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Multicriteria Evolutionary Weather Routing Algorithm in Practice

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ABSTRACT: The Multicriteria Evolutionary Weather Routing Algorithm (MEWRA) has already been introduced by the author on earlier TransNav 2009 and 2011 conferences with a focus on theoretical application to a hybrid-propulsion or motor-driven ship. This paper addresses the topic of possible practical weather routing applications of MEWRA. In the paper some practical advantages of utilizing Pareto front as a result of multicriteria optimization in case of route finding are described. The paper describes the notion of Pareto-optimality of routes along with a simplified, easy to follow, example. It also discusses a choice of the most suitable ranking method for MEWRA (a comparison between Fuzzy TOPSIS and Zero Unitarization Method is presented). In addition to that the paper briefly outlines a commercial application of MEWRA.

1 INTRODUCTION

Along with rapid development of multicriteria methods and algorithms in the last 15 years, popularity of multiobjective optimization in route finding has been constantly increasing. In such multicriteria approach the task is to find the most suitable route, taking into account two or more criteria (such as passage time and fuel consumption) simultaneously. The majority of generic multicriteria optimization algorithms utilize genetic or evolutionary computations (GC/EC), thus this approach has become a foundation for the most of multiobjective route finding applications.

The search space in evolutionary route finding process may be either discreet or continuous. The first case is usually utilized for vehicle optimal route finding. Kim *et al.* (2009), among other researchers, proposed a discreet space multicriteria route planning for vehicles based on the GC/EC approach. However, in case of ship route finding process the continuous search space is considered in most cases. Possible locations of consecutive route waypoints are limited by the optimization criteria and constraints only and hardly can be considered to form a fixed grid. That is the key reason behind selecting the continuous search space for ship route findings.

When a transoceanic voyage of a vessel is planned the weather conditions as well as some navigational obstacles (e.g. narrow passages) must be taken into account. This process, called “weather routing”, may be supported by software applications usually following the implementation of a single-criterion isochrone method (James, 1957). Numerous improvements to the original isochrone method were proposed since early eighties, with Hagiwara (1989), Spaans (1986) and Wisniewski (1991) among others. The modified isochrone methods are able to find a time-optimal or fuel-optimal route, yet are not suitable to handle multicriteria optimization. Thus, a multicriteria approach towards weather routing has been proposed so far by Hinnenthal (2007), Marie &

Courteille (2009) and by the author of this paper (Szlapczynska, 2007). All the proposed methods utilize some multicriteria GC/EC algorithm to search continuous search space to find Pareto-optimal (optimal in multiobjective sense) set of routes. Both the solutions by Hinnenthal and Marie *et al.* utilize Multi Objective Genetic Algorithm – MOGA, however are restricted to provide the Pareto-optimal set of routes as their final result. The multicriteria weather routing method proposed by the author, Multicriteria Evolutionary Weather Routing Algorithm (MEWRA) utilizes the more robust GC/EC algorithm – Strength Pareto Evolutionary Algorithm - SPEA (Zitzler & Thiele, 1999). But what is even more important, MEWRA includes a mechanism of selecting out of the Pareto-set a single route that is the most suitable for the decision-maker. It is provided by considering decision-maker's preferences towards the criteria by the additional multicriteria ranking method. Last but not least, difference between MEWRA and the other solutions is that MEWRA evolves only the feasible routes (ie. routes that do not cross the land obstacles), which makes the MEWRA's results acceptable from the navigational standpoint regardless of the computational time (number of generations).

MEWRA has already been presented by the author on previous TransNav'2009 and TransNav'2011 conferences with a focus on theoretical application to a hybrid-propulsion or a motor-driven ship. The objective of this paper is to present some aspects of practical MEWRA applications. The rest of the paper is organized as follows. Section 2 recalls the basic foundations of MEWRA algorithm. Section 3 presents selected aspects of practical MEWRA application. It describes the notion of Pareto-optimality of routes along with a simplified, easy to follow, example. Section 3 presents also a comparison between two multicriteria ranking methods: Fuzzy TOPSIS and Zero Unitarization Method and points the one more suitable for MEWRA. The next section briefly outlines the commercialization process of MEWRA as a part of NaviWeather tool by NavSim. Section 5 summarizes the presented material.

2 MULTICRITERIA EVOLUTIONARY WEATHER ROUTING ALGORITHM (MEWRA)

The multicriteria set of goal functions in the weather routing optimization process proposed by (Szlapczynska & Smierzchalski, 2009) is given by equations 1 - 4:

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

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

$$f_{voyage\_risks}(i_{risk}) = i_{risk} \rightarrow \min \tag{3}$$

$$i_{risk} = \frac{\sum_k \left(1 - i_{j\ safety}\right)^2}{k} \tag{4}$$

where:

t_r = [h] passage time for given route and ship model,

q_{fc} = [g] total fuel consumption for given route and ship model,

i_{risk} = [*dimensionless*] risk coefficient for given route and the ship model,

k = [*dimensionless*] number of route's segments with $i_{j\ safety} < 1$,

$i_{j\ safety}$ = [*dimensionless*] fractional safety coefficient for *(j-1)*-th and *j*-th waypoints and given ship model; values of the coefficient ranges [0; 1], where 1 depicts completely safe section of route and 0 – unacceptably dangerous section. Definition of the coefficient for a hybrid-propulsion ship was presented in (Szlapczynska, 2007) and for a motor-driven ship in (Krata & Szlapczynska, 2012).

The weather routing optimization process is defined as a constrained one. The key optimization constraint set includes landmasses and predefined minimum acceptable level of fractional safety coefficient $i_{j\ safety}$ for given route.

The abovementioned optimization model has become a foundation for MEWRA - Multicriteria Evolutionary Weather Routing Algorithm. MEWRA, as presented in Figure 1, utilizes two basic multicriteria mechanisms, namely multicriteria evolutionary algorithm – Strength Pareto Evolutionary Algorithm, SPEA (Zitzler & Thiele, 1999) and a multicriteria ranking method. The SPEA framework in the proposed algorithm is responsible for iterative process of population development. The result of SPEA is a Pareto-optimal set of solutions. The multicriteria ranking method (e.g. Fuzzy TOPSIS or Zero Unitarization Method) is responsible for sorting the resulting Pareto-optimal solutions according to the given preferences of the decision maker.

An individual in the evolutionary approach represents a single route. The route includes an array of waypoints constituting ship's track, 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 waypoint array includes also some additional parameters characterizing the ship track between the *(n-1)*-th and *n*-th waypoints.

The initial population is a set of pre-defined and randomly generated routes. Modified isochrone routes (Spaans, 1986 & Hagiwara, 1989) – a time-optimal and a fuel-optimal – may also be included in the initial set. The set becomes an input for SPEA - the evolutionary multicriteria optimization algorithm. The evolutionary process transforms the set by means of mutation, crossover & specialized operators to browse through the whole (or at least the most of) search space. The SPEA result is a Pareto-optimal set of routes.

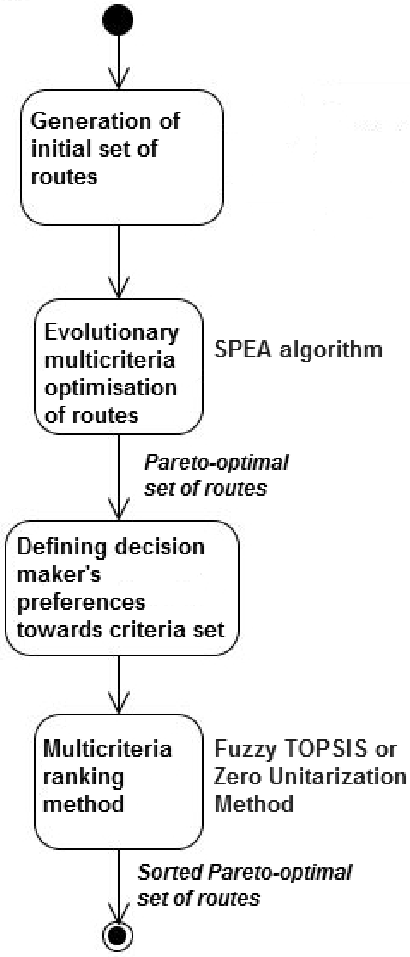

Figure 1. MEWRA's algorithm flow

The resulting set may include a variety of diversified, yet optimal in multicriteria sense, routes: some having short passage time, some other having low fuel consumption and possibly other assuring high safety though the voyage. Details on how the Pareto-set is constructed can be found further in the paper, in Section 3.1.

The final step is to sort the Pareto-set of routes according to the decision-maker's (e.g. captains of the ship) preferences. The decision-maker can assign a value (by a number e.g. 0.7 or linguistic value e.g. "good") to each of the three optimization criteria, thus reflecting their preferences to each criterion. Then a ranking method is able to sort the set. This way the first route is the Pareto-optimal one which is the most suitable for given preferences. Usually this route becomes a route recommendation. Unlike the SPEA processing, the sorting procedure is able to return its results immediately, thus, in case the decision-makers change their mind about the preferences, the last step can be repeated multiple times. Further discussion on the most suitable MEWRA ranking method can be found in Section 3.2.

3 MULTICRITERIA OPTIMISATION OF SHIP ROUTES IN PRACTICE

The author's earlier papers on MEWRA were met with question concerning the notion of multicriteria Pareto-optimality, especially in relation to ship routes. Therefore the first subsection introduces a practical definition of route Pareto-optimality accompanied by an easy to follow example.

The previous MEWRA papers (Szlapczynska, 2007, Szlapczynska & Smierzchalski, 2009, Krata & Szlapczynska, 2012) introduced Fuzzy TOPSIS as a multicriteria ranking method. In practice it appeared that the Fuzzy TOPSIS method has several disadvantages and another method has been proposed instead, namely Zero Unitarization Method (Kukula, 2000). The second subsection provides brief definitions of both methods, compares their properties and justifies the final selection between the two ranking methods.

3.1 *Pareto-optimal set of routes*

In order to define Pareto-optimality (optimality in pure multicriteria sense) first the notion of Pareto-dominance must be introduced. Let us consider two routes A & B. Route A Pareto-dominates B if and only if A has at least one parameter (a value for optimization criterion) better than B and all the other parameters of A are no worse than B. Then, a set of Pareto-optimal individuals is built by routes that cannot be Pareto dominated by any other route. To conclude the definition, the notion of Pareto-optimality always refers to a set of routes and its checking is performed via testing Pareto-dominance between every pair of routes in this set.

Now, let us consider an exemplary set of routes presented in Table 1 for which Pareto-optimality will be checked. It is assumed that there are three standard optimization criteria, namely passage time (given in hours), fuel consumption (given in tons) and safety of passage (dimensionless). The last criterion, to keep the example simple, is specified by linguistic values: "good", "moderate" and "only satisfactory". The time & fuel criteria should be minimized, but the safety criterion should be maximized (i.e. "good" safety is better than "moderate" one).

Table 1. Exemplary set of routes for which Pareto-optimality will be checked.

	Time[h]	Fuel[t]	Safety
Route #1	200	200	good
Route #2	210	180	good
Route #3	190	175	moderate
Route #4	250	190	good
Route #5	205	205	only satisfactory

The results of Pareto dominance check on this set is presented in Table 2.

The Pareto-optimal set of routes is constructed based on the original set (Table 1) taking into account Pareto dominance check results (Table 2). In Table 3 the final Pareto-optimal set for the considered example is presented.

Table 2. Results of Pareto dominance check on the exemplary route set.

Dominance check between a pair of routes	Check result
Does #1 dominate #2?	No
Does #1 dominate #3?	No
Does #1 dominate #4?	No
Does #1 dominate #5?	Yes (all parameters of route #1 are better than those of route #5), thus **remove route #5 as dominated**
Does #2 dominate #1?	No
Does #2 dominate #3?	No
Does #2 dominate #4?	Yes (better in time & fuel), thus **remove route #4 as dominated**
Does #2 dominate #5?	*Don't have to check, #5 is dominated & removed from the set*
Does #3 dominate #1?	No
Does #3 dominate #2?	No
Does #3 dominate #4?	*Don't have to check, #4 is dominated & removed from the set*
Does #3 dominate #5?	*Don't have to check, #5 is dominated & removed from the set*
All checks for #4	*Don't have to check, #4 is dominated & removed from the set*
All checks for #5	*Don't have to check, #5 is dominated & removed from the set*

Table 3. Pareto-optimal set of routes for the considered example.

	Time[h]	Fuel[t]	Safety
Route #1	200	200	good
Route #2	210	180	good
Route #3	190	175	moderate

The final set includes only three first routes, while routes #4 & #5 have been removed as dominated ones (route #4 is dominated by route #2 and route #5 is dominated by route #1). The resulting Pareto-optimal routes obviously differ in values of their parameters. One can choose the shortest and cheapest route (#3) for the cost of lowered safety level. Alternatively, one can go for higher safety level and pick the route with possible lowest fuel consumption with "good" safety (#2) or the one with moderate time & fuel values (#1).

It is common that routes in such sets differ. Even in real, much bigger Pareto-optimal route sets, there is always a route with shortest passage, possibly there is another (in the example it is the same one) having lowest fuel consumption, some other with highest safety level and finally a set of routes with parameter values in between the extremes. It is then up to the user of the Pareto-set to pick the most suitable route. In MEWRA the process of selection the most suitable route out of the Pareto-set is facilitated by the multicriteria ranking method.

3.2 *Comparison of ranking method in route selection*

Fuzzy TOPSIS is a multicriteria ranking method that has been originally proposed as part of MEWRA (Szlapczynska, 2007, Szlapczynska & Smierzchalski, 2009). The method, proposed by Chu & Lin (2003), is based on a technique of ranking building called Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). The technique utilizes an approach towards ranking building 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 Fuzzy TOPSIS implementation by Chu & Lin (2003) introduces additional support for linguistic values, fuzzy criteria and fuzzy weights (described by triangular fuzzy values).

Fuzzy TOPSIS is a commonly used multicriteria ranking method, valued mostly for allowing easily obtainable trade-offs between criteria and customizable fuzziness support. However, in a practical implementation of MEWRA (described briefly in the next section) the method exposes several important drawbacks. The most important one is its property of compensation. The compensatory methods, such as Fuzzy TOPSIS, allow for situation where a poor result in one criterion may be concealed by a good result in another criterion. In case of searching for ship routes such property is not welcomed, since for example poor safety level of a route should not be compensated by its short passage time. Another important issue is that the method require complex configuration, which may be not enough user friendly. Last but not least, the method assumes quite sophisticated calculus to return results, which may become significantly time-consuming for a vast set of routes.

To overcome the abovementioned problems another multicriteria ranking method has been applied to the practical MEWRA implementation, namely Zero Unitarization Method - ZUM (Kukula, 2000). The ZUM is a non-compensatory muticriteria ranking method allowing normalization of the diagnostic variables by the gap between the variable's value and the most or the least suitable variable value (depending on the optimization direction). Its configuration is straightforward and computations are limited to basic multiplication and division of real values. The author proposes also some obvious extensions to the method:

– introducing normalized weights assigned to the criteria,
– introducing linguistic values to ZUM by assigning fixed values to each linguistic value.

All these makes ZUM the more suitable ranking method for MEWRA purposes comparing to Fuzzy TOPSIS. Table 4 presents a direct comparison between the two methods.

Table 4. Comparison of Fuzzy TOPSIS and Zero Unitarization Method (ZUM).

	Fuzzy TOPSIS	ZUM
Type of method	compensatory	non-compensatory
Fuzziness support	yes	no
Linguistic values support	yes	yes (with additional extension by the author)
Computations	sophisticated	straight-forward
Configuration	complex	easy (or a bit more complex with additional extension for linguistic values by the author)

4 COMMERCIAL MEWRA APPLICATION

Soon after the NavSim Poland company had decided to include MEWRA into their weather forecast and analysis software – NaviWeather, a team of Gdynia Maritime University researchers started to build a software prototype of multicriteria weather routing tool onto the NaviWeather platform. It has been decided that MEWRA will be implemented as separate NaviWeather plugin (a dll library). The prototype weather routing plugin is planned to be fully implemented by the time of this paper publication. A summary of MEWRA commercialisation process has already been presented in (Szlapczynska, 2012).

The MEWRA implementation for NaviWeather follows its original algorithm's flow (depicted earlier in the paper in Figure 1). It also includes the Zero Unitarization Method as justified in Section 3.2. The key features of the MEWRA plugin, presented in Figure 2, are as follows:

– gathering origin and destination points from the map,
– uploading current weather forecast for given departure date,
– finding Pareto-optimal set of routes by the multicriteria evolutionary algorithm (SPEA),
– configuring decision-maker's preferences towards the optimization criteria,
– sorting the resulting Pareto-optimal set by the ZUM ranking method – the first route in the sorted set is the most suitable one according to the previously configured preferences.

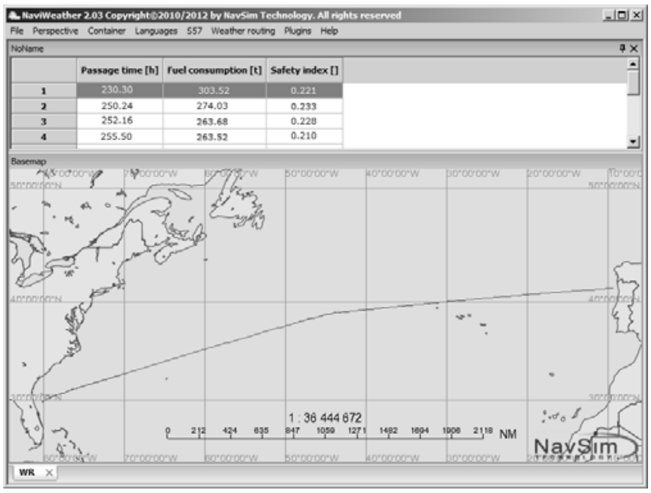

Figure 2. MEWRA prototype as a NaviWeather plugin – the final ranking of Pareto-optimal routes (Szlapczynska, 2012)

5 SUMMARY

The Multicriteria Evolutionary Weather Routing Algorithm (MEWRA) is a unique weather routing solution utilizing multicriteria, constrained Pareto-based optimization and providing users with support to select a single, the most suitable to their needs, route out of Pareto-optimal set. This paper, unlike the previous technical MEWRA papers, focuses on practical aspects related to MEWRA. It explains, in a practical fashion, the way of constructing the Pareto-optimal set of routes. It also presents a short discussion on selecting the most suitable ranking method applicable to MEWRA. As stated in Section 3.2 the Zero Unitarization Method (ZUM) has been selected by the author as such. Finally, it outlines the commercial MEWRA application as a part of NaviWeather software by NavSim.

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