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SHIP WEATHER ROUTING FEATURING W-MOEA/D AND UNCERTAINTY HANDLING

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Abstract

The paper presents a new version of Evolutionary Multi-objective weather routing (WR) for ships taking into account uncertainties of weather forecasts in route optimization. The method applies authors' w-MOEA/D algorithm: MOEA/D framework incorporating Decision Maker's (DM) preferences by means of w-dominance relation. Owing to this, DM preferences are taken into account throughout optimization, allowing the process to focus on the part of vast objective's space. Only the part of Pareto front being of interest to DM is generated, thus the process converges faster, without sacrificing quality of the final set. All of the above is essential for the WR method, which pursues three objectives while trying to meet multiple constraints and handling uncertainty of weather data. The final method has been implemented as a part of client-server system architecture, whose client part has been installed on board of a m/v Monte da Guia (MdG) vessel navigating between the Portuguese coast and the Azores. The method has then been verified in the course of computer simulations and its results have been compared with real MdG GPS routes. The comparison shows that the presented method is able to find routes that bring progress in terms of the objectives' while satisfying the constraints.

Keywords: weather routing, evolutionary multi-objective optimization, decision maker's preferences, dominance relation, trade-off.

1 INTRODUCTION

Due to their high efficiency and good approximation of a true Pareto-front, Multi-Objective Meta-Heuristics (MOMH) are often used to solve real-life optimization problems, including real-time [1–5] or large-scale [6,7] ones. However, a lot of real-life optimization problems suffer from having vast objective space, which, even for MOMHs, results in challenges for optimization process and in numerous final Pareto set. To deal with that, decision maker's (DM) preferences may be incorporated into the optimization process. Taking them into account allows the optimization method to focus on solutions of most interest to DM, which in turn leads to faster convergence and better solutions. This approach has been tried by the authors of this paper in [8], which addresses the problem of multi-objective weather routing (WR) of ocean-going vessels. WR's system purpose is to find routes offering a balance between voyage time and fuel consumption on one side and vessel's safety on the other. This problem belongs to a class of constrained multi-objective problems with large objective space. To cope with it, a new dominance relation – w-dominance [9] has been applied by the authors to boost up the computation process and limit the final set of solutions to the most important from DM's point of view. The current paper continues this thread, though this time, it addresses a significantly more complex problem by inclusion of uncertainties of weather predictions into the optimization process. The proposed optimization method this time is based on Multi-objective Evolutionary Algorithm Based on Decomposition – MOEA/D [10] (unlike, as in [8], Strength Pareto Evolutionary Algorithm – SPEA I/II [11]). The WR solution being described here is a fully functional and self-sufficient prototype [12] of a client-server weather routing system. The system downloads weather forecasts from dedicated sources and uses them to estimate objective values associated with each candidate route plan. It also makes sure that expected weather conditions are acceptable throughout the voyage and will not constitute a threat for the vessel, her cargo and crew [13].

The rest of the paper is organized as follows. Related works are presented in the next section, including overview of weather routing as well as dominance relations and tradeoffs in evolutionary multi-objective optimization. Weather routing as an optimization problem with uncertainties is addressed in Section 3. Following this, methodology of the proposed solution is described in detail in Section 4, covering all elements of the compound evolutionary algorithm. Architecture of the complete real time weather routing system is then provided in Section 5, followed by the system's example results and their discussion, which are given in Section 6. Finally, the paper is summarized and concluded in Section 7.

2 RELATED WORKS

The research being described here applies multi-objective heuristic optimization focused on the decision maker's preferences to solve a specific problem defined in ship transportation. Thus, to present a comprehensive overview of the related scientific works, this section is split into two following subsections. The first one presents literature overview of the real life problem (weather routing of ships), whereas the latter focuses on the solution – multi-objective heuristic optimization methods with special attention to incorporation of decision maker's preferences.

2.1 Ship weather routing overview

Ship weather routing is commonly defined as planning ship's route with regard to forecasted or expected weather conditions. In case of power-driven ships, the ship usually navigates for most of the voyage with constant engine settings (though they can be changed, if needed). However, depending on hydro-meteorological conditions (especially waves and wind) even the same engine settings may result in different fuel consumption and different speed values, the latter of which in turn affects the total time spent on the voyage. Reasonable weather routing allows for minimization of total fuel consumption, voyage time and risk caused by unfavorable conditions, though in practice it is hard to pursue all of those three objectives simultaneously. Historically, weather routing started with a traditional isochrone method [14] invented as manual and based on geometrical time fronts (isochrones). Computer implementations of the method were later developed, among others in [15]. Unfortunately, the isochrone method utilizes single-objective approach (usually a minimization of time) and is limited in terms of handling dynamic constraints. Multiple other more flexible, yet still single-objective, approaches to the weather routing problem have been developed. They include dynamic programming for a 2D [16,17] or 3D problem version [18,19]. Control methods have also been applied for finding time-optimal path [20] and Dijkstra-based algorithms were presented in [21,22] for motor-driven vessels and in [23,24] for sailing ones. As for multi-objective approaches to ship route planning, initially they were based on aggregating objectives into one [25]. A Pareto approach to such optimization has been proposed in [26–30]. The methods in

[27,28] utilize multi-objective genetic algorithms (MOGA), while more robust multi-objective evolutionary approach SPEA/SPEA II was used in [26,29,30]. Related research includes route optimization procedures in the daily operations of the seafarers [31,32] and weather routing dedicated to particular types of water areas [33]. Among others, it has been observed that ships try to avoid harsh weather and deviate from seasonal routes when necessary. Consequently, the weather that ships actually do experience during operations is safer. Those and other weather routing methods have been reviewed thoroughly in [34,35].

Weather routing approach presented in this paper aims to combine qualities of the above mentioned solutions i.e. combine a truly multi-objective approach with computationally efficient algorithms to handle weather-related uncertainties. When put together, this results in improved route planning by possible shortening passage time, reduction of fuel consumption and improving safety and security of crew, cargo and ship itself *en route*. The proposed system has been verified in real operational conditions and its results are provided and discussed in Section 6.

2.2 Dominance-based and tradeoff-oriented approaches to incorporating DM preferences into MOMH

Dominance-based algorithms use relations to extend dominance's scope beyond Pareto definition and thus to compare solutions non-dominated in Pareto sense. Dominance relations may do not take into account DM preferences or be based on them. An example of the former is epsilon-dominance [36], which does not utilize them. As for the latter, preference-oriented dominance relations include reference points-based (RP) g-dominance [37], r-dominance [38] and p-dominance [39]. RP-based dominance relations often compare solutions based on division of objectives' space (g-dominance [37]) or their Euclidean distance to an RP. This Euclidean distance may in turn consider account weights assigned to objectives (r-dominance [38]) and may be further enriched by indicators in the form of preference radius (p-dominance [39]) or preference angle [40]. Such indicators allow to combine algorithms' good convergence (being an effect of utilizing Euclidean distances) with diversity.

As for tradeoff based approaches to incorporate DM preferences, they can be roughly divided into objective (problem structure-based) and subjective (DM's-preference based) ones [41]. Subjective ones take numerical or linguistic values, which can then be transformed into objective weightings, weight intervals or coefficients as shown in [42] and [43]. This includes [44], where the authors define the tradeoffs as values reflecting how much the DM is ready to sacrifice some objectives for improving the other. E.g. DM may decide that improvement by a single unit in one objective is worth at most degradation by *n* units in another objective. This coefficients-based approach is well-suited for bi-objective optimization but, as stated in [41], the approach presented in [44] cannot be directly applied to more than two objectives. This problem was overcome in [9], where matrix of coefficients was replaced with weight intervals, which allowed to define w-dominance – a new dominance relation. W-dominance is a compromise between popular weighted average and unfocused Pareto-optimization approach. Instead of requesting precise weight values assigned to objectives, the proposed method accepts vague DM-given information. In practice, even quite wide weight intervals can greatly limit the objectives' space. What is more, this approach can be incorporated to multiple existing MOMH, including a popular and highly efficient MOEA/D [10].

3 WEATHER ROUTING AS AN OPTIMIZATION PROBLEM WITH DATA UNCERTAINTY

Classical approaches to ship voyage optimization implicitly assume that the weather forecast, the model employed to predict ship performance and the loading conditions are estimated with a sufficient accuracy and uncertainty related with the results of the optimization are neglected or, at most, quantified in the post-processing. However, in many cases, uncertainties can have dramatic consequences especially for trans-oceanic voyages which duration largely exceeds the range of reliable forecast, usually spanning between two and three days. In the worst case this may cause being caught in an unexpected storm jeopardizing safety and efficiency, while more commonly it results in the need of re-routing when updated forecasts are available, so reducing the awareness of the expectable performance at the departure, with consequent poor ability of efficiently planning operations and logistics.

Concrete attempts to deal with uncertainties in ship voyage optimization have been reported in the last twenty years, e.g. with a noticeable pioneering work [28], while other examples of applications are found in [45], [46] and [47]. Generally, the objective was to quantify the uncertainties in the predicted performance (e.g. confidence interval) rather than allowing the uncertainties to play an active role in driving the optimization towards different solutions. In [48] different methods to deal with uncertainties in the estimation of fuel consumption were analyzed.

Quantification of ship safety is a complex task for several reasons, including: the subjective nature of risk perception, the different types of safety related events that may occur during the navigation, their variable correlation and the difficulties in fusing them in a single indicator. Assuming that only risks related to the effect of waves on ship motions are taken into account, they can be represented by means of the hazards such as rolling or slamming, among others. In a classical deterministic approach, to each of these hazards corresponds a threshold that cannot be exceeded to ensure safe navigation. However, their estimation is affected by a large number of uncertainties, among which those related with weather forecast are the most relevant [48].

To cope with this, the proposed approach deals with safety in a probabilistic manner, both in terms of constraints and objective function, adopting ensemble forecast to evaluate the probability distribution of the ship responses. Differently from [49], where only integral statistical parameters of the weather forecast are used, the method presented here aims to analyze all members of an ensemble weather forecast in order to provide a more adequate estimation of the probability distribution of the weather parameters.

4 EVOLUTIONARY PROCESS – METHODOLOGY

Multi Objective Meta Heuristics (MOMH) are particularly well fitted for real life optimization problems, such as weather routing that has been presented in the previous section. What is more, flexibility of MOMHs makes it possible to combine them with other techniques thus forming hybrid solutions of higher performance [50]. Such solutions can then successfully deal with multiple optimization tasks ranging from operating electric powers systems [51] and power distribution networks [52] through specialized scheduling [53] and cross-docking strategies [54] to search-and-track [55] and vehicle routing [56]. Of various MOMHs, Multi Objective Evolutionary Algorithms (MOEA) are particularly open for incorporating new features, including both preferences-oriented (here: w-dominance relation) and problem-dedicated (multiple specialized operators). For those reasons, an algorithm belonging to MOEA group, namely MOEA/D (described in more detail in Section 4.3) has been selected as the framework of the process presented below. Combining it with w-dominance and customized operators (some of which are semi-deterministic) results in an optimization engine that can be loosely classified as a hybrid solution.

The overview of the evolutionary process is provided in Figure 1. The input data for the process are:

- the starting and destination points,
- start time (necessary for downloading appropriate weather forecasts),
- information on all optimization objectives being turned on or off,
- information on all risk-related constraints being turned on or off,
- configurable thresholds for excessive values of all risk elements,
- weight intervals assigned to all optimization objectives,
- a model of ship responses (a demonstration ship is used here).

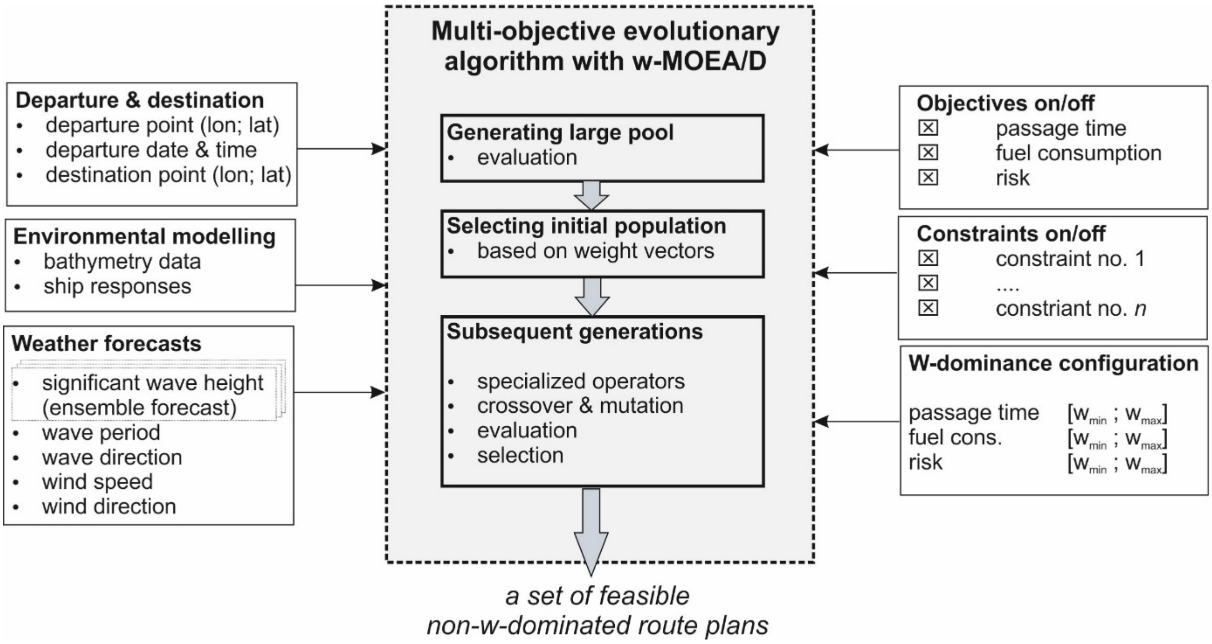

Figure 1. Overview of the evolutionary multi-objective weather routing (WR) process

4.1 Individual structure, optimization objectives and constraints

Each individual, a subject to the evolutionary process, is a **route plan** – a vector of waypoints defined by their geographical coordinates X and Y. Those waypoints' coordinates are main decision variables. Each route plan produces a number of possible **routes**, each of them being a realization of this route plan assuming a particular member of ensemble weather forecast. A route plan is assessed based on the three objectives, each of them aggregated over all ensemble forecast members: total voyage time, total fuel consumption and estimated risk index. Both the total time and fuel consumption are computed as arithmetic averages over all members of ensemble forecast. As for the risk, only risk elements related to the effect of waves on ship motions are taken into account here, and are represented by means of the following elements:

- Motion Sickness Incidence (r_1),
- RMS of rolling amplitude (r_2),
- Slamming probability (r_3),

- Green Water probability (r_4),
- Propeller Emergence probability (r_5).

Detailed algorithm responsible for risk estimation is described in Section 4.5.

As for the constraints, two types of them are taken into account. The first one are bathymetric or landmass-related constraints: a route segment cannot cross an obstacle or an area of insufficient water depth. Each violation of such constraints is stored as a set of the following data:

- numbers of route plan waypoints, between which violation occurs,
- geographical coordinates of the violation endpoints,
- a percentage of a route segment part, which violates the constraint.

The second type of constraints are weather-dependent ones. Here, a violation depends on which ensemble forecast member is taken into account. The following violations can occur here and if they do, they are stored as Boolean values in the route's structure:

- one of risk elements listed above (r_1 to r_5) exceeds a predefined threshold value,
- wave height exceeds a predefined threshold value.

Based on the above constraints and their potential violations, it is decided whether a route plan is valid and feasible. A route plan is **valid** if the route plan's segments do not violate bathymetric constraints. It is additionally **feasible** if all of the routes it produces are free of weather-dependent constraint violations.

4.2 Uncertainty handling

There are two possible approaches to uncertainty handling in ship weather routing: probabilistic and ensemble-based. In the probabilistic approach, the sea-state is represented by decreasing probabilities of various possible states around mean forecast conditions. In the ensemble approach, the predicted sea-state is modelled by a number of different but equally probable forecasts. Those different forecasts are called ensemble members and can be directly processed by the optimization method. While ensemble members can be in theory handled in various ways, in reality some approaches are impractical either in terms of effectiveness or because of poor efficiency. The approach applied here combines acceptable computational time (due to a limited number of optimization objectives) with satisfying safety checks (all weather forecast ensemble members are considered). It is briefly presented below.

All ensemble members are handled during a single run of the weather routing optimization process, taking into account all three optimization objectives simultaneously. For each assessed route plan, an objective's value is computed separately for all ensemble forecast members and then aggregated (Figure 2). As for time and fuel consumption, a simple arithmetic average over all forecast members is computed. However, in case of risk indicator, a more complex procedure is applied, which is described in detail in Section 4.5.

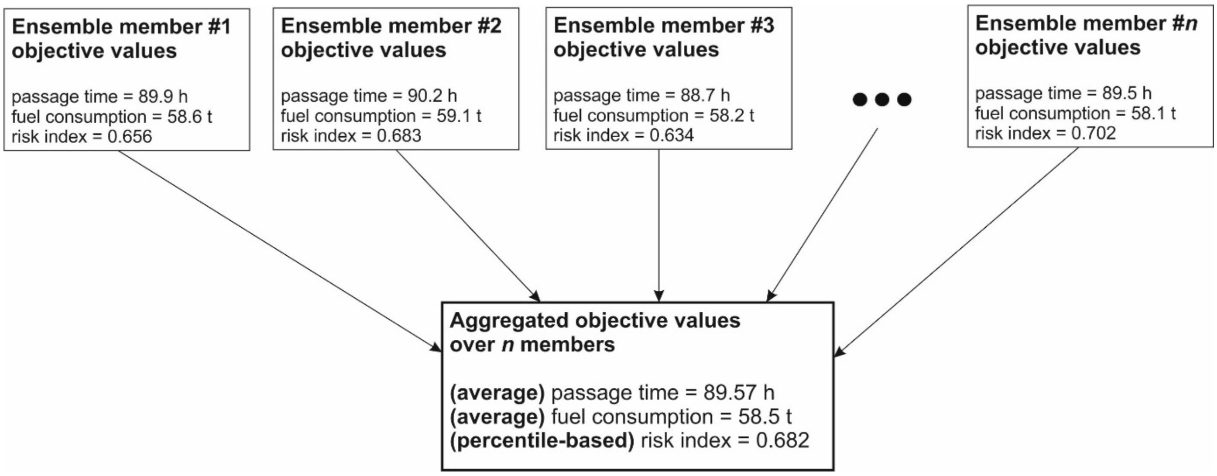

Figure 2. Aggregating objectives' values over all ensemble forecast members

As for weather-related safety constraints, they are checked separately for all combinations of considered routes and ensemble forecast members (Figure 3). The most pessimistic assessment obtained over all ensemble forecast members is taken into account. Owing to this, a route plan must meet constraints for all ensemble members, otherwise it will be considered unacceptable.

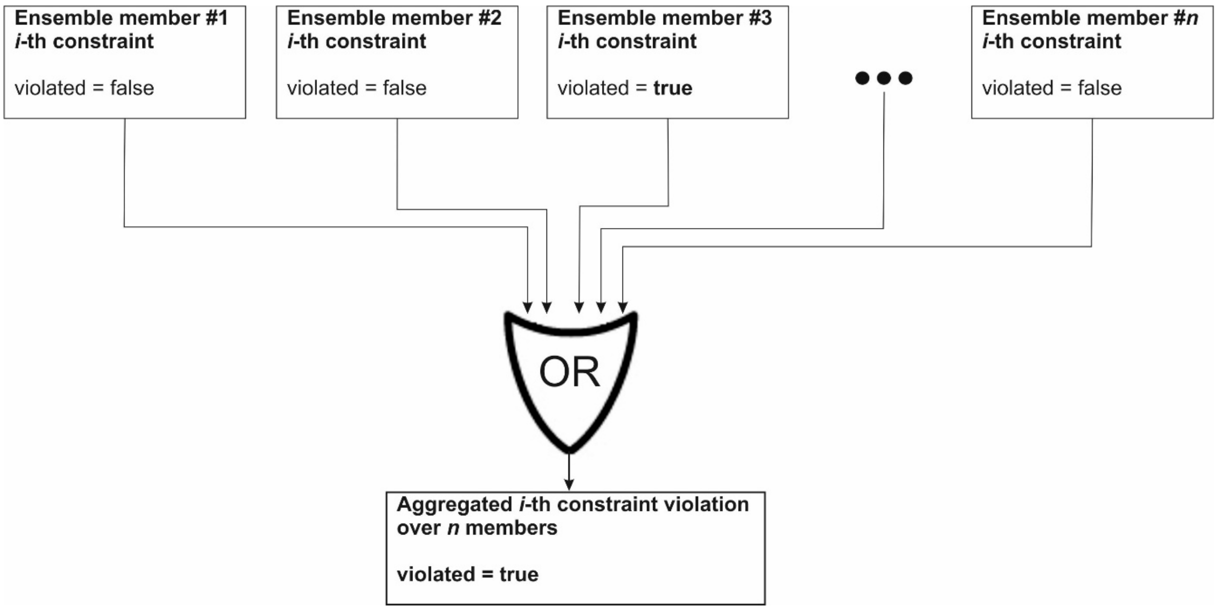

Figure 3. Aggregating *i*-th constraint's values over all ensemble forecast members

4.3 MOEA/D algorithm and w-dominance

MOEA/D [10] is a multi-objective evolutionary algorithm based on decomposition and a winner of CEC09 MOEA competition in 2009. Recently it is still one of the most popular MOMH applied to solve complexed problems [57], either used in hybrid solutions with other meta-heuristics [58] or further expanded [59–61]. All this confirms that it reasonable to apply it for solving up-to-date complex real-world optimization problems.

MOEA/D has been selected here as an evolutionary optimization framework because of its following advantages:

- has a very good coverage – spread of solutions over a true Pareto front,

– is able to find wider set of solutions than its classic rivals (e.g. SPEA II, NSGA II and IBEA),
– finds diverse solutions for complex dynamic problems [62],
– is rather simple, flexible and scalable,
– supports exploring multiple optimization directions given by vectors of weights assigned to objectives,
– allows for a full control over the optimization directions and distribution of solutions,
– enables handling decision maker's preferences easily.

Of the above, two first qualities are important for the general evolutionary purposes, while the third one allows for easy implementation and updates. As for the last three qualities, they are of particular interest, when it comes to combining the algorithm with w-dominance relation introduced by the authors in [8] and presented in detail in [9].

The main idea of MOEA/D is that the optimization is decomposed into a number of directions, each of them represented by a vector of weights assigned to the objectives.

The main idea of w-dominance is based on the observation that DM may specify weights assigned to objectives as intervals instead of single values. Let us consider the *i*-th and *j*-th objectives and denote weight intervals by DM to them:

$$w_i \in \langle w_i^{min}, w_i^{max} \rangle \quad w_j \in \langle w_j^{min}, w_j^{max} \rangle \qquad (1)$$

where w_i^{min}, $w_j^{min} \in \langle 0,1 \rangle$, $w_i^{max}, w_j^{max} \in (0,1\rangle$, $w_i^{min} \leq w_i^{max}$ and $w_j^{min} \leq w_j^{max}$.

This means that according to DM a single unit of improvement in $f_i(x)$ is worth at most $\frac{w_i^{min}}{w_j^{max}}$ units of degradation in $f_j(x)$.

Following this, a generalized objective function with unspecified weights takes a form of:

$$f(x) = \sum_{i=1}^{m} w_i f_i(x). \qquad (2)$$

If all w_i^{min} are equal to 0 than the quotient $\frac{w_i^{min}}{w_j^{max}}$ is also 0 for all *i*, which means that DM does not accept any degradation in any objective and thus a tradeoff is not possible. The other extreme case is that of $w_i^{min} = w_i^{max}$ for all *i*. The weight intervals are then replaced by crisp weight values and the proposed aggregated objective function (2) would become a typical weighted average.

For the minimization problem a solution *x* **w-dominates** solution *y* iff:
$f(x) < f(y)$, where $f(x)$ is a function given by (2).

It has been shown in [9] that this holds true if

$$\sum_{i=1}^{m} g_i(x,y) > 0, \text{ where} \qquad (3)$$

$$g_i(x,y) = \begin{cases} w_i^{min} d_i(x,y), & \text{for } d_i(x,y) \geq 0 \\ w_i^{max} d_i(x,y), & \text{for } d_i(x,y) < 0 \end{cases} \qquad (4)$$

The above condition allows for a time-efficient w-dominance checking, which is applied throughout the evolutionary process, especially for selecting non-dominated solutions (archive creation and updates).

4.4 Evolutionary process – w-MOEA/D algorithm framework

Evolutionary process applied here is based on MOEA/D algorithm but extends it with w-dominance relation (to limit objectives' space and make evolution more focused) thus forming a new w-MOEA/D algorithm. This algorithm framework is further extended by multiple problem-specific schemes and operators. It consists of the following stages.

A large pool of individuals

A large pool of individuals is generated to facilitate initial population creation. The large pool has a configurable size, which is a multitude of the population's size. The pool contains the following types of individuals (route plans) generated for user-set start and destination points.

1. Orthodromic (Great Circle) and loxodromic (Rhumb Line) route plans.
2. Route plans created as random mutations of either the orthodrome or loxodrome. For each of such route plans, two waypoints are randomly chosen and the segment between those waypoints is randomly shifted perpendicularly to it's main direction.
3. Route plans created as combinations of an orthodrome and loxodrome.
   a) Route plans, where geographic coordinates of waypoints are weighted averages of orthodrome and loxodrome waypoints
   b) Route plans generated by means of crossover between orthodrome and loxodrome, with a randomly chosen cutting point between orthodromic and loxodromic part of a route plan. Half of those route plans start with the orthodromic part, the other half – with a loxodromic part.

Weight vectors

Weight vectors are generated for each individual. They are produced according to w-dominance settings: they do not cover all combinations of weights (as is normally done in MOEA/D) but only those weight combinations that are compliant with user-specified weight intervals limits. This constitutes the first difference between MOEA/D and w-MOEA/D introduced here.

Initial population

According to MOEA/D algorithm, each individual within the population represents one weight vector and aims to optimize the fitness function being a weighted average of all objectives. This policy is also applied in the proposed w-MOEA/D. Therefore, when generating initial population, individuals (route plans) are selected from large pool, based on how they perform for the considered weight vectors. This is done as follows. First, all individuals within large pools are evaluated. Once we know their objective values (aggregated over all ensemble forecast members), all weight vectors are handled iteratively: for each of them an individual is selected from large pool that fits this particular weight vector best (results in the smallest weighted average of all objectives).

Evaluation

During evaluation phase all violations of active constraints (the ones that are turned on) are detected and values of all active objectives are computed. As for the objectives' values, all of them are determined separately for each ensemble forecast member and each segment of a route. Following this, they are aggregated: arithmetic average is used for both total fuel consumption and total passage time, while percentile-based method is applied for risk assessment (Section 4.5). As for constraints, most of them are also checked separately for each member of an ensemble forecast member. The sole exception is violation of bathymetric constraints, which is checked for each route plan's segment only once, independently of the weather forecast member.

Crossover

There are two types of crossover operators used, both working on pairs of individuals. For each individual within a population, two other individuals are chosen from its neighborhood. Then, a random merge or an averaging operator is randomly selected.

1. In a random merge operator, a cutting point is chosen as a random waypoint in one of the two route plans. Then, a waypoint closest to it is selected in the second route plan. Following this, a new route plan is created, which consists of parts of the two parents..
2. In an averaging operator. a new route plan is created, whose waypoints' geographical coordinates are weighted averages of the parent waypoints' coordinates (weights are generated randomly).

Mutation

During mutation phase, for each individual it is decided randomly, whether it will be a subject to mutation. If so, than one of the following operators is randomly selected, with the probability dependent on the evaluation data of the parent individuals (especially bathymetric constraint violations and smoothness).

1. A new waypoint is inserted.
2. A new segment is inserted.
3. A single waypoint is removed.
4. A segment is removed.
5. A single waypoint is moved. Waypoint's coordinates are randomly modified. A shift's direction is selected randomly, while the shift's size is selected randomly from the allowed configurable range. The maximum allowed shift is dependent on the evolution's progress: larger shifts are allowed at earlier stages and smaller – at later ones.
6. A number of waypoints are moved. A specified (randomly selected) number of waypoints is shifted perpendicularly from the route's main direction.

Both the mutation probability and mutation operator's volume diminish with successive generations, so as to stimulate abrupt changes in the early generations and smoother in the late ones.

Eliminating bathymetric constraint violations

The bathymetric constraint compliance is checked separately for each route plan's segment during evaluation phase and the information is stored in the individual's structure. In case of constraint violation, a repairing operator is applied, whose purpose is to eliminate those violations. It works as follows. Depending on the length of the segment part that violates a constraint and the length of the segment itself, one of the following approaches (or a combination of them) is tried.

1. A new route segment is inserted to replace the violating part with a detour.
2. One or more segments of a route are shifted perpendicularly from their main direction. Shift's direction is chosen randomly, while the shift's size is dependent on the length of the route's part that violates a particular bathymetric constraint.

   The number of shifted waypoints and the size of the shift are random, but roughly proportional to the violation's size.

Smoothing

Smoothing is only performed if a route plan does not violate bathymetric constraints. The angles between successive route plan's segments are then checked and if they exceed a predefined threshold value (e.g. 15 degrees), a particular angle is smoothen by applying one of the following approaches:

1. A critical waypoint is shifted perpendicularly towards the segment joining its two neighbors.
2. A critical waypoint is replaced with a new segment, whose endpoints are inserted between the critical waypoint and its neighboring waypoints. The exact coordinates of the new waypoints are chosen randomly based on the coordinates of the critical waypoint and its neighbors.

Following this, compliance with bathymetric constraints is again checked, and only if those conditions are met, a route is replaced with its smoothened version.

Normalization of route plan's objectives' values

Once the objectives' values are aggregated over all ensemble forecast members (possible realizations of a route plan), their normalization is performed. In practice differences between particular objectives' values may be relatively small (e.g. a few percent) thus it is important to retain those relative differences in the normalized values. Therefore, for fuel consumptions and passage times it has been decided to use a simple normalization formula given below.

$$normalized\_objective\_value = \frac{objective\_value}{max\_objective\_value},$$

where $max\_objective\_value$ is the maximum value of the given objective obtained over whole population in the current generation.

As for risk associated with a given route plan, once it is aggregated by means of a percentile-based method from Section 4.5, the normalization is done using the same formula as above for time and fuel.

Comparing two individuals

If both of the compared individuals (route plans) are feasible, the comparison is limited to checking w-dominance condition (3) from Section 4.3. However, during early generations of the evolutionary process, infeasible or even invalid solutions may be produced and they have to be handled too. If any of the compared pair of individuals is infeasible, condition (3) is not used and the following rules are applied instead.

1. A solution, which is valid (does not violate bathymetric constraints) dominates invalid one.
2. A solution, which is feasible (does not violate any constraints) dominates infeasible one.
3. If both solutions are invalid, the one with a shorter total length of bathymetric constraint violations dominates the other one.
4. If both solutions are valid but infeasible (weather-related safety constraint violations only), the one with a lower risk indicator (third objective value – Section 4.5) dominates the other one.

Owing to this policy, invalid solutions are removed first from subsequent populations, followed by elimination of valid but infeasible route plans.

4.5 Percentile-based method of risk quantification

Five risk elements – ship responses r_1 to r_5 – have been listed in Section 4.1. At each waypoint P_i along the route plan, ensemble forecast provides n_j estimations of the weather parameters; for each of them, the seakeeping model can quantify the k^{th} ship response r_{ijk}.
Firstly, the responses are normalized with respect to their limits:

$$\hat{r}_{ijk} = r_{ijk}/l_k.$$

This offers a straightforward indication of the severity of the response, though it must be pointed out that strong non-linearities in the responses, may reduce the significance of this indicator. Then, for each location and ensemble member, the most demanding response is considered:

$$\hat{r}_{ij} = \max_k(\hat{r}_{ijk})$$

The following step is to formulate a methodology to integrate the responses expected on all locations along the feasible routes in a single index, to be adopted as risk-based objective by the optimization algorithm. As a starting point, for each location an objective percentile po_i of $\hat{r}_{ij}$ is considered, in the current work set as the 75^{th} percentile. Different formulations have been evaluated, in the attempt to achieve a representative picture of the severity of the route with respect to the undesired effects on the ship and the crew. A single most demanding response (still below the constraint) cannot be considered significant of the overall conditions onboard. On the other hand, using an average value may hide undesirable storm crossings. The adopted formulation considers the weighted average over a predefined period of time $\hat{t}$, here taken as $1/3$ of the expected voyage duration t. This way, the benefits of these two previous approaches are preserved, while the negative aspects are significantly reduced.

Considering the $\hat{n}$ most severe locations for which $\sum_{\hat{n}} t_i = \hat{t}$ (where d_i indicates time required to sail the track), and the corresponding subset of highest objective percentiles, the risk index (as an optimization objective) is defined as

$$\text{Risk index} = \frac{\sum_{\hat{n}} t_i \, po_i}{\hat{d}}$$

It is worth noticing that the perception of the onboard conditions has a significant degree of subjectivity. For this reason, feedbacks from the crew are systematically been collected to fine-tune the three governing parameters, that is $\hat{t}$ and the levels of the constraint and objective percentiles, in order to obtain a final setting that better represents the perceived severity of the navigation.

The proposed risk quantification method does not only enable a customized definition of navigation safety according to the specific ship type, service, and risk attitude of the officers, but also allows a quantification of the effect of weather-related uncertainties. The most relevant novelty is to be found on the fact that uncertainties play an active role in the optimization, which in turn is expected to reduce the deviations from the initially proposed route plans when weather updates are received.

4.6 Pseudocode of the key elements contributing to the evolutionary process

All key elements of the optimization process have been described previously in Section 4.4. Below we present pseudocode of the main algorithm (Algorithm 1) which illustrates their place in the hierarchy of the process. Algorithms 2-4 present detailed pseudocode for the most important procedures, namely for:

- generating initial population (Algorithm 2),
- population evaluation (Algorithm 3),
- single individual evaluation (Algorithm 4).

Table 1. Pseudocode of the main algorithm (a loop handling the incoming optimization requests)

```
Algorithm 1: the main algorithm's loop
Input: incoming route optimization request (identified by request_ID)
for each (request_ID):
        # request input data: departure (lon, lat) & time, destination (lon, lat),
        # general ship propulsion settings, general optimization settings, w-dominance settings
        inputData = getRequestInputData(request_ID)
        loadBathymetry()
        loadWeatherForecast(input_data)
        if isFeasibleRequest(request_ID, input_data) then
                # only feasible requests can be processed
                archive = empty
                population, archive = initializeOptimization(request_ID, input_data)
                for i in max_generation_numer:
                        population, archive = evolutionary_update(population, archive)
                end for
        end if
        releaseLoadedData()
end for
Output: archive
```

Table 2. Pseudocode of the procedure for initialization of optimization (initializeOptimization)

```
Algorithm 2: initializeOptimization()
Input: request_ID, input_data
weight_vectors = produceWeightVectors(input_data)
large_pool = produceInitialLargePool(input_data)
for each route_plan in large_pool:
        if route_plan crosses land then
                route_plan.eliminateBathymetricConstraint()
        end if
        route_plan.evaluate()
end for
large_pool.normalizeRoutePlans()
initial_population = produceEmptyInitialPopulation()
```

```
for each empty individual in initial_population:
        individual = getBestMatch(large_pool, weight_vectors)
end for
archive = generateArchive()
selectNeighboringVectors(weight_vectors)
determineBestObjectiveValues(initial_population)
Output: initial_population, archive
```

Table 3. Pseudocode of the procedure for population evaluation (evolutionary_update)

```
Algorithm 3: evolutionary_update()
Input: current_population, archive
for each route_plan in current_population:
        route_plan.crossover()
        route_plan.mutate()
        if route_plan crosses land then
                route_plan.eliminateBathymetricConstraint()
        end if
        route_plan.smoothe()
        evaluateSingleRoutePlan(route_plan)
        if not isValid(route_plan) then
                # do only if the evaluated route_plan is not valid
                route_plan = getBestMatch(large_pool)
        end if
        route_plan.normalize()
        route_plan.updateBestObjectiveValues()
        archive.updateArchive(route_plan)
end for
Output: current_population, archive
```

Table 4. Pseudocode of the procedure for evaluation of a single evolutionary individual (evaluateSingleRoutePlan)

```
Algorithm 4: evaluateSingleRoutePlan ()
Input: route_plan
for each member in ensemble_forecast:
        N = total number of waypoints in route_plan
        for k = 2 … N in route_plan: # k is the current waypoint number in route_plan
                segment = route segment between the previous (k-1)th and current kth waypoint
                calculateRisk(route_plan, segment, member)
        end for
        calculatePassageTime(route_plan, member)
        calculateFuelConsumption(route_plan, member)
        checkConstraintsViolations(route_plan, member)
end for
aggregatedGoalFunctionsOverMembers(route_plan) # for display purposes
Output: route_plan
```

5 REAL TIME WEATHER ROUTING SYSTEM OVERVIEW AND ARCHITECTURE

The optimization methodology described in Section 4 has been applied in a real time WR system. The system, as shown in Figure 4, has a client-server architecture which allows to separate user data collection and results visualization layer (WR Client) from the core optimization procedures (WR Server). This is important, because the latter consumes more time and resources and thus it is best to perform it by means of a server unit ashore. Such architecture makes it possible to process a large number of route optimization requests sent by different users on board of multiple vessels. Upcoming requests are handled in accordance with the First In – First Out (FIFO) queue discipline on the server-side.

WR Server is supported by a weather forecast-collecting server providing access to up-to-date predicted data on wind, wave and sea current for the Azores and Portuguese coast. The server downloads forecasts from NOAA and Copernicus sources converts them to GRIB2 file format, when necessary, filters them and prepares a ZIP archive available for upload via HTTPS static link.

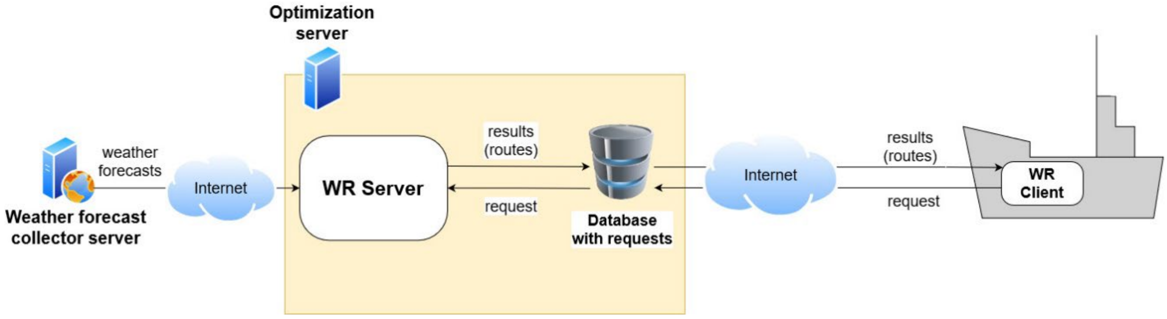

Figure 4. Routing system overview

The following subsections decompose the architecture to WR Client, WR Server and the interaction between those two.

5.1 WR Client-Server Interaction

WR Client software provides GUI for route optimization, that is, data input and obtained route plans. As for WR Server, it is an application responsible for business intelligence of weather routing: loading weather forecast data and performing route optimization. Data exchange between WR Client and WR Server takes place by means of a database (DB) on the server side. The communication between client and server is done with the use of WR data exchange protocol as follows:

1. A new user request is sent from WR Client (when the user finalizes their route planning request settings) to the server database;
2. WR Server periodically collects requests from database, when a new request is available it starts to handle the request:
   a. fetches it and updates its status;
   b. loads weather forecasts from up-to-date local files;
   c. starts the optimization procedure;
   d. when optimization is finished it saves the results (obtained route plans) in database and updates request's status;
3. WR Client checks periodically a status of the request. The user is able to cancel the current request or wait for the optimization procedure to complete;
4. When available in database (request status is "completed"), WR Client gets the results (route plans) and displays them to the user.

WR Client connects to WR Server periodically: first to make a request and then to check the optimization progress. Such asynchronous communication is a necessity due to time-consuming calculations, uncertainty of the Internet bandwidth on-board and potentially high costs in case of a satellite data transmission.

5.2 WR Client application

WR Client is an Electronic Navigational Chart (ENC) class software, installed on a PC on board of a vessel, able to present graphically ship routes, sea charts and weather forecast parameters among others. NaviWeather software by NavSim is utilized as the ENC-class container for this. A separate NaviWeather plug-in has been implemented in order to provide WR functionality. Basic elements of the WR Client application are shown in Figure 5.

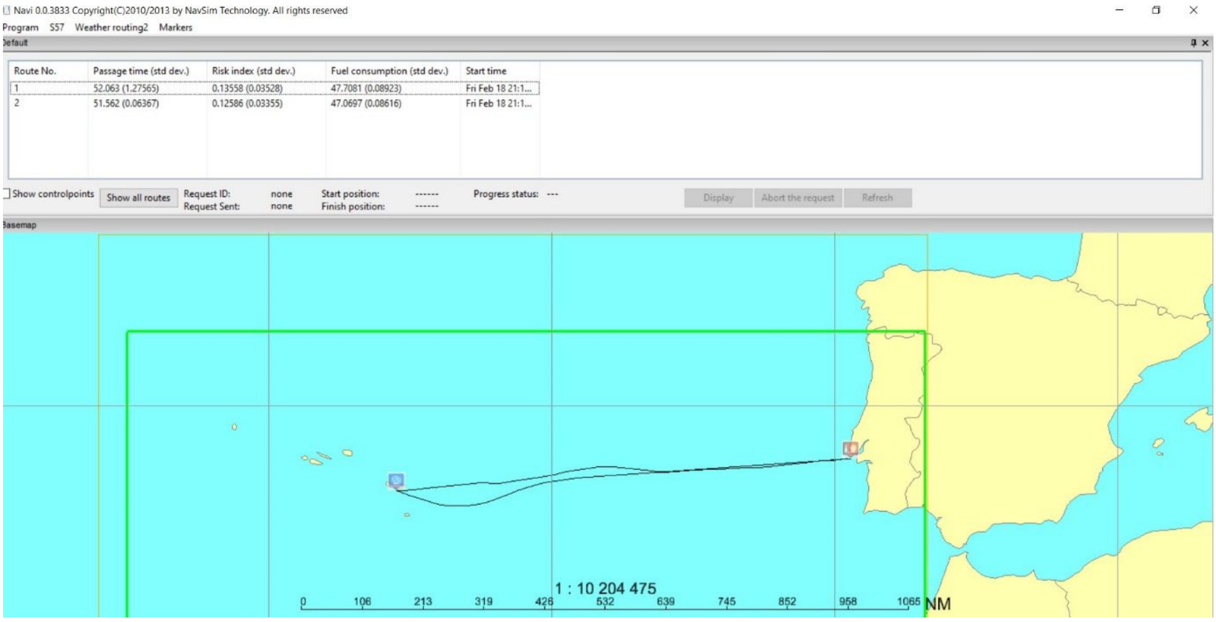

Figure 5. WR Client application

To set up a new route planning request (route optimization) the user specifies departure and destination positions and then – the departure time and some cargo-related parameters. Following this the user selects, which objectives and constraints will be active during optimization. The user is also able to set weight intervals (w^{min}, w^{max}) assigned to the objectives and boundary thresholds for all the constraints. If the user does not set them, default values are used. After user's approval, the request is sent to WR Server via database. Once the optimization is completed all returned route plans are saved on an on-board PC and displayed to the user, who can access their details.

5.3 WR Server application

WR Server is a console application responsible for route optimization as specified in requests sent by WR Client via client-server data exchange protocol. WR Server keeps monitoring database for a new request. When a new request comes, WR Server handles it, sends the results back to database and gets back to monitoring mode. If there are no new requests, it pauses for a configurable time and then checks for new requests again. Route optimization process (while handling the request) is strictly based on the methodology described in Section 4.

6 SIMULATION RESULTS & DISCUSSION

Results returned by the proposed method have been compared with GPS routes of the demonstration vessel m/v Monte da Guia (MdG). The MdG ship navigates continuously between Portuguese ports of Lisbon and Leixoes (near Porto) and the Azores. The cyclic routes of m/v Monte da Guia are shown in Figure 6.

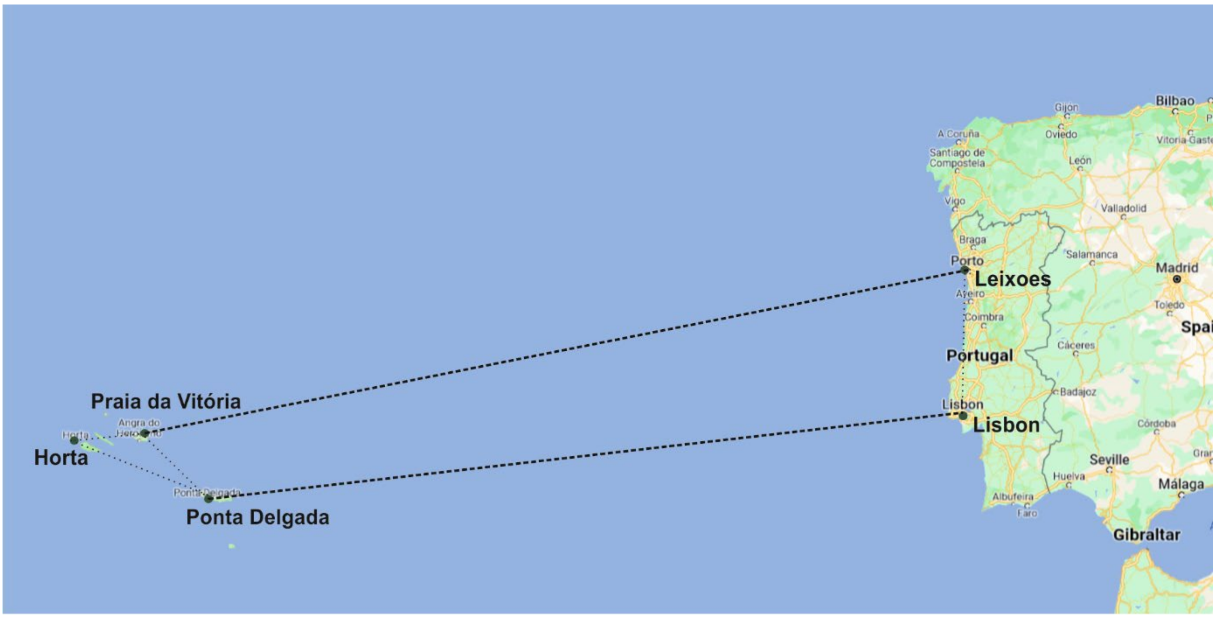

Figure 6. m/v Monte da Guia's voyage cycle and its two key legs

As can be seen, the whole cycle consists of two longer routes (Leixoes – Praia da Vitória and Ponta Delgada - Lisbon) and shorter middle segments (between Azorean islands and between Lisbon and Leixoes). For WR purposes we have focused on the longer route segments, as the shorter ones are hardly affected by weather forecasts uncertainty and in practice navigators make their decisions there based mostly on current weather conditions instead of forecasts.

6.1 Simulation settings

For the project purposes voyages of m/v Monte da Guia vessel made in January and February 2022 have been archived as sequences of logged *en-route* GPS locations with predefined time step. Six subsequent GPS routes from this period have been used in this comparison as reference routes (Table 5).

Table 5. GPS routes - m/v Monte da Guia's voyages between 14th January 2022 and 21st February 2022

GPS route no.	Departure	Departure date & time (GMT)	Destination	Constraints violated by the GPS route
1	Leixoes	14th Jan 2022, 10:59:00 PM	Praia da Vitória	-
2	Ponta Delgada	21st Jan 2022, 10:25:00 PM	Lisbon	-
3	Leixoes	28th Jan 2022, 11:05:00 PM	Praia da Vitória	-
4	Ponta Delgada	4th Feb 2022, 10:17:00 PM	Lisbon	motion sickness incidence
5	Leixoes	11th Feb 2022, 9:03:00 PM	Praia da Vitória	-
6	Ponta Delgada	18th Feb 2022, 8:13:00 PM	Lisbon	-

The objectives in the simulation (all values to be minimized) were:

- passage time (in hours),
- fuel consumption (in tons),
- risk index (normalized, dimensionless).

The constraint set in the simulation has consisted of:

- Motion Sickness Incidence (MSI),
- RMS of rolling amplitude (RA),
- Slamming probability (SL),
- Green Water probability (GW),
- Propeller Emergence probability (PE),
- Excessive high waves (HW),
- Land and shallow waters (LAND).

The constraint threshold values were set based on navigators' suggestions. The MdG real GPS routes were then evaluated using MdG digital model to obtain the objective values and check if all constraints were met. It turned out in scenario #4 that GPS route violated Motion Sickness Incidence constraint (Table 5). Therefore, it has been decided that in the simulation the constraint set would be adjusted to make GPS routes feasible and let direct comparison of the objectives' values between proposed WR system route plans and GPS routes. Constraint settings of the simulation run are provided in Table 6.

Table 6. Constraint settings of the simulation run

			Simulation run (constraint set adjusted for the GPS routes)					
			Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
	C1	MSI	+	+	+	-	+	+
	C2	RA	+	+	+	+	+	+
	C3	SL	+	+	+	+	+	+
	C4	GW	+	+	+	+	+	+
	C5	PE	+	+	+	+	+	+
	C6	HW	+	+	+	+	+	+
	C7	LAND	+	+	+	+	+	+

As for DM preferences concerning the importance of all three objectives, they are expressed here by means of weight intervals specified for each objective. Two settings of weight intervals have been applied, both given in Table 7.

Table 7. DM preferences expressed as weight intervals

	Passage time		Fuel consumption		Risk index		Description
	w^{min}	w^{max}	w^{min}	w^{max}	w^{min}	w^{max}	
Weight setting #1	0.50	0.75	0.75	1.00	0.00	0.25	ship-owner's preferences
Weight setting #2	0.75	1.00	0.75	1.00	0.25	0.50	navigators' preferences

In the first setting, fuel consumption is of the greatest importance, with time being close second and risk index – of least importance. This setting roughly reflects ship-owner's preferences. According to the ship-owner, the minimization of fuel consumption is the main objective, while minimizing risk index is not essential as long as safety related constraints are met. The second weight intervals setting reflects navigators' preferences. Here, time is of comparable importance to fuel consumption and the importance of risk index is considerably larger than in the first setting. This may be attributed to the fact that navigators prefer to arrive earlier at harbors (for multiple practical reasons) and they are also more interested in avoiding various harsh weather-related issues and discomforts (which grow with the rising risk index).

Table 8. Key evolutionary settings assumed in the simulation run

Parameter name	Value
Generation number	50
Weight steps	8
Neighborhood size	8
Large pool factor	2

Once all those values were decided, we have run the simulations for all the scenarios (voyage start times and endpoints) from Table 5, constraint settings from Table 6, the two weight interval settings from Table 7 and evolutionary settings from Table 8. Then we have compared the results with m/v Monte da Guia's actual GPS routes in terms of objectives' values.

Weather conditions forecast by Global Ensemble Forecast System (GEFS) model provided by National Oceanic and Atmospheric Administration (NOAA) have been used for route plans evaluation. Elements of the GEFS model utilized here are:

- ensemble forecast of significant wave height (30 members + 1 control set, in meters),
- mean wave period (in seconds),
- wave direction (in true degrees),
- wind speed (in m/s) and direction (in true degrees).

In order to facilitate reviewing the weather conditions for assumed scenarios, we have created and added as Supplementary Multimedia Data animation files (MP4) showing significant wave height (the control set) and wind speed for the scenarios and considered region.

Details of the simulation results for the six scenarios are provided in the following section.

6.2 Simulation results – constraint set adjusted for the GPS routes

Here we present results obtained by the proposed WR method for all the six scenarios. To offer a direct comparison, we have adjusted the constraint set. Namely, in Scenario 4 we have omitted a constraint which was not met there by GPS route (as listed in Table 6 from Section 6.1). As can be seen in the following subsections, all the route plans obtained by the proposed WR method w-dominate the GPS routes in every considered scenario.

6.2.1 Scenario 1: Leixoes → Praia da Vitória, 14th January 2022

Weather conditions forecast for the considered passage from Leixoes (Portuguese coast) to Praia da Vitória (the Azores) were mainly favorable in terms of wind and waves. In general, gentle breeze was forecast with temporary moderate gale coming from the Azores to the south and then returning into the north. The waves were small (around 2m), temporarily rising up to 4.5m (which is far below the assumed threshold of 7m).

The m/v Monte da Guia GPS route (depicted in green in Figure 7 and 8) in this scenario is almost straight rhumb line segment. By contrast, the WR system route plans (marked in black in Figure 7 and 8) for both weight settings (#1 and #2) roughly resemble the Great Circle route, all having visible bypasses of encountered unfavorable conditions during the second part of the voyage. Objectives' values are presented in Tables 9 and 10 (weight setting #1) and Tables 11 and 12 (weight setting #2).

Table 9. Simulation results obtained for scenario 1 weight setting #1

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**57.91**	**53.46**	**0.5898**	-	-	-	-	-	-
Result # 1	57.86	52.37	0.5648	0.05	0.09%	1.09	2.04%	0.0250	4.23%
Result # 2	57.85	52.70	0.5697	0.06	0.10%	0.76	1.42%	0.0202	3.42%
Result # 3	57.55	52.71	0.5761	0.35	0.61%	0.75	1.40%	0.0138	2.33%

Table 10. Simulation results obtained for scenario 1 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**55.9472**	**59.7072**	**3.76**	**52.8522**	**54.0869**	**1.23**
Result # 1	56.4547	59.6625	3.21	51.9059	53.0042	1.10
Result # 2	56.7981	58.9239	2.13	52.1227	53.4426	1.32
Result # 3	56.4056	58.8489	2.44	52.2623	53.2961	1.03

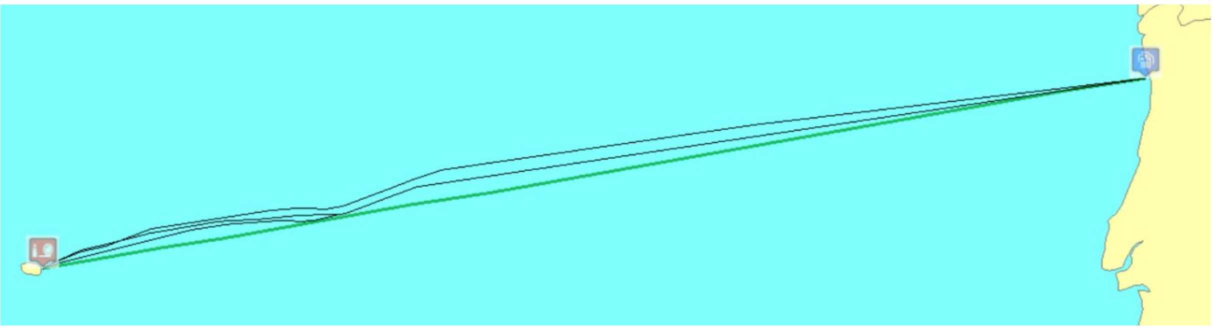

Figure 7. Simulation results obtained for scenario 1 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 11. Simulation results obtained for scenario 1 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)		
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]	fuel consumption [t]	risk index [-]

GPS route	**57.91**	**53.46**	**0.5898**	-	-	-	-	-	-
Result # 1	57.99	52.55	0.5591	-0.09	-0.15%	0.91	1.70%	0.0307	5.21%
Result # 2	57.88	52.50	0.5585	0.03	0.05%	0.95	1.78%	0.0313	5.30%
Result # 3	57.92	52.32	0.5541	-0.01	-0.02%	1.13	2.12%	0.0357	6.05%
Result # 4	58.02	52.64	0.5643	-0.11	-0.19%	0.81	1.52%	0.0255	4.32%
Result # 5	57.78	52.93	0.5700	0.13	0.22%	0.53	0.99%	0.0199	3.37%

Table 12. Simulation results obtained for scenario 1 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	**Passage time [h]**			**Fuel consumption [t]**		
	Min value (over members)	**Max value (over members)**	**Range of values (max – min)**	**Min value (over members)**	**Max value (over members)**	**Range of values (max – min)**
GPS route	**55.9472**	**59.7072**	**3.76**	**52.8522**	**54.0869**	**1.23**
Result # 1	56.7431	59.7194	2.98	51.9471	53.3628	1.42
Result # 2	56.0050	59.5725	3.57	51.9326	53.1305	1.20
Result # 3	56.6669	59.5756	2.91	51.6585	53.0231	1.36
Result # 4	56.3019	59.8111	3.51	52.1210	53.2819	1.16
Result # 5	56.4678	58.8944	2.43	52.3680	53.4689	1.10

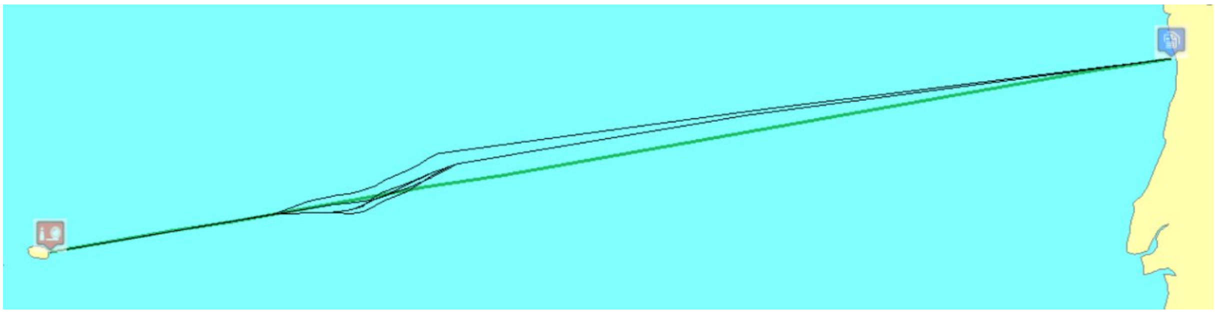

Figure 8. Simulation results obtained for scenario 1 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.2.2 Scenario 2: Ponta Delgada → Lisbon, 21st January 2022

Weather conditions forecast in the second scenario for passage from Ponta Delgada (the Azores) back to Lisbon (Portuguese coast) were calm to moderate. Fresh breeze was dominating around the Azores for the first 15 hours, later replaced by a gentle breeze. Moderate wave height (around 3m) was forecast in the considered water region.

The MdG GPS route (green route in Figure 9 and 10) in this scenario is again a straight rhumb line segment. The WR system route plans (black ones in Figure 9 and 10) for both weight settings (#1 and #2) are closer to the Great Circle route, with visible flattening towards the rhumb line to avoid constraint violations near the destination port. Numerical results are presented in Tables 13 and 14 (weight setting #1) and Tables 15 and 16 (weight setting #2).

Table 13. Simulation results obtained for scenario 2 weight setting #1

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**51.75**	**46.63**	**0.5913**	-	-	-	-	-	-
Result # 1	51.37	46.57	0.6073	0.38	0.74%	0.06	0.13%	-0.0160	-2.70%

Table 14. Simulation results obtained for scenario 2 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**50.4681**	**53.0628**	**2.59**	**46.5124**	**46.7651**	**0.25**
Result # 1	50.3939	53.0150	2.62	46.4985	46.7026	0.20

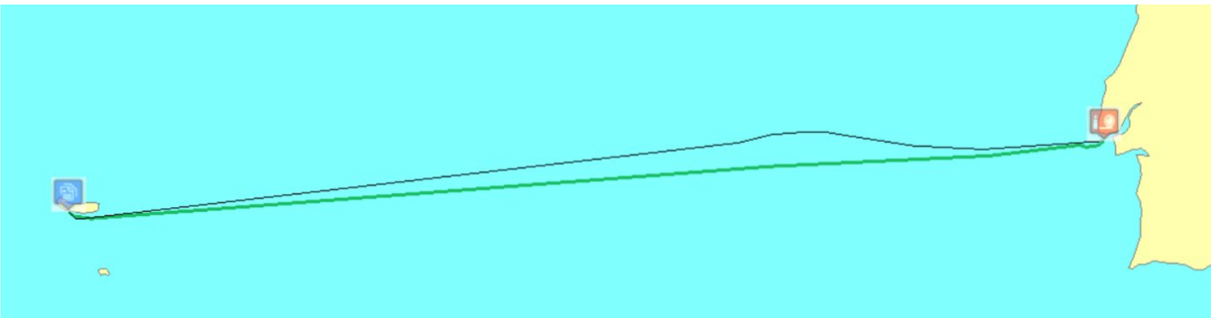

Figure 9. Simulation results obtained for scenario 2 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 15. Simulation results obtained for scenario 2 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**51.75**	**46.63**	**0.5913**	-	-	-	-	-	-
Result # 1	51.30	46.52	0.6038	0.46	0.88%	0.11	0.23%	-0.0125	-2.11%
Result # 2	51.38	46.58	0.6022	0.37	0.71%	0.05	0.10%	-0.0109	-1.85%

Table 16. Simulation results obtained for scenario 2 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**50.4681**	**53.0628**	**2.59**	**46.5124**	**46.7651**	**0.25**
Result # 1	50.1953	53.0350	2.84	46.4187	46.6466	0.23
Result # 2	50.3411	53.6008	3.26	46.4765	46.7057	0.23

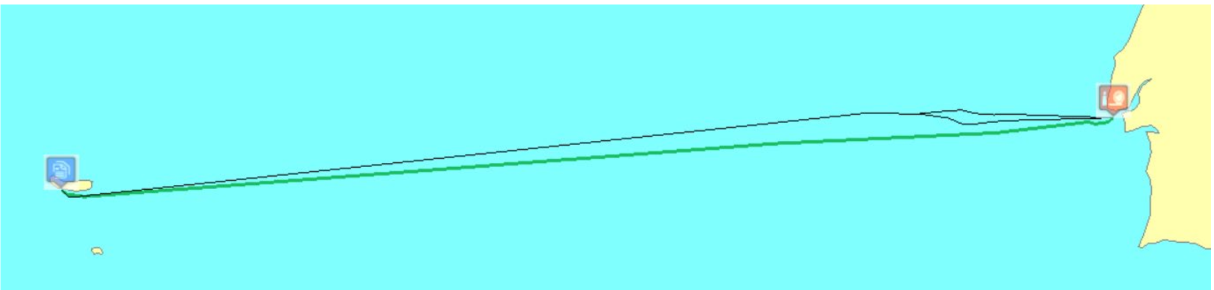

Figure 10. Simulation results obtained for scenario 2 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.2.3 Scenario 3: Leixoes → Praia da Vitória, 28th January 2022

In the third scenario for passage from Leixoes (Portuguese coast) to Praia da Vitória (the Azores) forecast weather conditions were moderate. Fresh breeze was dominating over the majority of the rhumb line segment (between departure and destination ports) for the entire considered time-span. Similarly to the scenario 2, moderate wave height (around 3m) was forecast in the considered region. However, it is worth noticing that m/v Monte da Guia had to sail against the waves for the most of her voyage, which heavily affected her speed.

The MdG GPS route (green route in Figure 11 and 12) in the third scenario is, as before, a straight rhumb line segment. The WR system route plans (black ones in Figure 11 and 12) for both weight settings (#1 and #2) are similar, with a turn to the south from the beginning and rapid maneuvering back to the track resembling the Great Circle during the second part of the voyage. Objectives' values are provided in Tables 17 and 18 (weight setting #1) and Tables 19 and 20 (weight setting #2).

Table 17. Simulation results obtained for scenario 3 weight setting #1

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)		
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]	fuel consumption [t]	risk index [-]

GPS route	**67.90**	**56.02**	**0.2848**	-	-	-	-	-	-
Result # 1	71.20	53.26	0.2694	-3.30	-4.86%	2.76	4.93%	0.0154	5.39%
Result # 2	73.00	50.58	0.2281	-5.09	-7.50%	5.43	9.70%	0.0567	19.91%
Result # 3	70.10	52.21	0.2590	-2.20	-3.24%	3.80	6.79%	0.0258	9.06%
Result # 4	71.60	52.61	0.2470	-3.70	-5.44%	3.41	6.09%	0.0377	13.25%

Table 18. Simulation results obtained for scenario 3 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**64.3969**	**71.0725**	**6.68**	**55.1289**	**56.9850**	**1.86**
Result # 1	69.9411	72.7739	2.83	52.5821	54.4638	1.88
Result # 2	69.4081	75.6056	6.20	49.4873	51.3420	1.85
Result # 3	68.4667	73.2164	4.75	51.4180	52.7988	1.38
Result # 4	68.1897	74.1456	5.96	51.5142	53.5610	2.05

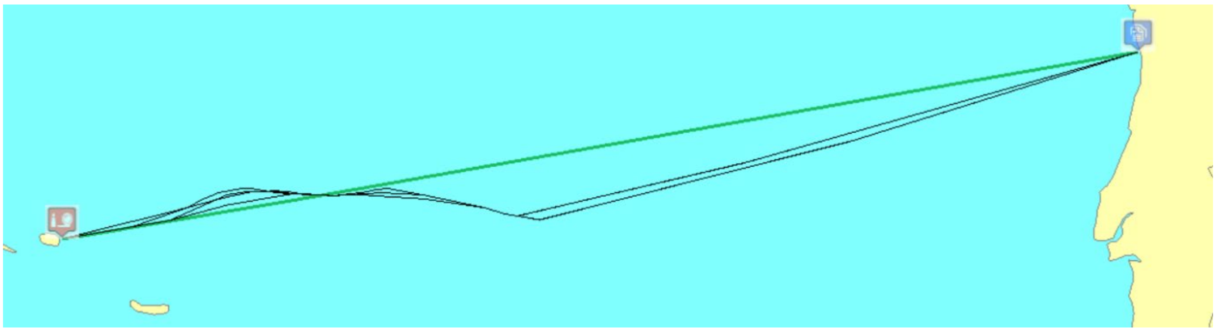

Figure 11. Simulation results obtained for scenario 3 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 19. Simulation results obtained for scenario 3 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**67.90**	**56.02**	**0.2848**	-	-	-	-	-	-
Result # 1	70.81	51.34	0.2491	-2.91	-4.29%	4.68	8.35%	0.0357	12.53%
Result # 2	70.97	52.41	0.2275	-3.07	-4.52%	3.61	6.44%	0.0572	20.10%
Result # 3	71.14	51.81	0.2207	-3.24	-4.77%	4.20	7.50%	0.0641	22.50%
Result # 4	70.44	52.49	0.2845	-2.54	-3.74%	3.53	6.30%	0.0003	0.10%

Table 20. Simulation results obtained for scenario 3 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**64.3969**	**71.0725**	**6.68**	**55.1289**	**56.9850**	**1.86**
Result # 1	68.7681	72.7592	3.99	50.8998	51.9112	1.01
Result # 2	68.7739	72.7653	3.99	51.8536	52.9627	1.11
Result # 3	69.3625	72.8444	3.48	50.9579	52.4471	1.49
Result # 4	68.0447	72.1931	4.15	52.2467	52.8295	0.58

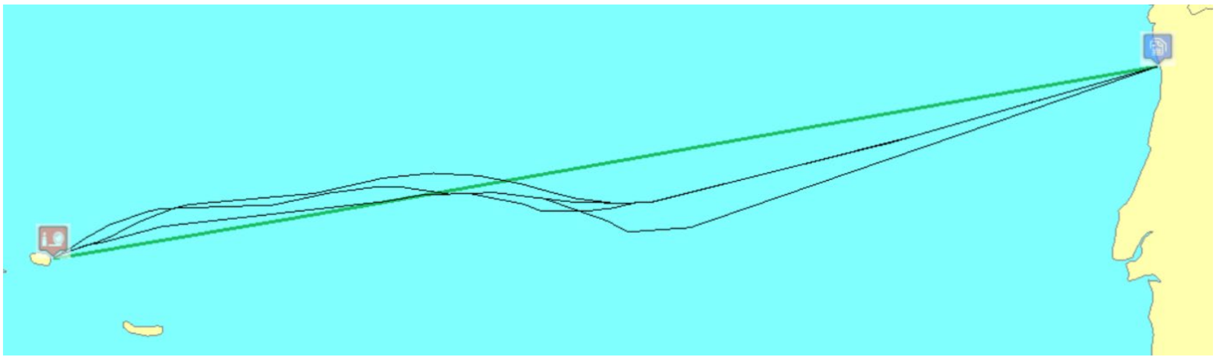

Figure 12. Simulation results obtained for scenario 3 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.2.4 Scenario 4: Ponta Delgada → Lisbon, 4th February 2022

In the fourth scenario for passage from Ponta Delgada (the Azores) back to Lisbon (Portuguese coast) forecast weather conditions were again moderate. A fresh or occasionally strong breezes were dominating the rhumb line segment between departure and destination ports for the entire considered time-span. Similarly to the previous scenarios, moderate wave heights (around 3m) were forecast with upcoming high waves (up to 4.5m) from north of Lisbon near the end of the voyage.

Despite slightly worse conditions in this scenario, the MdG GPS route (green route in Figure 13 and 14) is again very close to the straight rhumb line segment. The WR system routes plans (black ones in Figure 13 and 14) for both weight settings (#1 and #2) slightly turn to the north and are closer to the Great Circle, as long as the weather makes it possible. Objectives' values are given in Tables 21 and 22 (weight setting #1) and Tables 23 and 24 (weight setting #2).

Table 21. Simulation results obtained for scenario 4 weight setting #1

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**53.70**	**49.66**	**0.7434**	-	-	-	-	-	-
Result # 1	54.18	49.16	0.7255	-0.49	-0.91%	0.50	1.00%	0.0179	2.41%
Result # 2	52.76	49.14	0.7294	0.93	1.74%	0.52	1.05%	0.0140	1.89%
Result # 3	53.33	49.23	0.7224	0.37	0.68%	0.43	0.87%	0.0210	2.83%

Table 22. Simulation results obtained for scenario 4 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**48.2306**	**56.4156**	**8.19**	**49.0536**	**51.2575**	**2.20**
Result # 1	51.0700	57.2719	6.20	48.7706	50.0600	1.29
Result # 2	50.2778	55.2444	4.97	48.7305	49.8698	1.14
Result # 3	50.4683	56.6769	6.21	48.8191	50.0166	1.20

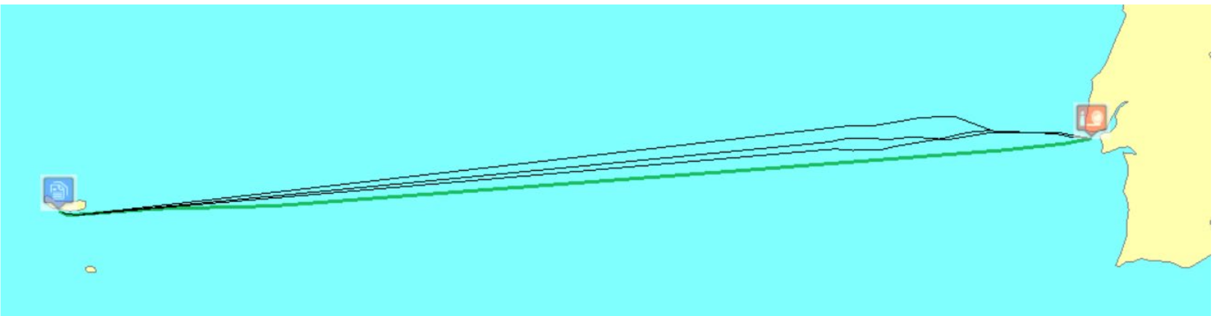

Figure 13. Simulation results obtained for scenario 4 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 23. Simulation results obtained for scenario 4 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**53.70**	**49.66**	**0.7434**	-	-	-	-	-	-

Result # 1	53.57	49.48	0.7443	0.13	0.24%	0.18	0.36%	-0.0009	-0.12%

Table 24. Simulation results obtained for scenario 4 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	**Passage time [h]**			**Fuel consumption [t]**		
	Min value (over members)	**Max value (over members)**	**Range of values (max – min)**	**Min value (over members)**	**Max value (over members)**	**Range of values (max – min)**
GPS route	**48.2306**	**56.4156**	**8.19**	**49.0536**	**51.2575**	**2.20**
Result # 1	51.7689	56.3508	4.58	48.9959	50.3485	1.35

Figure 14. Simulation results obtained for scenario 4 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.2.5 Scenario 5: Leixoes → Praia da Vitória, 11th February 2022

In the fifth scenario for passage from Leixoes (Portuguese coast) to Praia da Vitória (the Azores) forecast weather conditions were calm to moderate. The wind was mostly a moderate breeze with a fresh breeze coming from the north along the rhumb line segment in the middle of the considered time-span. Wave height was forecast as small (around 2m, up to 2.5m).

Unlike in the previous scenarios, the MdG GPS route (green route in Figure 15 and 16) in this scenario has a southern bypass from the rhumb line segment in the second part of the voyage. The WR system route plans (black ones in Figure 15 and 16) for both weight settings (#1 and #2) keep close to the rhumb line with only occasional (and much slighter than the GPS route) turns to the north (towards the Great Circle route). Numerical results are gathered in Tables 25 and 26 (weight setting #1) and Tables 27 and 28 (weight setting #2).

Table 25. Simulation results obtained for scenario 5 weight setting #1

Name	**Aggregated objective value**			**Progress of result's aggregated objective value (compared to the GPS route)**					
	passage time [h]	**fuel consumption [t]**	**risk index [-]**	**passage time [h]**		**fuel consumption [t]**		**risk index [-]**	
GPS route	**58.16**	**52.22**	**0.6206**	-	-	-	-	-	-
Result # 1	57.96	51.76	0.6496	0.20	0.35%	0.46	0.87%	-0.0289	-4.66%
Result # 2	57.36	51.54	0.6362	0.80	1.38%	0.68	1.30%	-0.0156	-2.51%

Result # 3	57.80	51.64	0.6437	0.36	0.62%	0.58	1.11%	-0.0231	-3.72%
Result # 4	57.28	51.53	0.6365	0.88	1.52%	0.69	1.33%	-0.0159	-2.56%

Table 26. Simulation results obtained for scenario 5 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**56.7264**	**59.9100**	**3.18**	**51.8175**	**52.5516**	**0.73**
Result # 1	56.6986	60.2175	3.52	51.4058	52.0479	0.64
Result # 2	55.6642	58.9942	3.33	51.3351	51.7546	0.42
Result # 3	56.3711	59.2831	2.91	51.2635	51.9671	0.70
Result # 4	55.5906	58.5978	3.01	51.2489	51.8358	0.59

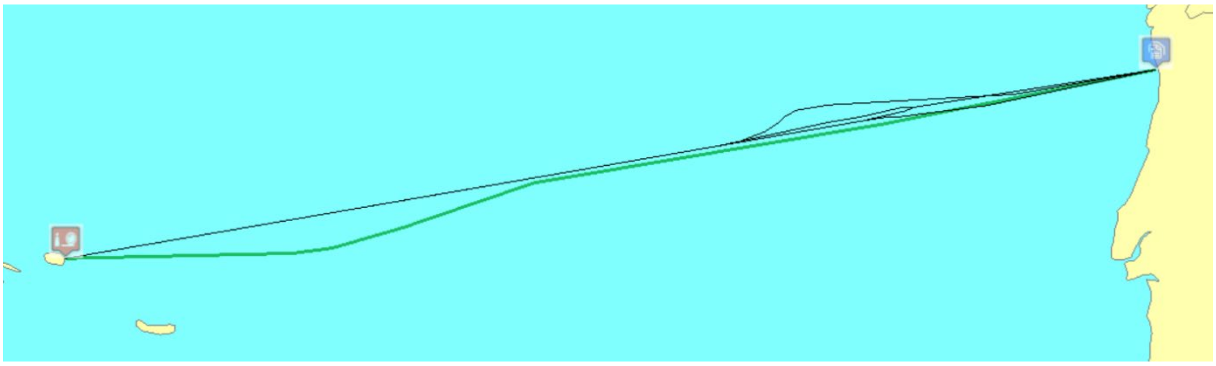

Figure 15. Simulation results obtained for scenario 5 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 27. Simulation results obtained for scenario 5 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**58.16**	**52.22**	**0.6206**	-	-	-	-	-	-
Result # 1	57.69	51.79	0.6370	0.47	0.80%	0.43	0.83%	-0.0164	-2.64%

Table 28. Simulation results obtained for scenario 5 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]	Fuel consumption [t]

	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**56.7264**	**59.9100**	**3.18**	**51.8175**	**52.5516**	**0.73**
Result # 1	56.3819	59.1419	2.76	51.5594	52.0146	0.46

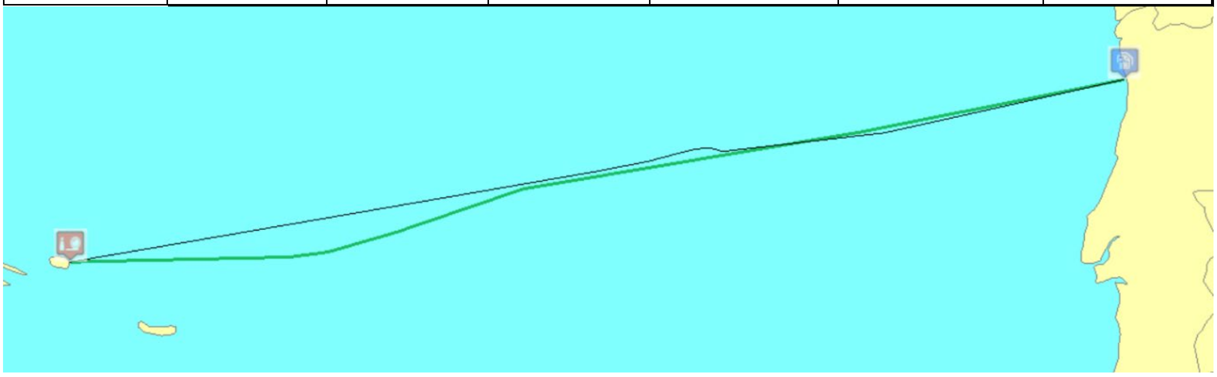

Figure 16. Simulation results obtained for scenario 5 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.2.6 Scenario 6: Ponta Delgada → Lisbon, 18th February 2022

In the sixth scenario for passage from Ponta Delgada (the Azores) back to Lisbon (Portuguese coast) forecast weather conditions were the hardest of all considered scenarios. Moderate to full gale (8 on the Beaufort scale) was forecast in the considered area and time-span. Waves were forecast mostly as large (around 5m) and occasionally rising above the assumed safety threshold (set up as 7m).

Despite the weather, the MdG GPS route (green route in Figure 17 and 18) in this scenario has only a minor northern bypass from the rhumb line segment in the middle of the voyage. The WR system route plans (black ones in Figure 17 and 18) for both weight settings (#1 and #2) also keep close to the rhumb line with a few very slight turns. As for objectives' values, they are presented in Tables 29 and 30 (weight setting #1) and Tables 31 and 32 (weight setting #2).

Table 29. Simulation results obtained for scenario 6 weight setting #1

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**52.14**	**47.02**	**0.8793**	-	-	-	-	-	-
Result # 1	50.99	47.05	0.8815	1.15	2.21%	-0.03	-0.06%	-0.0021	-0.24%

Table 30. Simulation results obtained for scenario 6 weight setting #1 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]	Fuel consumption [t]

	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**50.6625**	**53.4850**	**2.82**	**46.8400**	**47.1705**	**0.33**
Result # 1	49.7708	52.5722	2.80	46.8570	47.2108	0.35

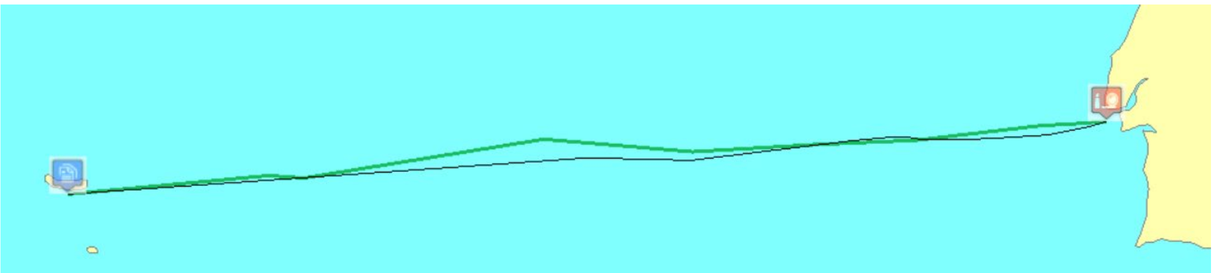

Figure 17. Simulation results obtained for scenario 6 weight setting #1 (the GPS route in green, proposed WR system route plans in black)

Table 31. Simulation results obtained for scenario 6 weight setting #2

Name	Aggregated objective value			Progress of result's aggregated objective value (compared to the GPS route)					
	passage time [h]	fuel consumption [t]	risk index [-]	passage time [h]		fuel consumption [t]		risk index [-]	
GPS route	**52.14**	**47.02**	**0.8793**	-	-	-	-	-	-
Result # 1	52.15	47.01	0.8786	-0.01	-0.02%	0.01	0.01%	0.0007	0.09%

Table 32. Simulation results obtained for scenario 6 weight setting #2 (min and max values of passage time and fuel consumption over members of the significant wave height ensemble forecast)

Name	Passage time [h]			Fuel consumption [t]		
	Min value (over members)	Max value (over members)	Range of values (max – min)	Min value (over members)	Max value (over members)	Range of values (max – min)
GPS route	**50.6625**	**53.4850**	**2.82**	**46.8400**	**47.1705**	**0.33**
Result # 1	51.2358	53.0547	1.82	46.8320	47.1559	0.32

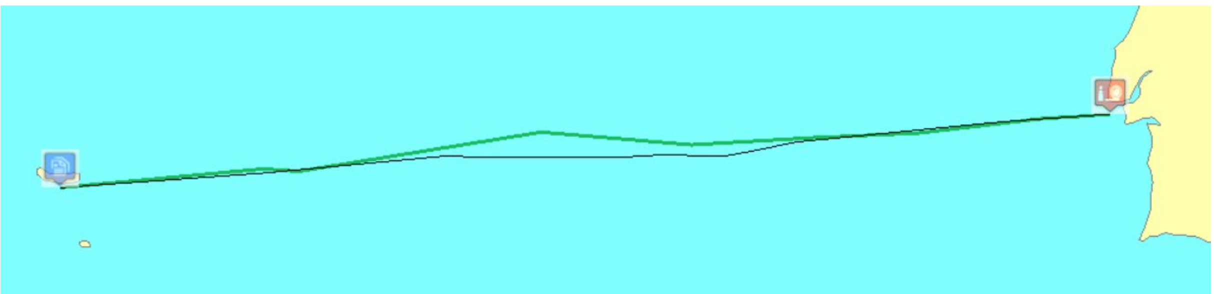

Figure 18. Simulation results obtained for scenario 6 weight setting #2 (the GPS route in green, proposed WR system route plans in black)

6.3 Results discussion

In total, the six considered scenarios (listed in Table 5) and two weight interval settings (given in Table 7), produced twelve different test cases presented in Table 33.

Table 33. Test cases presented in Section 6.2

Test case no.	Scenario no. (ref. Table 1)	Departure	Destination	Departure date	Weight interval setting (ref. Table 3)
1	1	Leixoes	Praia da Vitória	14th Jan 2022	Weight setting #1 (ship owner's preferences)
2		Leixoes	Praia da Vitória	14th Jan 2022	Weight setting #2 (navigator's preferences)
3	2	Ponta Delgada	Lisbon	21st Jan 2022	Weight setting #1 (ship owner's preferences)
4		Ponta Delgada	Lisbon	21st Jan 2022	Weight setting #2 (navigator's preferences)
5	3	Leixoes	Praia da Vitória	28th Jan 2022	Weight setting #1 (ship owner's preferences)
6		Leixoes	Praia da Vitória	28th Jan 2022	Weight setting #2 (navigator's preferences)
7	4	Ponta Delgada	Lisbon	4th Feb 2022	Weight setting #1 (ship owner's preferences)
8		Ponta Delgada	Lisbon	4th Feb 2022	Weight setting #2 (navigator's preferences)
9	5	Leixoes	Praia da Vitória	11th Feb 2022	Weight setting #1 (ship owner's preferences)
10		Leixoes	Praia da Vitória	11th Feb 2022	Weight setting #2 (navigator's preferences)
11	6	Ponta Delgada	Lisbon	18th Feb 2022	Weight setting #1 (ship owner's preferences)
12		Ponta Delgada	Lisbon	18th Feb 2022	Weight setting #2 (navigator's preferences)

All the six scenarios were based on three consecutive voyage cycles of the m/v Monte da Guia (ref. Figure 6) from Portuguese cost to the Azores (scenario 1, 3 and 5) and back (scenario 2, 4 and 6) during January and February 2022. Both WR system route plans and reference GPS routes were evaluated using the same ship model and weather conditions valid for given scenario, thus the results obtained by our WR solution are easily comparable with the reference routes. It is worth emphasizing that the GPS routes were not included in any way in the initial population of the evolutionary process of the WR system (details of the evolutionary process have been provided in Section 4.4).

Typical problem of having vast non-dominated set as a result of Pareto optimization was here reduced by applying w-dominance. Namely, in the considered six scenarios and for two weight settings the number of route plans returned by our WR system varies between 1 and 5, as presented in Table 34. The sets with a single solution were found for the most demanding (from the optimization point of view) cases. In scenario 6 where the weather conditions were rough, single solution were found for both weight settings (test cases #11 & #12). Similarly, single solution was also found for:

- scenario 2 and weight setting #1 (test case #3),
- scenario 4 and weight setting #2 (test case #8),
- scenario 5 and weight setting #2 (test case #10).

In all the other cases WR system offered a limited number of non-w-dominated route plans, whose objectives' values varied, but were still within the limits of acceptable gain/loss rates defined by the assumed weight interval settings.

Table 34. Number of route plans returned by WR system for test cases presented in Section 6.2

Test case no.	Scenario no. (ref. Table 1)	Departure	Destination	Departure date	Number of route plans returned by WR system
1	1	Leixoes	Praia da Vitória	14th Jan 2022	3
2		Leixoes	Praia da Vitória	14th Jan 2022	5
3	2	Ponta Delgada	Lisbon	21st Jan 2022	1
4		Ponta Delgada	Lisbon	21st Jan 2022	2
5	3	Leixoes	Praia da Vitória	28th Jan 2022	4
6		Leixoes	Praia da Vitória	28th Jan 2022	4
7	4	Ponta Delgada	Lisbon	4th Feb 2022	3
8		Ponta Delgada	Lisbon	4th Feb 2022	1
9	5	Leixoes	Praia da Vitória	11th Feb 2022	4
10		Leixoes	Praia da Vitória	11th Feb 2022	1
11	6	Ponta Delgada	Lisbon	18th Feb 2022	1
12		Ponta Delgada	Lisbon	18th Feb 2022	1

In **scenario 1**, weight setting #1 (test case #1) the WR system-returned set includes 3 route plans, which not only w-dominate but also Pareto-dominate the GPS route (gain in all three objectives' values simultaneously, as shown by positive values in "Progress of result's aggregated objective value" in Table 9). In this case the highest improvements are: 0.6% for passage time, 2% for fuel consumption and over 4% for the risk index. In scenario 1, weight setting # 2 (test case #2) the returned set includes 5 route plans. This time (Table 11) two route plans (Result #2 and Result #5) fully Pareto-dominate the GPS route, the other three results w-dominate the reference route, offering the highest improvements for passage time of 0.22%, over 2% for fuel consumption and more than 6% for risk index.

In **scenario 2** for both weight settings the route plans returned by WR system w-dominate the reference route. For weight setting #1 (test case #3) there is a single WR route plan (Table 13) offering gain of 0.74% for passage time and 0.13% for fuel consumption at the cost of increase in the least important objective for this setting – risk index (by 2.7%). Larger gains in passage time and fuel are offered for weight setting #2 (test case #4). The two-element WR result set (Table 15) shows 0.88% and 0.23% gains in time and fuel, respectively, at the cost of risk index increased by 2.11%.

Due to weather conditions forecast for **scenario 3** the WR system route plans, in comparison to the GPS route, were able to offer a reduction of fuel consumption and significant improvement in voyage safety for both weight settings (test case #5 in Table 17 and test case #6 - Table 19). These profits come at the cost of slight increase in passage time. Fuel consumption decreased by 4.9 – 9.7% (weight setting #1, test case #5) and 6.3 – 8.3 % (weight setting #2, test case #6). Even greater gains were obtained for risk index for both weight settings - up to 19.9% and 22.5%, respectively. Passage time increased by 3.2 – 7.5% for the first weight (test case #5) setting and 3.7 – 4.8% for the second one (test case #6).

In **scenario 4** WR system route plans Pareto-dominated GPS one. For weight setting #1 (test case #7) two out of three WR route plans (Table 21) offered progress for all the three objectives. The third WR result (Result #1 in Table 21) w-dominates the GPS route, gaining 1% for fuel and 2.4% for the risk index while having longer passage time by 0.9%. For weight setting #2 in this scenario (test case #8) it was tougher to compete with the reference GPS route. Here the single WR route plan (Table 23) w-dominates the GPS route with subtle gains in time & fuel and marginal loss in terms of risk.

All route plans returned by WR system for **scenario 5** w-dominate the GPS route by decreasing passage time and fuel at the cost of slight increase in the risk index. Namely, for weight setting #1 (test case #9) gains are (Table 25) up to 1.52% for time and up to 1.33% for fuel. The loss in risk index varies from 2.51 to 4.66%. Clearly, the reason why w-dominance still occurs (despite increase in risk index) is that this weight setting puts emphasis on time and fuel spent on the voyage. In case of weight setting #2 (test case #10) gains in time and fuel (Table 27) can still be observed, but are smaller, as is the increase in risk index (by 2.6%).

Scenario 6 was the most difficult due to unfavorable weather conditions severely reducing the search space: constraint violations during evolution occurred more frequently than in other scenarios. What is more, in this circumstances the GPS route scored very highly. Despite these facts, our WR system route plans w-dominated the GPS route for both weight settings. For weight setting #1 (test case #11) the route plan returned by WR system (Table 29) gains 2.2% in passage time while losing only slightly in fuel and risk index (0.06% and 0.24%, respectively). For weight setting #2 (test case #12) the WR system route plan (Table 31) subtly gains in fuel and risk index at the cost of insignificant increase in passage time.

Table 35. Aggregated objective function values for the GPS routes and the route plans returned by WR system for voyages **from the Portuguese cost to the Azores: Leixoes → Praia da Vitória** (scenarios 1, 3 and 5)

Scenario no.	**Test case no.**	**Name**	**Aggregated objective value**		
			passage time [h]	**fuel consumption [t]**	**risk index [-]**
Scenario 1	NA	**GPS route**	**57.91**	**53.46**	**0.5898**
	#1	Result # 1	57.86	52.37	0.5648
		Result # 2	57.85	52.70	0.5697
		Result # 3	57.55	52.71	0.5761
	#2	Result # 1	57.99	52.55	0.5591
		Result # 2	57.88	52.50	0.5585
		Result # 3	57.92	52.32	0.5541
		Result # 4	58.02	52.64	0.5643
		Result # 5	57.78	52.93	0.5700
Scenario 3	NA	**GPS route**	**67.90**	**56.02**	**0.2848**
	#1	Result # 1	71.20	53.26	0.2694
		Result # 2	73.00	50.58	0.2281
		Result # 3	70.10	52.21	0.2590
		Result # 4	71.60	52.61	0.2470
	#2	Result # 1	70.81	51.34	0.2491
		Result # 2	70.97	52.41	0.2275
		Result # 3	71.14	51.81	0.2207
		Result # 4	70.44	52.49	0.2845
Scenario 5	NA	**GPS route**	**58.16**	**52.22**	**0.6206**
	#1	Result # 1	57.96	51.76	0.6496
		Result # 2	57.36	51.54	0.6362
		Result # 3	57.80	51.64	0.6437

		Result # 4	57.28	51.53	0.6365
	#2	Result # 1	57.69	51.79	0.6370

Overall, the values of objective functions for passage time and fuel consumption obtained by both the GPS routes and route plans retuned by our WR solution are similar but vary depending on weather conditions forecast for particular scenario and the voyage direction:

- from the Portuguese cost to the Azores: Leixoes → Praia da Vitória (the GPS routes and the route plans returned by WR system for the scenarios 1, 3 and 5 are gathered in Table 35),
- from the Azores to the Portuguese cost: Ponta Delgada → Lisbon (the GPS routes and the route plans returned by WR system for the scenarios 2, 4 and 6 are gathered in Table 36).

Table 36. Aggregated objective function values for the GPS routes and route plans returned by WR system for voyages **from the Azores to the Portuguese cost: Ponta Delgada → Lisbon** (scenarios 2, 4 and 6)

Scenario no.	**Test case no.**	**Name**	**Aggregated objective value**		
			passage time [h]	**fuel consumption [t]**	**risk index [-]**
Scenario 2	NA	**GPS route**	**51.75**	**46.63**	**0.5913**
	#1	Result # 1	51.37	46.57	0.6073
	#2	Result # 1	51.30	46.52	0.6038
		Result # 2	51.38	46.58	0.6022
Scenario 4	NA	**GPS route**	**53.70**	**49.66**	**0.7434**
	#1	Result # 1	54.18	49.16	0.7255
		Result # 2	52.76	49.14	0.7294
		Result # 3	53.33	49.23	0.7224
	#2	Result # 1	53.57	49.48	0.7443
Scenario 6	NA	**GPS route**	**52.14**	**47.02**	**0.8793**
	#1	Result # 1	50.99	47.05	0.8815
	#2	Result # 1	52.15	47.01	0.8786

Scenario 3 clearly stands out of the comparison: GPS route passage time is about 17% longer than the GPS route average over scenarios 1 and 5; fuel consumption is also increased, but to a lesser extent. Similar tendency (longer passage times and larger fuel consumption) can be observed for system-returned route plans. At the same time, risk index is significantly lower. All of this can be attributed to very specific weather conditions: the vessel navigates against the waves, which results in a lower speed but does not pose a threat for ship's stability.

Tables 35 & 36 also reveal also that voyages from the Azores to the Portuguese coast (scenarios 2, 4 & 6) are less time (and consequently fuel) expensive than the ones in the other direction (scenarios 1, 3 & 5). The objective function for risk index is much more dependent on temporary weather conditions *en route*, obviously. That is why the risk index values are not directly comparable between the groups of scenarios to and from the Azores.

To sum up, for all 12 test cases (as listed in Table 33) our WR solution was able to find route plans that at least w-dominate the reference GPS route and occasionally – route plans that Pareto-dominate the reference ones. Gains in particular objectives varied over all cases, which can probably be attributed to varying quality of reference GPS routes determined by navigators.

Abovementioned results are based on the aggregated objectives' values (Figure 2). However, due to uncertain nature of the modelled environment, all the underlying computations are performed on members of ensemble forecast concerning significant wave height. That is why for the average-based objectives (i.e. passage time and fuel consumption) an objective value per each member is computed. Thus, in each scenario and weight settings we get an underlying vector of passage time and fuel consumption values, computed for weather conditions forecast for each ensemble member separately. Minimum and maximum values of those vectors (as well as "max – min" ranges) have been presented for:

- Scenario 1 – in Table 10 (weight settings #1, test case # 1) and Table 12 (weight settings #2, test case # 2),
- Scenario 2 – in Table 14 (weight settings #1, test case # 3) and Table 16 (weight settings #2, test case # 4),
- Scenario 3 – in Table 18 (weight settings #1, test case # 5) and Table 20 (weight settings #2, test case # 6),
- Scenario 4 – in Table 22 (weight settings #1, test case # 7) and Table 24 (weight settings #2, test case # 8),
- Scenario 5 – in Table 26 (weight settings #1, test case # 9) and Table 28 (weight settings #2, test case # 10),
- Scenario 6 – in Table 30 (weight settings #1, test case # 11) and Table 32 (weight settings #2, test case # 12).

The narrower the "max – min" ranges are, the smaller is the uncertainty associated with weather-dependant performance of a vessel sailing along a given route. Results gathered in the abovementioned tables reveal that in 5 out of 12 cases, namely test cases # 6, # 7, #8, # 10 and # 12, WR system was able to find results with lower "max – min" range values for both considered objectives (when compared to GPS routes). Especially in test case # 8 (Scenario 4 weights #2) the range values are significantly lower than those obtained for a GPS route. In the remaining seven cases WR system results are at least comparable with the reference GPS routes, usually offering narrower ranges for one objective and mixed results for the other. This indicates that the superior average objectives' values discussed before are accompanied with a lower uncertainty level, which should make WR system route plans even more attractive for navigators and ship owners alike.

7 SUMMARY AND CONCLUSIONS

Weather routing's purpose is searching for an optimal ship voyage plan with regard to forecast weather conditions. It is a multi-objective optimization problem with both static and dynamic constraints and a numerous set of decision variables (including coordinates of successive waypoints). It becomes even more complexed when uncertain nature of weather forecasts is considered. Thus, a method is needed, which would handle efficiently these objectives and constraints as well as take into account the uncertainty of weather conditions *en route*. The paper presents a solution to the abovementioned problem. It combines w-dominance-enhanced multi-objective optimization with problem-tailored uncertainty handling. An advantage of w-dominance is making the evolutionary process focused on the part of objectives' space, which is of most interest to DM. When combined with proposed problem-dedicated operators and uncertainty handling routines, it allows for reduction in computational time and DM-specified balance between objectives while ensuring that even in the worst-case weather scenario the safety-related constraints will still be met.

To model the environmental uncertainties in this research we utilized ensemble forecasts of wave height of Global Ensemble Forecast System (GEFS) model provided by National Oceanic and Atmospheric Administration (NOAA). The model offers wide set of members (30 perturbed members and 1 control set) allowing to consider diversified variants of weather condition developments. Proposed solution was verified with real life GPS route data of m/v Monte da Guia collected at the turn of January and February 2022 during her voyages between Portuguese cost and the Azores. As evidenced by the simulations' results, the proposed method is efficient and robust in finding near-optimal and feasible routes as long as forecast weather conditions make it possible. Furthermore, in terms of objectives' values, the obtained route plans outperform actual routes of m/v Monte da Guia, which were determined by navigators.

Future research on the WR system will head in two directions. Firstly, it will include developing a unified and universal ship model based on machine learning (artificial neural networks) approach. Owing to this our multi-objective WR method with uncertainty handling could be validated and verified for other ships with a possibility of the system's on-board deployment. Secondly, fixed engine settings will be replaced with handling a set of predefined propulsion working points. The latter will add one more dimension to the variable space and thus will result in new optimization challenges and opportunities alike.

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