Optimization of Ship Structures

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ABSTRACT: Limiting CO2 emissions is a great challenge being faced by society today. Society, through the United Nations Framework Convention on Climate Change (UNFCCC), and actors like the EU, is applying pressure on all industries, including the shipping industry, to reduce CO2 emissions. This paper presents a way to decrease the GHG emissions by ship scantling optimisation, i.e. decreasing steel weight and keeping the production cost at an acceptable level. The authors first review the links between "*Design*" and "*Optimization*" and secondly define the place of "*Ship Structure Optimization*" within the general framework of a "*Ship Optimization*". Then, the LBR-5 ship structure optimisation software is presented. It is based on a convex linearization coupled with a dual approach and is based on a rational assessment of the ship structures behaviour. Few applications of structures optimization are then presented.

1 INTRODUCTION

1.1 *Background*

Limiting anthropogenic GreenHouse Gas (GHG) emissions is a great challenge being faced by society today. Society, through the United Nations Framework Convention on Climate Change (UNFCCC), and actors like the EU, is applying pressure on all industries, including the shipping industry, to reduce CO2 emissions.

Global temperature increases above 2°C are expected to dramatically increase the risk of catastrophic global consequences, and are likely to occur if the concentration of CO2-equivalents in the atmosphere exceeds 450 ppm. The EU has adopted the 2°C stabilisation level as a goal, and is working towards a global agreement on this, Walker et al. 2008. In order to achieve stabilisation at 450 ppm, GHG emissions need to have been reduced by 50%-85% in 2050 compared to today's level, IPCC 2007. However, all scenarios indicate significant increases in GHG emissions up to 2050, which means that achieving the needed reductions will be very challenging.

1.2 *Ship emissions*

Historically, ship emissions have not been regulated, but the International Maritime Organisation (IMO) and EU have recently implemented requirements for ships. Focus for these regulations have been mainly on NOx and SOx emissions, but as international shipping is recognised as a significant contributor to global GHG emissions, pressure is mounting on shipping to contribute reduce these emissions. The IMO is currently working to establish GHG regulations for international shipping, and is under pressure, e.g. from the EU, to implement regulations with substantial impact on emissions, IMO 2008.

For shipping, there is an ongoing debate regarding how much the sector could be expected to reduce emissions and how the reduction could be achieved. As for the global GHG emissions, growth is expected also for shipping and achieving significant reductions will be challenging, Eide et al 2009.

However, a certain number of technical measures are available for shipping to reduce GHG emissions such as ship speed reduction, wind power, air lubrication, turnaround time in port, weather routing, optimization of the ship main dimensions, scantling optimization and use of lightweight structures, reduce ballast, etc. Longva et al 2008.

This present contribution focuses on the deep study of one of these previous solutions which is the optimization of ship structures but before to dive in this challenging topic, it is necessary first to review the links between "*Design*" and "*Optimization"* and secondly to define the place of "*Ship Structure Optimization"* within the general framework of a "*Ship Optimization"*.

2 SHIP DESIGN AND SHIP OPTIMIZATION

2.1 *Links between "Design" and "Optimization"*

It is impossible to talk about optimisation without a clear definition of the design stage(s) which are considered during the design of a ship. If the target is the conceptual design stage, the optimisation (tools and objectives) will be completely different of an optimisation performed at the detailed design stage.

In many teach books, "*Ship Design*" is usually presented through the "*Design Loop*" or "*Design Spiral"* (Fig. 1). We identify easily various technical tasks, often achieved by different teams:

- Main dimensions
- Hull form and Resistance
- General arrangement
- Propulsion
- Structure (material, scantling, hull section modulus, weight, gravity centre)
- Stability and manoeuvrability
- Cost
- Safety (Class rules, IMO, SOLAS, etc.)
- Production (block size, etc.)
- Etc.

Each of these design tasks is mandatory to, at the end; obtain a reliable design of the targeted ship. None of these tasks can be missed or discarded, whatever the design concerns a large cruise vessel, a cargo ship, a pleasure yacht, a tug boat, a barge or a fishing vessel.

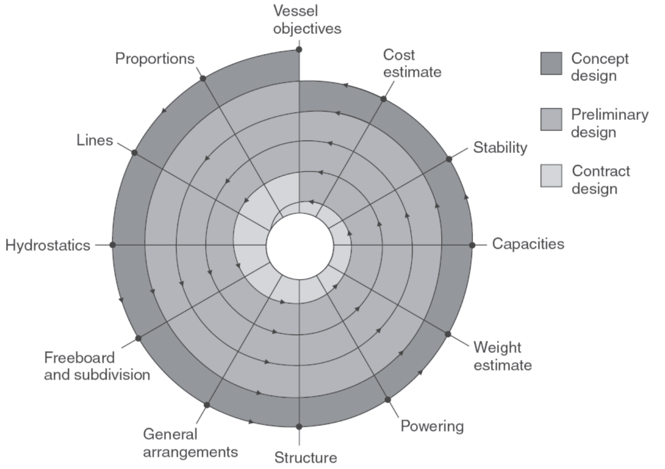


Figure 1. Typical Design Spiral as presented in various teach book, Eyres (2001)

These design tasks can be achieved sequentially or simultaneously. In the past, these tasks were performed sequentially but now, for the sake of production efficiency and to reduce the delivering time, most of these tasks are achieved through a concurrent engineering process (Fig. 2). Challenges and benefits of the concurrent engineering are discussed in Caprace (2010).

Everyone understands that as the design process progresses, more information becomes known, but at the same time it becomes more and more costly to make design changes. With better technical and cost information in hand, better technical decisions could be made. In addition, management could be invited to play a more significant role than it is traditionally the case. These ideas are reflected in Fig. 3, which depicts the decreasing ability to influence the outcome of a design, see Ross et al. (2002).

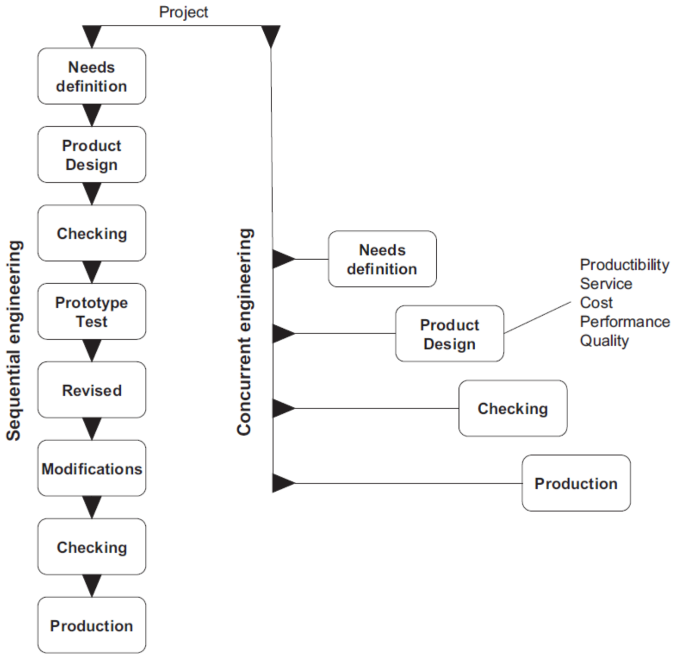
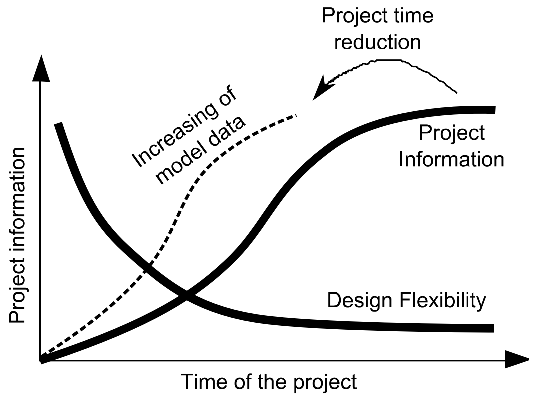


Figure 2. Concurrent engineering, Caprace (2010)



Conceptual Design	Basic Design	Detailed Design
Strategical Decision	Tactical Decision	Operational Decision
2-3 weeks	2-3 months	5-10 months

Figure 3. Design stage within shipbuilding industry, Caprace (2010)

In 2010 we can state that performing concurrent design tasks is nowadays the current practice, at least for the large design groups and shipyards. But, can we say the same concerning the optimization tasks? Is it possible to perform concurrently optimization tasks?

Here after, we try to answer at this question and to identify the place and the challenge of the "ship structure optimization" in the global context, which is the "ship optimization".

The ship design optimization is a kind of natural tasks that the naval architect tries to perform during the various loops of the design spiral (whatever is done sequentially or concurrently). The "Spiral" is definitively an optimization process. Each loop can be considered as an iteration of the optimization process. But when specialists are called, as it is usually the case at each step of the design (see spiral, Fig. 1), the concerned optimization s become definitively local optimization.

By local optimization we understand an optimization that tackles a single specific issue (hydrodynamics, propulsion, structure, safety, etc.), the others being frozen. For instance, is it popular to consider the hull form and the general Arrangement (GA) as fixed, when we optimize the ship structure (scantling) to reduce the weight and/or the production cost.

Similarly, in CFD optimization analyses we consider often the structure (weight, cost, gravity centre) as fixed. Alternatively, rules of thumb or statistical curves (weight = Fct (Δ, L, B, T, Cb, etc.)) are used to adjust the weight according to the hull form.

There are also the ship production teams, which try to optimize workflow and workload to reduce delivery time. They are working in the field of *Design for Production* and the target is to optimize the ship focusing on the production keeping fixed the other parameters (hull form, scantling, block splitting, etc.), Caprace (2008).

It is clear and obvious that it is not suitable neither efficient to perform sequential local optimization. But in 2010, it is still the current industrial practice to reach an improved design. For sure, engineers know that they do not reach the global optimum but they are confident to be in the right direction.

Local optimization is an industrial practice starting 20-25 years ago when were available advanced dedicated numerical tools, specialized in one design tasks, modifying the hull form to increase speed, reduce fuel consummation or improve seakeeping, improving ship structures to reduce weight or production cost, or modifying GA for better safety (fire escape) and increasing the number of cabins, etc.

Mathematicians have demonstrated that performing sequential local optimization may not drive to the global optimum. So the solution is definitively to move to a global optimization. That means an optimization in which the technical interacting tasks are considered simultaneously.

Here above, we have explained that for designing a ship it is nowadays possible to tackle all the technical tasks altogether. Therefore, the current solution is a series of concurrent design tasks.

On the other hand, for the optimization it is clear that it is nowadays impossible to perform a global optimization (all in one) – at least not with the current technologies available in the ship and marine industry. So the solution is to perform a series of local optimization. This is the current practice. There are indeed on the market efficient and reliable tools that perform hull form optimization, scantling optimization, GA optimization, etc.

Therefore the challenge for tomorrow is to move to a concurrent optimization. That means that several tools will run simultaneously, using the same data and the same initial design (geometry, loads, etc.). There are currently some tentative to initiate such procedure (such as VRSHIPS, VIRTUE (CFD) and IMPROVE (Structure) EU projects). All of them are facing similar problems:

- Difficulty to share similar data. Standard formats are required and must be accepted by the different developers, which are in fact often competitors. Currently, keeping a different format is a way to avoid competitors and repulse new developers with alternative modules (which can be more effective than own module).
- Difficulty to move from CAD data to CFD, from CAD to structural models (FEM) and above all, from CFD to structural models, and vice versa.
- Level of accuracy of the CAD data is rather different then the expected level required for structure analysis. Some data may be missing. But, more often, too much CAD data are available to easily and automatically produce a coarse mesh for FEA. In this case, how to automatically generate a simplified model from a detailed CAD model, and later, when the optimization is achieved, how to update a detailed CAD model with data (usually geometry) coming from a coarse mesh? The key issue is to avoid re-meshing and manual data-transfer, or even worse, retyping the data.
- Most of the tools are in fact "black boxes" for the other developers. Therefore data exchange is rather slow and cumbersome.

In conclusion, a promising direction of research is the development of a concurrent optimization platform, which could be the intermediate step between a series of sequential local optimization and a full global optimization (which remains a rather long term goal).

In the framework of this targeted concurrent and multidisciplinary ship optimization, Section 3 presents the author views on a limited area, which is the "*optimization of ship structures*".

3 SHIP STRUCTURE OPTIMIZATION

3.1 *State of the art*

Ship design traditionally has been based on a sequential and iterative approach. With the availability of non-linear optimization tools, many researchers have attempted to solve the ship design problem using different optimization techniques. This allows the development of competitive new designs while considering various interactions within the system in a shorter time span.

The first marine structure optimization studies were made practically by hand by Harlander (1960). Then, with computer assistance, researchers tried to develop design and optimization algorithms. Optimization appears in the works of Evans et al. (1963) and Nowacki et al (1970). Few years later, an important step for optimization of marine structures has been done by Hughes (1980, 1988).

Forty years ago, standard optimization tools focused on a single and limited aspect (e.g. shape, scantling, propeller, ultimate strength, etc.) and a single objective was targeted (weight, resistance, cavitations, etc.). Nowadays, optimization tools tend to adopt a more generic approach coupled with the fact that they have also become much more reliable.

The evolutions of design and optimization techniques are well reported by Cho et al (2006). Seo et al (2003), Rigo et al. (2003), Khajehpour et al. (2003), Parsons et al. (2004), Klanac et al. (2004), Zanic et al. (2005) and Xuebin (2009) have all integrated multi-criteria optimization model that incorporate structural weights and/or production costs. The differences concern the selected design variables and the constraints (yielding, buckling, deflection, weight, cost, fatigue, etc.) as well as the analysis used to assess structural response (2D FEM, 3D FEM, analytical linear, analytical non-linear, etc.). However all authors unanimous agree that one single objective is not sufficient to model accurately the various aspects of the marine structures.

Preliminary design is the most relevant and the most effective period to modify design scantling and to compare different alternatives. The earlier information is known, the better decisions are taken in the design process. Unfortunately, it is often too early for efficient use of many methods mentioned before.

3.2 *Definition*

Before to go ahead, it is necessary to clarify the meaning of "*ship structure optimization*". Indeed the meaning may defer according to the persons. Naval architects may understand general arrangement (GA) of the ship, location of the watertight bulkheads and decks, etc. The engineers of the structural units will probably think about scantling, types of framing (longitudinal, transverse or mixed), types of stiffeners (bulb profile, T bars, L shape, etc.), frame and stiffener spacing's but will consider the structural GA as fixed.

Both of them are right. The difference comes from the fact that the two problems also solved one after the other by different persons, even if their problems interact.

A possible way to avoid such misunderstanding is to rank structural optimization tasks and methods in relation with the design level(s) at which they are performed (keeping in mind that a structural optimization task always refers to a specific design stage).

3.3 *"Design stages" and "Structure Optimization"*

We usually identify three key steps in the design process, which are focusing on different levels (parts) of the ship structure and therefore have different optimization needs (or focuses):

- The Conceptual Design stage (CD)
- The Basic Design stage (BD)
- The Detail Design stage (DD)

3.3.1 *The conceptual design stage (CD)*

The conceptual design stage is characterized by (this is not an exhaustive list):

- Few data are available.
- Performed within few weeks (i.e. 3 weeks).
- It is done by the naval architect team, which often does not rely so much on advanced numerical tools (such as optimization tools).
- Focus is on the hull form, GA, propulsion and client requirements. Structure concerns are limited to structural material selection and weight and gravity centre estimation.
- Even if a significant benefit in production (design for production) can be obtained at this level it is usually not a concern of the naval architects. They mainly focus on propulsion efficiency and global weight (assuming the weight is a relevant measure of the cost – which completely wrong if we think in term of production cost).
- A first CAD model of the hull form is available as stability is assessed.
- Etc.

3.3.2 *The basic design stage (BD)*

The basic design stage is characterized by (this is not an exhaustive list):

- Performed at the tender stage and finished with the contract (if any).
- Performed within few months (i.e. 2-3 months).
- Data are available but a lot are still missing.
- First structural calculations rely on classification tools such as the MARS2000 software of Bureau Veritas.

- It is the time to build a first 3D structural analysis (coarse mesh model, if a FEA is achieved, which is not always the case for small and medium ships).
- Potential cost savings are huge but a lot of uncertainties remain (due to concurrent engineering all the data are not available such as hydrodynamics loads like sloshing, slamming, etc.).
- Fatigue, vibration, noise are not considered in deep, even if they are key issues for the life cycle cost (particularly fatigue).
- It is the last chance to optimize the structure considering the production aspects (Design for Production).
- Etc.

3.3.3 *The detailed design stage (DD)*

The detailed design stage is characterized by (this is not an exhaustive list):

- Start when the contract is signed.
- Performed within several months (i.e. 5-10 months) and requires a large staff.
- Data are usually available.
- This stage is in fact not focusing on design but much more on validation based on quantitative assessments (stress, deflection, fatigue, bucking, vibration, noise, etc.) using advanced calculation tools that are available.
- Problems identified at this stage (such as fatigue or vibration) will be solved, but usually at high costs (adding new elements as brackets, delay in production, late change in elements which are already under production, etc.).
- Time is lacking as there is a strong constraint on the delivery date. The production of some elements may be started before the completion of all the detailed analysis (that explains the cost of future changes).
- Detailed analyses are time consuming and require significant experienced staff.
- It is definitively too late to optimize!
- Etc.

Based on this design procedure and design stages, which are the challenges to optimize ship structures?

- Need specific tools for conceptual and basic design stages. Indeed the early design stages (CD and BD) are the only opportunities to select (by optimization) an effective scantling considering the production requirements (simplicity, accessibility, least production cost, etc.). Later will be too late.
- Need tools that can be used at the conceptual design stage and later at the basic design stage without re-meshing or re-modelling. It could be the same tool that can handle more advanced data and have a wider scope (not only hull girder bending but also local structural constraints and production constraints). Or it can be different tools but avoiding re-meshing and re-modelling.
- Need a tool (or IT platform) that can be used with the limited data available at the first design stages (CD and BD) to develop coarse mesh models dedicated to optimization. Later, at the detailed design stage, these models must to be able to be re-used (to save time and avoid re-meshing).
- Need fast and reliable modelling tools with interface with standard commercial CAD tools which are used by the naval architects and the classification societies.
- Need to target multi stakeholders (shipyard, ship-owner, classification society, IMO, etc.) and therefore multi-objective optimization.

3.4 *Description of a typical structural optimization tool*

As many optimization tools, to optimize the structures of a ship we need objectives functions (criteria), design variables and constraints. We also need an optimization algorithm (mathematical approaches as simplex, steepest descent, SQP or heuristic approaches (evolutionary strategies, genetic algorithms, neural network algorithms, etc.).

3.4.1 *Objective functions*

Objective functions depend on design variables in an explicit or implicit way, and may be assessed using numerical or mathematical expression. Typical objective functions are weight, production cost, life cycle cost, safety index, etc.

3.4.2 *Design variables*

The design variables refer to a list of variables characterizing the design being optimized. The design variables can be the main dimensions of the structure (or part of it) but also local parameters such as the web thickness of the stiffeners of a given structural region. Design variables can be the types of material or grade, the types of stiffeners (bulb, T, L), the overall section of a deck, etc. That explains we can have structural optimization problems with few design variables (10-50) when only few main dimensions or parameters are selected, but also optimization problems with few hundreds (100-1000) design variables (typically when the dimensions of each element are considered as independent design variables).

The selection of the design variables depends of the target of the optimization and the design stage. In the next parts of this paper, design variables will typically be the scantling of the stiffened panels that compose the ship structures. A ship is usually composed of stiffened panels (sub-elements of the decks, bottoms, side shells, bulkheads, etc.). The design variables relate to the scantling of these stiffened panels. The panel scantling varies from panel to panel even if standardization is usually achieved for obvious production considerations. By panel scantling we understand the plate thickness, the frame spacing, the stiffener spacing and the dimensions of these frames and stiffeners (for instance HP200 or FB100x10).

3.4.3 *Design constraints*

The design constraints mainly refer to a list of limits mathematically defined in order to keep a feasible solution at the end of the optimization process. Selection and modelling of the constraints are in fact the most difficult part of the optimization process. To get a reliable industrial solution, all the constraints involved in the structural design must be considered. Different types of constraints can be considered:

- *Technological constraints* (or side constraints) that provide the upper and lower bounds of the design variables.
- *Geometrical constraints* impose relationships between design variables in order to guarantee a functional, feasible and reliable structure. These are generally based on expert knowledge to avoid local strength failures (web or flange buckling, stiffener tripping, etc.), or to guarantee welding quality and easy access to the welds. For instance, welding a plate of 30 mm thickness with another one being 5 mm thick is not recommended.
- *Structural constraints* are selected to avoid yielding, buckling, cracks, etc. and to limit deflection, stress, etc (for the different limit states). These constraints are based on solid-mechanics phenomena and modelled with rational equations. By rational equations, we mean a coherent and homogeneous group of analysis methods based on physics, solid mechanics, strength and stability treatises, etc. and that differ from empirical and parametric formulations. Thus these structural constraints may limit the deflection level of the structure, the stress in an element and the safety level related to buckling, ultimate resistance and tripping.
- *Global constraints* impose limitations for centre of gravity to ensure ship stability, fabrication cost to ensure producibility or flexional inertia to ensure the respect of the classification rules.
- *Equality constraints* are often added to avoid discontinuity of design variables and promote standardization. Panels of a same deck normally have the same thickness, stiffeners spacing's are often homogeneous, etc.

Constraints find usually their origin from classification societies (rule based design) or from direct calculation (rational analysis, FEA, etc.), but also from the yard's best practice and yard's standards.

One of the main difficulties encountered when operating the optimization methods are to correctly define the problem to be solved. This generally must be extracted from the whole design set of constraints, and put in a very formal way, which is not a straightforward operation, and actually not a natural way of thinking for a designer. In practice, this often leads to bad formulated problems and to a trial and error process to define things correctly (Birk, 2003).

Note that the difference between an objective function and a constraint is rather limited. Cost, weight, stress, gravity centre can be consider as a criteria that we want to minimize (maximize) or as a constraint (for which an upper or lower bound is fixed). So it is convenient when the user can select a criterion as a constraint or as an objective function. The relationship between the function and the design variables does not change.

3.4.4 *Optimization algorithms*

There are basically two main types of optimization algorithms: the mathematical approaches (deterministic) and the heuristic approaches including concepts inspired by natural biological systems (Birk, 2003).

- The purely deterministic approaches: Starting from an initial design (feasible or not), the deal is to identify the best direction of propagation. Such methods are the simplex, the steepest descent, BFGS, SQP, Dual approach, etc. The author experience and best practice concerns the convex linearization and dual approach (CONLIN software, Fleury and Braibant, 1986)). Even with hundreds of design variables and thousands of constraints, the convergence in the feasible domain is guarantied and the optimum is reached within 10 iterations (this means 10 re-analyzed of the real problems). This approach is discussed here after in Section 4.
- The heuristic approaches are based on an "intelligent scanning" of all the feasible design space. These methods guaranteed to find the global optimum or at least to be close (if enough runs are performed) and are not influenced by the initial design. They are very efficient and effective methods if the computation time for each re-analysis is short as few thousands of runs are often required. This approach is discussed here after in Section 4.

It is not the relevant place to discuss here which approach is the best. In fact, there is no best method. The selection of a suitable method is highly problem dependant. In the framework of ship structure optimization few relevant advantages and shortcomings can be highlighted.

The *deterministic approaches* - these methods consist in minimizing a given objective function by searching in the design space with help of deterministic algorithms.

- They are prone to converge to a local optimum.
- They require expensive effort to assess the first derivative of the constraints. There are methods which do not require the first derivative but in that case much more iterations are usually required. It is a common practice to say that, at least, one iteration is needed per design variable if a linear approach is selected. Hopefully less iterations are required if the first (and sometimes the second) derivatives are used (Newton, BFGS, SQP, etc.). For instance, only few iterations can be required for a structure optimization with hundreds of design variables and thousands of constraints.
- The solution depends of the initial design as it is a convergence process.
- They are suitable to solve problems with continuous design variables. The discrete design variables induced some difficulties.
- They cannot be used with noisy or non-derivable functions, as good quality gradients are requested.
- They need a completely clean and reliable estimate of the functions and their derivatives, and are not robust with respect to any failure in this area.
- They usually have a quick convergence (5 to 10 iterations), which counteracts the time-consuming gradients calculation.

The *heuristic/stochastic approaches* - This other type of algorithms consists in introducing a dose of chance in the search for an optimum, which lets one expect to reach an absolute optimum after a sufficient number of trials.

- They are rather easy to implement, even if they require calibration to speed up the convergence for the specific problems.
- They are rather generic and the same algorithm can be use in many fields. That explains why they are now so popular.
- They are very efficient if the number of solutions is limited (that means a reduced number of design variables).
- Independent of an initial design.
- Prone to find the acceptable approximation of global optimum for a reasonable calculation costs.
- Effective for multi-objective optimization to find acceptable approximation of the Pareto front.
- Much more efficient with discrete design variables than with continuous design variables.
- They are very robust with respect to inaccuracy of failures in the analyses.

This "random" but oriented search can be based on several types of algorithms:

- the *simulated annealing methods* which take roots in thermodynamics and uses the analogy with energy minimisation of physical systems ruled by the Boltzmann law. In this case, there is always a probability of a temporary increase of energy, during the cooling process, this probability decreasing together with the temperature.
- the *genetic algorithm methods* which take roots in the concept of natural selection (evolution theory). They are based on the simulation of the evolution of a population on which different kinds of operations are applied (combination, mutation, etc.) and submitted to a selection at each generation.
- the *particle swarm methods* (Cui et al, 2008)
- etc.

3.5 *The future challenge of the ship structure optimization*

Currently, as for the design, the most challenging issues concerning ship structural optimization are the integration of fatigue as constraint and the implementation of direct calculations of the loads.

3.5.1 *Fatigue analysis*

To be cost effective optimization of scantling has to be performed at the basic design stage but the fine and very fine mesh models to assess fatigue are only available at detailed design stage. So, the challenge to implement fatigue in the ship structure optimization is to develop fast and simplified fatigue assessment module to be embedded in the optimization loop. Module requirements are to be fast and accurate. In optimization the most important is to identify the direction of optimization. The quality of the trend is more important than the quantitative quality of the values themselves. The importance is to identify the best alternative(s). At the end, a final assessment is performed in the DD stage, but it is essential to have a fatigue module at the BD stage to compare different alternatives and provide the best directions of the optimization.

3.5.2 *Direct calculation of loads*

Static loads and wave bending moments are quite well defined by classification societies. Still water bending moments are now easily assessed at the conceptual stage by the naval architects. But the hydrodynamic loads (sloshing, slamming, torsion moment, etc.), especially for innovative ships as trimaran or fast ferry which are strongly governing the ship scantlings, need advanced direct calculations that are usually not performed before de detailed design stage. So, as for the fatigue, the challenge to implement direct load assessment modules in the ship structure optimization is the development of fast and simplified load assessment modules to be embedded in the optimization loop.

4 FROM SINGLE TO MULTI-OBJECTIVE OPTIMIZATION

4.1 *State of art*

After each design loop (or iteration, see Fig. 1), a new design is obtained (in principle a better design), which has been assessed with regards to propulsion, stability, weight, cost, etc. This means that implicitly a series of objectives (or criteria) exists in the head of the designers/engineers. So naval architects, without knowing (as Mr Jourdin - Molière) are daily performing multi-objective optimization. Unfortunately, even with highly experienced naval architects there is a low probability to select an “optimum design”.

That explains why mathematicians and engineers are trying since 1960 to develop rational numerical models to assist the naval architect to identify the “optimum design”. The first tentative concerned single objective optimization of the ship structure minimizing its weight. Engineers obtained results but their methods were not applied by the industry. Indeed in practice, the design of such a complex object as seagoing ship structure is a solution of a multi-objective optimization task including many optimization criteria often counteracting each other, e.g. small hydrodynamic resistance vs. large cargo deadweight, high structure strength and reliability vs. low structural weight and cost. Multi-objective optimization does not yield an unequivocal determination of a single variant but a set of compromise solutions (infinite in general), which is used as a basis of taking a final design decision consisting in a selection of a solution to be further developed.

4.2 *Single criterion problem*

The single criterion optimization problem is usually formulated as Parsons and Scott (2004), Sekulski (2009).

$$\min_x F(\vec{x}) = F_1(\vec{x}) \text{ with } \vec{x} = [x_1, x_2, \ldots, x_N]^T \tag{1}$$

subject to the equality and inequality constraints

$$h_i(\vec{x}) = 0, i = 1, \ldots, I \text{ and } g_j(\vec{x}) \geq 0, j = 1, \ldots, J \tag{2}$$

where there is a single optimization criterion or objective function $F_1(\vec{x})$ that depends on the N unknown design independent variables in the vector $\vec{x}$. For a practical engineering solution, the problem is usually subject to I equality constraints and J inequality constraints $h_i(\vec{x})$ and $g_j(\vec{x})$, respectively, that also depend on the design variables in the vector $\vec{x}$. The minimization form is general because a maximization problem can be solved by minimizing the negative or the inverse of the cost function.

4.3 *Multi-criteria optimization*

Multi-objective design problems are those where two or more criteria included are measured in different units and there is no acceptable way to transform them to a single value. In practice the multi-objective optimization problem arises when there are targets to attain and there are various ways to attain these targets. In the design of seagoing ship these may be for example to achieve the lowest possible structural weight, and the lowest manufacturing cost.

The multi-criterion optimization problem involves $K > 1$ optimization criteria and can be formulated as, Parsons and Scott (2004):

$$\min_x \vec{F}(\vec{x}) = [F_1(\vec{x}), F_2(\vec{x}), \ldots, F_K(\vec{x})] \tag{3}$$

with $\vec{x} = [x_1, x_2, \ldots, x_N]^T$

subject to equality and inequality constraints

$$h_i(\vec{x}) = 0, i = 1, \ldots, I \text{ and } g_j(\vec{x}) \geq 0, j = 1, \ldots, J \tag{4}$$

where there are K multiple optimization criteria $F_1(\vec{x})$ through $F_K(\vec{x})$ and each depends on the N unknown design variables in the vector $\vec{x}$. In general, this problem does not have any single solution due to conflicts amongst the K criteria.

Attention should be paid to the fact that a general view of life cycle cost includes the costs of design, manufacturing, foreseen service costs, and also the costs of decommissioning and disposing of the structure.

It is worth noting that the value of money as a cost comparison basis is also changeable, and depends on social and economic conditions same as the mutual relations between particular components of construction/service cost. This tends to somewhat reduce the importance of cost-based criteria and leads to a situation where other criteria not expressly money-related are used more often, such as structural weight and reliability. Quite often the volume or weight of steel materials (plates and profiles) as a structure optimization criterion is used for the fabrication of a whole structure. The above criteria approximately reflect the costs of used-up material in case of structures built wholly of a single material, e.g. steel.

Some other criteria can be adopted as well, reflecting the approximate labour for the construction works or its maintenance works - these can be for example the length of joints, the number of connections for a given steel structure design, or its outer surface which is subject to maintenance.

4.4 *Pareto optimum front*

In case of a multiple criteria conflict, Pareto-optimality is a widely accepted measure of quality in the multi-objective selection problems. This has first been exposed by the Italian-French economist V. Pareto in 1906. This is also referred to today as Edgeworth-Pareto optimality: *A solution is Pareto optimal if it satisfies the constraints and is such that no criteria can be further improved without worsening at least one of the other criteria.* Note that this emphasizes the conflicting or competitive interaction amongst the criteria. These definitions typically result in a set of optimal solutions rather than in a single unique solution.

A particular design of a ship structure may be called Pareto-optimal under a condition that there is no other variant of this structure which would be better with regard to at least one criterion while at the same time being equally good with regard to all the remaining optimization criteria. This means that a Pareto-optimal structural variant cannot be improved without simultaneous worsening of at least one criterion. Pareto-optimal designs are also referred to in literature as being non-dominated ones, trade-offs, non inferior or Pareto efficient. The variant of a ship structure is not Pareto-optimal if there is any other variant, which improves at least one criterion while at the same time not worsening the values obtained for the remaining ones. Such variants are also called dominated ones or inferior ones.

Fig. 4 gives an example of a Pareto frontier. The boxed points represent feasible choices, and smaller values are preferred to larger ones. Point C is not on the Pareto Frontier because it is dominated by both point A and point B. Points A and B are not strictly dominated by any other point, and hence they lie on the frontier. Of course, such a presentation is easy in case of problems involving two objectives, but is much more difficult of even impossible in case three or more objectives are involved.

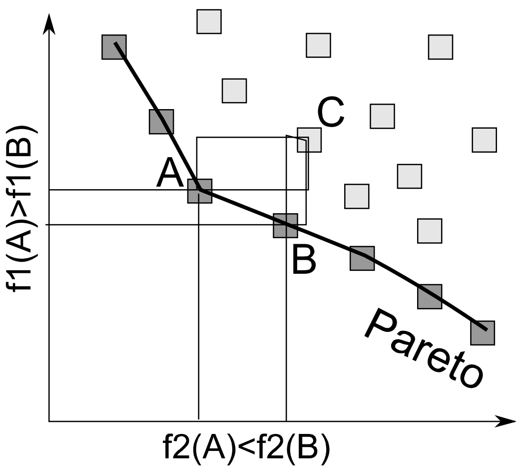


Figure 4. Example of a Pareto front

A design team, of course, typically seeks a single result that can be implemented in the design. This result should be an effective compromise or trade-off amongst the conflicting criteria. This can often be reached by considering factors that can not be included in the optimization model, *Zanic et al. (2003)*. Some additional tools can also be used to help the designer making his choices, and possibly defining a new unique objective function that gathers all his wishes, and that can be minimized/maximized afterwards (Multi Criteria Decision Making tools).

4.5 *Global optimum criterion*

As noted before, engineering design requires a specific result to be implemented, not a set of solutions as provided by the Pareto optimal set. The most intuitive ways to achieve an effective compromise amongst competing criterion are, amongst others, the weighted sum, the min-max and the nearest to the utopian solutions. These solutions can be obtained through the global criteria:

$$P\left[F_K(\vec{x})\right] = \left\{ \sum_{k=1}^{K} \left[w_k \left| \frac{\left(F_k(\vec{x}) - F_k^0\right)}{F_k^0} \right| \right]^{\rho} \right\}^{1/\rho} \qquad (5)$$

$$\text{with } \sum_{k=1}^{K} w_k = 1$$

F_k^0 is the value of the criterion F_K obtained when that criterion is the single criterion used in the optimization i.e. the best that can be achieved with that criterion considered alone. The scalar preference function $P\left[F_K(\vec{x})\right]$ replaces $F(\vec{x})$ in Eq. 1 for numerical solution.

The weighted sum solution results from Eq. 3 when $\rho = 1$, whereas the nearest to the utopian solution results when $\rho = 2$ and the min-max solution when $\rho = \infty$. The numerical implementation for the min-max solution uses the equivalent of Eq. 3 with $\rho = \infty$,

$$P[F_k(\vec{x})] = P\left[F_K(\vec{x})_k\right] = \max\left[w_k \left| \frac{\left(F_k(\vec{x}) - F_k^0\right)}{F_k^0} \right| \right] \qquad (6)$$

Moreover, a solution could be obtained for a number of values of ρ and then the design team could decide which solution best represents the design intent.

4.6 *Mapping the entire Pareto front*

When dealing with multi-criteria problems, it is highly recommended to study the entire Pareto front. This allows the design team to consider all options that meet the Pareto optimality definition. The final design decision can then be based on the considerations modelled in the optimization formulation as well as on the multiple additional considerations, factors, and constraints not included in the model. This is feasible when there are two criteria but rapidly becomes impractical due to computational time and visualization reasons when the number of criteria reaches three and up.

In order to map the entire Pareto front, the following three methods can be used:

a) *Repeated weighted sum solutions*. If the feasible objective function space is convex, weighted sum solutions can be obtained for systematically varied weighting factors.

b) *Repeated weighted min-max solutions*. If the feasible object function space does not have a slope that exceeding w_1/w_2, weighted min-max solutions can be obtained for systematically varied weighting factors.

c) *Multi-criterion optimization methods*. Multi-criterion implementations of Evolutionary Algorithms (Evolutionary Strategies, Generic Algorithms, etc), Simulated Aneealing, Particle Swarm Optimization, etc. can leads to the entire Pareto front

These methods (a) and (b), based on a scalarization of a vector objective function, have found wide-ranging applications also in the methods of evolution-based multi-objective optimization, as they allow for use of well researched single-objective optimization algorithms.

These classical methods used for the solving of multi-objective problems are easy to implement but the fundamental disadvantages are:

- Seeking only a single point on non-dominated solutions front and resulting necessity to make numerous calculation runs for a single optimization task.
- The fact that expert knowledge is required at the beginning to specify the weight coefficients used for component optimization criteria.

Evolutionary multi-objective optimization (c) algorithms developed in recent years have proved highly effective. Highly promising results in the field of genetic algorithms use for multi-objective optimization tasks have been obtained in the field of ship structures by Okada & Neki (1992) and Hutchinson et al (1998). Special evolutionary multi-objective optimization methods may be applied, as far as genetic algorithms are concerned. Fundamental advantages of these methods are:

- Effective search of solution space.
- Capability to illustrate the non-dominated solutions front in a single simulation run.
- Robustness of the procedure.

With simple genetic algorithms application however these major advantages are paid by high computational cost: a large number of fitness evaluation is needed to reach a satisfactory solution. If the fitness function is computed by means of complex simulation codes the total cost of the approach may take the problem impossible to face.

Excellent presentation of evolutionary methods of multi-objective optimization can be found in recently published books Coello et al (2007), Deb (2001) and Osyczka (2002).

NSGA-II (Deb et al, 2000) and SPEA2 (Zitzler et al, 2001) algorithms are commonly recognized and they are employed as reference algorithms by many authors for estimation of the efficiency of other formulations. The principal elements of these algorithms are:

- Selection strategies based on the Pareto-domination relation.
- Niche strategies to preserve diversity in the consecutive populations.
- Elitist strategy to ensure survival of non-dominated solutions in the time of evolution.

Despite the disadvantages of the algorithm employing scalarization of the objective functions are efficient algorithms transient from the classic methods to the advanced algorithms employing the Pareto-domination relation for the variant selection.

The researchers have reported for several years that if the number of the optimization criteria is greater than 3, the methods based on the domination relation turn to be ineffective since together with the increase of the number of optimization criteria the number of non-dominated variants decreases reducing the effectiveness of the selection operator, Hughes (2003 and 2005), Purshouse and Fleming (2003).

5 LBR-5, A LEAST COST STRUCTURAL OPTIMIZATION METHOD

5.1 *Introduction*

To be attractive to shipyards, scantling optimization has to be performed at the preliminary design stage. It is indeed the most relevant period to assess the construction cost, to compare fabrication sequences and, to find the best frame/stiffener spacing's and most suitable scantlings to minimize ships life cycle cost. However at this stage of the project, few parameters (dimensions) have been definitively fixed and standard FEM is often unusable, particularly to design offices and modest-sized shipyards. Therefore, an optimization tool at this design stage can provide precious help. This is precisely the purpose of the LBR-5 optimization software, Rigo (2001) and Rigo & Fleury (2001).

LBR-5 is the French acronym of "Stiffened Panels Software" version 5.0. The purpose of the tool is the sizing/scantling optimization of ship and offshore structures. The development of the LBR-5 module is included in the development of a module-oriented optimization approach, Rigo (2001). The goal is to create a multi-purpose optimization model, opened to users and compatible with other structure analysis modules based on codes and specific regulations. Such a model contains various analysis methods for strength assessment that can easily be enriched and complemented by users. The user must be able to modify constraints and add complementary limitations according to the structure type (hydraulic, ship and offshore structures, etc.), the code or the regulation in force and to his experience and ability in design analysis. The objective is to create a user-oriented optimization technique in permanent evolution, i.e., that evolves with the user and his individual needs.

The structural analysis is performed on a model based on an extrusion of the cross section of the structure (2D+) solving the stiffened plate differential equations with Fourier series expansions, Rigo (2005).

5.2 *The LBR-5 module oriented optimization concept*

A multi-purpose optimization model, open to users and compatible with different codes and regulations must contain various analysis methods for strength assessment that could be easily enriched and complemented by users. The user must be able to modify constraints and add complementary limitations/impositions according to the structure type studied (naval, offshore structures, etc), the code or the regulation in force and to his experience and ability in design analysis. The objective is to create a user-oriented optimization technique, in permanent evolution, i.e. that evolves with the user and his individual needs. We define this as "Module-Oriented Optimization ".

The LBR-5 optimization model is based on this concept and is composed of several modules. Neither the module number nor their type is imposed. The whole model is made up of 3 basic modules (objective function, optimization algorithm and constraints), which forms the framework of the tool.

Around the objective function and constraints modules there are a large number of sub-modules. Each of these sub-modules is specific to a type of constraint. In principle, it is necessary to have at least one sub-module for each constraint type. To date, only a limited number of modules are available (in general 1 or 2 for each constraint type). It is up to the user to complete, adapt and add new modules according to his specific requirements (type of structure, codes and regulations to be followed, technical and scientific level, available hardware, etc.). The objective is to enable the user himself to build the tool he needs.

Fig. 5 shows the basic configuration of the LBR-5 software with the 3 fundamental modules (objective function, optimization algorithm and constraints).

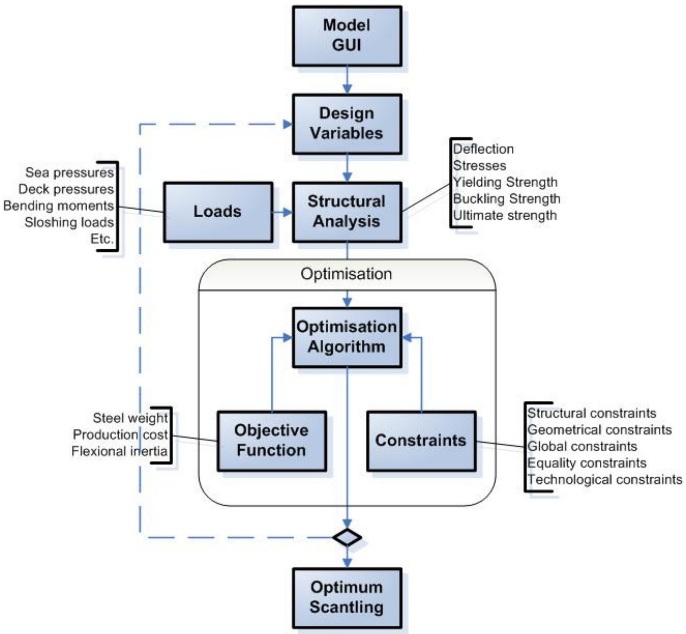


Figure 5. Flow chart of the LBR-5 optimization software

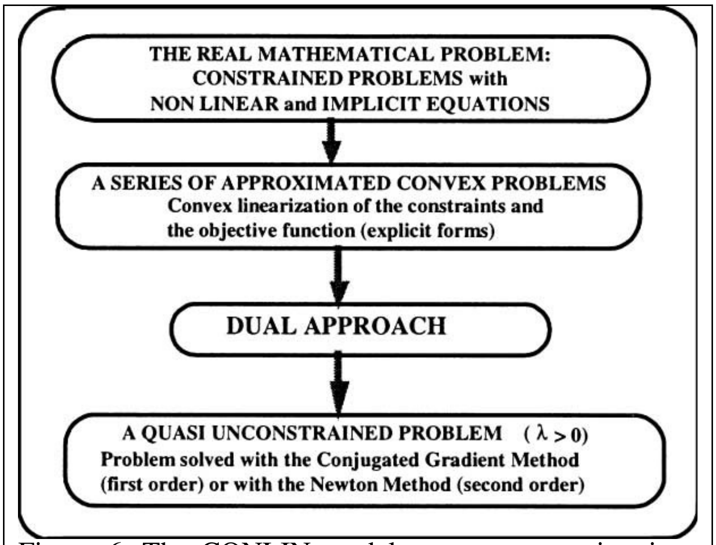


Figure 6. The CONLIN model: convex approximations and dual approach (Rigo and Fleury, 2001)

5.3 *The LBR-5 optimization algorithm.*

The LBR-5 optimization algorithm is based on the CONLIN code developed by Fleury and Braibant (1986) using a convex linearization of the constraints and the objective function combined in a dual approach. With this algorithm, large constrained problems with implicit and non-linear constraints can be easily solved (Fig. 6). The main difficulty in solving a dual problem is dealing with the non-linear and implicit constraints. In order to avoid a large number of time-consuming re-assessments of these non-linear and implicit functions, Fleury suggests applying convex approximations. At each iteration, all the functions (objective function and constraints) are replaced by an approximation called "convex". In a word, the complex initial optimization problem is decomposed in a sequence of simpler convex optimization problems (obtained through a convex linearization) that can be easily solved using a dual approach (Fig. 6).

In order to consider non-linear implicit constraints ($C(X_i)$), Fleury proposes replacing these constraints with approximated explicit linear constraints by using convex linearization. He suggests using the first term of the Taylor Series Expansion. Three linear alternatives are possible:

Linearization with standard design variables (X_i):

$$\tilde{C}(X_i) = C(X_i(0)) + \sum_{i=1}^{N} [X_i - X_i(0)] \frac{\partial C(X_i(0))}{\partial X_i} \quad (7)$$

Linearization with reciprocal design variables $(1/X_i)$:

$$\tilde{C}(X_i) = C(X_i(0)) + \sum_{i=1}^{N} \left[\frac{1}{X_i} - \frac{1}{X_i(0)} \right] \frac{\partial C(X_i(0))}{\partial (1/X_i)} \quad (8)$$

Convex linearization with mixed variables $(X_k, 1/X_j)$:

$$\tilde{C}(X_i) = C(X_i(0)) + \sum_{k=1}^{L} [X_k - X_k(0)] \frac{\partial C(X_k(0))}{\partial X_k} + \sum_{j=L+1}^{N} \left[\frac{1}{X_j} - \frac{1}{X_j(0)} \right] \frac{\partial C(X_j(0))}{\partial (1/X_j)} \quad (9)$$

As design variables refer to dimensions such as plate thickness, web height, etc., it is not suitable to use X_i to linearize constraints related to stress, strengthand displacement. It is better to use reciprocal linearization $1/X_i$. On the other hand, geometrical constraints must be linearized with standard design variables X_i instead of reciprocal ones $1/X_i$. Therefore, for a general case, it is obvious that mixed linearization is the better way. But the problem remains how to determine which linerization is the most suitable (reciprocal variable $1/X_i$ or direct variable X_i) for each design variable. Fleury has responded to this, proposing to make this selection in a way that replaces the actual design space (feasible domain for the design variables) by a smaller domain, included in the actual one, but convex. One can summarise in this way: since the substitution design space is conservative, this leads to a solution that is still admissible, but that could be "slightly" different from the real optimum. Step by step, this conservatism is released as one comes closer to the real optimum.

The convexity of the design space and conservation allow a safe and fast convergence. The convergence is safe because, at each iteration, the updated solution has a tendency to still remain in the feasible domain. Fleury et al (1986) has demonstrated that an efficient convex linearization can be achieved by selecting the group of variables X_i and the group of reciprocal variables $1/X_i$ according to the sign of the first derivative of the function to linearize, that is $\partial C(X_i(0))/\partial X_i$.

For a given design variable, X_i:

- A linearization with standard variable X_i is achieved if $\partial C(X_i(0))/\partial X_i > 0$
- A linearization with reciprocal variable $1/X_i$ is achieved if $\partial C(X_i(0))/\partial X_i < 0$

Therefore Eq. 9 becomes:

$$\tilde{C}(X_i) = C(X_i(0)) + \sum_{k=1}^{L} [X_k - X_k(0)] \frac{\partial C(X_k(0))}{\partial X_k} - \sum_{j=L+1}^{N} \left[\frac{1}{X_j} - \frac{1}{X_j(0)} \right] (X_j(0))^2 \frac{\partial C(X_j(0))}{\partial X_j} \quad (10)$$

With

$$\frac{\partial C(X_k(0))}{\partial X_k} > 0 \text{ and } (1 \le k \le N)$$

$$\frac{\partial C(X_j(0))}{\partial X_j} \text{ and } (1 \le j \le N) \text{ for } i = 1, \ldots, N$$

The proposed convex linearization is very powerful as only the values of $C(X_1(0))$ and $\partial C(X_k(0)/\partial X_k$ are required. The linearization is done automatically at each step (iteration) and the convergence order is 2. In addition, the main advantage of the proposed convex linearization is the conservatism of the approximated function. Let's note however that conservatism is only guaranteed with regards to initial linear functions in X_k and in $1/X_j$. To avoid numerical problem the equations have to be normalised before starting the convex linearization.

At each iteration the normalised problem to solve is the following:

$\min\left[\sum F_j / X_j - \sum F_i X_i\right]$ with N design variables X submitted to M constraints

$\sum C_j / X_j - \sum C_i X_i \le CM$ and $X_{i\min} \le X_i \le X_{i\max}$ the lower-upper bounds.

This problem is called a primal problem with reference to the X_i design variables, called primary or primal design variables. It is a constrained problem with N design variables and M constraints. This problem cannot be solved easily with classic methods such as, for example, the conjugated gradient. A dual approach will be used here to replace the primal constrained problem with N unknowns by an unconstrained problem with M unknowns (called the dual problem). This technique is especially advantageous when $M <<< N$: Unfortunately, with regard to the applications considered in this paper, this last advantage is not relevant since M and N are the same order of size.

To the primal problem (convex with separable variables), one can associate the dual problem:

$$\max(\lambda)\left[\min(X)\, de L(X,\lambda)\right] \text{ and } X_{i\min} \le X_i \le X_{i\max}$$

With $L(X,\lambda)$ the Lagrangien, λ_k the M multipliers of Lagrange (dual variables)

$$L(X,\lambda) = \sum_j \frac{F_j}{X_j} - \sum_i F_i X_i + \sum_{k=1}^{M} \lambda_k \left(\sum_j \frac{C_{jk}}{X_j} - \sum_i C_{ik} X_i - CM_k \right)_k \tag{11}$$

which is also a function with separable variables. Because the Lagrangien function is separable (Eq. 11), the single dual problem with N design variables (N dimensions) is replaced by a series of N problems with a single dimension:

$1(\lambda) = \min(X)$ of $L(X) = \sum_{i=1}^{N} \min L_i(X_i)$ with $X_{i\min} \le X_i \le X_{i\max}$ as $L(X) = \sum_{i=1}^{N} L_i(X_i)$ (as function with separable variables).

Each term of the $L(X)$ minimisation (Eq. 11) can be written in an explicit form:

$\min L_i(X_i) = A_i X_i + B_i / X_i$ where A_i and B_i are defined as $\sum_{k=1}^{N} C_i \lambda_k + F_i = fct(\lambda_k)$.

Note that the minimisation related to each X_i variable requires that $\partial L_i / \partial X_i = 0$. Then,

$X_{i\min} \le X_i = \sqrt{B_i / A_i} \le X_{i\max}$ and $X_i = fct(\lambda_k)$.

6 APPLICATION OF LBR-5 SOFTWARE TO STRUCTURAL OPTIMIZATION OF CRUISE VESSELS

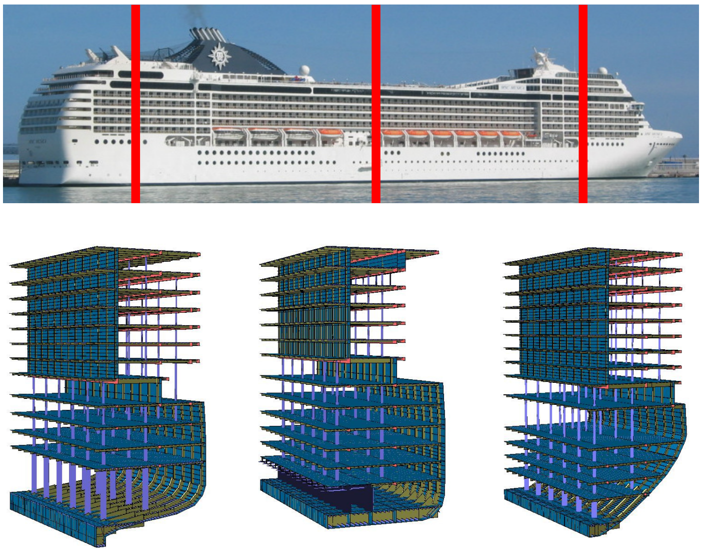
6.1 *Introduction*

This section relates to the structural optimization of a cruise ship. The length between perpendiculars is about 280m and the overall length is about 315m. Fig. 7 shows the outline of a similar ship.

6.2 *Model*

Three amidships sections of the ship has been simultaneously implemented inside LBR-5. The sections are characterized by 14 decks, 40 m breadth and 42 m height (STX-France). Fig. 7 shows the three considered sections. Based on structure symmetry, only the half structure is modelled.

The structural module of LBR-5 allows the analysis of 2.5 D structures, obtained from the definition of a 2D model and extruded through the longitudinal direction. It is obvious that fore and the aft sections of a ship could not be analysed and optimized together with the amidships section, but this optimization is possible independently. The main inconvenient of an independent optimization is that several design variables (for example the stiffeners spacing) that should be the same for the considered structures, may have different values at the local optimum.



81 panels
24 pillars
Aft ship section [A]

78 panels
25 pillars
Amidships section [M]

93 panels
28 pillars
Fore ship section [F]

Figure 7. Three amidships sections of a cruise ship (STX-France)

Recently a multi-structures module has been implemented in LBR-5 to optimize several substructures simultaneously. The main originality is to link design variables between these structures, for example the amidships section with the fore and aft sections of a cruise ship (see Fig. 7). The multi-structures module optimizes simultaneous the three sections in order to obtain compatible design variables.

However, only several common design variables can be taken into account such as stiffener spacing or plate thickness. The link between the three sections is done through design variables: new equality constraints are added between variables. Between substructures, there is no link at the level of strain & stress. In practice, the three sections are optimized independently but some design variables are linked together in order to find a realistic and global optimum solution.

6.3 *Load cases*

For each section the following load cases were considered:

- sagging and hogging wave vertical bending moments with a probability of 10^{-8}; still water pressures; static deck loads;
- sagging and hogging wave vertical bending moments with a probability of 10^{-5}; still water and wave pressures; static deck loads;
- no hull bending moment but maximum still water and wave pressures; static and inertial deck loads.

Deck bending efficiency coefficients were considered in order to take into account the participation degree of each deck to the longitudinal bending.

The main difficulty of the modelling is to get adequate moments and shear forces on the both side of the reduced part of the ship. In principle, the hull girder shear and bending depend on the distribution laws of gravity and buoyancy forces corresponding to each specific loading case. Indeed shear force is a resultant force coming from the general behaviour of the ship. It is influenced by its length, weight and water pressures. If we model only a part of the ship, we do not have the same behaviour: the shear force and moment in the studied section are not the same as in reality. To solve the problem we artificially modify the bending moment applied and the length of the model to get the adequate bending moment/shear force in the studied section for each considered load cases acting on the sections of the passenger ship.

Indeed our model is a 2D model extruded in the third direction. Hydrodynamic pressures and deadweight do not change along this direction. Consequently the resulting pressure on the structure p is also constant in this direction – our model is like a beam with a constant pressure p applied. If we apply a bending moment M_1 to the extremities of our model, the equations of the moment M and shear T are:

$$M = M_1 + \frac{px^2}{2} - \frac{pxL}{2} \tag{12}$$

$$T = p(\frac{L}{2} - x) \tag{13}$$

where x is the distance from the extremity and L the length of the model. For the whole ship the behaviour is more complex (p is not constant over the length) and must be studied to know the real distribution of the bending moment and the shear. With these distributions we can know the moment and the shear to apply at the section studied by LBR-5 – in other words we can know M and T.

In the LBR-5 model we must choose a position x where are applied the structural constraints: the equations above show that for each position x we have different values of M and T. For a section chosen (for a given x) we must then solve the above equation to find which bending moment apply to the extremity M_1 and which length L to select to have the good couple (M,T). Consequently the length of the model is virtual and varies for each load case.

6.4 *Optimization - Design variables*

The three ship structures are modelled respectively with 81, 78 and 93 stiffened plate elements (Fig. 8). The structural response of the model is solved with the resolution of the non-linear differential equations of each stiffened plate element, *Rigo (2001)*. For each element, nine design variables are available:

- Plate thickness.
- For longitudinal members (stiffeners, crossbars, girders, etc.),
  - web height and thickness,
  - flange width,
  - spacing between two longitudinal members.
- For transverse members (frames, transverse stiffeners, etc.),
  - web height and thickness,
  - flange width,
  - spacing between two transverse members (frames).

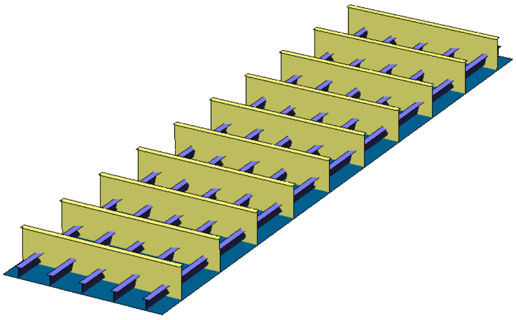


Figure 8. LBR-5 Stiffened Plate Element

In this case study 1694 design variables were activated for the whole ship model (3 ship sections) which represents an average of 6-7 design variables per stiffened panel. Only plate thicknesses and longitudinal members have been optimized.

To deal with this huge number of design variables the LBR-5 optimization algorithm which can solve non-linear constrained problems has been used. It is based on both a convex linearization of the non-linear functions and a dual approach, *Fleury et al. (1986).* It is especially effective because only few iterations are required; typically less than 10.

6.5 *Optimization - Objective functions*

Production cost and minimum weight constitute the double objective considered in this application.

Production costs (PC) has been subdivided into three categories according to Eq. 14:

- the cost of raw materials (MC) – The evaluation of material costs consists in quantifying volumes required for construction and obtaining prices from suppliers and subcontractors.
- the labour costs (LC) – The best alternative to using empirical formulations to evaluate labour costs is an analytic evaluation. Such an approach requires knowledge of the working time required for each standard labour task associated with a workstation as well as the subdivision by stations of the entire construction process. Eq. 15 provides the Cost Evaluation Relationships (CERs) of the labour cost of a stiffened panel for a simple manufacturing activity e.g. the welding of two assemblies, the tacking of steel profiles, etc. The production cost has been calculated with an advanced cost module taking into account a detailed shipyard database. Around 60 fabrication operations are considered, covering the different construction stages, such as girders and web-frames prefabrication, plate panels assembling, blocks pre-assembling and assembling, as well as 30 types of welding and their unitary costs, *Toderan et al. (2007).*
- the overhead costs (OC) – Overhead includes any expense that cannot be attributed to a specific work station of the construction process, but that is, however, linked to construction.

$$PC = MC + LC \times HC + OC \tag{14}$$

where
PC Production cost (€),
MC Material cost (€),
LC Labour cost (man-hours),
HC Hourly cost (€/hour),
OC Overhead costs (€).

$$LC = QC \times UC \times KC \times AC \times WC \tag{15}$$

where
LC Labour cost (man-hours),
QC Quantity (welding length, number of brackets, etc.),
UC Unitary costs (cost-per-unit),
KC Corrective coefficient used to calibrate the unitary costs,
AC Accessibility/Complexity coefficient,
WC Workshop coefficient.

The CER (Eq. 15) provides the basic tool to assess the cost. This relationships (QC × UC) is typically developed directly from the measurement of a simple physical attributes such as dimensional data (plate thickness, profile length, profile scantling, welding length, welding throat, etc.) or quantitative data (number of profiles, number of brackets, number of cut-outs, number of holes, etc.) for a given shipbuilding activity (QC), and the unitary cost of carrying out the activity (UC), e.g. the labour for steel block assembly (man-hours/ton) or the labour for welding in a vertical position (hours/meter).

The unitary costs (UC) vary according to the type and the size of the structure, the manufacturing technology (manual welding, robotic welding, etc.), the experience and facilities of the construction site, the country, etc. Usually, unitary costs are defined as a function of one or more design variables like (plate thickness, welding throat, welding type (butt or fillet), welding position, bevels, profile scantling, etc.).

The catalogued cost scales (cost-per-unit) available do not always reflect accurately the expected costs for the cost assessment. Therefore, these cost scales can be modified thanks to an appropriate adjustment factor (KC). This procedure has the double advantage of preserving the cost scales for control purposes and allowing the impact simulation of a facility or technology investment on the cost.

An additional coefficient (AC) is introduced to the equation to adjust manufacturing cost assessment in case of increase or a decrease in the relative accessibilities/complexities of the ship or its sub-assemblies (ship, blocks, panels, etc.). The more dense, difficult to reach and complex the structure is , the more the manufacturing cost will increase.

The productivity changes from a workshop to another. Usually shipyards wish to consider this type of change in their cost assessments. For that purpose we use another adjustment coefficient (WC) reflecting certain gains or losses in productivity within specified shipyard activities, such as in the workshop the product is assembled.

Beside the production cost a maintenance/repair oriented life cycle cost/earning model is currently being studied in order to improve the cost objective function. *Turan et al. (2009)* provided good theoretical and practical foundation but further research and progress are still required to develop a more mature maintenance/repair cost modelling systems.

6.6 *Optimization - Design constraints*

Constraints are linear or non-linear functions, either explicit or implicit of the design variables. These constraints are analytical relationships of the limitations that the user wants to impose on the design variables or parameters such as displacement, stress, ultimate strength, etc.

The problem is highly constrained (Table 1) and the adequacy of these constraints can greatly influence the solution provided. In this specific case study, 3388 technological constraints, 1696 geometrical constraints, 16809 structural constraints and 6 global constraints have been used. All the previous constraints have been applied to a ship at the end of his service life, i.e. for the corroded structure after 30 years of life.

Table 1. Design constraints of the 3 ship sections

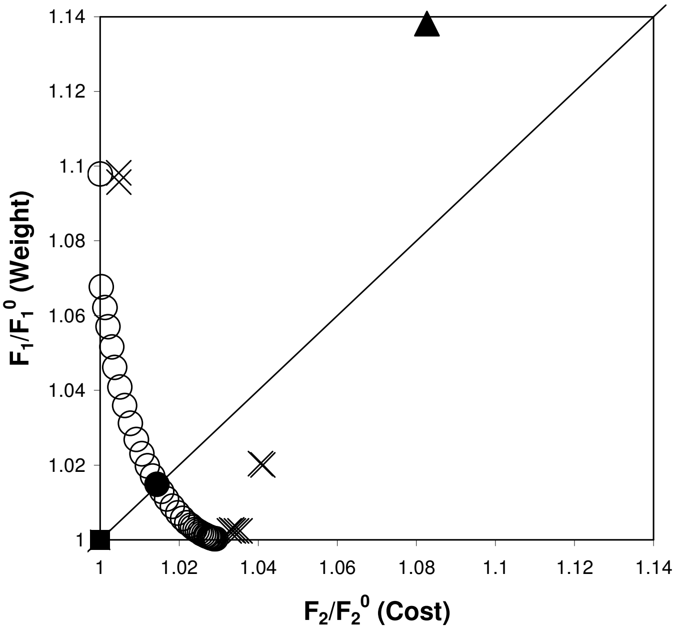
	Aft ship section [A]	***Amid ships section [M]***	***Fore ship section [F]***	***Total***
Number of strake elements	*81*	*78*	*93*	***252***
Design variables	*550*	*460*	*684*	***1694***
Technological constraints	*1100*	*920*	*1368*	*3388*
Geometrical constraints	*558*	*446*	*692*	*1696*
Structural constraints	*5734*	*4035*	*7040*	*16809*
Global constraints	*2*	*2*	*2*	*6*
Equality constraints	*0*	*0*	*0*	*0*
Total constraints	***7394***	***5403***	***9792***	***21899***

6.7 *Pareto front*

For the application case, Eq. 5 was used for the two criteria of the objective function. This leads to the Eq. 16 where P is the objective function and F_1, F_2 are the both criteria analysed in this paper i.e. respectively the steel weight and the production cost. Furthermore, F_0^1 represents the value of the criterion F_1 (i.e. steel weight) obtained when the optimization is performed only with this criterion in the objective function (single objective), while F_0^2 represents the value of the criterion F_2 (i.e. production cost) obtained when the optimization is performed only with this criterion in the objective function (single objective).

$$P = \left[\left[w_1\left|\frac{F_1 - F_1^0}{F_1^0}\right|\right]^{\rho} + \left[w_2\left|\frac{F_2 - F_2^0}{F_2^0}\right|\right]^{\rho}\right]^{1/\rho} \qquad (16)$$

The Pareto front has been mapped by using the repeated weighted sum solutions method using a process that altered the weighting factors in the weighted sum solution and solved the optimization for each of them. The resulting convex Pareto front is shown in Fig. 9 (50 points were calculated). The Pareto front required 28 hours with a laptop Pentium Dual Core 2.52 GHz and 3 Go of RAM. Thanks to the optimization algorithm features, all scantlings presented in Fig. 9 are feasible solutions, which mean that all of the constraints imposed to optimization are being satisfied.



▲ Initial design ■ Utopian point ○ Pareto optimal solutions

× Not converged points ● Min-Max Solution (ρ=∞)

Figure 9. Pareto front of the cruise ship optimization

Table 2. Cost and Steel Weight Savings

	Weight Optimization	***Cost Optimization***	***Min-Max Solution***
	Saving (%)	Saving (%)	Saving (%)
Steel weight	**-12.72%**	**+5.1%**	**-11.3%**
Production cost	**-0.88%**	**-4.52%**	**-1.58%**
Material cost	-8.5%	+0.89%	-8.38%
Labour cost	+4.22%	-8.8%	+2.96%

The utopian point, the min-max solution (ρ=∞), and the initial solution are also shown in Fig. 9. Min-Max solution has been obtained for a weighting factor equal to 0.59 for the production cost and 0.41 for the weight. This analysis has highlighted that the initial design is relatively far from the Pareto front. Using Fig. 9, the design team is now able to choose a compromise solution from the Pareto front, by considering additional factors and constraints that could not be included in the optimization problem.

6.8 *Results*

In this application, results are mainly presented in terms of ratios to avoid publishing sensitive confidential quantitative data. A comparative analysis has been carried out on the several optimal configurations. Table 2 provides the cost and steel weight savings respectively between the initial design and a cost optimization, between initial design and weight optimization and finally between initial design and the min-max solution.

Results show that a cost optimization generates an important increase of steel weight. Thus the cost optimal solution is far from the optimum in term of steel weight. Consequently for this ship the Min-Max solution is probably much more efficient than a weight optimization (i.e. production cost gain of 1.58% and weight gain of 11.3%). This case study clearly shows the advantage of a multi-objective optimization in comparison with a single one.

The breakdown of the gain for each main part of the ship, i.e. the bottom, the side shells, the inner desks and the accommodations', is presented on Fig. 10 and Table 3. The results shows that plate thickness has been reduced everywhere. The highest reduction as well as for production cost as for steel weight is given for the side shells of the ship.

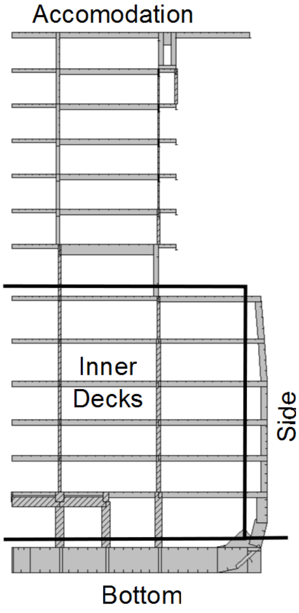


Fig. 10. Gain breakdown of the min-max solution

Table 3. Gain Breakdown of the min-max solution

	Production Cost Saving (%)	**Steel Weight Saving (%)**
Bottom	-0.1%	-7.71%
Side	-18.42%	-31.56%
Inner decks	+4.33%	-8.77%
Accommodations'	-1.92%	-10.43%
TOTAL	**-1.58%**	**-11.3%**

6.9 *Validation of the results*

The final scantlings of the min-max solution were verified with Bureau Veritas rules (Mars2000); all plates and stiffeners had thickness greater or equal to those required by the rules. Note that the optimization did not take fatigue into account. Information of structural details required for reliable fatigue assessment is available only in the next design stage. This is a significant obstacle for an early design stage, because the decisions taken at this stage have a strong influence on the fatigue life of the hull girder. Structural modifications after the early design stage are expensive. In order to overcome this problem, a study has been conducted to implement a rational model for fatigue assessment at the early design, Remes et al. (2009).

7 IMPROVE

A new forward-looking design for a 220,000m^3 capacity liquefied natural gas carrier (Fig 11) has emerged as part of the EU-funded IMPROVE project, following a study by STX France S.A (RINA 2009).

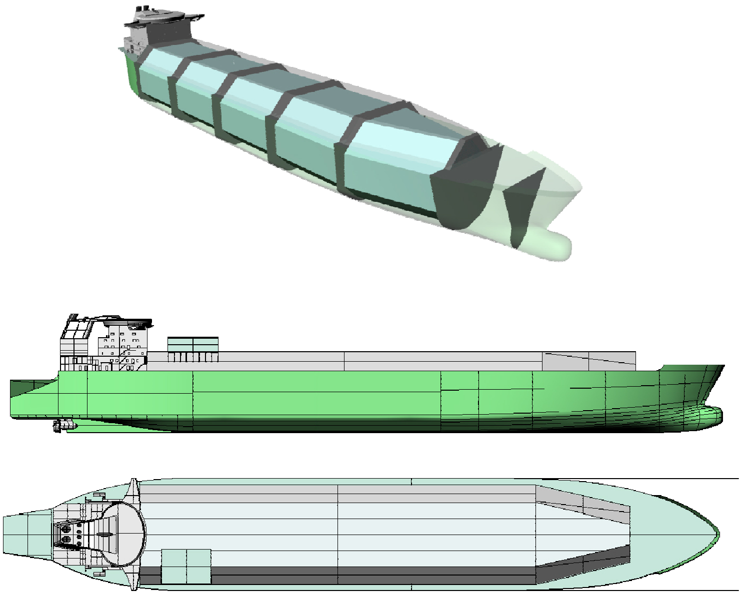


Fig 11: The STX France new concept suggests a 'two-draught' vessel, using minimal or even no ballast water in the unloaded condition.

The Saint-Nazaire shipyard's designers propose a solution to reduce the need for ballasting in order to prevent biological invasions of marine organisms transported in ballast water and sediment transfer. Moreover, energy and thus money will be saved by decreasing the huge amounts of sea water transported, almost unnecessarily.

The innovative part is a change of the hull shape in combination with an adapted with type of propulsion unit. The solution is based on a V-shape hull and pod type propulsion technology to make the need for ballast water unnecessary in good sea way conditions. The special hull form allows a sufficient draught in most loading condition with a reduced volume of ballast water.

In the framework of IMPROVE the scantling of the cargo tanks has been optimized (including frame spacing and stiffener spacing), considering sloshing assessment performed by BV.

The least weight optimization (objective function being the minimization of the weight) reveals a potentials gain of the order of 15 % (including the cofferdams). Concerning the production cost (least cost optimization) the gain is around 5%.

Similarly two other ships have been optimized in the frame work of IMPROVE. A large Ro-Pax ship, with capacity for 3000 lane meters of freight and 300 cars, plus 1600 passengers, designed by Uljanik Shipyard in Croatia (Fig. 12) has been optimized using Octopus-Maestro developed by V Zanic et al (2009)

The third ship is a 40,000dwt chemical tanker, designed by Szczecin Shipyard, in Poland (Fig. 13) and optimized using CONSTRUCT (Ehlers and Klanac, 2009).

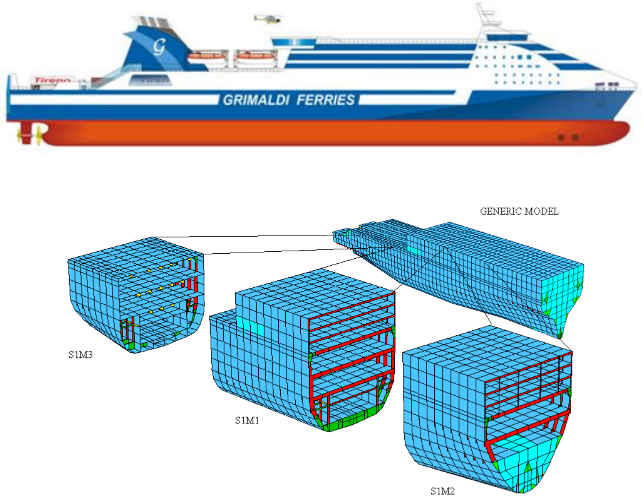


Fig 12: Structural assessment of the ROPAX (Zanic et al 2009).

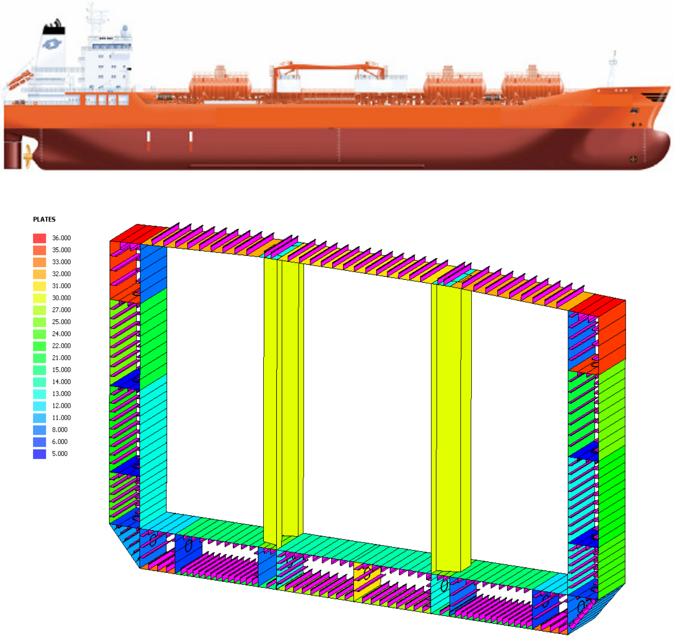


Fig 13: Structural assessment of the Chemical Tanker (Ehlers et al, 2009)

8 CONCLUSIONS

The future challenge in the field of ship structure optimization does not concern the optimization algorithm itself but the development of some specific modules and mainly their integration.

The identified challenges and needs are the following:

- Development of fast and reliable modules to assess structural constraints such as fatigue and loads, at the early design stage (conceptual design stage but more probably at the basic design stage).
- Develop interfaces and/or open platforms for an easy plug and play (integration) of external modules. Initiative started by the IMPROVE user group (Rigo et al, 2009) must be encouraged and development of open platforms as ModeFrontier or BOSS-Quattro is encouraged.
- Integrate the optimization tools in design chains, with direct links to the major CAD/CAM tools and FE software to avoid data retyping and time consuming remeshing.
- Implement multi stakeholders and multi objectives approaches to better converge towards reliable industrial solutions, which are always a fact of comprise between objectives of the different stakeholders.
- Integrate life cycle cost, and particularly the maintenance and operation costs within the global cost assessment for the entire life of the ship. In that case, optimization will be a supportive design tool toward the "Design

for Maintenance" and "Design for operation".

9 ACKNOWLEGMENTS

The authors thank Dr. Sekulski Z. from West Pomeranian Uniwersity of Technology, Szczecin for his contribution and valuable support, as well as the members of the IMPROVE project (FP6, 2006-031382).

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