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Steel Structural Damage Identification Algorithm Of Imperialist Competitive Algorithm

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ABSTRACT: *Omni-optimization assumes a capability to perform several types of optimization, e.g. single- and multi-objective, using the same optimization algorithm, or the omni-optimizer. Here we consider omni-optimization to investigate the capabilities of a proposed structural arrangement of a 40 000 DWT chemical tanker. The interest is to gain more knowledge about the capabilities of this arrangement and optimize it for reduction in weight and increase in safety. Omni-optimization is performed with a simple genetic algorithm though the re-formulated 'vectorized' structural optimization problem. The overall process is managed through Matlab where also the structural response and strength calculations are performed.*

KEYWORDS: *algorithm, Competitive Algorithm, optimizer*

I. INTRODUCTION

Steel Structural damage identification algorithm of Imperialist Competitive Algorithmfor a structural design under certain set of criteria. One structural design alternative can be represented with the vector of variables x, while its characteristics, i.e. the size, volume, weight, cost, reliability, safety, etc. can be represented as the functions of x. Depending on design scenario, some of the characteristics need to be maximized, some minimized, and some simply have to be above or below certain level. The later are generally called, from the mathematical programming point of view, the constraints, while the formed two are attributes, and when they are put to be maximized or minimized they are called the objectives.In this paper we aim to explore this identification algorithm of Imperialist Competitive Algorithmfor of a 40 000 DWT chemical tanker. We engage in treating numerous characteristics of the tanker's structure either as constraints or as objectives, depending on the assumed available information, resembling therefore a possible scenario in the early stage of design development. Early design stage is characterized with the missing information on e.g. precise loading, or structural details are not known, 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 would be then useful to venture into analysing the correlation between them, and thus investigate their sensitivity for the considered structural arrangement. This can then assist the designer in making optimal decisions.

To perform this task successfully we consider exploiting a novel approach based on vectorization and omni-optimization. Vectorization assumes converting constraints into additional objectives and their optimization alongside original objectives. This very fact enhances both the optimization search and the design investigation as the original problem principally becomes unconstrained. Precisely, vectorization has shown capability to significantly improve the search for the optimum design alternatives (Klanac and Jelovica 2007a, 2008), but it has also allowed for an easy handling of design criteria, thus benefiting the objective of this study. An algorithm that can solve then a vectorized structural optimization problem is in the end capable to maximize, or minimize, one objective, but also many more, as these problems usually involve numerous characteristics. An algorithm capable of this is then called an omni-optimizer; see Klanac and Jelovica (2007b), but also Deb and Tiwari (2005) for more, while the process of its application is called omni-optimization.The omni-optimization is performed here using a simple genetic algorithm, which is described in the following chapter. Chapter 3 follows with the problem description, while the Chapter 4 describes the optimization process and shows the results. In Chapter 5 we discuss the results, but also the effects of omni-optimization. Paper is concluded in Chapter 6.

II. VECTORIZATION AND THE OMNI-OPTIMIZER

The omni-optimization is conceived here to lead from the capability of the algorithm, the optimizer, to perform the multi-objective optimization. The choice has fallen on VOP (Klanac and Jelovica 2007b, 2008) – the genetic algorithm which features simple genetic operators, such as weighted roulette wheel selection, single-point cross-over, binary encoding and bit-wise mutation. The algorithm was until now applied in several different studies (Besnard et al. 2007, Romanoff and Klanac 2007, Ehlers et al. 2007) and returned satisfactory results.The only advanced feature that VOP possesses is its fitness function. It allows VOP to be used as the omni-optimizer, following the vectorization of the original optimization problem. But first we briefly present the applied concept of vectorization and then the algorithm.

2.1. Vectorization for structural omni-optimization

The original multi-objective structural optimization problem can be defined with the following

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

where **X** is the set of all possible alternatives defined between the lower and upper bounds of the variables. The same problem can be written in the vectorized form following Klanac and Jelovica (2007a, 2007b, 2008)

$$\min_{\mathbf{x}\in\mathbf{X}}\left\{ \mathrm{f}_1(\mathbf{x}),...,\mathrm{f}_M(\mathbf{x}),\mathrm{f}_{M+1}(\mathbf{x}),...,\mathrm{f}_{M+j}(\mathbf{x}),...,\mathrm{f}_{M+J}(\mathbf{x})\right\}. \tag{2}$$

The constraints $\mathbf{g}_j(\mathbf{x})$, which are now additional objectives $\left\{\mathrm{f}_{M+1}(\mathbf{x}),...,\mathrm{f}_{M+J}(\mathbf{x})\right\}$ in the equation above, are converted applying the Heaviside representation (Osyczka et al. 2000, Deb 2001), given as:

$$\mathrm{f}_{M+j}(\boldsymbol{x})=\begin{cases}-\mathrm{g}_j(\boldsymbol{x}), & \text{if } \mathrm{g}_j(\boldsymbol{x})<0\\ 0, & \text{othervise}\end{cases},\ \forall j\in[1,J] \tag{3}$$

The Heaviside representation is convenient when some of the criteria are treated both as constraint and as objective. Typically, such a criterion is adequacy of the structural element, or the normalized difference between the response and the strength of an element (Hughes et al. 1980), e.g. given for the buckling criterion

$$\mathrm{g}_j(\boldsymbol{x})=\frac{s_{buckling}(\boldsymbol{x})-\left|s_{response}(\boldsymbol{x})\right|}{s_{buckling}(\boldsymbol{x})+\left|s_{response}(\boldsymbol{x})\right|}. \tag{4}$$

When adequacy is calculated to be negative for some design alternative, that design is infeasible and the adequacy, following the Eq. (3), takes the positive value in the vectorized form and in this form it can be then minimized during the optimization through Eq. (2).. When treated as objective to be maximized, the same adequacy remains negative in the vectorized problem since in vectorization objectives are not converted as constraints. 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. The following Fig. 1 illustrates this interesting concept.

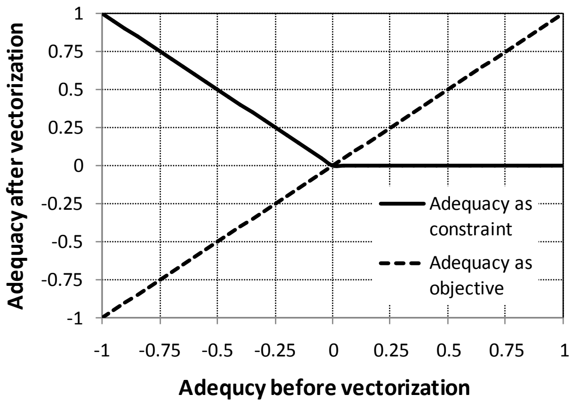

Fig. 1: Treatment of the same criterion in the vectorized optimization problem (in this case the adequacy) both as constraint and as objective

2.2. VOP – the omni-optimizer

VOP's fitness function is originally based on the weighted and linearly normalized distance that the design alternative closes with the origin of the attainable space (Klanac and Jelovica 2008). Here however, we update this fitness so that the distance is also penalized with the normalized distance of the design to the bounds of the feasible space. Assuming that we deal with J constraints, M original objectives and the population of size N, the following formula is used for fitness evaluation if there is at least one feasible design in the population:

$$\varphi_1(\boldsymbol{x}) = \left(\max_N \left[d(\boldsymbol{x})\right] - d(\boldsymbol{x})\right)^{\overline{d(x)}}. \quad (5)$$

The distance is calculated as:

$$\begin{aligned} &\mathrm{d}(\boldsymbol{x}) = \left\{\sum_j w_j \left[\mathrm{f}_j^{\mathrm{n}}(\boldsymbol{x})\right]^2 + \sum_m w_m \left[\mathrm{f}_m^{\mathrm{n}}(\boldsymbol{x})\right]^2\right\}^{1/2}, \\ &\quad \text{s.t. } 0 < w_j < 1;\ 0 < w_m < 1 \\ &\quad\quad \sum_j w_j + \sum_m w_m = 1 \end{aligned} \quad (6)$$

By using the following normalized distance:

$$\overline{d(\boldsymbol{x})} = \frac{d(\boldsymbol{x}) - \min d(\boldsymbol{x})}{\max d(\boldsymbol{x}) - \min d(\boldsymbol{x})} \quad (7)$$

the maximum value of fitness that one design can get is $\varphi_1(\boldsymbol{x}) = 1$ if $\overline{d(\boldsymbol{x})} = 0$, while the minimum is $\varphi_1(\boldsymbol{x}) = 0$ if $\overline{d(\boldsymbol{x})} = 1$, so the fitness is bounded within these values. If the whole population is infeasible, the fitness function slightly changes into:

$$\varphi(\boldsymbol{x}) = \left(\max_N \left[d(\boldsymbol{x})\right] - d(\boldsymbol{x})\right)^{\overline{\sum_j \mathrm{f}_j}} \quad (8)$$

where the normalized constraint sum $\overline{\sum_j \mathrm{f}_j}$ is defined as

$$\overline{\sum_j f_j} = \frac{\sum_j f_j - \min \sum_j f_j}{\max \sum_j f_j - \min \sum_j f_j} \quad (9)$$

Designs which are near the feasible space have low sum of normalized constraints using the Heaviside representation and therefore receive high fitness. Fitness however does not solely depend on the proximity to the feasible space as it is also a function of the objectives, depending on the distance, as noted from Eq. (8). These two features are generally contrary in the case of structural optimization, since design with e.g. low weight will likely violate many constraints, but using the fitness function from Eq. (8), the intention is that after finally striking the feasible space, the designs are relatively good in objective values. This is especially interesting knowing that large number of constraints prevents existence of feasible solutions in randomly created initial designs, and also makes it quite hard to create them manually.

This fitness function is only a stop on the way to define the 'best' fitness function. One can also wander if one such function exists as it might be strongly problem dependent – yet we persist. Important feature of this type of fitness function is the biased search. Since the problem which VOP is optimizing is vectorized, meaning that it has many objectives, which were initially mostly constraints, the obtainment of the overall Pareto frontier might be irrational. Further argument is that we in principle now the location of the optimal design alternatives with respect to the original objectives (Osyczka et al. 2000, Deb 2001, Klamroth and Tind 2007, Klanac and Jelovica 2008). When vectorizing constraints with the Heaviside representation the optima are always placed in the unique part of the attainable space of the vectorized problem, where the objectives leading from constraints equate zero, and so the feasible alternatives are placed on the original objective axis; see Klanac and Jelovica (2008) for more. For more objectives this axis will extend into hyperplane, but the general location will not be altered. In that case, the fitness function should apply low values of weights – nearing zero – in Eq. (6) for the original objectives. When facing large number of constraints, e.g. more than a few hundreds, the initial vector of weights could be symmetric between all the vectorized objectives and could be later on modified according to the desires of the user.

III. DESIGN SCENARIO

The beneits of omni-optimization of the 40 000 DWT and 180m long chemical tanker are investigated through the optimization of its midship section. The tanker's arrangement, as seen in Fig. 9, is characterized with two internal longitudinal cofferdams. The 'three perpendicular tank' arrangement is bounded with double sides and double bottom structure. The tanks' plating are built from duplex steel to resist the aggressive chemicals which might be transported.

3.1. Variables

We consider 47 longitudinal panels in optimization from one half of the ship's main frame. Two variables are considered per each strake, i.e. plate thickness and stiffener size, so the optimization problem consists in total of 94 variables. The strake division and position can be seen in Fig. 9. The number of stiffeners was not varied. Considered variable values are discrete, having the step for the plates of 1 mm, a value in general appropriate for early design stage. Stiffener sizes are taken as standard HP profiles (Rukki 2008). The lower and upper bounds of variables are defined following the experience of standard ship structures and capabilities of production, but are also taken in a generic way, avoiding any fine-tuning based on prior knowledge of the problem.

3.2. Objectives

Three objectives are considered in this study: minimize the total weight of hull steel (f_1), minimize the weight of duplex steel (f_2) and maximize the adequacy of deck strakes (f_3). Minimizing the weights would increase the payload capacity, but reduction in duplex steel would be the most significant for decrease in production costs since the material and labour costs for this steel are tenfold to those of high tensile 355 MPa steel used for the remaining structure. 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. 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 and Silvenoinen (1987). In addition we are interested to outline the most efficient way of increasing safety in the deck structure with respect to the former two objectives.The total weight of the hull and duplex steel were calculated by extending the calculated cross-sectional weight for the whole length of the ship, on top of which is added the weight of web frames of 10.7 t.

3.3. Structural model and constraints

The midship section is assumed to stretch between L/4 and 3L/4 cross-sections, without the change in scantlings. Computationally then one cross-section has to withstand 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. The section is exposed to four critical hull girder loads acting on a section at two positions, L/4 and L/2. For the former, the shear force of 72 960 kN is applied in hogging and -74 880 kN in sagging, while for the later, the total vertical bending moment of 2 933 000 kNm is assumed for hogging and -2 410 000 kNm for sagging.

The response under the hull girder loads is calculated applying the Coupled Beam method of Naar et al. (2005). The structure of the main frame is split into 22 beams, see Fig. 2, each centred about a hard point; see Niemeläinen (2007) for more. This model allows for more precise evaluation of response then for a hull girder beam model, e.g. as it more precisely accounts for the influence of shear flow. The response of the panel under the cargo and hydrostatic loads is calculated with uniformly loaded simple beam and added to the response from the hull girder loading. The needed data for the calculation of the lateral loads is given in Table I.

Table I: Loading condition

Scantling draught in analyzed loading condition, m	11.5
Density of sea water, kg/m^3	1025
Density of cargo in center cargo tank, kg/m^3	1850
Density of cargo in side cargo tank, kg/m^3	1250

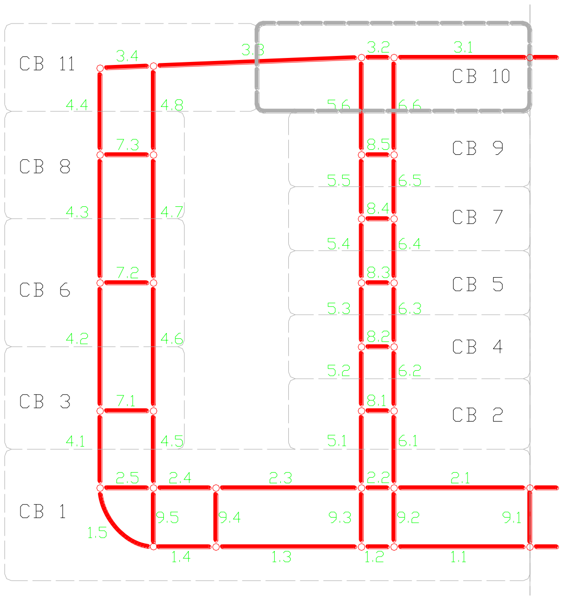

Fig. 2: Main frame's layout of coupled beams

The structure of each strake is checked for eight constraints concerning plate yield and buckling, stiffener yield, lateral and torsional buckling, stiffener's web and flange buckling for each loading condition. Additional cross-over constraint (Hughes 1988) is used to ensure controlled panel collapse due to extensive in-plane loading, where plating between stiffeners should fail first. 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 yield strength since it is based on geometry and not on the actual stress state. Altogether 4 x 376 failure criteria were calculated for each design alternative, but only the most critical values leading from the four loading conditions were considered as adequacies.

IV. OPTIMIZATION PROCESS AND THE RESULTS

One cannot rely on optimizer as the "black-box" tool and expect that will give good results. Instead, it is fruitful to guide the search for optima in the preferred direction, and explore the design space, especially when dealing with several objectives. Situation where some objectives are more important than others is frequently encountered, thus the bias towards some of them is also required. There are GAs intended to obtain whole Pareto front, e.g. NSGA-II (Deb et al. 2002), ε-MOEA (Deb et al. 2003), SPEA2 (Zitzler et al. 2002), but in their attempt to do so, they can be slow considering that there is no need for the whole front to be known. For this reason VOP can be used to direct the search towards interesting part of the Pareto front, and even to additionally explore some different part, if so desired. By having the possibility to observe obtained solutions at certain generation, one can steer the search by simply changing the corresponding weight factors of certain objectives and possibly acquire better results.Genetic algorithm requires certain number of designs to start the optimization. These designs can be made manually, thinking principally of satisfying as many constraints as possible. This can be cumbersome and somewhat boring task, having in mind not just their great number, but also their overall complexity. Easier way is to create the initial set of alternatives at random, using uniform distribution of variable values between lower and upper bounds, and start the optimization from there. However, the initial population will probably be fully infeasible if large number of constraints is considered, as was the case with the studied tanker problem. The optimizer however can find the feasible alternatives, and by exploiting those alternatives with less overall constraint violation, using fitness as in Eq. (8), VOP achieved this in 32 generations, as seen from Fig. 3 and Fig. 4. Throughout this study, we have used the population size of 60 design alternatives in each generation. Binary encoding was used to represent the values of variables. Thus, the total chromosome length, describing one design alternative, was 400 bits. Bit-wise mutation rate of p_m = 0.4%was used during the whole search. This corresponds to change of 1.6 bits per chromosome in average. It is somewhat greater than the recommended rule of thumb in p_m = 1/string size, being now 0.25%. See Deb (2001) and Deb (2002) for more. Higher mutation probability was used after investigations in the preliminary runs to skip local minima and explore the space further.

After reaching feasible region, algorithm was run for 350th generation. At first the two 'weight' objectives were considered the most important to be minimized, and the safety objectives was excluded. At the point when it was concluded that the optimization converged to the minima the importance of safety was included in the search. Namely, all constraints considered in the deck strakes were grouped into one joint function as described above. Equal importance of all objectives was maintained until the optimization process finished.Optimization was in the end stopped after 520 generation, when certain improvement in safety was achieved. The optimization history for the first 350 generations is shown in Fig. 3 and Fig. 4 for the total hull steel weight and duplex steel weight, respectively. Two designs are interesting from that run, since they constitute a small Pareto front: the design of minimal hull steel weight, **x**$TW_{1\text{-}350}$**, and the design of minimal weight of duplex steel, **x**$D_{1\text{-}350}$**. These weights are presented in Table II and are also depicted in Fig. 3 and Fig. 4, additionally marked with "**" to simplify the notation, e.g. **x**$TW_{1\text{-}350}$**. But neither of designs presented in this study can be considered globally optimal for associating objective, since dealing with many constraints and variables makes global optimum almost impossible to find.

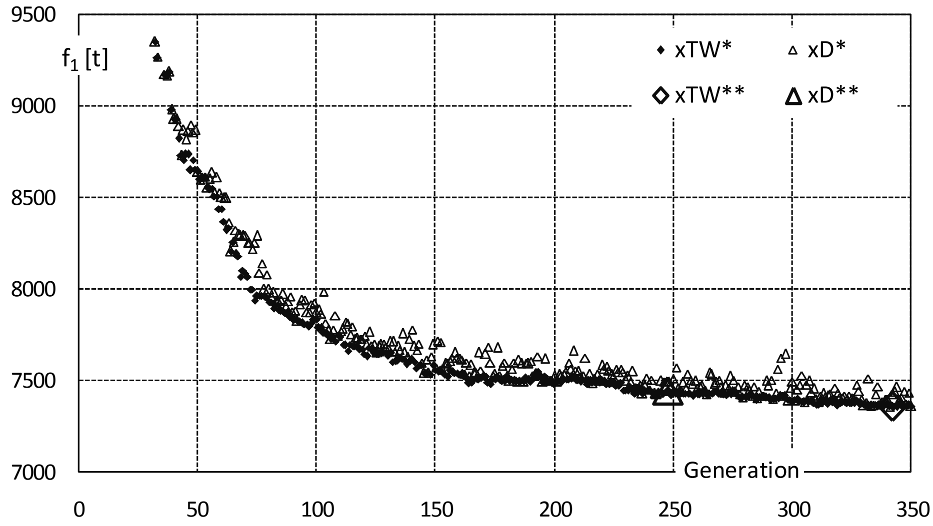

Fig. 3: Optimization history of the total hull steel weight for it's best designs, **x**TW*, it's minimum xTW**, best designs of duplex steel, xD*, and corresponding minimum xD**

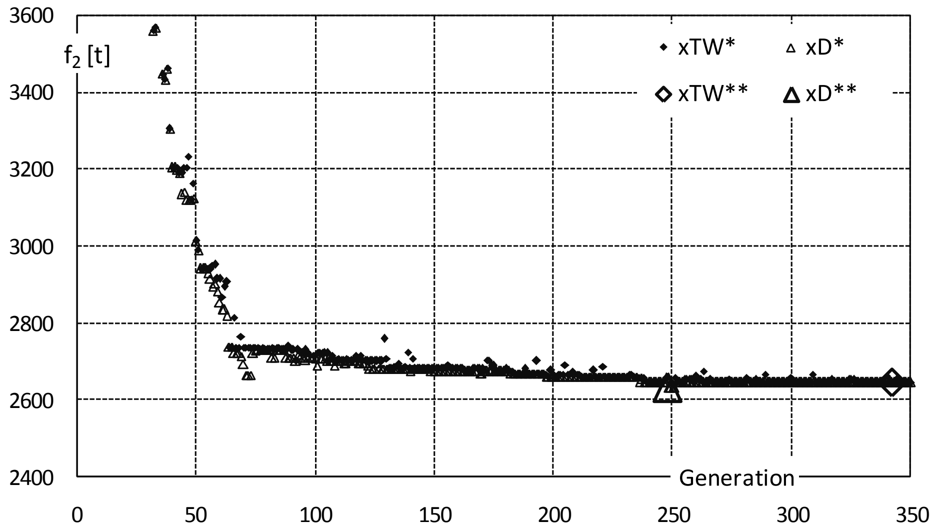

Fig. 4: Optimization history of the duplex steel weight for the best designs of total hull steel, xTW*, it's minimum xTW**, duplex steel weight for it's best designs, xD*, and corresponding minimum xD**

Table II: Objective values for the best designs in first 350 generations, also showing the generation in which they were found

	$\mathbf{x}TW_{1\text{-}350}^{**}$	$\mathbf{x}D_{1\text{-}350}^{**}$
f_1[t]	7354	7442
f_2[t]	2646	2632
$G_{\mathbf{x}^{**}}$	342	248

In order to enlarge the deck adequacy, the second part of the optimization started to increase the scantlings, causing higher values of the total hull steel weight and duplex steel in associated generations, as presented in Fig. 5 and Fig. 6, even though the importance of objectives remained unchanged. However, when significant improvements weakened, optimization was stopped. This can be seen in Fig. 7. From this second part of the optimization run, after including the deck adequacy in the search, three deigns from the edges of obtained Pareto front are shown in Fig. 9 and Fig. 10. Objective functions values for these three designs are given in Table III. Fig. 9 presents also the minimum rule scantlings obtained from the calculation of the rules of BV 2006.

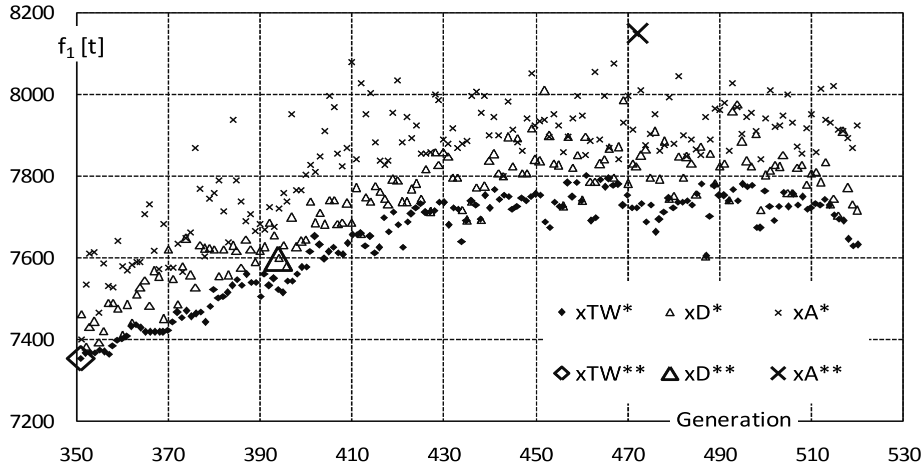

Fig. 5: Optimization history showing the total hull steel weight for it's best designs after including deck adequacy in the search, xTW*, it's minimum xTW**, best designs concerning duplex steel, xD*, and corresponding minimum xD**, best designs concerning deck adequacy, xA*, and it's maximum xA**

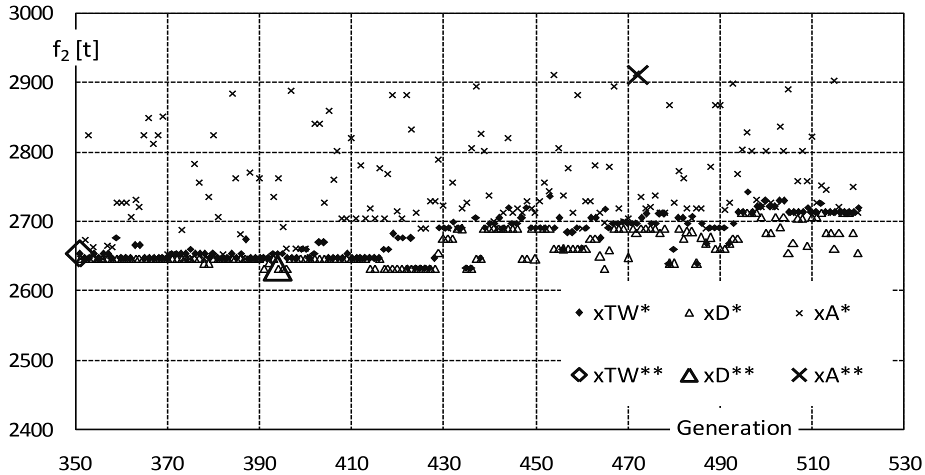

Fig. 6: Optimization history of the duplex steel weight for the best designs of the total hull steel weight after including deck adequacy in the search, xTW*, it's minimum xTW**, best designs of the duplex steel, xD*, and corresponding minimum xD**, the best designs concerning deck adequacy, xA*, and it's maximum xA**

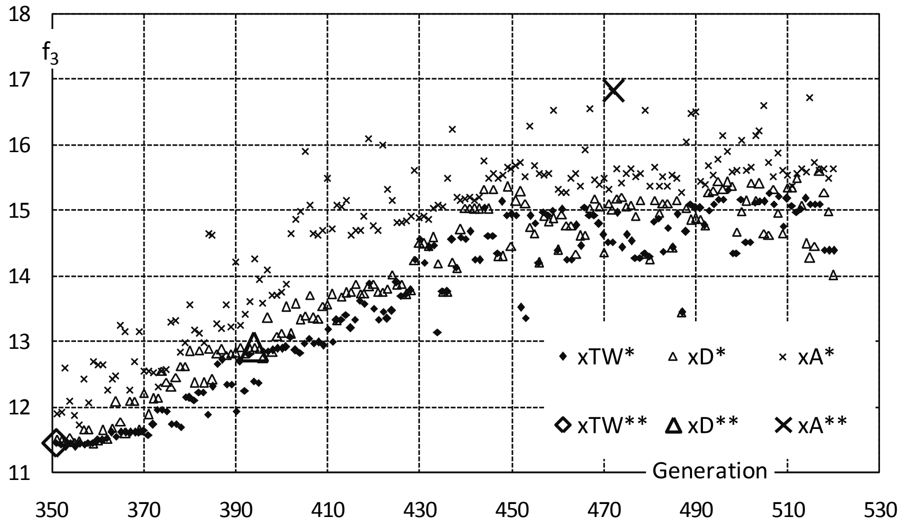

Fig. 7: Optimization history showing adequacy of deck strakes for the best designs of the total hull steel weight, xTW*, it's minimum xTW**, best designs of duplex steel, xD*, and corresponding minimum xD**, best designs of deck adequacy, xA*, and it's maximum xA**

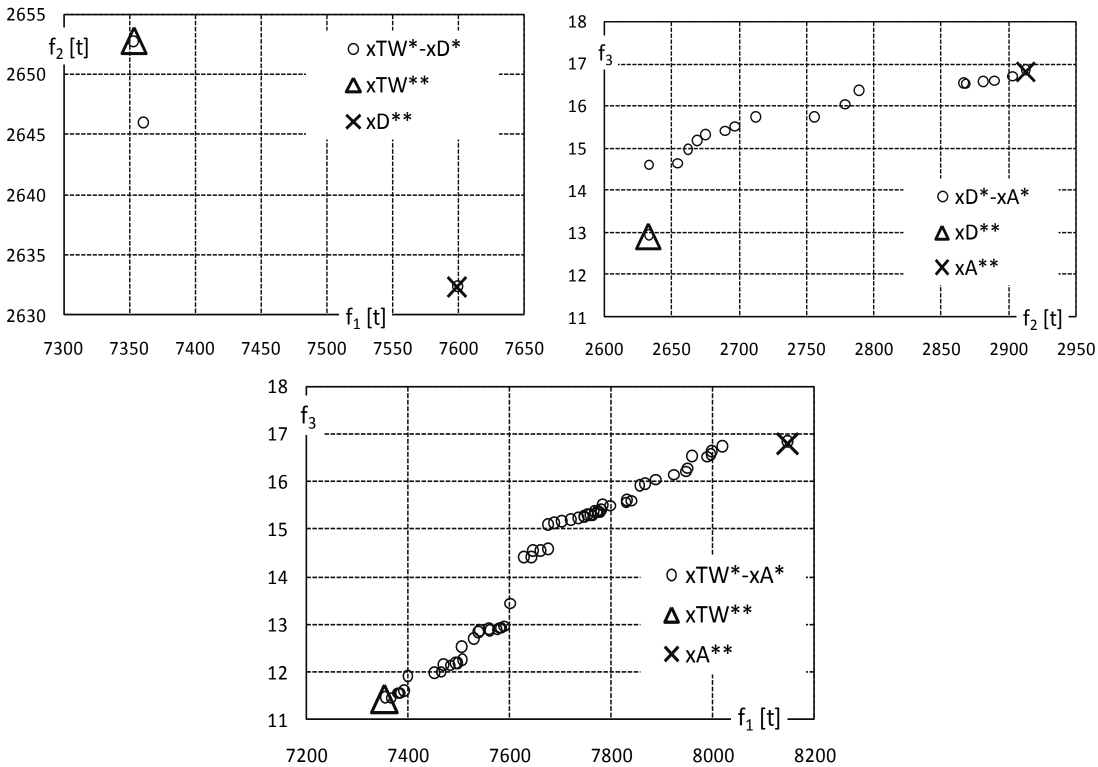

Fig. 8: Pareto front presented in 2D between each pair of objectives with their best designs

Pareto front between the three objectives is presented filtered in Fig. 8, only with alternatives which are Pareto optimal between each pair of objectives. Pareto front between total hull steel weight and duplex steel weight is quite small, consisting of three designs, but this is expected since minimization of hull steel contributes to minimization of duplex steel and vice versa. Other two fronts are well-distributed, providing many alternatives for the designer, which is important for the applied design scenario, and fulfils one of the objectives of the paper – the investigations of the trade-off between the safety of deck and the hull and duplex steel weights.

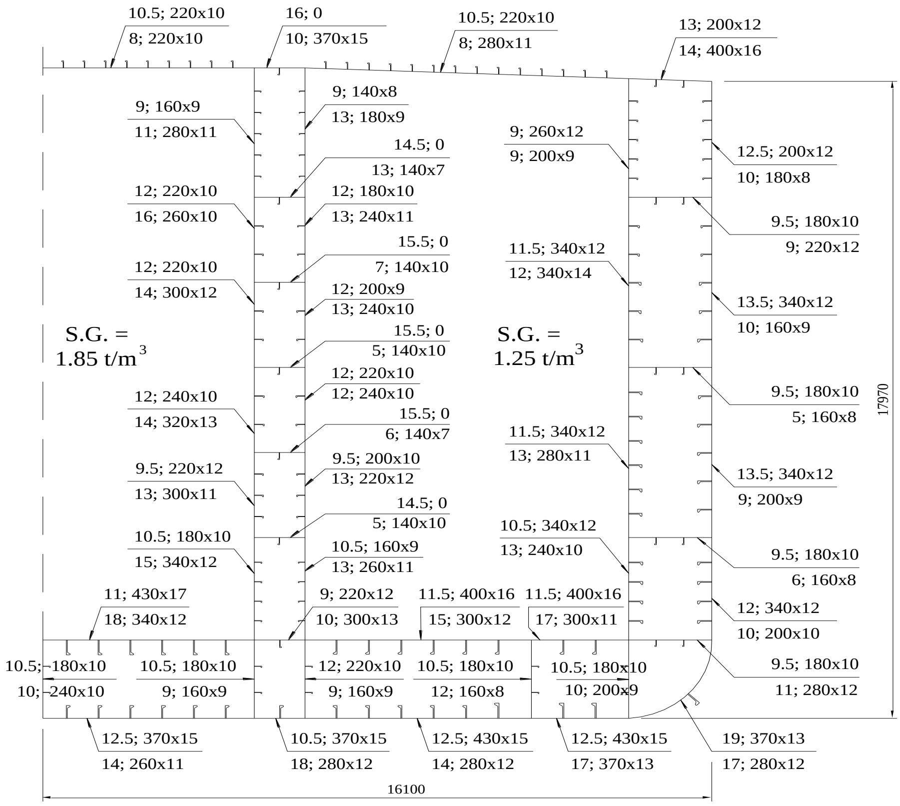

Fig. 9: Scantlings of the main-frame members for the design of minimal rule requirements, shown above dimension lines, and for the design **x**$TW_{351\text{-}520}$**, shown below dimension lines

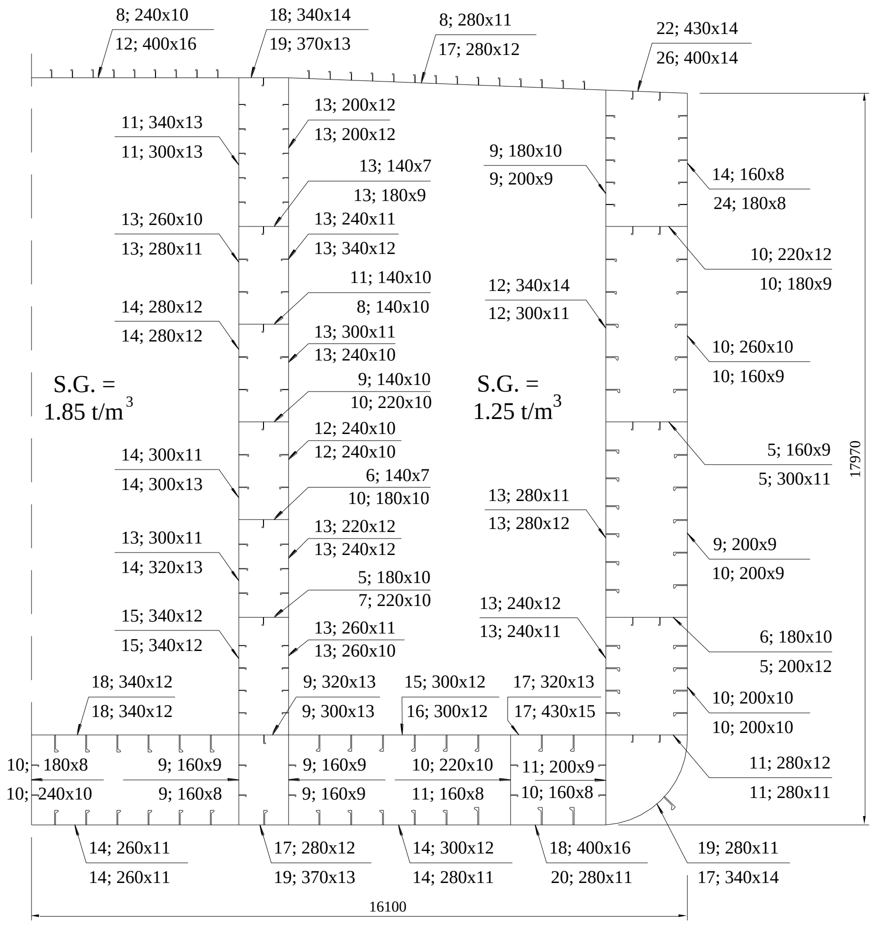

Fig. 10: Scantlings of the main-frame members for the design **x**$D_{351\text{-}520}$**, shown above dimension lines, and for the design **x**$A_{351\text{-}520}$**, shown below dimension lines

Note that designs xTW351-520**, xD351-520** and xA351-520** shown in Fig. 9 and Fig. 10 are not standardized, and there can be significant differences in plate thicknesses from neighboring strakes. Furthermore, in all presented designs, including the design of minimal rule scantlings, there is no corrosion addition.

V. DISCUSSION

It requires a skillful optimizer to handle as many variables and constraints as we have in this study. Although we gave no attempt to find global optimum for considered objectives, it can be observed that VOP significantly improved the main frame in a rather small number of generations. This chapter describes the best design of each objective, along with the design of minimal rule scantlings.In this study we have imposed high loads to act on the main frame, requiring that it is not only used in L/2, where it has to deal with maximum vertical bending moment, but also in L/4 and 3L/4 where it is subdue to maximum shear force. Due to this conservative consideration, the minimal rule scantlings design, shown in Fig. 9, violates 32 constraints, mostly plate and stiffener yielding from the vertical strakes in longitudinal bulkhead and also plate yield in inner bottom. The same figure shows the design **x**$TW_{351\text{-}520}$**, which has considerably higher plate thicknesses in longitudinal bulkhead, being the main reason for the increase of the weight of duplex steel, as seen in Table III. Corresponding stiffeners were increased, especially the ones at the lowest strakes, who deal with high cargo pressure. Because of the difference in pressure from cargo tanks, it is noticeable that the strakes in longitudinal bulkhead closest to the CL have higher scantlings than the one on the opposite side. Inner bottom and bottom plates are also thickened, but stiffeners were decreased, which is opposite than what happened to side shell. Plate thicknesses of the deck strakes 1 and 3 from CL were reduced, as they participate in duplex steel weight, but stiffeners were increased since they do not. Between **x**$TW_{351\text{-}520}$** and **x**$D_{351\text{-}520}$** there are less differences than in the previous comparison.

Weight of the duplex steel was reduced only by 20 t, as one plate in longitudinal bulkhead was decreased from 16 to 13 mm. Nevertheless, this design is an extreme member of the Pareto front regarding duplex steel weight. Beside some small changes in general, plates of deck strakes 2 and 4 from CL were enlarged, as they do not contribute to duplex steel weight, but increase the deck adequacy. There is a difference between design $\mathbf{x}D_{351\text{-}520}$** and $\mathbf{x}TW_{351\text{-}520}$** in a sense that the former one was found 40 generations after safety maximization was included in the search, and also 40 generations after $\mathbf{x}TW_{351\text{-}520}$**, see Fig. 7 and Table III. From this, one great aspect of optimization can be observed: in order to increase the deck adequacy, VOP first increased strakes which do not affect on the duplex steel weight and also cause small increase in total hull steel weight In order to obtain the highest values of adequacy, it is necessary to increase the deck strakes, which then caused the inevitable increase in hull steel weight, but it is better to do in a way which keeps the duplex steel weight as low as possible, as was done here.

Table III: Values of objectives for the best designs after adequacy of deck strakes has been taken in consideration, compared with design of minimal rule scantlings. Generation in which they were found is also presented and also the number of negative and active constraints

	$\mathbf{x}TW_{351\text{-}520}$**	$\mathbf{x}D_{351\text{-}520}$**	$\mathbf{x}A_{351\text{-}520}$**	Min. rule req.
f_1, t	7353	7599	8149	7550
f_2, t	2652	2632	2912	2270
f_3	11.44	12.91	16.82	10.72
$G_{\mathbf{x}**}$	351	391	472	-
Neg. con.	0	0	0	32
Act. con.	52	44	36	18

Table IV: The value of adequacy for the best designs per strake for stiffener yield, plate yield and plate buckling

	$\mathbf{x}TW_{351\text{-}520}$**			$\mathbf{x}D_{351\text{-}520}$**			$\mathbf{x}A_{351\text{-}520}$**			Min. rule req.		
deck - CL	0.45	0.13	0.02	0.48	0.17	0.06	0.56	0.28	0.44	0.45	0.13	0.25
deck – 2	0.34	0.08	0.06	0.37	0.12	0.31	0.47	0.24	0.42	0.34	0.08	0.25
deck – 3	0.43	0.10	0.00	0.46	0.14	0.04	0.54	0.27	0.51	0.41	0.11	0.24
deck - side	0.34	0.08	0.19	0.37	0.12	0.32	0.47	0.23	0.44	0.34	0.07	0.16

Between design of minimal duplex steel and maximum deck adequacy there are negligible differences beside the deck scantlings. Plate thicknesses and stiffener sizes were increased. Note that the third 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. Therefore, when it was noticed by VOP that further increase of deck strakes leads to excessive growth in weights, the search was re-directed to finding solutions with low duplex and hull steel weight while retaining the values of adequacy. This can be seen from Fig. 5, Fig. 6 and Fig. 7. If continued, the optimization would lead to solutions better in hull steel weight, for reasonably good deck adequacy, since that was the trend in last 10 generations.

When described designs are compared how well they have approached constraints, the design $\mathbf{x}TW_{351\text{-}520}$** is the best, followed by the $\mathbf{x}D_{351\text{-}520}$** and $\mathbf{x}A_{351\text{-}520}$**, while design of minimum rule requirements has the lowest number of active constraints. We have considered a constraint to be active if stress exceeded 3/4 of critical value.

VI. 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 quite adoptable to the designers' needs. By exploiting the possibilities of VOP as the omni-optimizer, objectives can be added, subtracted or even converted from constraints during the search for optima, as seen appropriate. If specific region of Pareto front is desired, optimization can be directed towards it during the search. This is beneficial when evaluation of objectives and constraints requests considerable time, saving money and effort in long-term. Real-life problems can be quite difficult even for world-known algorithms. To make optimization search easier, we propose a different approach:

first to optimize more difficult objectives, and after satisfactory results have been obtained, include supplementary objectives. It can be also beneficial if one knows the general behavior of objectives, as in used case where minimization of hull steel weight will likely lead to minimization of duplex steel and vice versa, but opposite of deck adequacy which is contrary to them. Then it is better to give more emphasis in the beginning for those objectives which require more effort to approach optima, and when good base for continuation has been acquired, include the easier objectives. This is the same as declaring the importance of easier functions equal to zero in the beginning. The point at which one will change importance factors to include other objectives can be different: either satisfactory results have been obtained, or improvement in terms of objectives became rather poor, as was in our case.

We have used the chemical tanker example to illustrate this possibility by first obtaining reasonably good design alternatives with respect to hull steel weight and weight of duplex steel. From that point, request was to increase safety of the structure, so the corresponding adequacy was maximized. If scantlings of deck strakes are maximized, there will be less probability of crack initiation. This objective caused increase of hull and duplex weight, and fairly distributed Pareto front between them was achieved. Since for the problem of chemical tanker's main frame VOP accomplished encouraging results, and handled large-scale optimization with ease, it would we interesting to observe how well can it behave with expanded problem. Additional frames could be included in the search so to optimize different sections of the hull. Additional effort will be given to further improve the fitness assignment in VOP. It would be also beneficial to devise more generic fitness function, one which does not make difference between the selection schemes based on feasibility. Comparison with other optimizers is necessary in order to claim how well can it perform, and this will be surely the topic of the future studies.

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