Multi-objective optimization of ship structures: using guided search vs. conventional concurrent optimization

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ABSTRACT: Structural optimization regularly involves conflicting objectives, where beside the eligible weight reduction, increase in e.g. safety or reliability is imperative. For large structures, such as ships, to obtain a well-developed Pareto frontier can be difficult and time-demanding. Non-linear constraints, involving typical failure criteria, result in complex design space that is difficult to investigate. Evolutionary algorithms can cope with such problems. However they are not a fast optimization method. Here we aim to improve their performance by guiding the search to a particular part of Pareto frontier. For this purpose we use a genetic algorithm called VOP, and use it for optimization of the 40 000 DWT chemical tanker midship section. Beside weight minimization, increase in safety is investigated through stress reduction in deck structure. Proposed approach suggests that in the first stage one of the objectives is optimized alone, preferably more complicated one. After obtaining satisfactory results the other objective is added to optimization in the second stage. The results of the introduced approach are compared with the conventional concurrent optimization of all objectives utilizing widespread genetic algorithm NSGA-II. Results show that the guided search brings benefits particularly with respect to structural weight, which was a more demanding objective to optimize. Salient optimized alternatives are presented and discussed.

1 INTRODUCTION

Design of modern ships introduces new complex structural solutions that must follow the increasing demand for more reliable and safe products. Innovation has become necessity which ensures survival in the market, and it requires improvements of multiple conflicting ship attributes. However, available time does not follow the increasing complexity of design procedure, thus more advanced support systems are required that can assist designers. This is conveniently performed through the optimization process, but with obstacles on the way.

Early design stage lacks precise information on e.g. loading or structural details, while the bounds of some requirements, such as e.g. weight, vertical centre of gravity, nominal stress levels or length of weld meters are not precisely defined. In general it is then useful to venture into analysing correlation between them and investigate their sensitivity for the considered structural arrangement.

Complex ship structures involve large number of variables and even larger number of constraints. Variables are in structural optimization regularly discrete, whether they represent element size, material type, stiffener spacing etc. Constraints are non-linear and non-convex typically involving yielding and buckling of structural elements. These reasons confine the choice of possible optimization algorithms to those that do not require gradient calculation of constraints and objective functions. Evolutionary algorithms have shown capability to handle such problems and provide sufficient benefits for the structure. Their prominent representative, genetic algorithm (GA), is used in this study. Several applications have shown that GA is a successful tool for practical problems in ship structural design and optimization, see e.g. Nobukawa & Zhou (1996), Klanac (2004), Romanoff and Klanac (2007), Ehlers et al. (2007), Klanac and Jelovica (2008).

Genetic algorithm operates in the space of design objectives, by having multiple design alternatives at hand when deciding where to continue the search from generation to generation. This number of available solutions is known as a population size and should grow with the number of considered variables. Literature suggests using population size in range from 50 to 500; see Osyczka (2002), Deb (2001). This lengthens the optimization process even for a simple engineering problem, so that the number of generated and evaluated designs before reaching the optima can be more than several thousands. Clearly, this can be rather costly when optimizing large ship structures, especially if *Finite Element*

Method is applied for structural assessment. In any case, optimization should be short, and if it is time-consuming, it is often, for convenience, stopped prematurely, immediately after noticing some improvements in objective values, and without attaining their optimal values. Making relevant conclusions based on such results can be misleading and costly in the later stages.

Several conflicting objectives that are typically interesting for ship structural optimization, e.g. weight and safety, form a distinctive Pareto frontier which gains in size with problem. Conventional and widespread multi-objective GAs, e.g. NSGA-II (Deb et al. 2002) or SPEA2 (Zitzler et al. 2002), attempt to attain whole Pareto frontier in one run, so that in the very end all Pareto optimal designs are attained. Designer then has a possibility to consider many alternatives that possess different objective values which are then selected based on some preference. But as shown in this paper limited population size restricts such algorithms to fully reach extreme parts of Pareto frontier. Those extreme locations (for which some objective is at minimum/maximum, regardless of the others) contain possibly innovative design principles that can provide new knowledge on possibilities of the structure. Recent study by Klanac et al. (2008) showed that increased crashworthiness of a ship side can be accomplished without significant sacrifice in weight, contrary to traditional belief. Such conclusion was possible by comparing the edges of the Pareto frontier.

In this study we consider a way to avoid unnecessary increase in number of evaluated designs to reach desired parts of a Pareto frontier. Simply said, sometimes the whole frontier is not required to be contained in the final population. Optimization can consist of several parts, each exploring a different part of the frontier. User knows his preference toward objectives included in the optimization. Progress can then be monitored and re-directed if considered appropriate, for example in the case of non-satisfactory results or simply different aspect of the structure wants to be known. Alternatives are then moving along the frontier towards the instructed direction. This is based on the assumption that Pareto optimal solutions predominantly share common variable values, see Deb & Shrinivasan (2006), so that the transition along the Pareto frontier should not require significant changes in the design and should be quick. To allow this manipulation, optimization progress must be monitored in order to conclude on the proper moment for changing the direction of the search.

To show the benefits of this approach we use a simple GA called VOP, and compare it with NSGA-II, a recognized algorithm that possesses several advanced features. VOP optimizes both constraints and objectives by using the *vectorization* principle. NSGA-II concurrently optimizes all the objectives with equal importance and works by utilising existing solutions in the front. It has difficulties to operate with single-objective optimization case to sufficient extent as there is simply no frontier then and it recombines the dominated alternatives in the population for the same purpose.

To demonstrate this comparison, a structure of a 40 000 DWT and 180m long chemical tanker will be optimized for two objectives: minima of weight and maximum of adequacy of deck structure.

In the continuation, we will use the term ‘non-dominated frontier’ instead of the Pareto frontier for the results we obtain, since the evolutionary algorithms strive to it for real-world engineering problems, but reach only certain designs which, when filtered, form non-dominated front.

In the following chapter we revisit theory behind the proposed approach, provide arguments for validity and show how re-formulated optimization statement can be utilized. Chapter 3 describes the VOP algorithm. Chapter 4 compares the optimization of the tanker problem by VOP and NSGA-II. Last two chapters discuss the findings and conclude the paper.

2 GUIDING MULTI-OBJECTIVE OPTIMIZATION

The original multi-objective structural optimization problem of M objectives and J constraints can be formalized with:

$$\min_{\mathbf{x}\in \mathrm{X}}\left\{ \mathrm{f}_1(\boldsymbol{x}),...,\mathrm{f}_M(\boldsymbol{x}) \,|\, \boldsymbol{g}_j(\boldsymbol{x}) \geq 0,\, j\in[1,J]\right\} \tag{1}$$

where we search for design alternatives $\boldsymbol{x}$ in the total design space $\mathbf{X}$ confined within variable bounds. Goal is to find such $\boldsymbol{x}$ that minimizes the objectives while satisfying all the imposed constraints. If constraints are satisfied, design is called feasible and belongs to a feasible set $\hat{\mathbf{\Omega}}$

$$\mathbf{\Omega} = \left\{ \boldsymbol{x} \in \mathbf{X} \,|\, \boldsymbol{g}(\boldsymbol{x}) \geq 0 \right\}. \tag{2}$$

The solution of Eq. (1) is a Pareto optimal alternative $\boldsymbol{x}^*$ which is non-dominated by other feasible alternatives, i.e. there is no alternative better than $\boldsymbol{x}^*$ in the objective space $\mathbf{Y}$ (whose feasible part is denoted with $\mathbf{Y}^{\mathbf{\Omega}}$). Such alternative represents then a rational choice and it belongs to a set of Pareto optima $\hat{\mathbf{\Omega}}$, called also the Pareto frontier and it is defined as:

$$\hat{\mathbf{\Omega}} = \left\{ \boldsymbol{x} \in \mathbf{\Omega} \,|\, \nexists \boldsymbol{x}^k,\, \boldsymbol{f}\left(\boldsymbol{x}^k\right) < \boldsymbol{f}\left(\boldsymbol{x}\right), \forall \boldsymbol{x}^k \in \mathbf{X} \setminus \boldsymbol{x} \right\}. \tag{3}$$

2.1 *Concurrent-search multi-objective optimization*

Standard concurrent-search multi-objective GAs seek the whole Pareto frontier in a single optimization run, requiring large population size to store all the encountered non-dominated solutions. Their working principle is based on recombination of such designs to yield new and better ones, thus their convergence is threatened when population size is not adequate. Progress direction of such optimizers in objective space can be seen in Figure 1 for the case of two objectives. Initial population spreads into multiple 'streams' where each progresses to different parts of the non-dominated frontier. Direction of advancement is pre-defined by non-domination concept, and the algorithm is intended to discover even the outermost designs in the frontier. If the results are not satisfactory enough, one can only tediously run the algorithm further, hoping to reach improvements in particular objective without a possibility to affect on the process.

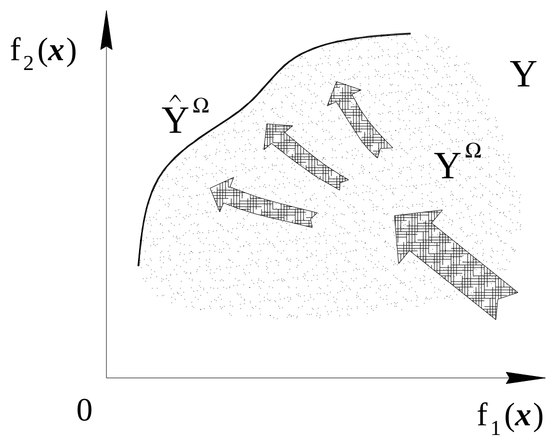

Figure 1. Standard concurrent approach to GA-based multi-objective optimization, shown in the bi-objective case (first objective to be minimized and second to be maximized)

2.2 *Guided search approach*

In this approach only a part of the Pareto frontier is searched based on the instructed direction. To allow control over this direction, specific manipulative weighting factors are applied. Before such manipulation can take place, problem statement in Eq. (1) is re-defined into vectorized form following Klanac & Jelovica (2008):

$$\min_{x\in X}\left\{ \mathrm{f}_1(\boldsymbol{x}),...,\mathrm{f}_M(\boldsymbol{x}),\mathrm{f}_{M+1}(\boldsymbol{x}),...,\mathrm{f}_{M+J}(\boldsymbol{x})\right\}. \tag{4}$$

where constraints $\boldsymbol{g}_j(\boldsymbol{x})$ are now treated as additional objectives $\left\{\mathrm{f}_{M+1}(\boldsymbol{x}),...,\mathrm{f}_{M+J}(\boldsymbol{x})\right\}$, after being converted with the Heaviside function, given as

$$\mathrm{f}_{M+j}(\boldsymbol{x})=\begin{cases}-\mathrm{g}_j(\boldsymbol{x}), \text{ if } \mathrm{g}_j(\boldsymbol{x})<0\\ 0, \qquad \text{otherwise}\end{cases}, \forall j\in[1,J] \tag{5}$$

Control over a particular objective is gained by multiplication of its normalized value within one GA population with the weighting factor w_k:

$$\begin{aligned}&\min_{x\in X}\left\{ w_k\overline{\mathrm{f}_k}(\boldsymbol{x})\right\}, \forall k\in[1,M+J]\\ &\text{s.t. } 0\le w_k\le 1,\ \sum_k w_k=1\end{aligned} \tag{6}$$

where normalization of objective f_k for design *i* is linearly performed using

$$\overline{\mathrm{f}_k}(\boldsymbol{x},i)=\frac{\mathrm{f}_k-\min\limits_{\forall x\in \mathbf{X}^i}\mathrm{f}_k}{\max\limits_{\forall x\in \mathbf{X}^i}\mathrm{f}_k-\min\limits_{\forall x\in \mathbf{X}^i}\mathrm{f}_k}. \tag{7}$$

Increased weighting factor leads to stronger minimization of corresponding objective and vice versa. For convenience, constraints can be set to share the same weighting factor. Figure 2a and b show the principle of guided search for two different directions of search. Guided search is divided in two stages, first to reach the frontier, and second to generate non-dominated designs, exploring thus the possibilities of the optimized structural arrangement. Weighting factors are altered freely by the user, in any manner and whenever desired. But the manipulation should be based on heuristics and not on random choice.

The basic idea of weight factor manipulation is to direct, or guide the 'cloud of alternatives' in search during the optimization process which would 'leave behind' a trail of 'good' alternatives.

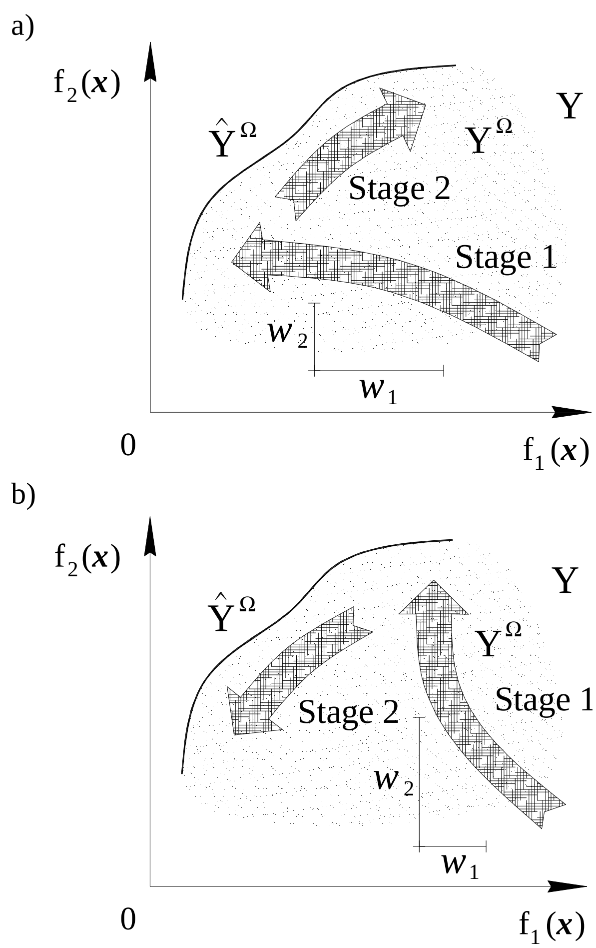

Figure 2. Two proposed routes of the search direction

Deb and Srinivasan (2006) indicate that the Pareto optimal design alternatives of one system possess many commonalities. If this is considered to apply for our problem, Pareto optima obtained in the first phase would share then most of the variable values with the Pareto optima obtained in the later phase(s) of optimization. Decomposing, therefore, the overall optimization problem as proposed should not negatively affect on the possibility to generate Pareto optima. On the contrary, it should affect positively, since a multi-objective GA would perform then a lesser amount of variable changes to generate Pareto frontier than if optimization would have been done concurrently.

3 VOP – A GA FOR GUIDED SEARCH

To guide the search in multi-objective optimization of ship structures, we employ a GA called VOP (Klanac and Jelovica 2007, 2008, Klanac et al. 2008a, 2008b, Jelovica 2008). VOP is a binary coded algorithm consisting of: a) a fitness calculator, b) the weighted roulette wheel selector operating on the basis of computed fitness values, and c) a subroutine executing the single-point cross-over with a probability of p_C and the bit-wise mutation with a probability of p_M. These are standard operators and are, except for the fitness calculator, elaborated in Jelovica (2008), Klanac and Jelovica (2008c).

VOP's fitness function is defined as:

$$\varphi_1(\boldsymbol{x},i) = \left(\max_{\boldsymbol{x}\in\mathbf{X}^i}\left[\mathrm{d}(\boldsymbol{x},i)\right] - \mathrm{d}(\boldsymbol{x},i)\right)^{\bar{\mathrm{d}}(\boldsymbol{x},i)} \qquad (8)$$

where the design's distance $\mathrm{d}(\boldsymbol{x},i)$ from the origin of normalized objective space is obtained as:

$$\mathrm{d}(\boldsymbol{x},i) = \left\{\sum_k \left[w_k \bar{\mathrm{f}}_k(\boldsymbol{x},i)\right]^2\right\}^{1/2}, \forall k \in [1, M+J] \qquad (9)$$

Minimization of the distance $\mathrm{d}(\boldsymbol{x},i)$ replaces the problem in (6).. Definition of the weighting factors w is elaborated in the actual example that follows.

4 OPTIMIZATION OF A TANKER STRUCTURE

Guided search for optimal solutions is examined on the 40 000 DWT and 180m long chemical tanker's midship section. Its main frame longitudinal elements are optimized for the smallest allowed scantlings, while keeping the topology of the structure unchanged. The tanker's arrangement, as seen in Figure 3, is characterized with two internal longitudinal cofferdams bounded with double sides and double bottom structure. The tank's plating is built from duplex steel to resist the aggressive chemicals which are transported and is the only part of the structure with yield strength of 460 MPa. For the remaining structure, 355 MPa steel is used.

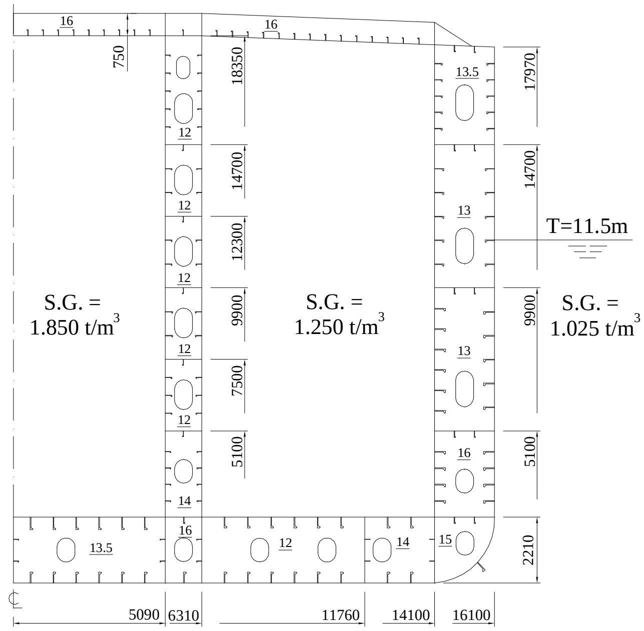

Figure 3. Half of the main frame section of a considered tanker and scantlings of the transverse structures (underlined).

4.1 *Variables*

The structure of one half of the ship's main frame is divided into 47 longitudinal strakes characterized by plate thickness, stiffener size and number, material type and, additionally, size of transversal elements. Former two are varied in this study while the later three are kept constant. Thus two variables are considered per each strake, so the optimization problem consists in total of 94 variables. Number of stiffeners per each strake is depicted in Figure 3 together with scantlings of the transversal structure. Considered variable values are discrete, having the step for the plates of 1 mm, a value in general appropriate for early design stage. Plate thicknesses in double bottom and double side structure are assumed to be available from 8 to 23mm, except of stringers whose range is the same as for longitudinal bulkhead and the deck, 5 to 20mm. Stiffener sizes are taken as standard *holland* profiles; see Rukki (2008).

4.2 *Structural model and constraints*

The midship section is assumed to stretch between L/4 and 3L/4 cross-sections, without the change in scantlings. It is subjected to the normal service loads, those being the hull girder loads, the cargo loads and the lateral hydrostatic loads, while ballast tanks are assumed to be empty. Pressure loads are calculated from liquid density indicated in Figure 3, while global loads are shown in Table 1.

Table 1. Wave loads acting on a ship.

Loading condition	Magnitude	Location
Sagging		
Vertical bending moment	2 452 000 kNm	L/4
Vertical shear force	74 880 kN	L/2
Hogging		
Vertical bending moment	2 932 000 kNm	L/4
Vertical shear force	72 960 kN	L/2

The response under the hull girder loads is calculated applying the numerical Coupled Beam method of Naar et al. (2005). On top of that is added the response of the panel under the cargo and hydrostatic loads, calculated with uniformly loaded simple beam.

Each strake is checked for eight failure constraints concerning plate yield and buckling, stiffener yield, lateral and torsional buckling, stiffener's web and flange buckling and crossing-over. These criteria are taken from DNV (2005), Hughes (1988) and Hughes et al. (2004). The last constraint is used to ensure controlled panel collapse due to extensive in-plane loading, where plating between stiffeners should fail first; see Hughes et al. (2004). Physically this means that the panel is not allowed to consist of thick plate and weak stiffening, and the stiffener size has to rise with plate thickness. However, in this study the cross-over constraint is activated only when stresses in stiffeners and plates exceed 2/3 of their buckling or yield strength, since it is pointless to consider controlled collapse if the collapse is unlikely to occur. Altogether 376 failure criteria are calculated for each loading condition, which raises their total number to 1504. They are transformed into adequacies, effectively describing an optimization constraint. Adequacy is considered as a non-linear normalization function between the structural capacity of some structural element *j*, $\mathrm{a}_j(\boldsymbol{x})$, and a loading demand acting on it, $\mathrm{b}_j(\boldsymbol{x})$, as proposed in Hughes et al. (1980):

$$\mathrm{g}_j(\boldsymbol{x}) = \frac{\mathrm{a}_j(\boldsymbol{x}) - |\mathrm{b}_j(\boldsymbol{x})|}{\mathrm{a}_j(\boldsymbol{x}) + |\mathrm{b}_j(\boldsymbol{x})|} \tag{10}$$

4.3 *Objectives*

Two objectives are considered in this study: minimize the total weight of hull steel (abbreviated as HULL) and maximize the adequacy of deck strakes (abbreviated as ADEQUACY). Minimizing the weight would increase the payload capacity and to certain extent provide cost savings. By introducing the latter objective, the goal is to explore the needed trade-offs when increasing the safety of some part of the structure. In this case this is the safety of deck structures which are according to experiences prone to failures, e.g. buckling or fatigue. To simplify the process, all the adequacies of the deck panels can be summed into one function which is in the end treated as the objective. The validity of such an approach is shown in Koski & Silvenoinen (1987).

The total weight of the hull is calculated by extending the obtained cross-sectional weight for the whole length of the ship, on top of which the weight of web frames of 21.4t each 3.56m is added.

Maximization of deck adequacies also positively influences on the feasibility of design alternatives. Although treated as the objective, they are also the constraints which, in case of negative value, receive double penalization: first they deteriorate the distance function in(9), coming from their transformation using (5) and second, their negative values decrease the sum that is meant to be maximized. This will then lead to the strong penalization of the alternatives with large infeasibility, while those with smaller infeasibility will become preferred, again leading to the increase in safety. If on the other hand, the adequacy of some alternative is positive, its value as vectorized constraint will now be zero, while as objective it will remain positive, and the alternative can be freely maximized.

If HULL is presented on abscise and ADEQUACY on ordinate in the objective space on Figure 2, one can expect similar location and shape of the Pareto frontier in the tanker case.

4.4 *Optimization using VOP: a guided search*

The optimization is carried out with a population of 60 design alternatives. This is significantly smaller than recommended in the literature, but accounting for overall optimization time it is considered sufficient, based on some preliminary results of weight minimization for the same case reported in Klanac et al. (2008). GA parameters are kept constant during the optimization: crossover probability is set to 0.8, while the mutation probability is 0.003. Both values are set based on the literature (Deb 2001) and previous experiences of the case (Klanac et al. 2008).

Two optimization runs are performed, each following a different search direction. The intention is to see the influence of search path on the non-dominated frontier obtained in the objective space. Initially we decide to start the first run with only HULL minimization and optimize for ADEQUACY afterwards. We name this search direction 'Strategy H-A' accounting for the sequence of objective consideration. The second run takes opposite path between the two objectives and is abbreviated as 'Strategy A-H'. In fact, these two strategies correspond to the two example routes in Chapter 2, first one seen in Figure 2a and the later in Figure 2b.

To prevent any bias towards particular objective, both optimization runs are initiated with the same randomly generated population of design alternatives. Each strategy in the Stage 1 performs single-objective optimization to reach the different edge of non-dominated frontier between HULL and ADEQUACY. Their weighting factors are accordingly set to emphasize improvements only in desired objective, as seen inTable 2. Reference value of the weighting factor is $2.646 \cdot 10^{-3}$, obtained from the fraction $1/(M+J)$, where M is taken as 2 and J equals to 376. Other weighting factors in the continuation are scaled relative to this value.

Stage 1 of the Strategy H-A is run until the point where the improvement rate becomes small, being the 1028th generation in this case, as seen inFigure 4. Assuming now that the further mass reductions will not be significant and that the 'light' alternatives have attained predominantly optimal variable values, Stage 2 is initiated by adding the ADEQUACY maximization to the minimization of HULL in order to generate the non-dominated frontier between them. To accomplish this, relative weighting factor of ADEQUACY is changed from 0 to 1, being now the same as for HULL. Thus the interest has moved to the 'middle' of the frontier, and the algorithm responds by starting to improve the ADEQUACY at the expense of the HULL; compare Figure 4 and Figure 5. Progress is monitored, and in the 1293th generation the interest is additionally moved towards the second objective to explore the frontier further. Optimization is stopped after 1500 generations, when it become obvious that current HULL values, nearing 8500t, are too high to even be considered as possible solutions in reality. ADEQUACY was increased from 12.3 to 18.8 which was declared sufficient.

Note that the second objective can theoretically take value from 0 to 32, consisting from four strakes having 8 constraints. But in order to have constraint value equal to one, stress in corresponding member should be zero, so obviously such a case cannot exist.

Table 2. Relative value of the weighting factors during the optimization for the two search directions (given values are obtained by fraction $w_{OBJECTIVE}/w_{CONSTRAINT}$)

	Stage	Generation	w_{HULL}	$w_{ADEQUACY}$	w_{CONSTR}
Strategy H-A	1	1	1	0	1
	2	1028	1	1	1
		1293	0.5	1	1
	Stage	Generation	w_{HULL}	$w_{ADEQUACY}$	w_{CONSTR}
Strategy A-H	1	1	0	1	1
	2	262	1	1	1
		941	1	0.5	1
		1215	1	0.3	1

Strategy A-H follows the same logic when reaching and exploring the non-dominated frontier, but it starts from the opposite direction, firstly searching for the maximum of ADEQUACY and in Stage 2 attaining the other edge of the frontier. The adjustments in the weighting factors during this optimization are presented in Table 2, with each leading the solutions to another part of the frontier. Initial increase in ADEQUACY is continued until generation 262 where certain 'plateau' is visible in Figure 5. Assuming no significant improvement in ADEQUACY is possible after that point, HULL is included in the search to attain the needed trade-offs. This leads to significant decrease of hull steel weight while retaining relatively sound values of ADEQUACY, see Figure 4 and Figure 5. What differs this strategy from the previous one is much higher number of variables that must be altered in order to come from maximal ADEQUACY design to minimal HULL solution. Also, we are in this optimization case more interested in reaching low hull steel weight, thus the algorithm is for Strategy A-H faced with demand to gain both extremes of the frontier. Therefore, the optimization is not stopped as in the Strategy H-A, but has to rapidly come from one end to the other. Optimization was stopped when meeting the stopping criterion of 1500 evaluated generations.

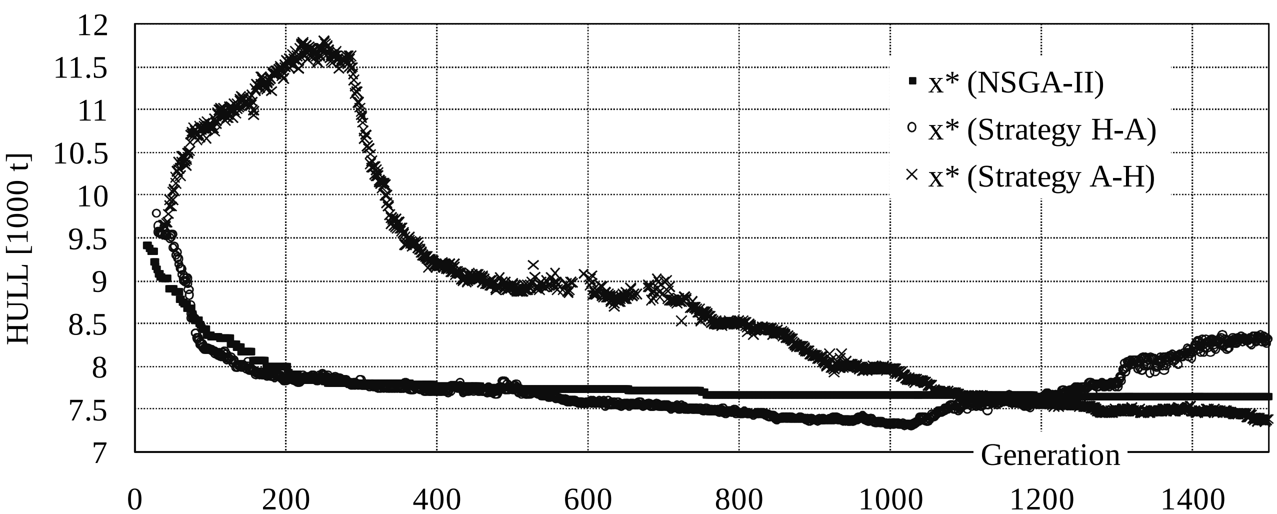

Figure 4. Progress of HULL optimization for VOP and NSGA-II, showing generation's best design

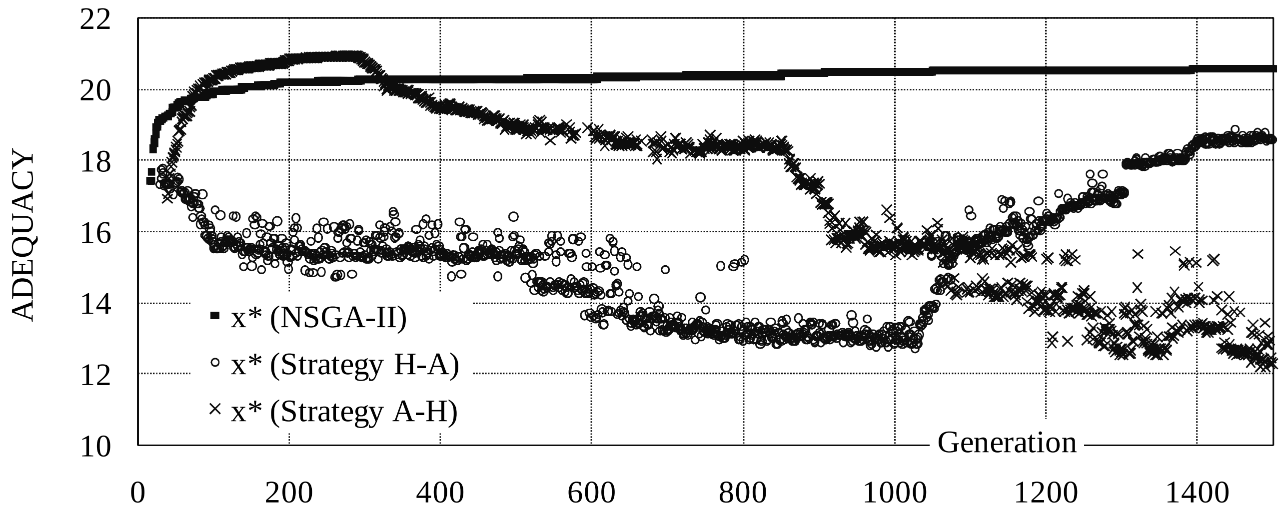

Figure 5. Progress of ADEQUACY optimization for VOP and NSGA-II, showing generation's best design

4.5 *Comparison with NSGA-II*

Binary coded version of NSGA-II (Deb et al. 2002) is applied to compare the results from the 'guided search' optimization described previously.

NSGA-II is characterized with:

- an elitism concept that ensures preservation of non-dominated solutions encountered from the beginning of the optimization run,
- ranking the solutions in the population according to non-dominated frontier in which it belongs to,
- giving advantage to solutions that belong to less crowded part of the objective space,
- constraint-domination which prefers any feasible solutions over the infeasible, or between two infeasible designs selects the one with less sum of violated constraints.

Optimization with NSGA-II is initiated using the same random population as VOP in Stage 1. The same crossover and mutation probabilities apply also. In difference to VOP, both HULL and ADEQUACY are considered from the beginning, and optimization is run conventionally for the same amount of generations. Optimization history for each objective is shown in Figure 4 and Figure 5.

5 DISCUSSION

Figure 6 depicts the essential comparison between the results of optimization performed with the 'guided search' approach, utilizing VOP, and with the standard multi-objective approach, utilizing NSGA-II. Minimizing solely HULL in the first stage of Strategy H-A, VOP managed to attain design with the hull weight of 7312t, 330t lower than with NSGA-II; see Table 3 for the alternatives located in the edges of the frontier, marked with '**' to simplify the notation. Continuing the optimization with the second stage, valuable trade-offs between the two objectives are created up to the point where the further increase in HULL is inadequate.

It can be clearly seen in Figure 6 that the Strategy A-H performed worse. This confirms the suspicion that changing too many variables can be difficult for the optimizer. All 94 variables had to be altered here in the Stage 2, while in the previous strategy effectively only 8 lead to initial increase of ADEQUACY.

NSGA-II starts the optimization with relatively high ADEQUACY value since the initial designs have large scantlings of the structural elements and therefore the stresses in the deck are low. NSGA-II proceeds by spreading the frontier towards both ends, but the HULL as the more difficult objective, stalls the progress in that direction. Although the second objective reached much better values, their hull weight is too high for practical use; see Figure 6 and Table 3.

VOP's non-dominated frontier for the Strategy H-A nicely covers the one from NSGA-II for the HULL value in range 7600-8600t. There are totally 191 non-dominated designs in the 'trail' left by guided search when maximizing for the second objective. Naturally, all of them are not interesting and their number is too large for this problem case, but can prove valuable when considering many objectives, or it can be filtered. NSGA-II on the other hand is limited by the population size that defines the maximal available non-dominated solutions in the end of optimization, which is 60 in this case.

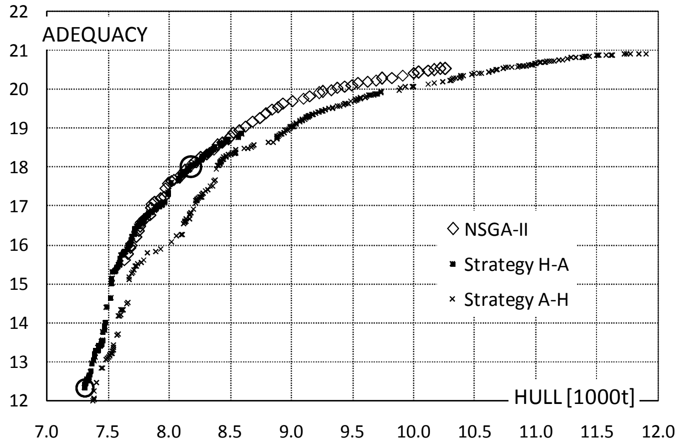

Figure 6. Overall non-dominated frontier from each of the three runs, showing also the two selected designs (O)

Table 3. Designs from the edges of non-dominated frontier (HULL values in tones)

	Guided VOP		NSGA-II	
	$\boldsymbol{x}_{\mathrm{HULL(VOP)}}^{**}$	$\boldsymbol{x}_{\mathrm{ADEQ(VOP)}}^{**}$	$\boldsymbol{x}_{\mathrm{HULL(NSGA\text{-}II)}}^{**}$	$\boldsymbol{x}_{\mathrm{ADEQ(NSGA\text{-}II)}}^{**}$
HULL	7312	8595	7641	10 262
ADEQ.	12.34	18.86	15.62	20.54

5.1 *Trade-off design alternatives*

Although neither of design alternatives obtained in this study cannot be proved to be globally optimal due to complexity of the problem, we present two design alternatives in order to see how the structure resembles the imposed loading condition and the objective values. We select the design of minimal hull steel weight from the VOP's non-dominated frontier and one design with increased ADEQUACY value for which the structural scantlings are still relatively acceptable. Both designs are shown in Figure 7 and their characteristics given in Table 4. The same table shows the differences in the adequacy values for the deck strakes between the two alternatives. Structure was not standardized before presented here nor was it given any corrosion addition.

Structural elements in double bottom, side shell and deck structure from the lowest hull steel weight design follow vertically the beam distribution of weight, as seen in Figure 7, in order to satisfy the area moment. Side has the lowest plate thicknesses and stiffener sizes, while the bottom elements are additionally increased to resist the water pressure. Inner bottom elements in a side cargo tank are larger than in the bottom because of the increased liquid density of $1.25 t/m^3$, and the same is valid for the inner side. For the same tank, reduction in scantlings can be seen in the longitudinal bulkhead when going upwards in the direction of decreasing cargo pressure. The same happens in a central tank but with generally higher plate thicknesses and stiffener sizes due to higher density. The deck and inner bottom strakes are in that tank also larger than in neighboring strakes.

When the design of the lowest hull steel weight is compared to the one selected from the non-dominated frontier with increased ADEQUACY value, most salient differences can be observed in deck and surrounding strakes. As expected, plates are thickened and stiffeners are enlarged in the deck, but also in a sheer strake since it contributes to stress reduction in deck. The highest strakes in the bulkhead, next to the deck, posses decreased scantlings in order to yield weight savings.

Other minor differences between the two design alternatives can be assigned to the working principle of the GA which makes certain variations between possible variable values when optimizing the structure.

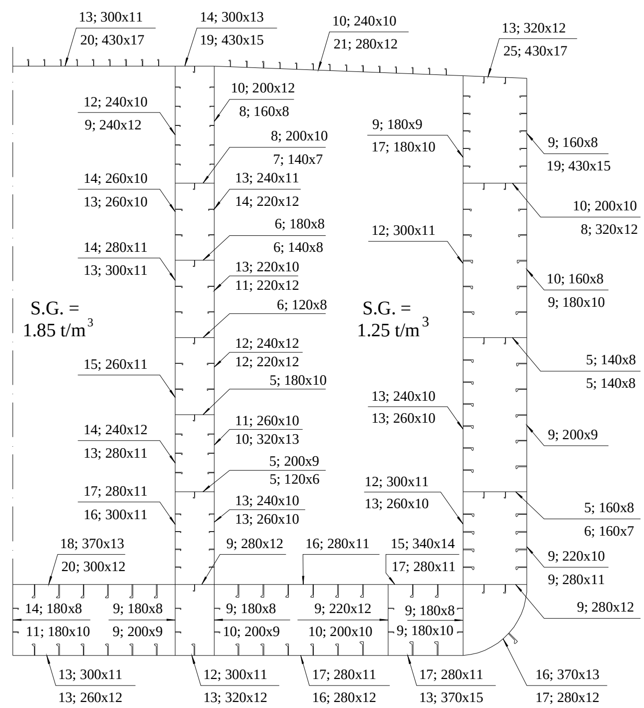

Figure 7. Scantlings of the main-frame members for the design $\boldsymbol{x}_{\mathrm{HULL(VOP)}}^{**}$ (shown above the dimension lines) and design $\boldsymbol{x}_{\mathrm{TRADE\text{-}OFF}}$ (shown below). One set of scantlings is shown for the strakes that are the same in both alternatives.

Reduction of stresses in the deck leads also to a decrease in number of active constraints for such solutions, as can be seen for the two previously described alternatives in the Table 4, where constraint is considered to be active if stress exceeds 3/4 of its critical value.

Table 4. Characteristics of two selected design alternatives, including the adequacy values of stiffener yield (Sy), plate yield (Py) and plate buckling (Pb) per each deck strake.

	$x_{HULL(VOP)}^{**}$			$x_{TRADE\text{-}OFF}$		
HULL [t]	7312			8177		
ADEQ.	12.34			18.04		
Act. con.	63			49		
Constraints	Sy	Py	Pb	Sy	Py	Pb
Deck-CL	0.462	0.15	0.349	0.599	0.33	0.564
Deck- 2	0.356	0.097	0.239	0.512	0.282	0.462
Deck - 3	0.432	0.131	0.226	0.575	0.317	0.564
Deck - side	0.352	0.092	0.177	0.507	0.276	0.473

6 CONCLUSION

To enable more qualitative decision-making in the beginning of design process, it is helpful to posses different trade-offs between crucial objectives. We have shown on example of the main frame of 40 000 DWT chemical tanker that this can be done using *vectorized* genetic algorithm - VOP in a way adoptable to the designers' needs. Relying only on the “black-box” approach one cannot expect to gain desirable results. Certain parts of the non-dominated frontier might be undiscovered or their attainment would be stipulated with quite long optimization run. Even then the possibilities to improve the structure in certain sense would not be known.

In this study a different approach is taken: firstly to optimize for the best possible design according to specific objective, and secondly, explore the non-dominated frontier by including the other objective to certain extent. This was achieved by weighting the importance of particular objective to steer the cloud of design alternatives in desired direction. This ‘guided search’ resembles then the desires of the user, who can particularly benefit from it when understanding the problem at hand. In that sense, it is the best to start the optimization with the ‘most difficult’ objective that requires manipulation of the highest number of variables. After reaching the optima in the difficult objective, it is relatively easy to attain its other parts that depend only on several variables, the point at which one changes weight factors can be different: either satisfactory results are obtained, or improvements, in terms of objectives, became rather poor, as was in our case.

In the future, the ‘guided’ search methodology should be tried on more practical examples involving ship structures, to allow for further testing of the concept. Nevertheless, some fundamental issues remain to be studied further:

– Finding best strategy for three and more conflicted objectives,
– Analysis of the heuristics of weight factors,
– Application of the ‘guided’ search approach to a widespread algorithm, e.g. NSGA-II.

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