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Multistage Multicriteria Dynamic Decision Making Framework For Fishing Route Planning And Optimization

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Abstract

Fishing is a main activity in the Barents Sea. Improving fishing vessel trip planning is a feasible way to improve fishing efficiency, profitability, sustainability and at the same time reducing accidental risk from hazardous weather conditions and reducing environmental impact by reducing fuel consumption. Today, fishing trip planning and route optimization is all up to skippers' experiences. Determine where and when to go for fishing is a challenge. This paper presents a multi-stage multi-criteria dynamic route planning and optimization framework for pelagic fishing in the arctic. Developing such algorithms will allow using available data in decision-making for more efficient fishing. At the same time, the algorithms can be used to transmit the empiric knowledge of the skippers to the new generations. Users can customize their objectives when using the proposed fishing route planning and optimization model. The route planning and optimization model uses graph theory, pareto-optimal and genetic algorithms to find a set of optimal routes which contains a set of sequential fishing grounds to visit and fishing factory to deliver the catch, a combination of speed to sail between locations and a combination of duration to stop at each location. Dynamic routing is used to determine next action after finding the optimal routes so that options are open to opportunities and information in future. Skippers can use this as a support tool for their fishing trip planning and route optimization. At the same time, the algorithms can be tuned and improved through daily application and feedback to form a rich body of knowledge.

Keywords: route planning, fishing vessels, multi-stage multi-criteria decision-making, dynamic routing and optimization

1. Introduction

1.1. Background

Optimizing fishing route is a feasible way to achieve safer, more sustainable and environmental-friendly fishing. The arctic environment is fragile and need more careful planning for future fishing. Better trip planning is of interest to skippers and ship owners (Granholm et al., 2017). However, optimizing fishing route is a challenge tasks due to uncertainty, dynamic in fish groups, multiple objectives and constraints that need to be considered. Even though route planning and optimization or weather routing is a popular topic in the sector of maritime. Still less is considered for the fishing vessels. Right now, experienced skippers take the role of route optimization. it is a very knowledge and experience demanding job. Among all factors to be considered, commercial catch per unit effort is one of them that ship owners and skippers use for route planning (Salthaug and Aanes, 2003).

Fishing is still one of the most dangerous occupations in the world. Fishing counted for 26% of the total-loss accidents according to the data of total loss marine accidents of ships of 100 gross tonnage or above between 1998-2018 based on the Lloyd's List Intelligence Casualty Statistics (Chen et al., 2020). Small fishing vessels less than 100 gross tonnage are even more prone to accidents (Davis, Colbourne, and Molyneux, 2019). In Norway, fishing is one of the major industries and its death rate remains high despite the fact that the accident prevention, survival training and search and rescue services offered are among the best in the world, partly due to the fishing fleet operates in areas with rapidly changing natural conditions where strong winds, frigid waters, darkness and ice constitute a considerable risk of loss of lives (McGuinness et al., 2013a, 2013b). Furthermore, there is a polar ward of fishery due to that fact that receding sea ice opens the way to widespread fishing (Fauchald et al., 2021; Stocker, Renner, and Knol-Kauffman, 2020). Fishing vessel operation is one of the main activities in the arctic (Silber and Adams, 2019). All those statuses imply that there is a need for more efficient, safer and sustainable fishing in the arctic which provides the rational for this work. As for the direction of research to meet the demand, it will be multi-disciplinary, use multiple data sources, and adopt advanced research methods, to account for complex interactions between the natural environment, the development of naval technology, human behaviour, and market conditions (Luo and Shin, 2019). Developing framework and algorithms for fishing route optimization follows such a research trend.

1.2. Existing research

1.2.1. Fishing optimization

Fishing optimization can be conducted in many ways, such as optimizing fishing seasons, targeted fish types, fishing routes, fishing gears, fish detection equipment. Alizadeh Ashrafi, Ersdal, and Nordli (2022) used multi-objective optimization method to determine the fishing region, targeted fishing type determination and season in the Norwegian coast by considering the migratory behavior of different type of fish influences the dispersal of species, relative availability of fish and its composition, and the bycatch likelihood across different locations over the course of a fishing year with respect to the individual vessel quota constraints and bycatch considerations.

For fishing route optimization, Granado et al. (2021), after a review work, concluded that the technology for classic route optimization is ready for such, but further research is needed to meet the need of different types of fishing vessels. The available algorithms and objective functions need to be improved to fit the needs of fishing particularities.

Vettor et al. (2016) used a weather routing system to optimize the route for a pelagic fishing vessel which transit from a port in Portugal origin to a zone in Norway. Ship response model is included in the algorithm to know the added resistance from environment forces and to estimate fuel consumption. The ship response model can be used to calculate the ship response to the forecasted sea states represented by wave spectra and to assist planning the ship operations and routing (Rusu and Guedes Soares, 2014). Vettor et al. (2016) used Strength Pareto Evolutionary Algorithm SPEA2 (Zitzler, Laumanns, and Thiele, 2001) to find a set of optimal routes. Prior single objective optimization is used to choose the most favourable route among the set of optimal routes; a rank of routes is obtained according to the importance rank of objectives to make sure the chosen route satisfies the most important objective.

1.2.2. Weather routing

Weather routing or metrological path planning (Zis, Psaraftis, and Ding, 2020) is the use of real-time weather data to find the optimal route for a ship’s voyage to enhance navigation safety and reduce navigation costs in terms of emissions (Yu et al., 2021), distance, energy, and time under multiple constraints. To seek the best route, it usually considers several types of factors, including weather forecast, ship characteristics and voyage mission requirements. Weather routing problems are commonly modelled as a constrained graph problem, a constrained nonlinear optimization problem or as combination of both (Walther et al., 2016). Based on the formulation of the ship weather routing optimization problem different methods are used to solve it ranging from Dijkstra's algorithm (an algorithm for finding the shortest paths between nodes in a weighted graph) (Dijkstra, 1959), dynamic programming and optimal control methods to isochrone methods or iterative approaches for solving nonlinear optimization problems. Those methods utilize single-objective or multi-objective optimization. The determination whether an approach is suitable, produces sufficient results and may be recommended, strongly depends on the specific requirements concerning optimization objectives, control variables and constraints as well as the implementation. Genetic algorithms have become a popular approach for routing (Charalambopoulos, Xidias, and Nearchou, 2023).

1.2.3. Fuel consumption modelling

To be able to achieve routing optimization, it is necessary to know the relationships between routes and objectives and constraints. Reducing fuel consumption is one primary focus of route planning and optimization, because fuel consumption accounts up 30% of the operational cost for some fishing vessels. To understand fuel consumption, Cepowski and Drozd (2023) used measurements from 4,800 TEU container carrier that was in operation for 1,187 days data after hull cleaning to determine the mathematical relationships between fuel consumption and operation parameters, such as rotational speed, draught, trim, hull fouling time, wind speed, wave height, and seawater temperature. Basurko et al. (2022) investigated the energy efficiency of tropical tuna purse seiners fleet by comparing the two fishing strategies employed by the fleet: fish aggregating device (FAD) and free-swimming school (FSC) fishing. Furthermore, it studied the activity and energy consumption patterns of a tuna purse seiner operating in the Indian Ocean and identifies the vessel and engine performance variables that can be used to classify the different vessel activities. A modular weather routing system developed by Vettor and Guedes Soares (2016) includes a ship model to control speed for fuel consumption optimization. Overall, fuel consumption of fishing vessels is dependent on (a) the structure and size of the vessel; (b) the engine conditions and use patterns; (c) the fishing gears used; (d) the fishing and trip patterns; (e) the distance to the fishing ground; (f) target species and their migration routes; and (g) the traditions onboard (Basurko, Gabiña, and Uriondo, 2013). In the maritime sector, various fuel consumption models have been proposed for ship fuel consumption estimation with a primary motivation to optimize energy efficiency (Fan et al., 2022). Those researches can be used for the establishment of cost function of fuel consumption for fishing routing.

1.2.4. Risk modelling

Another motive is to enhance safety. Fishing vessels at sea are subject to many types of threats, such as storm, polar low, icing (Dhar et al., 2022), improper loading, heavy winch or crane operation (Davis et al., 2019). Those threats can threaten the stability of fishing vessels (Davis et al., 2019) and potentially leads to capsizing (Manderbacka et al., 2019; Míguez González and Bulian, 2018). To take safety into account in route optimization, a working risk model is vital. Recent developments can contribute to the risk modelling of fishing vessels and route optimization based on both vessel's operation conditions and weather conditions. When it comes to collision, AIS data can potentially be used to assess the collision risk of a fishing vessel (Du, Goerlandt, and Kujala, 2020). When it comes to capsizing or stability loss, the risk model should include conditions that threatens vessel stability into account. Those conditions include but not limited to maintenance conditions, loading conditions (Mantari, Silva, and Guedes Soares, 2011), harsh weather conditions, vessel modifications that reduce vessel stability, port availability, compromised watertight integrity conditions, poor design, crew's competences (Davis et al., 2019). Santiago Caamaño, Míguez González, and Díaz Casás (2018) proposed a stability guidance system to measure the real time stability of fishing vessels. The stability guidance system calculates the metacentric height by estimating the natural roll frequency in operation. Kim and Yeo (2020) proposed methods for the estimation of drafts and metacentric heights of small fishing vessels according to loading conditions. Im and Choe (2021) proposed an index approach for the assessment of intact stability. Those methods can be used in the risk modelling of stability loss of fishing routes.

Extreme or harsh weather conditions are commonly talked risk factors for fishing vessels. Ship icing is a combined effect of ship characteristics (Dehghani, Naterer, and Muzychka, 2018), sailing velocity, weather conditions (Samuelsen and Graversen, 2019). For ships to be operated in the Arctic where ice is a hazard, ice classification of ships has been implemented. Still there are challenges in such classification due to the difficulties to describe the ship-ice interaction parameters such as ship-ice contact characteristics, pressure distributions, and load levels in all the various ice conditions (Kujala et al., 2019). The ice classification information of a ship can be a parameter which represent one characteristic of the ship and be used in the risk modelling.

1.2.5. Multi-objective optimization

For multi-objective optimization, several types of methods have been developed such as the weighted sum method (Marler and Arora, 2010; Yang, 2014), lexicographic optimization (Isermann, 1982), Ɛ-constraint multi-objective optimization method (Thunuguntla and Injeti, 2020), and pareto optimization (Deb et al., 2002). The weighted sum method is a classical optimization method which suggests converting the multi-objective optimization to a single-objective optimization problem by giving weight to different objectives. Thus, a single solution that gives the best objective value is obtained. Lexicographic optimization method ranks the importance of objectives and find the optimal which provides maximum achievement in the most important objectives. Ɛ-constraint multi-objective optimization method reformulates the optimization problem by taking one of the objectives as objective function and converting other objectives into constraints (by setting specific limits for them). Pareto optimization methods try to find a set of optimal solutions that are as diverse as possible to balance the relative importance of different objectives. Several algorithms (multi-objective evolutionary algorithms (MOEAs)) have been proposed to find the Pareto optima set, such as Elitist Non-dominated Sorting generic algorithms (NSGA) that use non-dominated sorting and sharing (Deb et al., 2002).

1.3. Research objective

The objective of this research is to provide a framework and mathematical models for route planning and optimization for fishing vessels in the arctic. The optimized fishing route can provide references and guidance of route selection and optimization for captains of fishing vessels.

1.4. Paper structure

The rest of the paper is structured as follows: section 2 is the problem description. Section 3 presents the proposed multi-stage multi-criteria dynamic routing framework, where the overarching framework and major mathematical models are described. Section 4 is the discussion section and section 5 concluded the research.

2. Problem description

Directed graph can be used as graphical representation of fishing route, as illustrated by Fig. 1. Here, a route is defined as geographical locations that the vessels should to for fishing, including the average speed to reach each location and duration to stay at each location.

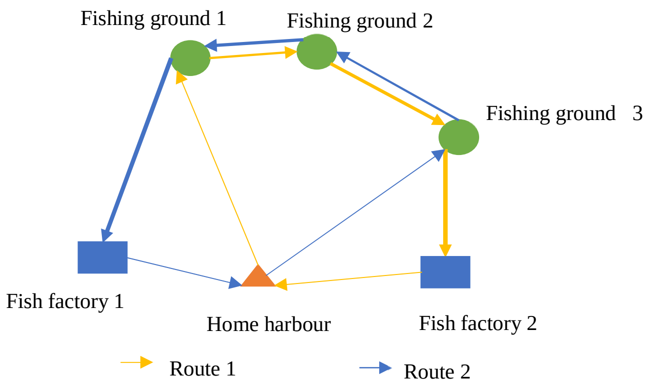


Fig. 1. An example of fishing routes.

A route r can be expressed as:

$$r = \left(grd_{1;d1} + r_{home,1;s1}\right) + \left(grd_{2;d2} + r_{1,2;s2}\right) + \left(grd_{3;d3} + r_{2,3;s3}\right) + \cdots + \left(grd_{n;dn} + r_{n-1,n;sn}\right) + \left(fac_{df} + r_{n,fac;sf}\right) + r_{fac,home;sh}$$

Where $grd_{n;dn}$ is fishing round n with a fishing duration d_n and $r_{n-1,n;sn}$ is the passage to fishing ground n from previous fishing ground at an average approaching speed s_n; fac is the fish factory where fish will be delivered to with a stop duration d_f; $r_{n,fac,sf}$ is the passage from the last fishing ground to fish factory with sailing speed s_f and $r_{fac,home;sh}$ is the returning from fish factory to home port with sailing speed s_h. The distance of each passage and average speed will determine the sailing time spent for each passage. The sailing speed of all previous passages and stop duration at previous places will determine the departure time and arrival time of each place. Therefore, a whole route is composed of arrays of locations, passages, speed, stop duration.

All places that a fishing vessel stops can be expressed as:

$$Loc = (home\ port \quad grd_1 \quad grd_2 \ \cdots \ fac \quad home\ port)$$

All passages between two places can be expressed as:

$$Pas = ((home\ port \quad grd_1) \quad (grd_2 \quad grd_3) \cdots (grd_n \quad fac) \quad (fac \quad home\ port))$$

The speed array of all passages of a route can be expressed as:

$$S = (\, s_1 \quad s_2 \quad s_3 \cdots s_f \quad s_h)$$

The stop duration array of all places of a route can be expressed as:

$$D = (\, d_1 \quad d_2 \quad d_3 \ \cdots\cdot\, d_f)$$

The length of stop duration array is 1 element shorter than the length of speed array. The length speed array and duration array are dependent on the number of stops on a route. A unique combination of locations, passages, speed array and duration array make a route. In reality, the final destination after fish be delivered may not be the same as home port where a vessel started. Their geographical positions can be defined individually. In addition, a fishing vessel may stop at a port to take a break or avoid extreme weather conditions. Therefore, port locations in addition to fishing grounds can be added in a route as well.

The route planning and optimization problem can be expressed as a multi-objective optimization problem, which is to find a set of routes (at least one) that could satisfy the minimization and/or maximization objectives and constraints. The general multi-criteria route optimization form can be formulated as:

Minimize/maximize	$O_i(r)$	$i = 1, 2, 3, \dots i;$
Subject to constraints	$g_j(r) \geq 0$	$j = 1, 2, 3, \dots j;$
	$h_k(r) = 0$	$k = 1, 2, 3, \dots k;$
	$r_m{}^{(L)} \leq r_m \leq r_m{}^{(U)}$	$m = 1, 2, 3, \dots m;$

A route r that does not satisfy all the constraints and is outside the variable bounds is called infeasible route. On the other hand, if any route r satisfies all the constraints and is within the variable bounds is called feasible route.

3. Proposed multi-stage multi-criteria dynamic routing framework

This section describes the details of the proposed framework. The overarching framework is described in section 3.1. The algorithm structure is presented in section 3.2 and mathematical model to determine the optimal route is described in section 3.3.

3.1. Proposed framework

Fig. illustrates the multi-stage multi-criteria decision-making framework for fishing route planning and optimization according to the common fishing practices. Level 1 Strategic decisions determines the targeted fish specifies, regions and seasons. Those decisions are usually made for long term fishing plan including quota to purchase and fishing gears to be equipped. Level 1 decisions do not relate to specific fishing trips but determines some key parameters for level 2 route decisions. Level 2 route decisions is for specific fishing trips. Level 3 next action decision is to determine the next location to go and speed to approach it. Level 4 is about generating more specific way points in the fishing route. Level 5 decisions are dropping and/or retrieving fishing gears.

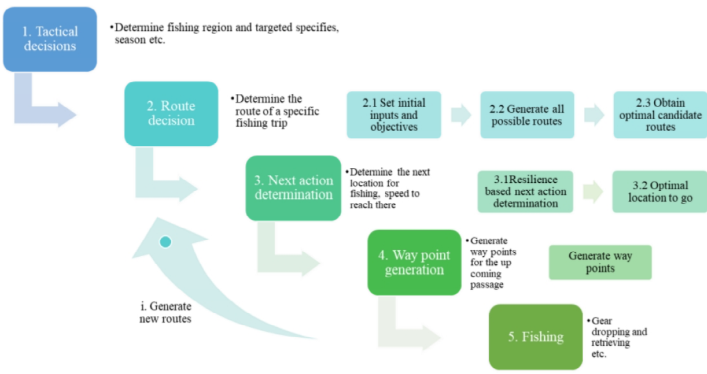


Fig. 2. Overarching framework of the proposed multi-stage multi-criteria dynamic routing.

The proposed framework assumes that a problem can be solved by solving all its subproblems. Global optimal can be achieved if all suboptimal are achieved. Due to dependency between different levels of decisions and status, the dynamic nature of fishing trip and unavoidable uncertainty in weather predictions, fish stock distribution, catch, hopeful, the level-by-level approach can somehow achieve certain degree of optimal.

3.2. Algorithm architecture

When it comes fishing route planning, Level 2 and level 3 decisions are included in the scope. Table 1 provides an overview of the algorithms used for the implementation of the framework. To implement the code by python language, ship, weather map, fish distribution map, ocean, graph classes, methods for objective function for nodes, passages, non-dominated sorting algorithm, genetic algorithm, dynamic routing etc. are programmed. To implement the algorithms, users just need to create a ship with its parameter values, targeted fish type, coordinates of home harbor, potential fish grounds and fish factories, constraints and objectives to be optimized.

Table 1. Main algorithms to implement the proposed framework.

Algorithm	Note
Result from global decisions	
Establish initial objectives, constraints, cost function, route network.	
While not done:	Starting or in a fishing trip
Update information regarding fish grounds, fish stock, weather forecast, inventory, objectives, etc.	Update vessel conditions, catch, and predictions about future conditions.
Determine the next stop, average speed to reach the next location and duration to stay at the next location:	
1) Using genetic algorithm to generate a defined number of pareto optimal speed and duration combinations for all possible routes from current location to the end.	Please see section 3.3.2 for pareto optimality and section 3.3.3 for the genetic algorithm
2) Apply pareto optimality again to select a defined number of optimal routes with speed and duration combinations.	Please see section 3.3.2 for pareto optimality.
3) Determine the next location to go from the selected pareto optimal routes by applying the most popular principle.	Please see section 3.3.4 for next action determination.
4) Determine the speed to go again from the filtered routes.	
5) Determine the duration to stay at next location.	

3.3. Detailed mathematical models

3.3.1. Cost function

To find the optimal routes, proper formulation of cost functions for objectives and constraints are vital. For each objective, the accumulated cost of a route can be expressed by:

$$O_i(r) = o_{i,r_{home,1;s_1}} + \sum_{grd=1}^{grd=k} \left(o_{i,r_{grd-1,grd};s_{grd}} + o_{i,grd;d_{grd}} \right) + o_{i,fac_{d_f}} + o_{i,r_{k,fac;s_f}} + o_{i,r_{fac,home;s_f}}$$

As for the contribution $o_{i,grd}$ from fishing ground grd or $o_{i,r_{grd-1,grd}}$ passing through a route $r_{grd-1,grd}$ toward a fishing ground grd can be expressed by a function of time, weather conditions, distances, condition of fishing ground, ship conditions, prediction accuracy etc.

$$o_{i,grd;d} = f_{grd}(W(t, loc, wind, current, wave, ir), fv_n(p_1, p_2, \dots, p_n), grd, d, prediction\ accuracy)$$

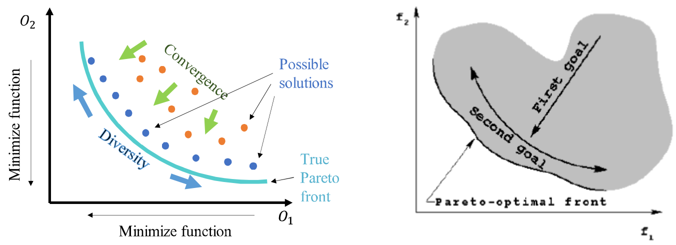
$$o_{i,r_{grd-1,grd;s}} = f_r\left(W(t, loc, wind, current, wave, ir), fv_n(p_1, p_2, \dots, p_n), r_{grd-1,grd}, \mathrm{s}, prediction\ accuracy\right)$$

Cost function of risk is associated with capsizing risk, collision risk, potential damage to fishing equipment, risk of running out of fuel. Operation cost is usually associated with personnel cost, fuel cost, degradation of fishing equipment and other administrative costs etc. User can define their customized cost function for their objectives and constraints of interests. The common objectives for a fishing vessel can be to maximize catch and minimize accidental risk and operational cost. The cost function for each objective and constraints can be formulated in a form provided above. Through this way, the objectives relate to a route which guide optimization algorithms to find the optimal routes.

3.3.2. Pareto-Optimality

Pareto-optimality is to find a set of dominate solutions without using weighted sum method to combine multiple objectives into one. A solution $r^{(1)}$ is said to dominate the other solutions $r^{(2)}$ if both the following conditions are true:

1) The solution $r^{(1)}$ is no worse than $r^{(2)}$ in all objectives.
2) The solution $r^{(1)}$ is strictly better than $r^{(2)}$ in at least one objective.



(a) (b)

Fig. 1. Pareto Optimality.

Pareto-Optimality is to find the set of feasible solutions that are 1) as close as possible to the Pareto-optimal front (convergence) and 2) as diverse as possible (diversity) so that they represent the entire Pareto-Optimal front. In this study, non-dominated Sorting algorithm proposed by Deb et al. (2002) are used to obtain a set of Pareto-optimal routes.

3.3.3. Genetic algorithms for speed and stop duration optimization of a path

For each path, to obtain a set of optimal combinations of speed and fishing or stop duration at each location, genetic algorithm is used. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. The genetic algorithm uses three main types of operations at each step to create the next generation from the current population:

- Selection: select a predefined number of individuals, called parents, that contribute to the population at the next generation. The top individuals sorted according to pareto optimality are selected.
- Crossover: combine two parents into a pair and randomly select a cutting point to perform crossover on the two parents.
- Mutation: apply random changes to parents after crossover operation to form children.

To start the evolution, a set of solutions are generated randomly from predefined gene spaces. Gene spaces are collections of feasible values of speed or duration for solution generation. To make sure that speed and duration fulfil certain constraints, the gene space for sampling speed and duration for each passage and node should be constrained. After each generation, a set of optimal solutions are selected using non-dominated sorting algorithms to achieve pareto optimal. Following such an evolutionary process, solutions converge to a local or global optimal after many generations.

3.3.4. Resilience-based next action determination for dynamic routing

. Fishing trip is a sequential activity with uncertainty about weather conditions and fish stock distribution. After obtaining the set of optimal routes, instead of randomly choose a route among the set of obtained pareto optimal routes, the strategy is only to decide the next place to go instead of determining the whole route following the obtained pareto optimal routes, with algorithms shown in Table 2. The next location to go is the location with the highest vote among the pareto optimal routes. For example, among the obtained 9 pareto optimal routes, 5 routes choose to go to location 1 to start the fishing trip, 3 routes choose to go to location 2 while only 1 route choose to go to location 3, then location 1 will be the next place to visit because it gets the highest votes (5 out of 9) and the other 2 locations get less votes. By doing so, it is not only to keep the optimal route but also to maintain a high level of resilience in route selection. Choosing the location with the highest votes will keep options open for future optimization with new information. Re-optimization can be conducted again to determine the next action based on new information. In case there is no location over compete the others, number of optimal solutions will be decreased until one over competes.

Table 2 Algorithm of resilience-based next action determination.

Algorithm of resilience-based next action determination
Assuming n optimal routes are found using pareto optimality and genetic algorithms: $$Optimal\ routes = \{r_1 \quad \cdots \quad r_n\}$$ Find the next location to go from all optimal routes by: $$Next\ locations = \{loc_1 \quad \cdots \quad loc_n\}$$ $$Next\ loc = mode(Next\ locations)$$ Obtain a reduced collection of optimal routes: $$Reduced\ optimal\ routes = \{r_i \quad r_j \quad \cdots\}$$ Find the optimal speed to reach the next location from the reduced collection of optimal routes: $$Speed\ collection\ to\ reach\ next\ loc = \{s_i \quad s_j \quad \cdots\}$$ $$Speed = mode(Speed\ collection\ to\ reach\ next\ loc)$$ The same way to determine the duration to stay at next location.
Note: $mode$ is the operator to find the element with the highest number of appearances in a collection.

4. Discussion

The proposed multi-stage multi-criteria dynamic routing framework can be used as a decision support tool by skippers for their fishing trip planning and optimization. The algorithms proposed for routing are with high possibility of customization. Ship owners and skippers can modify their objective functions based their preferences and ship characteristics and customize their objectives for route optimization. The computation speed is acceptable for onboard applications. In addition to onboard decision support, the algorithms can also be used for scenario simulation when making tactical decisions, and training of future skippers.

The proposed algorithms can be further developed into a platform for fishing routing combined with other data sources such as weather prediction data, historical oceanic weather data and hazard data base, historical AIS data of fishing vessels, fishing stock/grounds prediction and historical data. Potentially, data-driven cost functions can be obtained from historical data as well.

Still, there are some issues should be noted. Genetic algorithms cannot guarantee reaching definite optimal all the time. The calculation time for the evolutionary algorithm is dependent on complexity of functions used to calculate the values of objectives, No. of generations, required No. of optimal solutions, No. of pairs required for child generation creation. Fishing groups are dynamic, not static. The prediction of fishing group is demanding and has a big impact on routing.

To make the algorithms meaningful, the goodness of cost functions are the driver to guide the search of optimal route. Therefore, detailed cost function development, such as fuel, operation cost, risk modelling of passages and fishing activities are the next steps. Ship response model can be included in the optimization algorithm to estimate risk and fuel consumption etc. of a route for route planning and optimization.

To speed up calculation, dynamic gene spaces for the evolutionary algorithm can be implemented to reduce sampling size and speed up to find optimal speed and durations (Pan et al., 2021). Normalization of objective values can also be implemented to avoid disproportion between objectives for pareto distance calculation.

Another thing to bear in mind is that Pareto optimality treats all objectives equally import, which is useful for objectives that cannot be traded with each other, converted to others. However, it can be true that some objectives are more important than others. It might be beneficial to try the weight sum method for multi-objective optimization, or to combine pareto optimality and lexicographic optimization because it is possible that some objectives are more important than others. Therefore, the optimization algorithm can be designed to address such.

The purpose of route optimization is to achieve a global optimal which is challenging due to the dynamic, uncertainty, prediction inaccuracy. To achieve an optimal route, the over routing problem is divided into subproblems which are solved sequentially and based on knowledge of new state and availability of new information. A question is how many subproblems should be created, or how to know whether there are too many decisions or too few decisions. How to divide the global optimizations problems into sub problems can be discussed. In the study, the division is done by dividing the whole trip spectrum into segments in time sequence, which is logical because the framing of later sub problem is dependent on the results of earlier sub problem and newly arrived information. However, we did not try to prove that this is the optimal way of discomposing such type of problem.

5. Conclusion

This work proposes a multi-stage multi criteria dynamic routing framework for fishing vessels. NAGA-II algorithms are used to find a set of optimal speed and duration combinations for all possible paths. Again, pareto optimality is applied to select the optimal routes. A resilience-based concept is used to determine the next step from the calculated optimal routes in the previous step. This way reduces the impact of uncertainty and keeps more options available for future in cases of changes in the environment that predicted optimal is not optimal anymore. The proposed framework can be further developed into a standardized platform combined with other data sources to achieve a more sustainable, safer, environmental-friendly, efficient fishing and seafood supply.

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