Application of Genetic Algorithm to Structural Optimization of High Speed Craft

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Abstract. Selection of the „best” or „optimum” engineering design has always been a major concern of designers. In recent years tests have been undertaken to apply genetic algorithm (GA) optimisation techniques to design of ship structures. GA is applied to study the problem of weight minimization of a high speed craft hull structure with several design variables. A computer code has been developed for this purpose. Results of computations obtained using the code are presented. The fitness function is based on loads and strength criteria suggested by the classification society rules. The paper discusses of the GA behaviour on the base of numerical experiments. Results of those experiments show that GA can be an efficient optimisation tool for design of topology and sizing high speed craft structure simultaneously.

1 Introduction

The goal of ship structural optimization is to find the optimum positions of structural elements, also referred to as topological optimization, shapes (shape optimization) and scantlings (sizing optimization) of structural elements for an objective function subject to constraints. Formally, the selection of structural material can also be treated as a part of the optimization process (material optimization). An essential task of the optimization is to reduce the structural weight, therefore most frequently the minimum weight is assumed as an objective function. Topological optimization is searching for optimal existence and space localization of structural elements while shape optimization is searching for optimal shape of ship hull body. This problem is solved within computational fluid dynamics methods. Sizing optimization could be also expressed as the process of finding optimum scantlings of structural elements with fixed topology and shape. A choice of the structural material is usually not an optimization task explicitly but is rather done according to experience and capability of a shipyard. Optimization of structure of laminates is an example of such an optimization problem.

Thus the process of ship structural design and optimization can be considered in four areas: optimisation of shape, material, topology and scantling. Due to complexity of optimization problem related to ship structures, only partial optimization tasks are formulated in each of the four areas independently. No attempt to unify the optimization problems have been done so far.

Preliminary developments proved the genetic algorithm (GA) can be an efficient tool for ship structural optimization [16, 17, 18, 19, 20, 21, 26, 27]. The results of research on the GA application for optimization of high speed craft hull structure topology and sizing optimization is presented in the paper while the optimization of shape and material was not covered. The computer code for structural optimization by GA is described in Section 2. Structural, optimization and genetic models of a simplified fast craft hull structure are described in Sections 3, 4 and 5 respectively. The results of application of the computer code to the optimal design of the analysed structure is given in Section 6. Some general conclusions are formulated in Section 7.

2 Computer Code for Genetic Optimization of Structures

Applicability of GA for solution of the optimization problems unifying scantling and topology optimization of ship structure was verified using computer simulation. The computer code was developed as a general software tool for optimal analysis of real structures by adding the modules of the pre-processing, scantling analysis and post-processing to the genetic modules (selection, mutation, crossover) which form the Simply Genetic Algorithm (SGA). The flowchart of the code is shown in Fig. 1.

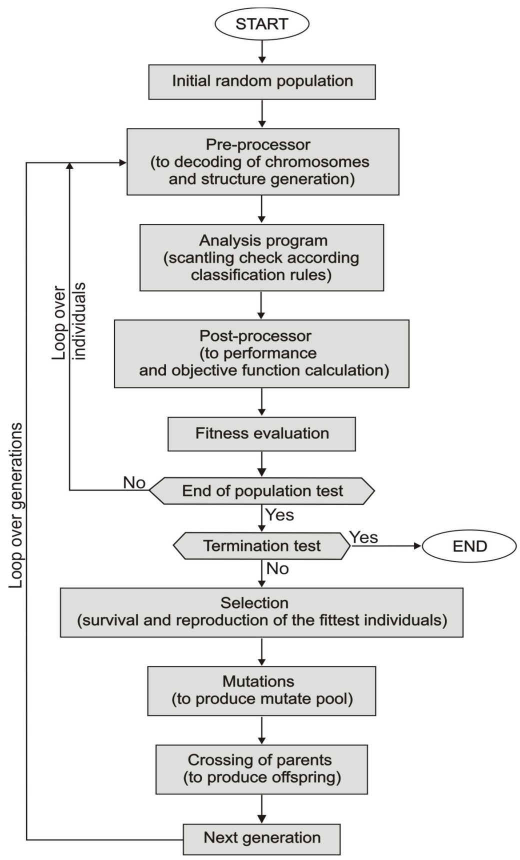

Figure 1. Flowchart of computer code for structural optimization by genetic algorithm.

In the computer code the optimization problem is solved by creating a random population of the trial solutions. All principal operators of the basic evolutionary process [4, 10, 14] are used in the code: crossover, mutation and natural selection. Two additional operators: the elitist [14] and update operator [23] are introduced for the selection as well.

Each new created variant of solution (an individual being a candidate to the progeny generation) is analyzed by the pre-processor. In the pre-processor binary strings of chromosomes are decoded into the corresponding strings of decimal values representing design variables. Then for the actual values of the design variables defining spatial layout of the structural elements (topology) and their scantlings it is checked whether the actual configuration complies with the rules of the classification society. In the next step performance of solution is calculated and it is checked whether the variant meets the constraints. At the end the value of the objective function is calculated for each variant – weight of the structure, and the value of the fitness function for selection. Variants are ordered with respect to this value. Knowing adaptation of each variant the random process is restarted to select variants of the successive progeny generation.

After selection, the code determines randomly, with probability equal to p_m, which genes of these whole population will mutate. After that the mutate pool is created. Then decision is made how much information is swapped between the different population members. That is done by creating, with probability equal to p_c, *n_x_site* „cutting points". The genes located between two „cuts" are switched. The resulting population member is then referred to as an offspring.

All genetic parameters are specified by the user before the start of calculations. This option is very important; the control of the parameter permits to perform search in the direction expected by the designer and in some cases it allows to find the solution much faster. The population size, number of variables and number of bits per variable, the total genome length, number of individuals in the population are limited by the available computer memory.

3 Structural Model

For the optimisation study a model based on the Austal Auto Express 82 design developed by Austal [7, 8, 9]. Main dimensions of the vessel are shown in Fig. 2. For the analysis a midship block-section (17.5 x 23.0 x 11.7 m) was taken. The vessel and its corresponding cross section are shown in Fig. 3. Bulkheads form boundaries of the block in the longitudinal direction. In the block 9 structural regions can be distinguished. All regions are longitudinally stiffened with longitudinal stiffeners with spacing different in each structural region. The transverse web frame spacing is common for all structural regions.

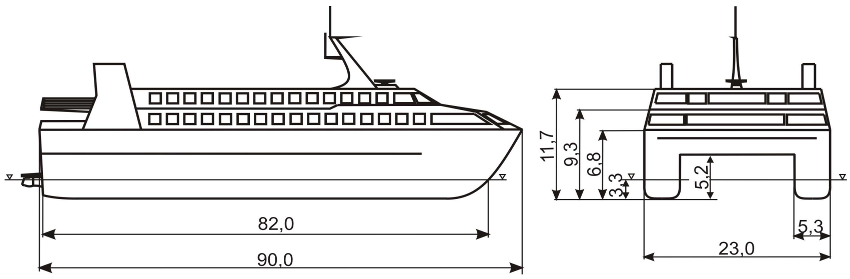

Figure 2. High speed vehicle-passenger catamaran, type Auto Express 82 – main dimensions.

The structural material is aluminium alloy having following properties: (1) yield stress, $R_{0,2} = 125$ N/mm^2 (5083 aluminium alloy for plates) or $R_{0,2} = 250$ N/mm^2 (6082 aluminium alloy for extruded bulbs), (2) Young modulus, $E = 70{,}000$ N/mm^2, (3) Poisson ratio, $\nu = 0.33$, (4) density, $\rho = 26.1$ kN/m^3. The plate thickness and the bulb and T-bulb extruded stiffener and web frame sections are assumed according to the commercial standards and given in Tables 2-4. The formulae for scantling calculation of plate thicknesses and section moduli of stiffeners and web frames are taken in accordance to the classification rules [25].

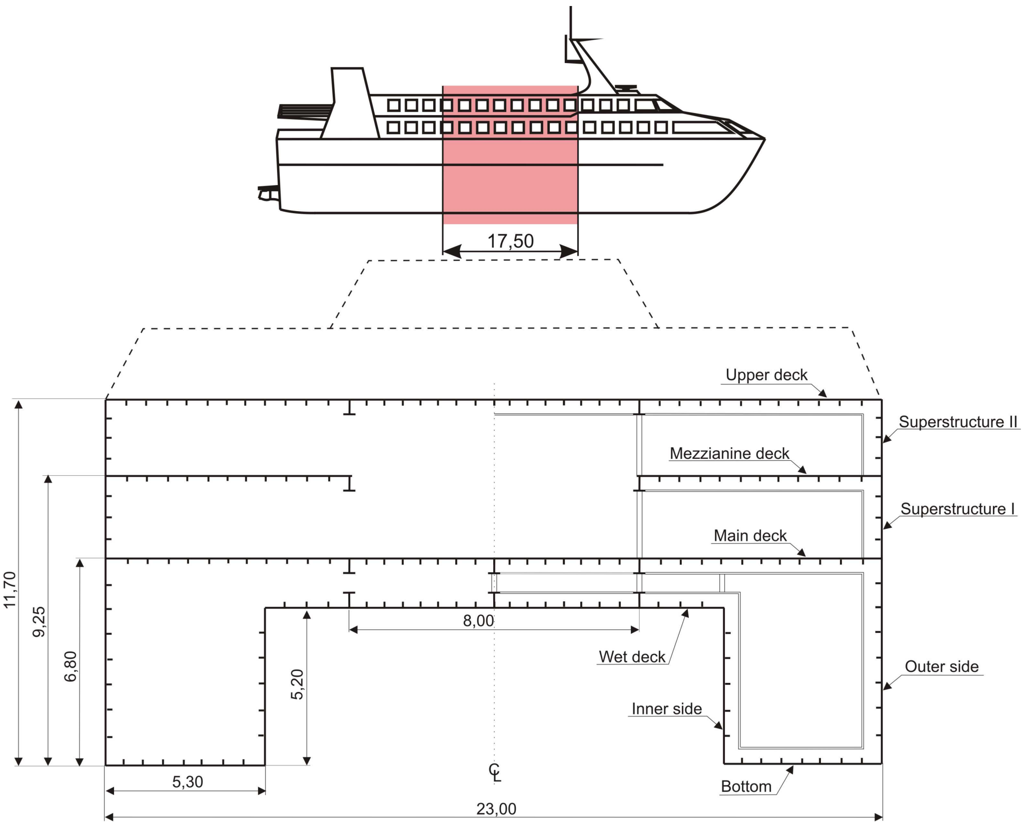

Figure 3. Assumed model of craft – midship block-section, frame system and structural regions.

A minimum structural weight (volume of structure) was taken as the criterion in the study and was introduced in the definition of the objective function and constraints defined on the base of classification rules. The assumed optimization task is rather simple one but the main objective of the study was building and testing the computer code and proving its application for unified topology-sizing structural optimization of a ship hull.

Table 2. Thickness of plates.

No.	Thickness t, mm	No.	Thickness t, mm
1	3.00	8	12.00
2	4.00	9	15.00
3	5.00	10	20.00
4	6.00	11	30.00
5	7.00	12	40.00
6	8.00	13	50.00
7	10.00	14	60.00

Table 3. Dimensions of aluminium bulb extrusions.

No.	Dimensions (h, b, s, s_1)[1)], mm	Cross-sectional area, cm^2
1	80 x 19 x 5 x 7.5	5.05
2	100 x 20.5 x 5 x 7.5	6.16
3	120 x 25 x 8 x 12	11.64
4	140 x 27 x 8 x 12	13.64
5	150 x 25 x 6 x 9	10.71
6	160 x 29 x 7 x 10.5	13.51
7	200 x 38 x 10 x 15	24.20

[1)] h – cross-section height; b - flange width; s - web thickness; s_1 - flange thickness.

Table 4. Dimensions of aluminium T-bulb extrusions.

No.	Dimensions (h, b, s, s_1)[2)], mm	Cross-sectional area, cm^2
1	200 x 100 x 8 x 15	29.80
2	200 x 140 x 8 x 5	35.80
3	200 x 60 x 10 x 12	22.50
4	200 x 50 x 8 x 9.5	21.04
5	210 x 50 x 5 x 16	14.78
6	216 x 140 x 7.6 x 8	37.60
7	220 x 80 x 5 x 8	17.00
8	230 x 80 x 10 x 8	28.60
9	230 x 80 x 5.8 x 8	19.28
10	235 x 170 x 8 x 10	35.00
11	240 x 140 x 6 x 10	27.80
12	260 x 90 x 5 x 9.5	21.08
13	275 x 150 x 9 x 12	41.67
14	280 x 100 x 5 x 8	21.60
15	280 x 100 x 8 x 10	31.60
16	300 x 60 x 15 x 15	51.75
17	310 x 100 x 7 x 16	36.58
18	310 x 123 x 5 x 8	24.94
19	350 x 100 x 8 x 10	37.20
20	350 x 100 x 5 x 8	25.10

[2)] h – cross-section height; b - flange width; s - web thickness; s_1 - flange thickness.

Table 4. Dimensions of aluminium T-bulb extrusions, cont.

No.	Dimensions (h, b, s, s_1)[2)], mm	Cross-sectional area, cm^2
21	390 x 150 x 6 x 8	34.92
22	390 x 150 x 6 x 12	40.68
23	400 x 140 x 5 x 8	30.80
24	410 x 100 x 6 x 8	32.12
25	420 x 15 x 5 x 10	35.10
26	420 x 15 x 8 x 10	47.80
27	450 x 100 x 9 x 10	49.60
28	450 x 150 x 10 x 12	61.80

[2)] h – cross-section height; b - flange width; s - web thickness; s_1 - flange thickness.

4 Formulation of Optimization Model

The set of the design variables for the 3D hull structural model in the present formulation is as following (Table 5., Fig. 4):

$$x_i = (x_1, x_2, ..., x_N), \quad N = 37 \tag{1}$$

where N - number of design variables.

Introducing a design variable representing the number of transversal frames in the considered section: x_4, and numbers of longitudinal stiffeners in the regions: x_5, x_9, x_{13}, x_{17}, x_{21}, x_{25}, x_{29}, x_{33}, x_{37} enables simultaneous optimization of both topology and scantlings within the presented optimization model.

Table 5. Simplified specification of bit representation of design variables.

No.	Symbol	Item	Substring length (no of bits)	Value		
				Lower limit	Upper limit	Discrete step
1	x_1	serial No. of mezzanine deck plate	4	1	10	0.60
2	x_2	serial No. of mezzanine deck bulb	3	1	7	0.86
3	x_3	serial No. of mezzanine deck T-bulb	4	42	52	0.67
4	x_4	number of web frames	3	10	16	0.86
5	x_5	number of mezzanine deck stiffeners	4	25	40	1.00
6	x_6	serial No. of superstructure I plate	4	1	10	0.60
7	x_7	serial No. of superstructure I bulb	3	1	7	0.86
8	x_8	serial No. of superstructure I T-bulb	4	42	52	0.67
9	x_9	number of superstructure I stiffeners	3	4	11	1.00
10	x_{10}	serial No. of inner side plate	4	1	10	1
11	x_{11}	serial No. of inner side bulb	3	1	7	1
12	x_{12}	serial No. of inner side T-bulb	4	42	52	1
13	x_{13}	number of inner side stiffeners	3	18	25	1
14	x_{14}	serial No. of bottom plate	4	1	12	1
15	x_{15}	serial No. of bottom bulb	3	1	7	1
16	x_{16}	serial No. of bottom T-bulb	4	42	52	1

Table 5. Simplified specification of bit representation of design variables, cont.

No.	Symbol	Item	Substring length (no of bits)	Value		
				Lower limit	Upper limit	Discrete step
17	x_{17}	number of bottom stiffeners	4	15	25	1
18	x_{18}	serial No. of outer side plate	4	1	12	1
19	x_{19}	serial No. of outer side bulb	3	1	7	1
20	x_{20}	serial No. of outer side T-bulb	4	42	52	1
21	x_{21}	number of outer side stiffeners	4	18	33	1
22	x_{22}	serial No. of wet deck plate	4	1	12	1
23	x_{23}	serial No. of wet deck bulb	3	1	7	1
24	x_{24}	serial No. of wet deck T-bulb	4	42	52	1
25	x_{25}	number of wet deck stiffeners	4	25	40	1
26	x_{26}	serial No. of main deck plate	4	2	12	1
27	x_{27}	serial No. of main deck bulb	3	1	7	1
28	x_{28}	serial No. of main deck T-bulb	4	42	52	1
29	x_{29}	number of main deck stiffeners	4	25	40	1
30	x_{30}	serial No. of superstructure II plate	4	1	10	1
31	x_{31}	serial No. of superstructure II bulb	3	1	7	1
32	x_{32}	serial No. of superstructure II T-bulb	4	42	52	1
33	x_{33}	number of superstructure II stiffeners	3	4	11	1
34	x_{34}	serial No. of upper deck plate	4	1	10	1
35	x_{35}	serial No. of upper deck bulb	3	1	7	1
36	x_{36}	serial No. of upper deck T-bulb	4	42	52	1
37	x_{37}	number of upper deck stiffeners	4	25	40	1
		Multivariable string length (chromosome length)	135			

Objective function $f(x_i)$ for optimisation of the hull structure weight is written in the following form:

$$f(x_i)=\sum_{j}^{R} w_j SW_j,\ R=9 \tag{2}$$

where x_i - i-th design variable; R - number of structural regions; SW_j - structural weight of the j-th structural region; w_j - relative weight coefficient (relative importance of structural weight) of regions varying in the range [0,1].

The behaviour constraints, formulated according to the classification rules [25], prevent to structural model to fall in the region prohibited considering its strength.

Side constraints for design variables are given in Table 5. They correspond to the limitations of the range of the profile set. Some of them are pointed according to the author' experiences for improving the calculation convergence.

The additional geometrical constraints were introduced due to fabrication and standardization reasons, for eg. assumed relation between the plate thickness and web frame thickness.

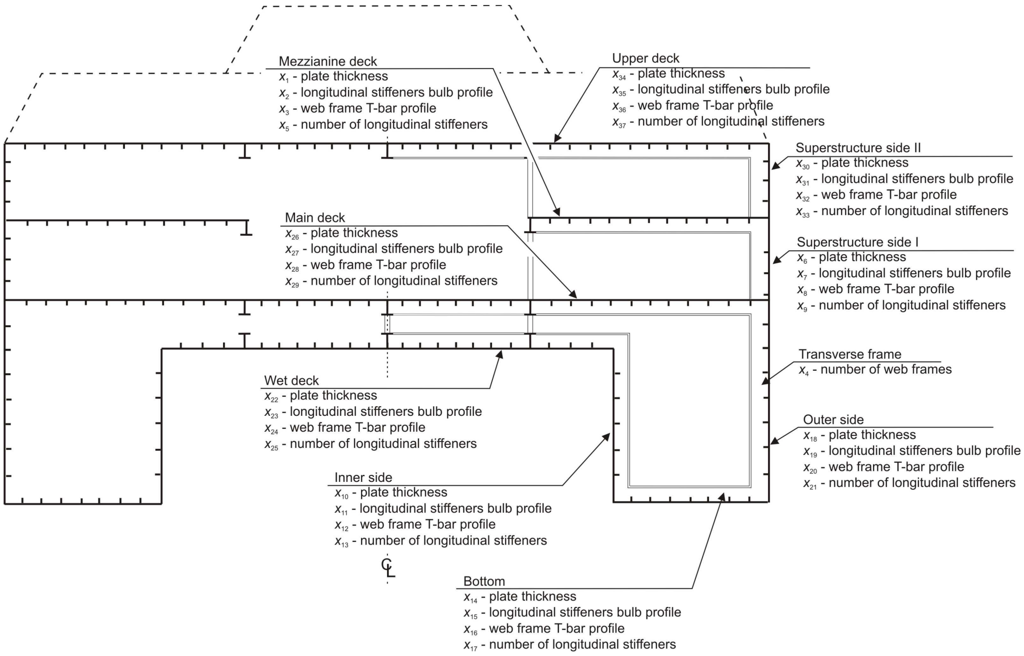

Figure 4. Assumed model of craft – specification of design variables.

5 Description of Genetic Model

5.1 General

Solution of the optimisation problem by GA calls for formulation of an appropriate optimisation model. The model described in Sections 3 and 4 was reformulated into an optimisation model according to requirements of the GA and that model was further used to develop suitable procedures and define search parameters to be used in the computer code.

The genetic type model should cover:
– definition of chromosome structure;
– definition of fitness function;
– definition of genetic operators suitable for the defined chromosome structures and optimization task;
– list of the searching control parameters.

5.2 Chromosome Structure

The space of possible solutions is a space of structural variants of the assumed model. The hull structural model is identified by the set of 37 design variables, x_i. Each variable is represented by a string of bits used as chromosome substring in GA. The simple binary code was applied. In the Table 5 a simplified specification for bit representation on all design variables is shown. A variant of solution is represented as a bit string. Chromosome length is equal to the sum of all substrings. Number of possible solutions is equal to the product of values of all variables. In the present work the chromosome length is equal to 135 bits, making the number of possible approximately equal to 10^{38}.

5.3 Fitness Function

The design problem defined in this paper is to find the minimum weight of a hull structure without violating the constraints. In order to transform the constrained problem into unconstrained one and due to the fact that GA does not depend on continuity and existence of the derivatives, so called "penalty method" have been used. In the method the augmented objective function of unconstrained minimisation problem is expressed as:

$$\Phi(x_i) = f(x_i) - \sum_{k=1}^{n_c} w_k P_k \tag{3}$$

where $\Phi(x_i)$ - augmented objective function of unconstrained minimisation; $f(x_i)$ - objective function given by Eq. (2); P_k - penalty term to violation of the k-th constraint; w_k - weight coefficients for penalty terms; n_c - number of constraints. Weight coefficients w_k are adjusted by trial.

Additionally a simple transformation of minimization problem (in which the objective function is formulated for the minimization) into the maximization is necessary for the GAs procedures (searching of the best individuals). It can be done multiplying the objective function by (-1). In that way, the minimization of the augmented objective function was transformed into a maximization search using:

$$F_j = \Phi_{max} - \Phi_j(x_i) \tag{4}$$

where F_j = fitness function for j-th solution; $\Phi_j(x_i)$ = augmented objective function for j-th solution; Φ_{max} = maximum value of the augmented function from all solutions in the simulation. The value of parameter Φ_{max} has to be arbitrary chosen by a user of the software to avoid negative fitness values. Its value should be greater than the expected largest value of $\Phi_j(x_i)$ in the simulation. In the presented approach the value Φ_{max} = 100000 was assumed.

5.4 Genetic Operators

The basic genetic algorithm (SGA) produces variants of the new population using the operators of selection, mutation and crossover. The algorithm was extended by introduction of elitism and updating.

Many authors described the selection operators, which are responsible on chromosome selection due to their fitness function value [1, 2, 3, 6, 11, 12, 16, 15]. After the analysis of the selection operators, there was a roulette concept applied for proportional selection.

The mutation operator which introduces a random changes of the chromosome was also described [3, 15, 16]. This allows to bring a new information to the population genes and diversify "parents". This operator supports exploration of the global search space.

Crossover operator is responsible for modifications of parts of the parent chromosomes. The crossover allows to explore a local area in the solution space. Analysis of the features of the described operators [3, 11, 16, 22, 24] led to elaboration of own, *n*-point, random crossover operator. The crossover parameters in this case are: the lowest *n_x_site_min* and the greatest *n_x_site_max* number of the crossover points and the crossover probability p_c. The operator works automatically and independently for each pair being intersected (with probability p_c), and it sets the number of crossover points *n_x_site*. The number of points is a random variable inside the set range [*n_x_site_min*, *n_x_site_max*]. The test calculations proved high effectiveness and quicker convergence of the algorithm in comparison to algorithm realizing single-point crossover. Concurrently, it was found that the number of crossover points *n_x_site_max* greater than 7 does not improve convergence of the algorithm. Therefore, the lowest and greatest values of the crossover points were set as following: *n_x_site_min* = 1, *n_x_site_max* = 7.

5.5 Control Parameters

Single program run with the defined genetic model is characterized by values of ten control parameters (Table 6). For selection of values of control parameters it is not possible to formulate quantitative premises there is not exist appriopriate mathematical models for analysis of GA convergency in relation to control parameters. They were set due to test calculations results to achieve a required algorithm convergence at established number of generations and population size. The values are presented in Table 6.

Table 6. Genetic model and values of control parameters.

No.	Symbol	Description	Value
1	n_g	Number of generations	5000
2	n_i	Size of population	2000
3	n_p	Number of pretenders	3
4	p_m	Mutation probability	0.066
5	p_c	Crossover probability	0.80
6	*c_strategy*	Denotation of crossover strategy (0 for set -, 1 for random number of crossover points)	1
7	*n_x_site_min*	The lowest number of crossover points	1
8	*n_x_site_max*	The greatest number of crossover points	7
9	p_u	Update probability	0.33
10	*elitism*	Logical variable to switch on (*elitism* = yes) and off (*elitism* = no) the pretender selection strategy	yes

6 Optimization calculations

To verify the correctness of the optimisation procedure several test cases have been carried out using the model described in Sections 3-5. Each experiment is characterised by 10 parameters given in Table 6. In Table 7 and Fig. 5 results of typical trial are presented. The set of experiment parameters are as follows (n_g, n_i, n_p, p_m, p_c, *c_strategy*, *n_x_site_min*, *n_x_site_max*, p_u, *elitism*) = (5000, 2000, 3, 0.066, 0.8, 1, 1, 7, 0.033, true). There were 10^6 tested individuals in the whole simulation. The lowest value of the objective function, $f(x_i)$ = 4,876.37 kN, was found in the 868th generation. The corresponding values of design variables are given in Table 7.

All values of the hull structural weight for feasible individuals searched in the simulation are presented in Fig. 6. The solid line represents the front of optimal solutions. It is composed of minimal (optimal) values of the structural weight received in the following simulation. All variants situated above the front of optimal solutions line are feasible but structural weight of these variants is greater than those situated on the front line.

Table 7. Optimal values of design variables.

No.	Symbol	Description	Optimal value
1	x_1	serial No. of mezzanine deck plate	5
2	x_2	serial No. of mezzanine deck bulb	1
3	x_3	serial No. of mezzanine deck T-bulb	49
4	x_4	number of web frames	12
5	x_5	number of mezzanine deck stiffeners	30
6	x_6	serial No. of superstructure I plate	2
7	x_7	serial No. of superstructure I bulb	4
8	x_8	serial No. of superstructure I T-bulb	47
9	x_9	number of superstructure I stiffeners	4
10	x_{10}	serial No. of inner side plate	8
11	x_{11}	serial No. of inner side bulb	4
12	x_{12}	serial No. of inner side T-bulb	44
13	x_{13}	number of inner side stiffeners	23
14	x_{14}	serial No. of bottom plate	8
15	x_{15}	serial No. of bottom bulb	6
16	x_{16}	serial No. of bottom T-bulb	50
17	x_{17}	number of bottom stiffeners	18
18	x_{18}	serial No. of outer side plate	5
19	x_{19}	serial No. of outer side bulb	1
20	x_{20}	serial No. of outer side T-bulb	50
21	x_{21}	number of outer side stiffeners	31
22	x_{22}	serial No. of wet deck plate	5
23	x_{23}	serial No. of wet deck bulb	1
24	x_{24}	serial No. of wet deck T-bulb	50
25	x_{25}	number of wet deck stiffeners	29
26	x_{26}	serial No. of main deck plate	10
27	x_{27}	serial No. of main deck bulb	3
28	x_{28}	serial No. of main deck T-bulb	48
29	x_{29}	number of main deck stiffeners	33
30	x_{30}	serial No. of superstructure II plate	2
31	x_{31}	serial No. of superstructure II bulb	4
32	x_{32}	serial No. of superstructure II T-bulb	47
33	x_{33}	number of superstructure II stiffeners	4
34	x_{34}	serial No. of upper deck plate	2
35	x_{35}	serial No. of upper deck bulb	3
36	x_{36}	serial No. of upper deck T-bulb	43
37	x_{37}	number of upper deck stiffeners	31

The graphs of the maximum, average, minimum and variance values of fitness across 5,000 generations for simulation are presented in Fig. 7. The saturation was nearly achieved in this simulation. The maximum normalised fitness value is nearly 0.645. The standard deviation value is approximately constant and equal to 0.075 for all generations what means that heredity of generations is approximately constant over simulation.

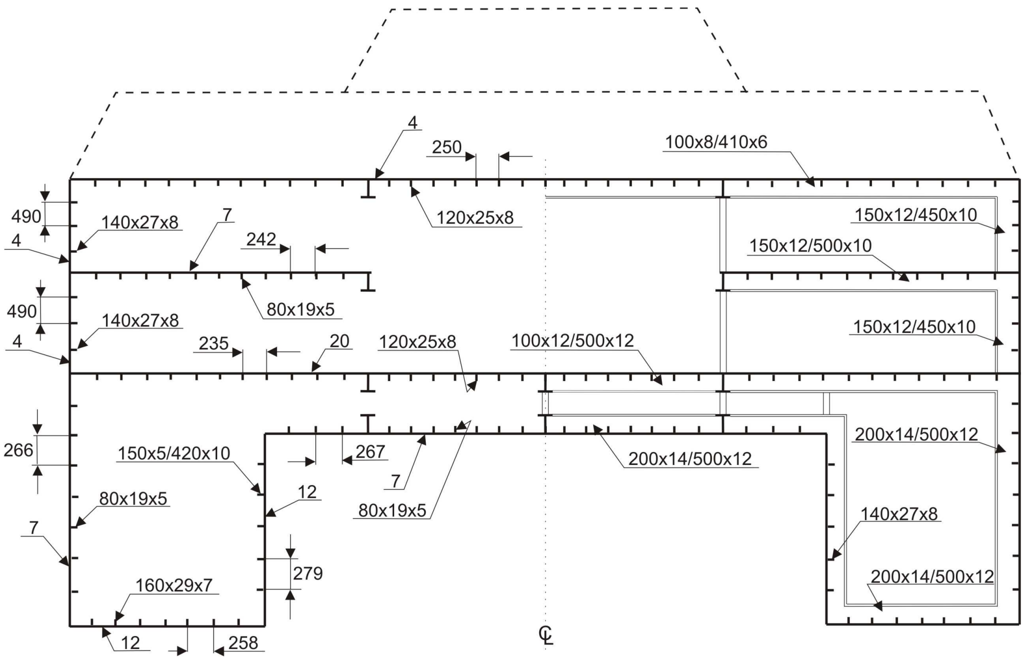

Figure 5. Result of optimization calculation - optimal topology and sizing of vessel structure.

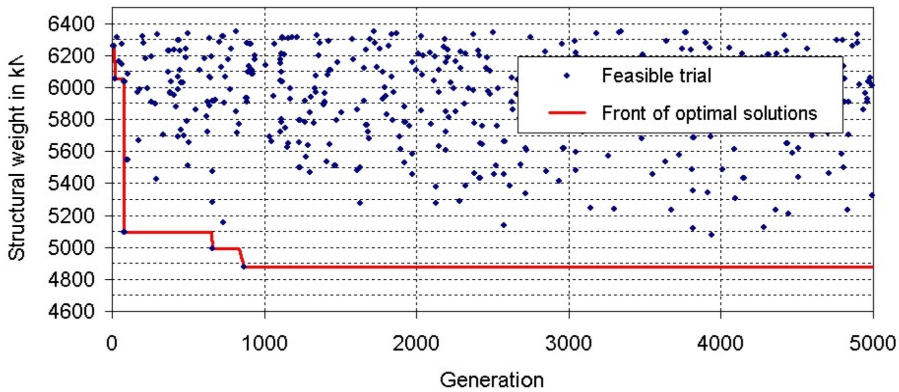

Figure 6. Evolution of structural weight values over 5000 generations; solid line for absolutely minimal structural weight found during simulation; only feasible solutions are shown.

Evolution of the fitness function values and the minimum values of structural weight are shown in Fig. 8. A correspondence of the diagrams can be seen. The increase of the fitness function values in successive generations is accompanied by the decrease of structural weight values.

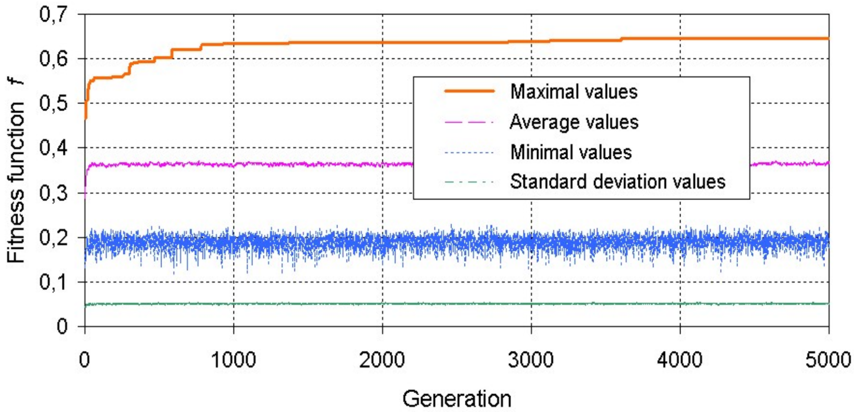

Figure 7. Evolution of maximum, average, minimum and standard deviation values of the fitness over 5,000 generations; fitness function values are dimensionless and normalised to produce extreme value equal to 1.0.

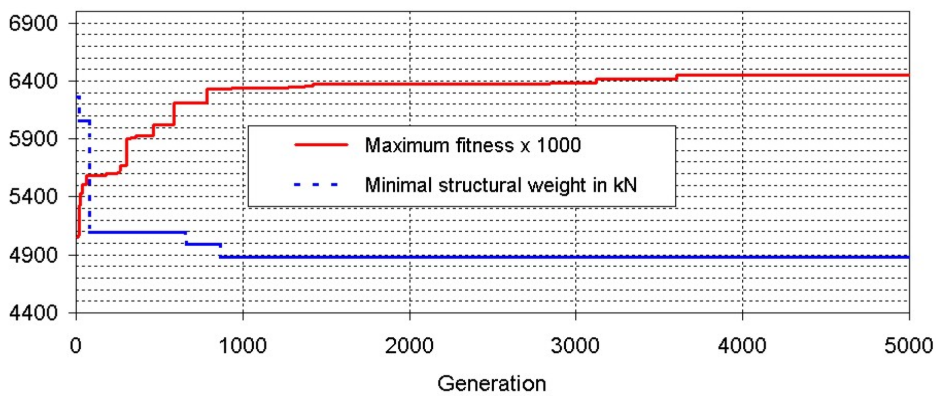

Figure 8. Evolution of maximal fitness value and absolutely minimal structural weight over 5,000 generations; absolutely minimal structural weight for simulation only for feasible solutions.

7 Conclusions

The application of the genetic algorithm concept to solve the practical design problem of the optimisation of hull structures of high speed craft was presented. The problem of weight minimisation for a three dimensional full midship block-section of the high speed catamaran hull was described.

Simultaneous optimisation of topology and scantlings is possible using the present approach. Enhancement of the sizing optimization (the standard task of the structural optimization) allowing for the topology optimization requires disproportional computational effort. It is an effect of both the increase of the search space by introducing design variables referring to the structural topology as well as the increase of number of generations and number of individuals to ensure satisfactory convergence of the optimization process.

Additionally the GA realisation described in the paper is also under continuous development directed towards implementation of other genetic operators, genetic encoding, multi-objective optimisation etc. as well as including some other constraints.

The present paper is a successful attempt of unification of problems of topology and sizing optimization of ship structures and their solution using the GA. It was proven that the GA can be considered as a good method for the solution of the unified shape-material-topology-sizing optimization problems.

8 Acknowledgement

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