Chapter 4
Evolutionary Computation for the Ship Routing Problem

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Abstract In this chapter, we present evolutionary algorithms for solving the real time ship weather routing problem. The objectives to be minimized are the mean total risk and fuel cost incurred along the obtained route while considering the time-varying sea and weather conditions and also a constraint on the total passage time of the route. In addition, for achieving a high safety level the proposed approaches should return only solutions compliant with the guidelines of the International Maritime Organization (IMO). Two different well-known genetic algorithms, namely SPEA2 and NSGA-II are applied to the ship routing problem and a comparative performance evaluation of the two algorithms is performed. The proposed approaches are tested on real data and compared with an exact algorithm which solves the same problem.

Keywords Multi-criteria optimization · Label setting algorithm · Time dependent networks · Resource-constrained shortest path

4.1 Introduction

This chapter presents genetic algorithms for the point-to-point ship weather routing problem which seeks for an optimal route of a ship from a departure to a destination port given a constraint on the total travel time. An optimal route reaches the destination port at minimum fuel consumption and maximum safety taking into account technical and operational restrictions. The problem can be formulated as

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a bi-objective, non-linear optimization problem with constraints where the optimal solution should be found between conflicting objectives. Note that the main factor that may determine the optimal route and actually makes ship routing a problem difficult to solve, is the weather conditions. In general, regardless of the particular objectives of the multi-objective ship routing problem, its basic parameters are strongly affected by the current weather and sea conditions. Consequently, the problem of finding an optimal ship route can be considered as a time-dependent shortest path problem. Besides weather variations, moving obstacles with known or unknown trajectories, such as other vessels, as well as marine protected populations or restricted areas are additional factors that make the problem even more dynamic and difficult to solve.

Since solving the ship routing problem takes into account weather forecasts and sea condition, appropriate modelling of the ship response to weather and sea conditions according to the specific characteristics of the ship, is a crucial factor for finding optimal solutions. Note that the weather and sea conditions largely affect all optimization criteria (passage time, fuel consumption and safety) and therefore, an effective solving approach for the ship weather routing problem will necessarily determine the optimal ship power settings and heading control given the particular sea and weather conditions.

A large number of exact as well as heuristic approaches have been proposed in the literature for solving the ship routing problem. Exact algorithms [1, 3, 4, 11, 22, 23, 25, 27, 28, 31–33, 35] derive an optimal solution of the problem, however, at the cost of increased computation time. In contrast, a heuristic approach [10, 15, 20, 24, 29, 34] seeks for a feasible solution only within a subspace of the solution space, hopefully close to the optimal solution, and therefore, the execution time is generally much lower than that of an exact approach. Since, long-term weather forecasts are available, calculus of variations methodology [5] has also proven to be successful for both coastal navigation and trans-oceanic seafaring. Another old but popular method for optimizing ship route is the isochrone method [12].

Although many multi-objective optimization methods exist, evolutionary multi-objective optimization, which applies evolutionary computation to multi-objective optimization, has attracted a great deal of attention. Specifically, there are many different kinds of Multi-Objective Genetic Algorithms (MOGAs), but the common goal is to obtain a Pareto-optimal set that indicates a trade-off relationship. Such studies are common because one characteristic of MOGAs is the multipoint search where multiple Pareto-optimal sets can be obtained by an application of a single search only. For example, in MOGAs, a population of solutions is maintained and used as a basis for search. As the population contains a number of individual solutions, the search makes use of multiple points in the search space. Although, many MOGAs have been proposed in the literature, SPEA2 [40] by Zitzler et al. and NSGA-II [9] by Deb et al. provide excellent results as compared with other MOGA approaches.

The focus of this chapter is on the study of MOGA techniques for the ship routing problem, using as a case study the area of the Aegean Sea. Apart from finding optimal routes with respect to economical objectives, we are also interested in reducing the possibility of an accident in the sensitive area of the Aegean Sea. The derived routes are optimized with respect to two conflicting objectives, the total fuel consumption and the mean risk of the route while taking into account the prevailing weather conditions. In this study, SPEA2 and NSGA-II were both applied to the optimal ship routing problem. Moreover, the performance of these algorithms were compared with that of an exact algorithm [35] for the same problem in order to assess the ability of the two MOGAs in finding the whole Pareto set. It is also worth mentioning that diversity of the obtained solutions and early convergence in MOGAs is achieved by employing the appropriate evolutionary operations and through the appropriate selection of the initial population.

The rest of the paper is organized as follows. In Sect. 4.2, we formally define the point-to-point ship routing problem as a special case of the dynamic multi-objective shortest path problem. The related work is presented in Sect. 4.3. Next, in Sect. 4.4, we describe the proposed genetic algorithm. Some critical modelling issues affecting the effectiveness of solving methods for the ship routing problem are presented in Sect. 4.5. The efficiency of the evolutionary computation in this maritime setting is evaluated in a number of experiments in Sect. 4.6, where both SPEA2 and NSGA-II algorithms are compared against the algorithm in [35] which is a forward label setting algorithm that has the best so far performance in the literature for the problem at hand. Finally, some concluding remarks and the directions for future work are presented in Sect. 4.7.

4.2 Problem Definition

In this subsection, the ship routing problem is formally defined as a non linear integer programming problem. The ship routing problem in its most general version is an instance of the dynamic multi-objective shortest path problem. However, in this study, we focus on the most realistic version of the point-to-point ship routing problem, where the ship speed does not change along the route and waiting at nodes is not an option.

Let $G = (V, A)$ be a directed graph, where V and A is the set of nodes ($|V| = n$) and A and the set of arcs ($|A| = m$) respectively. Each arc in $(i, j) \in A$ is associated with three time dependent positive costs $c^1_{ij}(t)$, $c^2_{ij}(t)$ and $c^3_{ij}(t)$ which are the travel time, the fuel consumption and the risk respectively along this arc when departure from node i takes place at time t. The frozen arc model of [26] is followed in this study where the above arc costs are assumed to be constant during the arc traversal. The problem can be defined as that of finding a shortest path P between a source $s \in V$ and a destination $d \in V$ with minimum total fuel consumption $FC(P)$ and risk $R(P)$, when the departure time at the source node is t_{start} and the voyage duration $VD(P)$ does not exceed a certain upper bound T on the maximum duration of the route.

For the problem formulation, we need an upper bound H on the number of arcs comprising a solution path. This is required because when waiting at nodes is forbidden, the optimal solution may contain infinite number of arcs, as a result of infinite loops along the route [26]. In fact, the obtained solution might be a walk and not a path. Since, this infinite number of arcs cannot be formulated with finite number of variables, an additional constraint on the arc number in a solution path should be enforced.

A number of variables are used for the formulation of problem as a non linear integer programming problem. Namely, we define $p_i \in \{0, 1\}$ with $p_i = 1$ when the solution path has exactly i arcs. We also use the variable α^r_{ij} with $\alpha^r_{ij} = 1$ when the arc α_{ij} is the r-th arc starting from s along the route and $\alpha^r_{ij} = 0$, otherwise. Also t^r_j is defined as the arrival time at node j immediately after traversing arc α_{ij} but only when that arc is the r-th arch of the solution path ($\alpha^r_{ij} = 1$). If such an arc does not exist, we assign a large value to t^r_j. In addition, we always set $t^0_s = t_{start}$.

$$min\ z = (FC(P), R(P)) \tag{4.1}$$

$$FC(P) = \sum_{r=1...H} \sum_{(i,j)\in A} c^2_{ij}(t^{r-1}_i)\alpha^r_{ij} \tag{4.2}$$

$$R(P) = \sum_{r=1...H} \sum_{(i,j)\in A} c^3_{ij}(t^{r-1}_i)\alpha^r_{ij} \tag{4.3}$$

$$VD(P) = \sum_{r=1...H} \sum_{(i,j)\in A} c^1_{ij}(t^{r-1}_i)\alpha^r_{ij} \le T \tag{4.4}$$

$$\sum_{j\in V-\{s\}} \alpha^1_{sj} = 1 \tag{4.5}$$

$$\sum_{(i,j)\in A} \alpha^r_{ij} \le 1,\ r = 2\dots H \tag{4.6}$$

$$\sum_{j\in V-\{d\}} \alpha^r_{dj} = 0,\ r = 2\dots H \tag{4.7}$$

$$\sum_{i=1..H} p_i = 1 \tag{4.8}$$

$$\sum_{j\in V-\{d\}} \alpha^r_{jd} = p_r,\ r = 1\dots H \tag{4.9}$$

$$\sum_{j\in V} \alpha^r_{ji} - \sum_{j\in V} \alpha^{r+1}_{ij} = 0,\ r = 1\dots H,\ i\ \in V - \{d\} \tag{4.10}$$

$$\begin{aligned} t^r_j &= \textstyle\sum_{i\in\{k|(k,j)\in A\}} \alpha^r_{ij}(t^{r-1}_i + c^1_{ij}(t^{r-1}_i)) \\ &+ (1 - \textstyle\sum_{i\in\{k|(k,j)\in A\}} \alpha^r_{ij})M,\ j \in V,\ r = 1\dots H \end{aligned} \tag{4.11}$$

$$t^0_s = t_{start} \tag{4.12}$$

$$c^q_{ij}(M) = M' \tag{4.13}$$

$$\alpha^r_{ij}, p_r \in \{0, 1\}, t^r_i \in R^+, i, j \in V, r = 1\dots H$$

Constraint (4.4) requires that the voyage duration of the solution path must not be longer than the maximum duration T. Constraint (4.5) ensures that the first arc of the solution path is actually an outgoing arc of the node s. Constraint (4.6) makes sure that at most one arc in the graph can be the r-th edge of the solution path. Constraint (4.7) states that the solution path cannot continue beyond the node d. Constraint (4.8) essentially specifies the number of arcs of the solution path. Constraint (4.9) states that the terminal node of the solution path will be the node d. Constraint (4.10) is a flow conservation constraint ensuring that there is only one incoming and one outgoing arc at each node along the solution path and also that these arcs are consecutive in the path. Equation (4.11) estimates the arrival time at node j when this node is the head of the r-th arc of the solution path. In this equation, we assume that $c_{ij}^q(M) = M'$ ($q = 1 \cdots 3$) where M and M' are large numbers.

Each solution z is the pair of the values of the two objective functions for the corresponding path. Also, although the proposed Integer Programming model is non linear, when the time dependent edge costs functions $c_{ij}^1(t)$, $c_{ij}^2(t)$ and $c_{ij}^3(t)$ are linear, the above formulation can be transformed into a linear model [6].

4.3 Related Work

An Evolutionary Algorithm (EA) is a generic population-based optimization approach which employs techniques inspired by the natural evolution. In an EA the whole solution space is searched randomly for finding an optimal solution. A Genetic Algorithm (GA) is a stochastic optimization algorithm which belongs to the larger class of EAs. A GA maintains a population set of possible solutions. In a number of iterations, the population set is transmuted by genetic operators, generating a new offspring at each iteration. In each generation, parent and offspring compete with each other with the evaluation of solutions being based on a properly defined fitness function. A low value of an individual in this function is essentially the criterion for eliminating that individual from the next generation step. As the search scope extends over the whole solution space and since no constraints are imposed on the fitness function, the GA is able to obtain optimal solutions with high probability. However, using an evolutionary approach for solving dynamic optimization problems is not always straightforward. A common technique in the literature for handling these problems is to increase genetic diversity and prevent early convergence.

Tsou in [34] proposes an evolutionary algorithm for obtaining a number of low cost and high safety routes that avoid narrow waters, bad weather conditions, areas with increased piracy threat, foggy areas, fishing areas, congested areas, etc. The proposed approach employs GIS for spatial data management, spatial analysis and geometric computations. The initial candidate route population is automatically generated by GIS. Specifically, three operations are performed, namely, obstacle detection/avoidance, route generation and route simplification. Then, this set of routes is given as input to the evolutionary algorithm for deriving a larger set of initial routes. Then, a tailor-made evolutionary procedure is applied for route elimination, which derives a set of efficient and feasible routes.

In [29] an evolutionary computation approach has been proposed for solving the multi-criteria ship weather routing problem with criteria the voyage time, the voyage risk and the fuel consumption. It is assumed that the risk depends on the wind speed during the ship voyage. The method is based on the Strength Pareto Evolutionary Algorithm (SPEA) designed for solving combinatorial multi-objective optimization problems. Each solution route is specified as a sequence of waypoints from the origin point to the destination point. The initial population consists of a set of basic routes namely, an orthodrome i.e., a 2-dimensional projection of the shortest curve between the origin point and destination point, a loxodrome i.e., a 2-D projection of the curve intersecting the meridians at a constant angle, a time-optimized isochrone route and another time-optimized isochrone route also optimized for fuel consumption. Then, the initial population is increased by applying random mutations of the basic routes. A method is also developed for route ranking based on the decision-maker preferences, which are expressed in terms of linguistic, fuzzy values. The authors have applied their technique to finding routes in the Atlantic Ocean.

Marie et al. in [24] present a GA for computing the Pareto optimal ship routes with respect to voyage time and fuel consumption. The fuel consumption estimation is based on resistances caused by the wind and the waves. The authors propose a new discretization of the search space based on a number of physical parameters, such as the origin and the destination, the maximum speed, the desired sailing time, the distance between the waypoints and the course changes per hour. The initial population is randomly chosen, as a random sequence of grid nodes. It is assumed that the sea and the wind conditions are time-dependent and a linear interpolation technique is employed for time instances lacking weather measurements.

A GA is proposed in [10] for finding real-time optimal ship routes with optimization criteria the estimated arriva timel, the mean total risk and the fuel consumption. Besides ship movements which affect ship stability, ship structural safety is considered for risk assessment. Ship operational restrictions are also taken into account for solving the optimization problem, while ship course and speed are the control variables. The well-known technique NSGA-II [9] was employed for solving the problem. Among others, the initial route population includes the shortest route in terms of the passage time only. In addition, penalty functions are introduced for preventing constraint violation. Thus, through this artificial increase of the objective value, infeasible solutions are avoided. Finally, an interesting finding in this work is that the Gaussian mutation operator and the two-point crossover operator achieve faster solution convergence.

Since the selection of the initial route population greatly affects the quality of the final solution of an evolutionary approach for solving the ship routing problem, Szlapczynska et al. in [30] proposed the modified isochrone method by Hagiwara in [14], for generating this population. The authors modified the isochrone method so as to ensure that the initial population will not contain routes crossing land since this "no land crossing" property of the initial route population reduces the computational time and improves the quality of the solution. The proposed algorithm has linear computational complexity with respect to the number of grid cells but the optimality of the derived solutions largely depends on the land bitmap resolution. The proposed method is suitable for trans-oceanic navigation, and the authors applied their approach for finding the best route from Plymouth to New York.

In [37], the authors propose a multi-objective route planning method for fishing vessels most suitable for coastal navigation. For faithfully predicting the ship performance in the prevailing sea and weather conditions, detailed models are employed for the seakeeping response of the vessel, the added resistance incurred in an irregular sea state as well as the engine of the vessel. Specifically, graphs of the power rate, fuel consumption and exhaust gases of the engine versus the speed rate are taken into account. The objectives to be optimized are the duration, the fuel consumption and the safety of the trip. For the measurement of the safety level of the trip, a number of criteria are considered, specifically, the slamming and the green water probability, the vertical acceleration at bridge as well as the lateral acceleration. For solving the multi-objective problem, the Strength Pareto Evolutionary Algorithm (SPEA2) is used which determines the Pareto frontier of the solution space. Besides, the heading of the ship, the ship speed is also considered as a decision variable which can be properly set for achieving optimality with respect to the three objectives. Also, for expediting the search of the Pareto-optimal solutions, as a first step, the proposed approach determines the single objective optimal solutions with respect to the three objectives and then these solutions are used as initial solutions for the evolutionary algorithm. Finally, the authors propose a ranking method for the obtained solutions so that the solutions that mostly conform to the user priorities are presented to the user.

In [38] a complete on-board ship weather routing system is described where ship responses are modelled for any sea-state condition taking into account the wave directional spreading. The system employs the multi-objective route planning method described also in Vettor et al. [37], to optimize the route between two ports minimizing fuel consumption, time of arrival and risk related to weather conditions. The performance of the ship weather routing approach has been evaluated in two different simulation scenarios: the first refers to the passage of a container ship departing from the Northern Europe and crossing the North Atlantic Ocean towards the south- east US coast, and the second considers a fishing vessel transiting the western Mediterranean Sea from the port of Valencia to a fishing area south of Malta.

Currently, there is a great deal of active research regarding algorithms and their applications in a variety of multiobjective problems. Among the MOGAs reported to date, the NSGA-II algorithm by Deb et al. and SPEA2 by Zitzler et al. have excellent performance. These algorithms include important search mechanisms, such as preservation of good solutions discovered in the search and reduction of the potential Pareto-optimal solutions.

In our study, the routes are optimized with respect to two conflicting objectives, the total fuel consumption and the voyage risk. For maintaining diversity in the obtained routes, SPEA2 and NSGA-II algorithms have been selected as they are the most promising approaches. The basic operators employed in these algorithms are the node-based crossover operator and three different types of mutation operators. In the initial population, we have included the shortest routes in terms of the traveling time as well as the routes optimized only with respect to a single criterion, either the fuel consumption or the voyage risk. We have also taken into account historic data, and we have added to the initial population all the routes which are usually followed by many ships in practice. Our method takes also into account the IMO restrictions. The performance of the two algorithms is evaluated not only in terms of execution time, but we also assess the ability of the algorithms in retrieving the whole Pareto set.

A preliminary version of the algorithms described in this chapter is presented in [36]. More specifically, a prototype version of the evolutionary algorithm based on the NSGA-II algorithm is described. The objectives of the optimized routes are the same, namely the mean total risk and fuel cost. Also, safety is taken into account and restrictions are applied according to the guidelines of the International Maritime Organization (IMO). However, in the preliminary version, the performance of the algorithm has not been thoroughly examined as in this study.

4.4 Customization of Evolutionary Algorithms

In general, meta-heuristic methods do not ensure the return of the whole set of Pareto-optimal solutions. Another problem is that they often return solutions with no sufficient population diversity. However, NSGA-II and SPEA2 algorithm successfully handle these issues by employing carefully designed operators. In the following, we present the basic operations and structures used by NSGA-II and SPEA2 algorithms in this particular maritime setting.

- Route gene coding: Each solution path (chromosome) comprises a number of nodes (genes) of the sea grid, termed also as waypoints. Each route has a different number of nodes. Also, for each node of the route, its longitude and latitude coordinates are stored as well as the arrival time at that node. Also, all routes are associated with the same ship speed which is assumed to be constant throughout the journey.
- Initialization of route population: The convergence rate of an evolutionary algorithm toward optimal solutions heavily depends on the quality and the diversity of the initial population. Oddly enough, many evolutionary approaches for generating obstacle-free routes perform a random generation of the initial population. Specifically, each route of the initial population comprises random waypoints picked from a predefined navigation area. However, as the random waypoints may be situated over land or obstacles, infeasible routes may be derived. Thus, a random initial population may slow down the convergence rate toward an optimal solution and this in turn may increase the execution time of the algorithm or may result in worse solutions.

In our study, the grid points of a route are exclusively selected from the sea area and not from land or obstacle areas. The initial population contains four different routes, specifically, the routes optimized either for the fuel consumption, navigation, safety or the traveled distance. A main concern in the ship routing problem is also the fact that each weather forecast is relevant only for a specific time interval. As a result, each weather update may alter the optimal routes that have been calculated for the initial population.

Next, the initial population is grown by creating random mutations of the above single-objective optimal routes. By taking into account historical data [39], routes that are followed by many vessels in practice are included in the initial population, as well. However, this sort of information may not be available for all possible departure and destination ports.

- Fitness function: The fitness function indicates the competence of an individual from one generation to the next during the evolutionary computation. Specifically, for the problem at hand, the fitness function should reflect the constraints and the objectives of the problem. Thus, the value of the fitness function for each individual is the pair of values (FC, R) where FC is the total fuel consumption and R is the accumulated risk of the path associated with the individual. Furthermore, the fitness function should be designed in such as way that solutions violating problem constraints will have lower fitness value. In particular, since some kinds of manoeuvre in vessel navigation are not allowed for safety reasons, there should be a constraint on the maximum permitted change of course direction. Lastly, solutions with travel time exceeding the maximum total passage time are discarded from the current population rather than assigned a lower fitness value.
- Route selection in NSGA-II: For elitism preservation and diversity during evaluation, two techniques are used, i.e. the non-dominating sorting and the crowded-comparison operator. Specifically, all solutions are categorized into a number of fronts at different levels and each solution is assigned to its respective front based on its dominance relationship. Thus, the solutions which belong to a front are dominated by at-least one of the solutions belonging to the previous level front. The non-domination rank r_i of a solution corresponds to the level of the front which this individual belongs to. The crowding distance d_i of a solution i is the extent of the search space around i which is not occupied by another solution in the population. Thus, NSGA-II achieves population diversity in the set of the non-dominated solutions by using a niching method.[1] With the above definitions, the crowded comparison operator [8] can now be defined. According to this operator, a solution i is the winner of the tournament with another solution j if (a) solution i has better rank ($r_i < r_j$) or (b) solutions i and j have the same rank but solution i has better crowding distance than solution j, that is, $r_i = r_j$ and $d_i > d_j$.

  Essentially, each route within a generation is associated with a fitness value which is determined first by the non-domination level of the route and then by the crowding distance of that route. Now, before producing the individuals of the next generation, the algorithm should select which of the existing individuals (those of the current

[1] a method for finding and preserving multiple favorable parts of the solution space.

and the past generations) will be the candidates for producing the offsprings of the next generation. These individuals should have high fitness values and their number should not exceed a certain size. For determining this set, the existing individuals are first sorted by the crowded comparison operator and then the first in this order individuals are placed in this set. By using the crowded comparison operator, faster convergence toward optimal solutions is achieved since the best solutions in every generation are saved from extinction.

Then, using the crowded comparison operator for deciding the winner, a binary tournament selection operator is applied to the members of the set above for selecting the individuals which will generate the offsprings of the next generation. Next, the new individuals are produced by applying cross-over and mutation operations to the winners of the tournaments.

Finally, the evolutionary process terminates when the performance improvement between successive generations is sufficiently small (smaller than a threshold value) or when a certain number of generations has been produced.

- Route selection in SPEA2: The second approach, the SPEA2 algorithm [40] is a new model of a multi-objective genetic algorithm that improves the search performance of SPEA [41]. The algorithm maintains an archive of fixed size which contains high fitness individuals from all the past generations. The fitness function of individuals in the archive differs from that of individuals in the current population. Specifically, the fitness value of an individual belonging to the archive is the normalized number of the individuals of the current population dominated by that particular individual, whereas for an individual in the current population, the fitness value is the sum of two values: (a) the sum of the fitness values of all archive members which dominate that individual and (b) the density value of that individual where density is defined as a decreasing function of distance of that individual to its k-nearest neighbor and k is a parameter commonly set to the square root of total population size.

  Then, the non-dominated individuals from both the current population and the archive will form the updated archive for the next generation. If the total number of these individuals is lower than the fixed size of the archive, then the archive is filled with individuals with the highest overall fitness values from both the current archive and population. If the available non-dominated individuals are more than the required size of the archive, a truncation operation is applied where individuals with many other members of the archive in close proximity are iteratively removed until the size of the archive will be reduced to the pre-determined size. This truncation operation achieves a good spread of non-dominated solutions and also maintains the boundary solutions which are essential for attaining that good spread. After the generation of the new archive, a binary tournament selection with replacement is performed and the mating pool is created. By applying cross-over and mutation operations to the members of the mating pool, the new offsprings of the next generation are produced. The evolutionary process ends when a specified number of generations have been created or if another stopping criterion holds.
- Crossover operation: This operation combines two different parts of two randomly chosen routes (chromosomes) from the mating pool. For making sure that this

combination is valid, the crossover operator from [7] is adjusted. Specifically, for two randomly chosen routes, a random point in the first route is selected for splitting that route (Fig. 4.1). If this point is also a point of the other route, the crossover operation is executed or another route is selected for crossover until the mating pool gets empty.

- Mutation operation: In this operation, there are three possibilities of how a route can be altered [34]. In particular, the first alternative is the Create-disturbance operation (Fig. 4.2) where the coordinates of a node of the route are randomly changed within a previously defined range. Another option is the Insertion operation (Fig. 4.3) where a new node is inserted into the route. More precisely, the new node is picked among all nodes which are inside the circle centered at the midpoint of the edge connecting the two adjacent nodes and with radius being half the edge length. The last possibility is the Deletion operation (Fig. 4.4) where a node along the route is randomly chosen for deletion provided that it is not the departure and destination point or a node in areas specified by the user. It is also guaranteed that all routes obtained from the above operations are not going through land, obstacles or other forbidden areas.

(a) The selected chromosomes routes. (b) Combination of the two randomly selected parts of the chromosomes.

Fig. 4.1 Crossover operation

(a) Randomly selected chromosome node.

(b) Pertubation of the selected node.

Fig. 4.2 Mutation operation: create-disturbance

(a) Randomly selected chromosome edge.

(b) Insertion of a new node.

Fig. 4.3 Mutation operation: insertion

(a) Randomly selected chromosome node.

(b) Deletion of the selected node.

Fig. 4.4 Mutation operation: deletion

4.5 Modelization Issues

There is a number of modeling issues that have a critical impact on the effectiveness of ship routing algorithms. Specifically, it is essential to have a ship model which accurately predicts the response of the vessel to the weather conditions and also predicts the effect of these conditions on the real speed of the ship. In addition, an accurate model is needed for the fuel consumption along the ship route since this precise estimation of the consumption is a prerequisite for finding routes with minimum fuel consumption in reality.

We used the Aegean sea as a case study and the grid structure modeling this sea area was developed within the framework of the the AMINESS system [13]. Static and dynamic information was considered, namely geographic and bathymetric data, protected areas, risk estimation [19] as well as predictions for the weather and sea conditions. Moreover, voyage safety was taken into account and dangerous situations were avoided by following the IMO recommendations [18]. In particular, surf-riding and broaching-to are two situations that should be avoided when navigating in non-agreeable weather conditions. Surf-riding and broaching-to arise when $135^\circ < \Theta < 225^\circ$ and $V_R > \dfrac{1.8\sqrt{L}}{cos(180 - \Theta)}$ where Θ, V_R and L are the relative ship-wave angle, the ship speed and the ship length, correspondingly. As the ship speed is constant, the only way to rule out surf-riding and broaching-to is by eliminating the grid edges where these conditions hold.

Parametric rolling motions is another hazardous situation that may arise in bad weather conditions and should also be avoided. It happens when the encounter wave period T_E is almost equal to the natural rolling period of ship T_R or the encounter period T_E is near one half of the ship roll period T_R. The period of encounter T_E is estimated by the following formula:

$$T_E = \frac{3T_W^2}{3T_W + V_R cos(\Theta)} (\mathrm{sec})$$

where T_W is the wave period, Θ is the relative ship-wave angle and V_R is the ship speed (in knots).

For determining the time required for navigating between two points, the actual ship speed should be considered. This speed is often lower than the nominal one because of the added resistance induced by irregular waves and wind during navigation. In this study, we use the model in [23] for predicting the actual ship speed. This is a generic model independent of specific ship features and the speed decrease is a function only the significant wave height H and the ship-wave relative direction Θ. Specifically, the actual ship speed V_R is calculated by the following equation:

$$V_R = V(H, \Theta) = V_0 - f(\Theta) \cdot H^2$$

The values of the coefficient f are listed in Table 4.1.

Table 4.1 Values of the coefficient f

	Sea condition	$f[kn/ft^2]$
$0° \leq \Theta \leq 45°$	following seas	0.0083
$45° < \Theta < 135°$	beam seas	0.0165
$135° \leq \Theta \leq 180°$	head seas	0.0248

If more detailed information about a ship is available, a more analytical model for the vessel response to weather/sea conditions could be employed. Namely, we could use the approximate method by Kwon [21] for estimating the speed loss caused by the added resistance from the wind and rough sea conditions.

The estimation of the fuel consumption rate along a ship route is a very complex issue and a topic of intense research. In practice, the following formula is used: [2, 16, 24, 29, 32]:

$$F = K \cdot P \tag{4.14}$$

where F is the fuel consumption rate measured in kg/h, K is the specific fuel consumption of the ship and P is the engine power in BHP[2] (kW) of the ship. Therefore, the total fuel consumption of the whole route is the product of its passage time PT and the fuel consumption rate F:

$$FC_{total} = F \cdot PT \tag{4.15}$$

4.6 Computational Results

In this section, the two MOGA approaches are compared with a forward label setting algorithm [35], which solves the bi-objective shortest path problem in a time-dependent network, with a maximum travel time constraint and waiting at nodes being forbidden. In our setting, all algorithms search for the Pareto-optimal ship routes between a departure and destination port, optimizing the total fuel consumption and risk, subject to the constraint of the maximum travel time. The departure from the departure port takes place at a fixed time and the nominal ship speed is considered to be constant. Specifically, the test parameters were fixed as follows: speed = 30 kn, K = 200 g/kWh (specific fuel consumption), engine power = 4000 kWh.

All algorithms were implemented in C++ and the tests were carried out on a server with an Intel(R) Xeon(R) E5-2430 v2 at 2.50 GHz processor and 16 GB RAM. Table 4.2 details the parameters of MOGAs in these tests.

[2] Brake HorsePower (BHP) is a measure of the engine power at the output shaft of the engine.

Table 4.2 MOGA parameters

GA parameters	
Population size	100
Terminal generation	100
Crossover rate	0.2
Mutation rate	0.8
Runs	10

Table 4.3 Computational results: execution time

Start	Destination	CPU time (in seconds)		
		NSGA-II	SPEA2	Exact Algorithm
Alonissos	Cythera	18	19	50
Kos	Elafonisi	21	23	69
SW Crete	Chios	20	21	59
Piraeus	Samos	39	42	176
Kalamata	Syros	35	37	158

The execution times of the algorithms for different routes are listed in Table 4.3. For each different route, 100 tests were performed and the average execution time is shown in the third and the fourth column. The execution time of algorithm from [35] is listed in the last column. MOGAs run faster than the algorithm of [35] in all tests. In addition, NSGA-II and SPEA2 have almost the same execution time.

In this study, we used the ratio of non-dominated individuals (RNI) for evaluating the accuracy of the derived solution set and the cover rate for evaluating the breadth of this solution set. Specifically, the ratio of non-dominated individuals is calculated as follows. If SU is the union of the solution sets $S1$ and $S2$ obtained by the two methods, the set of non-dominated solutions in SU is determined and then, the percent of these solutions found by each method is calculated. The higher the value of this ratio for a solution method, the larger the part of the Pareto-optimal front that has been found by this method. Regarding the performance of SPEA2 and NSGA-II, the ratio of non-dominated individuals in SPEA2 was slightly higher (50.9%) than that of NSGA-II (49.1%).

The cover rate of a solution method indicates the diversity of Pareto optimum individuals obtained by the method. This rate is calculated by focusing on a single objective each time. Then, for this particular objective, the distance between the individuals giving the maximum and the minimum value in this objective is calculated and then the interval between the maximum and minimum value is partitioned in subintervals whose number is given as input parameter. Next, the ratio of subintervals containing at least one Pareto optimum individual over the total number of these intervals is estimated. Finally, the same estimation is done for each different objective and then the cover rate is obtained by averaging the ratios above. A high value in the

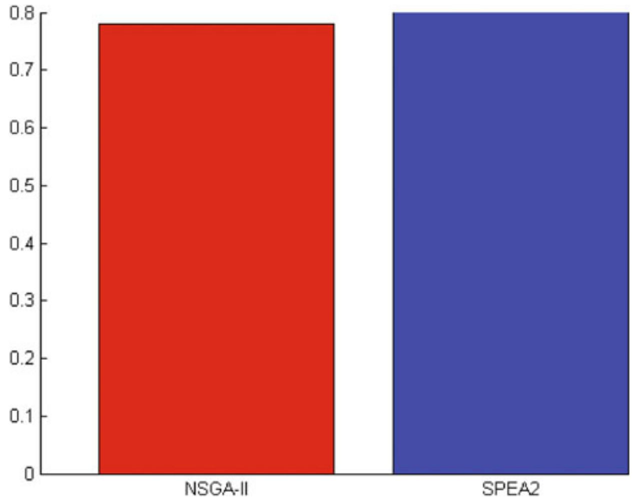


Fig. 4.5 Comparison of NSGA-II and SPEA2 with respect to the cover rate

cover rate clearly means that the Pareto-optimal solutions found are well distributed along the whole Pareto front. From Fig. 4.5, it is evident that the cover rate of the solution set obtained with NSGA-II was slightly lower than that of SPEA2. Also, the results of Fig. 4.6 shows how the cover rate varies with respect to the GA generation.

In principle, the distribution of the solutions could be evaluated by using generalized co-variance value. However, co-variance is not suitable for the solutions that have multiple peaks [17]. In that case, though the co-variance value is high, the diversity of the solutions is very low. For this reason, we opted for the cover rate for evaluating the diversity instead of the co-variance.

For a closer study of the performance of the three algorithms, we also examined the quality of the solution sets obtained for a journey between two specific ports. In Fig. 4.7, we can see the Pareto frontier retrieved by the exact algorithm along with the solution sets derived by the NSGA-II and the SPEA2 algorithm. Solutions of the NSGA-II are denoted with red dots. Blue circles represent the solutions of the SPEA2 algorithm, while solutions of the exact algorithm are denoted with green stars. The exact algorithm returned the whole Pareto set, consisting of 48 routes from Nafplio to Milos (Fig. 4.8a), while the NSGA-II returned 32 routes (Fig. 4.8b) and the SPEA2 retrieved 33 routes (Fig. 4.8c).

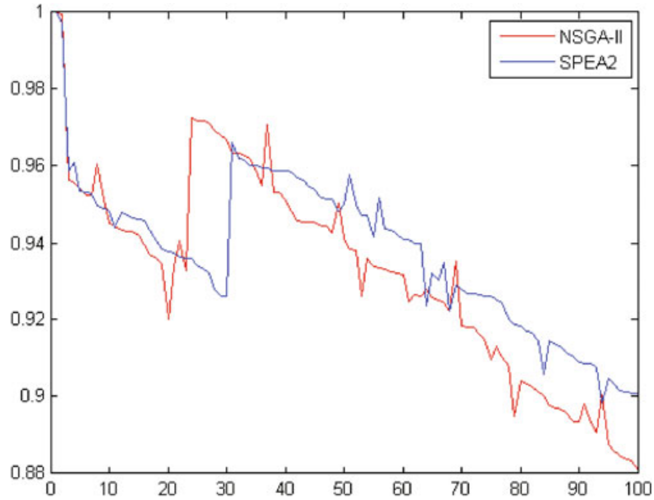


Fig. 4.6 Variation of the cover rate of NSGA-II and SPEA2 versus GA generation

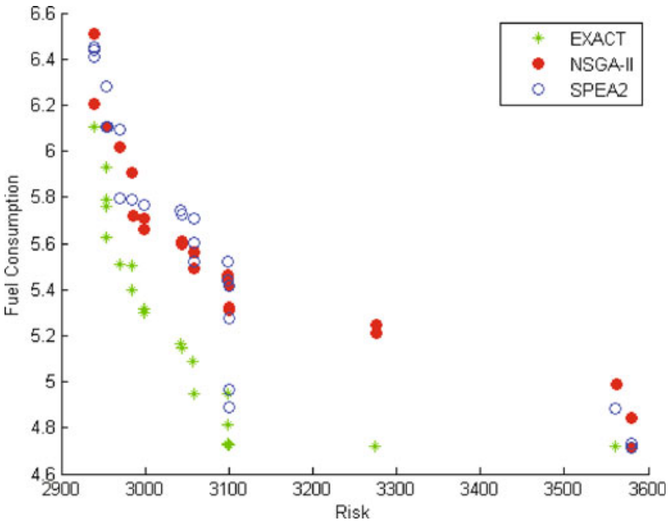
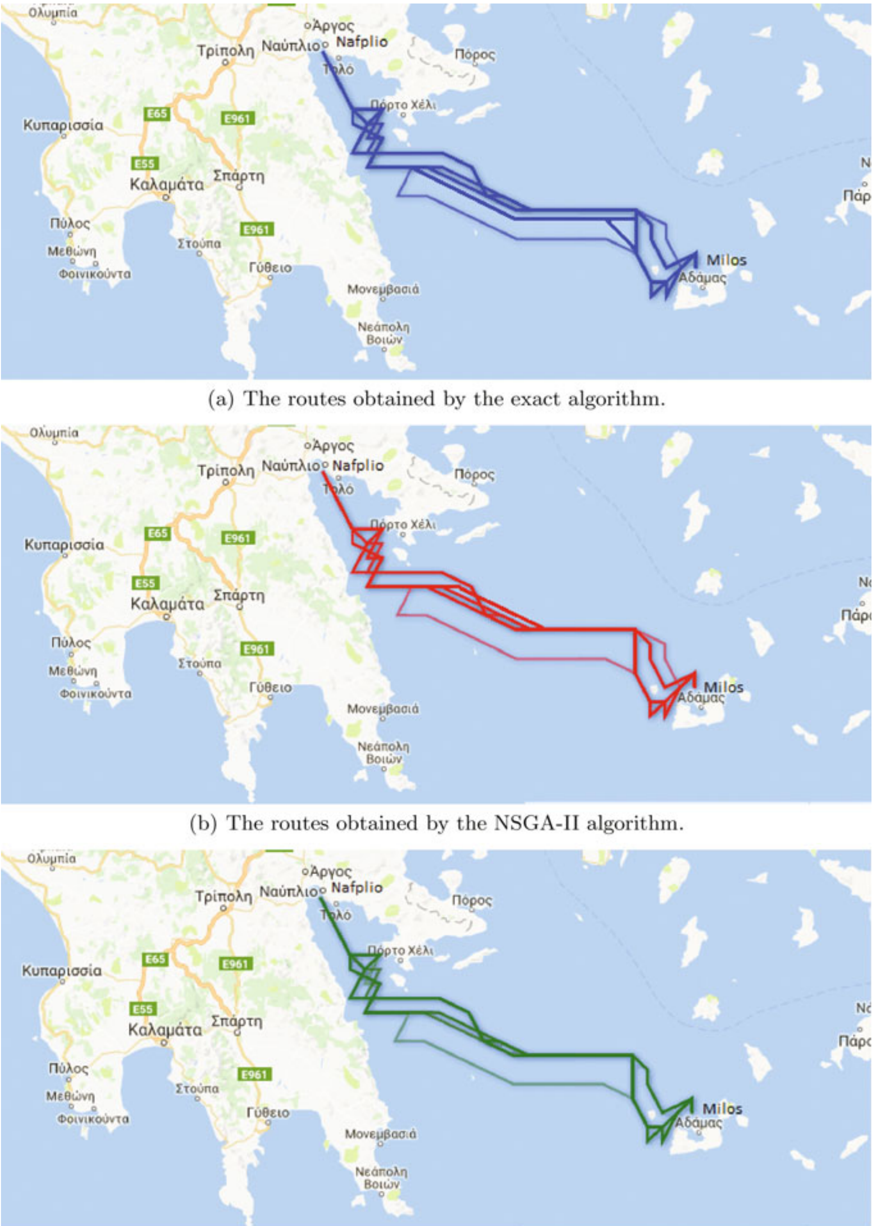


Fig. 4.7 The objective function values of the solutions returned by SPEA2, NSGA-II and the exact algorithm for a route between Nafplio and Milos



(a) The routes obtained by the exact algorithm.

(b) The routes obtained by the NSGA-II algorithm.

(c) The routes obtained by the SPEA2 algorithm.

Fig. 4.8 Solution sets for the route from Nafplio to Milos

4.7 Conclusion

In this chapter, we studied two evolutionary approaches for solving the time dependent, bi-objective ship routing problem with fixed departure time and a constraint of the maximum voyage duration. All techniques considered use a node based crossover operation and three different kinds of mutation operations. Also, by exploiting historic information, vessel routes which are preferred by many captains are identified and included in the initial population of the two MOGAs. Experimental results show that MOGAs have lower execution time than that of the exact algorithm of [35]. On the downside, the two evolutionary approaches did not manage to retrieve all Pareto-optimal solutions. Concerning the comparison between the two evolutionary algorithms, while NSGA-II slightly outperforms SPEA2 with regard to the execution time, SPEA2 achieves marginally higher accuracy in terms of the ratio of non-dominated individuals and sightly higher cover rate ratio. As a future work, we will study the same problem, allowing the ship speed to change along the route, however not frequently, since frequent speed change is not a common practice for short trips.

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