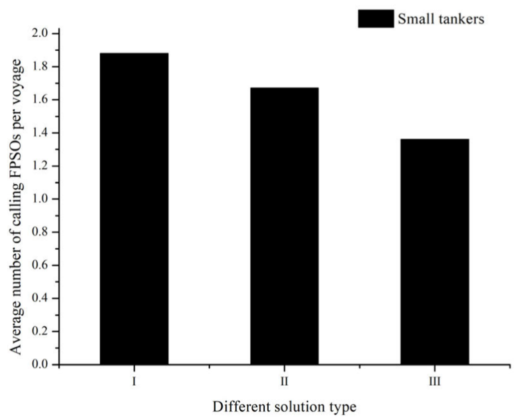

FIGURE 14. Average number of calling FPSOs per voyage.

preferences, the number of ships in the shuttle tanker fleet has gradually increased. The proportion of large tankers has shown a downward trend. In terms of ship scheduling schemes, it can be found that the FPSO inventory control preference has also significantly changed the trajectory of the tanker.

Fig. 14 shows the average number of FPSOs berthed by each Pareto optimal solution. As shown in the Fig. 14, in the solution I, the average number of FPSOs berthed by a shuttle tanker is 1.88. In the II solution, this value is reduced to 1.67, whereas in the III solution, this value is further reduced to 1.36. But interestingly, with the decrease in the average number of FPSO visits, the total distance traveled by the shuttle tanker showed a significant trend of increase. The total travel distance increase from 39,943 nautical miles in the I solution to 52,809 nautical miles in the III solution. The above results indicate that with the preference for increasing FPSO inventory capacity levels, decision-makers should use small tankers and rely on the "short voyage, multiple voyage" strategy to operate shuttle tankers. Although this method can improve the stability and reliability of the system, at the same time, it may lead to an increase in the total distance traveled by the tanker, which leads to a significant increase in the operating cost. On the contrary, if the requirements for system stability and reliability can be relaxed moderately, then large shuttle tankers have a higher application "potential." Although the application of a larger tanker does not provide enough flexibility for the scheduling, their application can significantly increase the number of docking on the FPSO platform during a single voyage. Therefore, by applying a larger tanker, many non-essential tanker transportation activities to and from the FPSO and unloading port are reduced, which in turn reduces the total distance traveled by tanker during the planned period, thereby achieving a significant reduction in system operating costs.

VII. CONCLUSION

This study has proposed the short sea inventory routing problem(SSIRP) issue, which considers system reliability and crude oil storage cost. Related models are constructed, and corresponding heuristic algorithms are proposed. SSIRP on the one hand exam the routing problem, which allows multiple docking of floating production storage and offloading (FPSO) with the heterogeneous fleet during a single voyage; on the other hand introduces the goal of depicting system reliability and inventory maintenance costs. This turns SSIRP into a complex optimization problem with multiple objectives.

In view of the complexity of the problem, this research takes two measures to simplify it. First, this article adopts the model design idea of the semi-continuous modeling to construct the SSIRP model, which reasonably portray the system reliability without increasing the complexity of the model. It is also helpful to reduce the complexity of individual coding in NSGA-II and compress the search space of the algorithm. Secondly, for the process of solving optimization, this chapter improves the basic framework of NSGA-II. By introducing DE operators, this study proposes improved selection and elimination operators and improves the computational efficiency of NSGA-II. It can be seen from the numerical experiment results that the improved NSGA-II is significantly better than the classic NSGA-II in exploring the frontier of Pareto.

The Pareto Front provided by the model and solving algorithm of this article could offer more optimal planning solutions. Through the practical case analysis, the proposed SSIRP model provides insight into the fleet composition setting preferences regarding the system reliability. If the high system reliability is required, the fleet is advised to have more small tankers instead of the large tankers.

Although this article addresses the SSIRP for improving operation efficiency, some aspects need to be studied in the future. Firstly, the semi-continuous model limits the application to operation type with discrete plan period. The optimization model and algorithm for continuous operation need to be further studied. Secondly, future studies could include more operation parameters in the model to more accurately guide the practical operation. For example, the speed of the shuttle tanker is set as a constant in this model. However, due to the short travel distance of the near-sea transportation system, the vessel speed could be adjusted to fit the transportation need. Thus, the variable tanker speed could be included in the optimization.

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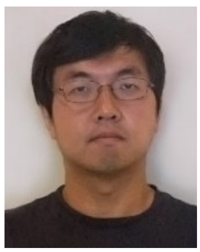

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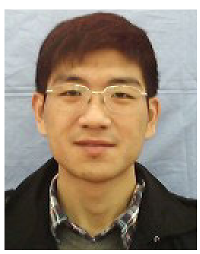

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