The benefits of co-evolutionary Genetic Algorithms in voyage optimisation

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Abstract

Reducing emissions is of increasing global importance. Within shipping, the International Maritime Organization's regulations are putting pressure on companies to quickly reduce emissions. One solution is the optimisation of a ship's route where even comparatively small reductions, in the order of 5%, provide sizeable cost and environmental benefits. The most recent advances from the Evolutionary Computation field have not been benchmarked on this problem, especially the co-evolutionary algorithms that provide the widest diversity of search. This paper compares state-of-the-art algorithms on three case studies, to show the impact of algorithm selection on the fuel consumption and expected voyage time. Four state-of-the-art Genetic Algorithms are selected to represent the leading families of Genetic Algorithm. The co-evolutionary approaches are shown to have the top performance, with cMLSGA (co-evolutionary Multi-Level

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Selection Genetic Algorithm) showing top performance on all the problems with the greatest potential reductions in fuel usage, 7.6% on average over the state of the art, and voyage times, 8.4% on average over the state of the art.
Keywords: Genetic Algorithm, Ship weather routing, Voyage optimisation, Maritime transport, Speed optimisation

1. Requirements for Voyage Optimisation Software

Voyage optimisation provides an immediate reduction in ship emissions. These systems have been recognised to cut these emissions in the region of 5-10% (1), helping ship operators to meet the International Maritime Organization's (IMO) target of reducing carbon intensity 40% by 2030 and greenhouse gas emissions 50% by 2050. In the longer term these tools will help to reduce the cost of using sustainable fuels, which are predicted to be more expensive than marine diesel and therefore a reduction in operational costs becomes more critical in encouraging the use of these fuels. They will also enable just-in-time arrival of ships at ports, helping to reduce the large quantity of emissions produced while ships wait to load/unload.

Voyage optimisation software is based on environmental data, a ship performance model, the restrictions for sailing and the voyage optimisation algorithm. The optimisation algorithm is a key element, with the literature showing a significant difference in performance between different solvers. The problem is in the selection of the best algorithm, as a wide range of methods are available to find the most fuel efficient routes for ships. In addition, the proposed methods utilise either single objective or multi-objective optimisation problems, with multi-objective optimisation becoming a more important factor from an industrial context. Genetic Algorithms are increasingly the most used method in the state-of-the-art to optimise the route and speed. However, the latest algorithms are not compared and the importance of this selection is not highlighted in the current literature.

2. State-of-the-art of voyage optimisation

From a methodological perspective, voyage optimisation algorithms can be divided into two categories for route planning: specific optimisation algorithms and general optimisation algorithms (2). Here, specific optimisation algorithms are designed for routing optimisation, such as the Modified Isochrone method (3) and the Isopone method (4). General optimisation algorithms are used to solve a range of optimisation problems in which users define their own models for specific problems and include methods such as dynamic programming and genetic algorithms. The early literature related to voyage optimisation has a focus on the specific optimisation algorithms and Dijkstra, whereas more recent approaches are mainly heuristics (5) or hyperheuristics. This literature has been reviewed in detail, (6) and (7) but it is difficult to draw conclusions about which algorithms provide the lowest fuel consumption, without compromising on the time of arrival.

Table 1 compares a number of these approaches, focusing on those that have solved the problem before the start of the voyage, without dynamic updates, and with a focus on a single arrival port. Isochrone and Isopone methods are included as one column, where Isopone methods are shown to have a stronger performance (8).

A* is a popular method method for current commercial Voyage Optimisation Software, despite limited benchmarking in the open literature. A comparison with the original Genetic Algorithm show similar results, although A* is selected as the results from the Genetic Algorithm are considered to be less robust and dependant on the initial population (9). However, more modern variants of the Genetic Algorithm, defined in Wang and Sobey as NSGA-II onwards (10), are more robust to the starting population. The problem with A* is that its computational time increases exponentially with the number of grids (6). While the benchmarking performed is on a reasonable length route, from Venezuela to the English Channel, there are a number of longer routes where it may not perform well and the increase in fidelity of weather data is increasing the number of nodes between destinations.

The most successful algorithms are 3DDP (3D Dynamic Programming) and Genetic Algorithms, where these approaches can be shown to outperform all of the others. 3DDP has been shown to be the highest performing dynamic programming approach, (11) and (8), showing a slightly better, but similar, level of performance to NSGA-II. A number of different Genetic Algorithms are used: especially SPEA, NSGA-II and the original Genetic Algorithm or those with similar mechanisms to it, such as the modified distance GA (12) or the Genetic Algorithm integrated with dynamic programming (13). The original variants of the Genetic Algorithm have not been compared to modern algorithms but various benchmarking exercises in other fields suggest that the new algorithms will have a considerably stronger performance (14).

Despite the success of the Genetic Algorithm on voyage optimisation problems, a number of modern highly-performing approaches are yet to be considered. Four main branches are recognized in the current state-of-the-art, (14) and (10): niching, decomposition, co-evolutionary and multi-level selection.

Niching is exemplified by the crowding mechanism based niching technique found in the most popular Genetic Algorithm, NSGA-II (34), which uses non-domination to select the fittest members of the population for reproduction. This approach has been extended to problems with higher numbers of objectives, 4+, through NSGA-III. U-NSGA-III (35) has been proposed as a single unified evolutionary optimisation procedure that solves single-, multi- and many-objective optimisation problems efficiently, eliminating the need to benchmark NSGA-II and NSGA-III separately.

Decomposition algorithms work by dividing the search space into multiple subspaces and solving each of them separately. The most popular approach in this family of algorithms is Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D) (36). In the MOEA/D the multi-objective problem is decomposed into a predefined set of subproblems, by assigning a distinct weight vector to each individual and utilising a scalarisation method for the fitness calculation. The MOEA/D based methods have been shown to outperform niching and other decomposition methods on unconstrained and dynamic functions by promoting convergence over diversity (37). However, as the vector

Table 1: Comparison of state-of-the-art voyage optimisation algorithms in chronological order, where x indicates the algorithms benchmarked in the paper, ✓ are the top performing algorithms, * indicates algorithms of a similar family with small adjustments, red columns are variants of Dynamic Programming, blue are Genetic Algorithms and grey represent other methods

Dijkstra	A*	Dynamic Programming	SPEA	NSGA-II	Original	PSO	DIRECT	Grid Search	Exact	Isochrone	Directed graph	Reference
x												(15)
x												(16)
			x									(17), (18), (19), (20)
		x										(21)
		✓	x	x		x						(11)
					x					x	x	(22)
							x					(23)
					✓*			x				(12)
							x	✓				(24)
				✓					x*			(25)
										x		(26)
					x							(27)
	x				x							(9)
		x										(28)
x		✓								x		(8)
				x								(29)
		x										(30)
					x							(31)
x												(32)
						x						(33)
					x*							(5)
x					✓*							(13)

approach is based on predefined reference points, these algorithms are less effective on constrained and discontinuous problems, due to the gaps on the search and objective spaces, or where there is a lack of a priori knowledge about the search space.

Co-evolutionary algorithms refer to an evolutionary algorithm based on the concept of two, or more, species that's evolution are dependant on each other. In these algorithms the individuals are evaluated based on their interaction with other individuals. The top performing co-evolutionary algorithm is Hybrid Evolutionary Immune Algorithm (HEIA) (38). In HEIA, two distinct evolutionary strategies, SBX and DE, are used independently on different sub-populations, instead of problem decomposition. It has shown high performance on discontinuous cases with a better spread of points along the Pareto optimal front than other methods, indicating that the reproduction process has strong diversity retention.

Multi-Level Selection (MLS) algorithms are based on the concept of selection being based on a fitness evaluation at multiple levels, for example in humans it might consider the fitness of an individual and the fitness of that individual's social group (39). This results in a sub-population algorithm that incorporates an additional selection procedure at the group-level, in addition to the individual level used in the standard Genetic Algorithm. In this case different sub-populations are allowed to compete with each other for reproduction and survival in a similar way to the individuals inside each group. This creates an additional evolutionary pressure that allows a wider exploration of the search space by different sub-populations (40; 41). It is the only GA to promote a diversity-first and convergence-second approach. This strategy has been combined with co-evolution, resulting in co-evolutionary Multi-Level Selection Genetic Algorithm (cMLSGA) (14). It is the first algorithm to exhibit co-evolutionary behaviour at the collective level, leading to the top general performance, with particularly strong performance on discontinuous and constrained problems, where diversity in the mechanisms is of importance.

As only niching, NSGA-II, is represented in the literature related to ship routing, this paper benchmarks the state-of-the-art Genetic Algorithms. Four GAs are selected to represent each of the major categories of Genetic Algorithms: U-NSGA-III (35), MOEA/D (36), HEIA (38), and cMLSGA (42). SPEA2 is also included due to its performance on voyage optimisation problems considering the travelling salesman problem (43) and (44). Based on Table 1 U-NSGA-III should have similar performance to NSGA-II and 3DDP, which show the top performance in the current literature and it's performance is used as a proxy for the performance of the current top performing algorithms.

3. Description of the Voyage Optimisation Software

Typically the ship-routing problem is developed as a minimisation of the fuel consumption and voyage time, while maximising the voyage safety. Emission reduction is often considered to be a natural consequence from reduction of the fuel consumption, as is the cost. A three objective minimisation problem is considered: fuel consumption, voyage time and voyage distance. The voyage time objective is to minimise the time for the voyage, with the Pareto Front finding a range of possible journey arrival times, from which the closest route to the preferred arrival time can be selected for the voyage. The objective for the voyage distance has been added, due to its positive impact on the effectiveness of all of the tested algorithms in pre-benchmarking. This is despite the direct dependency of the other two objectives on it and that it is not an objective of interest. Its inclusion leads to more "realistic" routes, where changes in the ship's course do not occur as often as in the two-objective pre-benchmarks. This is important, especially during open-sea sailing, where a ship's captain prefers to maintain a stable course instead of adjusting it every few miles. Safety is maintained by a set of constraints, to reduce the search space only on those routes deemed safe and allowing a binary definition of safety. For comparative purposes, all of the selected genetic algorithms have been incorporated into the T-VOS © engine. It was selected, as it allows different genetic algorithms to be incorporated as solvers, while benefiting from a high resolution of met-ocean data and a range of safety parameters.

3.1. Route representation

Voyage optimisation begins by discretizing the ship's possible sailing area into a mesh of 250 nodes. The mesh is developed around a predefined, first-order approximation of the route[1] in three steps:

[1] First order approximations are included in the data supplement for benchmarking: http://dx.doi.org/10.17632/ssdbwvsrm9.2

- The nodes are generated by solving the spherical triangle problem, while maintaining a similar distance between neighbouring nodes. In this study the target number of nodes in the first order approximation is set to 250 for each case. The resulting waypoints are, on average, 42.36km apart for the Dalian to San Francisco voyage, 43.92km apart for the Southampton to Karachi voyage and 27.6km for New York to Oslo voyage.

- Developing a minimum and maximum boundary for each node with a maximum allowed spread of 10 degrees in each direction.

- Reducing the size of the minimum and maximum boundary for the first and last 10% of nodes, so that the mesh size gradually "develops" from the starting point, and reduces near the destination. This reduces the computational effort and produces more feasible routes.

A separate parameter is maintained defining the ship's speed between nodes. Speed is changed every 5 waypoints, while remaining constant in between. This allows more realistic voyages, as it is unlikely that the ship's speed would be adjusted regularly. A high-fidelity hindcast met-ocean data model taken from HYCOM (HYbrid Coordinate Ocean Model), with a resolution of 0.08° for ocean currents and 0.25° for wind and waves taken from NOAA GFS for global and WRF for regional modelling, is used to simulate the actual weather-related updates[2].This data is taken for a period starting on the 13th August 2018 for

[2]The weather data is available as a supplement for benchmarking: http://dx.doi.org/10.17632/ssdbwvsrm9.2

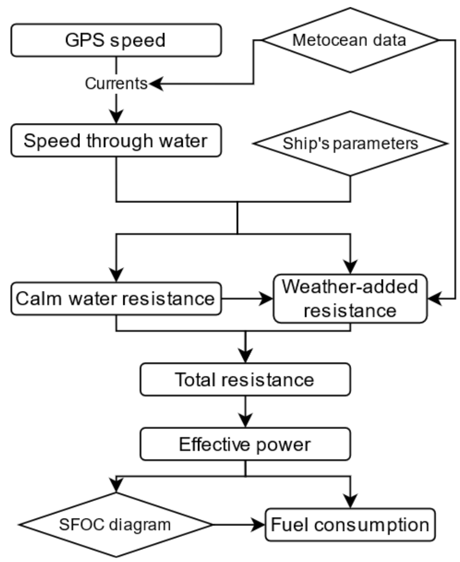


Figure 1: Fuel consumption calculation based on ISO15016:2015 (45)

each of the 3 voyages."

As the node grid is a different shape to the met-ocean grid, the route between each node is split into a set of sub-routes using linear interpolation, that matches to the met-ocean grid to calculate the fuel consumption. This provides the benefits from the high-fidelity met-ocean data, increasing the accuracy of the route-planning, while maintaining reasonable computational times.

3.2. Fuel consumption

To predict the fuel consumption the ISO15016:2015 (45) procedure is used, presented in Fig. 1, which is commonly used for this purpose.

The main components in evaluating the fuel consumption are: the speed of the ship through water, met-ocean conditions, resistance calculation model and ship-model. The speed through water was calculated by subtracting the speed of the currents from a ship's GPS speed. The calm water resistance was calculated using Holtrop and Mennen (46) with weather added resistance provided by the Kwon and Townsin (47) empirical formulas, which were derived from a large number of experimental data. The Kwon and Townsin model accounts for the wave and wind conditions through their impact on the ship's resistance and therefore the required engine's power. The current is used to calculate the speed through the water from the speed over the ground (GPS speed), which is used in the Kwon and Townsin model to calculate the power. The fuel consumption was calculated from the effective power, based on the ship-specific fuel oil consumption curve (SFOC), and voyage time. A 2800TEU container ship, taken from (48), is investigated, with ship's parameters detailed in Table 2. A maximum speed of 20 knots and minimum speed of 14 knots are assumed for the vessel, based on its size.

3.3. Safety and voyage constraints

To ensure that the route reduces the potential for grounding, larger land masses are removed from the pool of potential nodes during the mesh generation process. This is done using the difference between the ocean depth, from bathymetry data (49), and the draft of the ship, with an under keel clearance of 1.5 times the draft. This eliminates the infeasible sub-paths/edges and improves the efficiency of the optimisation process. Here, high-fidelity bathymetry data, with a resolution of 0.0045° taken from SRTM, is used to ensure safe under keel clearance during the voyage. A number of additional constraints are introduced in order to maintain ship's safety:

Table 2: Main particulars of the 2800TEU container ship

Ship particular	Value
Min speed	14 kn
Max speed	20 kn
Length	232 m
Beam	32.2 m
Depth	19 m
Draft	10.78 m
Block coefficient	0.685
Midship coefficient	0.98
Waterplane coefficient	0.75
Deadweight	40900 t

- the maximum allowed wind speed and wave heights are 20 m/s wind speed for all directions; 6m for head waves; 5m for following waves and 4m for beam waves.

- The maximum turning angle of the vessel at a single node is 20 degrees.

- The engine power can not exceed 90% of the maximum continuous rating.

- Route-specific traffic separation schemes are implemented by constraining the speed or allowable direction at each node in that region e.g. for Suez Canal and Gibraltar strait, taken from the IMO's Ship Routeing guidance (50)

4. Experimental plan

4.1. Voyage definitions

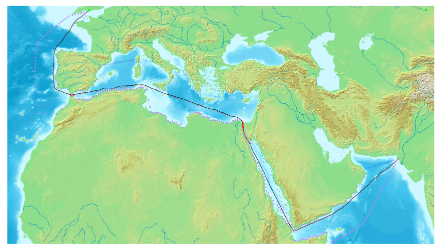
Three exemplar voyages are selected for this study, and illustrated in figure 2:

- Voyage 1: Dalian to San Francisco, as a long route with a large number of nodes.

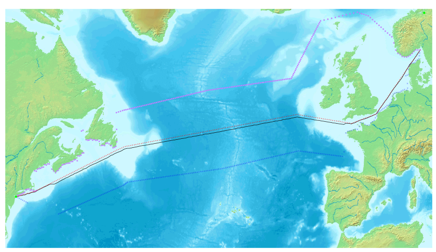
- Voyage 2: Southampton to Karachi via the Suez Canal as a route incorporating restrictions and traffic separation schemes.

- Voyage 3: New York to Oslo, which includes a bifurcation of the voyage, where the ships can take a northern route around the United Kingdom, and a southern route via the Channel.

(a) Voyage 1 - Dalian to San Francisco



(b) Voyage 2 - Southampton to Karachi



(c) Voyage 3 - New York to Oslo

Figure 2: Routes representing different voyage optimisation challenges used to benchmark the algorithms; the purple and blue dotted lines represent the boundaries of the mesh and the red dotted line represents the first order approximation of the route

The Traffic Separation Schemes included in the routes are: route 1: N/A, route 2: the Suez Canal and the Strait of Gibraltar and route 3: the Dover Straits. The Suez Canal has a speed limit of 7 knots, the Strait of Gibraltar has a speed limit of 13 knots and there are no speed restrictions through the Dover Strait. The weather on route 1 was the worst throughout the voyage from all of the evaluated scenarios. There are two hurricanes, one of these starts South of Japan and moves directly North, dissipating over the Japanese mainland and a second which starts in the East China Sea and moves North, dissipating over the South Korean Mainland. There are also high sea states over the main Pacific Ocean where the wind is blowing North/North-East. These are situated in the middle of the Pacific and which are level with the bottom of Korea, stretching North and East into the Arctic circle.The other routes have fair weather during the simulated journeys. More details of the weather are available in the data attachment.

4.2. Benchmarking methodology

The population size was set to 1500 as the best value for all of the algorithms, after testing in a range of values from 600 to 2000. The maximum number of fitness function evaluations was set to 500,000 and each simulation was repeated over 10 independent runs for each route. The algorithms[3] are all used with the hyperparameters documented in the original papers, shown in Table 3. cMLSGA

[3]The source code for the Genetic Algorithms utilised is in C++ and can be found here: https://github.com/pag1c18/cMLSGA.

has 1 collective replaced every 5 generations.

Table 3: Hyperparamters for the different Genetic Algorithms

Hyperparameters	cMLSGA	NSGA-II	MOEA/D	HEIA	SPEA2
Crossover type	SBX	SBX	DE	SBX and DE	SBX
Crossover rate			1		
Mutation type			polynomial mutation		
Mutation rate			0.003333		
Algorithm Specific	collectives= 6 $\eta = 20$, F =0.5, CR = 1	$\eta = 20$	F = 0.5, CR = 1	$\eta = 20$, F = 0.5, CR = 1	$\eta = 20$

The performance was evaluated based on the mimicked Inverted Generational Distance (mIGD) (51) and mimicked Hyper Volume (mHV) (52). mIGD is the average value of the minimum distance between uniform points on the Pareto Optimal Front and the non-dominated solution set. Lower values of mIGD emphasise better performance, focusing on the convergence of solutions, and is calculated according to (51). mHV is the measure of the volume of the objective space solutions that is dominated by the set of solutions, where bigger values indicate better performance, emphasizing a higher diversity of solutions on the Pareto Optimal Front. Here, the mHV metric is calculated according to (52), which provides the fastest and most widely used method for this calculation. Since the global Pareto Optimal Fronts are not known for the presented case studies, this front is approximated by non-dominated sorting of all of the

Pareto Optimal Fronts achieved from all of the separate tests, resulting in 653 points for voyage 1, 896 points for voyage 2 and 1001 points for voyage 3.

5. Benchmarking of the performance

The five algorithms are compared to generate optimum routes for the three case studies. The resulting performance measures for the investigated voyages are listed in Table 4. The lowest distance is included in the optimisation as it improves the results for the other 2 variables, but is not included in the discussion as it is not considered to be a useful characteristic, reducing the 3 dimensional Pareto Sets to 2 dimensional Pareto Fronts.

In all three cases cMLSGA shows the top performance in terms of reducing the fuel consumption and finds the route with the lowest travel time. This is followed by HEIA, MOEA/D, SPEA2 and U-NSGA-III for voyages 1 and 2 with MOEA/D finishing last for voyage 3. For voyage 1, the difference in the fuel consumption between cMLSGA and the next best performer, HEIA, is not significant, despite the length of the voyage. However, the results are significant for Voyages 2 and 3 with voyage 2 giving a difference of 17 tonnes and for voyage 3 a difference of 4.8 tonnes. When compared to the worst performer, U-NSGA-III, which approximates the strongest performance of the methods summarised in Table 1, this difference is more substantial. In all of these cases the difference is significant with voyage 1 showing a difference of 12.9 tonnes, voyage 2, 39.6 tonnes, and voyage 3, 12.2 tonnes. The top performing algorithms in each case are those with co-evolutionary elements, showing the importance of diversity of

Table 4: Performance measures of the optimized routes where low values of IGD and high values of HV indicate stronger Pareto Fronts

Voyage name	GA	IGD	HV	Most fuel efficient route		Most time efficient route	
				Fuel (tonnes)	Time (hrs)	Fuel (tonnes)	Time (hrs)
Voyage 1	cMLSGA	**6.2***	**0.041***	**258.5**	**467.4**	**345.5**	**393.8**
	HEIA	8.9	0.037*	258.6*	469.8	345.0	393.9*
	MOEA/D	9.2*	0.032	264.1*	464.3	333.5	400.8
	SPEA2	17.7	0.032	270.7	454.8	305.2	420.4
	UNSGA-III	14.8*	0.032	271.4	456.2	314.4	414.6*
Voyage 2	cMLSGA	**14.2***	**0.008***	**313.0***	**423.0**	**796.0**	**297.9***
	HEIA	17.5*	0.005	322.4*	422.6	807.4	300.8*
	MOEA/D	40.7*	0.007*	330.0	417.8	521.2	337.5*
	SPEA2	114.4	0.004	333.3*	405.6	520.9	333.8
	UNSGA-III	51.3*	0.006	352.6	398.3	488.2	345.1
Voyage 3	cMLSGA	**4.2***	**0.043***	**164.1***	**319.8**	**215.3**	**255.3***
	HEIA	8.5*	0.039*	168.9*	305.4	212.0	260.0*
	SPEA2	10.7*	0.011	174.5	300.1	197.5	270.9*
	UNSGA-III	12.1	0.032*	176.3	299.4	197.5	273.5
	MOEA/D	7.2	0.018*	179.2	288.7	205.6	262.6*

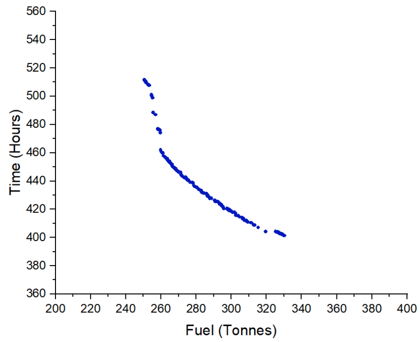
* indicates that the results are significantly better than the next score, using Wilcoxon's rank sum test with a significance level of $\alpha = 0.05$. Where green boxes are algorithms with co-evolutionary elements and the grey boxes show U-NSGA-III which acts as a proxy for the performance of algorithms used in the previous literature

search.

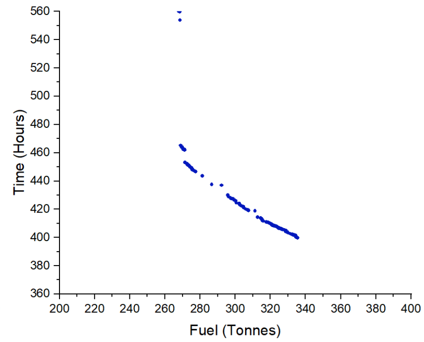
Figures representing the median Pareto Optimal Front achieved by each algorithm for all the case studies are shown in Figs. 3, 4 and 5.

When comparing Pareto Optimal Fronts for the Dalian to San Francisco route then U-NSGA-III and SPEA2 show narrow fronts, that do not contain the range of results obtained by the other algorithms. MOEA/D finds a wider range of points than these two algorithms and a complete range of points along the front. The front for HEIA is much more discontinuous, including two points with high time of arrivals that are not on the fronts for the other algorithms, likely showing that the algorithm has not yet converged in this area. cMLSGA shows a more jagged front than MOEA/D but with a wider range of points, that provides a greater selection of routes on the time to arrival side but that do not provide substantial benefits in fuel over HEIA. The Pareto Front looks more resolved in this case than HEIA in the centre, with the results demonstrating that this is a difficult problem to completely resolve in the number of function calls available and showing that the results of generally higher interest, the reduction in fuel consumption, are harder to find.

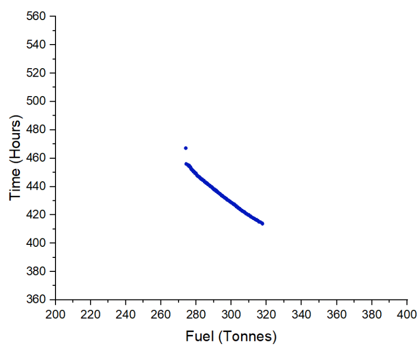
A similar behaviour is shown for voyage 2, between Southampton and Karachi. In this case the shortest front is U-NSGA-III, which also has a shift to the high fuel consumption/low travel time results and shows that the results have not converged. MOEA/D shows a shorter front, but well resolved, with a few points found at the extreme values. HEIA and cMLSGA have incomplete values along the fronts, but with a much wider spread. These have a higher diversity of



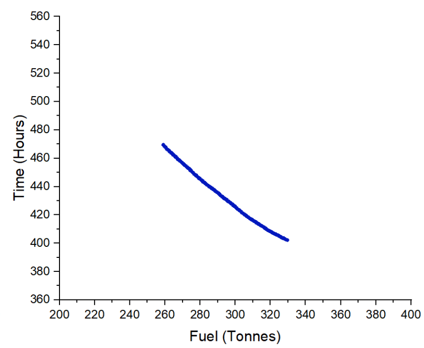
(a) cMLSGA



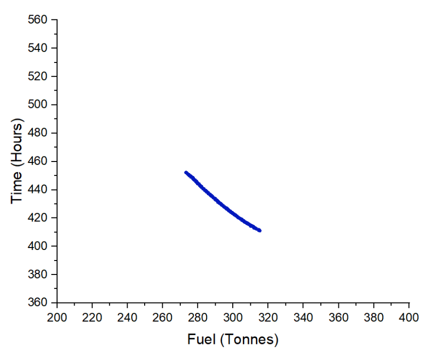
(b) HEIA



(c) U-NSGA-III

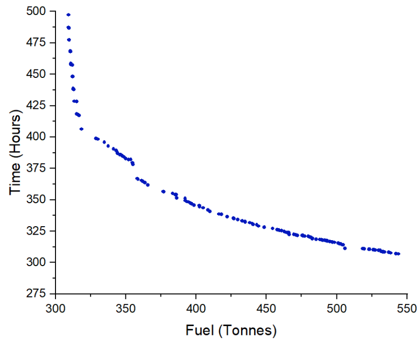


(d) MOEA/D

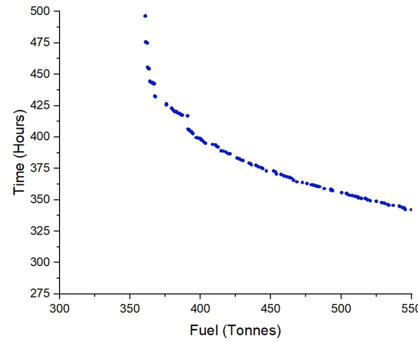


(e) SPEA2

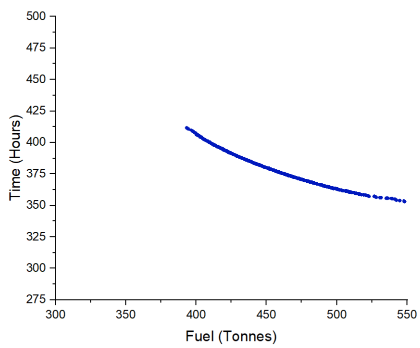
Figure 3: Pareto Optimal Fronts for minimum fuel consumption vs estimated time of arrival in Voyage 1



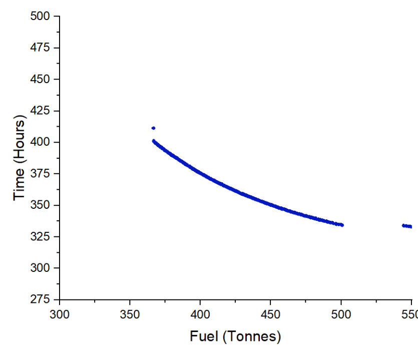
(a) cMLSGA



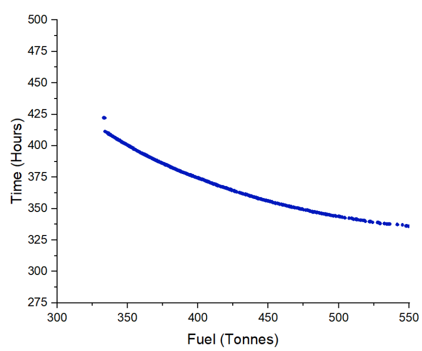
(b) HEIA



(c) U-NSGA-III



(d) MOEA/D



(e) SPEA2

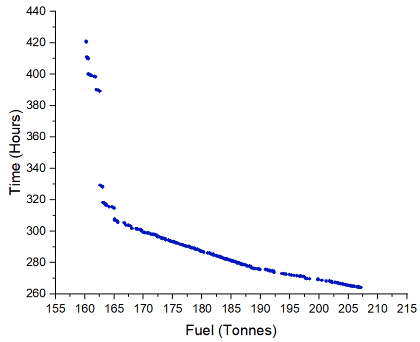
Figure 4: Pareto Optimal Fronts for minimum fuel consumption vs estimated time of arrival in Voyage 2

solutions but without having found all of the solutions in the middle area. This provides a considerably higher number of low fuel options compared to the other algorithms. HEIA in this case has not converged on the final solution and more runs will be required to find the optimal solutions in the cMLSGA Pareto Front. In this case many of the SPEA2 results might provide more realistic solutions than HEIA, despite not providing the lowest fuel consumption.

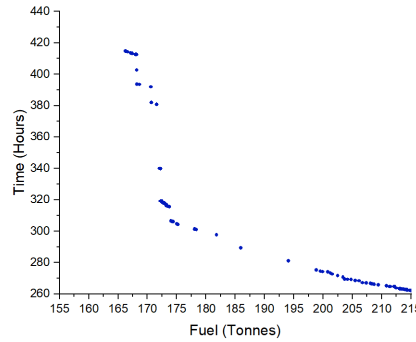
The Pareto Fronts for voyage 3, New York to Oslo, also show a similar trend to that for voyages 1 and 2, with U-NSGA-III, MOEA/D and SPEA2 showing shorter fronts and a focus on higher fuel/short time solutions. In this case the front for HEIA is sparse, with a number of points missing along the length, but with a wide range of results at both ends, demonstrating solutions with low fuel consumption and early arrival times. However, in these cases the results with the lowest fuel consumption have a considerable increase in time of arrival and it may be that the extreme fuel reduction adds too much additional time for a realistic voyage. cMLSGA is the only algorithm to provide a range of solutions that are close to optimal and that can be used to balance between arrival time and fuel cost.

6. Discussion

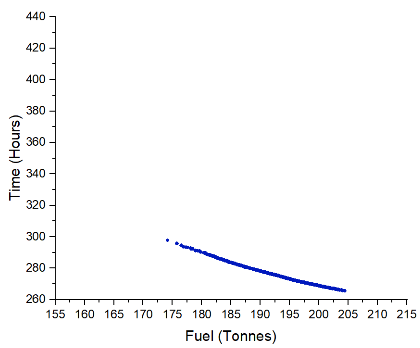
The results show that the selection of the optimisation algorithm is important. Small improvements in fuel reduction provide substantial cost savings and help to reduce green house gas emissions. The previous literature demonstrates a move towards the Genetic Algorithm to solve this problem, with NSGA-II



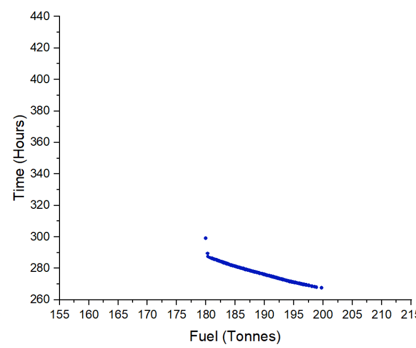
(a) cMLSGA



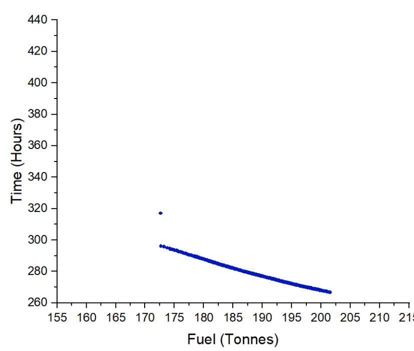
(b) HEIA



(c) U-NSGA-III



(d) MOEA/D



(e) SPEA2

Figure 5: Pareto Optimal Fronts for minimum fuel consumption vs estimated time of arrival in Voyage 3.

providing high performance, roughly equivalent to that of 3DDP. Testing of more recently developed algorithms shows that the co-evolutionary approaches demonstrate a clear improvement over the rest of the literature. The ability to have different algorithms searching different parts of the search space provides a diversity of search that is important in finding the extreme values. This is increased in cMLSGA through the use of collectives that can spread even more widely across the search space. These algorithms not only provide the best results, but they also provide a range of results that will become more important as Just-In-Time arrival becomes more prevalent. It indicates that for future applications the selection of the algorithm is likely to be even more critical. A high diversity of search provides a range of profiles that can be selected from, allowing selection of the one that is most beneficial for current ship operations. As we move towards just-in-time arrival, where the port specifies a time of arrival for the ship's captain to arrive and load/unload immediately, a range of results becomes more important. This is to allow the flexibility to determine what times will be possible and change route immediately to match changes in the arrival. The result should be slower steaming and reduced emissions.

An area of difficultly in benchmarking is the range of different algorithms that have been tested across a wide range of different problem types, with varying levels of realism, making a fair comparison difficult. However, determining the difference in performance of the top performing algorithms is shown to be significant. It is hoped that the open sourcing of the problems used for this benchmarking, with the relevant weather data, will provide some initial benchmarking problems for the community. These can be used in the future to directly compare to the results documented here and to grow a set of problems where high performance on the problem set will reflect high performance in the real-world, focusing the literature on the top algorithms [4].

An area that is not considered within the paper explicitly is the run time for the algorithms. Time dependant results are notoriously difficult to provide fairly, with the results being dependant on the implementation and the users computer. In this benchmarking the code bases are taken from the original developers of the algorithm, in the hope that this provides a reasonably optimised version, and run on the same desktop computer. In this case cMLSGA provides the fastest simulation times, with a mean value of 3 times faster resolution of the function calls than the other algorithms (in the range of 5-15mins), ranging from 2.6 times faster compared to SPEA2 on voyage 2 to 4.0 times faster for HEIA on voyage 1. In addition, there are elements of engine performance that are required to provide more realism, such as the inclusion of fouling, which will provide more accurate assessments of the fuel used in transit.

7. Conclusion

Voyage optimisation solutions are reported to reduce fuel consumption and greenhouse gas emissions up to 10-15%. However, it provides a complicated optimisation problem and the number of algorithms that have been tested is large. To see the full benefits of the approach requires benchmarking of the top

[4] Link to the dataset: http://dx.doi.org/10.17632/ssdbwvsrm9.1

available algorithms. The use of Genetic Algorithms to solve these problems is common but the current literature does not consider the state-of-the-art from Evolutionary Computation, especially co-evolutionary algorithms, which exhibit a high diversity of search. In this paper it is shown that these co-evolutionary approaches outperform the rest of the state-of-the-art, and the top performing algorithm is cMLSGA. In addition the benefits of the diversity of search are that a range of solutions are produced that will empower changes in ship operations, including Just-In-Time arrival. However, for these applications the selection of the algorithm is shown to be even more important. The top performing algorithm can result in a considerable difference in fuel savings, with a 7.6% improvement over algorithms previously tested in the literature.

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