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MULTI-OBJECTIVE DESIGNOPTIMIZATIONOF BULK CARRIERS

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Abstract:

This paper deals with the numerical optimization of bulk carrier design. The main objective is to minimize the construction cost, the transportation cost and to maximize the annual transported cargo. Four multi-objective optimization methods are used: the weighted aggregation method based on multi-attribute decision making (MADM), the control function, the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the hybrid method. The obtained results show that the MADM, NSGA-II and hybrid methods give more or less similar results for the three objective functions compared to the control function method. They also showed that although the weighted aggregation method MADM has certain advantage related to construction cost and voyage cost compared to both NSGA-II and hybrid methods, it remains deficient with regard to the transportation cost and the annual transported cargo.

Keywords: Bulk carrier, Optimization, Multi-objective, MADM, NSGA-II, Hybrid method.

NOMENCLATURE

AC	Annual transported cargo (t/year)	*L*	Length (m)
B	Beam (m)	*MADM*	Multiattribute Decision Making
C	Depth (m)	*MOOP*	Multi-Objective Optimization Problem
C_B	Block Coefficient	*NSGA-II*	Non-dominated Sorting Genetic Algorithm, version two
CS	Ship cost (£)	*T*	Draught (m)
CV	Voyage cost (£)	*TC*	Transportation cost (£/t)
KKT	Karush-Khun-Tucker	V_K	Velocity (knots)

1. Introduction

Shipbuilding is a promising industry and shipyards are increasingly building new ships that undergo minimal modifications during the construction process. This is mainly due to the development of design methods and the application of modern optimization techniques in all phases of ship design. The common interests of shipbuilders are related to optimizing facilities, saving capital costs, maximizing production efficiency and minimizing construction costs. Traditionally, ship design was based on approximate methods, but the rapid rise of computer technology has led to the development of new design methods using various optimization techniques.

Although ship deliveries declined by 12% in 2020 due to labor shortages caused by lockouts, which disrupted maritime activity, the capacity of the world's commercial fleet continues to grow and has reached 2.13 billion deadweight tons (dwt), according to The United Nations Conference on Trade and Development UNCTAD (2021).The rapid growth of port activity and cargo handling worldwide by 2025 requires the delivery of new ships with 30% more energy efficient than those built before 2014. In most cases these ships are bulk carriers, followed by tankers and container ships.

The design of this type of ships is generally dominated by a considerable number of objectives and constraints that are related to many competitive aspects relevant to the ships life cycle. Therefore, design methods based on optimization are increasingly being developed and the design of new ships is defined as a non-linear optimization problem whose decision variables constitute the main dimensions of ships belonging to a database. Most of these methods are based on gradient or genetic methods.

Filipa (2016) presented a parametric generation method based on the three-dimensional surface model for merchant ships hulls conception. This model is used at different stages of ship design optimization. Hao et al.

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(2011) proposed an approach for optimizing the structural design of a bulk carrier with two contradictory objectives weight and fatigue using an optimization system based on JAVA and ABAQUS. Malleswara et al. (2013) optimized the dimensions of two bulk carriers with different tonnages using three design softwares, Napa, Tribon and Catia. Brizzolara et al. (2015) optimized the complex shapes of ship hulls using both parametric and numerical design methods. The numerical optimization is performed through the NSGA-II. The authors showed that the optimization based on the genetic algorithms ensures the convergence of the iterative process and the global minimum is reached for most of the studied cases.

In another context, Moustafa et al. (2015) optimized the bulk carrier fuel consumption by varying the trim to achieve minimal resistance. Tomasz (2016) modeled the transfer function of the added wave resistance during the preliminary design of bulk carriers. The developed method is based on the theory of artificial neural networks using water plane area, water plane coefficient, ship speed and the frequency of the regular wave. Carlos (2016) used the Friendship Framework software to model the 3D geometric shape of the bulk carriers by combining naval architecture and Sobol and NSGA-II optimization algorithms. J.W. Yu et al. (2017) used multi-objective functions optimization techniques to minimize the wave resistance by designing the bow hull shape of the bulk carrier in calm water and in the presence of waves. Priftis et al. (2018) performed a multi-objective optimization of the container ship design, based on a parametric model of the ship's external and internal geometry, using genetic algorithms to compute all the required properties and verify the design constraints and key performance indicators. Maja et al. (2018) used a secondary genetic algorithm HOGA for a multi-objective design of the PV-diesel hybrid system for a specific ship, aiming to minimize both the net present cost (NPC) of the system and the life cycle of CO_2 emissions (LCE). Xinwang and Decheng (2018) used optimization tools for Japanese bulk carrier design (JBC) based on parametric hull surface modification techniques to generate a series of geometrically constrained hull shapes. Pinget al. (2019) performed the optimization of the hydrodynamic design of a hull of a bulk carrier (JBC). The adopted approach is based on the gradient method coupled to an effective discrete assistant solver. Five optimizations with different weights are used to obtain the Pareto front. Jianyun et al. (2019) proposed a bi-objective optimization for the design of a plug-in hybrid electric propulsion system for ships. The NSGA-II method is used to explore the set of Pareto optimal solutions. Garbatov and Georgiev(2021) presented a study to develop a risk-based conceptual ship design method for bulk carriers, taking into account the life cycle assessment and energy efficiency of the ship propulsion system.

The present work consists in the bulk carrier design optimization. The main objective is to minimize the construction cost, the transportation cost and to maximize the annual transported cargo. The database used consists of twenty-five bulk carriers built between (1990-2004), see Appendix A. The mathematical modeling of the objective functions and constraints is that proposed by Pratyush and Yang (1998). The solution of the optimization problem is solved using FORTRAN and MATLAB software.

The selection of these objective functions is justified because they combine technical and economic criteria, which are often contradictory. Furthermore, they provide a useful tool for evaluating other additional performance parameters such as the voyage cost, the annual cost and the required freight rate.

To achieve this objective, four multi-objective optimization methods were tested: the weighted aggregation method based on multi-attribute decision making MADM, the control function method which introduces a new function to control the optimization process, the NSGA-II (Non-dominated Sorting Genetic Algorithm) method based on the meta-heuristic approach, inspired by natural systems (Genetic Algorithm) and the hybrid method based on the combination of two different optimization methods.

2. Multi-objective Optimization

Multi-objective optimization simultaneously optimizes several objective functions that are often contradictory. The optimal solution is usually an assortment of solutions, which are distinguished by different compromises made between the objectives. In general, a multi-objective optimization problem consists of finding the design variables that optimize a vector objective function on a feasible design space. Objective functions are the quantities that the designer wishes to minimize, maximize, or achieve at a certain value. Multi-objective optimization does not imply a single optimal solution but a set of Pareto-optimal solutions.

The multi-objective optimization problem is defined as follows:

Optimize$\vec{F}(\vec{x})$:

$$\vec{F}(\vec{x}) = \{f_1(\vec{x}), f_2(\vec{x}), \ldots, f_m(\vec{x})\} \tag{1}$$

$\vec{x}$: Decision variable, $f_i(\vec{x})$: Single-objective function, m : Number of functions to optimize

The solution of a multi-objective optimization problem is based on four approaches:

- The non Pareto approach which is the simplest of the multi-objective optimization methods. This approach does not treat the problem as a true multi-objective problem. It reduces the initial problem to one or more single objective problems.
- The Pareto approach, which adopts a more global point of view by taking into account all the criteria and using the notion of dominance in Pareto sense.
- The Metaheuristic approach, which uses methods often inspired by natural systems.
- The hybrid approach which makes the hybridization between two different methods.

2.1 Weighted aggregation method

This method is the simplest of the multi-objective optimization methods. The multi-objective problem (MOOP) in this intuitive method is converted into a scalar preference function using a linear weighted sum function. This method consists of two successive steps. In the first step, the multi-objective problem is transformed into several single-objective problems and then the evaluation of the global objective function is performed by the multi-attribute decision making method (MADM).

The multi-objective optimization problem is treated as follows:

$$\text{Minimize } F(x) = \sum_{i=1}^{m} w_i . f_i(x) \tag{2}$$

$\vec{x} \in X$,$w_i \in [0 - 1]$and$\sum_{k=1}^{m} w_i = 1$

w_i: called the weight, is a weighting associated with the criterion, this weighting allows to express preferences on the decision criteria

Mono-objective functions are expressed in dimensionless units:

$$Z_i = \frac{estimatedpower - P_{ilower}}{P_{iupper} - P_{ilower}} \tag{3}$$

P_{ilower} and P_{iupper}: Minimum and maximum values of each objective

2.2 Control function method

In general, as the number of functions aggregated to a MOOP increases, more the Pareto set is extended in the design space comprising an infinity of non-dominated points. The pertinent question that arises is how to choose the appropriate solution. To facilitate the exploration of different multi-objective optimization results, it is recommended to integrate the concept of Pareto optimality. The choice of the particular solutions can only be obtained by involving the ship-owner and the designer for final decision making. In most cases, a new additional criterion called the “control function”, is introduced to guide the optimization process in order to obtain a practical solution that meets the imposed requirements. The optimization process consists of two distinct steps, the search for all non-dominated solutions and the selection of the solution that minimizes the control function.

2.3 NSGA-II method

The NSGA-II is based on the elitist mechanism of combining the best parents with the obtained best progeny. It uses a crowding comparison operator that takes into account both the non-dominance rank of an individual in the population and its crowding distance. The NSGA-II estimates the density of solutions surrounding a particular solution in the population by calculating the ratio between the population density and the solution density. The genetic algorithm (GA) is the most popular heuristic approach for multi-objective optimization and design problems. In this algorithm, three basic operations are applied in the genetic algorithm (GA): selection, crossover and mutation. For each generation, the design vectors, called parents, are selected and then combined together, by crossover to form new chromosomes called progeny. Iteratively, genes from good chromosomes are expected to appear more frequently in the population, which ultimately leads to convergence towards the overall solution. Evolutionary methods frequently used to solve multi-objective optimization problem, provide a discrete picture of the Pareto front in the criteria space.

2.4 Hybrid method

The hybrid method is used to improve the multi objective functions value. In the majority of cases, the hybridization is between a meta-heuristic approach and other approaches. The hybrid function will be applied at the end of the genetic algorithm.

3. Application to Bulk Carriers

The objective of this practical optimization concerns the design of merchant ship of the bulk carrier type based on three criteria, minimizing the construction cost, minimizing the transport cost and maximizing the annual transported cargo. The design variables used are L, B, T, C, C_B and V_K. The limits of these variables and the main design variables are shown in Table 1.

Table 1: Conceptual model for bulk carriers

Objective functions		**Design Variables**	
Minimize Transportation cost (£/t)	$TC = CA/AC$	Length, L(m)	$92.05 \leq L \leq 327.00$
Minimize Ship cost (£)	$CS = 1.3(2000W_S^{0.85} + 3500W_O + 2400P^{0.8})$	Beam, B (m)	$15.30 \leq B \leq 55.00$
Maximize Annual cargo (t/year)	$AC = DwtcRtpy$	Depth, C (m)	$8.05 \leq C \leq 28.95$
		Draught, T (m)	$5.46 \leq T \leq 20.00$
		Block Coefficient, C_B	$0.643 \leq C_B \leq 0.836$
		Velocity, V_K (knots)	$11.75 \leq V_K \leq 16.50$
Constraints			
Length-to-beam ratio	$L/B \geq 6$		
Length-to-depth ration	$L/C \leq 15$		
Length-to- draft ratio	$L/T \leq 19$		
Froude number	$F_r \leq 0.3$		
Deadweight	$3873 \leq Dwt \leq 272132$		
Empirical constraint on T and Dwt	$T - 0.45Dwt^{0.31} \leq 0$		
Empirical constraint on T and C	$T - 0.7C - 0.7 \leq 0$		
Empirical constraint for stability	$0.07B - 0.53T - \frac{(0.085C_B - 0.002)B^2}{TC_B} + 1.0 + 0.52C \leq 0$		
Ship attributes			
Steel Weight, (t)	$W_S = 0.034L^{1.7}B^{0.7}C^{0.4}C_B{}^{0.5}$		
Outfit Weight, (t)	$W_O = L^{0.8}B^{0.6}C^{0.3}C_B{}^{0.1}$		
Coefficient for power calculation, a	$a = 4977.06C_B{}^2 - 8105.61C_B + 4456.51$		

Coefficient for power calculation, b	$b = -10847.2C_B^2 + 12817C_B - 6960.32$
Displacement, (t)	$\Delta = 1.025LBTC_B$
Froude number	$F_r = 0.5144V_K/(9.81L)^{0.5}$
Power, (KW)	$P = \Delta^{\frac{2}{3}}V_K^3/(a + bF_r)$
Machinery weight, (t)	$W_M = 0.17P^{0.9}$
Ship lightweight, (t)	$W_L = W_S + W_O + W_M$
Deadweight, (t)	$Dwt = \Delta - W_L$
Daily Fuel Consumption, (t/day)	$D_{FC} = 0.2 + 0.00456P$
Sea Days	$D_S = 5000/24V_K$
Fuel Cost, (£)	$C_F = 105D_{FC}D_S$
Port Cost, (£)	$C_P = 6.3Dwt^{0.8}$
Fuel Carried, (t)	$F_C = D_{FC}(D_S + 5)$
Misc.Deadweight, (t)	$Dwtm = 2Dwt^{0.5}$
Cargo Deadweight, (t)	$Dwtc = Dwt - F_C - Dwtm$
Port Days	$D_P = 2(Dwtc/8000 + 0.5)$
Round Trips per Year	$Rtpy = 350/(D_S + D_P)$
Capital	$CC = 0.2CS$
Running Cost, (£)	$CR = 40000Dwt^{0.3}$
Voyage Cost, (£)	$CV = (C_F + C_P)Rtpy$
Annual Cost, (£)	$CA = CC + CR + CV$
Required freight rate, (£/t.miles)	$RFR = CA/(RtpyDwtDst)$

The implementation of the iterative optimization process in the case of the aggregation method required the treatment of about 800 concrete cases defined by the values of the weighting coefficients calculated according to the MADM method, see Appendix B. However, the numerical optimization based on the control function method needed only one treatment. The problem in this case is formulated as a single-objective optimization problem, with the control function to be minimized. The control function is defined by the voyage cost which depends on the deadweight, engine power and ship speed while the three performance functions are transformed into non-linear constraints, see Appendix C.

The real advantage of aggregation and control function methods is that the global multi-objective optimization problem can be easily handled by taking each objective function separately. It therefore seems that any nonlinear mono-objective optimization algorithm can be used. The calculation of the single-objective functions was carried out by the SQP (sequential quadratic programming) method using two different optimization subroutines: Colin for Fortran and fmincon for Matlab and this for several different starting points. The main results of the optimization of each mono-objective function are presented in Table 2. The analysis of the results shows that:

- Both Colin and fmincon optimization modules give almost the same results, CSmin = 3.00 10^6 £, TCmin = 7.49 £/t and ACmax = 1.15 10^6 t/year.

- The maximization of the annual cargo (AC = 1.15 10^6 t/year) generates large merchant ships (Dwt = 264 120 t), faster (V_K = 16.50 Knots) and more stable (GM = 7.53 m) compared to ships resulting from the optimization based on the minimization of the construction cost or the minimization of the transportation cost.

- The minimization of the construction cost (CSmin = 3.00 10^6 £) generates small merchant ships(Dwt = 3873 t), slower (V_K = 11.75 Knots), less stable (GM = 1.20m) and more itinerant (Rtpy = 17.81) compared to the other two objective functions.

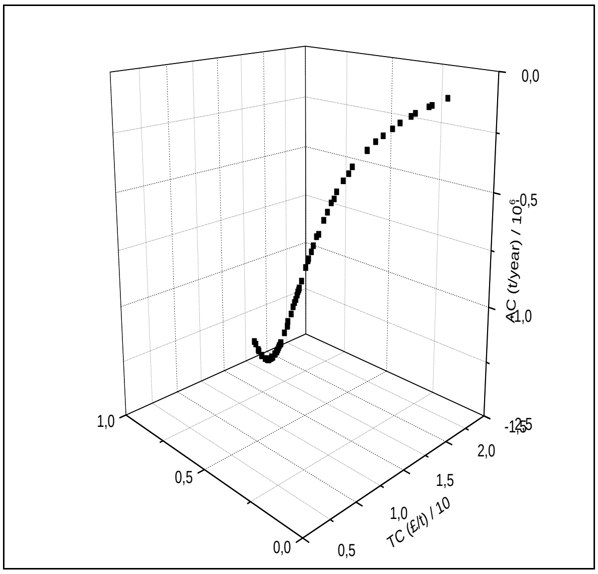
- The minimization of the transportation cost (TC = 7.49 £/t) generates merchant ships of full shape (C_B = 0.836), of intermediate size (Dwt = 81285 t), slower (V_K = 11.75 Knots), more or less stable (GM = 3.08m) and more or less itinerant (Rtpy = 9.02) compared to the other two objective functions.

Table 2: Single objective optimization results, Colin &fmincon Algorithms

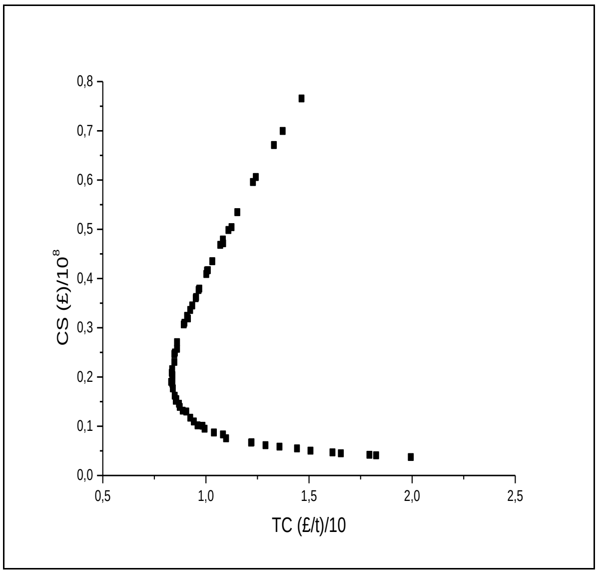
Design variables		Units	Bounds		Objective functions					
					Minimize		Minimize		Maximize	
			Lower	Upper	TC		CS		AC	
					Colin (Fortran)	Fmincon (Matlab)	Colin (Fortran)	Fmincon (Matlab)	Colin (Fortran)	Fmincon (Matlab)
Design Variables	*L*	(m)	92.05	327.00	209.6	209.8	92.0	92.0	327.0	326.9
	B	(m)	15.30	55.00	34.9	34.9	15.3	15.3	54.5	54.5
	C	(m)	8.05	28.95	20.3	20.3	8.0	8.0	27.5	27.5
	T	(m)	5.46	20.00	14.9	14.9	5.6	5.6	20.0	20.0
	C_B		0.643	0.836	0.83	0.83	0.64	0.64	0.83	0.83
	V_K	(Knots)	11.75	16.50	11.7	11.7	11.7	11.7	16.5	16.5
ShipAttributes	*TC*	(£/t)			7.49	7.49	19.69	19.69	10.85	10.84
	CS	(10^6 £)			16.70	16.70	3.00	3.00	46.60	46.50
	AC	(10^6 t/year)			0.72	0.72	0.06	0.06	1.15	1.15
	Dwt	(t)	3873	272132	81239	81285	3873	3873	264116	264120
	P	(Kw)			5174	5175	741	740	34858	34810
	GM	(m)			3.08	3.08	1.20	1.20	7.53	7.53
	Fr				0.13	0.13	0.20	0.20	0.15	0.15
	Rtpy				9.0	9.0	17.8	17.8	4.4	4.4

The NSGA II Algorithm was tested on different and independent runs. The adopted values correspond to a population size =100, a number of generations = 2000, a mutation probability = 0.2 and to a crossover rate = 0.8. The hybrid function runs after the genetic algorithm terminates in order to improve the value of the fitness function. The hybrid function uses the final point from the genetic algorithm as its initial point.

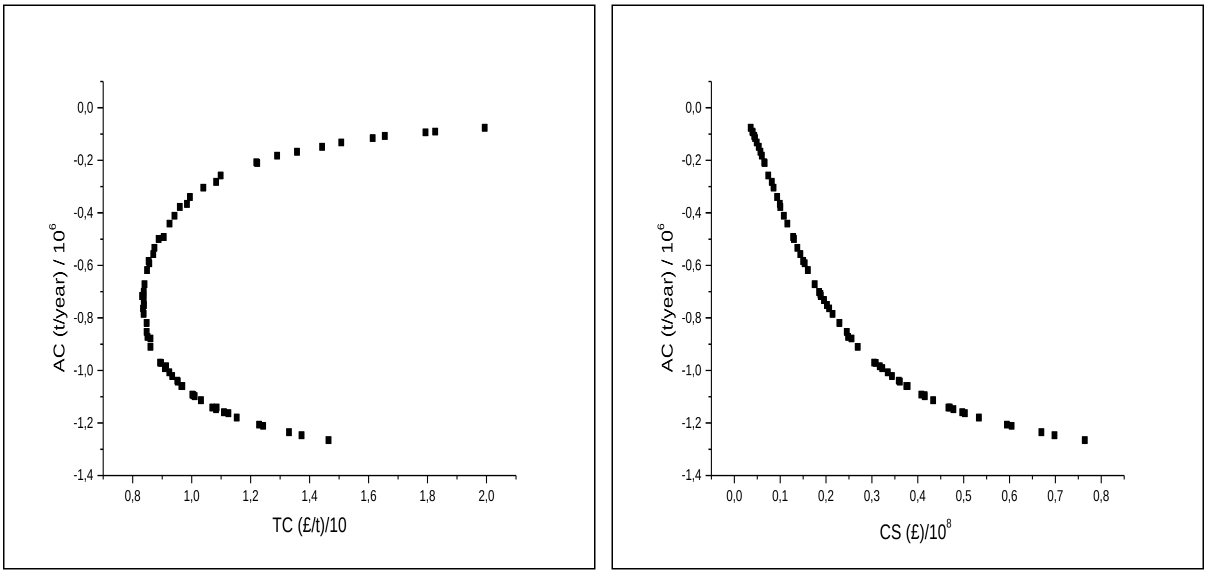
Figures 1 and 2 show the Pareto fronts obtained of the multi-objective function from the aggregation method and the NSGA-II genetic method. The analysis of the results shows that the solution range differs slightly for the two methods. Indeed, the solutions obtained by the aggregation method vary from 7.98 £/t to 20.33 £/t for the transportation cost TC, from 3 640 000 £ to 76 480 000 £ for the construction cost CS and from 77 500 t/year to 1 267 000 t/year for annual cargo AC. It should be noted that for the NSGA-II genetic method, the solution range varies from 8.33 £/t to 24.44 £/t for the transportation cost TC, from 1650000 £ to 79730000 £ for the construction cost CS and from 29100 t/year to 1315500 t/year for the annual cargo AC.



(a) Pareto front obtained by the MADM

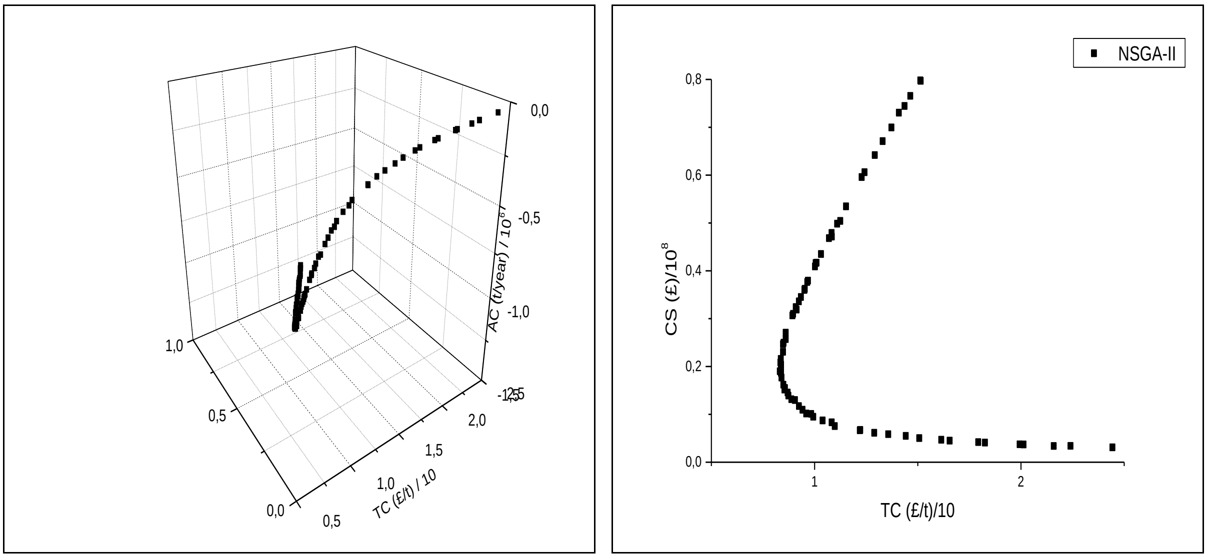


(b) x-y view of the Pareto front aggregation method



(c) x-z view of the Pareto front (d) y-z view of the Pareto front

Fig. 1: Pareto front obtained by the MADM aggregation method



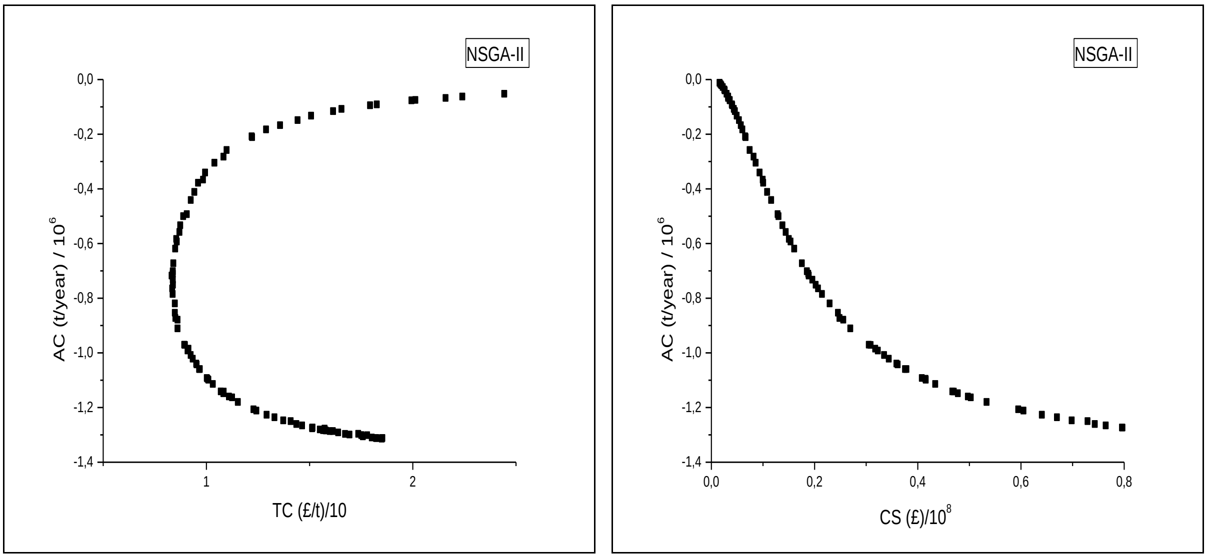
(a) Pareto front obtained by NSGA-II (b) x-y view of the Pareto front

The main results of the optimization of multi-objective function are presented in Table 3. The analysis of the results shows that:

- The three methods MADM, NSGA-II and hybrid give more or less similar results of TC, CS, AC and CV compared to the control function method.

- The ship resulting from the control function optimization is characterized by larger dimensions (L = 99.6m, B = 16.5m, C = 9.4 and T = 5.4m), a higher cruising speed (V_K = 13.9 knots) and by a more expensive voyage cost. The ship is less stable (GM = 1.09m) and the round trips per year in this case is greater by 20% compared to the other methods. It is noted that although the MADM weighted aggregation method has some advantages in terms of construction cost CS and voyage cost CV compared to both NSGA-II and hybrid methods, it remains deficient in terms of transportation cost TC and annual transported cargo AC.

- The minimum required freight rate corresponds to that obtained by the hybrid method (RFR = 0.002957 £/t.mile). This rate is the amount the owner must charge the customer in order to break-even.



(c) x-z view of the Pareto front (d) y-z view of the Pareto front

Fig. 2: Pareto front obtained by NSGA-II

Table 3:Multi-objective optimization results: MADM, control function, NSGA-II and hybrid

Design variables & Attributes		**Units**	**Bounds**		**Objective functions**			
			Lower	**Upper**	**MADM Aggregation**	**Control function**	**NSGA-II**	**Hybrid**
Design Variables	*L*	m	92.05	327.00	92.0	99.6	93.6	93.8
	B	m	15.30	55.00	15.3	16.5	15.5	15.5
	C	m	8.05	28.95	8.0	9.4	8.0	8.2
	T	m	5.46	20.00	5.6	5.4	5.5	5.8
	C_B		0.643	0.836	0.64	0.64	0.65	0.65
	V_K	Knots	11.75	16.50	11.7	13.9	11.7	11.76
Ship Attributes	*CV*	10^3 £			11.34	15.74	11.35	12.54
	TC	£/t			19.69	20.04	19.57	18.43
	CS	10^6 £			3.00	4.04	3.10	3.19
	AC	10^3 t/year			65.00	82.01	67.00	73.59
	Dwt	t	3873	272132	3873	4251	4011	4376
	P	Kw			741	1588	797	828
	GM	m			1.20	1.09	1.31	1.17
	Fr				0.20	0.22	0.19	0.20
	Rtpy				17.8	20.6	17.8	17.7
	RFR	10^3 £/t.mile			3.16	3.00	3.12	2.96

4. Conclusion

In the present study, the guidelines allowing the search for a multi-objective optimum in the bulk carriers design have been drawn. The calculations were performed through several constrained numerical optimization programs based on four different methods: the weighted aggregation method based on multi-attribute decision making (MADM), the control function method, the Non-dominated Sorting Genetic Algorithm (NSGA-II) method and the hybrid method. The mathematical modeling of the bulk carrier design was carried out by the method proposed by Pratyush & Yang. The obtained results are very promising. They showed that the three methods MADM, NSGA-II and hybrid give more or less similar results compared to the control function method. They also showed that although the weighted aggregation method MADM has certain advantages related to construction cost and voyage cost compared to both NSGA-II and hybrid methods, it remains deficient with regard to the transportation cost and the annual transported cargo. They showed also that the minimum required freight rate corresponds to that obtained by the hybrid method. In conclusion, the numerical optimization analysis is validated as a very efficient tool for the bulk carrier design.

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Appendix A

Table A: Bulk carrier database

Year	Name	L(m)	B (m)	T (m)	Dwt (t)	V_K (Knots)
1992	Bergeland	327.00	55.00	20.00	272132	15.2
1990	Hanjin Gladstone	300.00	50.00	18.00	207000	13.0
1994	Erradale	276.73	44.40	16.75	152000	15.5
1995	Merchant Prestige	270.00	45.00	16.50	149674	16.5
1993	Erridge	256.00	40.50	14.52	114012	14.1
1994	Corona Ace	220.00	36.00	12.79	77447	13.8
1995	Brazilian Venture	215.40	32.26	13.70	70728	14.0
1990	China Pride	215.00	32.20	13.11	65655	14.9
1991	Solidarnose	224.60	32.24	12.50	63000	13.8
1994	Romandie	221.00	32.24	12.50	62600	14.7
1994	ThalassiniTyhi	216.00	32.50	12.20	62158	14.6
1991	Dixie Monarch	194.00	32.20	10.70	44679	14.3
1994	Angel Wing	176.00	32.00	10.72	44950	14.3
1992	Pacific Endeavour	176.80	30.50	10.70	40750	14.3
1994	Saga Spray	190.00	30.50	10.00	37543	15.0
1992	Alam Selaras	171.00	30.50	9.75	33710	14.5
1995	AtlantieBulker	169.40	26.00	9.32	27492	14.0
1994	Erna Oldendorff	136.00	22.80	9.15	18355	14.0
1990	Igor Ilinsky	122.00	19.86	6.87	7365	15.2
1995	Arklow Brook	95.00	17.00	6.75	7182	11.7
1995	Baumwall	92.05	15.30	5.46	3873	14.0
2000	Jin Hui	182.00	32.26	10.75	44579	14.8
2001	Kohyohson (Ax)	279.00	45.00	16.50	157322	14.7
2003	IVS Viscount	172.00	28.00	10.20	32687	14.5
2004	Tai Progress	217.00	32.26	12.20	64000	14.5

Appendix B

Table B: The fundamental scale used in MADM environments

Intensity of importance on an absolute scale	Definition / Explanation
1.0	**Equal Importance**. Two activities contribute equally to the objective.
3.0	**Moderate importance of one over the other**. Experience and judgement strongly favour one over the other.
5.0	**Essential or strong importance**. Experience and judgement strongly favour one over the other.
7.0	**Very strong importance**. An activity is strongly favoured and its dominance demonstrated in practice.
9.0	**Extreme importance**. The evidence favouring one activity over the other is of the highest possible order of affirmation.
2.0, 4.0, 6.0, 8.0	Intermediate values between the two adjacent judgements, when compromise is required.

Multiattribute Decision Making (MADM):

Let [A] be a pairwise comparison matrix, of dimensions N x N, for N objectives to be weighted:

$$A_{ij} = W_i \,/\, W_j \qquad \text{(B.1)}$$

The values A_{ij} are derived from the fundamental scale of Multi-Attribute Decision Making (MADM), Table B.

The matrix [A] is reciprocal and consistent, i.e.:

$$A_{ij} = 1 \,/\, A_{ji} \qquad \text{(B.2)}$$
$$A_{ij} = A_{ik} \,/\, A_{jk} \qquad \text{(B.3)}$$

For i, j, k = 1, 2, …, N:

The bulk carrier design process is formulated as a nonlinear optimization problem and the weights can be obtained by solving the optimization constraint problem:

$$\text{Minimize} Z = \sum_{i=1}^{N} \sum_{j=1}^{N} (A_{ij}\, w_j - w_i)^2 \qquad \text{(B.4)}$$

Subject to $\sum_{i=1}^{N} w_i = 1$ (B.5)

Appendix C

The objective functions are divided into two groups:

a) The control function group, or simply, control function, which contains only one function.
b) The performance functions group, which is made up of the functions that will provide the Pareto set.

The multi-objective optimization problem can be written as:

Minimize: $f_c(X), f_p(X)$ (C.1)
Subject to: $g_i(X) \leq 0$, i = 1, 2,…, m (C.2)
$h_j(X) = 0$, j = 1, 2,…, l (C.3)
$X_{inf} \leq X \leq X_{sup}$ (C.4)

Where $f_c(X)$ is the control function,

$$f_p(X) = [f_1, f_2, \dots, f_p] : X \rightarrow R^p$$

is the vector composed of the p objective functions in the performance functions group.

To apply the proposed methodology, the performance functions, is substituted by the KKT necessary condition,

In such way that the problem’s final solution belongs to the Pareto front of the MOOP with the performance functions only.

It should be noted that the weighting factors: $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_p]^T$, $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_m]^T$, $\mu = [\mu_1, \mu_2, \dots, \mu_l]^T$ are not known. As unknowns in the problem, they will be incorporated into the vector of design variables, defining the extended vector of unknowns:

$$X_{extended} = (X, \alpha, \lambda, \mu) \qquad \text{(C.5)}$$

Finally, the problem is formulated as a single-objective optimization problem, with the control function, $f_c(X)$to be minimized and constrained by the conditions for obtaining the Pareto optimal solutions considering only the performance functions, $f_1(X)$, $f_2(X),\ldots,$ $f_p(X)$.

Mathematically, the optimization problem is formulated as:

Find$\mathrm{X}_{\mathrm{extended}}$ that

Minimize: $f_c(X)$ (C.6)

Subject to:

Pareto set condition for the performance functions:

$\sum_{i=1}^{p} \alpha_i \nabla f_i(X) + \sum_{j=1}^{m} \lambda_j \nabla g_j(X) + \sum_{i=1}^{l} \mu_i \nabla h_i(X) = 0$ (C.7)

$g_i(X) \le 0$, i = 1, 2,…, m (C.8)

$h_j(X) = 0$, j = 1, 2,…, l (C.9)

$\lambda_j g_j(X) = 0$ (C.10)

$\lambda_j \ge 0$ (C.11)

$\mu_i \ge 0$ (C.12)

$\alpha_i \ge 0;\ \sum_{i=1}^{p} \alpha_i = 1$ (C.13)

$X_{inf} \le X \le X_{sup}$ (C.14)