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Learning-based Pareto-optimum routing of ships incorporating uncertain meteorological and oceanographic forecasts

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ABSTRACT

In modern shipping logistics, multi-objective ship route planning has attracted considerable attention in both academia and industry, with a primary focus on energy conservation and emission reduction. The core challenges in this field involve determining the optimal route and sailing speed for a given voyage under complex and variable meteorological and oceanographic conditions. Typically, the objectives revolve around optimizing fuel consumption, carbon emissions, duration time, energy efficiency, and other relevant factors. However, in the multi-objective route planning problem involving variable routes and speeds, the extensive solution space contains a substantial number of unevenly distributed feasible samples. Traditional heuristic optimization techniques, such as multi-objective evolutionary algorithms, which serve as the core component of optimization programs, suffer from inefficiencies in exploring the solution space. Consequently, these algorithms may tend to converge toward local optima during population iteration, resulting in a solution set characterized by sub-optimal convergence and limited diversity. This ultimately undermines the potential benefits of routing optimization. To address such challenging problem in route planning tasks, we propose a self-adaptive intelligent learning network aiming at capturing the potential evolutionary characteristics during population iteration, in order to achieve high-efficiency directed optimization of individuals. Additionally, an uncertainty-driven module is developed by incorporating ensemble forecasts of meteorological and oceanographic variables to form the Pareto frontier with more reliable solutions. Finally, the overall framework of the proposed learning-based multi-objective evolutionary algorithm is meticulously designed and validated through comprehensive analyses. Optimization results demonstrate its superiority in generating routing plans that effectively minimize costs, reduce emissions, and mitigate risks.

1. Introduction

Maritime transport comprises approximately 80% of global trade, as reported by the United Nations Conference on Trade and Development (Sirimanne et al., 2020). In shipping logistics, a single ocean-going ship may consume thousands of tons of fuel to complete a trans-oceanic voyage, contributing to annual global maritime fuel consumption exceeding 200 million tons (IMO, 2022). Even a one percent improvement could lead to dramatic cost savings and emission reductions, prompting heightened awareness

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of economic benefits and environmental concerns among shipping carriers and public authorities (Wang et al., 2023a). In terms of sailing time, for cargoes such as fresh agri-food products, value creation heavily relies on shipments arriving within a narrow delivery window (Viet et al., 2020). Additionally, optimizing the time spent underway can help mitigate the loss of benefits associated with ship delays and maintain the efficient operation of the supply chain systems (Zhang and Lee Lam, 2014). During voyages, unfavorable meteorological and oceanographic (met-ocean) conditions, such as strong wind and high waves, can have a considerable negative impact on ships, resulting in notable increases in operating costs, greenhouse gas (GHG) emissions, fatigue damage, etc (Lee et al., 2023). Therefore, decision-makers must comprehensively consider factors such as ship performance, cargo characteristics, weather conditions, and port schedules to enhance competitiveness by formulating multi-objective routing plans (Fan et al., 2022).

Since the beginning of the 21st century, there has been an increased focus on routing plans that achieve greater benefits and flexibility. The pursuit has heightened the demand for optimization algorithms, such as multi-objective evolutionary algorithms (MOEAs), which serve as the core component of route planning programs. For instance, meticulously designed navigation arrangements, e.g., Pareto optimal solutions characterized by superior convergence, can substantially reduce voyage costs and GHG emissions, while mitigating potential risks to the ship, cargo and crew (Wang et al., 2019). Moreover, it is preferable to have routing plans available within each specified time horizon to accommodate port schedules or corporate strategies (Meersman et al., 2012), which will be achieved by optimization results with excellent diversity (Li and Yao, 2019). The optimization process of traditional MOEAs begins with a set of initial solutions, each of which searches along a random trajectory to discover other regions of the solution space and generate a new generation. Renewal strategies based on Pareto dominance retain better individuals to form new populations, from which the random search continues. While various innovations have been proposed, e.g., expanding the search size (Liu et al., 2023a) or modifying the renewal strategy (Ma et al., 2024), the effects have been exceedingly limited. This is primarily attributed to the prevailing improvement strategies that do not eliminate the random-based process in exploring feasible spaces and generating new solutions. Specifically, in the multi-objective route planning problem involving variable routes and speeds, the extensive solution space contains a substantial number of unevenly distributed feasible samples. As the iterative program progresses, relying solely on random search during the evolution can hinder MOEAs from properly and efficiently exploring the search space, resulting in a solution set with poor convergence and diversity (Tarkhaneh et al., 2021). Meanwhile, the number of feasible routing plans with short duration time but high fuel consumption is generally fewer than their opposite solutions, attributable to the influence of met-ocean factors. In such cases, the random search process of MOEAs may prefer to focus on the majorities, leading to locally optimal solutions that display an obvious gap from the actual Pareto front (PF^*) and exhibit a non-equilibrium distribution. Indeed, a fresh perspective is required to address such troublesome problem in route planning tasks.

As an algorithm inspired by natural evolution, although the search process of MOEAs is stochastic, individuals appear to evolve in an underlying direction during the iterations. Such evolutionary knowledge is independent of the population scale and sample distribution, representing a direction or tendency along which individuals have a higher probability of achieving superior outcomes in a given environment. Building on this belief, an intelligent learning network can be specifically designed to capture the positive evolutionary direction during the iterative process. Meanwhile, to enable the network to learn the population evolutionary knowledge more effectively and accurately, improvement strategies in the evolutionary process can be introduced to provide better training samples. By effectively exploiting the potential knowledge, the optimization algorithm will be able to purposefully and systematically explore the solution space, instead of aimlessly trying, thereby producing high-quality routing plans with lower costs, reduced emissions and minimized risks. Additionally, optimized plans for regions with fewer viable samples, such as a navigation plan with an earlier arrival time, can be complemented or improved, which caters to the diverse needs of shippers and supports the comprehensive scheduling of intermodal transport systems.

On the other hand, as a method to find safe, energy-efficient, and low-carbon sailing plans, the effectiveness of route planning depends heavily on the accuracy of met-ocean forecast data (Ksciuk et al., 2023). However, the inevitable uncertainties in the met-ocean forecasting system, via the optimization algorithm, will be reflected in the objective function values of optimal plans, e.g., fuel consumption, duration time, GHG emissions, and other key indicators (Li et al., 2022). Clearly, to achieve stable operations, decision-makers generally prefer a comprehensive plan with minimal uncertainty under complex and variable met-ocean conditions (Luo et al., 2023). Regrettably, concrete attempts to deal with uncertainties have been reported, generally with the objective to quantifying the uncertainties in the predicted or optimized performance (e.g., confidence interval), rather than allowing them to play active roles in guiding the optimization toward more robust solutions (Yoo and Kim, 2018).

In this work, our aim is to introduce a learning-assisted evolutionary algorithm and an uncertainty-driven module for sustainable, profitable and reliable multi-objective ship route planning. In specific, our main contributions lie in the following three aspects.

1. To fundamentally mitigate the negative effects of random processes and enhance the search efficiency, our proposed algorithm integrates a self-adaptive neural network module into the iterative process. Trained by samples exhibiting successful evolution, the intelligent learning network can progressively discern potential positive evolutionary direction, aiding in the efficient exploration of the solution space. Consequently, the proposed algorithm generates high-quality routing plans with greater benefits and flexibility, closely approximating the real PF^*.
2. Meanwhile, we propose a series of modification strategies in the evolutionary process. By generating solutions with superior convergence and diversity, these strategic improvements will provide the learning network with better training samples, enabling it to learn the potential population evolutionary knowledge more effectively and accurately. Then, an overall framework of the learning-assisted multi-objective evolutionary algorithm (L-MOEA) is carefully designed by integrating all the proposed modules.

3. Furthermore, to address the uncertainties inherent in met-ocean forecasts, we develop an additional uncertainty-driven module integrated as guidance for L-MOEA. The uncertainty-considered framework, defined as L-MOEA-U, aims to generate more reliable solutions with less potential risk. Finally, exhaustive experiments based on real-world cases verify the superiority of our framework in developing high-quality routing plans.

The remainder of this study is structured as follows. Section 2 covers an overview of the multi-objective ship route planning problem, including a brief problem description and related work. Section 3 elaborates on the proposed methodology, focusing on the principle and structure of our proposed L-MOEA. Section 4 verifies the superiority of the proposed method based on real-world cases, presenting and discussing the optimization results. Finally, in Section 5, overall conclusions and future directions are provided.

2. Overview of multi-objective ship route planning

Ship route planning is a complex decision-making process that has garnered significant attention in both academia and industry within modern shipping logistics. Prior to introducing our proposed L-MOEA, we provide a brief overview of the multi-objective ship route planning problem.

2.1. Problem description

A complete route planning procedure encompasses several key interactive components aimed at addressing various related issues, including the met-ocean forecasting systems, ship performance models, optimization algorithms, uncertainty handling strategies, etc (Zis et al., 2020). The core challenges in this field involve determining the optimal sailing plans (such as route and speed arrangements) for the case ship to complete a given voyage under complex met-ocean conditions, while considering multiple conflicting objectives (Yu et al., 2021). In general, the ultimate objectives are typically to optimize two or more of fuel consumption, ship emissions, voyage duration, energy efficiency, navigation safety, service level, or other related indicators (Wang and Meng 2012, Wang et al. 2016, Du et al. 2019, Zhen et al. 2019, Li et al. 2020, Tan et al. 2022, Chen et al. 2022). Taking a typical problem in shipping logistics, characterized by a pair of mutually exclusive objectives, i.e., fuel consumption and duration time, as an example, we will briefly introduce the workflow of the optimization program.

First, based on the met-ocean forecast data of the sea area involved in the target voyage, the ship performance model can estimate the fuel and time costs required for the case ship to complete the voyage along certain routes and at certain speeds (Yan et al. 2020, Li et al. 2023). With advancements in science and technology, ship performance models have evolved significantly, transitioning from physical white-box models (WBMs) (Wang et al., 2021) to data-driven black-box models (BBMs) (Guo et al., 2023), and then to hybrid gray-box models (GBMs) (Wang et al., 2023b). Currently, BBMs and GBMs based on machine learning technology demonstrate high accuracy without relying on numerous operating parameters or ship coefficients, indicating a promising development prospect (Wang et al., 2022). Even so, WBMs, which are based on deterministic physical mechanisms, remain widely used in multi-objective ship route planning due to the superior interpretability.

Then, the nonlinear programming problem, which takes route and speed as decision variables with seakeeping as constraints, is solved by the multi-objective optimization algorithm (Zhang et al., 2021). In general, heuristic algorithms represented by MOEAs (Zhao and Zhao, 2024) are widely employed, compared to exact techniques (Du et al., 2022), in such large-scale engineering problem due to their rapid solving speed and acceptable solving quality (Yu et al., 2021). Advanced MOEAs, as the core of the optimization process, are effective in providing practitioners with a broad spectrum of trade-off solutions, enabling them to make informed choices based on requirements or preferences (Zhen et al., 2024).

Peculiarly, some more realistic studies may take into account uncertain factors often ignored in idealized route planning problems, such as met-ocean condition forecasts (Luo et al., 2023), traffic densities (Wu et al., 2023), piracy risks (Azzqy, 2024), and emission control regulations (Ma et al., 2021a). Among these factors, the inevitable uncertainties in met-ocean forecasts are the most common, and will be reflected in the objective function values of optimal plans, hindering the effectiveness of route plannings. In recent years, the analysis and handling of uncertainties in shipping route planning problems have gradually gained attention.

2.2. Related work

To fill the research gap pertaining to the capable of delivering solutions with superior convergence, diversity, and robustness in ship route planning, our study concentrates on enhancements associated with optimization algorithm and uncertainty handling. Thus, let us provide a brief review of the related studies on these two aspects in the context of multi-objective route planning.

2.2.1. Optimization algorithm

In recent years, with the increasing complexity of optimization objectives and decision factors, heuristic MOEAs have gradually been introduced (Zis et al., 2020), replacing the design variables defined by integrals, gradients, or derivatives in exact techniques (James 1957, Haltiner et al. 1962, Calvert et al. 1991, Padhy et al. 2008). The fundamental procedure of MOEAs generally includes initial population generation, population renewal (fitness calculation), selection, crossover, and mutation. The optimization algorithm iterates according to the aforementioned process, ultimately yielding a set of recommended solutions, i.e., the Pareto optimal set (PS*), in which individuals can coordinate and weigh among various objectives to achieve the desired outcome. Afterwards, to enhance the ability to converge toward the real PF*, various innovative ideas have been suggested in the evolutionary process.

The initial population comprises a predetermined amount of solutions (individuals) randomly generated prior to the iterations commence, and its quality plays a crucial role in determining the efficiency of MOEAs. Hence, the direction of enhancements is to improve the convergence and diversity of the initial solutions, which involves strategies such as increasing the capacity of the initial population, incorporating transformation solutions based on the reference route (Szlapczynski et al., 2023), and employing single-objective optimization for pre-solving (Vettor and Soares, 2016).

To renew the population, the newly generated offspring must be compared with its parent generation, by the Pareto domination, to preserve superior solutions. However, if the population contains numerous non-dominated solutions, evaluating the quality or potential of individuals solely based on the dominance relation is insufficient. Additional criteria, e.g., K-nearest neighbor in the improving strength Pareto evolutionary algorithm (SPEA2) (Veneti et al. 2018, Sobecka et al. 2020), crowding distance in the non-dominated sorting genetic algorithm-II (NSGA-II) (Ma et al. 2021b, Shih et al. 2023), and knee point in knee point-driven evolutionary algorithm (KnEA) (Zhang et al. 2014, He et al. 2024), need to be employed during the renewal process.

In the iterative process, a well-designed selection operator ensures that superior individuals have opportunities to participate in evolution, such as roulette-wheel (Lipowski and Lipowska, 2012), tournament (Yadav and Sohal, 2017), and the quartering method in the modified genetic algorithm (MGA) (Wang et al., 2017), etc. The crossover and mutation operators play their roles through the random interchange and alteration of individual information, facilitating the exploration of sample space and the generation of novel solution. It is widely recognized that local intensification is helpful to improve the performance of algorithms (Ishibuchi and Murata, 1998), such as the property-based local search operators in multi-objective evolutionary algorithm based on multiple neighborhoods local search (MOEA-LS) (Shao et al., 2021). As a matter of fact, in the field of route planning, the focus is usually on customizing real number coding to address specific shipping problems, with relatively little emphasis placed on innovating or improving this aspect.

Taking the enhanced schemes that integrate single-objective optimization results into the initial population as an example, researchers have “inadvertently” adopted some strategies to deemphasize the randomness of initial solutions. However, current innovations have not got to the roots of randomness inherent in traditional MOEAs, i.e., the random search in crossover and mutation processes, resulting in inefficient exploration of solution spaces and limited improvement in optimization performances. Therefore, we adopt a more targeted approach, i.e., utilizing an evolutionary learning network to assist the optimization algorithm, to drive the optimization process with a “directed” search, while retaining the advantages of heuristic algorithms for fast solving to the greatest extent possible.

2.2.2. Uncertainty handling

The idealized route planning problem implicitly assumes that the met-ocean forecast data are estimated with sufficient accuracy, and uncertainty related to the optimized results is neglected or, at most, quantified in the post-processing (Szlapczynski et al., 2023). However, uncertainties in met-ocean conditions can have dramatic consequences, particularly for trans-oceanic voyages, potentially leading ships to be caught in unexpected storms, jeopardizing benefit even safety (Norlund and Gribkovskaia, 2017). Although this issue in route planning has garnered some attention, most studies have yet to comprehensively consider met-ocean conditions as the uncertain input factor (Ksciuk et al., 2023). The discussion about uncertainty mainly remains at the analysis level, with insufficient in-depth research and practical application of relevant solutions (Wang et al., 2020).

At present, researchers employ strategies to handle met-ocean uncertainty, which can be broadly categorized into two groups. To be specific, the first approach involves estimating ship sailing performance indicators based on the statistics, such as mean or median, derived from multiple ensemble forecast members, which are then incorporated into the route planning algorithm (Kepaptsoglou et al. 2015, Vettor et al. 2021, Moreira et al. 2021, Nuñez et al. 2023). In the second strategy, each member of the ensemble forecast is treated as an independent met-ocean data, and route planning is conducted separately and repeatedly. Afterwards, the optimization results from all members are averaged to derive routing plans that account for met-ocean uncertainty (Hinnenthal and Clauss 2010, Skoglund et al. 2015, Luo et al. 2023, Szlapczynski et al. 2023).

It is evident that existing efforts primarily concentrate on quantifying the uncertainty associated with ship performance estimation or final recommended plan, which manifests itself as a mathematical expectation or confidence interval. In this work, we are committed to developing an uncertainty-driven module to guide the optimization process toward more robust solutions, thereby ensuring the validity and reliability of the optimized routing plans.

3. The proposed L-MOEA

In this section, an innovative multi-objective optimization algorithm, i.e., L-MOEA, is proposed for sustainable, profitable and reliable ship route planning.

3.1. Evolutionary learning network

As a truism, MOEA is a population-based metaheuristic approach inspired by the biological evolution. Its random search process begins with a set of initial solutions, each of which explores the feasible space along a random trajectory to obtain a new generation, with each step forward being called an evolution. Similar to the law of species evolution in nature, in the iteration of MOEA, the individuals in the solution domain also evolve along the latent directions to acquire the optimal objectives in the presupposed environment. Hence, we devote ourselves to constructing an intelligent learning network that captures this positive evolutionary knowledge, to drive more purposeful search in the generation of new solutions, rather than relying purely on random search. In

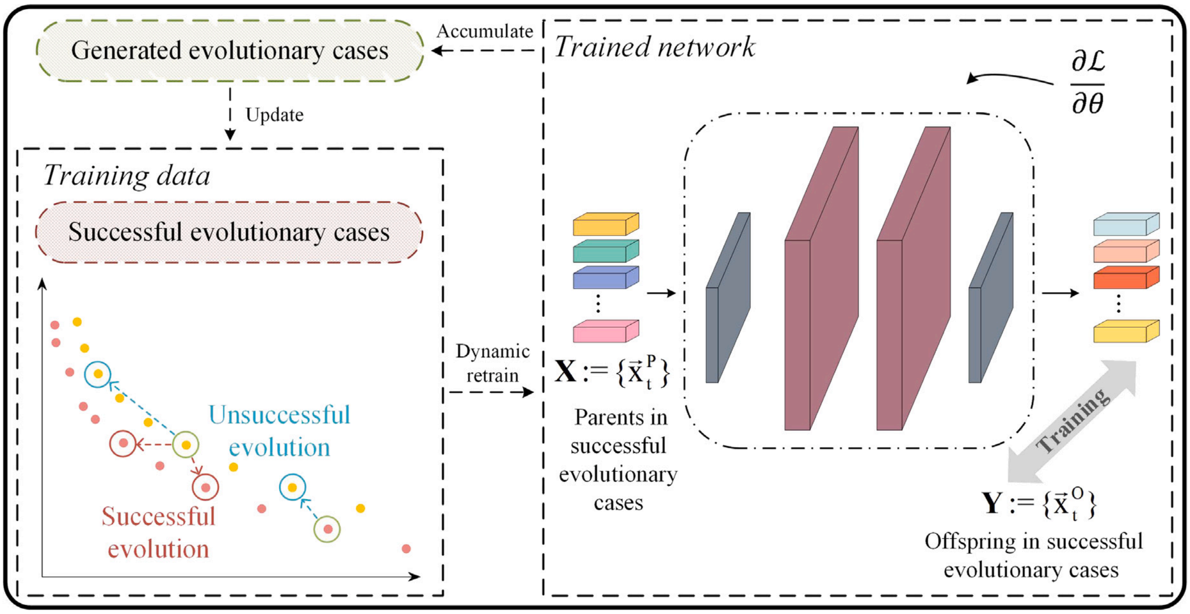

Fig. 1. The evolutionary learning network in the proposed L-MOEA and its dynamic retraining mechanism.

this way, we expect the proposed algorithm to efficiently approach the real PF*, achieving superior performance in route planning problems.

In consideration of potential limitations, such as the ambiguous internal evolutionary knowledge and the limited availability of training samples, a carefully designed learning network tailored to address these challenges can help mitigate the issues. We start by designing a learning network activated by rectified linear units (ReLU), as shown in Fig. 1. Next, it is crucial to gather suitable training data to learn the latent evolutionary knowledge, as the quality of this data often dictates the capability and effectiveness of the network module. However, unlike shipping-related performance models that are based on recorded data, there is little historical data available for reference in route planning problems. More importantly, the positive evolutionary direction hidden in the optimization procedure is typically an internal experience with no universal applicability, applicable only to a particular problem in a specific context. Thus, it behooves us to devise a remedy to the aforementioned predicament. Specifically, through the stochastic operations (e.g., crossover and mutation) in traditional MOEAs, multiple generations are derived, among which successful evolutionary cases harbor the needed latent knowledge to a certain extent. We devise a dedicated dataset to gather the successful cases emerging from the population derivation, i.e. cases in which the offspring Pareto dominates the parent. Then, an intelligent network with the aforementioned structure is constructed to learn the evolutionary characteristics of these samples, where the input and output variables represent the parent and offspring in the evolutionary process, respectively.

More formally, an individual in the population, representing a feasible sailing plan from departure to destination (with the route discretized into N stages) in a static orthogonal grid, is defined as $\vec{x} := \{(p_n, r_n)\}_{n=1}^{N}$, where p denotes the waypoint and r denotes the revolutions per minute (RPM) of ship engines at each waypoint. We then denote P_t and O_t as the parent and offspring sets in the tth generation, respectively. To ensure clarity in statements, let us assume that upon deriving the population in the iterative process up to the Dth generation, the accumulated cases have reached the predefined sample size necessary for network training. Our original learning network takes all the parental samples from successful evolution, i.e., $\mathbf{X} := \{\vec{x}_t^P | \vec{x}_t^P \in P_t, \vec{x}_t^O \in O_t, \vec{x}_t^P \prec \vec{x}_t^O\}_{t=1}^{D}$, as input variables, and fits the latent evolutionary directions with their offspring as output $\mathbf{Y} := \{\vec{x}_t^O | \vec{x}_t^P \in P_t, \vec{x}_t^O \in O_t, \vec{x}_t^P \prec \vec{x}_t^O\}_{t=1}^{D}$. The signal forward propagation in the network is as follows:

$$
\begin{aligned}
&\mathbf{Z}^{(l)} = \mathbf{A}^{(l-1)} \cdot \mathbf{W}^{(l-1)} + \mathbf{B}^{(l-1)}, \quad l = 2,3,4, \\
&\mathbf{A}^{(l)} = \begin{cases} \mathrm{ReLU}(\mathbf{Z}^{(l)}), & l = 2,3, \\ \mathrm{linear}(\mathbf{Z}^{(l)}), & l = 4, \end{cases}
\end{aligned}
\tag{1}
$$

where $\mathbf{Z}^{(l)}$ and $\mathbf{A}^{(l)}$ denote the input and output of the lth layer in network, and $\mathbf{A}^{(1)}$ is an encoding result of the input $\mathbf{X}$ in particular. $\mathbf{W}$ and $\mathbf{B}$ are the weight matrix and the bias vector, respectively. With the loss function based on the mean squared error, the network is guided to minimize the difference between the output and the ground truth by adjusting its weights and biases:

$$
\begin{aligned}
&\Delta^{(l)} = \begin{cases} (\mathbf{Y} - \mathbf{A}^{(l)}) \odot \mathrm{ReLU}'(\mathbf{Z}^{(l)}), & l = 4, \\ (\Delta^{(l+1)} \cdot {\mathbf{W}^{(l)}}^{\mathrm{T}}) \odot \mathrm{ReLU}'(\mathbf{Z}^{(l)}), & l = 2,3, \end{cases} \\
&\mathbf{W}^{(l)} \leftarrow \mathbf{W}^{(l)} + \alpha {\mathbf{A}^{(l)}}^{\mathrm{T}} \cdot \Delta^{(l)}, \quad l = 2,3,4, \\
&\mathbf{B}^{(l)} \leftarrow \mathbf{B}^{(l)} + \alpha \Delta^{(l)}, \quad l = 2,3,4,
\end{aligned}
\tag{2}
$$

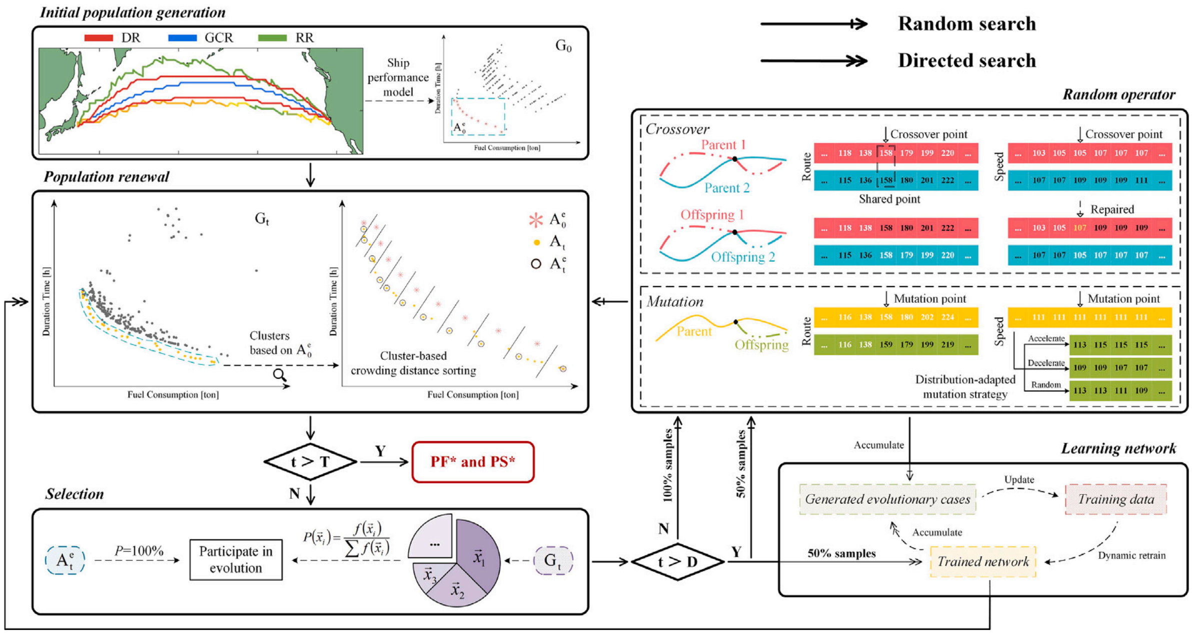

Fig. 2. Flowchart of the proposed L-MOEA framework, including initial population generation, population renewal, selection, random operator, and learning network.

where ReLU′ is the derivative of the activation function, and α denote the learning rate.

In subsequent iterations, the individuals are fed into the trained network, allowing them to evolve more efficiently along the fitted direction and generate superior solutions for the route planning problem. In addition, to continuously track and respond to changes in the population's positive evolutionary direction during the iteration process, we propose introducing a dynamic retraining mechanism into the learning network. By absorbing the accumulated successful cases in the optimization process (from both the learning network and the random operators), the mechanism constantly refreshes the training dataset, thereby promoting the ongoing self-optimization of the intelligent learning network.

3.2. Enhanced strategies for facilitating evolutionary learning

Combined with the evolutionary learning network, the proposed L-MOEA adheres to the basic procedure found in MOEAs, culminating in a comprehensive framework depicted by the flow chart in Fig. 2, which will be introduced sequentially in this section. Meanwhile, to facilitate the network in learning the population evolutionary knowledge more effectively and accurately, we introduce a series of improvement strategies in the evolutionary process.

3.2.1. Initial population generation

The randomly generated initial population, denoted as G_0, may comprise numerous invalid routes, such as those crossing rough met-ocean areas or taking unnecessary detours with an unjustified increase in cost and risk, which impedes the efficiency and quality of the optimization procedure. Thus, we introduce a conscious process (Ma et al., 2024) for generating the G_0. Firstly, each generated individual is represented as a set of chromosomes, comprising two types of numerical strings. These strings denote the waypoints from the origin to the destination and the RPM of the ship engine as it passes through each waypoint, respectively. During the initialization phase, along with the great circle route (GCR) and random routes (RRs), we incorporate into G_0 the route with the minimum duration time and the route with the minimum fuel consumption (denoted as DRs), both determined by single-object optimization under a constant RPM. Depending on the adjustment range of the engine, each optional RPM is assigned to the generated routes.

3.2.2. Population renewal

In scenarios where there are multiple individuals in the population, a crude assessment method may deprive the elites of the opportunity to further participate in evolution, hindering the extraction of positive evolutionary knowledge. Hence, it is essential to have reasonable metrics that evaluate the performance or potential of each non-dominated solution (Sun et al., 2020). We improve a novel cluster-based crowding distance sorting method to update the external archive, as depicted in the population renewal module in Fig. 2, thereby markedly enhancing the diversity of solutions generated.

Prior to iterating, we establish an infinite-capacity common archive A_t to store all the non-dominated solutions generated till the tth iteration, in which the favorable plans will be prioritized into another elite external archive A_t^e with a capacity upper bound

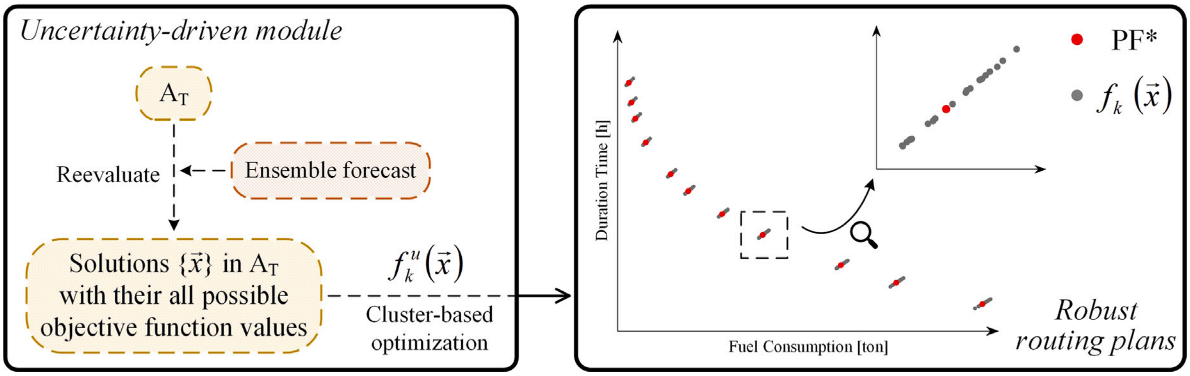

Fig. 3. Robust routing plan recommendation based on the proposed uncertainty-driven module.

determined by the number of samples in A_0. For the generated initial population, we identify all non-dominated solutions in G_0 and transfer them to the A_0^e. In subsequent iterations, A_t will be updated based on the new produced non-dominated solutions from G_t, with the provision that any solution dominated by others should be removed. If the number of non-dominated solutions in A_t surpasses the capacity of the external archive A_t^e, a prioritized selection process becomes imperative. To elaborate, multiple non-intersecting regions (clusters) are generated, each centered on a solution within the set A_0^e. The crowding distance of each internal non-dominated solution is calculated and sorted, with the region serving as the fundamental unit. Subsequently, solutions with superior crowding distances in each region are sequentially extracted and placed into A_t^e until its maximum capacity is reached.

3.2.3. Selection, crossover and mutation

Initially, it needs to be indicated that all individuals from A_t^e are selected into iteration, and a fitness-based roulette selection is implemented in the main population G_t, to expand the search scope while ensuring solution quality.

We employ distinct methods for route and RPM (speed) crossover, respectively, to adapt to the characteristics of trans-oceanic voyages. For the former, the precondition for two routes to cross requires the presence of at least one shared point (excluding the starting and ending points). Subsequently, utilizing a randomly selected shared point as a reference, the two parent routes interchange their sequences to create the new offspring routes. Regarding the RPM, although there is no similar prerequisite, instantaneous changes are not feasible due to limitations in the operating characteristics of the engines. Therefore, the resulting offspring must undergo repairs to ensure a gradual variation in the RPM near the crossing point until it aligns with the target value, as shown in the crossover module in Fig. 2.

As for the mutation operator, the route mutation requires only the identification of a random point, after which the path is re-generated. It is essential to emphasize the mutations in RPM. In optimization problems related to fuel consumption and duration time, generally, a faster RPM tends to correlate with a solution characterized by a shorter duration time but a higher fuel consumption. Hence, a deliberate mutation strategy is necessary. To achieve purposeful mutation and balance the distribution (improve the uniformity, to be more specific) of solutions, consequently facilitating the learning of evolutionary knowledge, a distribution-adapted RPM mutation method is designed herein. Delving deeper into the details, three strategies are designed, wherein, from a randomly selected point, the RPM will undergo acceleration, deceleration, or random changes and continue for a certain duration. In the tth iteration, the distribution of non-dominated solutions in the A_{t-1} is monitored, and a repair strategy is matched accordingly, as illustrated in Fig. 2.

Finally, even after the evolutionary learning network is trained, some samples are still randomly crossed and mutated to preserve their potential to generate better solutions, and to optimize the fitted positive evolutionary direction.

3.3. Uncertainty-driven routing plan recommendation

The ubiquitous uncertainty in met-ocean forecast products will eventually be inevitably reflected in the optimization plans. In this work, we leverage uncertainty as a catalyst to facilitate the optimization process toward robust solutions with less potential risks, by an uncertainty-driven module expatiated in Fig. 3.

Let $f_k^u(\vec{x}) = s(\sigma_k)$ denote the uncertainty representation of a certain sailing plan $\vec{x}$, where $k = 1, 2$ corresponding to the fuel consumption and duration time of the entire voyage, and σ_k represents the standard deviation of all possible $f_k(\vec{x})$ based on the ensemble forecast. Besides, the function $s(\cdot)$ signifies a standard Min–Max normalization procedure (Kiran and Vasumathi, 2020), crafted to mitigate the interference of magnitude.

During the optimization process of L-MOEA, the expectation of the multivariate ensemble forecast data is initially employed as the environmental information. The operator $f_k^u(\vec{x})$ will become a crucial component in the recommendation process of robust routing plans, serving as the basis for generating the PS* and PF* for a given voyage once the iteration concludes. In greater detail, at the conclusion of the iterations (i.e., t reaches the presupposed threshold T), for each plan within the optimal solution set A_T,

Table 1
Ship particulars of our research target.

Name	Value
Length on waterline	226.27 m
Length per perpendicular	233.00 m
Draft	11.00 m
Service speed	23.80 kn
Brake power	28710 kW
Brake specific fuel oil consumption	166 g/kWh
RPM adjustment range	101 to 125

Table 2
Overview of ensemble forecast products.

Name	Value
Member	1 to 20
Time step	0 to 360 by 6 h
Parameter	Significant wave height (SWH) Mean wave direction (MWD) Mean wave period (MWP) Wind speed (WSPD) Wind direction (WDIR)

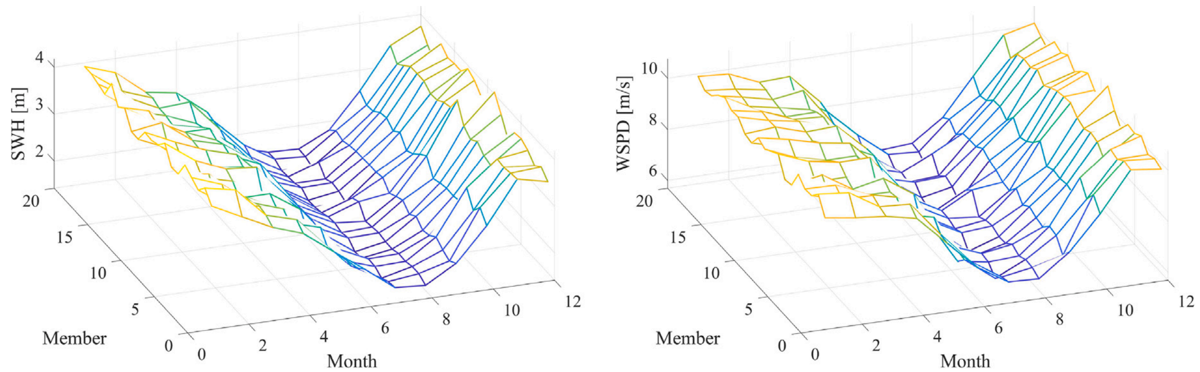

Fig. 4. Monthly evaluations of met-ocean conditions for the year 2022 based on ensemble forecast products with 20 members.

each member of the ensemble forecast serves as independent input data into the performance model successively. The aforesaid process yields multiple sets of objective function indices $f_k(\vec{x})$ corresponding to all non-dominated solutions under the ensemble forecast. By utilizing the obtained $f_k^w(\vec{x})$ as the replacement criterion of crowding distances calculated in Section 3.2.2, outstanding plans with lower uncertainty will be subsequently identified and recommended within a specific time window or cost range.

4. Optimization results and analyses

The principle and structure of the proposed L-MOEA for multi-objective ship route planning have been explicitly outlined in Section 3. To validate its effectiveness, a series of comprehensive analyses are conducted in this section.

4.1. Experimental case and statistics

The ship presented in the case study is a 3500 TEU container ship, as specified in the study by Eskild (2014), and its detailed characteristics are enumerated in Table 1. The intended voyage involves navigating the North Pacific Ocean, where the approximate origin and destination coordinates are (35.25N, 141.75E) and (37N, 122W), respectively, with departure scheduled for 12:00 A.M. on the 1st day of each month. Furthermore, the ensemble forecast products for 2022, obtained from the European Centre for Medium-Range Weather Forecasts, span from the 1st to the 15th day of every month, and their specific attributes are detailed in Table 2.

The sailing states of a given ship are intricately related to the prevailing met-ocean conditions it encounters during voyage. Therefore, we initiate a preliminary assessment of the 240 met-ocean forecast datasets from January to December, by respectively comparing the averages of SWH and WSPD in our case ocean area. As depicted in Fig. 4, the met-ocean environment in the North Pacific during winter is more severe, significantly impeding the navigation of ships during this period. Thus, a rational optimization plan is particularly important, as it can effectively mitigate sailing risks and enhance voyage benefits.

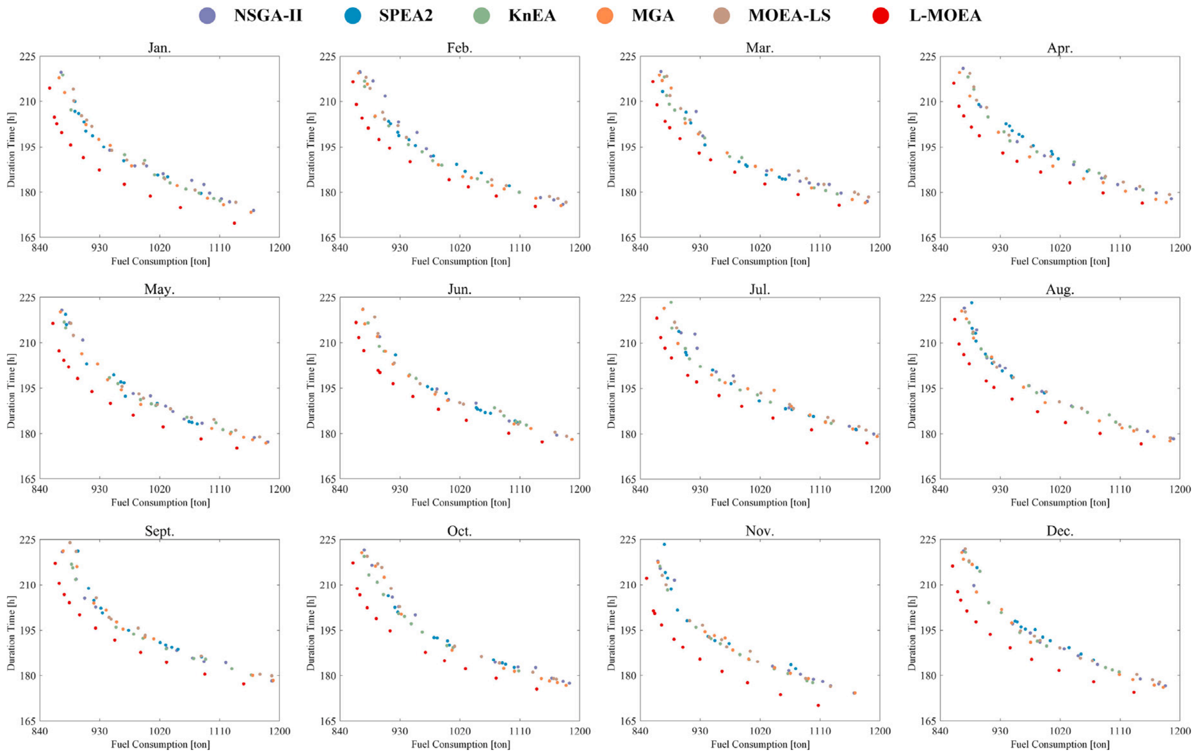

Fig. 5. The PF* of multi-objective route planning for each monthly voyage obtained by six optimization algorithms.

It should be noted that, since the primary focus of this paper is on improvements in the optimization algorithm and uncertainty handling, we adopt an existing ShipX-based performance model (Eskild, 2014) for the calculation of fuel consumption and duration time, based on ship particulars, navigational status, and met-ocean conditions. Meanwhile, a common static orthogonal grid system outlined by Eskild (2014) is employed to limit the navigation area of ocean-going ships to certain sea regions, excluding coastlines, islands, reefs, shallow waters, and other obstacles.

4.2. Superiority over state-of-the-art methods

In this section, we compare the proposed L-MOEA with the NSGA-II, SPEA2, KnEA, MGA, and MOEA-LS, which are widely-concerned algorithms for multi-objective ship route planning in relevant studies. Specifically, the Pareto optimal solutions, with objectives aiming to optimize fuel consumption and duration time, is generated through 200 iterations of a population with 200 individuals based on the mean of ensemble forecast, ensuring navigation safety as a priority.

Clearly, our proposed L-MOEA demonstrates obvious advantages across all voyages throughout the year, with a pronounced improvement effect observed in Fig. 5. On average, a saving of approximately 2.5% in fuel consumption and 2.0% in duration time is achieved during a single voyage over other algorithms, which allows shipping carriers with multiple in-service ships to realize substantial annual savings. Since there are typically steady northwesterly winds in the North Pacific during winter, providing a favorable boost for ships, the duration time of eastbound voyage is often smaller than that during summer. Undesirable inefficiencies occur where the evolutionary process of traditional MOEAs, based on random search, struggles to explore the vast feasible space with unevenly distributed samples. As depicted by the calculated Euclidean distance (the left subgraph of Fig. 6) between the current PF* and a unified initial PF*, existing MOEAs appear to overly prioritize samples in regions of high density, leading to significant efficiency and performance degradation as the iteration progresses. Hence, when the number of iterations exceeds 150, the PF* hardly changes. In other words, even if these algorithms spend more running time to perform additional iterations, the optimization results remain unsatisfactory (as shown by hexagons), which will be further analyzed in subsequent experiments. Our L-MOEA, in contrast, leverages the evolutionary knowledge within the sample optimization process through a learning network, enabling more efficient directed evolution, albeit with a slight increase in unit running time. Actually, when considering the quality of PF* as the criterion, our L-MOEA outperforms other MOEAs in terms of optimization results within a shorter time. In the test experiments conducted on a laptop equipped with a GeForce RTX 4060 GPU, our L-MOEA can generate a set of satisfactory solutions for multi-objective ship route planning within approximately 5 min, even for a route spanning around 4500 nautical miles, which indicates the applicability of the method in real scenarios. Simultaneously, owing to the self-optimization mechanism of the learning network, its capacity to produce Pareto-dominant navigation plans has even experienced a slight enhancement, as shown in the

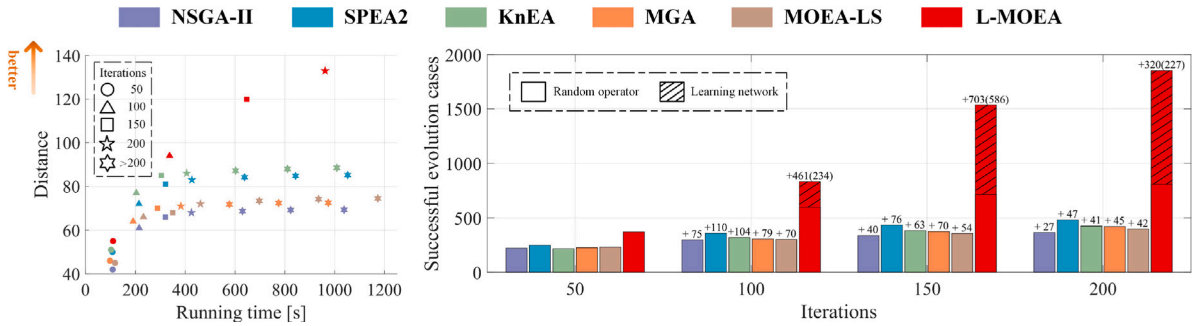

Fig. 6. The iteration time and performance records of each algorithm in the route planning for the voyage in January[1].

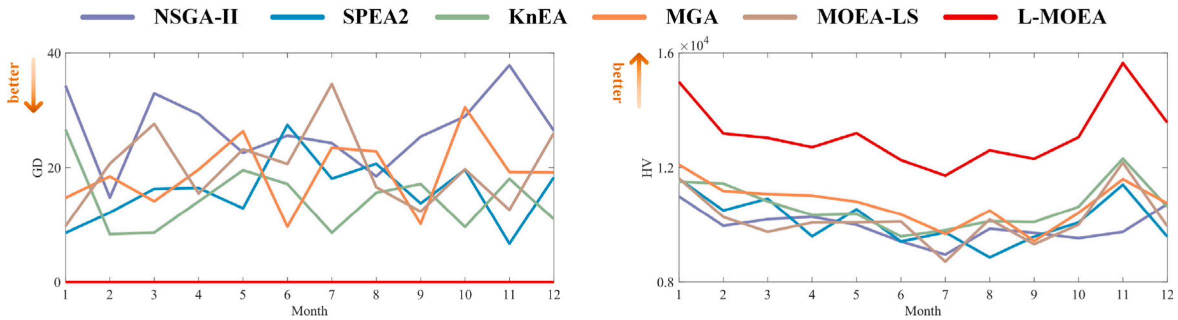

Fig. 7. Comparison of quality indicators of the PF* generated by six algorithms[2].

right subgraph of Fig. 6. Furthermore, the population modification strategies introduced in L-MOEA can effectively promote the evolutionary knowledge learning of the intelligent network, thus ensuring the convergence and diversity of the recommended plans. In comparison, the solution sets generated by other compared algorithms exhibit a somewhat uneven distribution, as illustrated in Fig. 5, which clearly fails to address diverse navigation needs and hampers effective coordination between ships and ports.

To provide a quantitative evaluation, we select two representative quality indicators: generational distance (GD) (Van Veldhuizen et al., 1998) for convergence, and hypervolume (HV) (Zitzler and Thiele, 1999) for both convergence and diversity. Among the indicators shown in Fig. 7, our algorithm exhibits the best GD, which directly and effectively demonstrates the convergence of optimization results. When considering spread and uniformity (collectively referred to as diversity), the frequently-used indicators for evaluating PF* are maximum spread (MS) (Zitzler et al., 2000) and spacing (SP) (Schott, 1995), respectively. Obviously, MS, which only considers the extreme solutions of the set, fails to effectively reflect the spread quality. Since it does not account for the convergence of the set, solutions that are far away from the PF* usually contribute significantly to the MS value (Adra and Fleming, 2010), such as the optimal plans (the voyages in Mar. and Nov. shown in Fig. 5) generated by NSGA-II. In addition, note that SP only gauges the distribution in the "neighborhood" of solutions. For instance, the SPEA2 may obtain a relatively good SP value, due to its optimization plans are mostly crowded in a very limited region, creating the illusion of superior uniformity. Even if working with MS, SP cannot cover the diversity quality of the set, though these two indicators were often used together to serve this purpose in the literature (Li and Yao, 2019). In summary, any measure of diversity alone lacks significance if it does not consider the convergence of the solution set. Hence, HV, arguably one of the most commonly used quality indicators with desirable practical usability and theoretical properties, is used to conduct a comprehensive assessment. Based on a reference point (1200, 225), the HV is sensitive to any improvement (both convergence and diversity) to a set with respect to Pareto dominance, demonstrating that L-MOEA has outstanding advantages over other approaches.

In addition, we provide visual results of optimized plans for analytical validation. Specifically, considering the February voyage as an example, an optimized route is depicted in red font in Fig. 8, along with the met-ocean conditions encountered by the ship at the time. The routing plan for comparison, i.e., the original route displayed in green font, involves the ship sailing at a fixed RPM (set as 111) along the GCR between the port of origin and destination. It can be observed that the optimized plan initially follows the GCR for a brief period, then turns toward higher latitudes, thus avoiding the high waves in the winter that can be foreseen by met-ocean forecasts. Due to the increase in distance, the ship needs to accelerate (RPM increased from 111 to 113) to ensure timely

[1] In the left subgraph, the Y-axis represents the Euclidean distance between the current PF* and a unified initial PF*. In the right subgraph, the marks above the bar chart indicate the superior plans generated every 50 iterations, with the values in parentheses representing the contributions of the evolutionary learning network.

[2] Note that due to the lack of a real PF*, the best sailing plan set for each voyage, which can be obtained, is used as its substitute in the calculation of GD.

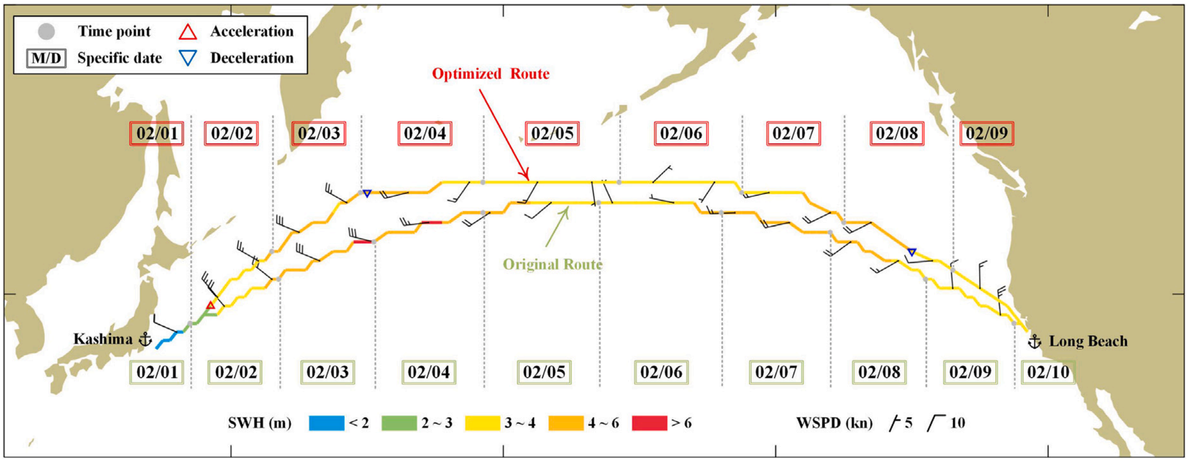

Fig. 8. An optimization example in the route planning for the voyage in February, including the route and sailing speed of the case ship, as well as the met-ocean conditions encountered.

arrival. Even with these adjustments, its completion of the voyage in the first three days is still slightly behind the original route, while also consuming more fuel. However, the original navigation plan will lead the ship through an area with waves exceeding six meters, posing a significant potential threat to the ship, crew, and cargo. According to the optimized plan, the ship then sails along the edge of the high wave zone and experiences a deceleration, returning to the originally set engine RPM. In contrast, adverse sea conditions severely affect the normal navigation of the ship on the GCR, causing its speed to significantly decrease and gradually fall behind the optimized route in terms of voyage completion. Toward the end of the voyage, in an effort to save fuel costs and reduce ship emissions, the ship in the optimization plan further reduces its RPM to 109. From a numerical standpoint, our optimization solution achieves an almost 2% savings in fuel consumption while arriving 5 h earlier.

4.2.1. More discussions

To verify that the random search in the evolutionary process largely contributes to the weak performance, within an acceptable range, we in this section further evaluate the existing optimization algorithms. Specifically, based on an extensive initial population consisting of 5000 individuals, a sample size of the same magnitude is selected for crossover and mutation operations in each iteration. We repeat the optimization process outlined above within an original framework, i.e., NSGA-II, conducting 1000 iterations. The exhaustive effort required to obtain the final solution sets necessitates tens of hours of calculation. To distinguish them from the results described in Section 4.2, we append a superscript "+" to the original symbol to signify the optimized plans derived from the extended algorithm, i.e., NSGA-II^{+}.

Let us take a glance at the initial populations generated by NSGA-II^{+}, NSGA-II, and L-MOEA, as illustrated in the left subgraph of Fig. 9. Through direct visual comparison, we can draw some preliminary conclusions. Firstly, when the initial population reaches a reasonable size, further random addition of new plans does not notably improve its quality. In the additional experiments conducted by sequentially increasing the population size to 10,000, 30,000, and 50,000, the aforementioned conclusion remains valid. Clearly, a deliberate generative strategy is more suitable than simply increasing its size indiscriminately. In our L-MOEA, the optimization results from Dijkstra's algorithm are integrated into the initial solution set, leading to a notable enhancement in population quality without the need to expand its size. Additionally, to enhance the diversity of the initial population, we incorporate the random variable speed sailing plans into NSGA-II^{+}. Unfortunately, these plans are clustered in a limited area of the feasible space, contrary to our expectations. This further reinforces our inference that random search tend to concentrate on regions with dense sample distribution, when there exists an uneven distribution of feasible samples. In conclusion, extending the initial population by generating plans with random speed and route does not effectively enhance its quality, but introduces unnecessary computational overhead.

According to the final optimized plans, as depicted in the right subgraph of Fig. 9, NSGA-II^{+} generates an additional approximately 0.4% savings, compared to NSGA-II, in fuel and time costs, which is less than the improvements brought about by L-MOEA. However, the iteration time required to obtain the optimal solutions ballooned drastically from minutes to dozens of hours. Clearly, sacrificing such a significant amount of time in exchange for an inappreciable improvement percentage is not desirable in the context of mass production reality. A detailed analysis reveals that even with the expansion of the sample size in the evolutionary process, the reliance on random evolutionary operators in traditional NSGA-II cannot overcome the inherent inefficiency. During each iteration, only a few individuals randomly evolve better navigation plans. In our L-MOEA, based on the evolutionary cases generated by the excellent iterative framework, the self-renewing intelligent learning network markedly enhances search efficiency, which has been verified in Fig. 6. Therefore, L-MOEA can purposefully explore the solution space in the optimal direction under small-scale search conditions, rather than aimless random attempts, resulting in the discovery of better solutions.

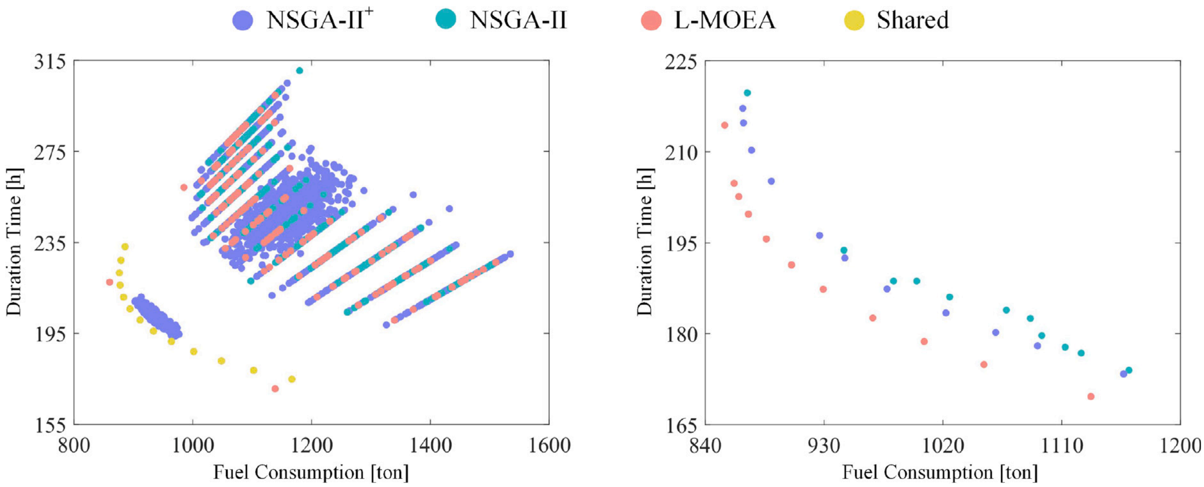

Fig. 9. The initial populations and PF* in the route planning for the voyage in January, where the "shared" indicates that the solution can be obtained by all methods.

Table 3
Aggregated objective function values in the route planning for the voyage in January under uncertain met-ocean forecasts.

Algorithm	Route	Aggregated objective value							
		FC_{max}	FC_{min}	FC_{mean}	FC_{var}	DT_{max}	DT_{min}	DT_{mean}	DT_{var}
NSGA-II	DT-Opt	1167.24	1153.39	1159.69	12.76 (+23%)	174.91	172.83	173.78	0.29 (+26%)
	BL-Opt	1033.82	1019.96	1025.43	15.10 (+397%)	187.42	185.16	186.06	0.42 (+180%)
	FC-Opt	874.24	868.80	871.55	1.71 (+11%)	220.30	218.94	219.62	0.13 (+86%)
SPEA2	DT-Opt	1188.13	1175.46	1180.72	12.81 (+24%)	180.62	178.58	179.42	0.28 (+22%)
	BL-Opt	913.32	905.70	908.84	6.21 (+100%)	201.18	199.49	200.18	0.26 (+73%)
	FC-Opt	894.44	889.58	891.08	1.81 (+18%)	218.41	216.72	217.24	0.14 (+100%)
KnEA	DT-Opt	1167.04	1153.39	1159.29	12.56 (+21%)	178.17	176.15	177.02	0.28 (+22%)
	BL-Opt	1017.92	1006.80	1010.92	8.58 (+168%)	186.72	184.77	185.51	0.27 (+80%)
	FC-Opt	876.58	871.65	873.90	1.85 (+20%)	219.26	217.03	218.60	0.13 (+86%)
MGA	DT-Opt	1163.22	1149.24	1155.62	12.85 (+24%)	174.31	172.21	173.17	0.29 (+26%)
	BL-Opt	932.08	925.57	928.07	7.74 (+142%)	198.26	196.78	197.35	0.20 (+33%)
	FC-Opt	871.51	866.00	868.61	1.89 (+23%)	218.39	217.03	217.67	0.12 (+71%)
MOEA-LS	DT-Opt	1145.74	1131.99	1138.04	12.56 (+21%)	177.66	175.61	176.51	0.28 (+22%)
	BL-Opt	921.28	914.74	917.52	6.15 (+92%)	202.52	201.01	201.65	0.22 (+47%)
	FC-Opt	892.64	887.54	889.56	2.11 (+37%)	216.62	215.37	216.87	0.13 (+86%)
L-MOEA-U	DT-Opt	1136.59	1124.45	1131.60	**10.38**	170.62	168.80	169.87	**0.23**
	BL-Opt	890.37	883.86	886.70	**3.20**	196.55	195.15	195.76	**0.15**
	FC-Opt	858.39	852.92	855.14	**1.54**	215.28	213.92	214.48	**0.07**

Note that FC and DT denote fuel consumption and duration time, respectively. The subscripts *max*, *min*, *mean*, and *var* represent the corresponding statistical indicators.

In conclusion, this section highlights the limitations in traditional MOEAs through a comparative experiment using "brute force". It is evident that the attempts to improve algorithmic performance still rely on the random search-based evolutionary process. In multi-objective route planning, which encompasses route and speed variations and involves countless feasible solutions, random exploration of solution space is bound to be inherently inefficient.

4.3. Validity of uncertainty reducing

Following a comprehensive demonstration of the superiority of our proposed L-MOEA over other models, we will further validate the capability of the uncertainty-driven module in generating stable routing plans. It should be noted that the experiments conducted continue to utilize the datasets and compared algorithms outlined in Section 4.2, wherein the uncertainty-driven module will be integrated into our L-MOEA (L-MOEA-U for short). The difference lies in that the information from each member of the ensemble forecast is used to reevaluate the final non-dominated plans, to generate their various possible objective function values under uncertain met-ocean conditions.

To avoid overly confusing visualizations, we present the numerical information (including the extreme value, mean value, and variance of the objective function values) for the case voyage in January here as an alternative, as listed in Table 3. To be specific,

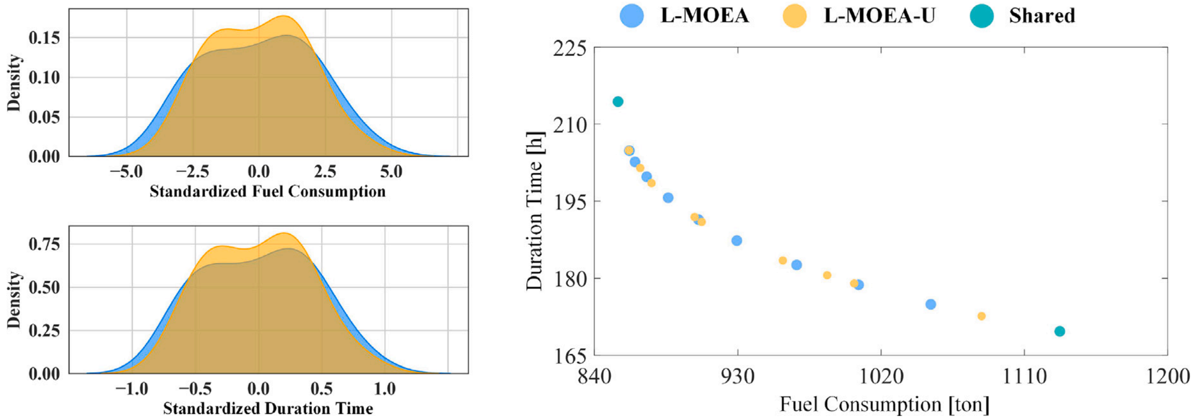

Fig. 10. Standardized kernel density histograms (Elman and Miller, 2012) and PF* in the route planning for the voyage in January.

three typical results (two endpoints and midpoint of PF*), i.e., the sailing plans with the shortest duration time but highest fuel consumption (DT-Opt), the least fuel consumption but longest duration time (FC-Opt), and a balance between fuel consumption and duration time (BL-Opt), are selected for quantitative analysis. It is worth noting that the percentage values in parentheses represent the increase in uncertainties of the navigation plans generated by other algorithms compared to L-MOEA-U. Evidently, the sailing plans produced by L-MOEA-U exhibit more stable time and fuel costs in the face of uncertain met-ocean conditions. The variances of the voyage cost generated by other algorithms are larger, generally more than 20% higher than that of L-MOEA-U, and even reaches nearly quadruple in the maximum. Such unstable routing plans can significantly impact the effective operation of the supply chain system. Therefore, the effectiveness of these optimization algorithms with high uncertainty in practical applications will be severely restricted.

In addition, we conduct an additional set of ablation studies to demonstrate that stable voyage costs are primarily due to the proposed uncertainty-driven module, by comparing optimization results from L-MOEA and L-MOEA-U. Taking the BL-Opt route defined above as an example, we first provide qualitative results in Fig. 10. Obviously, the optimized plans recommended by L-MOEA-U achieve a more concentrated distribution in objective functions. From a statistical perspective, the extreme value, mean value, and variance of fuel consumption and duration time of the L-MOEA-given BL-Opt route are respectively {907.19, 900.17, 903.32, 4.21} and {192.83, 191.37, 192.02, 0.19}, according to the order in Table 3. In contrast, the uncertainty-driven module in L-MOEA-U provides an additional improvement of about 30% in terms of cost stability on the January's BL-Opt route. More finely, we calculate the variances of objective function values across a total of 132 optimal sailing plans for 12 case voyages. From the quantitative results, L-MOEA-U reduces the uncertainty of fuel consumption and duration time of the final generated optimization plan by 16% and 10%, respectively. It should also be emphasized that after observing each optimization result, there is no Pareto dominance relationship between the non-dominated solution sets, respectively, provided by L-MOEA-U and L-MOEA, as the example in the right subgraph of Fig. 10. In other words, on the basis of ensuring the optimal convergence of the solution set, the proposed guidance module can further recommend more reliable plans to decision makers.

4.4. Long-term impacts on shipping logistics: An outlook

Ship route planning is an effective technique that aims to simultaneously optimize multiple objectives for a given voyage, such as minimizing fuel consumption, reducing voyage duration, avoiding hazardous weather, and decreasing ship emissions. In addition to directly minimizing voyage costs, reducing GHG emissions, and mitigating potential risks to the ship, cargo, and crew, the potential long-term impacts of our advanced L-MOEA on shipping logistics will be multifaceted:

1. Enhanced predictability and planning: More efficient route planning can enhance the predictability and reliability of shipping schedules, leading to improved logistical planning and inventory management for businesses reliant on maritime transport. From a system perspective, L-MOEA can boost overall supply chain efficiency.
2. Reduced congestion: L-MOEA can identify optimal routes within various delivery time windows to accommodate flow in heavily trafficked areas or align with port schedules. Over time, this will contribute to a balanced even distribution of maritime traffic, reducing bottlenecks in key shipping lanes and ports.
3. Gradual exploration of alternative routes: Traditional routes may be bypassed by L-MOEA in favor of alternative routes that offer better overall performance in terms of multi-objective criteria. This shift can facilitate the exploration and use of previously underutilized sea routes, thereby changing traditional shipping patterns.
4. Fuel efficiency improvements: One of the primary objectives of our proposed L-MOEA is to minimize fuel consumption and GHG emissions during voyages. Over the long term, consistent optimization of routes for fuel efficiency can lead to significant reductions in global maritime fuel consumption, supporting the international emission reduction targets and promoting greener maritime practices.

5. Adoption of green fuel and energy: The focus on fuel efficiency and emissions reduction in route planning can drive the adoption of eco-friendly technologies and fuels, such as liquefied natural gas and biofuels. This approach will support efforts to peak GHG emissions from international shipping as soon as possible and achieve net-zero emissions by or around 2050, in line with the Marine Environment Protection Committee's requirements presented in 2023.
6. Transition to environmentally sustainable navigation: The idea of driving the optimization process with learning-based networks in L-MOEA may be applicable to optimization tasks involving pure electric or sail-assisted ships, significantly accelerating the decarbonization process in the shipping industry.

5. Conclusions and future work

Multi-objective route planning, a task of paramount importance in the modern green shipping logistics, is dedicated to determining the optimal route and speed for a given voyage under complex and variable met-ocean conditions. Considering the inefficiency of existing MOEAs, we propose a L-MOEA framework along with an uncertainty-driven module (the integrated framework is defined as L-MOEA-U) for route planning, which offers the following advantages: Firstly, the proposed self-adaptive learning network can capture and respond to positive evolutionary directions in the iterative process, thereby driving the efficient exploration of the solution space and yielding preeminent routing plans. Compared to other state-of-the-art optimization methods, our L-MOEA achieves remarkable savings in fuel consumption and duration time during a given voyage, while also mitigating GHG emissions. Secondly, the multiple improvement strategies introduced in the evolution process effectively promote the learning of evolutionary knowledge, ensuring the convergence and diversity of the recommended plans. Therefore, for different voyage requirements, whether timely arrival or rapid travel, our L-MOEA can provide appropriate Pareto optimal plans within the corresponding region, which facilitates overall coordination between the ship and port, and even within the intermodal transport systems. Finally, the uncertainty-driven module based on ensemble forecast significantly contributes to generating more robust solutions while ensuring economic effectiveness, with a general improvement of over 20%. In real-world business scenarios, where complex and variable met-ocean conditions are the norm, our framework maximizes the reliability and safety of navigation plans, effectively averting inefficiencies and even disruptions in the supply chain systems.

While the proposed L-MOEA can generate high-quality navigation plans, our study represents only a preliminary attempt to utilize the learning network to drive multi-objective route planning. Building upon this foundation, further research aimed at enhancing the network performance to achieve superior optimization results holds great promise. In addition, the advent of advanced large language models like generative pre-trained transformer (GPT) has significantly impacted various fields (Liu et al. 2023b, Qu et al. 2023). Integrating GPT with L-MOEA presents exciting opportunities for future research. For example, GPT can be utilized to suggest a preliminary plan for the target voyage by analyzing large-scale historical shipping routes and met-ocean forecast datasets. Building on this foundation, further optimization with L-MOEA is expected to generate better solutions.

CRediT authorship contribution statement

Yuhan Guo: Writing – original draft, Visualization, Methodology. **Yiyang Wang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Data curation. **Yuhan Chen:** Validation, Investigation, Funding acquisition. **Lingxiao Wu:** Writing – review & editing, Validation, Funding acquisition. **Wengang Mao:** Validation, Supervision, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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