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Multiobjective Approach to Weather Routing

J. Szlapczynska
Gdynia Maritime University, Gdynia, Poland

ABSTRACT: The paper presents a weather routing solution for sail-assisted ships. Since the route finding optimisation process is a multiobjective one, the emphasis is put on possible application of multiobjective optimisation methods. The paper focuses on two such methods, namely evolutionary algorithms and ranking methods represented by Fuzzy TOPSIS. In addition, a proposed set of optimization criteria is presented. Descriptions of assumed ship and sail models as well as exemplary speed characteristic are also provided. Finally, a proposal of application to a weather routing tool is presented

1 INTRODUCTION

A problem of finding the most suitable vessel route taking into account changeable weather conditions and navigational constraints is referred to as a weather routing optimisation problem. Such a problem is mostly considered for ocean going ships where adverse weather conditions may impact both, often contradictory, economic and security aspects of voyage.

One of the first approaches to the problem was a minimum time route planning based on a weather forecast called an isochrone method. The method was based on geometrically determined and recursively defined time fronts, so called isochrones. Originally proposed by R.W. James (James 1957), isochrone method was in wide use through decades. In late seventies based on the original isochrone method the first computer-aided weather routing tools were developed. However, along with computer implementation some problems arose, i.e. with so called “isochrone loops”. Numerous improvements to the method were proposed since early eighties, with (Hagiwara 1989, Spaans 1986, Wisniewski 1991) among others. Since then several different approaches to the optimisation problem was in use, with dynamic programming or genetic and evolutionary algorithms among others.

Most of recent scientific researches in weather routing focus on shortening the passage time, reducing fuel consumption and avoiding severe weather i.e. tropical cyclones. Nowadays, evolutionary or genetic algorithms are common solutions for weather routing services. However, due to multiobjective nature of weather routing it is recommended to introduce some state-of-the-art multiobjective methods to the process of route finding. It may facilitate the process of reaching a trade-off between often conflicting economic and safety criteria sets. Thus, it is proposed to introduce multiobjective evolutionary algorithms as well as multiobjective ranking methods to the route finding process.

The remainder of the paper is organized as follows: section 2 introduces the basic idea of a single-objected evolutionary algorithm. Section 3 provides detailed description of multiobjective methods applicable to weather routing. The description includes multiobjective evolutionary algorithms (MOEAs) and multiobjective ranking methods represented by Fuzzy TOPSIS. Section 4 presents proposed application of the methods to weather routing. Finally, section 5 summarizes the material presented.

2 THE IDEA OF SINGLE-OBJECTED EVOLUTIONARY ALGORITHMS

Evolutionary algorithms are natural successors of genetic algorithms. The key difference between them is in the chromosome structure. Genetic algorithms assume binary and fixed-length chromosome strings, whereas the evolutionary ones allow more complicated chromosome structures. It implies that original genetic binary operators, namely mutation and crossover, are substituted by evolutionary operators specialized to fit given chromosome structure and the optimisation task. However, the general idea of both genetic and evolutionary algorithms remains the same. At first initial population of individuals is being generated and evaluated. After modifications by operators designed to improve algorithm's convergence some individuals are selected and a new population is generated. The process of evaluation, modification and selection lasts until a termination condition is met.

Single-objected goal function is utilized to evaluate the individuals by means of so called fitness function. The goal function is either equal to the fitness function or at least is an element of the latter. In general: the better the individual in terms of goal function the higher evaluation score it gets. By the evaluation process future modifications and selection is executed mainly for a group of "best fitted" individuals. This way the algorithm converges to a final set being sufficiently close to the optimal solution.

Apart from the goal function, constraints are another important issue in single-objected optimisation process. In the evolutionary framework the constraints are met due to specialized operators assuring that any modified individual remains in the feasible solution space.

3 MULTIOBJECTIVE METHODS APPLICABLE TO WEATHER ROUTING

3.1 *MultiObjective Evolutionary Algorithms (MOEAs)*

MultiObjective Evolutionary Algorithms (MOEAs) have been growing in popularity since its inception in mid-1980s. In general, MOEAs extend the functionality of regular single-objected evolutionary algorithms providing a method of dealing with multiple and often conflicting objectives.

When multiobjective problems are being considered one of the important issues is the problem of ranking the criteria in terms of their importance and impact on final result. It is often designated that a decision maker is a person who makes such a choice. There are three distinctive subgroups of MOEA solutions, differentiated by the way of involving the decision maker:

– "a priori" preference, where the decision maker combines all the objectives into a single scalar function;
– progressive preference, where the decision making and optimization processes alternate;
– "a posteriori" preference, where the resulting set of Pareto-optimal solutions is presented to the decision maker who selects the final solution from the set provided.

This paper is focused entirely on Pareto-based MOEA solutions with "a posteriori" preference. It is caused by the fact that decision-making in the proposal described in the next section is transferred to the multiobjective ranking method.

One should be aware that "MOEA" term refers to some algorithmic framework rather than a specific ready-to-use and universal solution. Thus, already known MOEA techniques should be applied prior to building a problem-oriented multiobjective evolutionary application. Thus, the following subsections describe core set of basic MOEA techniques.

3.1.1 *Secondary population*

Secondary population is an additional population maintained throughout MOEA execution time, collecting all Pareto-optimal solutions found so far during the search process. Its main goal is to preserve all desirable solutions throughout the generation process. In accordance with Pareto notation the secondary population is termed $P_{known}(t)$, where t denotes current generation number. Similarly, a current set of Pareto-optimal solutions determined at the end of each generation with respect to the current MOEA generational population is termed $P_{current}(t)$. It is assumed, though, that $P_{known}(0)$ is an empty set and P_{known} without t annotation stands for the final set of Pareto optimal solutions collected before MOEA termination. Several strategies of secondary population storage exist. The most obvious and commonly used is the strategy of adding $P_{current}(t)$ to $P_{known}(t)$ in the end of each generation t:

$$P_{known}(t) = P_{current}(t) \cup P_{known}(t-1) \tag{1}$$

The set of $P_{known}(t)$ must be periodically checked against obsolete Pareto solutions as Pareto optimality should always be evaluated within current Ω set. The simplest policy does not assume explicit copying $P_{known}(t)$ solutions back into the next population. However, other strategies exist where the secondary population participates in a tournament selecting next generations or is directly inserted into the next mating population.

3.1.2 *Multiobjective ranking*

Multiobjective evolutionary approach enforces that some transformation of the performance vector into a scalar fitness value is necessary. This transformation is achieved by means of a multiobjective ranking, often also referred to as Pareto ranking. In general, there are several ranking methods. All these methods are based on an assumption that preferred Pareto optimal solutions are ranked the same value whereas other solutions are assigned some less desirable rank value.

3.1.3 *Niching and fitness sharing*

The term niching refers to the process of clustering in either solution space or criterion space. In this process clusters consist of groups formed by some individuals selected from the entire population. Niching is primarily aimed at finding and maintaining multiple optima. In result, this technique should assure a good spread of discovered solutions and prevent MOEA algorithm from being swamped by solutions with identical fitness. Fitness sharing is the most popular realization of the niching technique. It is based on an assumption that individuals in a particular niche share available resources. Thus, the more individuals are located in the vicinity of a certain individual, the more its fitness value is deteriorated. The vicinity is most often determined by a distance measure d(i,j) and specified by niche radius σ_{share}. The distance function d(i,j) operates either in solution space or criterion space, resulting in appropriate type of fitness sharing.

3.1.4 *Mating restrictions*

The idea behind restricted mating is to prevent or minimize offsprings, so called lethals, created by recombination of chromosomes from different niches. Such individuals can lead to degradation of MOEA performance. To remedy the problem some restrictions to mating might be introduced providing a distance metric and a maximum distance value σ_{mate} for which mating is still permitted. The most popular solution for mating restriction is to introduce the fitness sharing niche radius σ_{share} into the problem and setting $\sigma_{mate}=\sigma_{share}$. However, it is questioned (Van Veldhuizen 2000) whether such restriction policy is indeed a compulsory MOEA component, especially when there is no quantitative evidence of its benefits.

3.2 *Fuzzy TOPSIS as a multobjective ranking method*

Ranking methods belong to a group of multiobjective optimisation methods where preferences of the decision maker are utilized to build a ranking of alternatives. The ranking is a list of all possible solutions ordered from the least to the most desirable one. Given order is achieved by casting all the objectives into a single-objective goal function. Preferences are reflected by weight values assigned to the original objectives in the aggregated goal function.

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is a multiobjective ranking method proposed by Hwang & Yoon (Hwang et al. 1982). The method is based on a concept that the best alternative among the available alternative set is the closest to the best possible solution and the farthest from the worst possible solution simultaneously. The best possible solution, referred to as an ideal one, is defined as a set of the best attribute values, whereas the worst possible one, referred to as a negative-ideal solution, is a set of the worst attribute values. In order to compare the alternatives and build the output ranking, the Euclidean distances between each alternative and both the ideal and the negative-ideal solutions are calculated. Then the closeness coefficient is determined to measure the two distances simultaneously. Sorting in descending order the coefficient values assigned to the alternatives creates the final TOPSIS ranking. The alternative with the highest ranking value is considered as the most desirable.

Based on the original TOPSIS method, an extension has been proposed by Chu & Lin (Chu et al. 2003) providing support for fuzzy criteria and fuzzy weights both described by triangular fuzzy values. The new method has already been applied to navigational problems in (Szlapczynska 2005).

Detailed Fuzzy TOPSIS algorithm differs from standard TOPSIS one in the following:

- each criterion can be either crisp or fuzzy, the latter means that the criterion is described by a linguistic variable with triangle fuzzy values;
- weight vector is described by a set of triangle fuzzy values assigned from another linguistic variable;
- decision matrix is converted to a fuzzy decision matrix;
- scaled V matrix is a result of multiplication of fuzzy weight vector and fuzzy decision matrix;
- in order to determine ideal and negative-ideal solutions first the scaled V matrix is defuzzified,

then the standard TOPSIS computations are continued.

As a result, similarly to original TOPSIS, final Fuzzy TOPSIS ranking consists of crisp values. The alternative with the highest ranking value is considered as the most desirable.

4 WEATHER ROUTING FOR SAIL-ASSISTED SHIPS AS A MULTIOBJECTIVE OPTIMISATION PROBLEM

4.1 *Model assumed*

For a sail-assisted ship separate ship and sail models are assumed. Ship model is based on a B-470 bulk carrier. Its basic parameters are shown in Table 1.

Table 1. Basic parameters of the ship model

Parameter name	Value
Length	172 m
Width	22.8 m
Draught	9.5 m
Height	14.3 m
Service speed	15 kn
Displacement	30,288 t

Sail model presented in Figure 1 is based on textile winds from “Oceania” ship. There are six sails forming a palisade. Each sail has 522m^2 sail surface area.

For given ship and sail models, the speed characteristic is determined based on algorithm by Oleksiewicz (Oleksiewicz in prep.). An exemplary speed characteristic for starboard tack is presented in Figure 2.

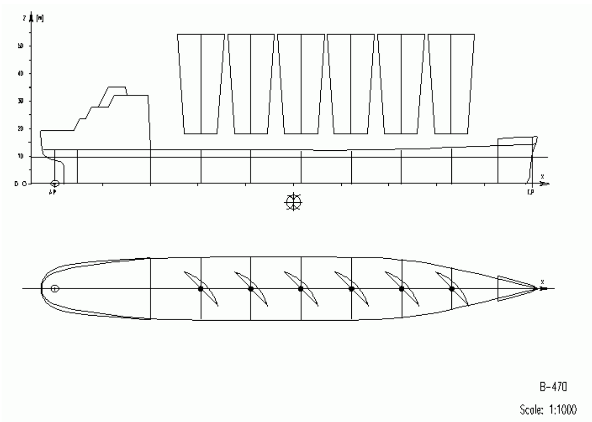

Fig. 1. Sail model

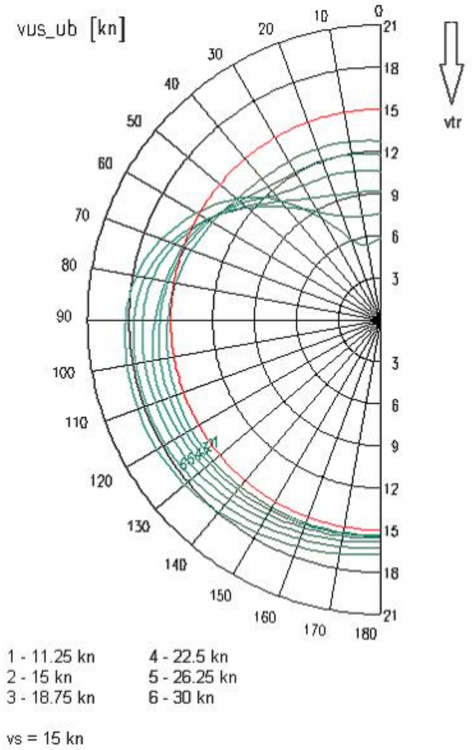

Fig. 2. Exemplary speed characteristic for given ship and sail model - starboard tack

4.2 *Problem definition*

Prior to a problem definition a model of ship movements is assumed as kinematical one with elements of ship’s dynamics according to possibility of manoeuvre execution.

The values to be found by the optimisation process of route finding are route’s waypoints defined by their geographical coordinates and ship speed between two consecutive waypoints. The optimisation criteria are split into two groups, namely:

– economic criteria, such as passage time and fuel consumption;
– safety criteria, represented by traffic intensity and constraint violation factors.

Thus, the goal function is defined as presented by equations 2 - 4:

$$f\ (t_r, v_{fc}, i_{traff}, r) = \{f_{economy}(t_r, v_{fc}), f_{safety}(i_{traff}, r)\} \xrightarrow{\quad} min \quad (2)$$

$$f_{economy}(t_r, v_{fc}) = \{f_{passage\_time}(t_r), f_{fuel\_consumption}(v_{fc})\} \quad (3)$$

$$f_{safety}(i_{traff}, r) = \{f_{traffic\_intensity}(i_{traff}), f_{constraint\_violation}(r)\} \quad (4)$$

where:

t_r – passage time [h],

v_{fc} – total fuel consumption [t],

i_{traff} – traffic intensity factor [/], r – penalty function for constraint violation [/].

All limitations to the problem domain in weather routing are purely navigational. Landmasses that cannot be crossed constitute the prime constraint. Even a small violation of the constraint results in a route unacceptable from navigational standpoint. Along with an assumption that land shore does not change its shape during a route execution this constraint is assumed static. However, other navigational constraints exist that do not fall into category of static ones, namely ice phenomenon and tropical cyclones. Available information about ice and cyclones is mostly derived from forecasted, that is probabilistic, data. Moreover, both ice concentration as well as a centre of a tropical depression changes with time. Thus these constraints are assumed fuzzy dynamic. Last but not least constraint is determined by the assumed ship's draught. Given ship model is able to navigate only through waters sufficiently deep for assumed draught value.

4.3 *Proposed solution for the problem*

The solution proposed is based on the optimisation criteria defined in the previous subsection. It utilizes two basic multiobjective mechanisms, namely multiobjective evolutionary algorithm (MOEA) and multiobjective ranking method - Fuzzy TOPSIS. In general, the main algorithm is presented in Figure 3.

In the proposed solution the evolutionary framework is responsible for iterative process of population development. MOEA-specific techniques, namely multiobjective ranking, secondary population and niching extend the framework to achieve a Pareto-optimal set of routes according to given criteria set. Mating restriction, as a MOEA technique of questionable profits, is not utilized in the proposal.

Initial population of routes will be generated based on an orthodrome and a route determined by the adopted isochrone method (Szlapczynska et al. in prep.). The population should consist of avg. 50 individuals, each being a random mutation of the basic routes. Also pure orthodrome and isochrone route should belong to the initial population. In addition to that, it is worth considering whether some other routes optimising one of the other criteria (fuel consumption, vessel traffic intensity, degree of constraints violation) should be included in the initial population.

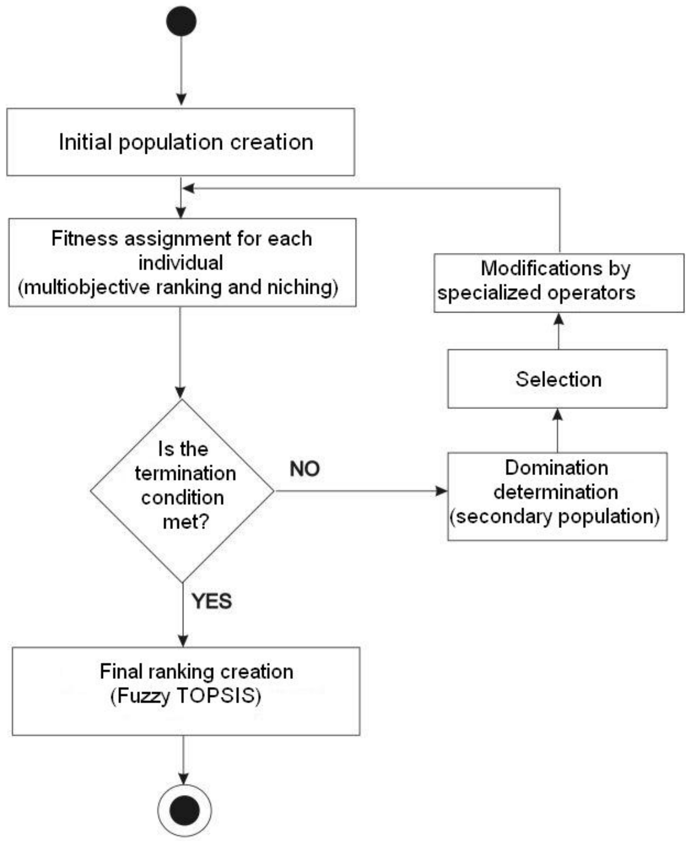

Fig. 3. Main algorithm of the proposed multiobjective weather routing

The process of fitness assignment will include multiobjective ranking and niching, necessary for assumed multiobjective goal function. In the end of each generation an increase of fitness function will be determined. The evolutionary process will be terminated whenever the increase will be satisfactorily small (smaller than some ε value). Then, the ranking Fuzzy TOPSIS method will prepare the output ranking facilitating the final decision which route to choose.

If the termination condition is not met the iterative process of population development must continue. First, dominance between individuals should be determined. Based on this information the secondary population will be updated. A new population will be created by means of selection and modification processes. Again all individuals in the population will be assigned their fitness values and the evolutionary iterations will proceed until the termination condition is finally met.

5 SUMMARY

The paper describes a possible multiobjective approach to weather routing. Two families of multiobjective decision-making methods are presented, namely multiobjective evolutionary algorithms and ranking methods. The author describes model assumed and defines problem of route finding in weather routing. Then a solution to given model and problem is presented. The proposal includes an algorithm determining a route satisfying given optimisation criteria and navigational constraints. Further details on the proposed algorithm will be provided as soon as the weather routing algorithm in finally implemented.

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