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Review

Towards a framework for fishing route optimization decision support systems: Review of the state-of-the-art and challenges

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ABSTRACT

Route optimization methods offer an opportunity to the fisheries industry to enhance their efficiency, sustainability, and safety. However, the use of route optimization Decision Support Systems (DSS), which have been widely used in the shipping industry, is limited in the case of fisheries. In the first part, this work describes the fishing routing problems, reviews the state-of-the-art methods applied in the shipping industry, and introduces a general framework for fishing route optimization decision support systems (FRODSS). In the second part, we highlight the existing gap for the application of DSS in fisheries, and how to develop a FRODSS considering the different types of fishing fleets. Finally, and using the diverse Basque fishing fleet as a case study, we conclude that fishing fleets can be summarized into four main groups whose fishing routes could be optimized in a similar way. This characterization is based on their similarities, such us the target species, fishing gear, and the type and distance to the fishing grounds. These four groups are: (i) small-scale coastal fleet; (ii) large-scale pelagic fleet; (iii) large-scale demersal fleet; and (iv) the distant-water fleet. Distant-water vessels are currently the fleet that can more easily benefit from FRODSS, and they are used as an example here. However, the rest of the fleets could also benefit through adequate adaptation to their operation characteristics, driven by their specific fishing gear and target species.

1. Introduction

Maritime shipping is the most important goods transport mode in the world, representing around 90% of global trade (George, 2013). Shipping, as well as fisheries, require a large amount of energy to operate, and this consumption represents a large portion of their cost and Greenhouse Gas (GHG) emissions. Therefore, improving efficiency in this industry could have a great impact on increasing profits, while reducing costs and environmental impacts. The efficiency improvements could focus on six main potential areas (Bouman et al., 2017): (i) hull design, which encompasses the hull dimension, shape and weight with the challenge of minimizing the water resistance faced by vessels (Lindstad et al., 2014); (ii) economy of scale, by means of using large vessels since they tend to be more energy-efficient per freight unit (Gucwa and Schäfer, 2013); (iii) power and propulsion, which includes the design of new systems aimed at improving efficiency and energy saving (Sciberras et al., 2015); (iv) fuels and alternative energy sources, which involves the improvement of existing ones and the search for new energy sources (Gabiña et al., 2019); (v) speed reduction, the so-called slow steaming where many ships operate at less than their maximum speed to reduce their fuel consumption (Cariou, 2011); and (vi) ship routing, which consists in finding the optimum route and speed (Christiansen et al., 2004).

Out of the six areas of efficiency cited previously, the present study focuses on ship routing and its application for fisheries. The planning horizon influences the problem objectives and constraints. Usually, these planning levels are defined as strategic (long-term), tactical (medium-term) or operational (short-term) (Christiansen et al., 2004). We will not discuss the strategic problems in detail here, and for further information readers may refer to some of these works (Christiansen et al., 2004, 2013). At tactical level, the ship routing problem is known as the ship *routing and scheduling* problem, whereas at operational level it is called ship *weather routing*. Therefore, here the ship routing problem refers to two different maritime problems according to the planning horizon level at which they are stated and solved (Table 1). The ship *routing and scheduling* is a distribution problem where the goal is to find a path – or paths – that visits a set of ports (routing),

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Table 1
Summary of the main characteristics of the studied planning horizon.

Problem	Formulation	Planning horizon	Scope	Main objectives	Main constraints	Example of problems
Weather routing (operational)	SPP	Short-term (1 day–1 week)	One vessel	Time or FOC	- Time window - Ship capacity - Draft limit	- Best course and/or speed between two points
Routing and scheduling (tactical)	TSP/VRP	Medium-term (1 week–1 year)	One vessel or multiple vessels	Cost or profits	- Land avoidance - Shallow waters - Safety	- Routing and scheduling - Fleet deployment - Scheduling and speed optimization - Cargo allocation

Notes: TSP is the travelling salesperson problems; VRP is the vehicle routing problem; and SPP is the shortest path problem; FOC is the fuel-oil consumption.

and arrange stops/visits in an optimal possible sequence (scheduling) in order to for a ship or multiple ships to pick up and deliver some cargoes. By contrast, the ship *weather routing* refers to a short path problem for a single ship that estimates the optimal path between two known points according to one or more objective functions, and considering the weather effect on the ship performance (Zis et al., 2020).

These tactical and operational ship routing methods are usually embedded into decision support systems (DSS) (Lazarowska, 2014; Vettor and Soares, 2015; Lee et al., 2018a), which are computer-based information systems developed in order to support managers in the decision-making processes. Fishing activities need similar levels of planning to other marine activities, but the development of fishing route optimization decision support systems (FRODSS) is scarce. This is because the tactical and operational fishing planning is one of the most challenging since fisheries must face additional uncertainties, such as fish ground location and policy limitations (e.g. catches or time at sea). Therefore, to define a fishing planning strategy, a FRODSS should consider these added uncertainties and other fishing particularities, such as the target species, fishing gear, specific legislation, or the distance to the fishing grounds.

In general, the shipping industry has a long history of implementing ship routing methods, especially for large ships and long distances (Takashima et al., 2009). Usually, the goal is to reduce their operation cost, fuel-oil consumption, sailing time, or increase their profit. However, recently, new regulations are also trying to minimize their environmental impact, such as the establishment of four emission control areas (ECAs) to reduce ship emissions (Ma et al., 2020). On average, global shipping and fishing contributed 2.6% of the annual global anthropogenic CO_2 emission for the period 2013–2015 (Olmer et al., 2017). This emission represented around 930 million tonnes of CO_2, of which the industrial fishing vessels accounted for approximately 40 million tonnes of CO_2. Nevertheless, this number is probably an underestimation, as other studies suggest that industrial and semi-industrial fishing vessel emissions account for 159 and 48 million tonnes of CO_2, respectively (Greer et al., 2019). Within the different marine sectors, shipping emissions increased by 1.8%, whereas the fishing emission increased by 17% for the period 2013–2015 (Olmer et al., 2017). Furthermore, future projections estimate an increase of maritime CO_2 emissions, including fisheries, of between 50% and 250% for the year 2050, depending on future economic and energy developments (IMO, 2015). Although, CO_2 is the main contributor of the fisheries carbon footprint, there are other greenhouse gases (GHG) that contribute to shipping's climate impact, such as black carbon (BC), methane (CH_4) and nitrous oxide (N_2O). These pollutants are estimated to contribute around 25% of the CO_2 equivalent (Olmer et al., 2017). Shipping activities also emitted other important air pollutants, such as nitrogen oxides (NO_x), sulphur oxides (SO_x) and particulate matter (PM).

Unlike shipping, the environmental impacts of fishing activities have mainly been focused on overfishing of the target stocks, incidentally caught organisms, physical damage to benthic communities and substrates, and the alteration of ecosystem structures and functions (Hospido and Tyedmers, 2005). By focusing on these biological impacts, the environmental analysis of fisheries has underestimated other impacts, such as energy and material use, anti-fouling paints, or gear use and loss at sea (Vázquez-Rowe et al., 2010). In this context, the use of life cycle analysis (LCA) can provide the opportunity to identify and assess all the fishing activities and hence, lead to a more effective reduction of the overall impacts of fisheries (Avadí and Fréon, 2013). For example, some LCA studies suggest that the fuel consumption of fishing vessels account for between 60% and 90% of the total life cycle GHG emission (Parker et al., 2015).

The first purpose of this manuscript is to give a definition of the fishing problem along with a review of the state-of-the-art of ship routing, specifically, in terms of the algorithms, objectives and constraints applied in the shipping industry, and how they can be applied to fisheries (Section 2). This review will allow readers to follow and evaluate the current procedures used, and how they are integrated into a DSS. The second goal is to identify the current gaps in the application of these routing methods to fishing vessels, and to give advice for future work in tactical and operational ship routing in fisheries (Sections 3 and 4). This review is intended for fishing companies, policy-makers, and research communities, to show the potential of these techniques and the needs for the development of a fishing routing decision support system (FRODSS). Research communities can find the technological and scientific gaps that need to be filled for the development of FRODSS. Fishing companies can see the economic benefits, and a guide to implement the decision systems. Policy-makers can understand the needs for the development of FRODSS to guide policies and funding. To the best of our knowledge, no studies have attempted to develop specific fishing routing methods while considering their fishing particularities.

2. A decision support system (DSS) for ship routing problem in fisheries

Fishing vessels increase their profit and long-term sustainability through different strategies, such as fuel consumption reduction, catching high value species, reducing time at sea, or catching larger size fish, whilst dealing with constraints, such as emissions, bycatch limitations, or catch quotas, among others. These goals and constraints can be balanced by means of FRODSSs to aid in tactical and operational decision-making processes.

1. Tactical decision varies from setting the departure–arrival dates, fishing ground selection, or landing port selection, among others. The planning horizon of this problem ranges from one week to several weeks. This problem refers to fishing vessels departing from port to search for fish schools, and once they catch enough fish or a specific fishing trip duration is met, returning to a port to discharge the catches. The departure and arrival port can be different, and each fishing vessel can visit one or several fishing grounds during the fishing trip. The number of fishing grounds visited may be based on the vessel capacity, the current catches, the fuel-oil consumption, or a predefined trip duration.
2. The operational fishing planning problem consists of defining the vessel's heading and/or speed between the departure/arrival port and each fishing ground. For that, once the problem has been solved at tactical level, and therefore the waypoints are

defined, the operational problem attempts to find the best path between each pair of known waypoints/fishing grounds, considering the weather effect on the vessel performance along the route. This operational planning is usually limited to the next few hours or days at most, due to changing environment conditions and potential fishing grounds.

Therefore, the fishing routing problem could be addressed in two phases: (i) as a ship weather routing system at operational level; and (ii) as a routing and scheduling problem at tactical level. At tactical level, the fishing problem, like most of the maritime shipping problems, could be formulated as a variant of the well-known travelling salesperson problem (TSP) or vehicle routing problem (VRP). These TSP or VRP problems could be formulated using two different scenarios: static (Mesquita et al., 2017) or dynamic (Groba et al., 2015). In the literature, there are a lot of studies working in dynamic VRP. However, in ship routing and scheduling problems, dynamic approaches are still scarce because the occurrence of dynamic scenarios is highly unlikely (Psaraftis et al., 2016). In contrast, dynamic scenarios are more common in weather routing problems since they deal with the high variation and uncertainty of weather conditions. However, a limitation to formulating a unique problem for the entire fishing sector is the high variety of target species, fishing gear, distance to fishing grounds and management constraints within the fishing fleets. For example, target species have a big impact on vessel characteristics, fishing pattern, management constraints, and fuel consumption.

A general framework for a ship routing DSS can be defined by four layers (Fabbri et al., 2018). However, an additional layer needs to be added for the fishing industry case in order to consider the fishing particularities, such as fishing gear used, the target species, the fleet composition, management regulations and/or target market logic (e.g., fresh or canned). These five layers, and how they are integrated together to create a fishing route optimization decision support system (FRODSS), are summarized in Fig. 1.

The five layers of a FRODSS are:

- **Environmental layer**, which provides the metocean information needed to model the ship behaviour under different weather conditions, and some of the fishing layer elements. The most common approach for ship routing is to use some of the critical weather variables (i.e., waves, wind and/or currents) affecting ships' performance (Sidoti et al., 2016). In the case of fisheries, these critical variables are those related to the target species distribution models.
- **Ship modelling layer**, which predicts the ship behaviour under different weather conditions by using the data provided by the environment layer along with the ship characteristics (Gkerekos and Lazakis, 2020). Nevertheless, its accurate estimation is a complex and difficult task due to the presence of uncertain stochastic processes and its dependence on many factors (Soner et al., 2018).
- **Fisheries layer**, which is the layer that considers the fishing particularities such as species distribution and abundance predictions (Galparsoro et al., 2009); fishing grounds selection (Iglesias et al., 2007); fishing pattern detection using automatic identification system (AIS) data (Taconet et al., 2019); fish price (Guttormsen, 1999), and demand models (Eales et al., 1997); and tuna or bycatch detection by means of echo-sounder buoys attached to Fishing Aggregation Devices (FADs) (Orue et al., 2019; Mannocci et al., 2021). However, the results of these models usually have high uncertainty, adding more complexity to the problem of finding the optimal route and fishing solution.
- **Routing and planning layer**, which searches for the optimal route according to the input of the previous three components. This layer is the core of the DSS, and the optimal route is computed according to the objectives and optimization algorithm. A review of the main objective functions and optimization algorithms used in weather routing is conducted in Sections 2.1 and 2.3, respectively.
- **Decision layer**, which is the graphical component that interacts with the final user by selecting the final route. The design of this software application will depend on the desired format to display the selected route and the needed interaction between the user and the routing and planning layer. Some examples are given in Lazarowska (2014) and Vettor and Guedes Soares (2016).

2.1. Objective functions

The objectives used in the ship routing problem can vary depending on the planning horizon. At tactical level, the objectives are usually more global, whereas at operational level the objectives focus on more specific goals. The **overall cost** reduction or the **increase of profit** are commonly used in ship routing and scheduling problems at tactical planning level. There are also other goals that have been gaining more interest recently to reduce shipping environmental impacts, such as emission reduction (Fagerholt et al., 2015). Fisheries can use similar indicators. However, assessing the overall cost and profits faces the uncertainty variable duration driven by catches.

At operational level, the most studied objectives have been the sailing time, fuel-oil consumption (FOC), and safety. Common approaches to optimize the **minimum-time** objective consider that ship speed is affected by the sea conditions (involuntary speed reduction). This can also include the voluntary speed reduction (Sen and Padhy, 2015; Mannarini et al., 2016a). One of the first approaches that optimized the **fuel consumption** was directly proposed by Klompstra et al. (1992), and nowadays this is one of the main concerns of the shipping industry. The operational fishing routing should use indicators that consider landings, such as fuel consumption per catch (L fuel/tn catch landed) (Damalas et al., 2015), and detailed by target species, fishing gear, fishing effort or region (Greer et al., 2019). A **safety** consideration was also studied with the aim of avoiding rough weather areas. In our case, we have to consider that fishery is one of the most dangerous occupations in the world with 80 deaths per 100,000 fishers per year (FAO, 2018).

In practice, the fishing routing problem is not limited to optimizing a unique objective function. Multiple objectives can be addressed in two ways. Firstly, by optimizing a weighted combination of the desired objectives in one objective function (Kosmas and Vlachos, 2012), and secondly, to use a multi-objective optimization solving strategy, which treat each objective separately (Vettor and Guedes Soares, 2016). In the first approach, these weighted parameters can be tuned to give a relative importance to each objective based on the user's preferences. However, the solution found might not be accepted as a good solution, requiring further tuning of the weights (Maki et al., 2011). In the second technique, the optimization of one objective often comes at the expense of the others. Hence, there may be no single solution that optimizes all objective functions at once. That is why there is a set of optimal solutions that form the so-called Pareto Front (Newbery and Stiglitz, 1984). This approach adds flexibility to the route optimization, allowing us to vary the preference for each objective depending on the interests at that time.

2.2. Constraints

At tactical planning level, the most studied and common constraints in shipping are the time windows, ship capacity, or draft limit. The time window usually refers to the unloading/loading service times allowed at ports, (Sigurd et al., 2005); ship capacity is the ship's cargo carrying capacity measured in weight or volume (Stålhane et al., 2015); and the draft limit depends on each port infrastructure and the load weight, which can limit the ports that a ship can visit (De et al., 2017; Yamashita et al., 2019). At operational level, the necessary constraints to consider are land and shallow water avoidance, since these constraints represent non-navigable geographic areas that a ship route cannot cross (Fang and Lin, 2015; Vettor and Guedes Soares, 2016).

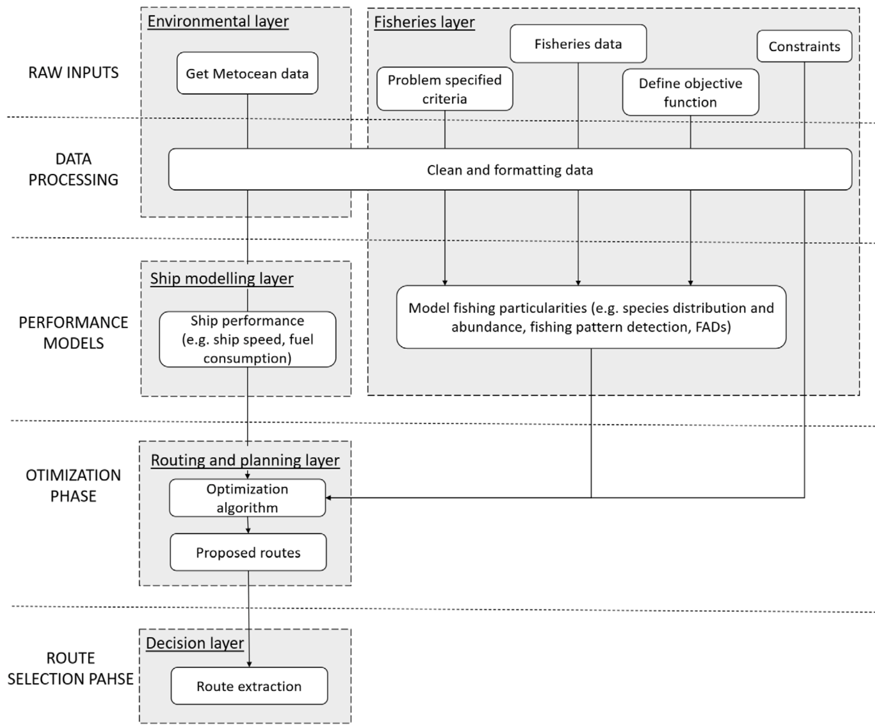


Fig. 1. A general scheme of a fishing route optimization decision support system (FRODSS).

There are other weather-related constraints, such as storm area avoidance, emission-controlled areas, or navigation safety constraints that try to keep the unstable ship motion-limiting criteria within some limits (Szlapczynska, 2015; Fang and Lin, 2015; Vettor and Guedes Soares, 2016).

Apart from the common constraints that are used in shipping and that can be translated directly to fishing routing, there are some specific fishing constraints. The main management constraints to consider in fishery planning include the total allowable effort (TAE), total allowable catch (TAC), quota regulations and landing obligation. TAE is the maximum number of fishing days by fishing area and by vessels during a specific period, whereas TAC is the maximum quantity of fish catch that can be caught from a specific stock over a given period of time (Prellezo et al., 2016). TACs are catch limits (expressed in tonnes or numbers) that are set for most commercial fish stocks. TACs are shared between EU countries in the form of national quotas. By 2019, all species subject to TAC limits or Minimum Conservation Reference Sizes (in the Mediterranean) were subject to the landing obligation (Reg, 2008). For mixed fishery, this could involve some problems as there will always be a choke species that can potentially limit their fishing effort on other species (Prellezo et al., 2016). Finally, there are more specific constraints based on the type of fishing vessel. This will be discussed for each fleet in Section 3.1.

2.3. Algorithms for solving ship routing problems

There are two types of optimization methods: exact and heuristic. Exact algorithms guarantee the optimal route, normally at the expense of the computation time, whereas heuristic approaches run faster but do not guarantee the optimal route. It should be emphasized that the following sections will focus on operational (see Section 2.3.1) and tactical (see Section 2.3.2) routing problems, and they do not present an extensive survey but rather provide an overall view of the main algorithms applied in each ship routing area.

2.3.1. Operational ship weather routing methods

Table 2 lists a number of papers related to ship weather routing, with respect to the algorithm used, and the optimized objectives, together with the main constraints and ship types. These constraints do not include land avoidance or control constraints (speed or heading limits) since they are mandatory to produce a realistic route. Furthermore, motion constraint encompasses the ships' unstable motions that are used as safety and comfort criteria. Some key optimization algorithms applied in the field are described.

In 1957, the **Isochrone** exact method was proposed for ship routing to minimize the sailing time (James, 1957). However, its computer implementation was problematic due to the occurrence of the so-called Isochrone loop, leading to the modified isochrone (Hagiwara, 1989). In contrast, the Isopone method was developed to optimize the fuel-oil consumption (Klompstra et al., 1992). There is a heuristic modification called the 3-dimensional modified isochrone (3DMI) (Fang and Lin, 2015).

Dynamic programming (DP) can be divided in two main approaches. First, 2D dynamic programming (2DDP), which takes two dimensions into account, latitude and longitude (Zoppoli, 1972). And second, 3D dynamic programming (3DDP), which can consider the time, in addition to the location, during the optimization process (Shao et al., 2012).

Dijkstra's and **A* algorithms** are the most common pathfinding algorithms used to solve the shortest path problem in a weighted graph. Dijkstra's algorithm has been widely used for ship routing with the aim of finding the minimal time route (Sen and Padhy, 2015), the minimum FOC routes (Takashima et al., 2009), or a combination of both by following a multi-objective approach (Skoglund, 2012). The A* algorithm derives from the Dijkstra's algorithm (low computational efficiency) and the greedy algorithm (fast search speed) (Hart et al., 1968). It gives a balance between search speed and global optimality. This method has been broadly used for route optimization in different situations, for example, in ice-covered waters (Guinness et al., 2014), routing in short distances (Grifoll et al., 2018) or transoceanic routing (Yoon et al., 2018).

Table 2
The main weather routing algorithms used in the literature according to the objective function and the main constraints considered in each case.

	Ref.	Ship type	Objective function	Main constraints	Algorithm
Exact	James (1957)	Trans-ocean ship	Min time		Isochrone
	Hagiwara (1989)	Sail-assisted ship	Min time, FOC, or cost		Modified Isochrone
	Klompstra et al. (1992)	Container ship	Min FOC	ETA, water depth	Isopone
	Zoppoli (1972)	Cargo-ship	Min time		Dynamic programming
	Shao et al. (2012)	Container ship	Min FOC	Motion	Dynamic programming
	Takashima et al. (2009)	Coastal merchant ship	Min FOC		Dijkstra's algorithm
	Skoglund (2012)	General	Min time and FOC		Dijkstra's algorithm
	Sen and Padhy (2015)	Coastal ships	Min time	Motion	Dijkstra's algorithm
Heuristic	Fang and Lin (2015)	Container ship	Min time and FOC	Motion, water depth	3D Modified Isochrone
	Guinness et al. (2014)	Ice-going ship	Min cost function	Motion	A* algorithm
	Yoon et al. (2018)	Container ship	Min FOC	Motion	A* algorithm
	Grifoll et al. (2018)	Ro/Ro ship	Min time		A* algorithm
	Marie and Courteille (2009)	Motor vessel	Min time and FOC		Genetic algorithm
	Lee et al. (2018b)	Container ship	Min FOC	ETA	Genetic algorithm
	Szlapczynska (2015)	General	Min FOC, time, and max safety	Water depth, piracy areas and high wind areas	Genetic algorithm
	Vettor and Soares (2015)	Container ship	Min FOC, time, and max safety	Motion	Genetic algorithm
	Ibarbia et al. (2011)	Oceanographic ship	Min time		Simulated Annealing
	Kosmas and Vlachos (2012)	General	Min time and max safety		Simulated Annealing
	Li and Qiao (2019)	Wind-assisted ship	Min FOC and max safety	ETA	Simulated Annealing
	Tsou and Cheng (2013)	Transoceanic ship	Min cost	Motion	Ant colony algorithm
	Lazarowska (2014)	General	Min distance	Motion	Ant colony algorithm
	Lee et al. (2018a)	Liner shipping	Min FOC and max service level	Speed, ETA	Particle swarm
	Zheng et al. (2019)	Ocean-going ships	Min FOC	ETA	Particle swarm
	Lin (2018)	Container ship	Min time and FOC	Motion	Particle swarm
Machine learning	Hagiwara et al. (1996)	Container ship	Min time		Artificial Neural Networks
	Torres Palenzuela et al. (2010)	Fishing vessels	Min FOC		Artificial Neural Networks
	Yoo and Kim (2015)	Theoretical	Min time	Motion	Reinforcement learning

Abbreviations are: fuel-oil consumption (FOC) and estimated time of arrival (ETA).

Nature inspired algorithms are heuristic methods based on mimic natural processes. Within this group, the most commonly used method is the **genetic algorithm** (GA), which is a population-based approach that iteratively improves the set of best solutions or population (Goldberg, 1989). One of the first approaches for ship routing optimization was using a multi-objective genetic algorithm (MOGA) technique (Marie and Courteille, 2009). Other methods incorporate elitism selection, which means keeping intact the best or a small portion of the best solutions from the current population for next generation (Szlapczynska, 2015; Vettor and Soares, 2015). Another method is the NSGA-II (non-dominated sorting genetic algorithm), which uses fast non-dominated sorting and crowd-distance comparison to select the next set of solutions in each iteration (Lee et al., 2018b). Other nature inspired methods used for ship routing are: (i) **Simulated annealing algorithm** (SA), which mimics the annealing process of metallurgy, which is a heat treatment that involves warming a material and then slow cooling (Ibarbia et al., 2011; Kosmas and Vlachos, 2012; Li and Qiao, 2019); (ii) **Ant colony algorithm** (ACA), which is a probabilistic technique inspired by ants' foraging behaviour (Tsou and Cheng, 2013; Lazarowska, 2014); and (iii) **Particle swarm optimization** (PSO), which is a population-based method that mimics the social behaviour of organisms in groups, such as birds or fish (Lee et al., 2018a; Lin, 2018; Zheng et al., 2019).

Machine learning is a growing research field that is involved in finding patterns or mine knowledge from data. A neural network algorithm (ANN) was among the first to be applied to weather routing (Hagiwara et al., 1996; Torres Palenzuela et al., 2010). A reinforcement learning algorithm (Q learning algorithm) was used for route planning to minimize the sailing time considering the current effects (Yoo and Kim, 2015).

2.3.2. Tactical ship routing and scheduling methods

Table 3 lists a number of papers related to ship routing and scheduling problems, with respect to the shipping mode, problem type, the optimized objectives together with the main constraints, and the solution method used to solve the problem. The main constraints considered to complete the table are time window (TW), ship capacity (SC), allocation (AL), ship/cargo compatibility (SC-C), port/ship compatibility (PS-C), customer/ship compatibility (CS-C), route/schedule compatibility (RS-C) and draft limit (DL). Some key optimization algorithms applied in the field are:

Branch-and-bound (B&B) consists of a systematic enumeration of all candidate solutions (branches), where large subsets of partial solutions are discarded if they cannot improve on the current best solution (bounds) (Land and Doig, 2010). This exact approach was used in tramp ship scheduling with both optional and contracted cargos (Appelgren, 1971). It was also used to solve the offshore wind farm maintenance problem (Stålhane et al., 2015). There are other variants, such as branch-and-cut (Malaguti et al., 2018; Homsi et al., 2020) or branch-and-price (Sigurd et al., 2005; Wen et al., 2017).

Fagerholt and Christiansen (2000b) used a **dynamic programming** (DP) method to solve a travelling salesman problem with allocation, time Window and precedence constraints (TSP-ATWPC). The DP algorithm was also used to solve a combined multi-ship pickup and delivery problem with time windows (m-PDPTW), and multi-allocation problem (Fagerholt and Christiansen, 2000a). Arnesen et al. (2017) used a forward dynamic programming method to solve a real ship routing and scheduling problem of a chemical shipping company. The problem was formulated as a TSP with Pickups and Deliveries, Time Windows and Draft Limits (TSPPD-TWDL).

Within the **local search**-based methods there are three main approaches used in ship routing and planning: **tabu search** (TS), **multi-start local search** (MLS), and **variable neighbourhood search** (VNS). TS method had been used for different routing and scheduling problems, such as with flexible cargo quantities (Korsvik and Fagerholt, 2010), or with multiple time windows, split loads and berth constraints (Charisis et al., 2019). Brønmo et al. (2007) implemented an MLS heuristic that was based on a partly randomized insertion heuristic for initial solution generation, and then improved by a local search heuristic. Based on a similar approach, Fagerholt et al. (2009) integrated an MLS heuristic into a DSS with the aim of presenting

Table 3
The main algorithms used in the literature to solve the routing and scheduling problem.

Ref.	Mode of shipping	Problem type	Objective function	Main constraints	Solution method	Solution
Appelgren (1971)	General	Ship's cargo scheduling	Max profit		Branch-and-bound	Exact
Stålhane et al. (2015)	Industrial	VRP with pickup and delivery	Min cost	SC, TW	Branch-and-bound	Exact
Arnesen et al. (2017)	General	TSP with pickup and delivery	Min cost	DL, SC	Branch-and-cut and Heuristic procedures	Exact and Heuristic
Malaguti et al. (2018)	Tramp/Industrial	TSP with pickups, deliveries, and draft limits	Min cost	SC, DL	Branch-and-cut and Heuristic procedures	Exact and Heuristic
Homsi et al. (2020)	Tramp/Industrial	PDP with time windows	Min cost	SC, TW, SC-C	Branch-and-price and a hybrid metaheuristic	Exact and heuristic
Wen et al. (2017)	General	VRP with pickup and delivery	Min time, cost and emissions	SC	Branch-and-price and constraint programming	Heuristic and Exact
Sigurd et al. (2005)	Liner	Periodic VRP with pickup and delivery	Min cost	TW, SC, PS-C	Branch-and-price	Heuristic
Battarra et al. (2014)	General	TSP with draft limits	Min cost	DL	Branch-cut-and-price	Exact
Fagerholt and Christiansen (2000b)	Industrial	TSP with allocation, time window and precedence constraints	Min cost	TW, AL, SC	Dynamic programming	Exact
Fagerholt and Christiansen (2000a)	Industrial	Multi-ship pickup and delivery with time windows and multi-allocation	Min cost	TW, SC, AL	Dynamic programming	Exact
Korsvik and Fagerholt (2010)	Tramp	Multi-vehicle PDP with time windows and flexible cargo quantities	Max profit	TW, SC	Tabu search	Heuristic
Charisis et al. (2019)	Tramp/Industrial	VRP with time windows and split deliveries	Min cost	TW, SC	Tabu search	Heuristic
Brønmo et al. (2007)	Tramp	PDP of bulk cargoes	Max profit	TW, SC	Multi-start local search	Heuristic
Fagerholt et al. (2009)	Tramp	Multi-vehicle PDP with time windows	Max profit	RS-C, TW, SC	Multi-start local search	Heuristic
Norstad et al. (2011)	Tramp	PDP with speed optimization	Max profit	TW, SC	Multi-start local search	Heuristic
Yamashita et al. (2019)	Industrial	PDP with time windows	Min cost	TW, SC, DL, PS-C	Multi-start heuristic	Heuristic
Malliappi et al. (2011)	Tramp	PDP with time windows	Max profit	TW, SC	Variable neighbourhood search	Heuristic
Castillo-Villar et al. (2014)	Tramp	VRP with time window	Min cost	TW	Variable neighbourhood search	Heuristic
Lin and Liu (2011)	Tramp	VRP with time windows	Max profit	TW, SC	Genetic algorithm	Heuristic
Al-Hamad et al. (2012)	Industrial	VRP with pickup, deliveries and time windows	Min cost	TW, SC	Genetic algorithm	Heuristic
Moon et al. (2015)	Tramp	Ship routing and scheduling + fleet deployment + network design	Min cost	SC	Genetic algorithm	Heuristic
Song et al. (2017)	Liner	Ship deployment + sailing speed + service scheduling	Min cost	TW, SC	Genetic algorithm	Heuristic
De et al. (2017)	General	Sustainable ship routing and scheduling with draft restrictions	Max profit and min emissions	TW, DL, SC, PS-C	Genetic algorithm and particle swarm optimization	Heuristic
De et al. (2016)	General	m-VRP with pickup and delivery	Min cost	TW, SC	Particle Swarm Optimization-Composite Particle	Heuristic

Abbreviations are: pickup and delivery problem (PDP); vehicle routing problem (VRP); travelling salesperson problem (TSP); time window (TW), ship capacity (SC), allocation (AL), ship/cargo compatibility (SC-C), port/ship compatibility (PS-C), customer/ship compatibility (CS-C), route/schedule compatibility (RS-C), and draft limit (DL).

a set of good solutions rather than the optimal one. Another multi-start heuristic was implemented to solve a real-life pickup and delivery problem for an oil company (Yamashita et al., 2019), and to solve the combined problem of a tramp ship routing and scheduling with speed optimization (Norstad et al., 2011). A VNS method was applied to a tramp ship scheduling problem by Malliappi et al. (2011). Furthermore, the VNS method was compared with a multi-start local search and a tabu search, showing that the VNS method outperforms both techniques in terms of solution quality and computational time (Malliappi et al., 2011).

A **genetic algorithm** (GA) approach was used by Lin and Liu (2011) to solve the ship routing problem of tramp shipping, considering the ship allocation, freight assignment, and ship routing simultaneously. A GA was also used in a ship routing and scheduling problem with time windows for industrial shipping (Al-Hamad et al., 2012). A GA with local search was proposed to address three NP-hard maritime problems (Moon et al., 2015): (i) a location–allocation problem, (ii) a TSP between hubs; and (iii) m-VRP of ship routing. The multi-objective genetic algorithm (MOGA) technique has also been used to solve maritime problems (Song et al., 2017; De et al., 2017). In De et al. (2017), a multi-objective **particle swarm optimization** method was implemented to solve a ship routing and scheduling problem, considering the time window concept, sustainability aspects, and vessel draft restriction. A variant of Particle Swarm Optimization of Composite Particle was employed for solving the ship routing and scheduling problem (De et al., 2016).

Table 4
Fuel consumption approach for different types of Basque fishing vessels and gear.

N° of vessels analysed	Fleet type	Gear	Gear abbreviation	Mean length (m)	Mean fuel (L/mile)	± SD fuel (L/mile)
1	Small-scale coastal fleet	Gillnet, handline	GN, LHM	9.2	2.4	–
4	Small-scale coastal fleet and Large-scale pelagic fleet	Gillnet, handline trolling	GN, LHM, LTL	17.9	3.2	1.6
1		Longline, handline	LLS, LHM	23.0	3.81	–
2		Longline, handline, trolling	LLS, LHM, LTL	13.0	1.9	0.7
1	Large-scale pelagic fleet	Handline, trolling	LHM, LTL	26.0	3.9	–
3		Purse seine, Pole and line	PS, LHP	36.4	10.8	0.2
3	Large-scale demersal fleet	Bottom trawl	OTB	40.0	17.9	1.2
2		Bottom trawl in pairs	PTB	37.0	20.2	0.1
5	Distant-water fleet	Purse seine	PS	90.3	74.2	4.3

Note: bottom otter trawl (OTB): fuel consumption during trawling 35–45 L/mile; bottom pair trawl (PTB): fuel consumption during trawling 50–55 L/mile.

3. Definition of a framework for fishing route optimization decision support systems (FRODSS) framework by fleet type

There is a general goal to reduce GHG emissions worldwide, and the fishing industry is also expected to contribute to GHG emission reduction. In Europe, for example, the objective is to reach zero emissions by 2050, and with an intermediate target reduction of 50% to 55% by 2030 (European Commission, 2019). LCA analysis reviews indicate that vessel fuel consumption is the main contributor to GHG emissions during fishing vessel life (Pelletier et al., 2007; Avadí and Fréon, 2013). Moreover, its consumption may represent a large portion of the total operational costs, this being one of the main concerns of fishing companies (Basurko et al., 2013). Conversely, fishing fuel consumption and emissions per landed tonne of catches increased up to 20% between 1991 and 2011 (Parker et al., 2018). This was due to the increase in fishing effort worldwide without an increase in fish landings (Bell et al., 2017). Furthermore, Lotze et al. (2018) forecast no increase of fish biomass in the best-case climate scenario, or up to a 30% decrease in fish catches under the worst-case scenario by the end of the century. This, along with the volatile fuel price, can have a big impact on the fishing industry, fish prices, and food security of some countries (Parker et al., 2018).

The use of planning and optimization methods in fisheries is sparse due to the complexity, which goes beyond the classical shipping needs, since fisheries must face the weather/problem uncertainty together with the uncertainty of finding the target species or not. Fisheries also have their own constraints, such as the need to consider quotas, bycatch (incidental fishing of non-targeted or even endangered species), fishing time window limitations, competing fleets, or even pirates in some distant-water fleets. Furthermore, there are another four main challenges that can explain the lack of technology integration into fisheries: (i) upfront costs and insufficient access to capital; (ii) legal and bureaucratic barriers; (iii) failure to implement data collection standards; and (iv) lack of trust and buy-in from fishers (Bradley et al., 2019).

This abundance of challenges may explain why fishing route optimization research has been limited to one vessel or activity at operational level (i.e., ship weather routing) (Mannarini et al., 2016a,b). For example, Vettor and Guedes Soares (2016) only optimize the routes from port to hypothetical fishing areas (Valencia to Malta waters), but not the search for fish or fishing operations. Another study used a machine learning approach (ANN model), optimizing the routes of six fishing vessels that operated in different fishing grounds (Torres Palenzuela et al., 2010). At tactical level, the only example in terms of fleets in the literature was the distant-water purse seiners searching for tuna, addressing it as a dynamic travelling salesperson problem (DTSP) (Groba et al., 2015). An improvement on the previous approach was carried out by considering that a fishing fleet designs a common FAD recollection strategy (Groba et al., 2018). Sharing FAD information between vessels with the correct incentives would further reduce fuel consumption as suggested by Groba et al. (2020).

This sparsity of applications shows the big potential for digitalization of the fishing fleets, and the application of DSS adapted to Fishing operations (FRODSS). Here, a characterization of the Basque fishing fleet is used as an example of worldwide fishing fleets for the formulation of FRODSS (Taconet et al., 2019).

3.1. *Characterization of fishing fleet types: Basque fishing fleet example*

Fishing gears used by the Basque fleet can be grouped into 12 main gears (Fernandes et al., 2019), which, in turn, can be classified as active, non-active or miscellaneous (Boopendranath, 2012). Active gears are mostly based on chasing the target species and catch fish by trapping or encirclement. Whereas non-active gears are usually placed for several days before being hauled, and the target species swing towards the net, trap, or hooks and lines. Recently, eight types of fishing gears have been analysed in several project at AZTI (Basurko et al., 2013; Gabiña et al., 2016; Uriondo et al., 2018), showing that their fuel consumption varies from 1.94 L/ mile to 74.2 L/mile (Table 4).

Targeted fish species can be classified as: (i) shellfish, which encompass various species without capacity for significant migration patterns that are targeted mainly by some non-active gears; (ii) demersal species, which live on or near the seafloor with limited migration capacity, targeted mainly by trawlers, gillnetters and bottom longliners; (iii) small pelagic inhabit the water column, either near the sea surface or in middle depths with seasonal migration patterns, and are targeted mainly by purse seiners, mechanized handlines and pole-lines; and (iv) large pelagic are mostly tunas and tuna-like, sharks and billfishes with large and seasonal migration patterns, targeted mainly by purse seiners and longliners. Fishing time windows can be important for some fisheries in order to know when the fish event may occur, or even to mitigate the bycatch (Auger et al., 2015). The relationship between each fishing gear and target species is shown in Fig. 2.

Excluding trawlers and distant-water vessels, the remaining fleets use more than one gear throughout the year (Table 4). Despite the high diversity of gears, we identified four groups of fishing fleets where a similar planning and optimization system could be applied. These groups are based on their similarities, such as fishing grounds, fuel patterns, target species, and management constraints (Table 5).

3.1.1. *Small-scale coastal fleet (non-active gears)*

The first group is comprised of small coastal vessels (usually under 12 m length): a multispecies fishery using non-active gears that are put into place, and then, after some hours or days the catch is retrieved. Their fishing grounds are located within the coastal waters and close to their base port. Therefore, they make short fishing trips with low fuel consumption per mile, and catches per trip of high value species (Tables 4 and 5). The main gears used by these fleets are longliners

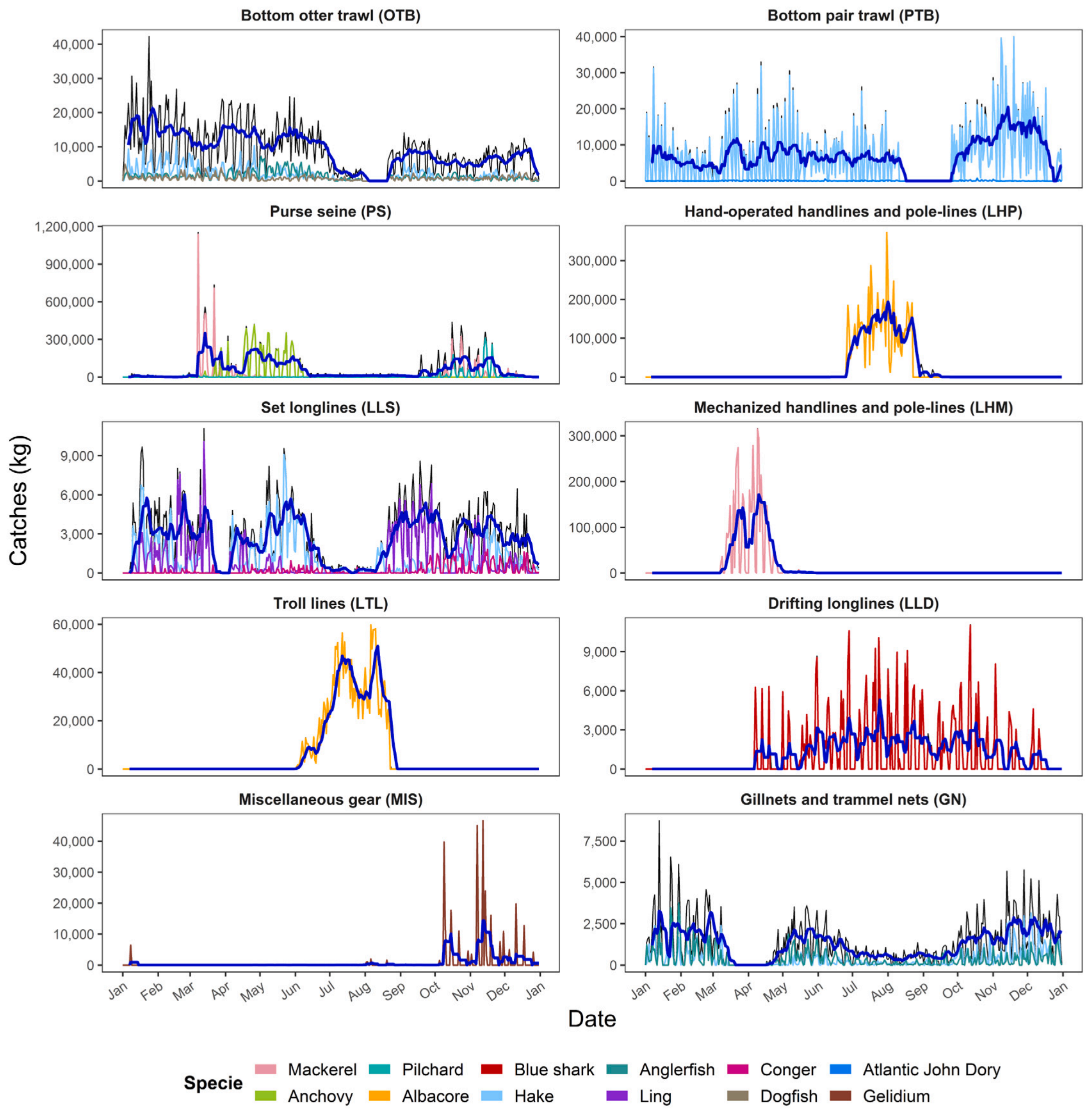


Fig. 2. Total catch (black line), weekly catch average (blue line) and main species catch series of the Basque fleet by fishing gear for 2018. Species are: Mackerel (*Scomber spp.*), anchovy (*Engraulis encrasicolus*), pilchard (*Engraulis encrasicolus*), albacore (*Thunnus alalunga*), blue shark (*Prionace glauca*), hake (*Merluccius merluccius*), anglerfish (*Lophius spp.*), ling (*Molva molva*), conger (*Conger conger*), dogfish (*Scyliorhinus canicula*), Atlantic john dory (*Zeus faber*), and algae (*Gelidium sesquipedale*). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Summary of the Basque fleet using the logbook from 2018.

Basque fleets								
Type	Gear type	GT	Overall length (m)	Trip length (days)	Mean catch per trip (tonnes)	Top 1 (%)	Top 2 (%)	Top 3 (%)
Small-scale coastal fleet	GN	30	14.7	0.6 ± 1.0	263	Hake (31)	Anglerfish (30)	Horse mackerel (4)
	LLD	81	19.3	4.5 ± 1.4	11,984	Blue shark (99)	Mako shark (< 1)	
	LLS	43	14.8	0.7 ± 1.2	713	Hake (43)	Ling (40)	Conger (8)
	MIS	18	11.4	0.3 ± 0.1	2,808	Gelidium (98)	Octopus (1)	Snakelocks anemone (< 1)
Large-scale pelagic fleet	LHP	178	32.9	5.9 ± 3.6	25,093	Albacore (98)	Bluefin tuna (~ 2)	
	LHM	25	14.1	0.4 ± 0.6	3,355	Mackerel (99)		
	LTL	77	22.2	6.4 ± 5.9	5,283	Albacore (99)	Bigeye (< 1)	
	PS	147	30.2	0.7 ± 0.3	7,471	Anchovery (41)	Mackerel (39)	Pilchard (13)
Large-scale demersal fleet	OTB	432	39.3	5.6 ± 1.4	14,059	Hake (22)	Anglerfish (15)	Dogfish (9)
	PTB	372	37.0	2.9 ± 0.8	11,036	Hake (97)	Atlantic John Dory (< 1)	
Distant-water fleet	OTB	901	52.0	47.3 ± 13.0	850,800	Cod (97)	Haddock (< 2)	
	PS	2,849	90.3	21.8 ± 7.0	844,000	Skipjack (67)	Yellowfin tuna (25)	Bigeye tuna (8)

Note: GT is the gross register tonnage.

(LLS), gillnets (GN) and drifting longliners (LLD). Longliners (LLS) mainly target the demersal species, hake, ling and conger. LLS has two downtimes (Fig. 2): (i) vessels start fishing the pelagic species, mackerel, using mechanized handlines and pole-line (LHM) gear in March; and (ii) they target albacore tuna by trolling lines (LTL) in summer. Gillnets (GN) target mixed fisheries dominated by demersal species, mainly hake, anglerfish and horse mackerel. They have a downtime from mid-March until May, when most of the vessels change their gear to LHM, whereas, in summer, some vessels change to LTL. Drifting longliners (LLD) target the pelagic species blue shark, from April until mid-December. Miscellaneous gear (MIS), which in our case also include FPO, includes many minor fishing gears, and over 98% of the total catches consist of algae (*Gelidium sesquipedale*) and high value species of importance for local tourism, such as lobster, octopus, velvet, and brown crab (Fernandes et al., 2019).

For this fleet, the following characteristics need to be considered for FRODSS development; (i) the departure and arrival port may be the same; (ii) as the travelled distance and trip duration are small the vessel speed must be assumed as constant; (iii) fishing ground areas must be known, but the ones with high biomass need to be forecast based on environmental conditions; (iv) best timing of deployment and retrieval must also be forecast based on environmental conditions; (v) as the net/trap locations are static, this problem could be formulated in a static environment; (vi) the vessels must not limited by their load capacity; (vii) there are no management constraints; and (viii) the main uncertainties must be market demand/prices and weather conditions affecting abundance for demersal and shellfish species, or migration patterns for pelagic species.

Finally, and because the fishing trips duration usually takes less than one day, and the use of non-active gears and the travelled distances are minimum, the implementation of tactical solutions (i.e., routing and scheduling) can be more useful than operational ones (i.e., weather routing). A FRODSS for this fleet would define the best locations and date to place and collect the nets/traps along with the optimal route that goes through these locations. The timing of the placing and collection is probably more important than in other groups, given that these gears target high value species that are caught in smaller quantities. Therefore, these fleets can aim at making a smaller number of trips when this is more profitable (e.g., tracking market demand and prices). The locations could be defined by the user or be based on some species distribution model predictions to select the areas with higher catch potential at lower cost (Galparsoro et al., 2009).

3.1.2. Large-scale demersal fleet (active gears)

A second group is comprised of bottom trawlers (OTB and PTB) targeting demersal and benthic species by means of nets, with a trip duration ranging from 3 to 5 days in the case of PTB, and 5 to 7 for bottom otter trawlers (Table 5). One characteristic of these vessels is that they consume the most energy during the trawling operations (Basurko et al., 2013). Furthermore, they do not change the gear throughout the year. PTB mainly fish mainly hake, whereas OTB targets a mix of demersal species including hake, anglerfish, dogfish (Table 5), and also megrim (*Lepidorhombus whiffiagonis*), due to its high market value. Trawlers make constant trips over the year with a 3–6 day duration (Table 5). Both gears have their own downtime period: OTB is from July to mid-August, and PTB runs from mid-August to the end of September (Fig. 2). Their main fishing grounds are in the Bay of Biscay, North Sea and Celtic sea (i.e., FAO subareas 27.8, 27.7 and 27.6, respectively), and limit their operations to sedimentary seafloor and to the continental shelf. The selection of these fishing areas is influenced by experience, regulations (mainly TAC), expected harvest, external information received, and fuel costs (Prellezo et al., 2009). The selection of the fishing grounds becomes particularly important for this fleet due to landing obligation (choke species) and quota management, as they fish mixed demersal species.

For this fleet, when targeting demersal species, the following assumptions can be used in a FRODSS: (i) the departure and arrival port may be different; (ii) fishing grounds are known, but the ones with high biomass need to be forecast based on environmental conditions; (iii) high biomass of choke species needs to be forecast to avoid quota issues; (iv) the weather effect on ship performance should be considered; (v) vessels are limited by their load capacity; and (vi) they are affected by fishing management constraints, such as landing obligation. This case is similar to the previous group with the difference of needing to consider choke species, and longer trips with multiple fishing events that permit the use of TSP/VRP approaches. Therefore, the routing problem of this fleet could be raised like the large-scale pelagic fleet routing problem during summer when they are targeting tuna. That is, as a tactical problem where the potential fishing areas are defined along with the visiting order, and all of this coupled with a weather routing system.

3.1.3. Large-scale pelagic fleet (active gears)

The third group encompasses vessels that target shoaling and highly mobile species such as small and large pelagic. The habitat of pelagic fishes is the largest aquatic environment, which generates the difficulty of finding the fish shoals. These vessels tend to consume more fuel during routing to fishing grounds and searching for fish (up to 80%) than during fishing operations, due to the target species migration patterns (Basurko et al., 2013). This category includes the following active gears: purse seine (PS), trolling (LTL), and pole and lines (mechanized and manually). Purse seiners (PS) operating in coastal waters of Bay of Biscay fish from March to mid-June, mainly fishing anchovy and mackerel; and from mid-September to mid-December, mainly targeting Atlantic chub mackerel and sardine (Fig. 2). Coastal PS vessels usually make a daily trip, and their downtime starts in Mid-December until mid-February. During the summer, most of the PS vessels change their gear to pole and line with live bait (LHP) to fish albacore tuna. The trip duration of vessels using LHP gear are longer and more irregular due to the spatial migration of tuna (6.4±5.9 days, see Table 5). Mechanized pole and line (LHM) gear consists of a hooked line attached to a mechanized pole in a daily fishing trip. LTL operates during summer with an irregular trip duration, mainly because they follow tuna migration routes.

During the summer (targeting tuna), their fishing trip duration and distance are more suitable for a combination of tactical and operational route optimization methods. At tactical level, the problem is to define the best location to fish, and the optimal route to reach them in a weekly horizon. During the rest of the year, the trip duration (less than one day) and distance are shorter, where the fishing route optimization approach could be quite similar to the approach followed for small-scale coastal fleet. The main difference with respect to the small-scale fleet is that the large-scale pelagic fleet searches for fish shoals, and a species distribution model may be more helpful to select the fishing ground. However, for this fleet, when targeting for tuna during summer, the following assumptions can be used in a FRODSS: (i) the departure and arrival port may be different, which opens the possibility of selecting the landing port based on the fish sale price; (ii) fishing grounds locations are more variable than in previous fleets, therefore the areas with high biomass need to be forecast based on environmental conditions; (iii) that is why this routing problem should be formulated in a dynamic environment; (iv) vessels might be limited by their load capacity; (v) the weather effect on ship performance should be considered; (vi) they are affected by fishing management constraints, such as catch quotas; and (vii) the main uncertainties are fish shoal location and weather conditions affecting fuel consumption, time at sea, and safety.

3.1.4. Distant-water fleet (active gears)

The last group encompasses the distant-water fleet, whose main fishing grounds are far from the country's domestic waters, targeting highly migratory species. This generates more variable fuel consumption costs and irregular trip durations (e.g., around one to two months). Within the Basque fleet, the fishing areas are the Atlantic, Pacific and Indian oceans targeting for tuna and tuna-like species,with a few trawlers (OTB) targeting cod in EU waters. Between these two fleets manly targeting tuna, there is a clear difference in fuel consumption intensity and species selectivity capacity (Parker et al., 2015; Ruiz et al., 2018). Distant-water purse seiners burn an average of 368 litres of fuel per tonne of landings, whereas longliners burn an average of 1070 litres per tonne (Parker et al., 2015). However, longliners tend to catch bigger fish with a higher economic value, and in certain areas they can be more selective, reducing bycatch (avoiding incidental fishing of non-targeted species).

A FRODSS for tuna longliners and trawlers follows the same assumptions as large-scale pelagic and demersal fleets, respectively, but considering that distant-waters fleets take longer trips, do more fishing events (Table 5) and use technology to reduce the effort to searching for fish. This technology includes the use of helicopters, bird radar, sonar, or FAD (Miyake et al., 2010). Hence, the routing problem could be formulated at a tactical level as a combinatorial problem (TSP, mTSP and VRP) to optimize the FAD collection, considering the habitat model information to award the routes between FADs with high probability of tuna presence (Groba et al., 2015, 2018). Moreover, and unlike the rest of fleets, better routes can be proposed by formulating the problem for multiple vessels instead of for a single vessel. Finally, this fleet is the one that can benefit most from the use of a weather routing system. This is mainly due to their higher consumption rate (see Table 4), and larger travelled distances.

For this fleet, when targeting for large pelagic species such as tuna by purse seiners, the following assumptions can be used in a FRODSS: (i) the departure and arrival port may be different; (ii) fishing grounds are often detected through the FAD biomass estimation and other location methods; (iii) fishing grounds change constantly, hence the problem should be formulated in a dynamic environment; (iv) bycatch species and choke species need to be forecast to avoid quota issues; (v) the weather effect on ship performance should be considered; (vi) they are affected by fishing management constraints, such as FAD use limitation; (vii) vessels are limited by their load capacity; and (viii) fishing events can only occur during daylight.

3.2. Example of a FRODSS for the distant-water fleet

A tuna purse seine vessel that belongs to the distant-water fleet was selected as an example due to the availability of data kindly provided by a fishing company operating in the Indian ocean. In this example, two historical fishing trips are compared with routes proposed by a FRODSS (Fig. 3). For that purpose, the five layers of a FRODSS (Fig. 1) are developed as follows: (i) in the environmental layer, the short-term weather forecast products come from the Copernicus marine environment monitoring service (CMEMS[1]); (ii) in the ship modelling layer, a Random forest method was used to develop a model to estimate the fuel consumption, but there are other approaches (Lu et al., 2015; Bal Beşikçi et al., 2016; Gkerekos and Lazakis, 2020); (iii) for the fisheries layer, a Naive Bayes classifier was used to estimate the probability of high catches at each FAD; (iv) in the routing and planning layer, a genetic algorithm (GA) was applied (see Section 2.3.2) to decide the FADs to be visited and the visit order, whereas a dependent A* pathfinder (see Section 2.3.1) weather routing method was used to provide the optimal path between two buoys to be visited, as advised by the GA algorithm; and, (v) in the decision layer, maps with the optimal route were used without interaction by end-user (Fig. 3). The fishing routing problem to be solved here consisted of planning a single vessel fishing trip that follows an exclusive FAD fishing strategy. The objective function used in this example was the relationship between the fuel-oil consumption (FOC) and the probability of catches ($FOC/1+P(catches)$). Therefore, the aim of the problem was to find the minimum cost tour starting and ending at a fishing port, which intercepts n targets (i.e., FADs), which are constantly moving due to the weather conditions. The number of targets, n, will be the same as the historical fishing sets, and each FAD have a fishing time window associated, i.e., fishing only occurs during the day, although routing also occurs overnight.

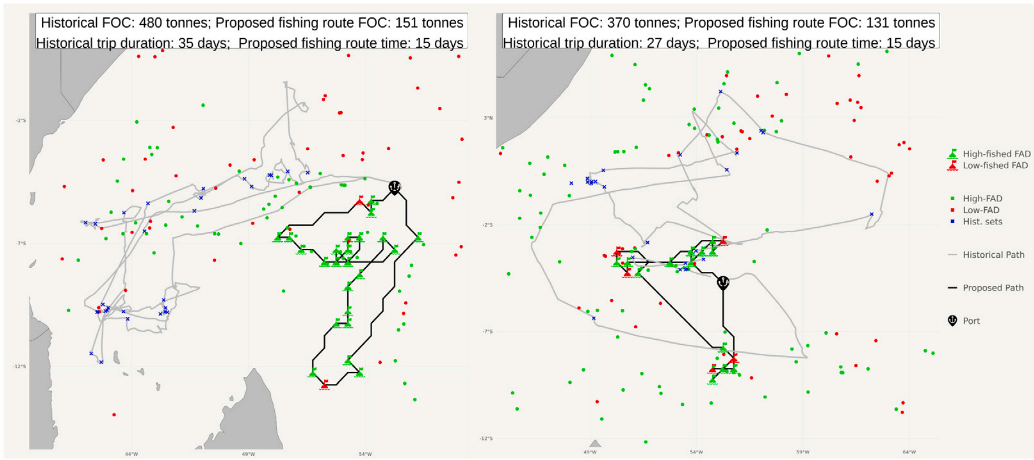
The first example shows that the historical and algorithm proposed fishing areas differ, since the historical route goes to the west, and the proposed route to the south (Fig. 3(a)). This highlights that early decision-making during the trip can be decisive to reduce fuel consumption. In the second example (Fig. 3(b)), both routes propose fishing in more similar areas. However, the proposed route fish the FADs closer to the port, while the historical route travels further to find the tuna. In both examples, the reduction in fuel and time at sea is significant using the FRODSSs, showing their high potential. These differences in the two examples seem to be driven by shorter distances travelled, and because of improve use of night-time for routing. Still the comparison is not fully equitable due to some assumptions and modelling carried out.

4. Conclusions and future directions

This study shows that there is a gap in the application of route and planning optimization decision systems in fisheries. Most of the existing technology required to develop a FRODSS for a smart fishing strategy is currently available. However, further research is needed to meet the fishing vessel needs, and bear in mind their particularities. For example, available algorithms and objective functions need to consider the trade-offs between the classical objectives and fishing particularities. Data availability is another issue to be faced. Although the emergence of new data acquisition technologies is reaching to fisheries, their implementation and availability is unequal among the different fishing fleets. Some reasons are the upfront costs and insufficient access to capital for small-medium fishing vessels, and the lack of trust to share data by the industry. Therefore, another key field for improvement would be to enhance the trust and collaboration between the research community and fishing industry, to reduce reluctance to join in with the development and testing of FRODSS.

As this work suggests, dozens of fishing gears could be addressed with four optimization strategies based on their similarities. The fishing-related technology available to develop a FRODSS will be different in each group. The distant-water fleets group can optimize their operations by integrating multiple sources of data with improved species distribution, and/or with echo-sounder buoys, estimating the amount of fish and its type to enhance their efficiency. The large-scale demersal fleet can benefit from species distribution forecasting when selecting the optimal fishing areas. This selection should be based on the target species prediction, but also avoiding areas where the presence of non-desired species could be high (due to low market value or lack of quotas). The group of large-scale pelagic vessels using active gears can benefit from species distribution models that significantly reduce searching times, and also, maybe from smart buoys. Finally, the group of small-scale coastal fleets using non-active gears is probably the one that would get less benefit from a FRODSS. Nevertheless, a mix of species distribution models forecasting their target species biomass hotspots in combination with a market analysis could optimize the relationship between fuel consumption and value of landings.

[1] http://marine.copernicus.eu/



(a) Example 1 (b) Example 2

Fig. 3. Comparison between two historical fishing routes and the ones proposed by a FRODSS. The dots represent the available FADs, and the colour indicates if there is a forecast of high probability of high catches (green) or low catches (red). The grey line represents the historical route, and the blue lines crosses the sets conducted, whereas the black line indicates the proposed route, and the dots the visited FADs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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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