GLOBAL OPTIMIZATION OF ENVIRONMENTAL IMPACT BY A CONSTRAINT SATISFACTION APPROACH – APPLICATION TO SHIP-ECODESIGN

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ABSTRACT
After demonstrating the feasibility of the inversion of a ship emission model with the CSP approach [1], we will now discuss about the optimization of emissions. In a first time, a single-objective approach with an aggregation function of the emissions will be used, then, it will be a multi-objective approach and the Pareto frontier will be computed. The objective of this paper is triple: first, to show that a full ship model, linking a propulsion model and an emission model, can be inverted. Then, to bring to light that a propulsion system can be sized by an approach minimizing the emissions and using an aggregate function. Finally, to demonstrate that, in this case, computing the Pareto frontier provides the same global optimum as the mono-objective approach.

Keywords: Constraint Satisfaction Problem (CSP), Propagation, Intervals, Global Optimization, Multi-objective, Pareto frontier, Emissions

1 INTRODUCTION
Everyone agrees that environmental performance is a central consideration in product design, operations management and end of life processes methods. Until now, the Eco-design community was only proposing methodologies to evaluate environmental impacts, in advanced design phases (after the product definition), when the main design parameters are already valued. In these cases, designers often lead to suboptimal solution [2], and this involves iterations in the design process [1, 3]. In [1], it has been demonstrated that the inversion of emission models by constraint propagation on intervals makes possible to ensure that the environmental impact of the product remains lower than a level defined by the designer (in general, this level is defined lower than the standards). To model as a CSP and make a set inversion of an emission model, it must be composed of algebraic relations and/or tables of values. This requirement will be shown through the MOPSEA model. In the present paper, our goal is to link the emission interval vector with the control parameters of the ship, and to minimize the emissions. In the first part, the use of constraint programming in design and the problematic of global optimisation will be introduced. Then, the emission model used in our experimentations will be presented and our previous results published in [1] will be summarized. In paragraph 3 the ship propulsion model linked with the emission model will be introduced. Eventually, the last part will present the results of the different types of optimisation and the impact on the control parameters.

2 CONSTRAINT PROGRAMMING IN DESIGN AND OPTIMIZATION

2.1 Introduction
Basis of interval mathematics and analysis can be said to have begun with the appearance of R. E. Moore's book Interval Analysis in 1966 [4]. Then, with the development of computer science and the explosion of computing capabilities, constraint programming was developed, at first, by computers scientists and mathematicians. Over the past few decades, some researchers have been interested in applying Constraint Programming in Design. They have demonstrated that the use of CP must be interesting in many research fields such as pre-design [5], dimensioning and configuration problems [6], optimization problems [7], robotics [15]... Furthermore, the CSP community has developed work applicable in product and systems design as in [11, 12, 13, 14].

2.2 Constraint Satisfaction Problem

A CSP is defined by a Triplet (X, D, C) such that [16]:

- X = {X1,X2, . . . ,Xn} is a finite set of variable called constraint variables with n being the integer number of variables in the problem to be solved.
- D = {D1,D2, . . . ,Dn} is a finite set of variables value domains of X such that :

$$\forall\ i \in \{1,..,n\},\ Xi \in Di \tag{1}$$

A domain should be a real interval or a set of integer values.

- C = {C1, C2, . . . ,Cp} is a finite set of constraints, p being any integer number representing the number of constraints of the problem.

$$\forall\ i \in \{1,..,n\},\ \exists\ Xi \subseteq X\ /\ Ci(Xi)\quad Xi \in Di \tag{2}$$

A constraint is an explicit relation between two or more variables and imposes restrictions on areas of possible values for the variables of the problem. It should be any type of mathematical relation (linear, quadratic, non-linear, Boolean...) i.e. equations and/or inequalities, covering the value of a set of variables.

Solving a CSP consists in instantiating each variable of X, and at the same time satisfying the set of problem constraints C.

2.3 CSP solving process

Function of the type of the constraint variables, the solving process will be different. In fact, CSP on integer variables, called discrete CSP, are different from CSP on real variables also called continuous CSP.

- On the one hand, for solving discrete CSP, the methods come from operational research and artificial intelligence. The first work that has been done is about forty years old [8]. These discrete CSP methods, which complexity goes exponential, are based on enumeration and filtering. This filtering, also called constraint propagation, enables the definition domains of variables to be reduced as the resolution process evolves.
- On the other hand, CSPs have been developed using real variables with values in intervals. This interval-based resolution technique is a synthesis between interval-based analysis [4] and CSPs [9]. Several techniques have been developed, one of which is presented as an example in [10]. This study will focus on the use of CSP on intervals.

2.3.1 Constraint propagation

The aim of propagation techniques is to contract as much as possible the domains of the variables without losing any solution. This step removes the values of the variables included in the initial intervals, which makes inconsistent the constraints of the problem. It often allows binding the value domains of the variable and gives a better idea of the range of the variable.

2.3.2 Solving

A CSP can be solved using different kinds of algorithms, more or less efficients. A simplistic approach is based on the generate-and-test algorithm, which systematically generates each possible values assignment and tests if it satisfies all the constraints. The most common algorithm for performing systematic search is based on backtracking: it incrementally attempts to extend a partial solution toward a complete solution, by repeatedly choosing a value for another variable. The late detection of generate-and-test and backtracking algorithms being their main disadvantage, various consistency techniques have been implemented. The consistency-enforcing algorithm makes any partial solution of a small sub-network extensible to some surrounding network. Thus the inconsistency is detected as soon as possible. The consistency techniques range from simple node-consistency and the very popular arc-consistency, to full but expensive path-consistency.

2.4 Global Optimization

Global optimisation with constraint programming (using interval Newton and/or consistency methods) can prove the existence and uniqueness of a solution for a given problem.

2.4.1 *Single-Objective optimization*

The mono-objective optimization with CSP methods consists in solving by dichotomy a mathematical series in which a constraint is added in each next element calculation. At each step, a constraint, expressing that the next CSP must be better than the last, is added. The process stops on the CSP which minimizes the performance variable.

2.4.2 *Multi-Objective "p-criteria" Optimisation*

In the real world, optimisation problems can rarely be modelled like a single-objective problem. Multi-objective optimization is an answer to the need of satisfying both many conflicting constraints. Because there is rarely a solution better than another at any point, different compromises depending on individuals can be chosen. Such choice is subjective, so it is essential to propose all the possible choices in order to avoid excluding any possibility.

A multi-objective problem is defined such that:

$$X = (x_1, x_2, \dots, x_n) \text{ called decision vector}$$

$$F = (f_1, f_2, \dots, f_m) \text{ called performance vector}$$

$$\exists p \in \mathbb{N}, \forall j \in \{1, \dots, p\}, \exists g_j: \mathbb{R}^n \to \mathbb{R}, \exists \mathcal{X} \subseteq X, g_j(\mathcal{X}) = 0 \quad (3)$$

$$\exists q \in \mathbb{N}, \forall j \in \{1, \dots, q\}, \exists h_j: \mathbb{R}^n \to \mathbb{R}, \exists \mathcal{X} \subseteq X, h_j(\mathcal{X}) \leq 0 \quad (4)$$

$$\forall\, i \in \{1, \dots, m\} f_i: \mathbb{R}^n \longrightarrow \mathbb{R}^+ \quad (5)$$

$$Find \quad X / \min F \quad (6)$$

Because one solution rarely minimizes all the f_i, it is necessary to propose a comparison operator to determine if a performance vector is better than another or if they are equivalents. A possibility is to use the relation of domination according to the definition given by Pareto. Noting $\preccurlyeq$ this relation in its wide sense and $\prec$ in its strict sense, Fi dominates Fj in Pareto sense if and only if:

$$\forall k \in \{1, \dots, m\},\ f_{ik} \preccurlyeq f_{jk} \quad (7)$$

$$\text{and}$$

$$\exists k \in \{1, \dots, m\},\ f_{ik} \prec f_{jk} \quad (8)$$

The problem consists in determining the non-dominated set of points in the performance space. For any m, the Pareto hyper-surface can theoretically be obtained although its calculation is usually difficult and expensive.

3 USING CONSTRAINT PROGRAMMING TO INVERT AN EMISSION MODEL

Since an emission model is composed by a set of algebraic relations and / or tables, it can be modeled as a Constraint Satisfaction Problem and thus set inversion becomes possible. This is what is demonstrated and applied within the MOPSEA model (which appears to be the most relevant after the state of the art realized in [1] but any other emission model could be used).

3.1 MOPSEA Model

Belgian Science Policy financed the MOPSEA project [17] to make Belgium comply with international and European agreements. First, an inventory of the legislation and international reporting obligations was made to have a better overview of maritime transport. Then, the MOPSEA project developed a new activity based model in order to map historical emissions and to make a projection of the emissions for the near future.

The MOPSEA model enables to quantify the most important produced gases and is available for a very large part of sea-going vessels. This model makes the distinction between fuel related emissions (CO_2, SO_2) and technology related emissions (HC, CO, NO_x, PM). It is composed by Basic Emission Factors, averages of all stages of navigation and based on test cycles. To be representative of each vessel and each individual stage of navigation, tables of correction factors are implemented. These properties make the MOPSEA model particularly relevant for an application in dynamic simulation. Equations of this model are detailed in the project report [17] and also in [1].

The MOPSEA emission model can be illustrated by figure 1. There are three main inputs categories; emissions are highly impacted by the fuel used and by some characteristics of the engine such as its age, technology or its instant operating point. This last point leads to another important and necessary parameter in emissions calculation: the parameter time. Depending on these inputs, one is able to estimate ship instant emissions factors but also the mass of fuel related emissions (CO_2 and SO_2), and technology related emissions (NO_x, HC, CO, PM) for a defined mission.

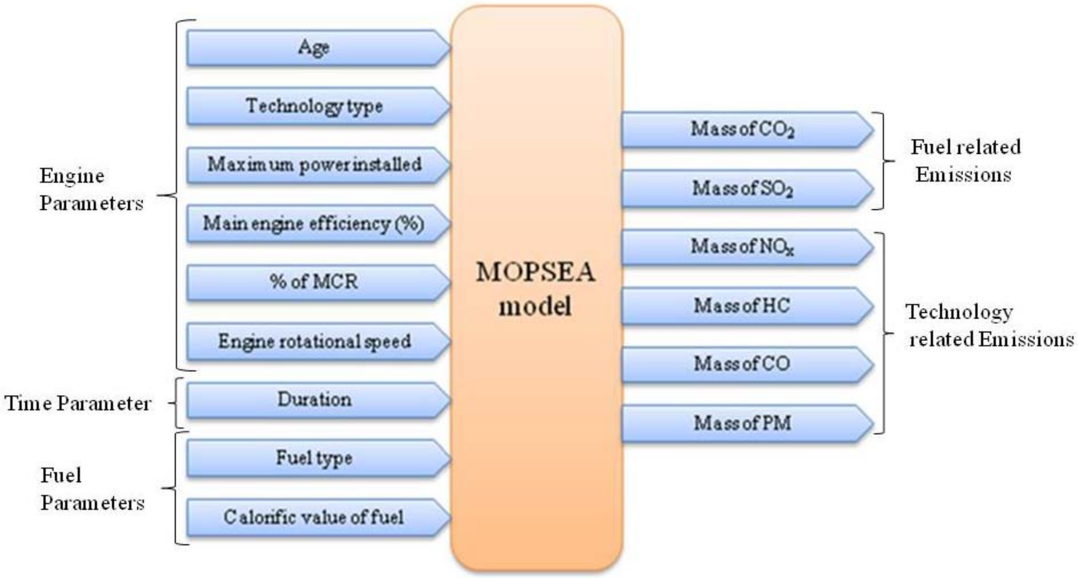

Figure 1: Input / Outputs of the MOPSEA model

3.2 Propagation

In [1], the results obtained with a CSP modelling of a 4-Stroke-Engine have been introduced. In table 1, the variables introduced are divided in 3 categories: the characteristics of the ship, the basic emission factors (befXX) and the emission factors (efXX). The emission factors are calculated by multiplying basic emission factors with some correctors for the age, the technology, ... of the main engine. The first propagation step (Table 1, column (1)) includes only the model constraints (equations). The algorithm reduces the intervals as weak as possible and thus bounds the half-opened ones. Then the model is used as a direct model: the specifications of the engine (fuel type, date of building, minimum power, minimum rotational speed...) are added as constraints and a second propagation witch contracts again the intervals (Table 1, column (2)) is made. In the third part, it has been demonstrated that the model can be inverted: by adding a constraint on the NO_x emission factor, the others intervals are then automatically reduced as in Table 1, column (3).

Table 1 : Emission model inversion steps

Variables	Initial Intervals	(1)	(2)	(3)
Ship characteristics				
Power (kW)	[0, 1e5]	**[0, 62.05]**	[36.5, 62.05]	[36.5, 62.05]
RPM (round per minute)	[0, 1e7]	**[290, 1e7]**	[2000, 1e7]	[2000, 1e7]
%ofMCR	[0, 85]	[0, 85]	**[50, 85]**	[50, 85]
oilType	{0, 1, 2}	{0, 1, 2}	**0**	0
Date of Building	{0,…, 6}	{0,…, 6}	**5**	5
Basic emission factor				
befHC (g/kWh)	0.6	0.6	0.6	0.6
befCO (g/kWh)	3	3	3	3
befNOx (g/kWh)	12	12	12	12
befPM (g/kWh)	{0,5, 0.8}	{0,5, 0.8}	**0.8**	0.8
Emission Factors				

efHC (g/kWh)	[0, + ∞]	**[0, 2.0676]**	**[0.337, 0.414]**	**[0.337, 0.3497]**
efCO (g/kWh)	[0, + ∞]	**[0, 15.66]**	**[1.4, 2.251]**	**[1.4, 1.527]**
efNOx (g/kWh)	[0, + ∞]	**[0, 21.3864]**	**[10.7, 11.04]**	**10.7088**
efPM (g/kWh)	[0, + ∞]	**[0, 1.304]**	**[0.68, 0.711]**	**[0.682, 0.689]**

4 PROPULSION MODEL AS A CSP

4.1 Propulsion system

We choose to model a ship propelled by a mechanical transmission between the engine and the propeller. It is the most common type of propulsion in the merchant navy (tankers, bulk carrier...). This kind of propulsion is composed of an engine, a gearbox, a transmission shaft, a propeller and a hull (figure 2).

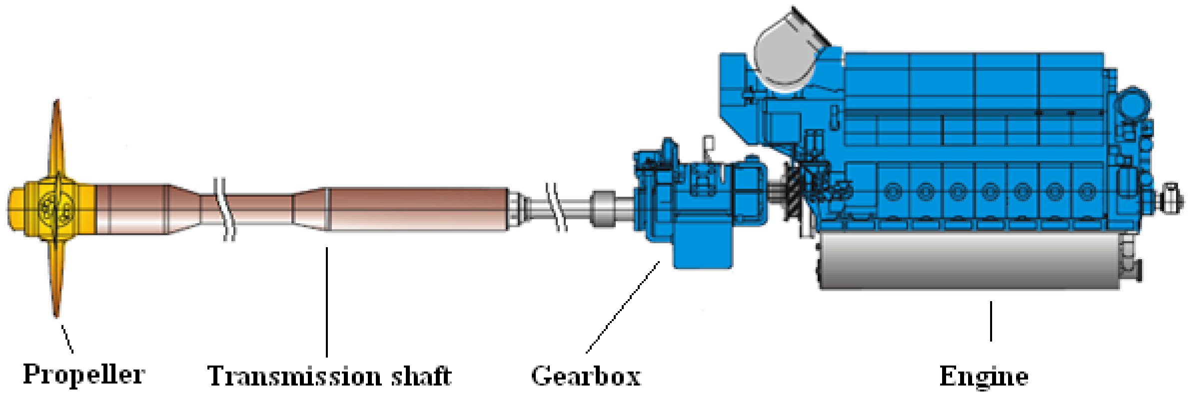

Figure 2 : Direct propulsion

Each component model is composed by some variables which domain can be discrete or continuous, such that it can be modelled as a CSP. For example, the gearbox is modelled by equations (9), (10), (11), where M_{xx} represents torques, n the reduction ratio and ω_{xx} the rotational speed.

$$M_{in} = n * M_{out} + R * W_{out} \tag{9}$$

$$\omega_{out} = n * \omega_{in} \tag{10}$$

$$R = P_{nom} * (1 - efficiency) / {\omega_{nom}}^2 \tag{11}$$

In this study, the deformations of the mechanical transmission components and the losses in the mechanical connections (except inside the gearbox) are being ignored. The characteristics of the propulsion modelled in these conditions are detailed in table 2.

Table 2 : Case study propulsion parameters

Hull		**Propeller**		**Gearbox**		**Engine**	
Wake coefficient	0.2	Diameter [m]	9	Nominal power [kW]	50000	Maximal Power [kW]	58 000
Suction coefficient	0.17	Pitch/diameter	1	Nominal rotational speed [rad/s]	10.47	Minimum rotational speed [RPM]	10
		Number of blades	4				
				Efficiency [%]	96	Minimum rotational speed [RPM]	110
				Reduction ratio	1		
						Fuel type	Heavy Fuel Oil
						Date of Building	1995-1999

4.2 Hydrodynamic model

The Holtrop-Mennen model, defined in [18] and [19], already implemented by the Scilab community (http://www.scilab.org) is used in order to quickly determine the running resistance of a given ship according to its speed. Then, one is able to calculate a polynomial function that best approximates this curve (fig. 4). In the CSP approach, this function will be considered as a constraint. The modelled vessel characteristics are introduced in Table 3 and figure 3.

Table 3 : Model parameters

Waterline area A_{wl} [m^2]	8210
Length waterline L_{wl} [m]	320
Breadth waterline B_{wl} [m]	43
Draught D [m]	12.2
Volume [m^3]	89 000
Half angle of entrance at bow [deg]	6.04
Wetted Area [m^2]	13415
Water density [kg/m^3]	1025
Water kinematic viscosity [m^2/s]	$1.188*10^{-6}$

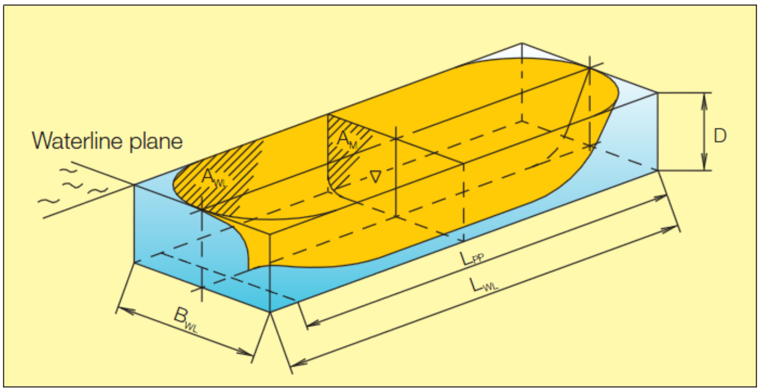

Figure 3: hydrodynamic parameters

The interpolated function is given in figure 4. A polynomial of degree 3 is a sufficient approximation for this application case but the exact formulation of the Holtrop-Mennen model will have to be used if the hull fouling effect is to be taken into account.

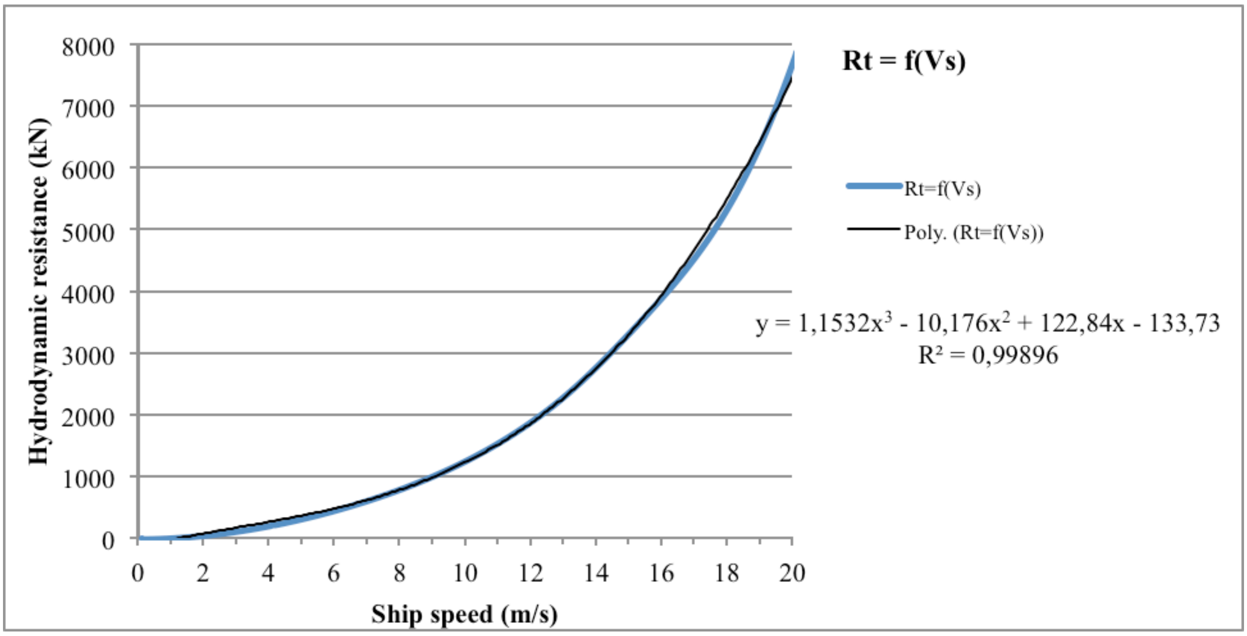

Figure 4: Hydrodynamic resistance function of the ship speed

4.3 Propulsion modelling

All the components of the propulsion system were modelled as boxes, linked with connections. The connections between components are illustrated in figure 5. Each box contains equations characterizing the internal behaviour of the component, for example (9), (10), (11).

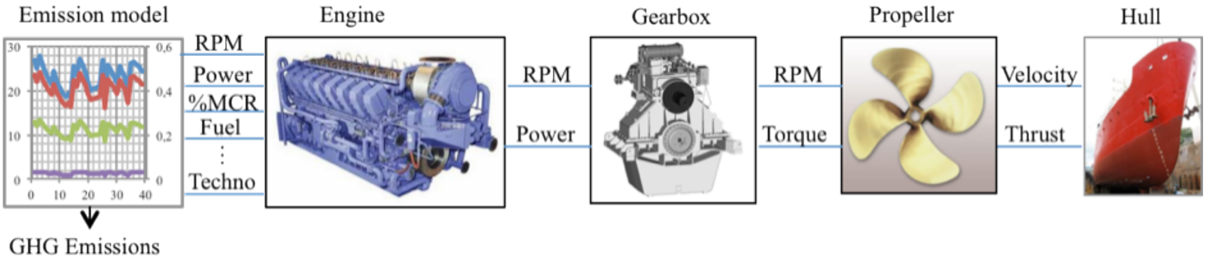

Figure 5: Propulsion model

5 OPTIMIZATION OF THE EMISSIONS

In this part, variability on some component parameters of the system will be introduced: the objective is to determine which design parameters minimize the emissions.

Among all the decision parameters and variables available to the designer, let's show how modifying some preliminary design parameters can influence the emissions ratio. Modifications on the shape of the hull for a ship with given dimensions (written down in the specifications for example) are allowed. Hulls are mainly characterized by a wake coefficient and a thrust deduction factor (The Holtrop-Mennen model is only related to ship dimensions and not to hull's shape so the resistance to the advancement does not change) (Table 4)

Table 4: Suction and wake coefficients for each Hull type.

hullType		1	2	3	4	5
wake coefficient	w	15	20	25	29	33
suction coefficient	t	14	17	15	20	25

A choice among some elements of the propulsion, namely the reduction ratio of the gearbox and the propeller diameter is also possible (in our case a constant Pitch/ Diameter ratio will be kept) (Table 5)

Table 5: Diameter and reduction ratio for each Gearbox and Propeller type

propellerType		1	2	3	4	5
Diameter	D	8,5	8,75	9	9,25	9,5

gearBoxType	1	2	3	4	5
Reduction ratio	0,8	0,9	1	1,1	1,2

In the current experimentations, in order to reduce the number of possible combinations, some discrete choices can be made but one would give an interval for those design parameters. MOPSEA's emission model affording the possibility of evaluating six different gases emissions, the optimization problem is clearly multi-objective.

5.1 Mono-objective optimization

To preserve the deterministic way that characterizes the CSP approach, a stochastic optimization algorithm isn't to be used. The CSP solver [20] used here has a feature of single-objective optimization strictly deterministic. In a first approach, to transform the multi-objective problem in a mono-objective one, an aggregation function is built. The easiest aggregation function buildable consists in summing the masses for each gas.

$$VariableToMinimize = emCO_2 + emSO_2 + emHC + em\ CO + emNO_x + emPM \tag{12}$$

The solution generated by the solver is given in table 6 (the mass of emissions are calculated for a one hour service).

Table 6: Mono-objective solution

hullType	**reducRatio**	**propDiam (m)**	**$emCO_2$ (tons)**	**$emSO_2$ (tons)**	**emHC (tons)**	**emCO (tons)**	**$emNO_x$ (tons)**	**emPM (tons)**
2	1,1	9,5	17,86	0,1723	0,0120	0,0653	0,3202	0,0206

5.2 Multi-objective optimization

To perform a multi-objective optimization, the CSP solver is used to generate all the feasible solutions to the design problem. It founds out 327 solutions that respect for sure all the problem constraints (Table 7).

Table 7: Some solutions extracted from the set of generated solutions

hullType	reducRatio	propDiam (m)	$emCO_2$ (tons)	$emSO_2$ (tons)	emHC (tons)	emCO (tons)	$emNO_x$ (tons)	emPM (tons)
1	0,9	9,25	26,79	0,2584	0,0156	0,0717	0,4706	0,0300
1	1	9	23,93	0,2308	0,0147	0,0719	0,4247	0,0271
1	1	9,25	22,50	0,2170	0,0141	0,0705	0,3994	0,0255
1	1,1	9,5	18,57	0,1792	0,0124	0,0667	0,3330	0,0214
1	1,2	8,75	19,29	0,1860	0,0127	0,0674	0,3458	0,0220
2	0,9	9,25	25,36	0,2446	0,0151	0,0720	0,4455	0,0287
2	0,9	9,5	23,57	0,2274	0,0145	0,0716	0,4184	0,0267
2	1	8,5	27,14	0,2618	0,0158	0,0718	0,4769	0,0304
2	1	8,75	25,72	0,2481	0,0153	0,0722	0,4518	0,0291
2	1,1	8,5	26,79	0,2584	0,0156	0,0717	0,4706	0,0300
2	1,1	9,5	17,86	0,1723	0,0120	0,0653	0,3202	0,0206
3	0,9	8,75	25,72	0,2481	0,0153	0,0722	0,4518	0,0291
3	0,9	9	24,64	0,2377	0,0150	0,0716	0,4330	0,0279
3	0,9	9,25	23,21	0,2239	0,0144	0,0712	0,4120	0,0263
3	0,9	9,5	21,79	0,2102	0,0138	0,0704	0,3867	0,0249
3	1	9,5	19,29	0,1860	0,0127	0,0674	0,3458	0,0220
3	1,1	8,5	26,07	0,2515	0,0153	0,0715	0,4581	0,0292
4	0,8	9,25	26,43	0,2549	0,0155	0,0716	0,4644	0,0296
4	0,9	9,5	24,29	0,2343	0,0147	0,0713	0,4267	0,0275

On Table 8, one can see that emissions are strongly depending on some key pre-design parameters. To perform a same mission, the environmental impact will be significantly different between two solutions. For example, to perform a one-hour mission, solution 25 (hullType 1, reducRatio 0.9, propDiam 9.25) is widely better than solution 26 (hullType 2, reducRatio 1.1, propDiam 9.5).

Table 8 : Comparison between solution 25 and 26

hullType	reducRatio	propDiam (m)	emCO2 (tons)	emSO2 (tons)	emHC (tons)	emCO (tons)	emNOx (tons)	emPM (tons)
1	0,9	9,25	26,79	0,2584	0,0156	0,0717	0,4706	0,0300
2	1,1	9,5	17,86	0,1723	0,0120	0,0653	0,3202	0,0206

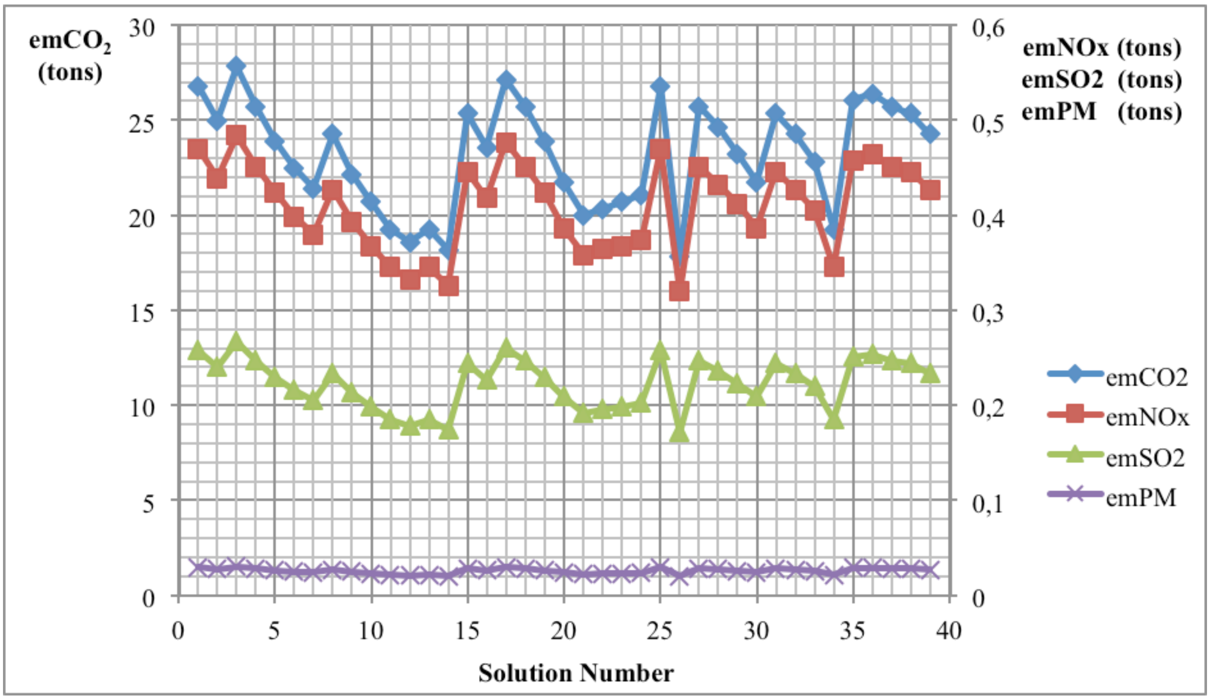

Figure 6: Comparison of the emissions for some solutions

Then, a deterministic optimization algorithm built in C++ is used to search, among all the generated solutions, the set of optimal solutions in the Pareto sense, that is to say, the set of all solutions that dominate the rest of the solutions but do not dominate themselves. Using a deterministic algorithm ensures that the founded optimum is a global one.
This points out that, for the present optimization problem, the Pareto front is reduced into a single solution that dominates all the others on all criteria (Table 9).

Tableau 9: The Pareto frontier is composed by a unique solution

hullType	reducRatio	propDiam (m)	$emCO_2$ (tons)	$emSO_2$ (tons)	emHC (tons)	emCO (tons)	$emNO_x$ (tons)	emPM (tons)
2	1,1	9,5	17,86	0,1723	0,0120	0,0653	0,3202	0,0206

5.3 Results analysis

The Pareto frontier is reduced into a single solution, which is to compare with the one obtained with the mono-objective approach. The report is as following: the solutions are identical. This shows that, in this case, using multi-objective optimization algorithms has no interest, except to show the uniqueness of the global optimum. It has also been shown that with the CSP approach, one is able to invert a full system model, composed of various multi-physics models. Moreover, it has also been shown that eco-design in the proper sense can be done, that is to say that ship propulsion can be sized by a performance objective, which includes not only dynamic performances, but also emissions targets.

6 CONCLUSION

After having demonstrated in [1] the possibility of reversing an emission model with the CSP approach, this article permits to demonstrate its interest: the inversion of emission models indeed allows (even with a relatively high-level model) to integrate environmental issues into preliminary design phases, before making any choice of pre-sizing, which effects will be irreversible later in the design process.
In the current case, an optimal solution to a design problem for a defined operating state has been determined. For the continuation of this research, in order to be more representative of the reality, new models representing the various systems of the ship are going to be implemented and a representative mission for the vessel will be determined. Even if from the propulsion system point of view the

continuous state is largely dominating on a mission, depending on the systems configuration at each instant t, the optimization of energy consumption of the ship on the entire mission will be strongly impacted.

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