Strength Pareto Evolutionary Approach to Weather Routing – Preliminary Results

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Abstract. This paper describes application of Strength Pareto Evolutionary Algorithm (SPEA) to an optimization problem in weather routing. The paper includes a description of SPEA algorithm and defines the constrained weather routing optimization problem. It also presents a proposal and preliminary test results of SPEA-based weather routing evolutionary algorithm.

1 Introduction

The term “weather routing” refers to a process of finding the most convenient route for a vessel while taking into account available weather forecasts. Various optimisation techniques and decision making methods applied to the process aim at finding a trade-off between, sometimes contradictory, economic and security aspects of voyage.

When a ship with hybrid propulsion is considered, that is a ship equipped with motor engine and additional sails, the weather routing problem is getting even more complicated. Namely, even moderate winds can introduce a risk of safety for commodities and people on board. On the other hand, the same winds may significantly reduce fuel consumption by sails power utilization.

It is a fact that weather routing for ships with hybrid propulsion belongs to a class of multiobjective optimization tasks. Thus, a method for such a class of problems is required to provide an appropriate route recommendation.

Available solutions for weather routing can be divided into following categories ([8]):

- methods based on modified isochrone method, also available for vessels with hybrid propulsion,
- methods based on evolutionary approach, with no special solutions for hybrid ships,
- methods based on other approaches, such as dynamic programming, with no special solutions for hybrid ships.

Nowadays, evolutionary algorithms seem to be the most promising for weather routing services. However, due to multiobjective nature of weather routing, especially the one for vessels with hybrid propulsion, it is recommended to introduce some state of the art multiobjective methods to the process of route finding. This may facilitate the process of reaching a trade-off between economic and safety criteria sets.

Current multiobjective evolutionary algorithms (MOEAs) can be categorized [6] into one of the distinctive subgroups, namely:

- algorithms with “a priori” preference, where the decision maker combines all the objectives into a single scalar function;

- algorithms with progressive preference, where the decision making and optimization processes alternate;
- algorithms with “a posteriori” preference, where the found set of Pareto optimal solutions is presented to the decision maker who selects the final solution from the set provided.

According to numerous reviewers (eg. [7, 9]), Pareto-based approach has been most extensively researched during the last decade and has been successfully utilized in various fields of application. Recently, among several generic Pareto-based methods, Strength Pareto Evolutionary Algorithm has been increasingly holding researchers’ attention. This is mostly due to a fact that no other MOEA algorithm is able to actively utilize one of the basic multiobjective evolutionary techniques, namely secondary population.

Taking former into account, it is proposed to introduce Strength Pareto Evolutionary Algorithm to the route finding process for a ship with hybrid propulsion.

This paper is organized as follows: section 2 presents general description of the Strength Pareto Evolutionary Algorithm. Section 3 describes the weather routing as an optimisation problem. Section 4 presents proposed solution to the former problem definition. In section 5 some preliminary test results of SPEA-based weather routing algorithm are presented. Finally, section 6 summarizes the paper.

2 Strength Pareto Evolutionary Algorithm (SPEA)

The Strength Pareto Evolutionary Algorithm (SPEA), proposed originally in 1999 by Zitzler et al. in [9], is a multiobjective evolutionary algorithm able to find multiple Pareto-optimal solutions in parallel. The general algorithm flow is presented in Figure 1.

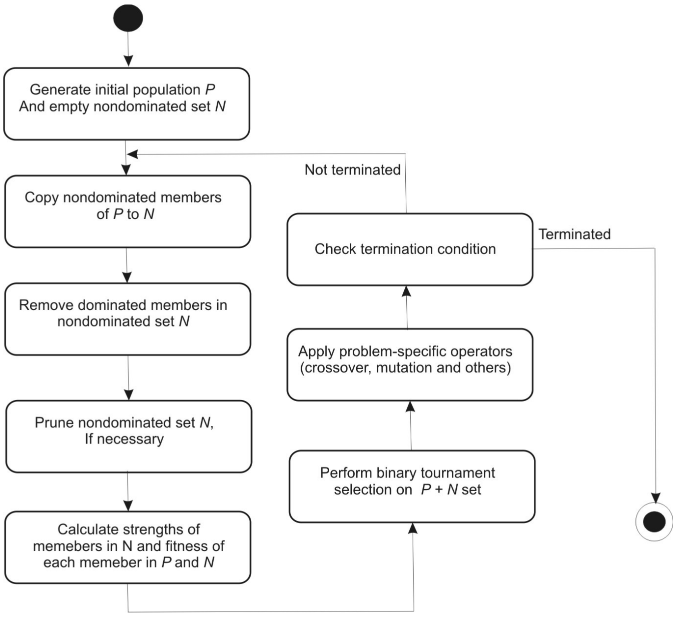


Figure 1. SPEA algorithm flow

Given SPEA algorithm flow reflects the generic evolutionary algorithm. Its key elements are:

- initial population creation,
- fitness assignment,
- selection,
- applying problem-specific operators,
- checking for termination condition.

These elements are supplemented by additional steps concerning maintenance of a nondominated set *N*. Here, throughout the evolution process two populations are maintained, the basic population *P* and the secondary one – *N*. The main purpose of the latter is to sustain all nondominated individuals during the complete generation process. Individuals from the nondominated set *N* also participate in fitness assignment, thus selection procedure is able to utilize a multiset union of individuals from *P* + *N*.

The nondominated set *N* is initialized as empty during the creation of initial population in *P*. Then, in each generation current nondominated individuals from *P* are added to the nondominated set *N*. However, adding new individuals to *N* may cause some of the old elements already in *N* becoming dominated. Thus, the checking and removal of the dominated individuals from nondominated set *N* must be performed. In cases of exceeding the defined maximum size *N*, the nondominated set must be pruned in terms of clustering.

Fitness assignment in SPEA is organized in a twofold way. Firstly, for each individual from the secondary population *N* a fitness value, so-called “strength”, is calculated. The strength of given individual from *N* is proportional to the number of individuals from basic population *P* that are covered by him (which means that are dominated or equal to). In the second step all individuals from population *P* are assigned a fitness value that is a sum of strengths of elements from *N* that cover given individual from *P*.

3 Constrained Multiobjective Optimization Problem in Weather Routing

A set of goal functions in the weather routing optimization process, revised comparing to [6], is presented below by equations 1 – 3:

$$f_{passage\_time}(t_r) = t_r \rightarrow min \tag{1}$$

$$f_{fuel\_consumption}(v_{fc}) = v_{fc} \rightarrow min \tag{2}$$

$$f_{voyage\_risks}(i_{safety}) = (1 - i_{safety}) \rightarrow min \tag{3}$$

where:

t_r	– [h] passage time for given route and ship model,
v_{fc}	– [t] total fuel consumption for given route and ship model,
i_{safety}	– [/] safety coefficient for given route and ship model. It is defined as a value ranging [0;1], describing a level to which the route is safe to be passed. “0” depicts totally impassable route and “1” absolutely safe route. Values of this coefficient will be assigned to routes based on weather wind speed forecast.

When a route for assumed ship model ([4]) is sought, a set of constraints includes:

- landmasses (land, islands) on given route,

- predefined minimum acceptable level of safety coefficient for given route,
- shallow waters on given route (defined as waters too shallow for given draught of ship model),
- floating ice bergs expected on given route during assumed ship's passage,
- tropical cyclones expected on given route during assumed ship's passage.

4 Proposed SPEA-based Weather Routing Algorithm

The general description of SPEA-based weather routing algorithm has already been presented by the authors in [6]. However, some of the elements have been upgraded during the implementation process. Following subsections describe the already implemented elements of the proposed algorithm, differing from the previous general description in [6].

Constraint-dominance handling. Because the weather routing optimization problem belongs to a class of constrained problems, it was necessary to exchange classic dominance by constraint-dominance [1]. The constraint-dominance is determined based on a three-step procedure, exemplified below for two individuals. An individual *i* constraint-dominates another individual *j* if and only if one of the following holds:

1. *i* is feasible and *j* is not,
2. both *i* and *j* are infeasible, but *i* has less constraint violation,
3. both *i* and *j* are feasible and *i* dominates *j*.

Chromosome structure. An individual here is represented by a route. The route includes an array of waypoints constituting ship's trajectory, where the first one is equal to the position of the origin port and the last one – to the destination port. A single entry of the waypoints array includes:

- geographical coordinates (longitute, latitude) of the waypoint,
- motor engine relative settings (cms) valid from the previous to the given waypoint, ranging [0;1],
- propulsion type (there are two different propulsion modes distinguished for assumed ship model: "motor only" and "motor & sails"),
- time of reaching given waypoint,
- velocity of the ship, assumed constant on a sector between two waypoints, valid from the previous to the given waypoint,
- uncertainty index for given waypoint (value representing uncertainty of the waypoint's data).

Only the first three elements of the waypoint entry remain under direct control of the evolutionary mechanisms: the coordinates, motor settings and propulsion type. All the other values can be calculated as functions of the former and are stored in the chromosome in order to improve on efficiency of the algorithm.

Initial population. Just before generation of the initial population, a set of basic routes for given origin and destination ports is determined. The basic route set includes:

- a loxodrome – a route connecting directly the origin and destination ports without necessity of course changes, represented on a Mercator map as a straight line,
- an orthodrome – a shortest possible route between given pair of origin and destination ports. The orthodrome requires constant changes of ship's course and is represented on a Mercator map as an arc bended towards the nearest pole,
- an isochrone – a time-minimum route avoiding land crossings, determined by an isochrone method [2].

Due to the fact, that both loxodrome and orthodrome may cross land, the first operation is to make them feasible by means of applying one of the repair algorithms for fixing land crossings.

After determining the feasible basic routes set, an initial population is built by means of random average over given waypoints set. Pure feasible basic routes are also included to the initial population.

Repair algorithms. Two repair algorithms have been implemented, namely:

- algorithm for fixing land crossings,
- algorithm for removing loops in a route.

The algorithms are utilized during initial population creation as well as before the evaluation procedure in each generation**.**

Specialized operators. There are several specialized "genetic" operators required, customized to the established chromosome structure. Current set of implemented specialized operators include:

- one-point crossover,
- non-uniform mutation,
- route smoothing by means of average weighting.

5 Preliminary Results

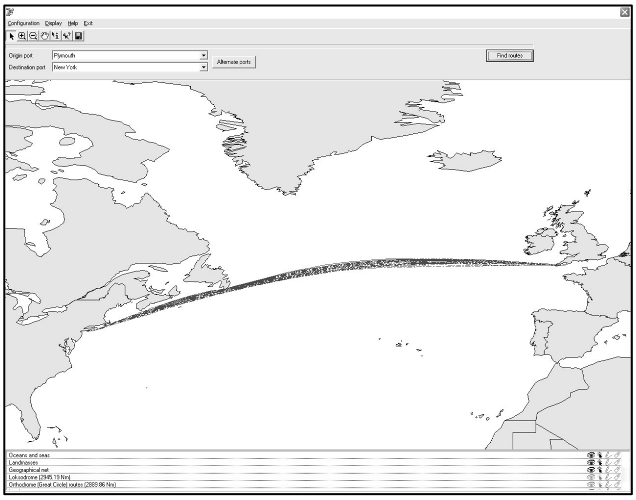
The preliminary results refer to the tests performed in the implemented weather routing environment for a problem formulation limited to:

- first two elements of goal function – passage time and fuel consumption (equations 1–2),
- the first constraint only (avoiding land crossings).

During the tests two transatlantic voyages: Plymouth – New York and New York – Plymouth for the assumed ship model ([4]) has been investigated. Departure test date was set to 6th November 2006 00:00 AM, appropriate weather forecasts have been taken from NOAA WaveWatch III ([3]). The routes (final nondominated sets) obtained for the investigated voyages are presented in Figures 2 and 3 respectively. Basic parameters of the SPEA-based weather routing test-bench are presented in Table 1.

Table 1. Basic parameters of the SPEA-based weather routing test-bench.

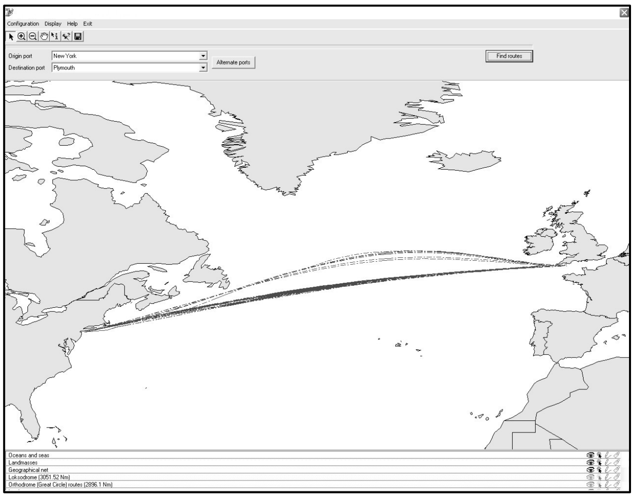
Parameter name	Value
Mutation probability	0.1
Crossover probability	0.4
Basic population max. size	200
Secondary population (nondominated set) max. size	100



Origin port: Plymouth
Destination port: New York

Oceans and seas
Landmasses
Geographical net
Loksodrome (2945.19 Nm)
Orthodrome (Great Circle) routes (2889.86 Nm)

Figure 2. Resulting nondominated routes for Plymouth – New York voyage



Origin port: New York
Destination port: Plymouth

Oceans and seas
Landmasses
Geographical net
Loksodrome (3051.52 Nm)
Orthodrome (Great Circle) routes (2896.1 Nm)

Figure 3. Resulting nondominated routes for New York – Plymouth voyage

The results obtained show some of the expected tendencies, even though the criteria assumed for the tests are not evidently competitive. Trajectories found for both voyages differ significantly, which is a result of strong winds effect on the vessel's speed. Forecasted wind conditions in the investigated period of time have been favoring routes in south-western directions, thus attainable vessel's speed value for the Plymouth – New York routes has been slightly greater. The resulting routes for Plymouth – New York voyage remain close to the most favorable winds and are located between the loxodrome and the orthodrome. In contrast, the New York – Plymouth routes are close to either the loxodrome or the orthodrome, depending on the criterion that is dominating. In such case routes closer to the loxodrome allow to reduce total fuel consumption, whereas the ones closer to the orthodrome – more to shorten the passage time.

Pareto fronts obtained for the resulting routes for both voyages (Figures 4 & 5) depict the differences in both crossings. Obtainable minimum passage time for the Europe – Northern America voyage is 183.49 h, whereas for the return voyage – 186.88 h. Even fuel consumption tendencies in both these cases are similar: 241.77 t for Plymouth – New York voyage and 246.24 t for New York – Plymouth voyage. However, it was possible, in case of the North America – Europe voyage, to reduce total fuel consumption up to 156.17 t at the cost of much longer passage time – 244.79 h.

In order to improve the distribution of final nondominated individuals across the Pareto front it is planned to allow more radical engine power reductions (up to turning off the motor engine and using sails only). Other plans concern applying a multiobjective ranking method ([5]) facilitating making the final decisions by end-users.

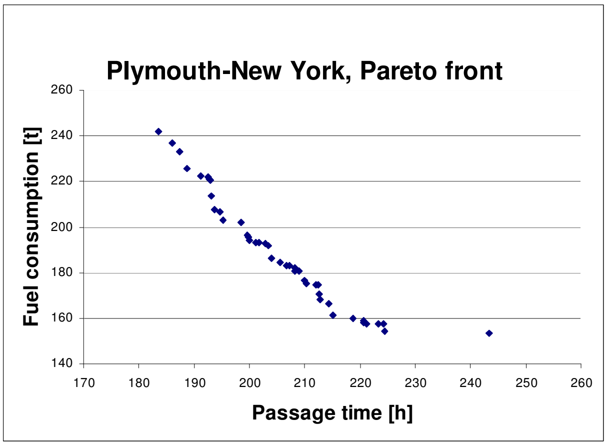


Figure 4. Pareto front of routes for Plymouth – New York voyage

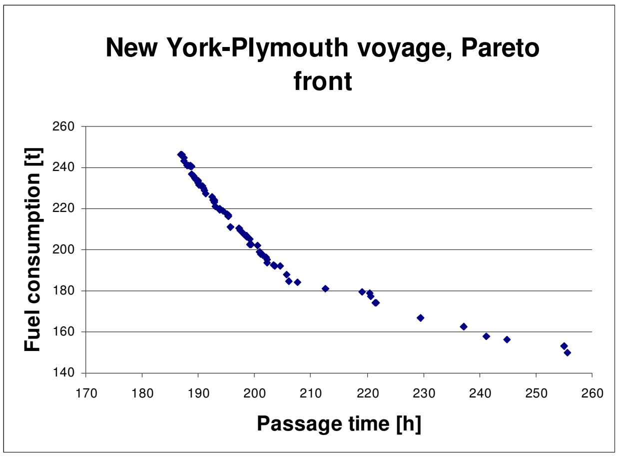


Figure 5. Pareto front of routes for New York – Plymouth voyage

6 Summary

The paper presents an updated proposal, comparing to [6], of weather routing algorithm based on Strength Pareto Evolutionary Algorithm (SPEA). The proposal is exemplified by test results obtained for a limited decision problem. The preliminary results of the experiments carried out thus far confirm the aptness of the chosen approach to the defined problem.

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