Solving Fishing Routing Problems with Metaheuristics

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by

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Ezina, ekinez egina

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sobera izan begiko.
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nahiz topikoak topiko,
hurrengo bertso sorta ondo dut
edukitzeko betiko
bihotz-bihotzez, benetan, urte
askotarako ekipo!

Hainbeste gauza esan nahi eta,
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bidea hasi genuen eta
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sentimenduak adierazi
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Hemen guztiek erein duzue
hori ezin da ukatu,
baina, nola ez, lana sekula
santa ezin da bukatu.
Bertsoak eta sentimentuak
nik nahi nituen uztartu,
baina langile fin ugari da
guztiak ezin aipatu,
beraz esan ez dudan izenik
baldin balego, barkatu.

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Nire kasuan, zuek, bai, izan
zarete nire iparra
eta espero det ez itzaltzea
nire ikertzeko harra.
Nire partetik jaso musu zein
besarkadak barra-barra!

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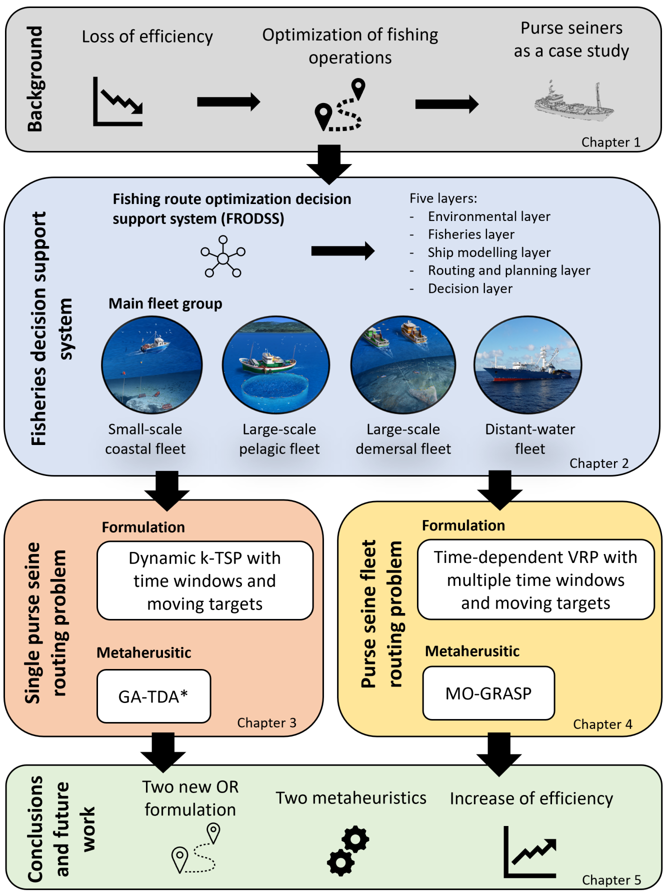
Arrantzak iraganean, eginkizun garrantzitsua izan du gizartean, eta hala jarraituko du etorkizunean ere, biztanleriari proteina eta beste mantenugai batzuen iturri garrantzitsua eskainiz. Arrantzak aurrerapen teknologikoak izan dituen arren, bere iraunkortasunaren eta eraginkortasunaren inguruko kezkak geroz eta handiagoak dira. Aipagarria da, gaur egun, mende hasieran arrantzatzen zuten arrain kopuru bera harrapatzeko, munduko arrantza-flotak %20 gehiago kutsatzen duela. Arrazoi asko daude ingurumen-errendimenduaren joera negatibo honen atzean, besteak beste, arrantza gaitasunaren gorakada eta arrainen biomasaren beherakada. Gainera, zenbait ikerketek, klima-aldaketaren ondorioz arrainen biomasa eta gorputz-tamaina murriztu, eta haien distribuzio espaziala aldatuko dela aurreikusten dute. Honek, arrainen biomasarekiko presioa, eta ingurumen-errendimenduaren joera negatiboa areagotuko ditu etorkizunean.

Motor eraginkorragoetan, ontzi handiagoetan eta erregai hobeagoetan inbertitzea izan da arazo honi irtenbidea aurkitzeko hartu den bide nagusia, baina bide hau kostu handiekin eta epe luzera bakarrik da bideragarria. Bide horren alternatiba bat, arrantza ontzien operazioak optimizatzea da, arrantza-estrategia eraginkorragoak zehaztuz. Epe laburreko arrantza-estrategia eraginkorragoak zehazteko prozesu honen barruan, ontzien ibilbideak optimizatzea barne sartzen da. Hala ere, hau oso problema konplexua da arrantzan erabiltzen dituzten objektu mugikor dinamikoen ezaugarriengatik.

Arrantzaleek historikoki, beraien arrantza-estrategia eta operazioak urteetan zehar lortutako ezagutzan oinarritu izan dituzte. Hala ere, arrantza-sektoreak gero eta gehiago izaten ditu kontuan teknologia berritzaileak, hala nola, modelo ozeanografikoak, itsasontzien errendimendu modeloak eta espezieen distribuzio modeloak. Informazio iturri berri hauek hainbat aplikazioren esplorazioa erraztu dezakete, besteak beste, modelizazio matematikoetan oinarritutako teknikak erabiltzea. Honen adibide da arrantza-estrategia hobeak diseinatzeko ikerketa operatibo eta ikerketa automatikoen arteko konbinazioa. Hala ere, arrantza-sektoreak ez du balio potentzial guztia ateratzen biltzen diren datuetatik eta beste sektoreetan baino gutxiago erabiltzen dira datuak.

Arrantza-sektorearen ikerketa operatiboan oinarritutako aplikazio gutxi proposatzen dira literaturan, nahiz eta ikerketa operatiboak ikuspegi eta estrategia baliotsuak izan jasangarritasun erronkei aurre egiteko. Ikerketa gehienak eguraldiaren bideratze-problemetan oinarritu izan dira, hau da, puntu batetik besterako ibilbidea, eguraldiaren ziurgabetasunaren arabera zehaztean. Hala ere, arrantza-optimizazioak aurre egin behar dio ere harrapatu nahi den arrain espeziea aurkitzeari lotutako ziurgabetasun handiari. Horrela, arrantza bideratze-problemek helburu klasikoen eta arrantzako berezitasunen arteko trukaketak kon-

tuan hartu behar dituzte (adibidez, lehorreratutako arrain bakoitzeko erregai-kontsumoa). Ikerketa batzuk arrantza-ibilbideak optimizatu dituzte, arrantzaren berezitasun batzuk kontuan hartuta. Hala ere, problemaren formulazioa nahiko sinplea zen, arrantza estrategia bat egun gutxi batzuetarako definituz, eta distantziak funtzio objektibo gisa erabiliz. Ikerketa horiek ez zuten kontuan hartu ez arrantza-bidaiaren iraupen osoa, ez ontziaren errendimendua, ez atunaren kokapena eguraldi-baldintzen arabera, ez eta arrantza denbora-tartea. Horrez gain, ikustatu beharreko arrainak batzeko gailuen (dFAD) kopurua txikia eta finkoa zen, itsasontzi batek itsasoan dauden dFAD guztien artetik onenak hautatzen dituela kontuan hartu gabe.



Irudia 0.1: Doktorego-lanaren eta ikerketaren egitura nagusiaren eskema.

Guzti honegatik, tesi hau arrantzarako estrategien eta operazioen hobekuntzan oinarritzen da, ibilbideak optimizatzeko metodo ezberdinak erabiliz. Helburu hau gogoan, arrantzarako bideratze-problema berri eta errealistak formulatzen dira eta horiek konpontzeko algoritmo metaheuristikoak proposatzen dira. Gaur arte, ez dago beste lan zientifikorik arazo honi bere konplexutasun osoan heldu dionik. Tesi honetan lortutako emaitzei esker, arrantzaleen jardueraren jasangarritasuna eta efizientzia nola hobetu daitekeen ezagutuko da, esfortzua, kostua eta ingurumen-inpaktua murriztuz.

0.1 Irudiak tesi honen marko orokorra erakusten du. 1. Kapituluak arrantza-efizientziaren egoerari, ikerketa operatiboaren aplikazioari, eta bideratze-problema bezalako arloei buruzko informazioa eskaintzen du. Era berean, inguratze arrantza-flotaren ezaugarriak eta arrantzan egiten diren operazioak ere azaltzen ditu, flota hau kasu praktiko gisa erabiltzen baita tesi honetan zehar. 2. Kapituluak, arrantza erabakietan laguntzeko sistemaren (DSS) marko orokor bat eskaintzen du, ontziaren bideratzearen arloan dauden lanetan oinarrituta. Kapitulu honek, gainera, existitzen diren arrantza flota-motak lau talde nagusitan sailkatzea proposatzen du, ibilbideak modu berean optimizatu daitezkeela kontuan hartuta. Behin arrantza-ibilbideen optimizazioa erabakitzeko laguntza-sistema (FRODSS) baten markoa definituta, hurrengo kapituluak, bi arrantza-problema desberdinen aplikazio praktikoan zentratzen dira: (i) inguratze itsasontzi bakar baten bideratze-probleman (3. Kapitulua); eta (ii) inguratze arrantza-flotaren bideratze-probleman (4. Kapitulua). Problemen arteko ezberdintasun nagusia da lehenengoan ontzi bakar baten ibilbidea optimizatzen dela, eta bigarrenean berriz, ontzi batzuen ibilbideak optimizatzen direla aldi berean. Ondorio orokorrak eta etorkizuneko lanak 5. Kapituluan aurkezten dira. Tesi honen kapitulu eta helburu nagusiak hurrengo parrafoetan zehazten dira.

Lehen helburua, 2. Kapituluan deskribatzen den bezala, honako hau da:

1. Helburua

Arrantza-flota bakoitzeko arrantza-ibilbideen optimizazioa erabakitzeko laguntza-sistemen (FRODSS) marko orokor bat proposatu kontuan hartuta arrantza aparailuen egungo egoera.

Helburu hori lortzeko, lehen urratsa arrantza-flotaren ibilbide taktiko eta operatiboaren problema definitzea da, eta, horrekin batera, FRODSS sortzea. FRODSS honek bost geruza ditu: (i) ingurumen-geruza; (ii) itsasontzia modelatzeko geruza; (iii) arrantza-geruza; (iv) bideratze eta planifikazio geruza; eta (v) erabaki-geruza (ikusi 0.1 Irudia). Gainera, funtzio objektiboei, murrizketei eta optimizazio-algoritmoei buruzko berrikuspen integral bat egiten da, ontzien bideratze problema operatibo eta taktikoetan zentratuz eta arrantzara egokituz. Euskal arrantza-flota desberdinak kasu azterketa gisa erabiliz, ondorioztatu da, arrantza ontziak lau multzo nagusitan sailka daitezkeela, arrantza ibilbideak modu berean optimizatuz lau multzoetako ontzientzat. Karakterizazio hau haien antzekotasunetan oinarritzen da, hala nola, xede-espezieak, arrantza-aparailuak eta arrantza-eremuen mota eta distantzia. Lau talde hauek dira: (i) itsasertzeko flota txikia; (ii) flota pelagiko handia; (iii) flota demersal handia; eta (iv) urruneko flota.

Behin FRODSS bat garatzeko marko orokor bat definitzen denean, flotaren agregazioarekin batera, hurrengo urratsa FRODSSen geruza desberdinak definitzea da. Tesi hau, batez ere, bideratze eta planifikazio geruzan zentratzen da, nahiz eta itsasontziaren modelatze eta arrantza geruzei ere ekarpenak egin. Lan honetan zehazki, bi arrantza bideratze-problema formulatzen dira eta bi soluziotan zehazten da (ikusi 0.1 Irudia). Horretarako, kontuan hartzen ditu eguraldiak duen eragina ontzien errendimenduan eta arrantza-eremuen aukeraketan.

Bi problemak aztertzeko, urruneko inguratze-ontzia erabili da, Indiako ozeanoan atun tropikalak arrantzatzen dituena. Atunontziak teknologikoki, munduko arrantza flota aurreratuenetakoak dira. Garrantzi berezia izan du honetan dFAD erabilerak. dFAD-ak objektu artifizialak dira, ozeanoan askatzen direnak arrainak erakartzen dituen habitat artifizial bat sortzeko. Honako dFAD-ek ekozunda eta GPS-a izaten dute integratuta, beren ibilbidean zehar pilatutako arrainen biomasaren estimazioa eta bere posizioa ematea ahalbidetuz. Haien erabilerak, beraz, arrainen bilaketa-denbora eta funtzionamendu-kostuak murriztu ditzake, edozein unetan dFAD-ak azkar koka bait daitezke haien azpiko arrain-biomasaren estimazioa ezagutuz.

Tesiaren 3. Kapituluan definitutako lehen arrantza bideratze-problemaren helburua honako hau da:

2. Helburua

Inguratze ontzi bakar baten bideratze-problemaren formulazioa eta hura konpontzeko algoritmo metaheuristiko bat proposatu.

Inguratze ontzi baten praktika operatiboa, arrantza ontziak portutik atera eta sartzen denerarte egiten duen ibilbidea da, non hainbat arrantzaldi egiten diren. Helburua, bidaia-kostu osoaren eta bisitatutako arrantza-eremuetan espero den sariaren arteko trukaketa minimizatzen duen ibilbide bat aurkitzea da. Tesi honek, atuna arrantzatzen duen inguratze itsasontziaren bideratze-problema dinamikoa aztertzen du, ikuspuntu taktiko eta operatibotik. Bideratze-problema taktikoa, k-saltzaile ibiltariaren problema, xede mugikorrekin, eta denbora-tarteak aldakorrak direla kontuan hartuz formulatzen da (DkTSP-MTTW). Dakigunez, hau da DkTSP-MTTW-ren lehen formulazioa literaturan. Problema operatiboa, berriz, denboraren araberako bide laburrenaren problema gisa formulatzen da.

Problema hau ebazteko GA-TDA* izeneko algoritmo bat proposatzen da. Algoritmo hau algoritmo genetiko (GA) batean oinarritzen da eta problemen menpeko operadoreak erabiltzen ditu, gainera denboraren menpeko A* algoritmoa akoplatzen du. Arrantza-enpresa baten datu errealak erabiliz, diseinatutako GA-ko operadoreak ebaluatzen dira. Horretarako, definitutako bi objektiboen arteko konbinazioa erabiltzen da: erregai-kontsumoa eta harrapaketa handiak egiteko probabilitatea.

Algoritmo honekin lortutako emaitzak arrantzako datu historikoekin alderatzen dira eta erregaien kontsumoan eta itsasoan aurreztutako denbora potentziala kalkulatzen da, %57 eta %33 hurrenez hurren. GA-TDA* dinamikoak adierazten duenez, arrantza-eremu hobeak hautatzeak eta eguraldi-baldintzak kontuan hartzeak, arrantza-industriari klima-aldaketara egokitzen lagun diezaioke, kostu nagusietako bat (erregai-kontsumoa, alegia) murriztu bitartean.

Bigarren bideratze-problemaren helburua 4. Kapituluan azaltzen da, eta honako hau da:

3. Helburua

Inguratze itsasontzi flotaren bideratze-problemaren formulazioa eta hura konpontzeko algoritmo metaheuristiko bat proposatzea.

Kapitulu honetan helburu bikoitzeko programazio lineal oso misto-ko (MIP) bi modelo aurkezten dira: bat problemaren bertsio estatikoarentzat, eta bestea denboraren araberako aldakortasuna kontuan hartzen duena. Helburu anitzeko GRASP (MO-GRASP) algoritmo bat proposatzen da MIP modeloen soluzio zehatzaren instantzia-tamainaren mugak gainditzeko eta problemaren instantzia errealei aurre egiteko eta ebazteko. Bi-objektiboen planteamenduak, erabiltzaileari, helburu ekonomikoak eta erregai-kontsumoa trukatzeko aukera ematen diote. Denbora-tarte anitzeko arrantzaren bideratze-problemaren aldaera estatikoa aztertzeak konputazio-proba zabalak eta algoritmoen doikuntza zehatzak ahalbidetzen ditu denboraren menpeko problema askoz konplexuagora igaro aurretik, denbora-tarte anitzeko arrantza bideratzeko arazoarekin.

Instantzia sintetikoekin egindako konputazio-esperimentuek GRASP algoritmoaren errendimendu ona erakusten dute, eredu estatikoaren soluzio global optimoekin alderatuta. Era berean, parametroen baldintza ezberdinetarako algoritmoaren sentikortasuna ere ikertzen dute, hau da, nodo kopurua (arrantzatu edo askatu beharreko dFADak). Soluzio-metodoak ontzi bakarreko problema batera murriztuz gero, 3. Kapituluan inplementatutako algoritmoarekin alderatu ahal izango genituzke. Horrez gain, Ozeano Indikoan jarduten duen arrantza flota baten urtebeteko datu historikoekin esperimentu konputazionalak egiten dira. Esperimentu hauek aukera ematen dute GRASP algoritmoa testuinguru erreal batean aplikatzearen bideragarritasuna frogatzeaz gain, arrantza-flota baten arrantza estrategia bateratuaren onurak aztertzea (estrategia kolaboratiboa) ontzi bakoitzaren estrategia indibidualista batekin alderatuta (estrategia ez kolaboratioboa). Esperimentu hauek erakusten dute, estrategia kolaboratiboek, erregaikontsumoa nabarmenki murrizten dutela (%17,3) eta itsasoan denbora gutxiago ere ematen dutela (%10,1), nahiz eta estrategia indibidualistekin alderatuta, zertxobait gutxiago (%2,9) arrantzatu. Azken esperimentuak ontzi bakoitzak eskuragarri dituen dFAD kopurua murriztearen eragina aztertzen du bi estrategietan (kolaboratiboan eta ez kolaboratiboan). Ontzi bakoitzeko dFAD aktiboen kopuruaren murrizketa aztertzea garrantzitsua da, kudeaketa-erakundeak dFAD-ak murrizteko neurriak hartzen ari baitira. Emaitzek nabarmentzen dute, estrategia kolaboratiboaren garrantzia, dFADen kopurua murrizten den heinean, erregaikontsumoa murriztea eta itsasoan denbora gutxiago izatea dakarrelako, arrantzaerrendimendu onari eutsiz.

5. Kapituluak ondorio orokorrekin eta etorkizuneko lan posibleak aztertzen ditu. Ondorio orokorrak bi taldetan bana daitezke: lehenengo taldean, tesiak optimizazio konbinatorioaren eremuari egiten dizkion ekarpenak azaltzen dira, non bi problema berri formulatzen diren eta bi metaheuristiko garatzen diren; bigarren taldean tesiak arrantza sektorearen kudeaketa estrategiei egiten dizkion ekarpenak biltzen dira, non ondoriozta daitekeen, arrantza bideratzeko problemaren soluzio batzuk egoera multzo jakin batean azkar ebalua daitezkeela ibilbide egokiena aukeratuz. Azkenik, tesi honen etorkizuneko luzapenak eta ikerketak aztertzen dira.

Laburbilduz, tesi honek bi optimizazio konbinatorioko problema berri planteatzen ditu, arrantza-sektoreko aplikazio erreal batean oinarrituta. Gainera, arazo bakoitzerako metaheuristiko bat proposatzen da, eragiketa jasangarriak eta eraginkorrak garatzen lagun dezakeena, bideragarritasun ekonomikoaren eta kontserbazio ekologikoaren arteko oreka bermatuz.

Contents

1

Introduction

This chapter provides an overview of the current state of efficiency in the fishing industry. It then explores the potential use of operational research methods to optimize fishing routes. A description is then given of the tuna purse seine fleet, which serves as a case study throughout this thesis. This description highlights the opportunities available for optimizing their routes. Finally, a brief literature review is provided of the main approaches applied to fishing route problems.

1.1 The State of Efficiency of World Fisheries

Historically, fisheries have played a crucial role in the sustainability of the planet by providing an important source of protein to the population. Until the end of the nineteenth century, the main idea was that the ocean could provide almost unlimited quantities of fish indefinitely. Unfortunately, this misconception was reinforced by data indicating a general increase in catches. It is now clear that increasing catches are mainly due to increased fishing pressure and the use of more efficient fishing methods.

Fisheries will continue to play an important role in providing food and nutrition in the future. However, there is a growing consensus that all fisheries are vulnerable to overfishing, and there are growing concerns for the sustainability and efficiency of fisheries. This is happening despite technological developments, with the global fishing fleet emitting 20% more emissions per tonne of fish landed to catch the same amount of fish as at the beginning of the century [Bell et al., 2017, Parker et al., 2018]. This trend in catches can be seen in Figure 1.1, where catches have remained relatively constant since 1990, indicating growing acknowledgement that some fish stocks are close to their limits.

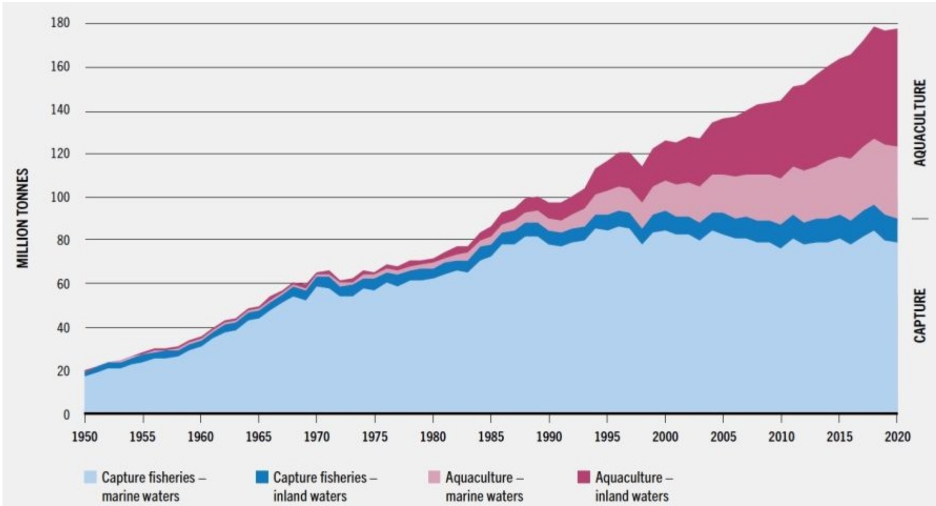


Fig. 1.1: World capture fisheries and aquaculture production. Notes: Excluding mammals, crocodiles, alligators, caimans and algae. Data expressed in live weight equivalent. Source: [FAO, 2022].

There are many reasons for this negative trend in environmental performance, including overcapacity and declining fish stocks [Parker et al., 2018]. In addition, some studies suggest that the biomass and size of fish may be reduced due to the effects of climate change, along with a change in their spatial distribution and size [Lotze et al., 2019, Tittensor et al., 2021, Erauskin-Extramiana et al., 2023]. This will put additional pressure on fish stocks and exacerbate this negative environmental trend in the future.

Coupled with the urgent need to adapt to climate change and mitigate its impacts, these concerns are becoming a global priority. For example, with the adoption of the European Green Deal, the European Union (EU) has set itself the goal of achieving zero emissions by 2050, with an interim target of reducing emissions by 50 to 55% by 2030 [European Commission, 2019]. In the fisheries sector, the interim target is to reduce greenhouse gas (GHG) emissions by 30% by 2030 compared to 2005 levels. However, fishing is still heavily dependent on the use of fossil fuels, whose consumption can account for between 30 and 75% of total operational costs [Tyedmers and Parker, 2012]. In addition to representing a high proportion of operational costs, their consumption is also a major contributor to global greenhouse gas emissions [Basurko et al., 2013a]. The EU therefore requires fisheries to be environmentally friendly, economically viable and socially sustainable in order to ensure long-term European food security.

A combination of short-term and long-term strategic measures can be implemented to achieve these objectives. However, long-term strategic solutions focus on the development and implementation of more energy-efficient vessels and management regulations, which are only feasible in the long term and may be associated with high costs [Alma-Maris, 2023]. In contrast, short-term technological solutions provide an opportunity to decarbonise the fisheries sector and meet the GHG reduction target in the short term. These solutions can also improve their efficiency and sustainability, and the technologies can be divided into four main areas of action: (i) vessel technologies; (ii) fishing gear technologies; (iii) regulatory and management measures; and (iv) fisheries strategy [Alma-Maris, 2023].

Towards Sustainability and Efficiency in Fisheries

This thesis will focus on improving fishing strategy and operations by formulating novel, realistic fishing routing problems and implementing optimization algorithms to solve them. This will make it possible for fishermen to engage in a more sustainable activity by reducing effort, cost and environmental impact, thus ensuring their sustainability and efficiency.

1.2 Optimization of Fishing Operations

In the past, fishermen have based their fishing strategy and operations on knowledge acquired over the years. This knowledge was mainly based on their experience, local knowledge and weather conditions. However, this approach has its limitations and can lead to sub-optimal routes. Today, fishermen have access to and collect better fisheries, oceanographic and vessel performance data. However, they do not extract all the potential value from the data they collect and their use of data lags behind other sectors. This thesis explores the application of mathematical modelling techniques, such as the combination of operational research (OR) and machine learning methods, to design better operations using the available data.

OR is a multidisciplinary field that applies advanced analytical methods and mathematical modelling to optimize complex systems and decision-making processes. Using mathematical and computational approaches, OR aims to improve efficiency, sustainability and overall performance by finding optimal or near-optimal solutions to complex decision problems. OR has been applied in various fields such as transportation, logistics, manufacturing, healthcare and finance [Luss and Rosenwein, 1997]. However, few applications of OR have been proposed for the fishing industry, although OR can provide valuable insights and strategies to address the sustainability challenges faced by the industry by optimizing fishing operations.

The optimization algorithms used to solve operational problems can be divided into two categories:

- **Exact algorithms** guarantee optimal solutions. That is, given enough time on a problem of reasonable size, they find the optimal solution when there is no other solution with a better objective function value. Examples include Branch and bound, dynamic programming, etc.
- **(Meta)heuristic algorithms** do not guarantee optimal solutions, but they can find near-optimal solutions faster. This can be useful when the running time of exact algorithms is an issue and the problem size is too large. Examples include local search-based algorithms, such as tabu search, and evolutionary algorithms, such as genetic algorithms, etc.

In both approaches, the main idea is to find the best possible solution to a problem within a given set of constraints, seeking to optimize one or more objective functions. However, exact solution methods usually have an exponential running time, making it difficult to apply them to real problems due to their size. A comprehensive review of exact and heuristic algorithms with a focus on our context is given in Section 2.2.3.

Besides the choice of algorithm, another crucial aspect of an optimization problem is the definition of the objective function. There are two main approaches to defining an objective function: the mono-objective approach, and the multi-objective approach. The former focuses on finding an optimal solution that es a specific objective in a single objective function. The latter involves optimizing more than one objective function simultaneously, taking into account the trade-off between two or more conflicting objectives.

Multiple objectives can be addressed in two ways: first, by optimizing a weighted combination of the desired objectives in an objective function [Kosmas and Vlachos, 2012]; and second, by using a multi-objective optimization solution strategy that treats each objective separately [Vettor and Guedes Soares, 2016]. In the first approach, these weighted parameters can be adjusted to give a relative importance to each objective based on the user's preferences. In the second technique, the optimization of one objective is often at the expense of the others. Therefore, there may be no solution that optimizes all objective functions at once. Accordingly, there is a set of optimal solutions called the Pareto front [Newbery and Stiglitz, 1984]. The solutions are based on the Pareto optimality criterion, which states that one solution dominates another if it gives better results in at least one objective without worsening any of the others. This approach adds flexibility by allowing users to vary the preference for each objective according to their current interests or priorities.

OR can be applied in fisheries in many ways, such as in fisheries management [Gaither, 1980, Azadivar et al., 2009], the selection of fishing grounds [Millar, 1996], operational production planning [Randhawa, 1995, Bakhrankova et al., 2014], fleet design [Harding and Haley, 1982, Weerasooriya et al., 1992], and vessel design [Gammon, 2011]. However, this work will focus specifically on fishing route problems, in particular, the definition of fishing strategies that take into account vessel performance, and the selection of fishing grounds based on changing weather conditions.

1.3 Fishing Routing Problems

Routing Problems

Routing problems are a class of combinatorial optimization problems that involve determining the most efficient or optimal routes for vehicles visiting a set of locations that minimize or maximize a given number of objectives, taking into account various constraints. There are several variations and specialisations of routing problems based on problem characteristics, such as number of vehicles, time windows, vehicle capacity, dynamic vs static etc. These problems are of great importance because many real situations or problems can be modelled in this way.

Routing problems are commonly formulated and solved in the maritime or road transport industries to solve real-world problems. However, there is a lack of real-world applications in the fisheries sector due to the complexity that goes beyond the classical shipping needs of getting from one point to another with weather uncertainty as the main problem. Fishing optimization has to face this weather uncertainty and the uncertainty of finding the target species. Thus, fishing route problems have to take into account trade-offs between classical objectives and fishing specificities (e.g., fuel consumption/emissions per fish landed, catch or by-catch).

The consideration of multiple objectives when optimizing fishing routes, such as maximizing catches while minimizing environmental impact, is an important factor. Adding these factors together is not straightforward due to the highly dynamic nature of the fisheries problem, which leads to high uncertainty associated with vessel performance, information on species distribution, and the fact that gear deployment is not always successful. The overall objective in defining a fishing strategy is usually to minimize total costs (e.g., fuel consumption and time at sea) while maximizing profits (e.g., catches).

Fisheries also have specific constraints such as quotas, bycatch, restrictions on fishing windows, competing fleets or even pirates in some distant water fleets. In addition, there are four other main challenges that can explain the lack of technology integration in 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 fishermen [Bradley et al., 2019].

In the case of fishing routes, at least two objectives need to be considered: total costs and expected rewards (e.g., total catch). For example, if a skipper defines a fishing trip based only on minimizing total cost without considering expected reward, this may result in a route with low fuel consumption but also low catches, or even no catches of significance, making the route unprofitable. On the other hand, if the trip is defined only in terms of maximizing catches, it may lead to significantly higher fuel consumption, resulting in higher costs and greenhouse gas emissions, again making the route unprofitable. Therefore, in a real fishing planning problem, it is crucial to find a balance between total costs (e.g., fuel consumption or greenhouse gas emissions) and expected benefits. Of course, consideration can also be given to other objectives, such as increasing safety, reducing bycatch or minimizing time at sea.

A General Fishing Problem

A simple version is to find the fishing grounds that minimize (or maximize) a function f that at least takes into account the relationship between the total costs and expected rewards of the fishing grounds visited, subject to a set of constraints. That is, find π such that:

$$
\begin{aligned}
\text{min (or max) total } f \text{ value of grounds visited by } \pi & \quad (1.1)\\
\text{s.t. } \pi \text{ is a simple cycle} & \quad (1.2)\\
\pi \text{ has a length lower than } d_{max} & \quad (1.3)\\
\pi \text{ starts and ends in a port} & \quad (1.4)
\end{aligned}
$$

where d_{max} is the maximum length of the cycle (e.g., days at sea, distance, number of fishing sets).

This optimization task can have different degrees of complexity, from the simplest definition to a variety of more well-defined complex problems, such as the routing of one or more fishing vessels, taking into account the dynamic (time-dependent) moving target characteristics of the fishing grounds. The solutions to fishing routing problems can help fishermen to quickly evaluate a given set of solutions or scenarios in order to select the most appropriate route. However, in order to define a fishing routing problem, it is important to consider the specifics of each fishing fleet, such as target species, fishing gear and distance to the fishing grounds.

1.4 Routing Opportunities in the Purse Seine Fleet

This thesis focuses on the fishing routing problems faced by the distant-water purse seine fleet targeting tropical tuna in the Indian Ocean. Tuna and tuna-like species are among the four most valuable commercial fish groups, with a total catch of 7.8 million tonnes in 2020 [FAO, 2022]. In addition, the global tuna fishery is one of the largest in the world, targeting large pelagic fish with high migratory patterns [Artetxe-Arrate et al., 2020]. Vessels targeting tuna tend to have higher and more variable fuel consumption than other fisheries targeting small coastal pelagic fish [Parker and Tyedmers, 2015]. Compared to other fishing gears targeting tropical tuna (i.e. longliners, trollers or pole-and-line vessels), purse seine vessels perform relatively better in terms of fuel consumption per tonne of tuna landed [Tyedmers and Parker, 2012]. As a result, purse seine fishing is the most common method of catching tropical tuna, accounting for 66% of total catches [ISSF, 2022].

The deployment of the purse seine consists of several phases, starting with the detection of the school of tuna and the assessment of the species and size of the tuna in order to determine its catchability (Figure 1.2). The operation begins by deploying the net around the school of tuna with the help of an auxiliary boat. Once the school is encircled, the net is closed at the bottom and the tuna are transferred to the fishing vessel.

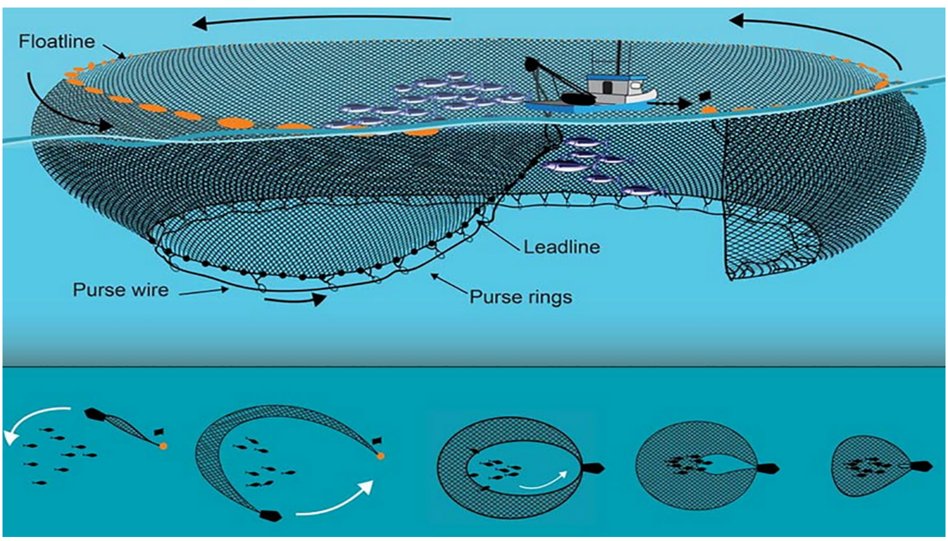


Fig. 1.2: Different phases in the deployment of a purse seine. Source: Australian Fisheries Management Authority.

Nowadays, purse seines have two different types of sets [Basurko et al., 2022]: free-swimming school sets (FSC); and sets on dFADs. The former are sets deployed on unrelated schools of tuna, relying on visual cues for detection. The latter, used specifically in this fishery, are sets made around a school of tuna associated with a drifting fishing aggregation device (dFAD). These dFADs are artificial floating objects deployed in the ocean to create an artificial habitat that attracts fish, including tuna [Orue et al., 2019a]. The reason for this associative behaviour is still unclear, but there are two main hypotheses (see Orue et al. [2019b] for more details). Since around 2000, dFADs have incorporated a satellite-linked echosounder which, together with a global positioning system (GPS), provides a rough estimate of the biomass of aggregated fish along their trajectory [Lopez et al., 2014]. As a result, their use can reduce search time and operational costs, as they can be quickly located at any time and can also indicate whether there is fish biomass beneath them. In addition, the dFAD sets have shown higher success rates compared to free-floating sets [Basurko et al., 2022]. Accordingly, the number of dFAD sets has steadily increased, with more than 80% of fishing sets in the Indian Ocean using dFADs [Báez et al., 2020a].

Evolution in the use of acoustic information on the presence of fish has greatly facilitated the route planning of the purse seine fleet. Figure 1.3 illustrates this evolution, from the search for schools of tuna using mainly visual cues 1.3(a), to the use of logs or dFADs equipped with GPS but without acoustic information 1.3(b), to current practices where dFADs have integrated both GPS and echo-sounder technologies 1.3(c). This technology makes it possible for fishermen to efficiently locate their dFADs and estimate the biomass of fish below, thus reducing search time and operating costs.

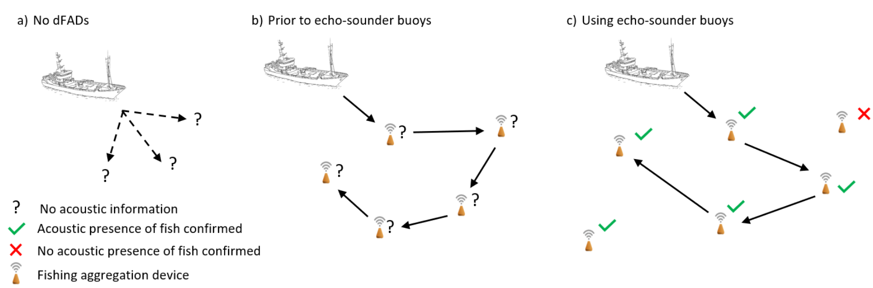


Fig. 1.3: Evolution on the establishment of drifting fishing aggregation device (dFAD) fishing in the purse seine fleet from fishing without drifting fishing aggregation devices (dFADs) (a), fishing with dFAD equipped only with a GPS (b), to dFADs with GPS and echo-sounders (c).

Despite the use of dFADs and other technological advances, fishermen often fail to make the most rational decision for dFAD deployment that would further reduce their fuel consumption and GHG emissions [Basurko et al., 2022]. This creates an opportunity to use vessel routing tools to help fishermen in the fishing planning process to quickly evaluate a certain set of solutions or scenarios and consider several factors at once, such as dFAD information, weather conditions, fuel consumption, travel time and tuna distribution.

The Purse seine Fleet Routing Problem

The operational practice of the purse seine fleet targeting tropical tuna is to design a route that starts and ends at a port where multiple sets are made. The objective is to find a route that minimizes the trade-off between total travel cost and the expected reward of the visited fishing grounds from all available fishing zones or dFADs.

1.5 Related Work

The aim of this section is to provide a comprehensive background and overview of the main approaches proposed in the literature for fishing routing problems. This review will serve as a basis for introducing the contributions of this thesis.

In the literature, ship routing methods have been widely used in maritime transport [Zis et al., 2020, Christiansen et al., 2013]. However, their application in fisheries has been low-key, despite the fact that significant theoretical and experimental progress has been made in the field of ship routing [Fagerholt et al., 2009a]. The use of routing methods in fisheries has focused mainly on weather routing, i.e. from one point to another, where weather uncertainty is the main problem [Vettor and Guedes Soares, 2016, Vettor et al., 2016, Mannarini et al., 2016a,b, Palenzuela et al., 2010].

In Vettor and Guedes Soares [2016] and Vettor et al. [2016], a multi-objective genetic algorithm (MOGA) was used to develop an optimization system considering the objectives of ETA, fuel oil consumption (FOC) and safety. Furthermore, the MOGA was coupled with a modified Dijkstra's algorithm to perform a prior optimization for the first generation of the route population. This method was called the ES (Evolution Strategy)-Dijkstra method. In Vettor and Guedes Soares [2016], the fishing vessel travels from the port of Valencia to a hypothetical fishing area in Malta, while in Vettor et al. [2016] it travels from Portugal to Norwegian waters. Another graph search algorithm based on Dijkstra with time-dependent edge weights used a fishing vessel as a case study [Mannarini et al., 2016a,b]. For the environmental data used, a distinction was made between static fields (i.e. bathymetry and coastline) and dynamic fields (i.e. waves). A machine-learning approach (ANN model) was used to optimize the routes of six fishing vessels operating in different fishing grounds Palenzuela Torres et al. [2010]. However, these operational optimization methods do not take into account specific fishing factors and operations.

To the best of our knowledge, the only studies that have optimized the routes of a fishing vessel by considering some of the fishing operations were performed by Groba et al. [2015, 2018]. In these studies, a dFAD recovery strategy for a few days was optimized by minimizing the distance travelled for a single fishing vessel [Groba et al., 2015] or for multiple vessels [Groba et al., 2018]. The former was formulated as a dynamic travelling salesperson problem (DTSP), while the latter was formulated as a multiple travelling salesperson problem (mTSP). In addition, their routing horizon was limited to a few days instead of an entire fishing trip, which spans approximately 25 days. In both approaches, a genetic algorithm was proposed with the support of a prediction technique to forecast the movement of the dFADs. However, these approaches did not take into account the performance of the vessel and the distribution of tuna based on weather conditions or fishing windows. Furthermore, they assumed a small, fixed number of pre-selected dFADs to be visited, without considering the selection of the best dFADs to fish from all the available dFADs a vessel normally uses at sea ($\sim$200).

In conclusion, the use of planning and optimization methods in fisheries is low-key due to the complexity that goes beyond the classical navigation needs of going from one point to another with weather uncertainty as the main problem, without taking into account the specificities of fishing. This shows the great potential of the digitalisation of fishing fleets and the application of Decision Support Systems (DSS) adapted to fishing.

1.6 Overview of the Dissertation

This thesis is divided into five chapters, organised as follows: chapter 1 provides a self-explanatory introduction to a number of basic concepts necessary for understanding the following contributions. Specifically, section 1.1 describes the current state of efficiency in world fisheries; section 1.2 provides a general introduction to operational research algorithms, objectives and constraints with a particular focus on fisheries; section 1.3 explains the general fishery routing problem; section 1.4 describes the purse seine fleet and explores the opportunities for operational optimization through the use of routing algorithms; and finally, section 1.5 provides a literature review of existing approaches proposed for fishing routing problems.

The following chapters describe the main contributions of this thesis. Chapter 2 establishes the basis for the development of different DSSs according to existing fleets, along with the main algorithms, objectives and constraints used in the literature. Chapter 3 focuses on the formulation of the dynamic fishing routing problem for a single vessel, while Chapter 4 focuses on the formulation of the fishing routing problem for multiple vessels. Chapters 3 and 4 propose respective metaheuristics to solve these problems.

Finally, Chapter 5 gives the general conclusions of the thesis, points out possible future work and lists the publications and main achievements produced during this thesis.

2

Towards a Fishing Route Optimization Decision Support System

In this chapter, a general framework to develop a fishing route optimization decision support system (FRODSS) is suggested, along with a review of the state-of-the-art with respect to the main objectives, constraints and algorithms used at tactical and operational level. Furthermore, suggestions are made on how to modify these objectives and constraints, taking into account the fishing particularities to address the existing gap in the literature. Finally, an aggregation of existing fleets into four main groups is proposed, where similar optimization approaches can be applied to develop a FRODSS for each group.

2.1 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, requires 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]. The strategic problems will not be discussed in detail here, and for further information readers may refer to some of these works [Christiansen et al., 2013, 2004]. 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 2.1). 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), and arrange stops/visits in an optimal sequence (scheduling) in order to, for a ship or multiple ships, 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].

Problem	Formulation	Planning horizon	Scope	Main objectives	Main constraints	Example of problems
Weather routing (operational)	SPP	Short-term (1day-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

Table 2.1: Summary of the main characteristics of the studied planning horizon. 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.

These tactical and operational ship routing methods are usually embedded into decision support system (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 (FRODSSs) 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 (FOC), 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 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 (bycatch), 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 [Avadíand 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 [Tyedmers and Parker, 2012].

The first purpose of this chapter 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 2.2). 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 2.3 and 2.4). 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 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.

2.2 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 FRODSS, are summarized in Fig. 2.1.

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., 2019b, Mannocci et al., 2021]. However,

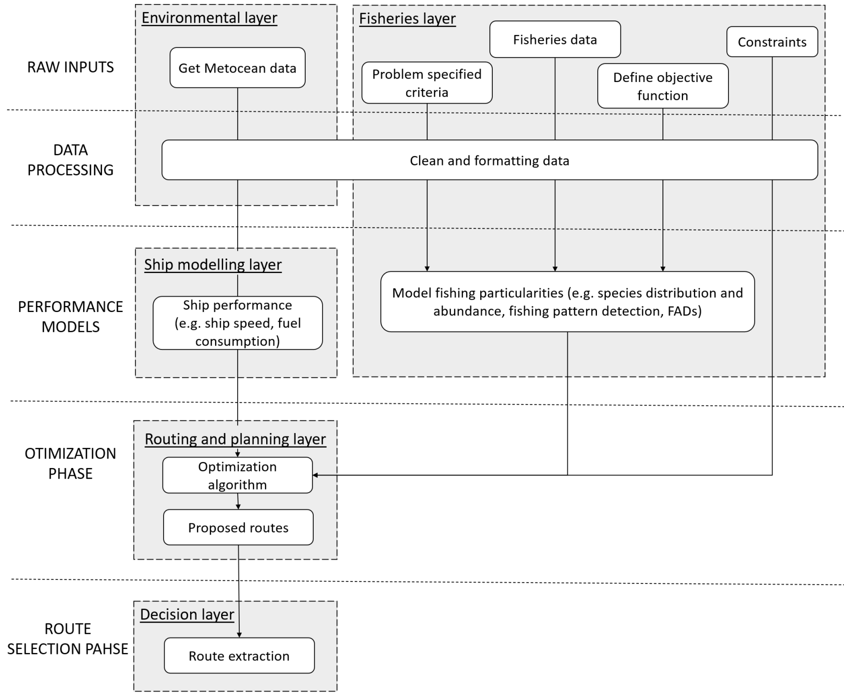


Fig. 2.1: A general scheme of a fishing route optimization decision support system (FRODSS).

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 Section 2.2.1 and Section 2.2.3, 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 [Vettor and Guedes Soares, 2016, Lazarowska, 2014].

2.2.1 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, 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 [Mannarini et al., 2016a, Sen and Padhy, 2015]. One of the first approaches that optimized the **FOC** 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].

2.2.2 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 [Vettor and Guedes Soares, 2016, Fang and Lin, 2015]. 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 [Vettor and Guedes Soares, 2016, Fang and Lin, 2015, Szlapczynska, 2015].

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 2.3.1.

2.2.3 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 Subsection 2.2.3.1) and tactical (see Subsection 2.2.3.2) 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.

2.2.3.1 Operational ship weather routing methods

Table 2.2 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].

	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
	[Palenzuela Torres et al., 2010]	Fishing vessels	Min FOC		Artificial Neural Networks
	[Yoo and Kim, 2015]	Theoretical	Min time	Motion	Reinforcement learning

Table 2.2: The main weather routing algorithms used in the literature according to the objective function and the main constraints considered in each case. Abbreviations are: fuel-oil consumption (FOC) and estimated time of arrival (ETA).

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].

Nature inspired algorithms are metaheuristic 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 [Vettor and Soares, 2015, Szlapczynska, 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 [Kosmas and Vlachos, 2012, Ibarbia et al., 2011, Li and Qiao, 2019]; ii) **Ant colony algorithm** (ACA), which is a probabilistic technique inspired by ants' foraging behaviour Lazarowska [2014], Tsou and Cheng [2013]; 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, Zheng et al., 2019, Lin, 2018].

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 [Palenzuela Torres et al., 2010, Hagiwara et al., 1996]. 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].

2.2.3.2 Tactical ship routing and scheduling methods

Table 2.3 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].

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, 2000a]	Industrial	TSP with allocation, time window and precedence constraints	Min cost	TW, AL, SC	Dynamic programming	Exact
[Fagerholt and Christiansen, 2000b]	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., 2009b]	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 neighborhood search	Heuristic
[Castillo-Villar et al., 2014]	Tramp	VRP with time window	Min cost	TW	Variable neighborhood 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

Table 2.3: The main algorithms used in the literature to solve the routing and scheduling problem. 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).

Fagerholt and Christiansen [2000a] 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, 2000b]. 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 algorithm that was based on a partly randomized insertion operator for initial solution generation, and then improved by a local search strategy. Based on a similar approach, [Fagerholt et al., 2009b] integrated an MLS algorithm into a DSS with the aim of presenting 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 [De et al., 2017, Song 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].

2.3 Definition of a Framework for Fishing Route Optimization Decision Support Systems (FRODSS) 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. LCA analysis reviews indicate that vessel fuel consumption is the main contributor to GHG emissions during fishing vessel life [Avadíand Fréon, 2013, Pelletier et al., 2007]. 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., 2013b]. 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].

In this thesis, 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].

2.3.1 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 analyzed in several project at AZTI [Basurko et al., 2013b, 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 2.4).

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 Figure 2.2.

Excluding trawlers and distant-water vessels, the remaining fleets use more than one gear throughout the year (Table 2.4). Despite the high diversity of gears, four groups of fishing fleets were identified 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 2.5).

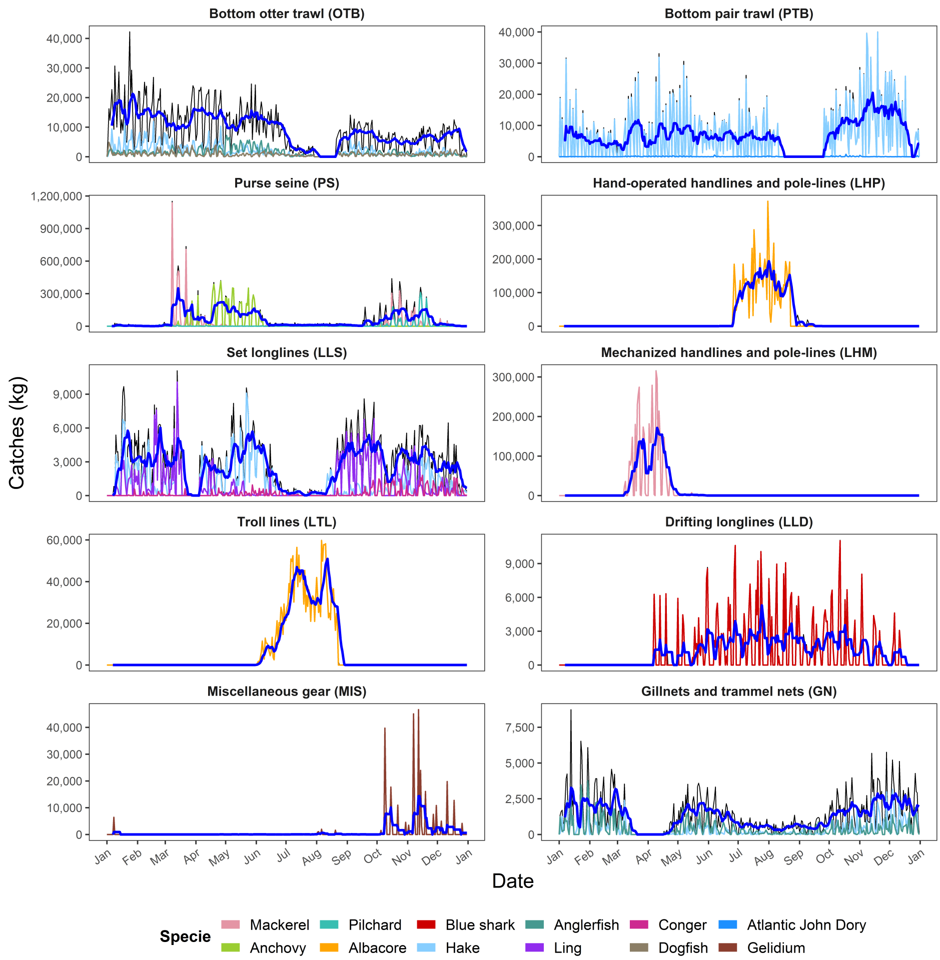


Fig. 2.2: Total catch (black line), weekly catch average (blue line) and main species catch series of the Basque fleet by fishing gear for 2018. Species are: Mackerel (*Scomber spp.*), anchovy (*Engraulis encrasicolus*), pilchard (*Engraulis encrasicolus*), albacore (*Thunnus alalunga*), blue shark (*Prionace 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*).

Nº of vessels analyzed	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		Handline, trolling	LHM, LTL	26.0	3.9	-
3	Large-scale pelagic fleet	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

Table 2.4: Fuel consumption approach for different types of Basque fishing vessels and gear. 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.

					Basque fleets			
Type	**Gear type**	**GT**	**Overall length (m)**	**Trip length (days)**	**Mean catch per trip (kg)**	**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	11,0.36	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)

Table 2.5: Summary of the Basque fleet using the logbook from 2018. Note: GT is the gross register tonnage.

2.3.1.1 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 2.4 and 2.5). The main gears used by these fleets are longliners (LLS), gillnets (GN) and drifting longliners (LLD). Longliners (LLS) mainly target the demersal species, hake, ling and conger. LLS has two downtimes (Figure 2.2): 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 pots and traps (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 be 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].

2.3.1.2 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 2.5). One characteristic of these vessels is that they consume the most energy during the trawling operations [Basurko et al., 2013b]. 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 2.5), 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 2.5). 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 (Figure 2.2). 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.

2.3.1.3 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., 2013b]. 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 (Figure 2.2). 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 2.5). 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.

2.3.1.4 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 [Tyedmers and Parker, 2012, 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 1,070 litres per tonne [Tyedmers and Parker, 2012]. 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 2.5) 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 2.4), 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.

2.4 Conclusions

This chapter 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 to consider their particularities. For example, available algorithms and objective functions need to consider the trade-offs between the classical objectives (e.g., cost, profit, fuel consumption, or time) and fishing particularities (e.g., management regulations or landed tonne of fish). 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 main 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 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.

3

The Single Purse Seine Vessel Routing Problem

In this chapter, we focus on the dynamic purse seiner routing problem for a single vessel. We propose a mathematical formulation of the problem that aims to model the real situation as realistically as possible. Additionally, a new metaheuristic algorithm that takes advantages of the problem particularities is proposed. Concretely, the solution couples a genetic algorithm (GA) that uses problem-dependent operators with a time-dependent A* algorithm. The results indicate potential savings in terms of fuel consumption and time at sea when compared to historical fishing trips.

3.1 Introduction

Despite the use of dFADs and other technological advancements, skippers do not often take the most rational decision for collecting the dFADs that would further reduce their fuel consumption [Basurko et al., 2022]. This creates the opportunity to employ vessel routing tools to help skippers in the fishing planning process by considering several factors at once, such as dFAD information, weather conditions, fuel consumption, travel time and tuna distribution. In the literature, ship routing methods have been widely used in maritime transportation [Zis et al., 2020, Christiansen et al., 2013], however, their application in fisheries has been scarce [Granado et al., 2021].

The aim of this chapter is to develop a FRODSS that can estimate the best dFAD-dependent fishing strategy to assist skippers in their decision-making process. To do so, a FRODSS is proposed that combines the tactical and operational fishing routing problems in one system. The operational problem (i.e., weather routing) enables us to find the minimum cost path (e.g., fuel consumption) between any two known points considering the effect of weather conditions on ship performance. The tactical problem (i.e., ship routing and scheduling) enables us to estimate a tour at minimal cost for visiting a subset of the total dFADs together with the best order of collection while considering the dFADs movement and fishing time window. To this end, the operational problem is formulated as a time-dependent shortest path problem, and the tactical one is formulated as the dynamic k-travelling salesperson problem with moving targets and time windows (DkTSP-MTTW). To solve this twofold problem, a genetic algorithm (GA) coupled with a time-dependent A* algorithm is proposed. The aim of the time-dependent A* is to solve the operational problem, while the aim of the GA is to solve the tactical one. Moreover, this study seeks to optimize fuel consumption and the expected reward (i.e, probability of high tuna catches) by combining them in a single objective function.

Finally, to evaluate the proposed algorithm, called GA-TDA*, three different experiments are defined. In all the experiments, the problem instances considered are built by using real data. That is, the values of the instances are obtained by means of different models that take as input real historical fishing and environmental data. The aim of the first analysis is to assess the proposed problem-specific crossovers. In the second analysis, a performance comparison between the GA-TDA* and a multi-objective approach is conducted, evaluating how the proposed objective function behaves along the Pareto front. In the final analysis, the fishing routing problem is solved dynamically by updating the data, and therefore the route, every time a dFAD is fished, and then the results are compared with historical fishing routes.

This chapter therefore presents an innovative operational research (OR) application for fishing routing problems that has not been addressed before. In addition, the problem is formulated as a DkTSP-MTTW, and to the best of our knowledge, this is the first time that this variant of the k-TSP is formalized and that a k-TSP variant is solved by means of a GA. Moreover, existing GA operators in the literature work on permutations [Groba et al., 2015, Schmitt and Amini, 1998, Kobeaga et al., 2018, Christophe et al., 2019] or variations with a variable chromosome length [Karbowska-Chilińska and Zabielski, 2013, Dutta et al., 2016, Maskooki et al., 2022], whereas our proposed representation works on variations with a fixed length. This may encourage the development of new crossover operators that take advantage of this particular feature. In addition to solving the k-TSP, these crossovers can be taken into account when solving other variation-based problems.

The rest of the chapter is organized as follows. Section 3.2 provides a description of the problem along with its mathematical formulation. Section 3.3 explains the developed algorithm, and Section 3.4 presents the data source used to estimate the data input needed to define the instances. The computational experiments and results are given in Section 3.5. Finally, some conclusions and future research directions are provided in Section 3.6.

3.2 Problem Description

This thesis aims to plan a single fishing trip for a tuna purse seiner that follows an exclusive dFAD sets fishing strategy. This routing planning refers to the problem of generating a schedule to fish a number of dFADs out of all the ones that are available, setting out to optimize an objective function and subject to a set of constraints. However, the dFADs (e.g., future location or availability), tuna distribution and vessel performance (e.g., fuel consumption or travel time) are affected by changing weather conditions and fishers' decisions. For example, some dFADs may be beached, lost, or fished by other vessels despite the dFAD information only being available to the owner. However, these events are rare since the route is driven by the information they get from their own dFADs.

3.2.1 Dynamic fishing routing problem

A previous study addressed the fishing routing problem of a single vessel as a dynamic TSP with a small fixed number of pre-selected moving-targets [Groba et al., 2015]. Therefore, they did not address the selection of the best dFADs to fish from all the ones available that a vessel usually has deployed at sea ($\sim$200), and furthermore, only a few days were planned instead of a whole fishing trip. According to this previous study, the vessel route starts at some point in the middle of the sea and ends at the last dFAD collected, instead of departing from and arriving at a known fishing port, as in this study. In addition, they did not consider the vessel's performance based on the weather conditions or the fishing time windows.

In our proposed dynamic fishing routing problem (DFRP), there is no predefined set of dFADs to fish, and a complete fishing trip is defined by considering the fishing grounds forecast and the fishing time window. Only a limited number of all the available dFADs can be visited in each fishing trip. This limit can be set by defining the number of sets to be made during the trip or by setting the trip duration. The limitation of both approaches is that the user does not know in advance either the number of sets or the time at sea. The former can be seen as a variant of the k-travelling salesperson problem (k-TSP) [Pandiri and Singh, 2020], while the latter can be understood as a variant of the orienteering problem [Vansteenwegen et al., 2011]. Both approaches have their pros and cons; however, here the problem will be formulated as a variant of the k-TSP. This formulation has received very limited attention in the literature, and to the best of our knowledge, this study is the first to apply a variant of the k-TSP to fisheries. The reason for selecting this formulation is the flexibility that it gives to the end user when defining possible scenarios or fishing strategies. For example, they can compare trips with different numbers of sets (e.g., 15, 20, 25 or 30). Another example is when the skipper wants to fish a particular dFAD, the k-TSP will allow them to set this dFAD at the last point of the route and set the number of other dFADs to be fished (k) until the desired dFAD is reached.

Therefore, the DFRP for a tuna purse seine is formulated as a variant of the dynamic k-traveling salesperson problem with moving targets and time windows (DkTSP-MTTW). The goal of the DkTSP-MTTW is to determine a tour at minimal cost that visits k of the targets, considering their movement and time window.

3.2.1.1 Instance definition and formulation

This subsection presents the data needed to define a problem instance along with the mathematical formulation used.

- $\mathcal{N} = \{1, 2, ..., N\}$ is the set of available dFADs to fish, with N being the number of available dFADs.
- k is the number of dFADs to fish, with $k < N$.
- 0 is the departure and arrival point, not considered in $\mathcal{N}$ ($0 \notin \mathcal{N}$).
- $l_i^t = (longitude_i^t, latitude_i^t)$, $i = 1, ..., N$, $t \geq 0$, is the geolocation of dFAD i at time t. Therefore, an $L_{i,t}$ matrix with the dFADs' future locations at each instant t is given:

$$L_{i,t} = \begin{pmatrix} l_1^0 & l_1^1 & \cdots & l_1^{t_h} \\ l_2^0 & l_2^1 & \cdots & l_2^{t_h} \\ \vdots & \vdots & \ddots & \vdots \\ l_N^0 & l_N^1 & \cdots & l_N^{t_h} \end{pmatrix}$$

  where the jth column contains the geolocation of each dFAD i at the jth time instant. The initial time ($t = 0$) is the time for the first available position, and the last time ($t = t_h$) is the forecast horizon. After t_h, all the locations are considered static and set to the last known geolocation $l_i^{t_h}$.
- $TW = [a, b]$ denotes the daily fishing time window for all dFADs, since the fishing event cannot occur during the night. If the vessel arrives before a or after b, it should wait until the time window is open to start fishing and then depart to the next target. a and b are real numbers expressed in 24-hour format ($0 \leq a, b < 24$).
- t_{max} denotes the maximum number of days that the fishing trip can last, expressed as an integer number.
- f_j denotes the time that a vessel spends during the fishing operations at dFAD j.
- $er_j(t)$ is the expected reward of dFAD j, i.e., the probability of high catches of tuna at the jth dFAD at time t.
- $c_{i,j}(t)$ is the cost (fuel consumption) of travelling from dFAD i to j, departing at time t from i.

- $t_{i,j}(t)$ is the number of hours needed to reach dFAD j departing at time t from dFAD i, expressed as a real number.
- Exclusive economic zone (EEZ) fishing restrictions: the fishing vessels cannot fish within some EEZs, but they can navigate through them. Here, EEZ_t represents the set of dFADs that cannot be fished at instant t as some dFADs may enter these zones at certain times.

3.2.1.2 Problem assumptions

In this research, it will be assumed that a typical fishing trip meets the following criteria.

1. *Fishing time.* The time spent fishing at all the dFADs will be the same. Based on historical $f_j = 3$ hours, $\forall j = 1, \ldots, N$ is assumed.
2. *Expected reward.* To penalize the dFADs with a low expected reward, it will be assumed that if $er_j(t) < 0.5$, then $er_j(t) = 0$.

3.2.1.3 Search space

A fishing trip planning problem consists of defining the subset of dFADs to fish, the visit schedule along with the waiting times and the route to reach each dFAD. To do so, the starting and ending points are established together with the number of dFADs to fish, k, within a predefined period of days, t_{max}. The problem solutions are formulated as variations without repetitions, that is, vectors of size k where all the elements are different integers from the set $\mathcal{N} = \{1, \ldots, N\}$. In case $k = N$, they would be permutations. A solution will be codified as $(e_0\ e_1\ ...\ e_k\ e_{k+1})$, where $e_i \in \mathcal{N}$, $\forall i = 1, \ldots, k$, and $e_0 = e_{k+1} = 0$, meaning that a vessel departing from e_0 has to fish first e_1, then e_2 and so on until e_k, and finally return to e_{k+1}. Note that 0 is known beforehand, so we need to look for the solution among the $(e_1\ ...\ e_k)$ variations. Therefore, the search space, $S = \{(0\ e_1\ ...\ e_k\ 0) \mid e_i \in \mathcal{N},\ i = 1, \ldots, k,\ e_i \neq e_j, \forall i \neq j\}$, is a finite set with all possible ordered arrangements of k different elements from the set $\mathcal{N}$, and its size can be calculated by ${V_N}^k = N!/(N-k)!$.

3.2.1.4 Objective function and restrictions

Given a set of dFADs, $\mathcal{N} = \{1, 2, ..., N\}$, located at l_i^t at instant t, each one having the same $TW = [a, b]$ associated, the aim of the DFRP is to find the minimum cost tour starting and ending at known points, which intercepts k targets $(k < N)$ taking into account their time windows and movement. To fulfil the restriction of the time window, the time at which each dFAD of the solution is reached, at_{e_i}, should be considered, where at_{e_i} is expressed in hours. The at_{e_i} can also be codified by two components $[DD_{at_{e_i}}, HH_{at_{e_i}}]$, which represent the number of days from a reference time t_s, and the current time of day expressed in 24-hour format, respectively. Thus, $DD_{at_{e_i}} = \lfloor at_{e_i}/24 \rfloor$ and $HH_{at_{e_i}} = at_{e_i} - 24\lfloor at_{e_i}/24 \rfloor$ [1]. It is also important to know the departure time from each dFAD, dt_{e_i}, in order to know the travel cost, $c_{e_i,e_j}(dt_{e_i})$, and time, $t_{e_i,e_j}(dt_{e_i})$. Therefore, having established, that the dt_{e_0} is equal to the departure time from the port:

$$at_{e_i} = dt_{e_{i-1}} + t_{e_{i-1},e_i}(dt_{e_{i-1}}),\ i = 1, \ldots, k,$$

$$dt_{e_i} = at_{e_i} + f_{e_i} + tw_{e_i},\ i = 1, \ldots, k,$$

meaning that the arrival time, at_{e_i}, is calculated as the sum of the last visited dFAD's departure time, $dt_{e_{i-1}}$, and the travelling time, $t_{e_{i-1},e_i}(dt_{e_{i-1}})$, while, the departing time, dt_{e_i}, is estimated as the sum of the arrival time, at_{e_i}, and the time spent on fishing operations, f_{e_i}, and the possible waiting time, tw_{e_i}, at e_i. The waiting time is computed as follows:

$$tw_{e_i} = \begin{cases} a - HH_{at_{e_i}} & , \mathit{if}\ HH_{at_{e_i}} < a \\ a + 24 - HH_{at_{e_i}} & , \mathit{if}\ HH_{at_{e_i}} > b \\ 0 & , \mathit{otherwise}. \end{cases}$$

Furthermore, the objective function is designed to balance the high cost of going to some dFADs with a possible higher probability of a larger tuna catch (i.e., expected reward) in such dFADs. The DFRP can be formulated as follows:

$$\text{minimize } J(e_0\ e_1\ \ldots\ e_k\ e_{k+1}) = \frac{1}{1 + \sum_{j=1}^{k} er_{e_j}(at_{e_j})} \cdot \sum_{i=0}^{k} c_{e_i,e_{i+1}}(dt_{e_i}) \tag{3.1}$$

subject to:

$$t_{trip} = dt_{e_k} + t_{e_k,e_{k+1}} \leq t_{max} \tag{3.2}$$

$$e_i \notin EEZ_{at_{e_i}},\ \forall i = 1, \ldots, k \tag{3.3}$$

where $(e_0\ e_1\ \ldots\ e_k\ e_{k+1}) \in S$, and $e_0 = e_{k+1} = 0$ is the departure/arrival point.

The aim of the objective function (3.1) is to minimize the relationship between the fuel consumption and the expected reward. Constraint (3.2) ensures that the trip duration is never greater than the maximum trip duration limit. Constraint (3.3) ensures that none of the dFADs fished are within any of the invalidated EEZs.

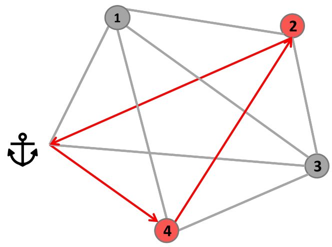
[1] $\lfloor \frac{a}{b} \rfloor$ is the floor function that gives as output the integral part of $\frac{a}{b}$.

3.2.2 Sub-problem formulation: time-dependent shortest path problem

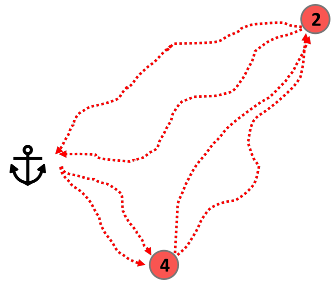
A simple example of a solution of a DFRP is shown in Figure 3.1(a), where a fishing route (in red) that leaves port (the anchor icon representing $e_0 = 0$) fishes, first, the 4 dFAD, and second, the 2 dFADs, and then returns again to port 0. The ideal situation to compute Equation (3.1) for this fishing route, $J(0\ 4\ 2\ 0)$, would be to have straightforward $c_{e_i,e_j}(dt_{e_i})$ and $t_{e_i,e_j}(dt_{e_i})$, $\forall(i,j) \in \{(0,4),(4,2),(2,0)\}$. However, in the sea, the great circle is the path of shortest distance between two points on the surface of a sphere (e.g., earth), as opposed to a straight line through the interior of the sphere. Hence, the great circle does not mean that it is the fastest path or the cheapest, thus, it is not known in advance which is the best path to link two dFADs. This situation is simulated in Figure 3.1(b), where the dashed lines represent some of the possible fishing routes that a vessel can follow to fish 4 and 2 dFADs. Therefore, a new sub-problem arises to calculate the minimum fuel path between a pair of dFADs, and thus enables us to calculate the cost between e_i and e_j, $c_{e_i,e_j}(dt_{e_i})$, and consequently the time spent on going from e_i to e_j, $t_{e_i,e_j}(dt_{e_i})$, and the arrival time at e_j, at_{e_j}, $\forall e_i, e_j$.

This new sub-problem can be formulated as the classical shortest path problem (SPP), which consists of finding the minimum cost path in a weighted graph between a source and a destination node [Bellman, 1958]. However, in many real problems the cost of travelling between two nodes is time-variable, as in our case, where the weather conditions affect the vessels' fuel consumption, $c_{e_i,e_j}(dt_{e_i})$, and the travel time, $t_{e_i,e_j}(dt_{e_i})$. Therefore, this sub-problem is formulated as a time-dependent shortest path problem (TDSPP), which works on a time-dependent weighted graph [Cooke and Halsey, 1966]. A time-dependent weighted graph can be described as $G_T = (V, E, \hat{C}, \hat{T})$, where $V = \{v_1, ..., v_z\}$ is the set of nodes, $E = \{(v_i, v_j)|v_i, v_j \in V\}$ is the set of edges, $\hat{C} = \{\hat{c}_{v_i,v_j}(dt_{v_i})|(v_i, v_j) \in E\}$ is the set of time-dependent travel cost (i.e., fuel consumption), and $\hat{T} = \{\hat{t}_{v_i,v_j}(dt_{v_i})|(v_i, v_j) \in E\}$ is the set of time-dependent travel times. Hence, the $\hat{c}_{v_i,v_j}(dt_{v_i})$ and $\hat{t}_{v_i,v_j}(dt_{v_i})$ values define this sub-problem instance. A path, or route, between a source node v_s and a destination node v_d can be expressed by a node sequence $r(v_s, v_d) = (v_1, v_2, \ldots, v_m)$ where $v_1 = v_s$, $v_m = v_d$ and $(v_i, v_{i+1}) \in E$, $\forall i = 1, \ldots, m-1$. A path $(v_1, v_2, \ldots, v_m)$ is called simple if $v_1, v_2, \ldots, v_m$ are distinct. Therefore, the size of the search space of this sub-problem is the number of all the possible simple paths that link the source node v_s and the destination node v_d.

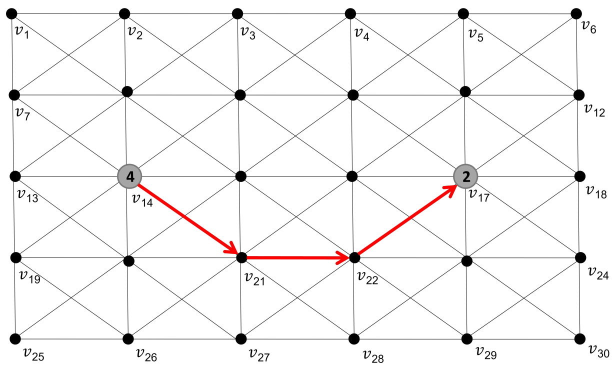
An illustrative example of a TDSPP is given in Figure 3.1(c), where the source-destination nodes are the dFADs 4 and 2, and the red edges indicate the minimum fuel path (minimum cost path). In our problem, a grid is usually considered to determine the possible paths (see Figure 3.1(c)), and when the TDSPP is solved, the $c_{e_i,e_j}(dt_{e_i})$ and $t_{e_i,e_j}(dt_{e_i})$ corresponding to the DFRP can be estimated. Hence, the minimum cost path between the pair of dFADs, $(4 = v_{14}, 2 = v_{17})$, in Figure 3.1(c) is $r^*(4,2) = (v_{14}, v_{21}, v_{22}, v_{17})$, and there-



(a) A solution for the DFRP problem, which first selects the dFAD 4 and then the dFAD 2.



(b) Different possible routes that a vessel can follow in order to fish 4 and 2 due to the weather conditions.



(c) The solution approach for the new sub-problem: time-dependent shortest path problem (TD-SPP). The grid represents a spatial discretization around the locations of 2 and 4 dFADs.

Fig. 3.1: The fishing routing problem scheme. In (a), a fishing route example is shown, where the nodes indicate the dFADs, the anchor is the port of departure and arrival, and the nodes and edges in red indicate the dFADs selected to fish and the link between them. In (b) some of the possible fishing routes that a vessel can follow to fish 4 and 2 dFADs. In (c) an example of a time-dependent shortest path problem is shown, where the grid represents a spatial discretization around the locations of 2 and 4. Hence, in each node of the grid the vessel can follow any edge leading from the current node to reach the next node. The edges in red represent the optimal solution to go from 4 to 2.

fore, $c_{4,2}(dt_4) = \hat{c}_{v_{14},v_{21}}(dt_{v_{14}}) + \hat{c}_{v_{21},v_{22}}(dt_{v_{21}}) + \hat{c}_{v_{22},v_{17}}(dt_{v_{22}})$ and $t_{4,2}(dt_4) = \hat{t}_{v_{14},v_{21}}(dt_{v_{14}}) + \hat{t}_{v_{21},v_{22}}(dt_{v_{21}}) + \hat{t}_{v_{22},v_{17}}(dt_{v_{22}})$.

Then, given a G_T, a source node $e_i = v_s \in V$, a destination node $e_j = v_d \in V$, and a departure time $dt_s = dt_{e_i}$, the TDSPP enables us to establish the optimal path, $r^*(e_i, e_j)$, between two dFADs along with the vessel's fuel consumption, $c_{e_i,e_j}(dt_{e_i})$, and travel time, $t_{e_i,e_j}(dt_{e_i})$, considering the weather conditions. The TDSPP objective function is defined as follows:

$$\text{minimize } c_{e_i,e_j}(r(v_s, v_d), t_s) = \sum_{i=1}^{m-1} \hat{c}_{v_i,v_{i+1}}(dt_{v_i}) \tag{3.4}$$

where $v_1 = v_s = e_i$, $v_m = v_d = e_j$, $dt_{v_1} = t_s$, and $dt_{v_i} = dt_{v_{i-1}} + \hat{t}_{v_{i-1},v_i}(dt_{v_{i-1}})$.

Equation (3.4) represents the objective function whose aim is to minimize the fuel consumption between a pair of dFADs $(e_i, e_j) = (v_s, v_d)$.

To sum up, the fishing routing problem could be formulated as the combination of two problems: 1) dynamic fishing routing problem (DFRP); and 2) time-dependent shortest path problem (TDSPP). Figure 3.2 shows a hierarchy diagram of how the data and problems are connected. The first step is the collection of the raw data, which is explained in Section 3.4.1. The second step is the estimation of the problem instances by means of machine learning models, which are explained in Section 3.4.2. Once we have the problem inputs, the TDSPP can be solved, enabling us to establish the time-dependent optimal path in terms of fuel consumption (i.e., vessel heading), as well as the travel time between two dFADs, while considering the effect of the weather conditions on the vessel's performance. The final step is to solve the DFRP, the aim of which is to establish a tour at minimal cost, in terms of the relation between fuel consumption and expected reward in a visit to a subset of the total dFADs, considering the movement and time window of each dFAD.

3.3 Solution Approach

A metaheuristic algorithm to solve the DFRP is proposed, which works on a deterministic discrete time-dependent dynamic network. The proposed heuristic algorithm couples a genetic algorithm (GA) [Goldberg, 1989] and a time-dependent A* algorithm [Ohshima et al., 2011] to obtain near-optimal solutions. It is called GA-time-dependent A* (GA-TDA*). The proposed GA-TDA* algorithm scheme is shown in Figure 3.3, where the GA uses a scheme based on the one implemented in the GA R package [Scrucca, 2013]. It starts by creating an initial population with random solutions, and evaluates the fitness of each individual by using a time-dependent A* algorithm. Then at each iteration the GA-TDA* generates a

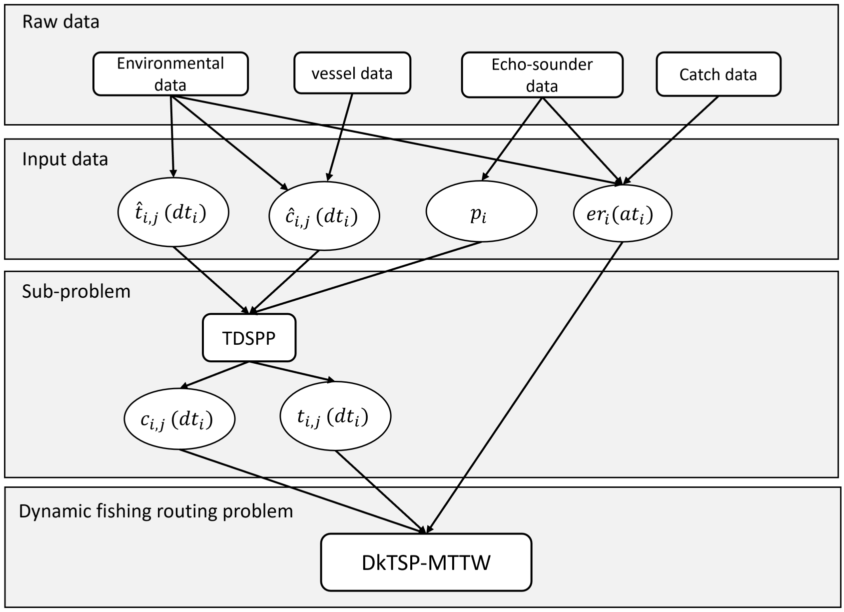


Fig. 3.2: Hierarchical diagram of how the data and problems are connected.

new offspring (new solutions) from the current set of best solutions by means of the genetic operators selection, mutation and crossover.

The main contribution of the GA-TDA* is the adaptation of new crossover operators (Section 3.3.3) designed for permutation-based problems (i.e., paths that necessarily need to visit all the nodes once) to variations without repetition problems (i.e., paths that only need to visit a subset of them). To the best of our knowledge, there is no proposal for this kind of space in the literature. The existing approaches in the literature work on permutation space [Schmitt and Amini, 1998, Kobeaga et al., 2018, Silberholz and Golden, 2007, Yu et al., 2011], or on variation space but with a chromosome of variable length [Karbowska-Chilińska and Zabielski, 2013, Dutta et al., 2016]. The main advantages of the proposed approach with the existing methods are: i) the search space is reduced since the size of the permutation space is $N!$, whereas for variations without repetitions it is $N!/(N-k)!$, reducing significantly the search space and avoiding duplications; and ii) the required memory is reduced since in the permutation object all the N available elements are part of a solution, so that a numeric vector of size N is needed to store each solution, whereas for variations only the k selected elements are part of a solution, and thus, a numeric vector of size k (with $k < N$) is enough to maintain each solution. This is an important characteristic for large instances [Kobeaga et al., 2018], and particularly where $k << N$ is concerned. An important feature of the proposed crossovers is that besides combining the elements of two parents, they allow us to select any possible element that is not in either parent. Finally, the proposed crossovers can be generalized to the cases where the solution space consists of permutations by simply using a value of $k = N$.

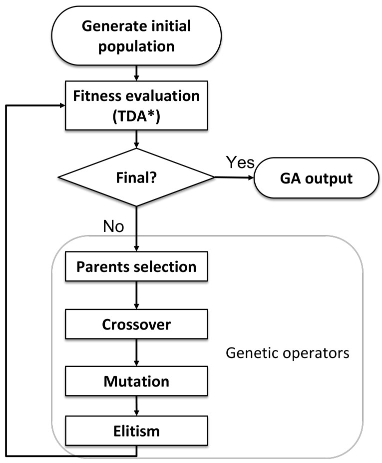


Fig. 3.3: Diagram of the genetic algorithm with time-dependent A* (GA-TDA*) algorithm.

3.3.1 Initialization

The initial population is chosen randomly with the aim of creating a diverse population that represents the whole search space. To do so, a chromosome of length k is filled with the available dFADs, $\mathcal{N} = \{1, 2, ..., N\}$, chosen at random without repetition, and then the departure/arrival ports are added to the chromosome. The population size, N_s, depends on the available number of dFADs, N, of each instance, and it is set by $N_s = 2 \cdot N$.

3.3.2 Selection

A portion of the current population in each iteration is selected to be the parents where the crossover and mutation operators will be applied. To do so, a tournament selection is used, where K solutions are selected randomly from the current population and the best solution among the K is chosen to pass to the next phase for reproduction. This process is repeated until $N_s = 2 \cdot N$ parents are chosen, and using a tournament of size $K = 3$.

3.3.3 Crossover

The aim of the crossover operator is to enhance the average quality of the population by combining two parents and, in our case, obtaining two children. The crossover operator is applied by means of a probability p_c, which establishes if the crossover will happen or not. Therefore, if the crossover occurs, the two parents are replaced by the children in the population. New crossover operators are designed to address the specific characteristics of our problem avoiding unfeasible solutions. A distance function is defined between each pair of elements, (i.e., (i, j)) to account for the problem characteristics:

$$distance(i, j; t) = \frac{d_{euc}(i, j)}{1 + er_j(t)}, \tag{3.5}$$

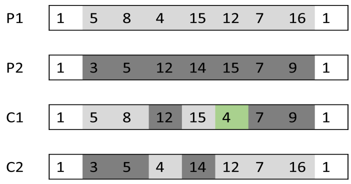
where $d_{euc}(i, j)$ is the Euclidean distance between i and j dFADs, and $er_j(t)$ is the expected reward at dFAD j at time t. It is worth noting that the time t to select the dFADs positions and $er_j(t)$ to compute the Eq. (3.5) is the departing time of the current position, $t = dt_{e_i}$. Moreover, the Euclidean distance is used instead of the great-circle distance to reduce computational time.

The repair uniform crossover (RUX) is selected as the baseline for comparison, since it does not consider the problem characteristics. Then, three crossovers are proposed for being gradually more problem-specific since they consider the problem characteristics by applying Equation 3.5. The proposed common-point crossover (CPX) only accounts for the distance function in the repair function. The random bidirectional circular sequential constructive crossover (RBCSCX) and the greedy crossover with nearest new insertion (GX-NNI) use the distance every time a new element is added to the child. However, the GX-NNI also allows new elements that are not in any parent to be added.

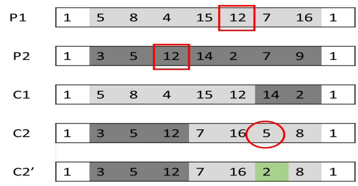
- **Repair uniform crossover (RUX)**, where each element of the children can be selected from either parent with an equal probability. This probability is generated for each position by a random number between 0 and 1, and if the probability is below 0.5, then the element is taken from P1, or from P2. Figure 3.4(a) shows an example of the RUX, where, given two parents (P1 and P2) and having the following probability vector, (0.3, 0.2, 0.6, 0.1, 0.9, 0.9, 0.7), the children (C1 and C2) are built as follows: if probability is below 0.5, C1 takes the element from P1 and C2 from P2, else, C1 takes the element from P2 and C2 from P1. However, this crossover can lead to invalid solutions since duplicated elements (dFADs) can be entered in a child. Therefore, a repair function randomly removes one of the duplicated values and inserts a random element from all the available elements (dFADs) that are not considered in the child (Figure 3.4(a)).

- **Common-point crossover (CPX)** creates a child by searching for common elements in both parents, and from these common elements one is selected at random as the cut-off point. If no common elements are found, a random element from P1 is selected as the cut-off point and to establish the cut-off point in P2, the element with the minimum distance (Equation (3.5)) from the cut-off point of P1 will be selected. Then, to build C1, everything from the first element of P1 until the cut-off point are taken from P1 along with the other elements from the cut-off point onwards, from P2. Figure 3.4(b) shows an example, where the common elements are 5, 12, and 7, and element 12 is selected as the cut-off point. Then, C1 is filled with the P1 elements from the first one up to the cut-off point (i.e., 5, 8, 4, 15, 12). The other elements are provided by P2 from the cut-off point onwards (i.e., 14, 2). The C2 is built by following the same approach, but starts with the elements of P2. Note that, when there are no more elements to add after reaching the end of a parent, the rest of the required elements are taken from the beginning of the parent (see elements 5 and 8 in the building of C2 in Figure 3.4(b)). However, this approach can create invalid solutions by introducing duplicated elements, such as element 5 in C2. Therefore, the repair function randomly removes one of the duplicated elements and inserts the new valid element that minimizes Equation (3.5) from all the available dFADs that are not already considered in the child.

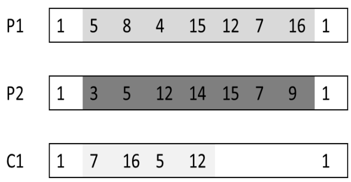
- **Random bidirectional circular sequential constructive crossover (RBCSCX)** is based on Kang et al. [2015]. First, a random element from P1 is selected as the first element of C1. The legitimate elements of a given element are defined as those that are in the closest positions of the parents and have not been previously used in the child. Then, at each step this crossover searches in both parents for the legitimate elements of the last added element. Figure 3.4(c) shows an example, where it is assumed that the elements in gray are already in C1 and the last added element to C1 is 12. Considering that the solutions are cyclical, the legitimate elements of 12 are 8 and 15 in P1, and 14 and 3 in P2 (Figure 3.4(d)). If the last added element is only in one parent, only the legitimate elements of this parent will be considered. Then, from these legitimate elements, the one with the minimum distance according to Equation (3.5) is added to C1. These steps are repeated until the child is completed. The C2 construction follows the same steps, except for the case of the initial element that is selected from P2.
- **Greedy crossover with nearest new insertion (GX-NNI)** is based on the work of Yang [1997]. The first element of C1 is selected randomly from P1, and then the adjacent elements in P1, and also in P2 if P2 contains the selected element, are identified. This is shown in Figure 3.5(a), where element 15 is randomly selected as the first added element to C1, and 14, 7, 3, and 14



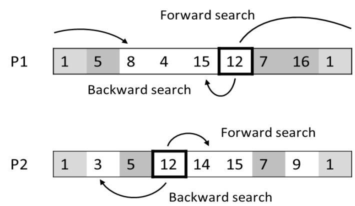
(a) Repair uniform crossover (RUX) diagram. Green indicates the element that has been inserted by the repair function in order to avoid repetitions.



(b) Diagram of the common-point crossover (CPX). Green indicates the element that has been inserted by the repair function in order to avoid repetitions.



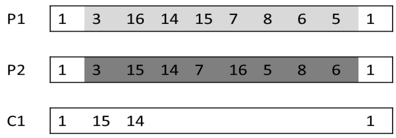
(c) Diagram of an intermediate step of the random bidirectional circular sequential constructive crossover (RBCSCX).



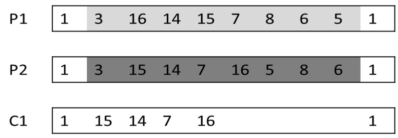
(d) Example of the legitimate elements search process for element 12. Gray elements are already in the child (see Figure 3.4(c)).

Fig. 3.4: Schemes of the crossovers.

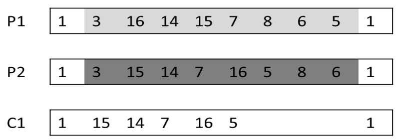
are its adjacent elements. Then, to select the new element to be added to C1 among the adjacent elements, there are four possible situations. First, if there are common elements among the adjacent elements, and if they are not in C1, the one with the lowest distance (Equation (3.5)) is selected. If there is only one common element, and if it is not already in C1, then this one is chosen (i.e., 14 in Figure 3.5(a)). The second option is to select the one with the lowest distance (Equation (3.5)) among the right-adjacent elements of both parents (i.e., elements 8 and 16, in Figure 3.5(b)). Third, if one of the right-elements is already in C1, the other one is chosen (Figure 3.5(c)). The last option is when all the right-adjacent elements are already in C1. In this case, from all possible elements (i.e., all the available dFADs) that are not in C1, the one at the lowest distance using Equation (3.5) is selected (Figure 3.5(d)). The C2 is constructed in a similar way, but when there are no common elements, the left-adjacent elements are considered instead of comparing right-adjacent elements.



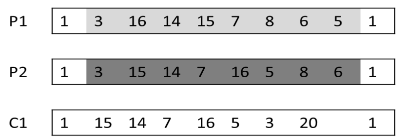
(a) Example when there is a common adjacent element.



(b) Example when there is no common adjacent element and among the right-adjacent elements, the one with the lowest distance is selected.



(c) Example when there is no common adjacent element and among the right-adjacent elements, there is only one that is not in C1.



(d) Example when there is no common adjacent element and all the right-adjacent elements are already located in C1, hence, from all possible elements that are not in C1, the one with the minimum distance is selected.

Fig. 3.5: Diagram of the greedy crossover with nearest new insertion (GX-NNI).

3.3.4 Mutation

The mutation operator's aim is to increase the exploration of solutions, preventing the algorithm from getting stuck. This is done by altering one or more elements in a chromosome based on a defined probability p_m. Here, different mutations schemes are considered (Figure 3.6).

- **Random mutation**, which works by randomly selecting an element and exchanging it for another one chosen randomly from the subset of the dFADs that are not in the current solution.
- **Scramble mutation**, which randomly selects a subset of adjacent elements that are then randomly scrambled.
- **Displaced inversion mutation**, which selects two random points in the chromosome, then reverses the elements between these two points, and finally displaces them somewhere along the chromosome.

3.3.5 Elitism

The goal of the elitism selection operator is to guarantee that the best solutions in each generation pass to the next one. Therefore, this operator guarantees that the

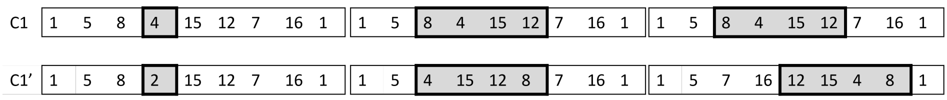


Fig. 3.6: Mutation schemes: random mutation (left), scramble mutation (middle), and displaced inversion mutation (right).

quality of the solutions does not decrease from one generation to the next. Note that $N_s = 2N$ parents were chosen (with repetition) from the previous generation, and then the crossover and the mutation operators are applied with probabilities p_c and p_m, respectively. So, in the case where one or both operators are applied, the new solutions replace their parents. At this step of the algorithm, the objective function values of these new solutions are unknown. However, in the cases where none of the operators are applied, both parents remain in the current generation, and for them the objective function value is known because it had been calculated in the previous generation. Therefore, the worst $5\% \cdot N_s = 2N \cdot 5/100$ inherited parents will be replaced by the top 5% solutions of the previous generation. If the amount of inherited parents is less than $2N \cdot 5/100$, the remaining required solutions to be replaced will be randomly selected.

3.3.6 Fitness evaluation

The fitness value of each solution is used as a measure of its quality. A general diagram of the process to calculate the fitness value of a solution of the DDRP is shown in Figure 3.7. There are three main steps:

1. The dFADs' location at each arrival time from the $L_{i,t}$ matrix is selected. To do so, the travel time is estimated by applying the following formula:

$$tt_{i,j} = \frac{dist_{i,j}}{vel} \tag{3.6}$$

where $dist_{i,j}$ is the great circle distance between i and j dFADs, and vel is the vessel speed that is assumed to be constant with a value of 12 knots. Once the arrival time is known, the dFAD position is selected from $L_{i,t}$ based on the estimated arrival time. Note that the movement of the dFADs is ignored while the vessel is travelling to collect them in order to simplify the mathematical computation. Moreover, since the study area is spatially discretized in 0.5° cells and the dFADs average velocity is usually around 1 knot, the time that a dFAD needs to leave a cell is usually bigger than the time necessary to reach the dFAD. These simplifications can introduce minor deviations in the fitness value (between 0.4% and 1.5%), hence the effect on to the solutions rank within the GA-TDA* will be insignificant.

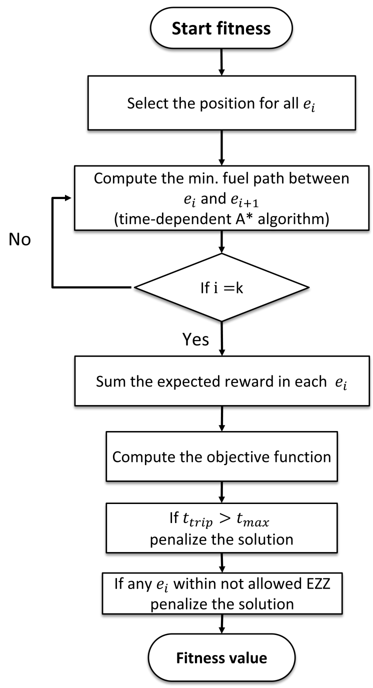


Fig. 3.7: Diagram of the evaluation of a solution of DFRP fitness.

2. The minimum fuel path $c_{e_i,e_j}(r(v_s,v_d)),t_s)$ and $t_{e_i,e_j}(r(v_s,v_d))t_s)$ is calculated, using the time-dependent A* algorithm (detailed in Section 3.3.6.1).
3. The objective function is calculated. In order to consider the constraints of the problem, the objective function (3.1) is modified as follows:

$$J(e_0\ e_1\ ...\ e_k\ e_{k+1}) = \frac{1}{1+\sum_{j=1}^{k} er_{e_j}(at_{e_j})} \cdot \sum_{i=0}^{k} c_{e_i,e_{i+1}}(dt_{e_i}) + M \cdot \tau + M \cdot \mu_{t_{trip}} \tag{3.7}$$

where $M = 10^6$ is a large number to penalize the invalid solutions if a fished dFAD is within some of the forbidden EZZs, or if the $t_{trip} \geq t_{max}$, and where τ and μ_{trip} are defined as follows:

$$\tau = \begin{cases} 1\ ,\ if\ any\ e_i \in EEZ_{at_{e_i}} \\ 0\ ,\ otherwise \end{cases} \quad \mu_{t_{trip}} = \begin{cases} 1\ ,\ if\ t_{trip} > t_{max} \\ 0\ ,\ otherwise. \end{cases}$$

3.3.6.1 Time-dependent A* algorithm

The A* algorithm is a goal-directed search algorithm that finds the optimal route according to a cost function (Equation (3.8)). It was originally described by [Hart et al., 1968]. The time-dependent A* algorithm employs an estimator (i.e., heuristic function) to guide the search process towards the destination node. To do so, the A* algorithm selects the path that minimizes the following cost function:

$$f(v,t) = g(v) + h(v,t) \tag{3.8}$$

where $f(v,t)$ is the travel cost value at node v and time t, $g(v)$ is the time-dependent cost from the departure to the node v, $h(v,t)$ is a heuristic estimation of the cost from the node v to the destination at time t. Note that the heuristic is problem specific and the search efficiency and optimal quality depends on $h(v,t)$ if $h(v,t) = 0$, A* is equivalent to Dijkstra's algorithm [Nannicini et al., 2008]. In addition, if $h(v,t)$ never overestimates the actual cost to the destination, then A* always finds the shortest path. Hence, the $h(v,t)$ is defined as the great circle distance divided by a coefficient, allowing us to set a cost (i.e., fuel consumption) that never overestimates the real cost of crossing each edge. This coefficient is set to 21.5 $kg\ fuel/km$, which is the minimum recorded fuel consumption per km for the specific study vessel at 12 knots.

Given a directed time-dependent graph $G_T = (V, E, \hat{C}, \hat{T})$, a source node $v_s \in V$, a destination node $v_d \in V$, and a departure time t_s, the A* algorithm finds the minimum cost path between the source v_s and destination v_d that departs from v_s at time t_s. The implemented Algorithm 1 is a variant of the time-dependent A* algorithm proposed by Ohshima et al. [2011], since in our approach the edge cost is the fuel consumption rather than the travelling time. This requires the cost $g(v)$, time of arrival $time(v)$ at each node, and the predecessor node of node v, $p(v)$ to be stored.

Algorithm 1: *time-dependent A** $(G_T(V, E, \hat{C}, \hat{T}), v_s, v_d, t_s)$

Input: a time-dependent graph G_T, source v_s, destination v_d, and departure time t_s.

Output: precedent nodes $p(v)$, total cost $g(v_d)$, and total travel time $time(v_d)$.

initialize:

1: $status(v_s)$:="labeled", $g(v_s) := 0$, $time(v_s) := t_s$, $p = \emptyset$

2: **for** all $v_i \neq v_s \in V$ **do**

3: $\quad status(v_i)$:="unlabeled", $g(v_i) := \infty, time(v_i) := \infty$

main loop:

4: **repeat**

5: $\quad$ Choose a "labeled" node v_i with the smallest $g(v_i) + h(v_i, t)$. {In the case that there are multiple candidates, choose one with the smallest $g(v_i)$.}

6: $\quad$ **for** each edge $(v_i, v_j) \in E$ **do**

7: $\quad\quad$ **if** $status(v_j)$ ="unlabeled" **then**

8: $\quad\quad\quad status(v_j)$:= "labeled", $g(v_j) := g(v_i) + \hat{c}_{v_i,v_j}(t)$, $time(v_j) := time(v_i) + \hat{t}_{v_i,v_j}(t)$, $p(v_j) := v_i$

9: $\quad\quad$ **else if** $status(v_j)$ ="labeled" AND $g(v_j) > g(v_i) + \hat{c}_{v_i,v_j}(t)$ **then**

10: $\quad\quad\quad g(v_j) := g(v_i) + \hat{c}_{v_i,v_j}(t)$, $time(v_j) := time(v_i) + \hat{t}_{v_i,v_j}(t)$, $p(v_j) := v_i$

11: $\quad status(v_i)$:= "finished". **goto 5**

12: **until** $v_i = v_d$

13: **return** $p(v)$, $g(v_d)$, $time(v_d)$

Note that the outputs of the time-dependent A*, $g(v_d)$ and $time(v_d)$, are the desired $c_{e_i,e_j}(dt_{e_i})$ and $t_{e_i,e_j}(dt_{e_i})$, respectively. Moreover, Algorithm 2 is used to generate the shortest path found by Algorithm 1. The *reverse* function is used to modify the sequence of path r in order to start from node v_s.

Algorithm 2: *Path generation*

Input: predecessor nodes $p(v)$, source node v_s, and destination node v_d.

Output: Optimal v_s-v_d path r.

initialize:

1: $r[0] := v_d$, $k := 1$

main loop:

2: **while** $r[k-1] \neq v_s$ **do**

3: $\quad r[k] := p(r[k-1])$

4: $\quad k++$

5: **return** $r := reverse(r)$

3.4 Problem Instances

The problem instances used for the experiment (Section 3.5) are defined by real historical data given by a fishing company and environmental modelled data from the EU Copernicus marine environment services (CNEMS). By, using this historical data, different models are developed in order to predict the values of the problem instances (e.g., fuel consumption, expected reward, etc.). This section explains the historical data that is used (Section 3.4.1) and how the instance values are estimated for the starting time onwards (Section 3.4.2).

3.4.1 Data source

Before describing the historical data, two points should be mentioned. First, the fishing vessel data (Section 3.4.1.3) and the historical tuna catches (Section 3.4.1.4) are only used to train the machine learning models (Sections 3.4.2.2 and 3.4.2.4). Second, the remaining data (Sections 3.4.1.1, 3.4.1.2 and 3.4.1.5) are also used to train the models, but they are also needed to create the problem instances. Furthermore, these data are always available before the vessel departs from port and also every time they are updated during the vessel fishing trip.

3.4.1.1 Fishers' echo-sounder buoys data

The acoustic data from the dFADs are supplied mainly by two buoy manufacturers, hereinafter referred to as M1 and M2 manufacturers. The echo-sounder buoys provide a rough estimation of aggregated biomass by detecting the assemblage of various fish species beneath them by means of acoustic signals, along with their geo-location [Moreno et al., 2016, Lopez et al., 2016]. These estimations do not discriminate between the targeted tunas and non-targeted species. Differences in the signal outputs between companies create the need to develop independent models for each manufacturer in order to predict $er_i(t)$.

3.4.1.2 Environmental data

The environmental variables affect the tuna distribution (e.g., expected reward, $er_j(t)$) and the ship performance (e.g., fuel consumption, $c_{i,j}(t)$, and travel time, $t_{i,j}(t)$). The environmental data used here comes from the Copernicus marine environment monitoring service (CMEMS[1]). Here, the following short-term forecast products are used: i) global sea physical analysis and forecasting product; ii) global ocean wave analysis and forecasting product; and iii) global biogeochemical analysis and forecasting product. Table 3.1 shows a summary of each environmental product characteristic and its use. Notice that the value of these variables can be known up to 5/10 days in advance.

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

Product	Variables	Forecast horizon	Spatial resolution	Temporal resolution	Update frequency	Depth (m)
BIO	Chlorophyll (chl) Nitrate (NO_3) Primary production of phyto (nppv) Dissolved oxygen (O_2), Phosphate (PO_4) Dissolved silicate (Si)	10 days	1/4 degree	daily	Weekly	500 m
WAV	Significant wave heigh (H_s) Wave direction (H_d) Wave period (Tm10 and Tm02)	10 days	1/12 degree	3 hourly	daily	surface
PHY	Potential temperature (thetao) Salinity (so) Current velocity (uo, vo) Sea surface height (zos) Mixed layer thickness (mlost) Sea floor potential temperature (bottomT)	10 days	1/12 degrees	daily	daily	500 m
	Oceanic general circulation: (uo,vo) Tide currents (utide, vtide) Total current (utotal, vtotal)	5 days	1/12 degrees	hourly	daily	surface

Table 3.1: Environmental data used. BIO refers to global sea biogeochemical analysis and forecasting products; WAV refers to global wave analysis and forecasting products; and PHY refers to ocean sea physical analysis and forecasting products.

3.4.1.3 Fishing vessel data

The vessels' onboard sensors provide information about time, latitude, longitude, main engine fuel consumption, propeller shaft power, engine speed, propeller pitch, and actual ship speed. In addition, the dry docking, which is the number of months since the ship's hull and propeller were last cleaned, is also considered. This variable affects fuel consumption, $c_{i,j}(t)$, since the biofouling attached to the hull and propeller increases the ship's resistance and reduces propeller efficiency [Adland et al., 2018].

3.4.1.4 Tuna catch data

The historical tuna catch data come from the Spanish fisheries observer programme from 2014 to 2020 [Báez et al., 2020b], which monitor fishing activities. The observations are collected by onboard scientific observers, and the program has a minimum coverage rate of 10% of the fishing trips. However, the company providing the data to this work have 100% coverage for the study period.

3.4.1.5 Spatial discretization

The studied area is spatially discretized by implementing a regular square grid, $G_T = (V, E)$. The area is located in the Indian Ocean, and it extends through all the water from 30, 75 longitudes to -20, 22.5 latitudes. Fishing sets are allowed only in the Seychelles, Madagascar, France, and Comoros exclusive economic zones (EEZs) and high seas (outside national EEZs). However, vessels can navigate through all EEZs. The distance between the nodes of the grid is of 0.5 degrees and each node is connected to 8 vicinity nodes. Each edge that links the nodes in V with their neighbours can be considered to form the path that a vessel can follow.

3.4.2 Estimation of the input data of the problem instances

3.4.2.1 Travel time

The time that a vessel spends travelling from one node v_i to another node v_j departing from v_i at time dt_{v_i}, $\hat{t}_{v_i,v_j}(dt_{v_i})$, depends on the edge length and the vessel's speed. This speed is affected by an involuntary speed reduction due to the added resistance caused by the weather conditions. In order to consider this involuntary speed loss due to the wave effect, the formula proposed by Bowditch [1975] is used:

$$v(H, \theta, dt_{v_i}) = v_0 - q(\theta) \cdot H^2(dt_{v_i}) \tag{3.9}$$

where $v(H, \theta, dt_{v_i})$ denotes the final speed at time dt_{v_i}, v_0 is the vessel speed when unaffected by the weather conditions, $H(dt_{v_i})$ is the significant wave height at time dt_{v_i}, and $q(\theta)$ is a coefficient based on the relative ship-wave direction found in the edge (v_i, v_j). The values of $q(\theta)$ are given in Table 3.2 according to the angle θ between the ship's and the wave's directions, and it is expressed in kn/ft^2. In this study, v_0 is considered as a constant vessel speed of 12 knots.

Ship-wave relative angle	**Wave direction**	q
$0° \leq \theta \leq 45°$	Following seas	0.0083
$45° \leq \theta \leq 135°$	Beam seas	0.0165
$135° \leq \theta \leq 180°$	Head seas	0.0248

Table 3.2: Values of the q coefficient of Equation (3.9).

Hence, the estimated travel time between nodes, $\hat{t}_{v_i,v_j}(dt_{v_i})$, departing from v_i at time dt_{v_i}, is defined by:

$$\hat{t}_{v_i,v_j}(dt_{v_i}) = \frac{dist_{v_i,v_j}}{v(H, \theta, dt_{v_i})} \tag{3.10}$$

where $dist_{v_i,v_j}$ is the great circle distance between the v_i and v_j nodes.

3.4.2.2 Fuel consumption

With the historical data a machine learning model is developed to predict the ship's fuel consumption during cruising, $\hat{c}_{v_i,v_j}(t_{v_i})$ (Figure 3.8). The vessel's fuel consumption is affected by many factors such as the vessel's speed, weather conditions, loading conditions, and hull design [Bialystocki and Konovessis, 2016]. The developed model therefore uses environmental variables (Section 3.4.1.2), the vessel's speed and dry docking as predictors, whereas the response variable is fuel consumption per hour (kg/h), $FOC(t)$, at time t that comes from the onboard sensors (see Section 3.4.1.3).

The modelling starts with the data pre-processing, which consists of two steps: 1) data cleaning, which is carried out on the vessel's data by selecting the steady-state data, data aggregation, outlier detection, and correction for environmental factors [Internartional Standar, 2016]; and 2) feature engineering, which consists of transforming the environmental northward and eastward component, or angle and magnitude into the vessel body-fixed frame of reference to obtain the longitudinal and transversal components as suggested by Gkerekos and Lazakis [2020]. Then, the model is trained and validated by the following steps: 1) the data is randomly split between a training set (80% of the data) and a test set (20% of the data); 2) a feature selection is carried out on the training set [Azadkia and Chatterjee, 2019], then a model tuning using a 10-cross validation technique, and with the best parameters, a random forest (RF) algorithm is learnt [Breiman, 2001]; and 3) the model performance on the test set is measured and validated, using the mean absolute percentage error (MAPE) as the performance metric [de Myttenaere et al., 2016]. The trained model showed a MAPE of 3.8%, indicating that the model can predict the fuel consumption $FOC(t)$.

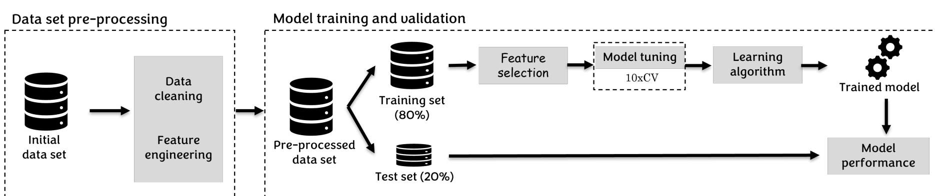


Fig. 3.8: The building and validation methodology of the fuel consumption model.

Finally, with the model output the fuel consumption needed to go from v_i to v_j departing from v_i at time dt_{v_i}, $\hat{c}_{vi,vj}(dt_{v_i})$, is estimated by:

$$\hat{c}_{v_i,v_j}(dt_{v_i}) = FOC_{v_i,v_j}(dt_{v_i}) \cdot \frac{dist_{v_i,v_j}}{v(H,\theta,dt_{v_i})} \tag{3.11}$$

where $FOC_{v_i,v_j}(dt_{v_i})$ is the vessel's fuel consumption at edge (v_i, v_j) at time dt_{v_i}, $dist_{v_i,v_j}$ is the great circle distance between the v_i and v_j nodes, and $v_{v_i,v_j}(H, \theta, dt_{v_i})$ is the vessel speed in the edge (v_i, v_j) (Equation (3.9)).

Another fuel-intensive activity that consumes a high amount of fuel and is considered here is the fishing operation. In Basurko et al. [2022], they estimated an average fuel consumption rate during fishing operations of 72.4 kg/h and 190.8 kg/h for the main and auxiliary engines, respectively. Therefore, using these estimations and assuming that a fishing event has an average duration of three hours in this study, the fuel consumption in each fishing set is assumed to be $3 \cdot (72.4 + 190.8) = 789.6$ kg.

3.4.2.3 dFAD geolocation

The historical and current geolocation of each dFAD, $l_i^t = (longitude_i^t, latitude_i^t)$, is accessible at any time. However, the dFADs drift in any particular course and speed based on the weather conditions, which creates the need to forecast their trajectory in order to establish their geolocation when the vessel arrives. To do so, there are several methods that range from more complex Lagrangian models that use environmental data [Özgökmen et al., 2000], to simpler motion equations that require only the last locations of each dFAD [Groba et al., 2015]. Here, the historical geolocations will be used as future geolocations in order to test the proposed algorithm, since trajectory forecasting is not the objective of this work.

3.4.2.4 Expected reward under drifting fishing aggregating devices (dFADs)

To predict the expected reward (i.e, probability of high catches of tuna) $er_i(t)$, a machine learning model is developed by using the historical data. In order to forecast the tuna distribution and abundance, the physical and biogeochemical variables are commonly used as predictors [Arrizabalaga et al., 2015, Orúe et al., 2020]. Thus, the dFADs signal source (Section 3.4.1.1) and the environmental data (Section 3.4.1.2) are used to gather the information about the predictor variables, while the information from the catches data (Section 3.4.1.4) is considered for the target variable. Figure 3.9 shows the model building and validation methodology. This model enables us to establish $er_{e_i}(t)$ at each dFAD e_i and time t.

The data pre-processing consists of cleaning the dFADs' data as suggested by Orue et al. [2019a], and the catch data. The three sources of data are aggregated to a 0.5 degree resolution and merge, and finally the target variable (i.e., tonnes of catches) is discretized into two possible values: low or high amount of catches. The threshold used to discretized the target variable is 35 tonnes of tuna. A simple approach is used to build and validate the model (Figure 3.9). Firstly, the pre-processed data is split between the training and test sets. Then the features in

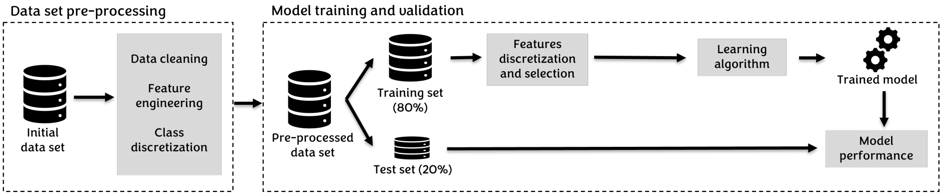


Fig. 3.9: Tuna model building and validation methodology.

the training set are discretized according to Fayyad and Irani [1993] method, and then a feature selection is conducted as suggested by Hall [1999]. Finally, a Naïve Bayes classifier is learned and its performance is evaluated [Granado et al., 2019]. To evaluate the models, the accuracy, sensitivity, and specificity metrics are considered. The accuracy indicates the proportion of the total number of predictions that were correctly classified, while specificity and sensitivity indicate the proportion of real positive (high) or negative (low) cases that were correctly classified, respectively [Granado et al., 2019]. The accuracy enables the overall performance of the model to be established, whereas the specificity and sensitivity enables us to measure the performance in each class.

The above mentioned process is applied to each manufacturer of dFADs. That is, two tuna models are created, one for M1 and other for M2. For M1, the model accuracy is 58.1%, and its sensitivity and specificity are 61.0% and 54.2%, respectively. For M2, the accuracy, sensitivity, and specificity are 61.8%, 85.9%, and 27.7%, respectively. Existing studies that tried to predict tuna under dFADs show accuracies of around 75-85% in recognising the presence/absence of tuna aggregations under dFADs [Baidai et al., 2020], between 58 and 66% to differentiate between high and low bycatch occurrence [Mannocci et al., 2021], or around 50% for the classification of size categories of tuna aggregation [Baidai et al., 2020]. Therefore, our results match the one that predicted between low and high bycatch occurrence. The differences with the other two studies are mainly due to the target variable, since the model with the highest accuracy only differentiates between presence/absence of tuna, whereas the model with the lowest accuracy classifies between four groups (i.e., No tuna, $<$ 10 tons, 10-25 tons and $>$ 25 tons). Hence, the model performances are enough to estimate the problem instances values in order to work with a framework as real as possible.

3.5 Results of Experiments

Three different experiments were developed to analyze the proposed time-dependent algorithm and its dynamic version using real fishing trips data. The aim of the first analysis is to evaluate the performance of the proposed crossover and mutations operators explained in Sections 3.3.3 and 3.3.4. The second analysis compares our mono-objective approach detailed in Section 3.3 with a multi-objective approach, since our proposed objective function combines two independent objectives (i.e., fuel consumption and expected reward). The aim is to check if the defined objective function accomplishes both goals. The last analysis consists of solving the DFRP as a real dynamic problem with route updates every time a dFAD is fished (usually one or two times per day). This approach is the most similar one to a real situation, allowing changes to be made in the proposed route as forecasts or fishers' decisions vary.

All the instances used in the three experiments have the same departure and arrival point (e_0), which is the Seychelles port. As regards the dFADs positions, $L_{i,t}$, the historical positions are used as future positions (see Section 3.4.2.3). The fishing time window, $TW = [a, b]$, is set at $a = 5$ am and $b = 5$ pm. The expected reward at each dFAD, $er_j(t)$, is computed with the model explained in Section 3.4.2.4. The time-dependent travel cost, $\hat{c}_{v_i,v_j}(t)$, and travel time, $\hat{t}_{v_i,v_j}(t)$, are computed according to the description in Sections 3.4.2.2 and 3.4.2.1, respectively. For the travel time, a vessel's constant speed of $v_0 = 12$ knots is assumed. These costs are assigned to each edge of the grid defined in Section 3.4.1.5, in order to know how long it takes to travel through these edges from one node to another and the consumption incurred. In addition, the data used as input in the models are the same as those explained in Section 3.4.1.

3.5.1 GA-TDA* operator selection

The data used as input are the ones explained in Section 3.4, and the specific instances considered are based on five real fishing trips (i.e., instances 2, 3, 4, 5, and 6). The numbers of available dFADs together with the number of dFADs to fish in each of the five instances are shown in Table 3.3.

Trip	Available #dFADs	#dFADs to fish
2	$N = 189$	$k = 33$
3	$N = 185$	$k = 22$
4	$N = 201$	$k = 20$
5	$N = 195$	$k = 24$
6	$N = 231$	$k = 15$

Table 3.3: Instance parameters based on the five real fishing trips.

The specific setup parameters used for the GA-TDA* are detailed in Table 3.4, with the difference that the scramble is used as the mutation operator.

3.5.1.1 Analysis of the crossover operator

The performance between the four crossover operators explained in Section 3.3.3 is compared by running the algorithm with each one 30 times in each instance and using the scramble as the mutation operator in all the runs. Figure 3.10 summarizes the 30 runs for each operator and instance. A first glance shows that the RUX is the worst performing crossover, perhaps because it is the simplest one and does not consider any problem particularities. The CPX performs better, but not as well as the GX-NNI and RBCSCX crossovers. This may be due to the fact that the CPX only considers some of the problem characteristics in the repair function, whereas the GX-NNI and RBCSCX crossovers consider the problem particularities whenever any new dFAD is added to the child by using the Equation (3.5). Since the best crossover operators are GX-NNI and RBCSCX, a new crossover that combines both operators is proposed with the hope of getting the best out of both. This new crossover, called GreedyBcscx randomly selects GX-NNI or RBCSCX at each step to create the children. Figure 3.11 shows the results of the 30 runs for the best two crossovers (i.e., GX-NNI and RBCSCX) with the new GreedyBcscx operator.

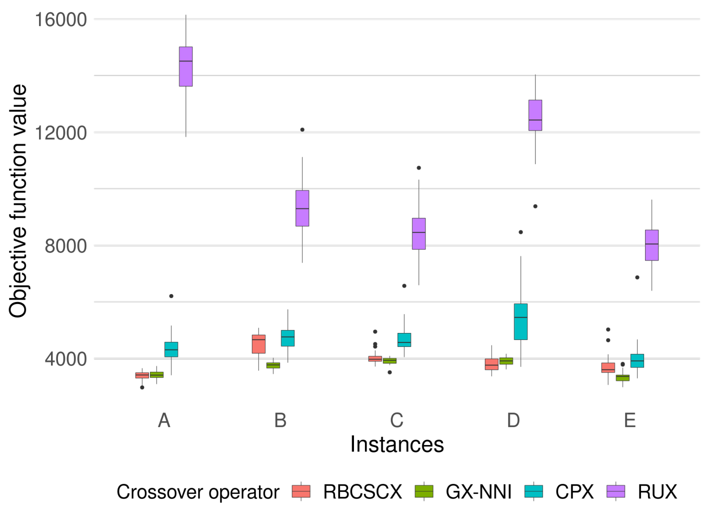


Fig. 3.10: Box plot for GX-NNI, RBCSCX, CPX, and RUX crossovers.

According to the Bayesian ranking analysis [Calvo et al., 2018], which is implemented in the scmamp R package [Calvo and Santafé, 2016], the GreedyBcscx crossover has the best performance with an expected probability of being the best

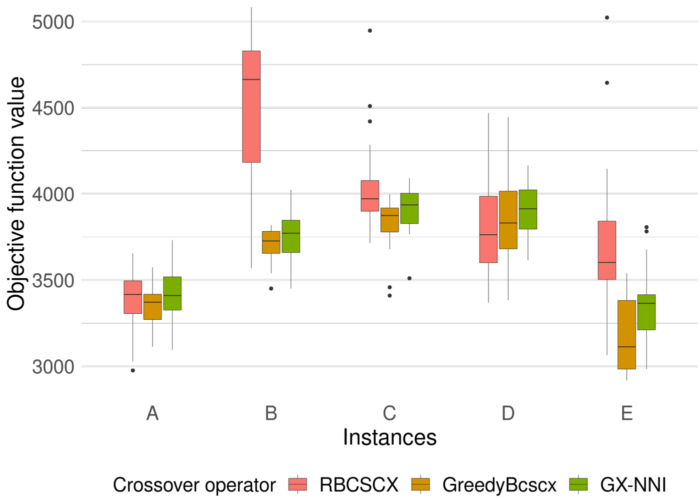


Fig. 3.11: Box plot for GX-NNI, RBCSCX, and GreedyBcscx crossovers.

of 0.506. The expected probability of being the best for the other operators is: GX-NNI 0.312, RBCSCX 0.154, CPX 0.027, and RUX 0.001. Figure 3.12 shows the samples from the posterior distribution of the probability of being the best when considering the 3 best crossovers: RBCSCX, GX-NNI, and GreedyBcscx.. GreedyBcscx. The region at the bottom-right of the triangle is relative to the case where GX-NNI is more likely to be better than RBCSCX and GreedyBcscx. The top region of the triangle shows the case when the GreedyBcscx is more likely to have a better performance than the other two crossovers, and the bottom-left region corresponds to the case where RBCSCX is more likely to be better than GX-NNI and GreedyBcscx together. Since most of the points fall inside the GreedyBcscx region, we conclude that the hypothesis of GreedyBcscx being the best crossover is true with a probability of ≈ 1.

3.5.1.2 Analysis of the mutation operators

A performance comparison of the three mutation operators explained in Section 3.3.4 is conducted by running the algorithm with each one 30 times in each instance and using the GX-NNI as the crossover operator. Figure 3.13 summarizes the 30 runs for each mutation and instance. As can be observed, the three mutations have a similar performance in the five instances.

The Bayesian approach is applied to compare them, giving an expected probability of winning of 0.471 for the Disp-inv operator, while for Scramble and Ran-

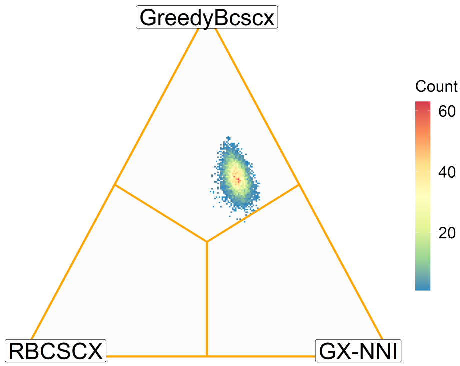


Fig. 3.12: Distribution of the posterior probabilities for Bcscx, Greedy and Greedy-Bcscx crossovers obtained from the Bayesian ranking analysis.

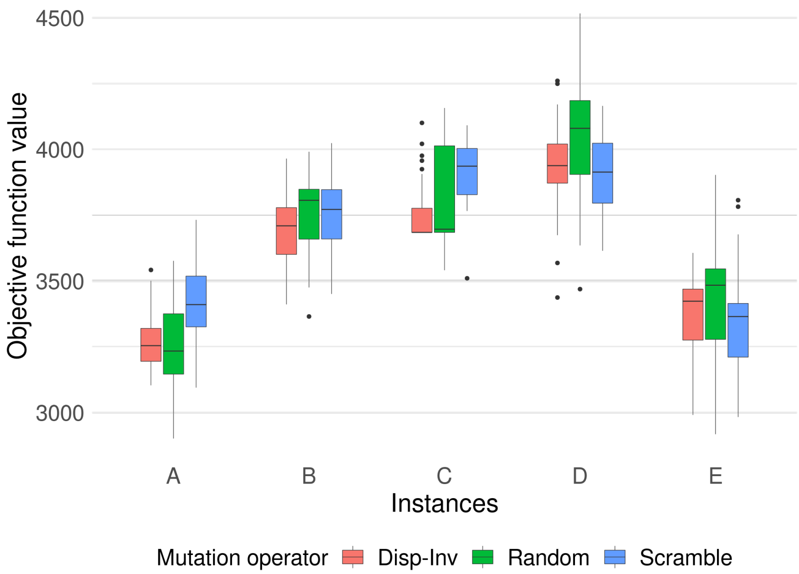


Fig. 3.13: Box plot showing the objective function values for all the 30 runs for each mutation operator.

dom mutations, it is 0.262 and 0.267, respectively. Figure 3.14 shows the posterior distribution of the probability of being the best for the three mutations. Note that although Figure 3.13 does not show much difference between operators, after the Bayesian analysis there is not much uncertainty about Disp-inv being the best.

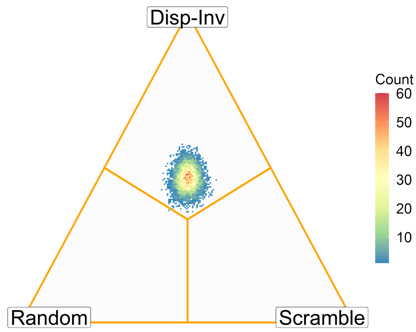


Fig. 3.14: Distribution of the posterior probabilities for all the mutation operators using the Bayesian ranking analysis.

3.5.2 Comparison of mono-objective and multi-objective algorithms

Many real world problems involve the optimization of several objectives simultaneously, which can be addressed in two ways: by combining the desired objectives in a single objective function, or by using a multi-objective optimization (MOO) approach that considers each objective independently in the process of optimization. However, with MOO methods, it might not be possible to find a solution that optimizes all objective functions at once. Hence, the aim of this analysis is twofold. First, to see if the proposed GA-TDA* is able to obtain good solutions by comparing it with a multi-objective approach. Second, to validate the proposed objective function (Equation 3.1), by looking at the relative importance of each objective (i.e., fuel consumption and expected reward) by observing the Pareto front. For the multi-objective optimization approach, the fast non-dominated sorting genetic algorithm II (NSGA-II) is selected, which is a multi-objective evolutionary algorithm (MOEA) developed by Deb et al. [2002].

Since the NSGA-II is based on a genetic algorithm, the genetic operators used in the GA-TDA* can be used in the NSGA-II. The NSGA-II therefore uses the same operators to make the comparison as fair as possible. In addition, the NSGA-II algorithm also makes use of the A* algorithm to calculate the objective function values of the solutions, in the same way as the GA-TDA* does. The GA-TDA* and NSGA-II setting parameters are showed in Table 3.4. These parameters and were set as per the results of preliminary experiments, where different values for each parameter were tested and tuned.

	GA-TDA*	**NSGA-II**
Initial population	Random	Random
Population size	$2N$	$2N$
Selection	Tournament	Tournament
Crossover	GreedyBcscx	GreedyBcscx
Mutation	Disp-inv	Disp-inv
Elitism	5%	-
Stopping criteria	50 iterations	50 iterations
Probability of crossover	0.7	0.7
Probability of mutation	0.3	0.3

Table 3.4: Algorithm parameters used to compare GA-TDA* and NSGA-II performances.

In this experiment, 20 instances coming from real fishing trips are used, five of which were used in the previous section. Moreover, each configuration is applied 5 times in each of the 20 instances, giving a total of 100 executions for each algorithm. The number of available dFADs together with the number of dFADs to fish in each of the 20 instances are set according to the 20 historical fishing trips and these values are shown in Table 3.5.

Instance	**Available #dFADs**	**#dFADs to fish**	**Instance**	**Available #dFADs**	**#dFADs to fish**
1	$N = 203$	$k = 29$	11	$N = 231$	$k = 13$
2	$N = 189$	$k = 33$	12	$N = 232$	$k = 20$
3	$N = 185$	$k = 22$	13	$N = 255$	$k = 27$
4	$N = 201$	$k = 20$	14	$N = 247$	$k = 25$
5	$N = 195$	$k = 24$	15	$N = 176$	$k = 23$
6	$N = 231$	$k = 15$	16	$N = 168$	$k = 29$
7	$N = 192$	$k = 31$	17	$N = 159$	$k = 19$
8	$N = 164$	$k = 23$	18	$N = 133$	$k = 11$
9	$N = 220$	$k = 32$	19	$N = 190$	$k = 25$
10	$N = 212$	$k = 10$	20	$N = 125$	$k = 21$

Table 3.5: Instance parameters based on the 20 real fishing trips.

3.5.2.1 Objective functions for the MOO approach

The objective function defined for the DFRP is the combination of the fuel consumption, $\sum_{i=0}^{k} c_{e_i,e_{i+1}}(dt_{e_i})$ and the expected reward (i.e, probability of high tuna catches) $\sum_{j=1}^{k} er_{e_j}(at_{e_j})$. Therefore, for the MOO approach, the proposed Equation (3.1) is decomposed in the following two objectives:

- Fuel consumption:

$$\text{minimize } J(e_0\ e_1 \dots e_k\ e_{k+1}) = \sum_{j=0}^{k} c_{e_i,e_{i+1}}(dt_{e_i}) + M \cdot \tau + M \cdot \mu_{t_{trip}} \tag{3.12}$$

- Expected reward:

$$\text{maximize } J(e_0\ e_1 \dots e_k\ e_{k+1}) = \sum_{j=1}^{k} er_{e_j}(at_{e_j}) + M \cdot \tau + M \cdot \mu_{t_{trip}} \tag{3.13}$$

Note that the fuel consumption objective is also taken into account in the A* algorithm, whereas the expected reward is also considered in the genetic operators by using Equation (3.5). Furthermore, M, τ, and $\mu_{t_{trip}}$ are defined as in Section 3.3.6.

3.5.2.2 Results of the comparison between the GA-TDA* and the NSGA-II

The simulation results of the 20 instances are shown in Figure 3.15. The blue points represent the solutions found by the GA-TDA*, whereas the black points and the red line represent the solutions found by the NSGA-II and the Pareto front estimated by using the outputs of all the MOO executions. The solutions that fall inside the shaded area would be non-dominated by the solutions found by the NSGA-II. Thus, it can be observed that the proposed GA-TDA* algorithm obtains solutions close to the Pareto front or even solutions non-dominated by the solutions given by the NSGA-II. In none of the instances are any of the solutions obtained by the GA-TDA* dominated by those of the NSGA-II. In some instances, the GA-TDA* obtains a number of solutions dominated by the ones obtained by the NSGA-II, such as instances 1, 14, 19 or 20. However, there are other instances where all the solutions obtained with the GA-TDA* are non-dominated by the ones of the NSGA-II, such as routes 8, 13, 15 or 18.

The behaviour of the objective function (Equation (3.1)) along the Pareto front shows that fuel consumption is more important than the expected reward since most of the solutions found by the GA-TDA* are the minimum-fuel route or close to this. Hence, the GA-TDA* does not provide solutions with high expected reward if this involves major fuel consumption, which is desirable in a real world application. Then, the catches objective (i.e., expected reward) seems to have less importance in the objective function (Equation (3.1)). This can be seen in routes 1, 2, 5, 6, 7, 11, 12, 14, 18, and 20, where the solutions found have less expected reward compared to those with the highest expected reward. However, it is worth highlighting that the average expected reward obtained is competitive and over 0.7 with the exception of instance 7.

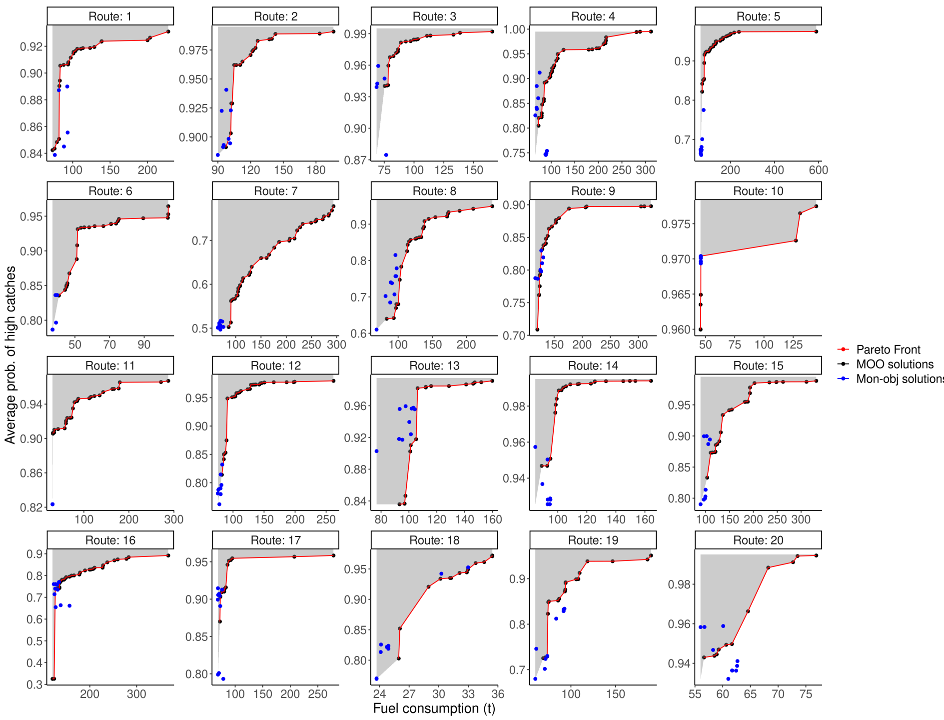


Fig. 3.15: Results of the MOO and mono-objective approaches for the 20 DFRP instances. The Y axis represents the average expected reward ($\sum_{j=1}^{k} er_{e_j}(at_{e_j})/k$), while the X axis indicates total fuel consumption $\sum_{j=0}^{k} c_{e_i,e_{i+1}}(dt_{e_i})$. The blue points represent the mono-objective results, and the black points and the red line (Pareto front) represent the MOO results. The mono-objective solutions within this shaded area are non-dominated by the solutions found by the NSGA-II. (For interpretation of the references to colour keys in this figure, the reader is referred to the web version of this article).

3.5.3 Using the dynamic version of the GA-TDA* to plan a fishing trip with data update

The problem inputs may change over time in real applications, and therefore, the approach for the solution should be dynamic to account for these changes. This experiment is the most similar one to a real application, where the decisions are made according to the last available information. Thus, all the instance data will be updated every time a dFAD is fished. The route update approach starts executing the GA-TDA* algorithm and obtains a fishing route from the departure to the arrival port. Once the vessel fishes the first dFAD, all the data is updated with the latest available information. Then the GA-TDA* is re-run with the new information, departing from the last fished dFAD to the arrival port. This process is repeated until only three dFADs are left to be fished, since the GA-TDA* cannot be executed for solutions with less than three elements. Each time the GA-TDA* has been run, the top 5% solutions are transferred to the initial population of the next run (see Appendix D for further details).

An example of the dynamic approach is shown below, where $pop1$ is the population after the first run of GA-TDA* with a size of 60 solutions. Assuming that the solutions are ordered from best to worst, the first fished dFAD is 3. The next step is then to create the suggested solutions, $sugg1$ by using the top 5% solution (e.g., the top three solutions). Once the top 5% solutions are defined, the first element of each one is removed and 3 is set as the departure location (See $sugg1$). However, this approach can create invalid solutions in $sugg1$ due to the fact that the fished dFAD may be in other solutions. This can be seen in the example below, where the second solution in $pop1$ includes the fished dFAD, 3, creating an invalid solution. Therefore, once the dFADs information is updated, and if needed, the fished or lost dFADs (i.e., beached or broken) are removed from the solutions and from the available dFADs, new ones are inserted randomly (See $sugg1^*$).

$$pop1 = \begin{pmatrix} 0\ 3\ 10\ 1\ 2\ 0 \\ 0\ 8\ \ 5\ \ 6\ 3\ 0 \\ 0\ 2\ \ 1\ \ 9\ 8\ 0 \\ \cdots\cdots \\ 0\ 7\ \ 3\ \ 9\ 1\ 0 \end{pmatrix}, sugg1 = \begin{pmatrix} 3 & 10 & 1 & 2 & 0 \\ 3 & 5 & 6 & NA & 0 \\ 3 & 1 & 9 & 8 & 0 \end{pmatrix} sugg1^* = \begin{pmatrix} 3 & 10 & 1 & 2 & 0 \\ 3 & 5 & 6 & 9 & 0 \\ 3 & 1 & 9 & 8 & 0 \end{pmatrix}$$

The GA-TDA* parameters used in this experiment are the same as in the previous experimental study (Table 3.4). In this experiment, 16 instances used in Section 3.5.2 are considered: 1, 2, 3, 4, 5, 6, 7, 10, 11, 12, 13, 15, 16, 17, 19, 20. Instances 8, 9, 14, and 18 were not considered in this experiment due to some malfunction in the sensor that measures the vessel's fuel consumption, making it unfeasible to compare these routes and the proposed ones. The dynamic GA-TDA* is run 10 times in each instance.

3.5.3.1 Results of the comparison between the dynamic GA-TDA* and sixteen real fishing trips

A summary of the comparison between the best routes obtained with the dynamic GA-TDA* and the real historical fishing trips is shown in Table 3.6. The historical data come from the vessel onboard sensors and the Spanish fisheries observer programme, which are explained in Sections 3.4.1.3 and 3.4.1.4. In order to differentiate between the days spent searching, fishing, and inactive in the historical data, the method suggested by [Basurko et al., 2022] is used. The average reduction between the historical and the proposed routes of the time at sea, fuel consumption, and miles travelled are 33.0%, 56.8%, and 70.0%, respectively. These results indicate the high potential gain of a FRODSS method applied to fisheries.

The reduction of the time at sea comes mainly from a reduction on the inactive periods and the time spent searching/navigating for tuna since the vessel speed is similar in both. Moreover, the inactive periods in the route proposed by the dynamic GA-TDA* are limited to waiting times until the fishing time window is open. It is also important to highlight that in our study we do not consider the free-swimming schools sets or other operations that can occur during a fishing trip (e.g., deployment of new dFADs or vessel failure, among others) since these events are rare nowadays. The free school sets represent less than 20% of the total sets in the last decade and decrease with a minimum peak of 4% recorded in 2018 [Báez et al., 2020a]. In addition, the deployment of new dFADs occurs during navigation without any need to stop the vessel. Moreover, the new dFAD deployment is mainly carried out by supply vessels, which is why purse seiners usually do not make travel extra to deploy new dFADs. Therefore, these excluded activities may increase time and fuel consumption, but their influence on the comparison is limited.

Another important difference is in the number of sets over 35 tonnes, since the proposed dynamic GA-TDA* doubles the number of sets with a high amount of catches. This indicates that the dynamic GA-TDA* not only reduces fuel usage and time at sea, but is also effective when it comes to selecting high potential fishing grounds (i.e., from all the available dFADs, it selects good dFADs to fish). The reduction in the miles travelled and fuel consumption is mainly because the proposed approach knows the order of collection in advance and does not spend time on searching, being adrift at night, deploying new dFADs or in free schooling, among others.

Figure 3.16 shows the proposed route (blue line) and the historical route (gray line) in four different periods. Panel A shows the initial proposed route, where the blue line indicates the route already travelled and the label gives information about fuel usage, time spent, and the number of sets with a high expected reward. Panels B, C, and D show the moment when the vessel has already fished 10, 20, and 29 dFADs, respectively. The dynamic GA-TDA* implies fish in the north where there are the dFADs with a high expected reward, while the historical route shows

Variable	**Historical**	**Proposed**	**Difference (%)**
Days at sea	25.1 ± 7.6	16.8 ± 3.4	-33.0
Days searching	16.2 ± 6.2	11.8 ± 2.7	-26.2
Days inactive	5.6 ± 4.5	2.1 ± 1.0	-62.5
Days fishing	2.4 ± 0.9	2.9 ± 0.7	20.8
Number of sets	23.4 ± 5.7	23.4 ± 5.7	0.0
Set over 35t	6.5 ± 4.6	13.1 ± 2.8	101.5
FOC (main)	216.6 ± 81.8	75.6 ± 19.1	-65.1
FOC (aux)	83.9 ± 16.5	54.2 ± 10.7*	-35.4
Total FOC	300.5 ± 93.8	129.7 ± 18.9	-56.8
Cruising speed	11.8 ± 2.8	11.9 ± 0.1	0.1
Distance	4800.8 ± 1499.8	1439 ± 339.5	-70.0
Distance (day)	3084.4 ± 999.2	729.3 ± 179.9	-76.3
Distance (night)	1716.4 ± 538.7	745.7 ± 246.7	-56.5

Table 3.6: Comparison between the historical fishing trips and the proposed ones. Units: fuel consumption is measured in tonnes, vessel speed in knots, and distance in miles. FOC (main) is the fuel consumption of the main engine, and FOC (aux) is the fuel consumption of the auxiliary engines (FOC aux), which for the proposed route is assumed to be the same as in the historical one but proportional to the time at sea.

fishing mainly in three grounds (close to Madagascar, Seychelles, and Maldives) far away from each other, meaning that longer distances are travelled. Therefore, the main difference between both routes is the distance travelled (7320 vs 2495.7 miles), and consequently the fuel consumption (344.5 vs 115.9 tonnes) and time at sea (32.6 vs 16.4 days).

3.6 Conclusions

This chapter shows the potential use and benefit of a FRODSS for the tuna purse seine fleet to mitigate climate change and reduce their operational costs. The reduction of fuel consumption and consequent emissions allows the industry to contribute to climate change mitigation according to United Nations and European development goals, while reducing their operational cost and therefore making them more resilient to market changes. The problem is formulated as the k-travelling salesperson problem with moving targets and time windows (DkTSP-MTTW). This mathematical model is the most realistic to date for modelling the fishing routing problem. The proposed GA-TDA* is the first method in fisheries that dynamically optimizes the fishing strategy of a tune purse seiner during a whole fishing trip, considering the selection of the fishing grounds, the order

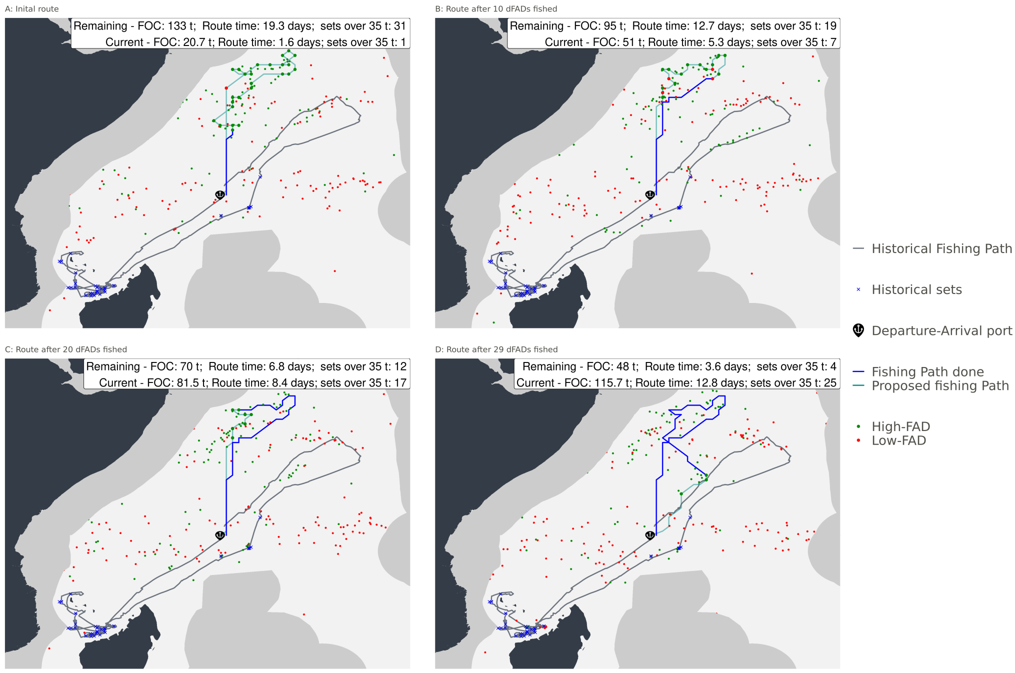


Fig. 3.16: Example of a proposed route by the dynamic GA-TDA*, which is updated every time a dFAD is fished. The label at each panel indicates the fuel usage, time spent, and the predicted probability of high tuna catches over the dFADs for the route considered in that specific moment. The gray line indicates the historical fishing route and the blue crosses indicate where the historical fishing sets occurred. (For interpretation of the references to colour keys in this figure, the reader is referred to the web version of this article).

in which to visit them, the fishing time windows, and the vessel's performance based on weather conditions. The algorithm is designed to be dynamic with recalculations every time a dFAD is fished to account for changing environmental conditions and end-user's decisions that are likely to deviate from planning as in a real world application. Moreover, the GA-TDA* solutions are encoded by means of fixed-length chromosomes based on variations without repetitions. This encoding can be used in similar problems, which were previously encoded as permutations. The solutions obtained by the proposed GA-TDA* are compared to 16 historical fishing trips, showing a potential saving in fuel usage and time at sea of around 56.8% and 33.0%, respectively.

4

The Multiple Purse Seine Vessel Routing Problem

In this chapter, we extend the previous work shown in Chapter 3 to address the challenges of multiple vessels and the deployment of new dFADs. Hence, a novel fishing routing problem for a fleet is formulated, considering its full complexity due to its dynamic (time-dependent) moving target characteristics. To overcome the limitations of exact solutions of the problem, a multi-objective greedy randomized adaptive search procedure (MO-GRASP) algorithm is proposed. In addition, computational experiments demonstrate the feasibility of applying the MO-GRASP algorithm in a real context and explore the benefits of joint planning (collaborative approach) compared to a non-collaborative strategy. Additionally, an analysis of the effect of reducing the number of available dFADs per vessel in both strategies is conducted.

4.1 Introduction

The routing of a fleet of fishing vessels is a complex problem due to its dynamic (time-dependent) moving target characteristics. To the best of our knowledge, no other scientific study has approached this problem in its full complexity, i.e., as a dynamic vehicle routing problem with multiple time windows and moving targets. In Chapter 3, the problem variant for a single vessel extends the previous works in the literature by considering: i) the selection of the best dFADs to fish from all those available that a vessel usually has deployed at sea based on the probability of high catches; ii) the optimization of a whole fishing trip of about 25 days, starting and ending at the port; iii) the consideration of the weather effect on the vessel performance (i.e., fuel consumption); iv) taking into account the time windows of dFADs as they cannot be fished at night. The problem proposed in this study extends the work done in Chapter 3 by (i) optimizing the routes for a fishing fleet instead of a single vessel, (ii) by considering the need to deploy new dFADs during the fishing trip, and (iii) by explicitly considering the bi-objective nature of the problem.

Two variants of the problem are considered in this chapter, the static fishing routing problem with multiple time windows (SFRP-MTW) and the time-dependent fishing routing problem with moving targets and multiple time windows (TDFRP-MTMTW). The study of the simpler SFRP-MTW was motivated by the possibility of extensive computational testing and fine-tuning of the solution approach before moving on to the much more complex time-dependent variant (TDFRP-MTMTW), which is of particular interest, as it closely represents the real-world problem. The TDFRP-MTMTW problem is formulated as a variant of the vehicle routing problem (VRP), specifically as the time-dependent vehicle routing problem with multiple time windows and moving targets. However, most of the existing studies in the literature focus on the time-dependent vehicle routing problem [Malandraki and Daskin, 1992, Haghani and Jung, 2005], or some of its variants, such as the time-dependent vehicle routing problem with time windows [Figliozzi, 2012, Balseiro et al., 2011, Pan et al., 2021] or the vehicle routing problem with moving targets [Groba et al., 2018, Gambella et al., 2018]. Nevertheless, to the best of our knowledge, no previous work has combined the existence of multiple time windows and the moving target characteristic in the time-dependent VRP. Moreover, both problems need to consider that only a subset of the nodes can be visited. These routing problems, where each node has a reward associated, and not all nodes have to be visited, are usually called (team) orienteering problems (TOP) [Vansteenwegen et al., 2011, Chao et al., 1996]. However, the main difference with existing TOP problems is that in the SFRP-MTW and TDFRP-MTMTW, the subset size is known, i.e., the number of nodes to visit by the fleet is fixed and known before the route starts.

To provide a formal and clear definition of the problem, a bi-objective mixed integer programming (MIP) model is presented for each variant. While the MIP for the SFRP-MTW is used in the computational experiments to help determine the quality of the proposed solution approach, the model for the TDFRP-MTMTW has the inherent difficulty that the time and cost of travelling between nodes, and the fishing reward associated with each node, are time-dependent, i.e., "data" is dependent on decision variables, and therefore has not been implemented. To overcome this limitation and to be able to solve the real problem at hand, a metaheuristic algorithm is proposed based on a greedy randomized adaptive search procedure (GRASP) algorithm [Feo et al., 1994]. The algorithm introduced, called multi-objective GRASP (MO-GRASP), is designed to overcome the natural instance size limitations of exact methods and to be able to tackle and solve real instances of the problem. The bi-objective nature of MO-GRASP contributes to increase the economic and environmental sustainability of the fleet by allowing the user to trade-off between the two objectives. These objectives are modelled using the expected reward (i.e., the probability of high catches at each dFAD and the probability of successful deployment of a new dFAD) and fuel consumption as proxies.

To validate MO-GRASP and evaluate its performance, three experiments are designed. The first experiment uses synthetic and small-size instances for the SFRP-MTW. The aim of this experiment is to evaluate the performance of the MO-GRASP compared to the optimal solutions, resorting to the solution of the MIP model of the static variant of SFRP-MTW with IBM CPLEX solver. The second experiment compares the performance of the MO-GRASP in its time-dependent variant against the GA-TDA* algorithm proposed in Chapter 3, by using time-dependent and medium-size real instances. For that, it is used a down-sized version of the MO-GRASP, considering a single-vessel without the deployment of new dFADs. The final experiment uses real instances from a one-year period of a fishing fleet operating in the Indian Ocean. In this final set of experiments the potential of the MO-GRASP approach to be used in a decision-support context and to derive managerial insights is shown by: i) studying the potential benefits of a joint fishing planning of a fleet (collaborative approach) compared to a non-collaborative strategy of each vessel, and ii) analyzing the impact of a hypothetical reduction in the number of allowed dFADs per vessel in both fishing strategies. The former is of interest because it can demonstrate that, in addition to the use of routing optimization methods, cooperation between vessels can further improve the economic and environmental sustainability of the fleet. The latter is an important topic for the fishing industry, as over the last years, the tuna regional fisheries management organizations (tRFMOs) have adopted various measures to reduce the number of daily active dFADs per vessel [Zudaire et al., 2023]. In short, the main contributions of this work are the following:

- To the best of our knowledge, this is the first study to deal with a bi-objective dynamic vehicle routing problem with multiple time windows and moving targets.
- It deals with the real-world routing application of a purse seiner fleet, helping in effective decision making in the fishing industry.
- MIP models are proposed for both the static and dynamic variants of the problem, and the model for the static variant is extensively tested.
- A general bi-objective GRASP metaheuristic, capable of tackling both variants of the problem, is proposed and extensively tested and compared with the literature, after the introduction of a set of simplifying assumptions that meet the form of the problem previously tackled in the literature.
- Using as a case study the purse seiner fleet targeting tropical tuna in the Indian Ocean, managerial insights are derived regarding the use of more or less collaborative approaches between the vessels of the fleet, and testing scenarios regarding changes in the legislation regarding the number of dFADs per vessel.

Figure 4.1 explains how the chapter is organized. Section 4.2 provides a description of the problem along with the formulation of the static and time-dependent variants of the problem. Section 4.3 explains the proposed multi-objective algorithm, and Section 4.4 presents the problem instances used for validation and managerial insights. These results are presented in Section 4.5, where the first two experiments evaluate the performance of the proposed algorithm, while the last experiment two scenarios are examined: the first one compares the collaborative and non-collaborative fishing strategies, while the second experiment analyses the impact of a reduction in the number of available dFADs in both strategies. The final conclusions are provided in Section 4.6.

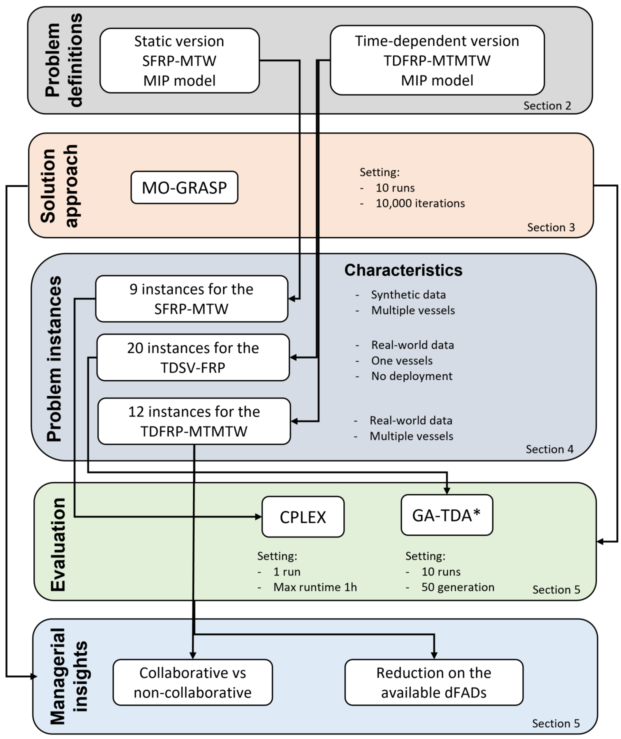


Fig. 4.1: Structure of the chapter.

4.2 Problem Description

The operational practices of the purse seiner fleet targeting tropical tuna involve designing a route that begins and ends at a port, where different fishing sets are carried out. A dFAD-dependent fishing strategy is assumed here, meaning fishing sets are only accounted on dFADs. Fishing with dFADs involves deploying a network of dFADs across the sea, and since dFADs are continuously fished or washed ashore, new dFADs must be deployed to ensure availability for future trips. Therefore, purse seiners also deploy new dFADs along their routes, in addition to fish. All dFADs have a time window when they can be fished since tuna schools cannot be fished at night, but dFADs can be deployed at any time. Moreover, it is assumed that all vessels depart simultaneously from the same port and return after completing their trips within the allowed maximum time at sea.

The common fishing strategy among purse seiners is the non-collaborative one, where each vessel possesses and deploys its own dFADs at sea and whose dFAD information is restricted to the respective vessel [Basurko et al., 2022]. However, this problem is generalized to encompass the routing of a fleet, specifically to design a fishing strategy where all the dFADs' information, the fishing and the deployment requests (i.e., the total number of dFADs to deploy and fish) are shared among vessels of the same company. In the non-collaborative approach, the decision-maker is the skipper, making decisions based on personal and crew benefit, whereas in the collaborative approach, the decision-maker is the fishing company considering the overall benefit. The definition of these two fishing strategies will allow us to compare the performance of current practices with a joint plan. Hence, the fishing routing problem aims to find the optimal set of routes for a fleet of fishing vessels to visit a subset of dFADs and also to deploy a predefined number of new dFADs.

This fishing routing problem can be seen as a variant of the time-dependent VRP with time windows [Figliozzi, 2012]. However, to account for the fact that only a subset of the total dFADs/deployment locations can be visited and that these dFADs are constantly moving, two new definitions of the fishing routing problem are proposed in this study: the static fishing routing problem with multiple time windows (SFRP-MTW) and the time-dependent fishing routing problem with moving targets and multiple time windows (TDFRP-MTMTW). The SFRP-MTW is proposed to generate benchmark instances for which the global optimum is known since they will be solved by an exact approach. However, the SFRP-MTW does not consider the fact that the real-world problem is dynamic due to changes in the weather and species distribution. Therefore, the TDFRP-MTMTW is presented as a problem more similar to real cases, where the aim is to find the best routes for a fleet of fishing vessels to perform a predefined number of dFAD deployments and fishing sets, taking into account the dFADs time windows, their movement, and the effect of weather conditions on vessel performance and species distribution. For this purpose, an objective function is proposed that combines the travel cost and the expected rewards using a weighted sum.

4.2.1 The static fishing routing problem with multiple time windows

The SFRP-MTW consists on a set of similar vessels $\mathcal{V} = \{0, 1, 2, \ldots, V\}$ and a set of nodes $\mathcal{N} = \{0, 1, 2, \ldots, N\}$ defined on a directed graph, $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. The set of nodes $\mathcal{N}$ represents the locations of the available dFADs to fish or deploy, and $\mathcal{E} = \{(i,j)|i,j \in \mathcal{N}, i \neq j\}$ is the set of edges, and each edge (i,j) has a non-negative travel cost c_{ij} and a crossing time t_{ij}.

The binary parameters p_j distinguish the nodes to fish or to deploy. If $p_j = 1$, node $j \in \mathcal{N}$ is a dFAD, and if $p_j = 0$, node $j \in \mathcal{N}$ is a deployment location. If node $j \in \mathcal{N}$ is a dFAD, the expected reward er_j represents the probability of high catches at that location, whereas, if $j \in \mathcal{N}$ is a deployment location, er_j represents the probability of deployment success. The geolocation l_j of each node $j \in \mathcal{N}$ is also known.

Each node can only be visited once by a vessel $v \in \mathcal{V}$. All the vessels leave node 0 (i.e., the port) at time t_0 and return to node 0 after completing their fishing requests. The set of vessels, $\mathcal{V}$, must perform a total of Nf fishing sets and deploy a total of Nd dFADs within the maximum number of days at sea, D. Each vessel $v \in \mathcal{V}$ must visit a total number of nodes between g_{min} and g_{max} and from these visited nodes, a minimum of them should be dFADs, f_{min}, and deployment locations, d_{min}.

Each node $j \in \mathcal{N}$ also has a set of time windows TW_j associated:
$TW_j = \{(a_{j1}, b_{j1}), \ldots, (a_{jd}, b_{jd}), \ldots, (a_{jD}, b_{jD})\}$, where a_{jd} and b_{jd} are the earliest and latest time to start fishing/deploying at day d, and D is the maximum number of days allowed at sea. All a_{jd} and b_{jd} are expressed as a cumulative time from a reference date. For example, if for a certain node j, the time windows open at 5:00 am and close at 5:00 pm for all days, $a_{j1} = 5, a_j2 = a_{j1} + 24, \ldots, a_{jD} = a_{j1} + (24 \cdot (D-1))$ and $b_{j1} = 17, b_{j2} = b_{j1} + 24, \ldots, b_{jD} = b_{j1} + (24 \cdot (D-1))$, expressed in hours. If a vessel fishes the dFAD $j \in \mathcal{N}$ on the day d, it must arrive at the dFAD j before b_{jd}. If it arrives before a_{jd}, it has to wait until a_{jd} to start fishing. Once the vessel arrives at the jth dFAD it spends f_j hours on fishing operations.

The main assumptions of the proposed SFRP-MTW are the following.

- The maximum time at sea per vessel, D, is defined using the 0.75 percentile of the historical trip durations. This value is the same for all vessels and fishing trips, and it is assumed that $D = 29$ days.
- The time spent fishing a dFAD is based on historical data and we assume a value of three hours $f_j = 3,\ \forall j \in \mathcal{N} : p_j = 1$.
- The time spent deploying a dFAD is considered zero, as the vessels do not slow down to deploy dFADs: $f_j = 0, \forall j \in \mathcal{N} : p_j = 0$.

- Newly deployed dFADs are not considered eligible to fish on the same trip, as tuna usually takes around 21 days to aggregate at the dFADs [Orue et al., 2019b].
- The time windows at the fishing nodes are the same for all the days of the fishing trip and for all the nodes $j \in \mathcal{N} : p_j = 1$.
- There are no time windows for the deployment nodes $j \in \mathcal{N} : p_j = 0$.

The notation utilized in the formulation is summarized as follows:

Indices

$v \in \mathcal{V}$, $\mathcal{V} = \{1, 2, \dots, V\}$ – v is used to denote the vessels and V is the number of vessels.

$i, j, k \in \mathcal{N}$, $\mathcal{N} = \{0, 1, 2, \dots, N\}$ – i, j, k are used to denote the nodes and N is the number of nodes.
$\mathcal{N}$ is the set of nodes (i.e., dFADs to fish and deployment locations) available for all vessels, where 0 represents the departure and arrival node.

$d \in \mathcal{D}$, $\mathcal{D} = \{1, 2, \dots, D\}$ – d is used to denote the days and D is the number of days of the fishing trip.

Parameters

A. Parameters related to the nodes

$$p_j \in \{0,1\} = \begin{cases} 1, & \text{if node } j \text{ indicates the location of a dFAD to be fished} \\ 0, & \text{if node } j \text{ indicates the deployment location for a dFAD} \end{cases}$$

er_j is the expected reward of node j, i.e., the probability of high catches at the dFAD at node j or the probability of successful deployment at node j.

f_j is the service time that a vessel spends during fishing operations at node j.

$\mathcal{TW}$ is the set of time windows associated with nodes $j \in \mathcal{N} : p_j = 1$.
$\mathcal{TW} = \{(a_1, b_1), \dots, (a_d, b_d), \dots, (a_D, b_D)\}$, where a_d and b_d are the earliest and latest time to start fishing at day d, and D is the number of days of the fishing trip.
The deployment nodes do not have associated time windows.

B. Parameters related to the edges

c_{ij} is the cost of traveling from node i to node j.

t_{ij} is the travel time needed to reach node j departing from node i.

C. Parameters related to the fishing trip

Nf is the total number of dFADs to fish by all vessels during the fishing trip.
Nd is the total number of dFADs to deploy by all vessels during the fishing trip.
f_{min} is the minimum number of dFADs each vessel must fish.
d_{min} is the minimum number of dFADs each vessel must deploy.
g_{min} is the minimum number of dFADs that each vessel must either fish or deploy: $g_{min} \geq f_{min} + d_{min}$.
g_{max} is the maximum number of dFADs each vessel can fish or deploy: $g_{max} \geq g_{min}$.
D is the maximum number of days of the fishing trip.
t_0 is the time at which all the vessels depart from the port $(i = 0)$.
t_{max} is the maximum time all the vessels must return to the port $(i = 0)$: $t_{max} = t_0 + 24 \cdot D$.

D. Parameters related to the MIP model

c_{min} is the coefficient used to normalize the cost in the objective function.
er_{max} is the coefficient used to normalize the expected reward in the objective function.
λ is the weight given to each objective, expressed as a real number with $0 \leq \lambda \leq 1$.
M is a sufficiently large number.

Decision Variables

$$x_{ij}^v \in \{1, 0\} = \begin{cases} 1, & \text{if the edge from } i \text{ to } j \text{ is traversed by vessel } v \\ 0, & \text{otherwise} \end{cases}$$

$s_k^v \geq 0$ is the arrival time of vessel v at node k, expressed as a real number.

$$z_{kd}^v \in \{1, 0\} = \begin{cases} 1, & \text{if vessel } v \text{ fishes the dFAD } k \text{ on day } d \\ 0, & \text{otherwise} \end{cases}$$

Using the above notation and definitions, the SFRP-MTW can be formulated as follows.

$$\min \ J = \frac{\lambda}{c_{min}} \sum_{v \in \mathcal{V}} \sum_{i,j \in \mathcal{N} j \neq i} c_{ij} \cdot x_{ij}^v + \frac{(1-\lambda)}{er_{max}} \sum_{v \in \mathcal{V}} \sum_{i,j \in \mathcal{N} j \neq i} -er_j \cdot x_{ij}^v, \quad (4.1)$$

subject to:

$$\sum_{v \in \mathcal{V}} \sum_{i \in \mathcal{N}} x_{ik}^v \leq 1, \ \forall k \in \mathcal{N}, k \neq 0, \quad (4.2)$$

$$\sum_{i \in \mathcal{N}} x_{ik}^v = \sum_{j \in \mathcal{N}} x_{kj}^v, \ \forall k \in \mathcal{N}, \forall v \in \mathcal{V} \quad (4.3)$$

$$\sum_{j \in \mathcal{N}} x_{0j}^v = 1, \ \forall v \in \mathcal{V} \quad (4.4)$$

$$x_{ii}^v = 0, \ \forall v \in \mathcal{V}, \ \forall i \in \mathcal{N} \quad (4.5)$$

$$\sum_{v \in \mathcal{V}} \sum_{i,k \in \mathcal{N}, k \neq 0} p_k \cdot x_{ik}^v = Nf, \quad (4.6)$$

$$\sum_{v \in \mathcal{V}} \sum_{i,k \in \mathcal{N}, k \neq 0} (1 - p_k) \cdot x_{ik}^v = Nd, \quad (4.7)$$

$$\sum_{i,k \in \mathcal{N}, k \neq 0} p_k \cdot x_{ik}^v \geq f_{min}, \ \forall v \in \mathcal{V} \quad (4.8)$$

$$\sum_{i,k \in \mathcal{N}, k \neq 0} (1 - p_k) \cdot x_{ik}^v \geq d_{min}, \ \forall v \in \mathcal{V} \quad (4.9)$$

$$g_{min} \leq \sum_{i,k \in \mathcal{N}, k \neq 0} x_{ik}^v \leq g_{max}, \ \forall v \in \mathcal{V} \quad (4.10)$$

$$s_0^v < t_{max}, \ \forall v \in \mathcal{V} \quad (4.11)$$

$$s_k^v \geq t_0 + t_{0k} + (x_{0k}^v - 1) \cdot M, \ \forall v \in \mathcal{V}, \ \forall k \in \mathcal{N}, k \neq 0 \quad (4.12)$$

$$s_k^v \geq s_i^v + f_i \cdot p_i + t_{ik} + (x_{ik} - 1) \cdot M, \ \forall v \in \mathcal{V} \ \forall i, k \in \mathcal{N}, k \neq 0, i \neq k \quad (4.13)$$

$$a_d - (1 - z_{kd}^v) \cdot M \leq s_k^v, \ \forall v \in \mathcal{V}, \ \forall d \in \mathcal{D}, \ \forall k \in \mathcal{N} : p_k = 1 \quad (4.14)$$

$$b_d + (1 - z_{kd}^v) \cdot M > s_k^v, \ \forall v \in \mathcal{V}, \ \forall d \in \mathcal{D}, \ \forall k \in \mathcal{N} : p_k = 1 \quad (4.15)$$

$$\sum_{i \in \mathcal{N}} x_{ik}^v = \sum_{d \in \mathcal{D}} z_{kd}^v, \ \forall v \in \mathcal{V}, \ \forall k \in \mathcal{N} : p_k = 1 \quad (4.16)$$

The objective function (4.1) minimizes the weighted sum of the travel cost and the expected reward. Constraints (4.2) guarantee that each dFAD can only be fished/deployed once. Constraints (4.3) and (4.4) describe the vessel path, namely, they define the path continuity by ensuring that each vessel leaves the port, after arriving at a node the vessel leaves again, and finally it returns to the port. Constraints (4.5) are the loop elimination constraints that prevent a vessel from going from one node to itself. Constraints (4.6) and (4.7) ensure, respectively, that a fixed number of dFADs is fished and deployed by all the vessels. Constraints (4.8) and

(4.9) impose, respectively, that each vessel carries out a minimum number of fishing sets and deployments. Constraints (4.10) ensure that each vessel fishes/deploys a number of dFADs between a minimum and a maximum. Constraints (4.11) impose a maximum trip duration to do the fishing trip. Constraints (4.12) and (4.13) ensure that a vessel cannot arrive at node k before departing from node i plus travel and fishing time if needed. Constraints (4.14), (4.15), and (4.16) guarantee that the time windows for the fishing nodes are satisfied.

4.2.2 The time-dependent fishing routing problem with moving targets and multiple time windows

The need to formulate a time-dependent version of the SFRP-MTW arises since most of the problem inputs (e.g., travel cost and time, dFADs position, tuna distribution, and deployment success) change over time. For example, the dFADs drift through the ocean due to weather conditions, or the travel cost between two points will also depend on the weather conditions. Therefore, the formulation and notation for the time-dependent problem are similar to the SFRP-MTW, though with the following differences.

The problem is also defined in a directed graph $\mathcal{G}$. However, the travel cost and the travel time on an edge (i, j) now depend on the departure time from node i, dt_i, i.e., $c_{ij}(dt_i)$ and $t_{ij}(dt_i)$. Moreover, each node in $\mathcal{N}$ has an associated expected reward and geo-location $l_j(at_j)$ dependent on the arrival time at node j, at_j. In the TDFRP-MTMTW, as dFADs drift along the ocean, some dFADs may at any time enter an Economic Exclusive Zone (EEZ) where fishing is not allowed. To prevent dFADs from being fished in EEZs where fishing is not allowed, a new constraint must be added. A new set $EEZ = \{l_0, l_1, \ldots, l_h\}$ is defined, containing all geolocations where fishing is prohibited. The dFAD deployment locations remain static, while the probability of a successful deployment at each location changes over time. Therefore, the problem also consists in carrying out a predefined number of sets Nf and deployments Nd within a maximum time at sea D, taking into account their time windows, the movement of the dFADs and the effects of changing weather conditions on the performance of the vessels.

It is required to estimate the arrival time at_{ij} and departure time dt_{ij} at node j when departing from node i. Note that at_{ij} and dt_{ij} depend on which node the vessel is coming from, but for simplicity, we only consider the destination node in the notation (i.e., at_j and dt_j), assuming that the predecessor i is known. Hence, the arrival time at node j, when departing from node i, is computed using the following expression:

$$at_j = dt_i + t_{ij}(dt_i), \ \forall j \in \mathcal{N}, i \neq j, \tag{4.17}$$

where dt_i is the departure time at node i and $t_{ij}(dt_i)$ is the travel time between nodes i and j, departing at time dt_i from node i. Note that the departure time from the port is $dt_0 = t_0$ and, for the remaining nodes the departure time is estimated with the following expression:

$$dt_i = at_i + f_i \cdot p_i + tw_i, \ \forall i \in \mathcal{N} \setminus \{0\}, \tag{4.18}$$

where f_i is the time spent during the fishing operation if i is a fishing node ($p_i = 1$), and tw_i is the waiting time at node i. To calculate the waiting time tw_i, it is important to know the day d on which the node i is reached in order to be able to select the time window of this day (i.e., a_d and b_d on day d). This can be done by $d = \lceil at_i/24 \rceil$ where at_i is expressed in cumulative hours, and therefore, tw_i is estimated using the following expression:

$$tw_i = \begin{cases} a_d - at_i & , \text{ if } at_i \leq a_d \text{ and } p_i = 1 \\ a_{d+1} - at_i & , \text{ if } at_i > b_d \text{ and } p_i = 1 \\ 0 & , \text{ otherwise.} \end{cases} \tag{4.19}$$

A solution is codified as a set of routes $S = \{S_1, S_2, \ldots, S_V\}$, where each route $S_v = (e_0^v \ e_1^v \ e_2^v \ \ldots \ e_{q_v}^v \ e_{q_v+1}^v)$ represents the tour that vessel v must follow and q_v indicates the number of fishing/deployment events to be carried out by vessel v, with $e_i^v \in \mathcal{N}, \forall i = 0, \ldots, q_{v+1}$, and $e_0^v = e_{q_v+1}^v = 0$. Note that to distinguish between a dFAD and a deployment location within a solution, there exists a binary variable p_j, $\forall j \in \mathcal{N}$, explained in Section 4.2.1. For example, a route $S_v = (0 \ 2 \ 4 \ 6 \ 0)$ means that the vessel v must depart from port, 0, and visit, in this order, nodes 2, 4, and 6, and finally return to port 0. Note that all routes start and end at node 0.

Therefore, using the above notation and definitions, the TDFRP-MTMTW can be formulated as follows.

$$\min\ J(S_1,\ldots,S_V) = \frac{\lambda}{c_{min}} \sum_{v=1}^{V} \sum_{j=1}^{q_v+1} c_{e^v_{j-1} e^v_j}(dt_{e^v_{j-1}}) + \frac{(1-\lambda)}{er_{max}} \sum_{v=1}^{V} \sum_{j=1}^{q_v} -er_{e^v_j}(at_{e^v_j}) \tag{4.20}$$

subject to:

$$\sum_{v=1}^{V} \sum_{k=1}^{q_v} p_{e^v_k} = Nf, \tag{4.21}$$

$$\sum_{v=1}^{V} \sum_{k=1}^{q_v} (1 - p_{e^v_k}) = Nd, \tag{4.22}$$

$$\sum_{k=1}^{q_v} p_{e^v_k} \geq f_{min},\ \forall v \in \mathcal{V} \tag{4.23}$$

$$\sum_{k=1}^{q_v} (1 - p_{e^v_k}) \geq d_{min},\ \forall v \in \mathcal{V} \tag{4.24}$$

$$g_{min} \leq q_v \leq g_{max},\ \forall v \in \mathcal{V} \tag{4.25}$$

$$at_{e^v_{q_v+1}} < t_{max},\ \forall v \in \mathcal{V} \tag{4.26}$$

$$l_{e^v_k}(at_{e^v_k}) \notin EEZ,\ \forall v \in \mathcal{V},\ \forall k = 1,\ldots,q_v \tag{4.27}$$

The objective function (4.20) minimizes the weighted sum of the travel cost and the expected reward of all the vessels. Constraints (4.21) and (4.22) ensure, respectively, that a fixed number of dFADs are fished and deployed. Constraints (4.23) and (4.24) impose that each vessel should carry out, respectively, a minimum number of fishing sets and deployments. Constraints (4.25) ensure that each vessel fishes/deploys a number of dFADs between a minimum and a maximum. Constraints (4.26) impose a maximum trip duration to do the fishing trip. Constraints (4.27) ensure that no dFAD is fished within the EEZs where fishing is not allowed.

It should be noted that the inherent difficulty of time dependence, which is concertized in the fact that the time and cost of travelling between nodes is time dependent, as well as the fishing reward associated with each node (i.e., “data” is dependent on decision variables), is not overcome in this model.

4.3 Solution Approach

This section presents the solution approach proposed for the SFRP-MTW and TDFRP-MTMTW problems, which is based on a greedy randomized adaptive search procedure (GRASP) [Feo et al., 1994]. The basic structure of a GRASP consists of two phases: the first is used to construct a solution by applying a randomized greedy constructive algorithm (see Section 4.3.1), while in the second phase, a local search is applied to improve the constructed solution (Section 4.3.2). These two steps are repeated in each iteration, along with the update of the c_{min} and er_{max}, until the stopping condition is satisfied. The best solution found over all iterations is returned as the final solution of GRASP. This study proposes a multi-objective GRASP (MO-GRASP), where both phases are guided by a weighted sum of both objectives (i.e., travel cost and expected reward).

Algorithm 3 presents the pseudo-code of the proposed MO-GRASP, which only takes three input arguments: the maximum number of iterations $maxIter$, α, and λ. The parameter α controls the balance between random and greedy construction, with $\alpha = 0$ leading to a greedy construction and $\alpha = 1$ indicating a fully random construction. The parameter λ determines the weight of each objective in the multi-objective problem. In line 1, the cost of the best solution J^*, the c_{min}, and the er_{max} are initialized.

The main loop of MO-GRASP is executed from lines 2 to 16, terminating when the maximum number of iterations is reached. In line 3, the solution construction phase is performed, and in line 4, the local search phase takes place. These two phases are described further in Sections 4.3.1 and 4.3.2. In line 5, the algorithm checks the maximum time at sea and the Exclusive Economic Zone (EEZ) constraints. To do so, the expression $time(S) < t_{max}$ indicates if the arrival time at the port of all the vessels is $< t_{max}$, while the expression $position(S) \notin EEZ$ states that none of the dFADs fished is within a non-allowed EEZ. The last condition is only checked for the TDFRP-MTMTW, since in the SFRP-MTW, the dFADs are static and, therefore, will not enter any EEZs. If the solution violates these constraints, it is considered infeasible, and the algorithm returns to line 3 to build a new solution. During the construction phase of the MO-GRASP algorithm, infeasible solutions may be generated. However, after the local search phase, these solutions can be transformed into feasible ones or vice versa. Therefore, the feasibility constraints are checked only at the end of both phases to ensure that the final solution is feasible and satisfies all problem constraints.

Parameters c_{min} and er_{max} are used to normalise both objectives. These parameters represent the minimum travel cost and the maximum expected reward and, in the best scenario, the value of these parameters would be the value of the optimal solution for each in a mono-objective approach and known in advance. However, these values are unknown, and hence are updated dynamically during the algorithm execution. Whenever a new solution with a lower travel cost $c(S)$ or a higher expected reward $er(S)$ is found, the parameters c_{min} or er_{max} are updated accordingly, and the best solution J^* is updated with the new values (lines 9 and 13).

Finally, if the objective function value of the current solution, $J(S)$, is better than J^*, then S is retained as the new best solution S^*, and its objective function value is recorded as J^*, (lines 14-16). Once all iterations are completed, *MO-GRASP* returns the best solution (local optimum) found, S^*.

Algorithm 3: *MO-GRASP*$(maxIter, \alpha, \lambda)$

Input: $maxIter$: number of iterations, α: balance factor between greediness and randomness, λ: objectives weights.
Output: A solution S^*.
initialize:
1: $J^* := \infty$, $c_{min} := \infty$, $er_{max} := 0$
main loop:
2: **for** $i = 1, \ldots, maxIter$ **do**
3:   $S := MO - GreedyRandomConstruction(\alpha, \lambda)$
4:   $S := MO - twoOpt(S, \lambda)$
5:   **if** $time(S) < t_{max}$ **AND** $position(S) \notin EEZ$ **then**
6:     **if** $c(S) < c_{min}$ **then**
7:       $c_{min} := c(S)$
8:       **if** $i \neq 1$ **then**
9:         $J^* := J(S^*)$
10:     **if** $er(S) > er_{max}$ **then**
11:       $er_{max} := er(S)$
12:       **if** $i \neq 1$ **then**
13:         $J^* := J(S^*)$
14:     **if** $J(S) < J^*$ **then**
15:       $S^* := S$
16:       $J^* := J(S)$
17: **return** S^*

4.3.1 Construction phase

For the construction phase of the MO-GRASP, we propose a new heuristic algorithm described in Algorithm 4. An example of the proposed heuristic construction algorithm is illustrated in Figure 4.2, where a solution for three vessel (i.e., vessel red, vessel blue, and vessel black) departing and arriving at port, represented by the anchor, is constructed. In brief, the first step of the heuristic is to select the first dFAD or deployment location to visit for each vessel (i.e., arrows 1 to 3). Then, the vessel that first arrives at its destination will be the next to select a dFAD to fish or a deployment location (i.e., arrow 4). To construct the remainder of the routes, the same logic is followed: the vessel that reaches its destination first is the next to choose. In the example shown in Figure 4.2, vessel 1 crosses arrow 5, then vessel 3 crosses arrow 6, then vessel 1 again crosses arrow 7, and vessel 3 crosses arrow 8, and so on. These steps are repeated until the route for each vessel has been fully constructed, considering the constraints of the problem. A more formal description of the heuristic is provided in the following paragraphs.

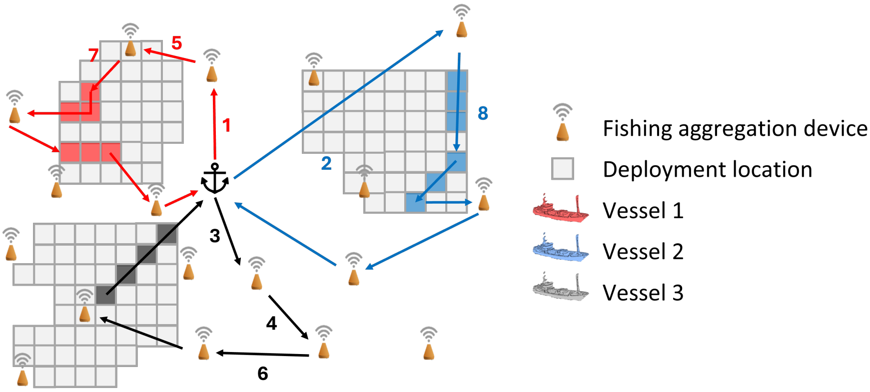


Fig. 4.2: Example of the proposed heuristic construction algorithm.

The algorithm initializes the route S_v, set of candidate nodes C_v, and current time ct_v for each vessel in lines 1 to 4. The sets of candidate nodes, C_v, are initialized by adding all feasible nodes in $\mathcal{N}$ except for the port ($i = 0$). Note that, as elements are added to the solution at each step of the algorithm, each vessel may have different candidate elements due to constraints (4.6), (4.7), (4.8) and (4.9) for the SFRP-MTW or (4.21), (4.22), (4.23) and (4.24) for the TDFRP-MTMTW.

The current time for each vessel $ct_v \in CT = \{ct_1, ct_2, \ldots, ct_V\}$ is estimated as the departure time of the last node visited. In line 5, the total work to be done $(Nf + Nd)$ is randomly assigned among the vessels considering the problem constraints. For that, the function *getWork* creates a set $W = \{w_1, w_2, \ldots, w_V\}$ where w_v indicates the total number of dFADs and deployment locations that vessel v must visit. The w_v must respect the following constraints for all v: $w_v \geq f_{min}$, $w_v \geq d_{min}$, $g_{min} \leq w_v \leq g_{max}$, and $\sum_{v \in \mathcal{V}} w_v = Nf + Nd$.

In lines 6 to 12, the algorithm selects the first node t visited by each vessel. The route S_v of vessel v is updated to account with the inclusion of the randomly selected element s, and the current time is updated accordingly ($ct_v = dt_s$). The candidate sets are then updated by removing the added element s from the candidate sets of all vessels.

Additionally, in line 11, the algorithm checks the problem constraints using the function *checkConstraints*. This function checks if a vessel has reached its minimum allowed dFADs to fish f_{min} or to deploy d_{min}, and it also checks if the total number of dFADs to fish Nf or to deploy Nd has been reached. If any of these constraints are reached, the remaining fishing or deployment nodes are removed from the corresponding candidate set.

Algorithm 4: *MO-GreedyRandomConstruction*(α, λ)

Input: α: balance factor between greediness and randomness, λ: objectives weights.
Output: a solution S^*.
initialize:
1: **for** $v = 1, \ldots, V$ **do**
2: $S_v := ()$
3: $C_v := \mathcal{N} \setminus \{0\}$
4: $ct_v = t_0$
5: $W := getWork()$
6: **for** $v = 1, \ldots, V$ **do**
7: Select $s \in C_v$ at random
8: $S_v := S_v \cup \{s\}$
9: $ct_v := dt_s$
10: $C_{v'} := C_{v'} \setminus \{s\}, \forall v' \in \mathcal{V}$
11: $C_{v'} := checkConstraints(C_{v'}), \forall v' \in \mathcal{V}$
12: $w_v := w_v - 1$
13: Select the vessel to fish or deploy: $v := argmin\{ct_v \in CT \mid v \in \mathcal{V}, w_v \neq 0\}$
14: Evaluate the incremental weighted cost $f(e)$ for all $e \in C_v$
main loop:
15: **while** $W \neq \{0, 0, \ldots, 0\}$ **do**
16: $F_{min} := min\{f(e)| \ e \in C_v\}$
17: $F_{max} := max\{f(e)| \ e \in C_v\}$
18: $RCL := \{e \in C_v| \ f(e) \leq F_{min} + \alpha(F_{max} - F_{min})\}$
19: Select $s \in RCL$ at random
20: $S_v := S_v \cup \{s\}$
21: $ct_v := dt_s$
22: $C_{v'} := C_{v'} \setminus \{s\}, \forall v' \in \mathcal{V}$
23: $C_{v'} := checkConstraints(C_{v'})$, $\forall v' \in \mathcal{V}$
24: $w_v := w_v - 1$
25: Select the vessel to fish: $v := argmin\{ct_v \in CT \mid v \in \mathcal{V}, w_v \neq 0\}$
26: Re-evaluate the incremental weighted cost $f(e)$ for all $e \in C_v$
27: **return** S^*

Once the initial nodes have been selected for all vessels, the next step is to define which vessel, whose remaining work (i.e., number of dFADs and deployment locations to visit) is different from zero, should select a node. The vessel with the minimum current time ct_v is selected as the next vessel to fish/deploy (line 13). This approach reflects a realistic case or simulation, where the availability of dFADs or deployment locations depends on whether another vessel has visited the node. Then, in line 14, the incremental weighted cost $f(e)$ is calculated for all nodes $e \in C_v$ using the following expression:

$$f(e) = \frac{\lambda}{c_{min}} c_{se}(dt_s) + \frac{(1-\lambda)}{er_{max}} - er_e(at_e) \tag{4.28}$$

c_{min} and er_{max} are the minimum travel cost and the maximum expected reward of all nodes $e \in C_v$. That is, $c_{min} = min\{c_{se}(dt_s)|e \in C_v\}$ and $er_{max} = max\{er_e(at_e)|e \in C_v\}$.

Finally, from lines 15 to 26, the vessels add dFADs or deployment locations to their routes as if it were a real simulation. To select the best candidates to add to the routes S_v, a restricted candidate list (RCL) is created. The strategy followed is to select the nodes with $f(e)$ values between

$$[F_{min}, F_{min} + \alpha \cdot (F_{max} - F_{min})],$$

where $F_{min} = min\{f(e)|e \in C_v\}$ and $F_{max} = max\{f(e)|e \in C_v\}$. The parameter $\alpha \in [0,1]$ regulates the size of this RCL, from the maximum size (i.e., $RCL = C_v$ or random construction) to the minimum size (i.e., $RCL = min\{f(e)|e \in C_v\}$ or greedy construction). Once the RCL is built, a node s of the RCL is selected randomly. Then, from lines 20 to 26, the selected node is added to S_v, the current time ct_v, and all candidate sets are updated. Moreover, the problem constraints are checked, and the remaining work is updated. Finally, the next vessel to fish/deploy is selected, and the incremental weighted cost $f(e)$ for all the elements in C_i is re-evaluated.

4.3.2 Local search

The objective of MO-GRASP is to improve the starting solution. The local search is based on the 2-opt neighborhood developed by Croes [1958], and the pseudo-code of the proposed multi-objective local search (*MO-twoOpt*) is shown in Algorithm 5. The *MO-twoOpt* follows the first-improvement approach, i.e., the current solution will be replaced by the first neighbor found whose objective function value is better.

Algorithm 5: *MO-twoOpt*(S, λ)

Input: S: a solution, λ: objectives weights.
Output: S^*: a new solution.
initialize:
1: $S^* := \emptyset$
main loop:
2: **for** $v = 1, 2, \ldots, V$ **do**
3: $\quad len := size(S_v)$
4: $\quad c_{min} := c(S_v)$
5: $\quad er_{max} := er(S_v)$
6: $\quad J^* := J(S_v)$
7: $\quad improve := true$
8: $\quad$ **while** $improve$ **do**
9: $\quad\quad improve := false$
10: $\quad\quad k := 1$
11: $\quad\quad$ **while** $k < len - 2$ **AND** $!improve$ **do**
12: $\quad\quad\quad j := k + 2$
13: $\quad\quad\quad$ **while** $j < len$ **AND** $!improve$ **do**
14: $\quad\quad\quad\quad S_v^* := 2 - opt(S_v, k, j)$
15: $\quad\quad\quad\quad$ **if** $J(S_v^*) < J^*$ **then**
16: $\quad\quad\quad\quad\quad improve := true$
17: $\quad\quad\quad\quad\quad S_v := S_v^*$
18: $\quad\quad\quad\quad\quad J^* := J(S_v^*)$
19: $\quad\quad\quad\quad j := j + 1$
20: $\quad\quad\quad k := k + 1$
21: $\quad S^* := S^* \cup S_v$
22: **return** S^*

The *MO-twoOpt* takes as input a solution S and λ. From lines 2 to 6, the length of the route S_v, the travel cost $c(S_v)$, the expected reward $er(S_v)$, and the cost $J(S_v)$ are stored. Next, in line 14, the classical *2-opt* operator proposed by Flood [1956] is applied, which reverses the elements between the indices k and j. If the objective value of the new solution, $J(S_v^*)$, is better than the best one found until that moment, the best solution and its cost are updated. These steps are performed for each route until no route can be improved, i.e., a local optimum is reached. Finally, the best route found, S_v, is added to the final solution S^*.

To sum up, the construction phase selects the nodes to visit, whereas the local search improves the order in which these nodes are visited.

4.4 Problem Instances

In this study, three different sets of test instances are used to evaluate the performance of the proposed algorithm. Each set of instances presents its own unique challenges and characteristics. Instances vary in complexity, including different numbers of vessels and nodes, which presents challenges in finding optimal solutions.

The first set of test instances consists of synthetic instances specifically designed for the SFRP-MTW problem. These instances are used to compare the solutions obtained with the CPLEX solver for the model (4.1) - (4.16) with the solutions generated by the MO-GRASP algorithm. The synthetic instances allow us to assess the algorithm's ability to find optimal solutions and its performance in solving relatively smaller and simpler instances.

The second set of test instances, introduced in Chapter 3, is used to compare the effectiveness of the MO-GRASP and GA-TDA* algorithms for the time-dependent single-vessel fishing routing problem (TDSV-FRP). This problem models a single vessel without the deployment of new dFADs. The instances in this set provide a time-dependent scenario and medium-size real instances, allowing us to assess the performance of both algorithms under different conditions.

Finally, the last set of test instances is designed for the TDVRP-MTMTW problem and is based on real-world data. These instances represent real fishing fleet scenarios and involve various vessels and nodes, making the problem more complex. This set of instances enables us to evaluate the performance of the MO-GRASP algorithm in real-world situations, where the size and complexity of the problem are more significant.

4.4.1 Instances for the SFRP-MTW

The benchmark data set consists of nine randomly generated instances designed to serve as test cases. Table 4.1 provides an overview of the main characteristics of the test instances. Each instance varies in the number of nodes, the amount of fishing sets and deployments, and the number of vessels.

The *Nodes* column denotes the total number of nodes available, while the values inside the parentheses indicate the number of nodes allocated to dFADs and deployment locations, respectively, out of the total nodes. All instances share a common departure time from the port at $t_0 = 0$. The values of these instances were selected to cover a wide range of parameter values relevant to the problem, enabling the generation of instances that CPLEX can solve easily, as well as instances where CPLEX is unable to prove the optimality of the found solutions within the given time limit.

The remaining inputs for the problem are estimated as follows. The time windows for all days are set to open at 5 AM and close at 5 PM since tuna cannot

Instance	**Nodes**	Nf	Nd	V	t_{max}	g_{max}	g_{min}	f_{min}	d_{min}
A	10 (5-5)	3	3	2	13	4	2	1	1
B	12 (4-8)	2	4	2	16	4	2	1	1
C	20 (10-10)	7	7	2	27	10	4	2	2
D	20 (10-10)	5	7	3	27	6	2	1	2
E	25 (10-15)	5	8	3	25	6	2	1	2
F	33 (8-25)	3	8	3	31	6	2	1	2
G	35 (15-20)	8	12	2	41	15	5	3	4
H	35 (15-20)	7	12	3	41	10	3	2	3
I	50 (25-25)	10	10	2	41	15	5	3	3

Table 4.1: Summary of the problem instances values for the SFRP-MTW.

be fished at night. They are denoted as $TW = \{(5, 17), (29, 41), \ldots, (5 + (24 \cdot D), 17 + (24 \cdot D))\}$, where D represents the maximum number of days in the planning horizon. The travel time between each pair of nodes (i, j), t_{ij} is computed as $t_{ij} = \beta \cdot c_{ij}$, where β is randomly selected in $[0.9, 1.1]$. The travel cost between each pair of nodes (i, j), c_{ij}, is randomly selected in $[0.5, 60]$, while the travel time is computed as $t_{ij} = \beta \cdot c_{ij}$, where β is randomly selected in $[0.5, 60]$. Additionally, the expected reward for each node is randomly selected in $[0, 1]$.

4.4.2 Instances for the TDSV-FRP

The instances used for the TDSV-FRP are the same as those employed in Chapter 3, which were designed for single-vessel routing in a time-dependent scenario. The TDSV-FRP is a particular case of the TDFRP-MTMTW, in which no deployment is considered ($Nd = 0$), only the route of one vessel ($V = 1$) is optimized, and the set of nodes $\mathcal{N}$ is composed only by dFADs. The values for travel time and cost between nodes, and the expected rewards (i.e, probability of high catches at each dFAD) remain the same.

4.4.3 Instances for the TDFRP-MTMTW

The instances used for TDFRP-MTMTW were obtained from real data provided by a fishing company over a one-year period. A total of 12 instances were used, each corresponding to a different month of the year. For all instances, we assume $V = 3$ and $D = 29$ days.

Table 4.2 shows the total number of nodes, along with the number of nodes assigned to dFADs and deployment locations, respectively (in parentheses), as well as the number of dFADs to fish (Nf) and deployment locations (Nd). In addition, the minimum number of dFADs to fish and deploy (f_{min} and f_{min}) and the minimum/maximum number of dFADs that each vessel can fish or deploy

(g_{min} and g_{max}) are estimated using the following expressions: $f_{min} = \lfloor(1/2 \cdot Nf)/V\rfloor$; $d_{min} = \lfloor(1/2 \cdot Nd)/V\rfloor$; $g_{min} = \lfloor(1/2 \cdot (f_{min} + d_{min}))/V\rfloor$; and $g_{max} = \lfloor(3/2 \cdot (f_{min} + d_{min}))/V\rfloor$.

Instance	**Nodes**	Nf	Nd
Trip 1	1544 (421-1123)	74	90
Trip 2	1119 (529-590)	93	46
Trip 3	1126 (511-615)	62	67
Trip 4	996 (475-521)	54	89
Trip 5	964 (491-473)	55	128
Trip 6	808 (508-300)	77	100
Trip 7	934 (502-432)	74	43
Trip 8	1164 (521-643)	71	98
Trip 9	982 (535-357)	69	19
Trip 10	1317 (459-858)	65	34
Trip 11	909 (375-534)	85	38
Trip 12	997 (327-670)	30	58

Table 4.2: Summary of the problem instances values for the TDFRP-MTMTW.

Additionally, the values of the other parameters of the problem instances, such as dFAD and deployment positions, travel time, travel cost, and expected rewards, are estimated using the following methods.

4.4.3.1 dFADs and deployments geolocations

The historical data for the dFADs and deployment geolocations, $l_j(at_j)$, will be utilized as future geolocations to evaluate the proposed algorithm with real instances.

4.4.3.2 Travel time and cost

To estimate the travel time and cost between two nodes (i, j), a regular square grid $G_s = (N_s, A_s)$ is implemented to spatially discretize the studied area. The set of nodes is denoted as $N_s = \{n_1, n_2, ..., n_z\}$, and the set of edges is denoted as $A_s = \{(n_i, n_j) | n_i, n_j \in N_s, n_i \neq n_j\}$. The distance between the nodes is 0.5 degrees, and each node is connected to eight adjacent nodes through the edges, forming a grid structure (see Figure 4.3).

To navigate from one node to another, the vessels can only traverse the grid's edges. Each edge (n_i, n_j) has associated time-dependent crossing times $ct_{n_i,n_j}(dt_{n_i})$ and costs $cc_{n_i,n_j}(dt_{n_i})$, where dt_{n_i} represents the departure time from node n_i. A path of a vessel between an origin node n_o and a destination node n_d

is defined as a node sequence $r(n_o, n_d) = (n_1, n_2, \ldots, n_l)$, where $n_1 = n_o$, $n_l = n_d$, and $(n_i, n_{i+1}) \in A_s$ for all $i = 1, \ldots, l-1$. The Bresenham's line algorithm [Bresenham, 1965] is used to approximate the shortest path between two nodes in the grid. The total travel cost c_{ij} and the travel time t_{ij} between the nodes i and j are then computed by summing the crossing values associated with all the edges that form the path $r(i,j)$, linking the node $i = n_o$ with node $j = n_d$. Thus, the expressions for the total travel cost $c_{ij}(dt_i)$ and the travel time $t_{ij}(dt_i)$ are given by:

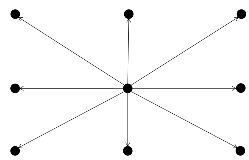


Fig. 4.3: Scheme of connections between nodes, departing from the central node.

$$c_{ij}(dt_i) = \sum_{k=1}^{l-1} cc_{n_k,n_{k+1}}(dt_{n_k}), \forall n_k \in r(i,j), \tag{4.29}$$

$$t_{ij}(dt_i) = \sum_{k=1}^{l-1} ct_{n_k,n_{k+1}}(dt_{n_k}), \forall n_k \in r(i,j). \tag{4.30}$$

To compute the expressions presented in Eq. (4.29) and (4.30), the crossing time and cost associated with each edge $(n_i, n_j) \in A_s$ need to be determined. These values are estimated through the following methods.

A. Travel time

To account for the impact of wave-induced resistance on the crossing time $ct_{n_i,n_j}(dt_{n_i})$, which may result in a decrease in vessel speed, v_s, we use the formula proposed by Bowditch [1975]. Therefore, the estimated travel time between nodes $ct_{v_i,v_j}(dt_{v_i})$ is defined by:

$$ct_{n_i,n_j}(dt_{n_i}) = \frac{dist_{n_i,n_j}}{v_s(dt_{n_i})}, \tag{4.31}$$

where $dist_{n_i,n_j}$ is the great-circle distance between the n_i and n_j nodes, and $v_s(dt_{n_i})$ is the vessel speed in the edge (n_i, n_j).

B. Travel cost

Fuel consumption will be used to estimate the crossing cost $cc_{n_i,n_j}(dt_{n_i})$ that each vessel spends to go from node n_i to node n_j. This travel cost is predicted using a machine learning model detailed in Chapter 3. In brief, the model uses environmental variables, vessel speed and dry docking as predictors to forecast fuel consumption per hour (kg/h). The dry docking refers to the number of months since the last ship's hull and propeller cleaning, which affects fuel consumption due to attached biofouling [Adland et al., 2018]. Once the average fuel consumption per hour (kg/h) for each edge is estimated, the total fuel (kg) needed to cross the edge (n_i, n_j), $cc_{n_i,n_j}(dt_{n_i})$, can be estimated using the following equation:

$$cc_{n_i,n_j}(t_{n_i}) = FOC_{n_i,n_j}(dt_{n_i}) \cdot \frac{dist_{n_i,n_j}}{v_s(dt_{n_i})}, \tag{4.32}$$

where $FOC_{n_i,n_j}(dt_{n_i})$ is the vessel's average fuel consumption per hour on edge (n_i, n_j) at time dt_{n_i}, $dist_{n_i,n_j}$ is the great-circle distance between nodes n_i and n_j, and $v_s(dt_{n_i})$ is the vessel speed in the edge (n_i, n_j).

4.4.3.3 Expected rewards

The expected reward at each node j, er_j, is estimated by one of the following models, depending on whether the node is a dFAD for fishing or a location for the deployment of a new dFAD. For the reward at each fishing dFAD (i.e., probability of high catches of tuna), the machine learning models proposed in Chapter 3 are used. These models take as predictors the dFADs' signal and the physical and biogeochemical environmental variables, whereas the target variable consists of the historical tuna catches (kg). The results given by the models are the probability that the tuna catches are over 35 tonnes. The learning classifier is the Naive Bayes, a probabilistic model based on Bayes' theorem.

A machine learning model is developed to estimate the expected reward of a new dFAD deployment, which is defined as the probability of success. The probability of success, $er_j(at_j)$, is defined as the likelihood that a dFAD deployed at a specific location will end up within a fishable area, avoiding areas where fishing is prohibited, such as the EEZ or land. The proposed model utilizes various predictors, including the month, location, and physical variables such as currents and wave data. These predictors are used to predict a binary target variable that indicates whether the dFAD ends up within a fishable Exclusive Economic Zone (EEZ) or not.

The model is built following the scheme in Figure 4.4. In the preprocessing phase, the data is cleaned by removing inaccurate records and dFAD transects with less than ten observations. The target variable is then created as a binary variable to indicate whether the last recorded dFAD position is located on land or

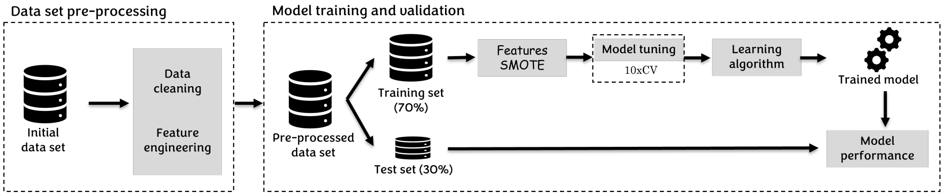


Fig. 4.4: dFAD deployment model building and validation methodology.

within an EEZ where fishing is prohibited. In the model training and validation phase, the data is split into a training set (70%) and a testing set (30%). To address the imbalance in the target class, the synthetic minority oversampling technique (SMOTE) is applied to the training set using the *unbalanced* R package [Chawla et al., 2002]. This results in an equal representation of both classes in the target variable. The model hyperparameters are tuned using a 10-fold cross-validation method, and optimal parameters are used to train a random forest (RF) model with the *randomForest* R package [Liaw and Wiener, 2002]. The trained model exhibits an accuracy of 81.6%, a sensitivity of 83.7%, and a specificity of 77.6%.

Finally, the available deployment locations will be limited based on historical data. Specifically, vessels deploy new dFADs in different areas depending on the month. Therefore, we restrict new deployment locations based on the past deployment record for each month. This approach reduces the number of potential deployment sites, and the specific number of locations for each month is presented in Table 4.2.

4.5 Results of Experiments

This section presents the results of two numerical experiments conducted to evaluate the performance of the proposed heuristic, along with the last experiment focusing on real cases (see Figure 4.1). The first experiment evaluates the performance of MO-GRASP against CPLEX using small-sized and static instances introduced in Section 4.4.1. This experiment enables the evaluation of MO-GRASP with instances where optimal solutions are known in most of the cases. The second experiment employs larger and time-dependent real-world instances for a single vessel (explained in Section 4.4.2) to further evaluate MO-GRASP with the existing approach in the literature. The final experiment utilizes real case instances of the TDFRP-MTMTW to compare two different fishing strategies: the collaborative strategy, where all vessels share the dFADs and exchange information regarding the fished dFADs and the next dFADs to be fished, and the non-collaborative strategy, where each vessel has its own dFADs and no information is shared between vessels. Additionally, this experiment investigates the impact of a possible reduction in the number of dFADs on the performance of both strategies. This analysis is particularly relevant as the number of dFADs allowed per vessel has decreased in recent years [Zudaire et al., 2023].

The MO-GRASP algorithm is used with the same settings in all the experiments. The maximum number of iterations, $maxIter$, is set to 10,000 based on preliminary experiments that identified the point where the algorithm became mature and showed little or no improvement afterwards. The parameter α, which controls the level of randomness in the construction phase, is set to values within the range of $[0, 0.2]$ because low values of α are found to produce better results with fewer iterations. The parameter λ varies from 0.1 to 0.9, except in the comparison with CPLEX where it ranges from 0 to 1. The extreme cases, $\lambda = 0$ and $\lambda = 1$ are not considered with real data as they are not relevant to fishing vessels. These cases represent either the minimum cost route or the selection of dFADs with the maximum expected reward without considering the trade-off between both objectives.

4.5.1 Comparison between CPLEX and MO-GRASP performance for the SFRP-MTW model

The objective of this comparison is to assess how well MO-GRASP performs in relation to CPLEX using SFRP-MTW instances. In the research community, it is a common practice to utilize a general-purpose solver like CPLEX as a benchmark for evaluating the solution quality and computation time of (meta)heuristic algorithms [Silva et al., 2022]. In this context, the MO-GRASP algorithm is executed ten times for each SFRP-MTW instance, and the results are then compared with those obtained from CPLEX. Notably, CPLEX is constrained by a maximum runtime of one hour (3.600 sec) for each instance. The experiments utilize the static instances described in Section 4.4.

Figure 4.5 illustrates a comparison between the solutions obtained by CPLEX and MO-GRASP for different instances, where fuel consumption (X-axis) is minimized, and expected reward (Y-axis) is maximized. The graph demonstrates that the significance of each objective varies depending on the assigned weight, represented by the λ value, showcasing MO-GRASP's capability to find the Pareto front.

For instances A, B, C, D, and E, CPLEX successfully finds the global optimal solutions. However, for instances F, G, H, and I, CPLEX is unable to prove the optimality of the found solutions within the given time limit for most of the λ values. In contrast, MO-GRASP achieves solutions on or close to the Pareto front for all instances in significantly less computational time, as shown in Table 4.3. Particularly, for instances G, H, and I, MO-GRASP outperforms CPLEX for certain λ values. It is important to note that as the instance size increases, CPLEX's computation time grows significantly more compared to MO-GRASP.

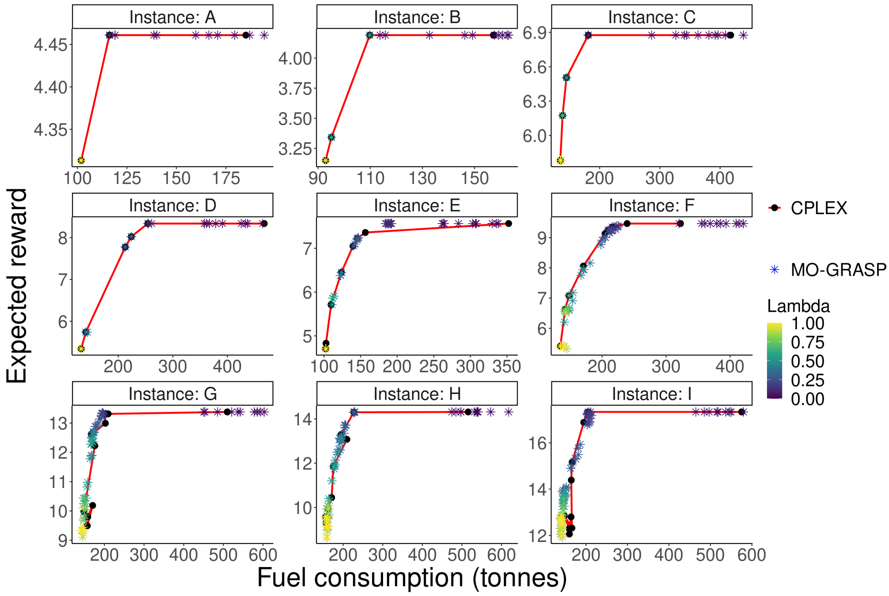


Fig. 4.5: Comparison between the solutions obtained by CPLEX and MO-GRASP for the SFRP-MTW instances. The X-axis represents the total fuel consumption, while the Y-axis indicates the expected rewards. The black points and red lines on the graph indicate the solutions and Pareto front, respectively, discovered by CPLEX, while the crosses depict the solutions found by MO-GRASP.

An exception to this is the special case of $\lambda = 0$, where CPLEX consistently finds the global optimum swiftly.

Instance	**Runtime (s)**	
	CPLEX	**MO-GRASP**
A	0.2	11.2
B	0.3	11.1
C	12.8	22.6
D	370.7	15.0
E	1087.2	16.3
F	2318.3	14.8
G	3281.9	42.1
H	3279.5	24.6
I	3276.8	43.7

Table 4.3: Comparison of the average runtimes for the CPLEX and MO-GRASP.

Furthermore, to evaluate the performance of MO-GRASP in comparison to CPLEX, a performance metric called “gap" is utilized. This gap measures the difference between the solution value obtained by MO-GRASP, denoted as f_{gr}, and the solution value obtained by CPLEX, denoted as f_c. The formula to calculate the gap is as follows:

$$gap = \left(\frac{f_{gr} - f_c}{f_c} \right) \cdot 100 \tag{4.33}$$

In this formula, f_{gr} represents the solution value obtained by MO-GRASP, and f_c represents the solution value obtained by CPLEX. The gap provides a percentage-based measure of how much the MO-GRASP solution differs from the CPLEX solution. A negative gap indicates that MO-GRASP’s solution is better than CPLEX’s, while a positive gap suggests that CPLEX’s solution is better. A gap of 0% indicates that both methods produced identical solution values. This metric allows a direct comparison of the performance of MO-GRASP relative to CPLEX across different instances and objectives.

Figure 4.6 presents a comparative analysis between CPLEX and MO-GRASP, focusing on the gap in fuel consumption (FOC) and in expected reward (ER) for each λ and instance. Notably, to enhance the comprehensiveness of Figure 4.6, the sign of the ER gap has been reversed, ensuring that all objective signs share a consistent meaning. Consequently, a positive gap indicates that the CPLEX approach surpasses the performance of the MO-GRASP algorithm. For the smallest instances A, B, C, and D both approaches yield comparable results, except for the case of $\lambda = 0$, where the behavior becomes more unpredictable concerning fuel consumption (FOC) since this objective is not taken into account for this specific value of λ. CPLEX and MO-GRASP generally generate similar solutions for instances E and H, except for the case of $\lambda = 0.1$ in instance E. For this specific value of λ, CPLEX can find a solution that significantly reduces fuel consumption while only slightly decreasing the amount of fish caught compared to MO-GRASP. In instances F, G, and I, MO-GRASP consistently obtains solutions with lower fuel consumption (FOC) than CPLEX. Meanwhile, CPLEX tends to find solutions with higher expected rewards (ER). However, the reduction in FOC achieved by MO-GRASP is typically more substantial compared to the marginal improvement in ER observed with CPLEX.

In conclusion, the experiments revealed that the MO-GRASP algorithm can provide competitive solutions for the SFRP-MTW problem, particularly for the larger instances where exact methods like CPLEX become less efficient. While CPLEX may have outperformed MO-GRASP in certain instances, the results demonstrate that MO-GRASP can deliver effective solutions with significantly lower computing time. This makes MO-GRASP a valuable alternative when dealing with larger instances where exact methods may struggle to find optimal solutions within a reasonable timeframe. The study indicates that MO-GRASP is

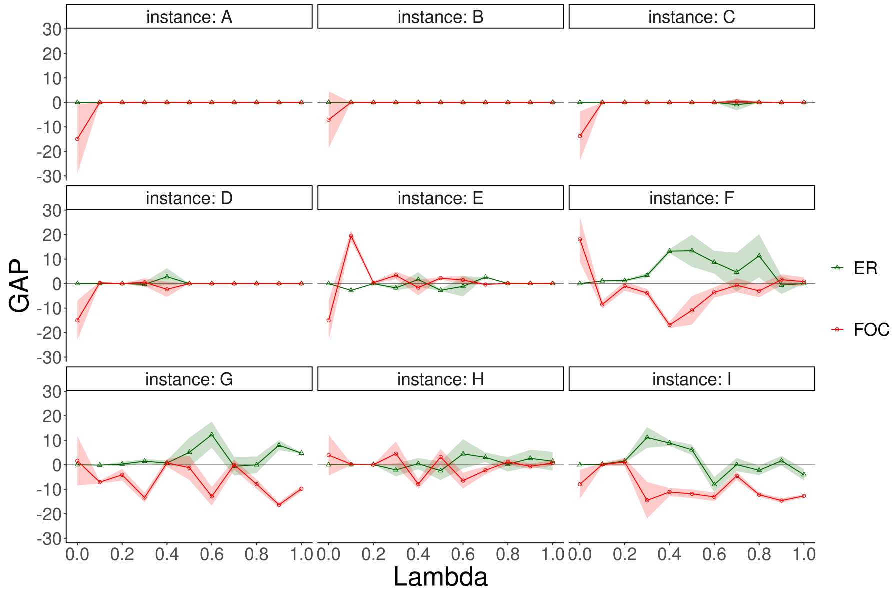


Fig. 4.6: Comparison of the gap between the solutions obtained by CPLEX and MO-GRASP for the SFRP-MTW instances. The X-axis of the graph represents the λ values, while the Y-axis represents the gap. The red line on the graph represents the average fuel consumption (FOC) gap, and the green line represents the average expected rewards (ER) gap. The shaded areas around the red and green lines represent the standard deviation in the gap values for the FOC and ER objectives, respectively.

a promising choice for solving the SFRP-MTW problem efficiently and obtaining solutions close to the optimal Pareto front.

4.5.2 Evaluation of the MO-GRASP algorithm for the TDSV-FRP problem

This experiment conducts a performance evaluation of the MO-GRASP algorithm by comparing it with the GA-TDA* algorithm. The GA-TDA* algorithm combines a genetic algorithm (GA) with a time-dependent A* and has been previously employed in a similar problem, focusing on optimizing the route of a single vessel without considering the deployment of new fish aggregating devices (dFADs). Notably, the TDSV-FRP problem corresponds to a special case of the TDFRP-MTMTW, where the number of vessels $V = 1$, for all nodes $k \in \mathcal{N}$ $p_k = 1$, and there are no new dFAD deployments ($Nd = 0$).

The primary objective of this comparison is to assess the reliability and solution quality of MO-GRASP, particularly in time-dependent scenarios and for medium-size real instances. The instances utilized in this experiment are detailed in Section 4.4.2.

The experiment setting is as follows: the GA-TDA* is limited to 50 generations as the stopping criterion, and ten runs are conducted. This approach allows GA-TDA* to obtain mature solutions similar to those of MO-GRASP. Additionally, the MO-GRASP algorithm is also executed ten times. The parameters utilized for the GA-TDA* are tha same that those used in Chapter 3. This experiment setup, where we allow the algorithms to converge without considering runtime or any other criteria, will enable us to study both approaches and see where they stand on the Pareto front. Hence, the behaviour of MO-GRASP in time-dependent instances is evaluated by assessing the Pareto front obtained by MO-GRASP in addition to the solutions produced by GA-TDA*. It is important to note that the objective function used for the GA-TDA* corresponds to the one used in Chapter 3, and is defined as follows:

$$\min\ J(S) = \frac{1}{1 + \sum_{j=1}^{q_v} er_{e_j}(at_{e_j})} \cdot \sum_{i=1}^{q_v+1} c_{e_{i-1},e_i}(dt_{e_{i-1}}) \tag{4.34}$$

In contrast, the MO-GRASP algorithm used a weighed sum objective function that is defined in Eq. (4.20). This approach allows for a combination of fuel consumption (FOC) and expected reward (ER) objectives, offering the flexibility to assign weights to each objective. In Chapter 3, on the other hand, the combination of objectives is achieved through a division without the flexibility to assign separate weights. Consequently, the solutions obtained using MO-GRASP will vary along the Pareto front depending on the λ value, whereas the solutions generated by the GA-TDA* approach will not exhibit such variations due to the fixed combination of objectives.

Figure 4.7 shows the results of the 10 runs for GA-TDA* algorithm and 10 runs x 9 lambdas for the MO-GRASP, according to fuel consumption and expected reward. These results demonstrated the good performance of the MO-GRASP algorithm in time-dependent and medium-size real instances. Furthermore, it is evident that MO-GRASP produces different results based on varying the importance assigned to each objective. The exceptions are in instances I and P where the solution of MO-GRASP are more clustered together with a low variability between them. However, even in these two instances, higher λ values yield solutions with lower fuel consumption (FOC), while lower λ values lead to solutions with higher expected rewards (ER). For most instances, MO-GRASP outperforms GA-TDA* in terms of solution quality.

These results clearly show that the MO-GRASP is competitive in time-dependent instances and can be effectively applied to the largest real instances.

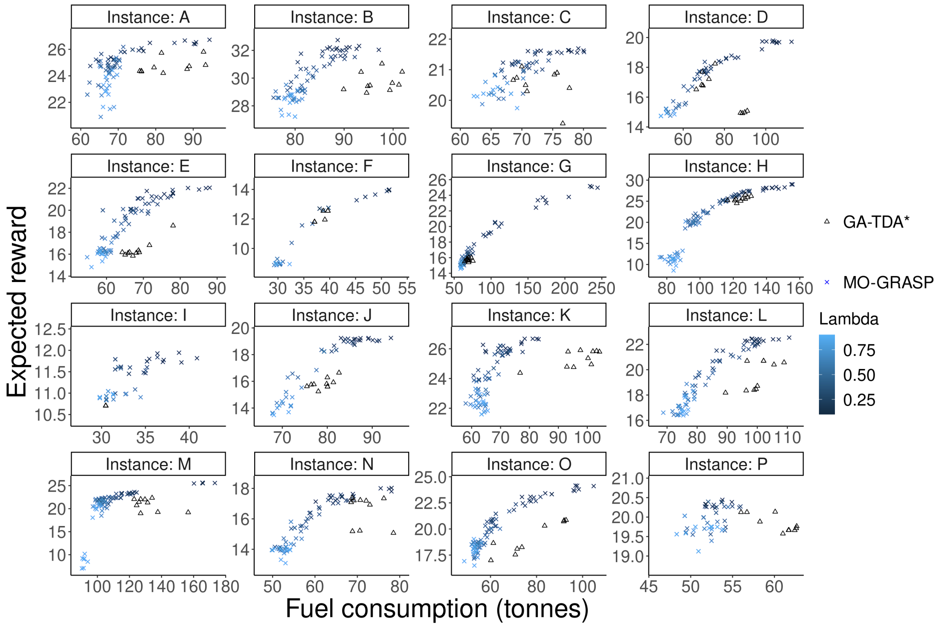


Fig. 4.7: Comparison between the solutions obtained by GA-TDA* and MO-GRASP for the TDSV-FRP. The X-axis represents the total fuel consumption, while the Y-axis indicates the expected reward.

Moreover, MO-GRASP is able to model the actual bi-objective nature of the problem, yielding distinct results depending on the importance given to each objective. This flexibility makes MO-GRASP a valuable tool for solving practical problems with conflicting objectives.

4.5.3 Real fishing cases: Comparison of collaborative and non-collaborative strategies

The purpose of this experiment is to determine the possible benefits of a collaborative strategy versus the current non-collaborative strategy. The potential impact of a reduction in the available number of dFADs in both strategies is also studied.

This experiment compares a collaborative strategy with a non-collaborative strategy for the TDFRP-MTMTW problem using real instances described in Section 4.4.3. In the collaborative strategy involves all vessels sharing their dFADs and defining a common strategy as described in Section 4.2.2. In contrast, in the non-collaborative strategy, each vessel has its own dFADs. This means they can only fish on their own dFADs and not on dFADs associated with other vessels.

The lack of connections between vessels means they do not share any information, and as a result, they are unaware of the locations of dFADs associated with other vessels. Hence, it is a special case of the TDFRP-MTMTW problem where $V = 1$, and the total number of dFADs to fish and deploy (i.e., Nf and Nd) are exclusive for each vessel. Both strategies are executed 10 times, with identical deployment areas, MO-GRASP settings, and optimization of the same objective function (Eq. (4.20)).

Figure 4.8 presents the results of the 10 runs of both the collaborative and non-collaborative strategies for each instance and λ, where a comparison is made between the fuel consumption (X-axis) and expected reward (Y-axis). The results show that the collaborative approach outperforms the non-collaborative in most of the instances (Trip 2, Trip 3, Trip 6, Trip 7, Trip 8, Trip 9, Trip 10, and Trip 11). On the other hand, the non-collaborative strategy achieves better or similar solutions, depending on the λ value, in instances Trip 1, Trip 4, Trip 5, and Trip 12. Overall, the collaborative strategy achieves better results in 8 out of 12 instances, while the non-collaborative strategy performs better or similarly only in 4 out of 12 instances. In the disputed instances, in Trip 1 the collaborative strategy gives better results for most of the λ values, while in Trip 4, Trip 5, and Trip 12 the non-collaborative strategy performs better.

In instances where there is a discrepancy in the expected reward (ER), the non-collaborative strategy is always able to obtain higher ERs. This can be attributed to two factors. Firstly, in the non-collaborative strategy, there is no sharing of information or limitations among vessels, allowing them to deploy their new dFADs in the same locations, which can generate solutions with higher ER. In the non-collaborative strategy, all vessels can deploy their new dFADs in the best deployment areas, whereas when they collaborate this situation is not possible as each location can only be visited once. Secondly, this reduction in the ER when vessels collaborate may be due to the possibility of selecting slightly less optimal fishing or deployment areas in exchange for a significant reduction in fuel consumption (FOC). In contrast, when vessels do not collaborate, selecting these fishing grounds or others may not be possible, or it may result in increased FOC.

To analyse the differences more clearly, the performance of both strategies is evaluated by measuring the gap between their solutions based on λ by using Eq. (4.35).

$$gap = \left(\frac{f_{ncs} - f_{cs}}{f_{cs}} \right) \cdot 100 \tag{4.35}$$

Where f_{ncs} represents the solution value obtained by the non-collaborative strategy, while f_{cs} represents the solution value obtained by the collaborative strategy. In this case, a positive gap indicates that the collaborative strategy is better than the non-collaborative, while a negative gap suggests that the non-

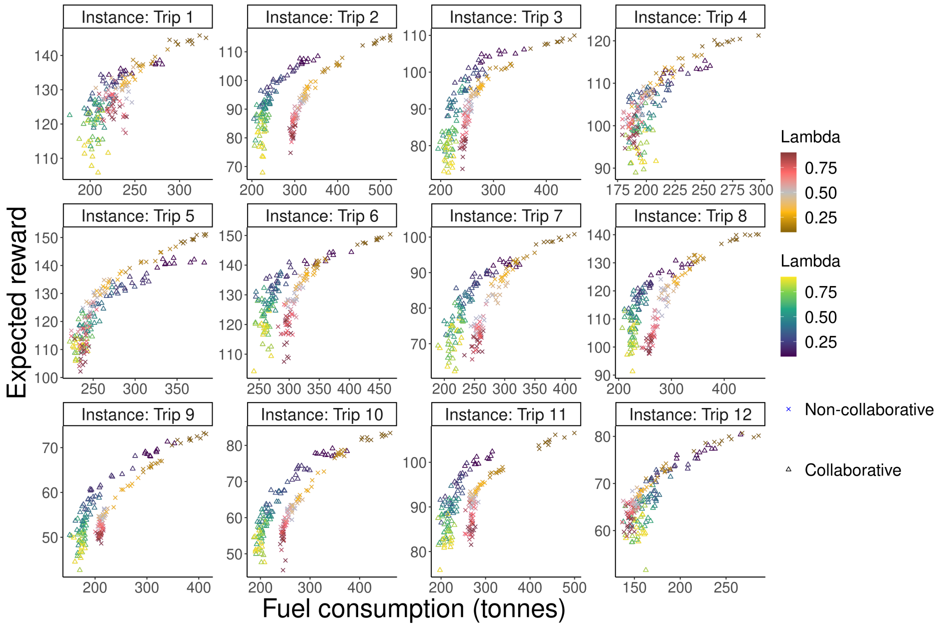


Fig. 4.8: Comparison between the solutions obtained by the collaborative and the non-collaborative strategies for the TDFRP-MTMTW instances. The X-axis represents the total fuel consumption, while the Y-axis indicates the expected rewards. The triangles indicate the collaborative solutions, while the crosses denote the non-collaborative solutions.

collaborative is better. A gap of 0% indicates that both strategies produced identical solution values.

Figure 4.9 shows the average gap (lines) and standard deviation (shaded areas) for each trip and λ values, concerning fuel-oil consumption (FOC), expected reward (ER), time spent at sea ($Time$), and FOC/ER ratio (FOC/ER). The FOC/ER ratio is a reliable metric for evaluating the overall economic sustainability of a route as it combines the costs and potential benefits of a trip. A line above the X-axis indicates that the collaborative strategy outperforms the non-collaborative strategy. Note that the sign of the ER gap has been reversed to ensure consistency in Figure 4.9 and Table 4.4, allowing for a clear and unified interpretation of the objectives across the comparison of collaborative and non-collaborative strategies. This adjustment ensures that positive and negative gaps consistently represent improvements or deteriorations in the respective objectives, providing a better understanding of the performance of each strategy.

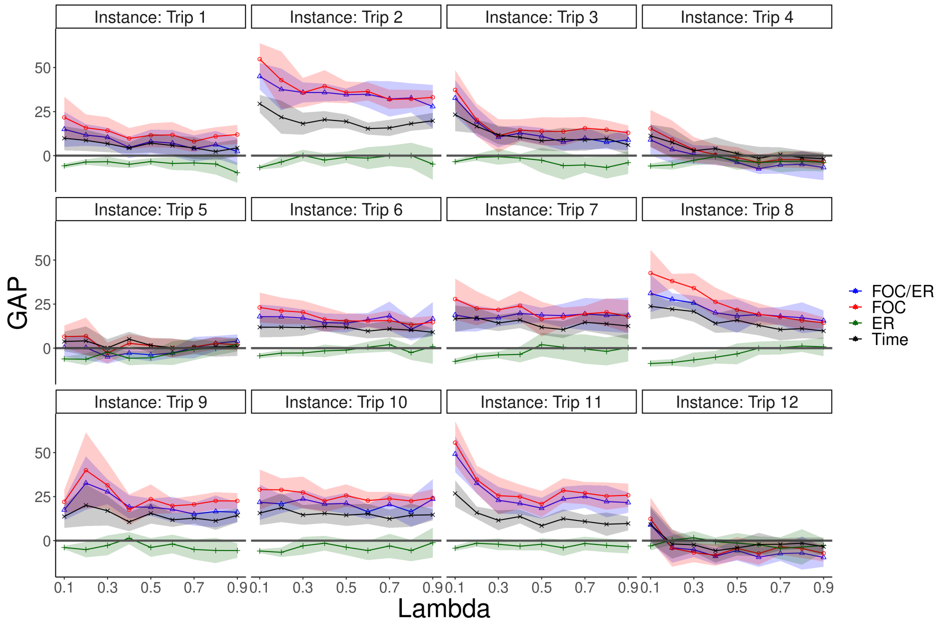


Fig. 4.9: Comparison of the gap between the solutions obtained by the collaborative and the non-collaborative strategies for the TDFRP-MTMTW instances. The X-axis indicates the λ values, and the Y-axis represents the gap. The blue line represents the average gap for the FOC/ER ratio, the red line represents the average gap for the fuel consumption (FOC), the green line represents the average gap for the expected rewards (ER), while the black line represents the average gap for the time spent at sea. The shaded areas around the lines represent the standard deviation.

As previously observed, the collaborative strategy demonstrates superior performance for most instances and λ values, particularly when comparing FOC, Time, and FOC/ER ratio. However, it is essential to note that the non-collaborative approach consistently yields slightly higher ER values, although the differences seem to be small and are statistically significant in 2/3 of the trips (see *gap ER* column in Table 4.4). Despite this, the collaborative strategy achieves a better balance between maximizing ER and minimizing FOC, leading to an overall improvement in fleet sustainability and efficiency.

Furthermore, considering the FOC/ER as a reliable metric to evaluate the quality of a route, the collaborative strategy outperforms the non-collaborative strategy in most instances (see Table 4.4). There are, however, few exceptions in Trip 4, Trip 5, and Trip 12, where the non-collaborative performance is slightly better, although the differences are not statistically significant. On average, the collaborative strategy consumes less fuel (17.3%) and spends less time at sea (10.1%) compared to the non-collaborative strategy. While the non-collaborative strategy is capable of achieving slightly higher expected rewards (2.9%), the savings in fuel consumption and time at sea more than justify the slight decrease in expected rewards.

Instance	**gap FOC (%)**	**gap ER (%)**	**gap Time (%)**	**gap FOC/ER**
Trip 1	12.6 ± 3.8**	-4.8 ± 1.9**	5.8 ± 2.3**	7.4 ± 4.0**
Trip 2	37.7 ± 7.1**	-2.1 ± 2.4	19.7 ± 4.1**	34.8 ± 4.7**
Trip 3	16.7 ± 7.9**	-3.2 ± 2.1**	11.4 ± 5.2**	13.1 ± 7.9**
Trip 4	1.5 ± 6.4	-3.4 ± 1.6**	2.4 ± 4.4	-1.9 ± 5.3
Trip 5	2.1 ± 3.0	-3.0 ± 3.0*	1.7 ± 1.9**	-0.8 ± 3.0
Trip 6	17.1 ± 3.3**	-1.2 ± 2.1	10.9 ± 1.1**	15.7 ± 2.4**
Trip 7	20.6 ± 3.5**	-1.9 ± 3.2	14.0 ± 2.2**	18.2 ± 0.9**
Trip 8	25.3 ± 10.2**	-3.2 ± 4.0	15.5 ± 5.3**	21.2 ± 5.4**
Trip 9	23.9 ± 6.3**	-3.4 ± 2.2**	13.9 ± 2.8**	19.8 ± 5.7**
Trip 10	25.0 ± 2.5**	-3.8 ± 2.0**	14.9 ± 1.6**	20.3 ± 2.6**
Trip 11	29.4 ± 10.3**	-2.7 ± 1.0**	13.1 ± 5.5**	26.0 ± 9.4**
Trip 12	-4.1 ± 6.1	-1.6 ± 1.9*	-1.7 ± 4.1	-5.6 ± 5.7
Total	17.3 ± 12.4**	-2.9 ± 1.0**	10.1 ± 6.6**	14.0 ± 12.1**

Table 4.4: Comparison of the gap between the non-collaborative and collaborative strategies. FOC refers to fuel consumption; ER refers to expected reward; Time refers to the time spent at sea; and FOC/ER ratio is the relationship between fuel consumption and expected reward. Statistical significance is determined using the Wilcoxon Rank Sum tests. Significance codes: $^{**}p < 0.01$ and $^{*}p < 0.05$.

Four examples of the proposed routes by the MO-GRASP for the same instance, are shown in Figure 4.10. Panels A and C show the routes where more importance is given to obtain a high expected reward ($\lambda = 0.2$), while Panels B and D show the routes where more importance is given to use less fuel ($\lambda = 0.8$) for both fishing strategies, respectively. The importance of the λ value becomes evident when comparing the same strategies. With a low λ value, the routes are larger, covering more distance, and consequently, using more fuel with the aim of obtaining a higher expected reward. On the other hand, with a higher λ value, the routes tend to be closer to the port, resulting in shorter distances covered and less fuel use in exchange of a lower expected reward. When comparing the routes between the collaborative and non-collaborative approaches (Panels A with C and Panels B with D), it becomes evident that sharing the dFAD information allows the vessel to fish and deploy in areas with a similar expected reward without necessarily covering more distance. This example confirms the previous results, where the collaborative strategy outperforms the non-collaborative strategy in terms of fuel use (-14% and -21%) and time at sea (-8% and -14%) with similar expected rewards (5% and -8%). The overall benefits of the collaborative strategy are evident, making it a more efficient and sustainable strategy.

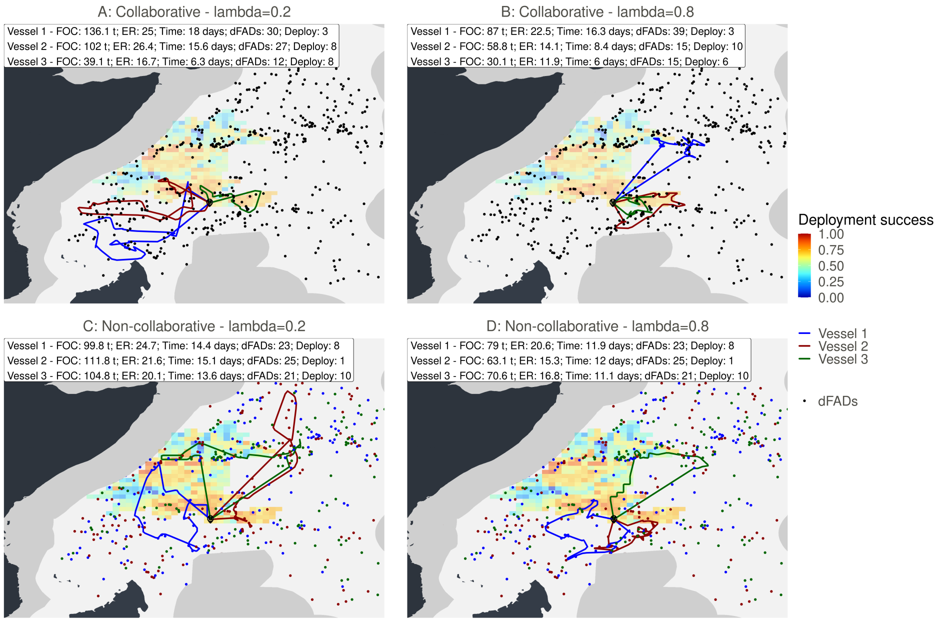


Fig. 4.10: Example of the proposed routes by the MO-GRASP. The label in each panel indicates the fuel usage, time spent, and the expected reward for each route. Each line represents the route of one vessel, the points indicate the available dFADs to fish, and the colored area indicates the deployment locations along with the success probability. Note that, in the non-collaborative Panels the color of the points (i.e., dFADs) and lines (i.e., routes) indicates the vessel to which they are associated.

Finally, the potential impact of reducing the number of available dFADs on the fishing fleet is examined for both strategies. This analysis offers insights into how the reduction in the number of available dFADs affects both strategies and their respective performance in different instances and contributes to a better understanding of the strategies' robustness and adaptability under varying resource constraints.

To conduct the analysis, the same 12 instances are used with a variation of the available dFADs to fish (n_{FAD}), ranging from 100 to 450, with an increase of

50 in each new instance. Hence, $n_{FAD} = \sum_{i=1}^{N} p_i$. The dFADs selection process to create each new instance is random. Both strategies have the same number of available dFADs and fishing requests (Nf). However, in the non-collaborative strategy, the dFADs and fishing requests (Nf) are divided equally among the vessels. In some instances (Trip 1, Trip 11, and Trip 12), there are not enough dFADs to create new instances for some n_{FAD} values, as the historical data has fewer dFADs, and therefore, they are not created in these cases.

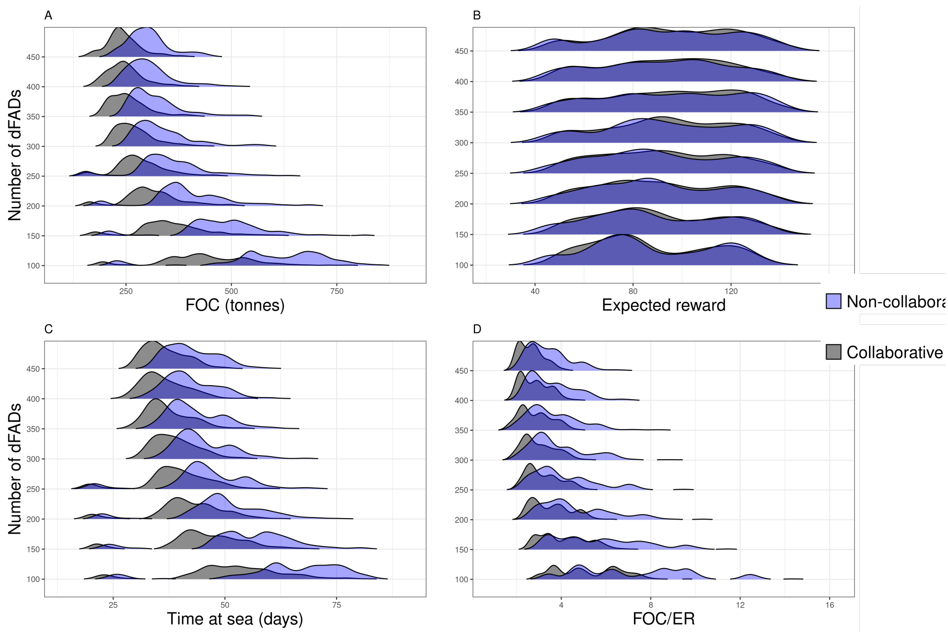


Fig. 4.11: Comparison between the collaborative and non-collaborative strategies solution distributions for the TDFRP-MTMTW instances for different quantities of available dFADs. The Y-axis represents the number of available dFADs, while the X-axis corresponds to the value of the different performance metrics for each panel. Panel A: fuel consumption (FOC); Panel B, expected reward (ER); Panel C, time spent at sea; Panel D, ratio of fuel consumption and expected reward (FOC/ER).

This experiment examines the effect of the number of available dFADs on fuel consumption, expected reward, time at sea, and the FOC/ER ratio for both the collaborative and non-collaborative strategies. Figure 4.11 presents the distribution of the solution values for each strategy, n_{FAD} value, and objective (i.e., FOC, expected reward, time at sea, and the ratio of FOC/ER).

As the number of dFADs increases, both the collaborative and non-collaborative strategies show a similar behavior regarding fuel consumption and time at sea (Figure 4.11). That is, the FOC and time at sea are reduced, while the ER increases slightly. Furthermore, the difference between them reduces as the number of available dFADs increases (Panels A and C in Figure 4.11). The expected rewards show small differences between both strategies, and the impact of the number of available dFADs is less significant (Panel B in Figure 4.11). On the other hand, the FOC/ER ratio also indicates that the collaborative approach consistently outperforms the non-collaborative one, particularly with a reduced number of available dFADs (Panel D in Figure 4.11).

Table 4.5 provides further insight into the impact of the number of available dFADs by presenting the mean and standard deviation of the gaps for all instances and lambdas. Note that the ER gap's sign has been reversed in Table 4.5 to ensure a comprehensive understanding of the comparison. The collaborative strategy's ability to outperform the non-collaborative one becomes especially significant for FOC, Time, and FOC/ER, as the number of available dFADs decreases. These findings indicate that sharing dFADs can increase sustainability and efficiency in the fishing fleet, particularly when the number of dFADs is reduced. The results shed light on the potential benefits of collaboration among vessels in resource-constrained environments and demonstrate the advantages of adopting a collaborative approach to this problem.

n_{FAD}	**gap FOC (%)**	**gap ER (%)**	**gap Time (%)**	**gap FOC/ER**
100	36.7 ± 13.6**	-0.4 ± 4.8*	23.8 ± 8.4**	36.5 ± 15.4**
150	33.0 ± 9.6**	1.7 ± 6.3	21.1 ± 5.9**	35.9 ± 14.2**
200	27.6 ± 9.8**	1.3 ± 4.9*	18.2 ± 6.1**	39.7 ± 14.0**
250	23.2 ± 10.3**	1.8 ± 4.8**	15.8 ± 6.2**	25.9 ± 14.3**
300	24.3 ± 9.5**	1.5 ± 4.6*	15.8 ± 5.3**	26.5 ± 12.7**
350	24.7 ± 7.1**	0.7 ± 4.6	16.2 ± 4.4**	26.0 ± 10.5**
400	23.1 ± 6.9**	2.3 ± 4.2**	16.3 ± 3.8**	26.2 ± 9.5**
450	24.4 ± 6.0**	2.0 ± 4.6**	16.3 ± 3.3**	27.3 ± 9.4**

Table 4.5: Comparison of the gap between the non-collaborative and collaborative strategies for different quantities of available dFADs. FOC refers to fuel consumption; ER refers to expected reward; Time refers to the time spent at sea; and FOC/ER ratio is the relationship between fuel consumption and expected reward. Statistical significance is determined using the Wilcoxon Rank Sum tests. Significance codes: $^{**}p < 0.01$ and $^{*}p < 0.05$.

These results highlight how the number of available dFADs affects the performance of the vessels in both strategies (in general the more buoys, the better). Specifically, as the number of dFADs increases, the performance gap between the two strategies diminishes. However, for expected rewards, no significant effect is observed between both strategies as the number of dFADs increases.

4.6 Conclusions

This chapter introduces two bi-objective mixed linear integer programming (MIP) models with potential applications in the fishing routing problem. The proposed metaheuristic, called the multi-objective greedy randomized adaptive search procedure (MO-GRASP), proves to be an efficient and effective algorithm for solving real-size instances of the fishing routing problem. MO-GRASP effectively balances solution quality and computational time, making it a valuable tool for handling large-scale and practical problems. Moreover, it effectively models the bi-objective nature of the problem, providing valuable insights for decision-makers in the fishing sector to optimize their operations and achieve better overall performance.

The comparison between collaborative and non-collaborative strategies reveals the potential benefits of a collaborative planning approach for a fishing fleet. The collaborative strategy significantly reduces fuel consumption (approximately 17.3%) and time at sea (approximately 10.1%), reducing fishing companies' operational costs and contributing to climate change mitigation by reducing their emissions. Although the collaborative strategy may yield slightly lower expected rewards (-2.9%), the overall benefits in terms of fuel consumption and time at sea outweigh this slight decrease.

Furthermore, the study highlights the impact of the number of available dFADs on both fishing strategies. As the number of available dFADs decreases, there is a negative effect, particularly on fuel consumption, time at sea, and expected rewards. However, the impact on fuel consumption and time at sea is more significant compared to expected rewards, indicating that expected rewards are less influenced by the fishing strategy or the number of dFADs available. As the number of dFADs increases, the performance gap between the collaborative and non-collaborative strategies diminishes, particularly regarding fuel consumption and time at sea. However, the expected rewards demonstrate less sensitivity to the number of available dFADs, with the performance gap between strategies remaining relatively constant.

5

General Conclusions and Future Work

This chapter summarises the general conclusions of this thesis and suggests possible future directions for extending the contributions. It also highlights the main achievements made during the PhD thesis.

5.1 Conclusions

The contributions of this thesis are covered by the expanding fields of operational research with a specific focus on the real-world needs of routing problems in the fishing sector. In this thesis, various fishing routing problems are formulated for the first time and two metaheuristic algorithms are developed to solve them. Thus, the gap in the application of routing and planning optimization decision systems in fisheries has been addressed, despite the existence of technology that can facilitate the optimization of fishing strategies. The contributions presented in this thesis have opened up two main research directions, which can be divided into two groups: (i) methodological research proposals for real-world fishing routing problems; and (ii) managerial insights for the fishing sector.

The contributions to the field of combinatorial optimization achieved in this PhD thesis are the following:

- A decision support system (DSS) framework for fishing routing problems is proposed for the first time, together with an introduction to the tactical and operational fishing routing problem. Furthermore, a review of the state of the art is provided, focusing on the main objectives, constraints and algorithms applied to ship routing problems at tactical or operational level.
- The proposal of four main fishing fleet groups from an optimization point of view. This thesis proposes that dozens of fishing gears could be addressed with four optimization strategies. These are based on their similarities, since the

particularities of each group make it necessary to use different approaches. The four main groups are:

(i) Distant water fleets, which have the most advanced technology and therefore the most to gain from optimizing their routes.
(ii) Large-scale demersal fleets, whose main concern is the selection of fishing grounds to avoid choke species that may limit their future fishing due to lack of quotas.
(iii) The large pelagic fleet group is made up of vessels that use more than one fishing gear throughout the year, which makes it necessary to modify the optimization approach according to gear, season and target species.
(iv) The small coastal fleet group, made up of small vessels (less than 12 m in length) that fish close to the coast, and therefore the group that is in the most difficult situation to benefit from optimizing its routes.

- Motivated by the lack of mathematical models for the different fishing route problems, two new definitions of route problems are proposed that have not yet been addressed in the literature. These problems arise from a real need in the fishing sector when defining fishing strategies. However, their potential applicability is not limited to the same context, i.e. tuna fishing, as they can be adapted to solve analogous or similar problems. The two problems defined are the following:
  i) The first problem is formulated as a k-travelling salesperson problem with moving targets and time windows (DkTSP-MTTW). The k-travelling salesperson problem and its variants have not received as much attention from researchers as other TSP variants, despite their potential applications in resource-constrained environments. In addition, to the best of our knowledge, this is the first time that a TSP -or its k-TSP variants- has been formulated in dynamic scenarios considering moving targets and their associated time windows. Most studies focus on either the moving target characteristic or the time window characteristic, but not at the same time.
  ii) The second routing problem is formulated as a time-dependent VRP with moving targets and multiple time windows. It extends the previous work described in Chapter 3 by considering a fishing fleet instead of a single vessel. It also considers the deployment of new dFADs along the journey and the bi-objective nature of the problem. This is the first time that a problem combines the multiple time windows and moving target characteristics of time-dependent VRP.
- The final contributions are the proposal of two metaheuristic algorithms to address the problems defined above, which are the following
  i) A genetic algorithm (GA) is proposed, capable of solving the k-TSP for the first time. This contribution is not only valid for the fishing problem, but for all problems based on variations without repetition (i.e. the arrangement of k elements from a set of n elements ($k \leq n$), where the order

of selection is important and the repetition of elements is not allowed). The existing approaches in the literature work on permutation space or on variation space, but with a chromosome of variable length. Therefore, there is a lack of GA operators that can handle variation problems with a fixed-length chromosome. This served as a motivation to develop new crossovers capable of addressing the problem search space, which includes two aspects: (i) subset selection (selecting a subset containing k elements); and (ii) variations (finding the best circular permutation of the k elements within the selected subset). Furthermore, the proposed crossovers could be generalised and applied to problems where the solution space consists of permutations (i.e. all nodes have to be visited) by simply using a value of $k = n$.

ii) A multi-objective greedy randomised adaptive search procedure (MO-GRASP) for solving the time-dependent VRP with moving targets and multiple time windows. Computational experiments show that the proposed algorithm can generate a high-quality solution within a reasonable computational time for real instances, as well as model the actual bi-objective nature of the problem. Furthermore, the heuristic for constructing a greedy random solution has been developed using the fishing routing problem as inspiration. However, it can be applied to similar problems where a fleet of vehicles needs to visit or deliver to a given set of customers, or even a fixed subset of them. For example, by removing the $checkConstrain()$ function, which validates fishing or specific problem constraints, the heuristic can be generalised to a wider range of problems.

With regard to the managerial insights for the fisheries sector gained in this thesis, the following conclusions are drawn:

- A novel aspect is that a complex decision problem has been modelled as a decomposed bi-objective optimization problem. Using real cases, it is shown that a significant reduction in fuel consumption per tuna caught is possible. The proposed GA-TDA* is the first method in fisheries that dynamically optimizes the fishing strategy of a tuna purse seine during an entire fishing trip, taking into account the selection of fishing grounds, the order in which they are visited, the fishing time windows, and the performance of the vessel based on weather conditions. The computational experiments have shown that the GA-TDA* achieves good results, demonstrating its applicability in this innovative application of operational research and presenting novel approaches to solving real-world problems.
- • The final contribution is the comparative analysis between collaborative and non-collaborative strategies. The results show that a collaborative fishing strategy significantly reduces fuel consumption and time at sea, with only a minimal reduction in expected reward. The final experiment focuses on assess-

ing the effect of a reduction in available dFADs. The results have shown that this reduction has a negative effect on both fishing strategies, i.e. the lower the number of available dFADs, the more fuel vessels consume, the longer they spend at sea and the lower the reward they expect. However, this negative effect is significantly more pronounced in the non-cooperative strategy, demonstrating the potential for the industry to explore the benefits of joint planning among vessels.

In conclusion, novel routing problems based on actual fishing requirements have been formulated and different metaheuristics have been developed to solve them. This thesis has demonstrated the promising benefits of using routing algorithms with the tuna purse seine fleet. These methods can help fisheries to mitigate climate change and reduce operational costs, thereby improving overall efficiency and sustainability.

5.2 Future Work

This thesis has highlighted the existence of a gap in the application of routing and planning decision support systems in fisheries. It also presents and discusses various problems and solutions in fisheries routing. Fisheries have the opportunity to use operational research in combination with other fields, such as artificial intelligence, to drive innovation and cost-effective decarbonisation of the sector. This approach can lead to win-win solutions by increasing fleet sustainability and reducing environmental impacts. The potential future extensions and research directions of this PhD thesis are discussed briefly below.

Further research is needed to meet the needs of fishing vessels, such as the issue of data availability and quality. Although the emergence of new data collection technologies is reaching the fishing industry, their implementation and availability is uneven across fishing fleets. Reasons for this include up-front costs and lack of access to capital for small and medium-sized fishing vessels, and the industry's lack of trust in data-sharing. Therefore, another key area for improvement would be to increase trust and cooperation between the research community and the fishing industry. This could reduce the reluctance to participate in the development of new solutions.

Although this thesis is applied to the specific case of tuna purse seiners, other fishing fleets can benefit from the problems and solutions proposed. Future work could therefore focus on applying these or similar approaches to other types of fishing fleets. In Chapter 2, four main groups of fishing fleets are proposed, highlighting their main fishing characteristics that need to be taken into account. These peculiarities serve as the main differences between the fleet types that require the adaptation of the algorithms proposed in this thesis. Furthermore, the mathematical models and metaheuristics developed in this thesis are based on the specificities of the fishing routing problem. However, the results of this work have the potential to extend beyond fishing and contribute to the formulation and solution of similar real-world problems. For example, scenarios that can be formulated as a time-dependent k-TSP or a VRP with mobile targets and multiple time windows could be addressed using the insights gained from this study.

Another interesting area of research is problem formulation. In particular, it would be valuable for fishermen to have other options to limit their fishing trips, such as the time spent at sea. One way to achieve this is to formulate the problems as a variant of the (team) orienteering problem, which gives fishermen additional flexibility in defining their strategies. Another possibility is to formulate the fishing routing problem as a variant of the open TSP or open VRP, where the vessel(s) end their route at one of the fishing grounds without having to return to port. This allows fishermen to plan, for example, the next few sets rather than an entire fishing trip.

The modelling of the problem can also be improved by the assumptions made and the approach used. For example, the use of historical data for dFAD positions is sufficient to validate the proposed algorithms and see the potential benefits of optimizing fishing routes. However, for practical implementation, the drift of the dFADs has to be predicted. In addition, the inclusion of additional factors such as bycatch, quotas or the search for free schools of tuna can make the planning strategies take further sustainability and management needs into account. Fishermen should pay particular attention to the issue of bycatch, as it is becoming an increasingly important part of the industry due to management regulations. Such functionality would help fishermen plan their fishing strategies more effectively by taking into account more realistic situations.

Further improvements can be made to input data, such as data collection and modelling for fuel consumption and tuna catch models. The industry is actively engaged in this effort, as evidenced by the ongoing development of improved dFADs that will enable more accurate estimates of tuna biomass below them and even species discretisation. Fuel models can also be improved as on-board sensors continue to accumulate information, resulting in a longer historical data set. Combined with improving or testing other machine learning models, this would allow for improvements in the accuracy of the models used here.

5.3 Main Achievements

As a result of this research work, several achievements have been accomplished in terms of publications in peer-reviewed journals, oral presentations in international conferences, posters, research internships, dissemination and collaborations with other authors related lines of research.

A. ***Peer-Reviewed Publications***

- **Granado, I.**, Hernando, L., Galparsoro, I., Gabiña, G., Groba, C., Prellezo, R., & Fernandes, J. A. (2021). Towards a framework for fishing route optimization decision support systems: Review of the state-of-the-art and challenges. Journal of Cleaner Production, 320 (February), 128661. https://doi.org/10.1016/j.jclepro.2021.128661.
- **Granado, I.**, Hernando, L., Uriondo, Z., & Fernandes, J. A. (2024). A Fishing Route Optimization Decision Support System: The case of the tuna purse seiners. European Journal of Operational Research, 312 (2), 718-732. https://doi.org/10.1016/j.ejor.2023.07.009.
- **Granado, I.**, Silva, E., Carravilla, M.A., Oliveira J.F., Hernando, L., & Fernandes, J. A. (2023). A multi-objective GRASP for the tuna purse seiner fishing fleet routing problem. Submitted to transportation Research Part E: Logistics and Transportation Review. Under review.

B. ***Oral Presentations***

- **Granado, I.**, Hernando, L., & Fernandes, J. A. (2021). Towards a framework for fishing route optimization decision support systems: Review of the state-of-the-art and challenges. The 3rd NOAA Workshop on Leveraging AI in Environmental Sciences. 13-17 September. Virtual.
- **Granado, I.**, Hernando, L., & Fernandes, J. A. (2022). Towards a framework for fishing route optimization decision support systems. The Ocean Sciences Meeting. 17 February - 4 March. Virtual.
- **Granado, I**. Hernando, L. Fernandes, J.A. (2022). Fishing route optimization to enhance the economic and environmental sustainability. XXXIX Congreso internacional de estadística e investigación operativa (SEIO). 7–10 June 2022. Granada, Spain. (Presented by Leticia Hernando).
- **Granado, I.**, Hernando, L., & Fernandes, J. A. (2022). Towards a framework for fishing route optimization decision support systems in tune purse seiners. ICES Annual Science Conference (ASC). 19-22 September. Dublin, Ireland.
- **Granado, I**., Silva, E., Caravilla, M. A., Oliveira, J. F., Hernando, L., & Fernandes-Salvador, J. A. (2023). Fishing route optimization to enhance the economic and environmental sustainability. 5th International Symposium: The Climate Change Effects on the World's Ocean. 17-21 April. Bergen, Norway.

C. ***Posters***

- **Granado, I.**, Hernando, L., & Fernandes, J. A. (2021). Towards a framework for fishing route optimization decision support systems. International Conference on Sustainable Technology and Development. 31 October - 2 November 2021, Live and On-demand.

D. ***Research Stays***

- 12 September - 16 December 2022. DEGI team. Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), Porto, Portugal. Supervisor: Prof. José Fernando Oliveira.

E. ***Dissemination***

- Intelligent Systems Group Seminar in UPV/EHU.
- Internal Seminar in AZTI.
- Talk to the members and collaborators of the DEGI Team entitled: "Fishing route optimization to enhance the economic and environmental sustainability of tuna purse seiners". 22th October 2022, Porto.

F. ***Other collaboration works carried out during the thesis***

Peer-Reviewed Publications

- Hernández-González, J., Inza, I., **Granado, I.**, Basurko, O. C., Fernandes, J. A., & Lozano, J. A. (2019). Aggregated outputs by linear models: An application on marine litter beaching prediction. Information Sciences, 481. https://doi.org/10.1016/j.ins.2018.12.083.
- **Granado, I.**, Basurko, O.C., Rubio, A., Ferrer, L., Hernández-González, J., Epelde,I., & Fernandes, J.A. (2019). Beach litter forecasting on the south-eastern coast of the Bay of Biscay: A bayesian networks approach. Continental Shelf Research, 180, 14–23. https://doi.org/10.1016/j.csr.2019.04.016.
- Ruiz, I., Basurko, O. C., Rubio, A., Delpey, M., **Granado, I.**, Declerck, A., Mader, J., & Cózar, A. (2020). Litter Windrows in the South-East Coast of the Bay of Biscay: An Ocean Process Enabling Effective Active Fishing for Litter. Frontiers in Marine Science, 7(May), 1–12. https://doi.org/10.3389/fmars.2020.00308.
- García-Barón, I., Giakoumi, S., Santos, M. B., **Granado, I.**, & Louzao, M. (2021). The value of time-series data for conservation planning. Journal of Applied Ecology, 58(3), 608–619. https://doi.org/10.1111/1365-2664.13790.
- Basurko, O.C., Gabiña, G., Lopez, J., **Granado, I.**, Murua, H., Fernandes, J.A., Krug, I., Ruiz, J., & Uriondo, Z.(2022). Fuel consumption of free-swimming school versus FAD strategies in tropical tuna purse seine fishign. Fisheries Research, 245, 106139. https://doi.org/10.1016/j.fishres.2021.106139.
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- Zorrozua, N., **Granado, I.**, Fernandes-salvador, J. A., Louzao, M., Basterretxea, M., & Arizaga, J. (2023). Evaluating the dependence of opportunistic Yellow- legged Gulls (Larus michahellis) on marine habitat and fishing discards. Ibis. https://doi.org/10.1111/ibi.13227.
- Zhou, Y., Pazouki, K., Murphy, A. J., Uriondo, Z., **Granado, I.**, & Fernandes-salvador, J. A. (2023). Predicting ship fuel consumption using a combination of metocean and on-board data. Ocean Engineering, 285(2), 115509. https://doi.org/10.1016/j.oceaneng.2023.115509.

Conference Papers

- Zhou, Y., Pazouki, K., Murphy, Alan. J., Uriondo, Z., **Granado, I.**, Quincoces, I., & Fernandes-salvador, J. A. (2022). Modelling tuna purse seiners fuel efficiency in real-world operations using machine learning approaches. In N. Vladimir, S. Malenica, & I. Senjanovic (Eds.), 15th international symposium on practical design of ships and other floating structures PRADS 2022 (pp. 1410–1426). https://doi.org/10.5281/zenodo.7533412.

Contributed Presentations

- Ferrer, L., Basurko, O.C., **Granado, I.**, Ruiz, I., Rubio, A., Mader, J.,Nogues, M., Epelde, I., Liria, P., de Santiago, I., Asensio, J.L., Caballero, A.,Del Campo A. (2018). Modelling the drift of maritime litter in the Bay of Biscay. Sixth International Coordination Meeting of the Coastal and Shelf Seas Task Team (COSS-TT) 19-21 September. Madrid, Spain.
- Basurko, O.C., Beldarrain, B., Larreta, J., Kukul, D., Rubio, A., Ruiz, I., **Granado, I.**, Cózar, A., Galli, M., Martin, I., Uriarte, A., Louzao, M., Dávila, X., Puillat, I. (2018) From coastal to oceanic micro-meso and macroplastics in the SE Bay of Biscay. Fate and Impact of Microplastics: Knowledge, Actions and Solutions (MICRO 2018). 19-23 November. Lanzarote, Spain.
- García-Barón, I., Giakoumi, S., Santos, M.B., Saavedra, C., **Granado, I.**, Louzao, M. (2019). Identifying high priority areas for marine top predators in southern Europe. 1st Meeting of the Iberian Ecological Society& XIV AEET Meeting. 4-7 February. Barcelona, Spain.
- Fernandes, J.A., Inza, I., Hernandez-Gonzalez, J., **Granado, I.**, Basurko, O.C., Andonegi, E., Boyra, G., Ferrer, L., & Irigoien X. (2019). Machine learning is not only for big data and big data is not only a lot of data: successful examples in marine sciences with sparse and heterogenous data. ICES Annual Science Conference (ASC). 9-12 September. Gothenburg, Sweden.
- Ruiz I., Abascal A.J., Rubio A., Basurko O.C., **Granado I.**, Mader J. (2020). Assessment of marine litter distribution from sea-based activities: a risk study on the impact of the fishing sector in the Bay of Biscay. Workshop sobre Basuras Marinas. BAMAR 2020. 1-3 July 2020. Barcelona, Spain.

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- Zhou, Y., Pazouki, K., Murphy, Alan. J., Uriondo, Z., **Granado, I.**, Quincoces, I., & Fernandes-salvador, J. A. (2022). Modelling tuna purse seiners fuel efficiency in real-world operations using machine learning approaches. The 15th international symposium on practical design of ships and other floating structures PRADS 2022. 9-13 October. Dubrovnik, Croatia.
- Lekunberri, X., Ballester-Berman, J. D., **Granado, I.**, Galparsoro, I., Arganda-Carreras, I. & Fernandes-Salvador, J. A. (2023). Computer vision and artificial intelligence for fisheries sustainability and marine protection. 6th world conference on Marine biodiversity. 2-5 july. Penang, Malaysia..

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