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Multi-objective optimization of high speed vehicle-passenger catamaran by genetic algorithm

Part II
Analysis of the results

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ABSTRACT

Real ship structural design problems are usually characterized by presence of many conflicting objectives. Simultaneously, a complete definition of the optimum structural design requires a formulation of size-topology-shape-material optimization task unifying the optimization problems from the four areas and giving an effective solution of the problem. Any significant progress towards solving the problem has not been obtained so far. An objective of the present paper was to develop an evolutionary algorithm for multi-objective optimization of the structural elements of large spatial sections of ships. Selected elements of the multi-criteria optimization theory have been presented in detail. Methods for solution of the multi-criteria optimization problems have been discussed with the focus on the evolutionary optimization algorithms. In the paper an evolutionary algorithm where selection takes place based on the aggregated objective function combined with domination attributes as well as distance to the asymptotic solution, is proposed and applied to solve the problem of optimizing structural elements with respect to their weight and surface area for a high - speed vehicle-passenger catamaran structure, with taking into account several design variables such as plate thickness, scantlings of longitudinal stiffeners and transverse frames, and spacing between longitudinal and transversal members. Details of the computational models were kept at the level typical for conceptual design stage. Scantlings were analyzed by using the selected classification society rules. The results of numerical experiments with the use of the developed algorithm are presented. They show that the proposed genetic algorithm may be considered an efficient tool for multi-objective optimization of ship structures.

The paper has been published in the three parts: Part I: Theoretical background on evolutionary multi-objective optimization, Part II: Computational simulations, and Part III: Analysis of the results.

Keywords: ship structure; multi-objective optimization; evolutionary algorithm; genetic algorithm; Pareto domination, set of non-dominated solutions

ANALYSIS OF THE RESULTS AND CONCLUSIONS DRAWN FROM THE COMPUTATIONAL SIMULATIONS

Three series of the computer simulations, signed sym1, sym2 and sym3, confirmed effectiveness of the developed computational algorithm and computer code for solution of the formulated problem of ship structure topology-size multi-objective optimization. As a result of the calculations an approximation of the Pareto-optimum set containing, in each simulation, from a few to more than ten non-dominated solutions, was found. The obtained results do not allow to unequivocally conclude which of the examined factors: (1) objective function aggregation strategies, (2) domination attributes included into selection process, and (3) distance to asymptotic solution included into selection process, is most advantageous.

In the case of studying the influence of optimization criteria aggregation strategy, visual assessment of the shape of the obtained approximations of the Pareto-optimum set suggests an advantage of the strategy with random values of the weight coefficients w_s (sym1-2) and the least effectiveness of the strategy with fixed values of the weight coefficients w_s (sym1-1).

The effectiveness of the strategy with random selection of single optimization criteria in the selection process (sym1-3) is intermediate. In the case of the constrained problems it also turns out that the components of the penalty functions introduce a random contribution to the fitness function thus causing the strategy with the fixed weight coefficients w_s to be practically a strategy similar to the two others and it also allows to find approximation of the Pareto-optimum set with the adequate accuracy.

From the found sets of the compromise solutions a user can select, in the next stage, one or a few solutions by applying additional premises which are not included in the optimization model. He can also select suggested non-dominated solutions the closest to the asymptotic solutions $\mathbf{f}^{\approx}$:

$$\mathbf{f}^{\approx}_{sym1\text{-}1} = [1086.28\ 7422.10]^{T}\cdot[\mathrm{kN\ m^2}] \Rightarrow$$
$$\Rightarrow f_{1,sym1\text{-}1}(\mathbf{x}) = 1086.28\ \mathrm{kN},\ f_{2,sym1\text{-}1}(\mathbf{x}) = 7422.10\ \mathrm{m^2}$$

$$\mathbf{f}^{\approx}_{sym1\text{-}2} = [1113.65\ 7361.45]^{T}\cdot[\mathrm{kN\ m^2}] \Rightarrow$$
$$\Rightarrow f_{1,sym1\text{-}2}(\mathbf{x}) = 1113.65\ \mathrm{kN},\ f_{2,sym1\text{-}2}(\mathbf{x}) = 7361.45\ \mathrm{m^2}$$

$$\mathbf{f}^{\approx}_{sym1\text{-}3} = [1153.68\ 7381.57]^{T}\cdot[\mathrm{kN\ m^2}] \Rightarrow$$
$$\Rightarrow f_{1,sym1\text{-}3}(\mathbf{x}) = 1153.68\ \mathrm{kN},\ f_{2,sym1\text{-}3}(\mathbf{x}) = 7381.57\ \mathrm{m^2}$$

Since this way three solutions are obtained, the next question is which of them can be recommended as the best[1)]. Here the following procedure is suggested by this author: non-dominated solution sets obtained in subsequent simulations can be merged into a temporary solution set presented in Fig. 39a. In this set only a part of solutions is non-dominated ones, Fig. 39b. In the set of 15 non-dominated solutions obtained by using the results of three simulations, a distance of each of them from the asymptotic objective in normalized objective space, can be determined, Fig. 39c. The least distance equal to 1.082, was obtained for the solution $f_1(\mathbf{x}) = 1113.65$ kN and $f_2(\mathbf{x}) = 7361.45$ m² found in the simulation sym1-2 (random values of the weight coefficients w_1 and w_2 in the range [0, 1]). The solution can be recommended as a single solution of the formulated problem of multi-objective optimization.

Effectiveness of the three examined multi-objective optimization strategies which use optimization criteria values and functions representing violation degree of constraints,

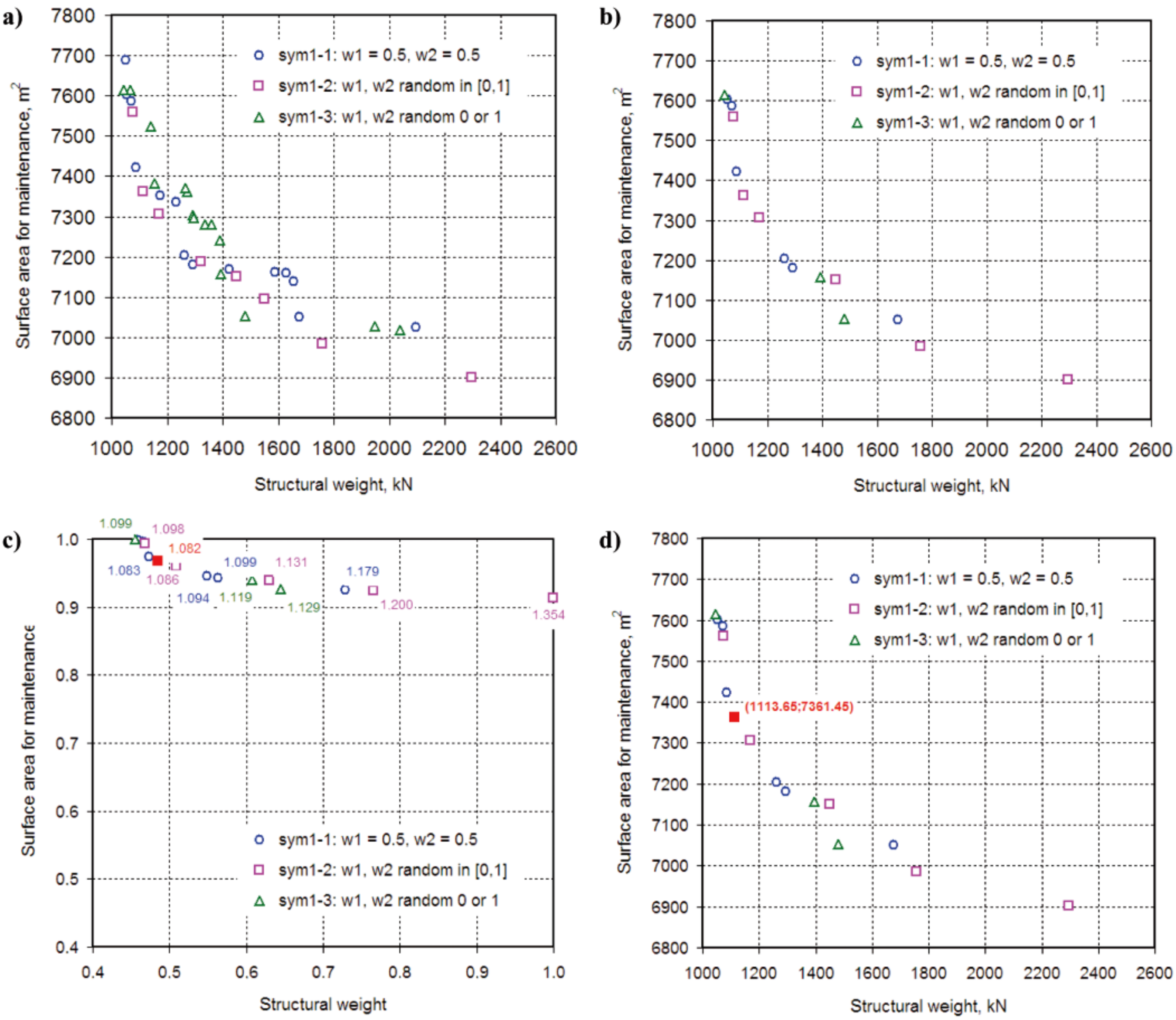

*Fig. 39. Selection of single, recommended solution of multi-objective optimization problem by using non-dominated solution sets obtained in the three series of computer simulations: **sym1-1**, **sym1-2**, **sym1-3**: **a)** temporary set composed of non-dominated solutions of each simulation, **b)** selection of non-dominated solutions in temporary set, **c)** determination of distance of non-dominated solutions from asymptotic objective in normalized objective space, **d)** values of optimization criteria for the found closest solution: $f_1(\mathbf{x})$ = 1113.65 kN and $f_2(\mathbf{x})$ = 7361.45 m²*

1) Let us remember that in the multi-objective optimization there is not the single best solution of the problem and the formulated recommendation should be treated as a subjective choice by a person taking decision.

can be roughly evaluated also by assuming that the number of solutions produced by a given algorithm, that is a part of set of non-dominated solutions obtained on the basis of results produced by all algorithms, Fig. 39, is a measure of algorithm effectiveness. In the examined example the particular simulations: sym1-1, sym1-2 and sym1-3 have brought respectively 6, 6 and 3 non-dominated solutions into set of non-dominated solutions. On this basis a conclusion may be suggested that the strategies of fixed values of the optimization criteria weight coefficients $\mathbf{w_1 = w_2 = 0.5}$ and random values of the weight coefficients $\mathbf{w_1}$ **and** $\mathbf{w_2}$ in the range [0, 1] show similar effectiveness whereas the strategy of random values of the weight coefficients $\mathbf{w_1}$ **and** $\mathbf{w_2}$ equal to **0** or **1** proved to be the least effective. The issue of examining the effectiveness of multi-objective evolutionary algorithm is very relevant and not fully solved hence it requires a separate research which exceeds however content of this case study.

The conducted analysis of computer simulation results of the problem of ship structure multi-objective optimization in question allows to state that in the studied cases the most effective strategies were the following: (1) that with random values of the weight coefficients $\mathbf{w_1}$ and $\mathbf{w_2}$ in the range [0, 1], and that with fixed values of the optimization criteria weight coefficients $\mathbf{w_1 = w_2 = 0.5}$. Less effective was the strategy with random values of the weight coefficients $\mathbf{w_1}$ **and** $\mathbf{w_2}$ **equal to 0** or **1**.

The recommended non-dominated solution was obtained for the values of design variables specified in Tab. 8. The corresponding dimensions of the ship cross-section are given in Fig. 40.

From the study of influence of dominance attributes and distance from asymptotic solution on the effectiveness of the algorithms of sym2-1, sym2-2 and sym2-3, also satisfactory results were achieved as follows:

$$\mathbf{f}^{\approx}_{\text{sym2-1}} = [1105.95\ 7345.11]^T \cdot [\text{kN m}^2] \Rightarrow$$
$$\Rightarrow f_{1,\text{sym2-1}}(\mathbf{x}) = 1105.95 \text{ kN},\ f_{2,\text{sym2-1}}(\mathbf{x}) = 7345.11 \text{ m}^2$$

$$\mathbf{f}^{\approx}_{\text{sym2-2}} = [1192.04\ 7327.41]^T \cdot [\text{kN m}^2] \Rightarrow$$
$$\Rightarrow f_{1,\text{sym2-2}}(\mathbf{x}) = 1192.04 \text{ kN},\ f_{2,\text{sym2-2}}(\mathbf{x}) = 7327.41 \text{ m}^2$$

$$\mathbf{f}^{\approx}_{\text{sym2-3}} = [1060.03\ 7485.93]^T \cdot [\text{kN m}^2] \Rightarrow$$
$$\Rightarrow f_{1,\text{sym2-3}}(\mathbf{x}) = 1060.03 \text{ kN},\ f_{2,\text{sym2-3}}(\mathbf{x}) = 7485.93 \text{ m}^2$$

In the case of necessity to identify a single solution from a series of simulations one can apply the earlier described procedure of aggregation of set of non-dominated solutions obtained in particular simulations and identify the non-dominated solution nearest the asymptotic solution.

The performed calculation investigations have positively verified the effectiveness of the combined fitness multi-objective evolutionary algorithm developed by this author, as well as the calculation tool built for solving the unified ship structure topology-size multi-objective optimization problem. Particular computer simulations have produced a dozen or somewhat more of non-dominated solutions which constitute the set of trade-off solutions from among which decision makers may choose one or more of them for further development. The algorithm developed as a part of the underlying work allows also to pinpoint a single variant closest to the asymptotic solution which may be proposed as a single solution of the multi-objective optimization problem.

Fig. 41 presents the comprehensive results of the multi-objective optimization of the ship hull structure: (1) general arrangement and main particulars of an example ship, (2) optimization criteria, (3) simulation main parameters and control variables, (4) values of optimization criteria for the obtained non-dominated variants, (5) values of optimization criteria for the variant closest to the asymptotic solution, and (6) structural dimensions and scantlings for this variant.

Tab. 8. *Values of design variables recommended as a result of multi-objective optimization*

No.	Symbol	Description	Value
1	x_1	serial No. of mezzanine deck plate	5
2	x_2	serial No. of mezzanine deck bulb	6
3	x_3	serial No. of mezzanine deck T-bulb	48
4	x_4	number of web frames	13
5	x_5	number of mezzanine deck stiffeners	29
6	x_6	serial No. of superstructure I plate	8
7	x_7	serial No. of superstructure I bulb	5
8	x_8	serial No. of superstructure I T-bulb	47
9	x_9	number of superstructure I stiffeners	5
10	x_{10}	serial No. of inner side plate	6
11	x_{11}	serial No. of inner side bulb	2
12	x_{12}	serial No. of inner side T-bulb	48
13	x_{13}	number of inner side stiffeners	21
14	x_{14}	serial No. of bottom plate	9
15	x_{15}	serial No. of bottom bulb	5
16	x_{16}	serial No. of bottom T-bulb	52
17	x_{17}	number of bottom stiffeners	16
18	x_{18}	serial No. of outer side plate	5
19	x_{19}	serial No. of outer side bulb	2
20	x_{20}	serial No. of outer side T-bulb	52
21	x_{21}	number of outer side stiffeners	30
22	x_{22}	serial No. of wet deck plate	8
23	x_{23}	serial No. of wet deck bulb	6
24	x_{24}	serial No. of wet deck T-bulb	51
25	x_{25}	number of wet deck stiffeners	36
26	x_{26}	serial No. of main deck plate	10
27	x_{27}	serial No. of main deck bulb	1
28	x_{28}	serial No. of main deck T-bulb	46
29	x_{29}	number of main deck stiffeners	26
30	x_{30}	serial No. of superstructure II plate	8
31	x_{31}	serial No. of superstructure II bulb	5
32	x_{32}	serial No. of superstructure II T-bulb	47
33	x_{33}	number of superstructure II stiffeners	5
34	x_{34}	serial No. of upper deck plate	10
35	x_{35}	serial No. of upper deck bulb	1
36	x_{36}	serial No. of upper deck T-bulb	48
37	x_{37}	number of upper deck stiffeners	36

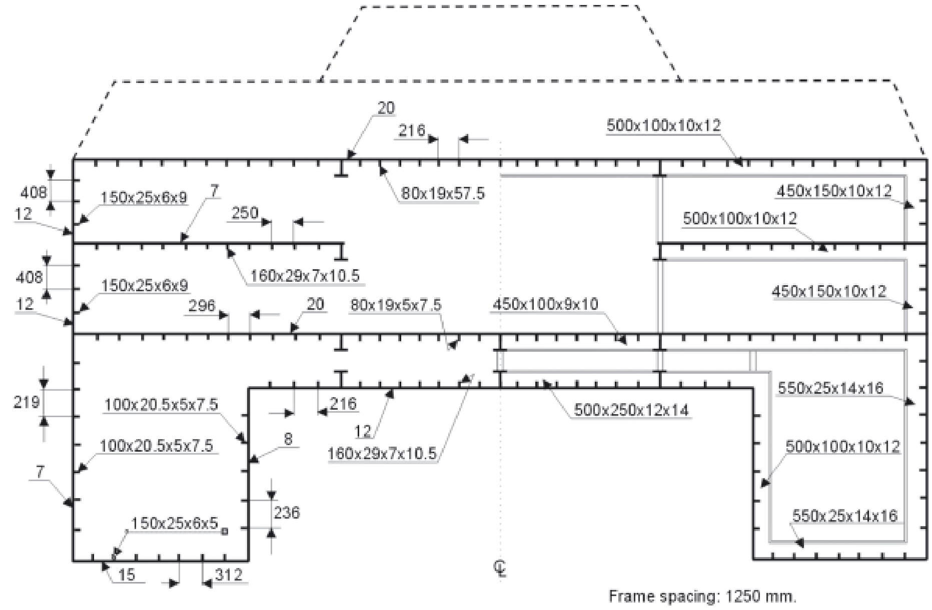

Fig. 40. *Ship structural dimensions and scantlings recommended as a result of multi-objective optimization; structural material: for plates - 5083-H111 Al alloy, for profiles - 6082-T6 Al alloy*

PERFORMANCE ASSESSMENT OF THE DEVELOPED MULTI-OBJECTIVE OPTIMIZATION ALGORITHM

The question should be answered if the proposed combined fitness multi-objective evolutionary algorithm (Eq. 28) is more efficient than the evolutionary algorithms used in the process of selection of only optimization criteria (in the form of scalar substitute optimization criteria) and functions representing the degree of constraint violation (Eq. 8). Unfortunately the answer cannot be simple and unequivocal.

In practical problems the ship structural multi-objective optimization which produces a set of Pareto-optimum solutions may be very computation time-consuming or even impossible to be performed. In the cases the evolutionary algorithms of multi-objective optimization do not guarantee identification of Pareto-optimum compromises but can help identifying a satisfactory approximation, i.e. a set of solutions hoped to be not too far distant from searched front of optimum solutions (in the sense of Pareto). However in this case methods are necessary to evaluate how good produced solutions of formulated problems are. And, this leads to the question: how to compare effectiveness of different algorithms? In the context of the presented work the question may be formulated as follows: how to compare effectiveness of the studied evolutionary multi-objective optimization of ship hull structure, assumed for different evaluation strategies of fitness function.

In the case of the evolutionary algorithms of multi-objective optimization, statistical in their nature, evaluation of obtained results and comparison of effectiveness of optimization algorithms implementing different strategies is a very difficult task, arousing much controversy and misunderstanding. Whereas visual and qualitative comparison of the sets approximating Pareto front is commonly used for deduction of quality of evolutionary multi-objective optimization, in the case of quantitative methods the searching of proper standards are just under way [Knowles, Thiele, Zitzler (2006)].

Generally accepted procedures enabling to compare quality of solutions obtained by different algorithms (usually in many runs) or solutions of the same algorithm obtained in many runs, quantitatively taking into account their statistical characteristics are necessary [Sarker, Coello Coello (2002)], [Knowles, Thiele, Zitzler (2006)].

The problem is extremely difficult also because in this case, as opposed to single-objective optimization, it is necessary to compare not individual solutions, but vectors representing sets of non-dominated solutions under assumption that they are an approximation of a practically unknown set of Pareto-optimum solutions, referred to as a front of Pareto-optimum solutions. In consequence, most comparative studies are based on different methodologies and assumptions, and therefore results obtained from such studies are difficult to be used in mutual comparisons [Knowles, Thiele, Zitzler (2006)].

In the case of single-objective optimization the selection of quality measure is obvious and simple: optimization criterion. The quantity is unequivocally defined, optimization criterion value calculated for every test solution, and smaller or greater depending on the task, which corresponds to better solution. In the case of multi-objective optimization it is not clear what „better" means: is it that located closer to the front of optimum solutions, covering a wider range of solution characteristics, or something else? And, it should be realized that the front of Pareto-optimum solutions is unknown. That is why it is difficult to define proper quality measure for approximations of an unknown front of Pareto-optimum solutions. Therefore for comparing and evaluating results of qualitative evaluation of multi-objective evolutionary algorithms, graphical presentation of obtained non-dominated solutions has been first of all used until recently [Veldhuizen (1999)].

In recent years in this field a certain progress has been made and several papers concerning the quantitative comparing of different approximations of Pareto-optimum set can be found. The most popular is the unary quality measure, i.e. that which attributes, to every single approximation set, one numerical value which reflects a specified quality aspect [Veldhuizen, Lamont (2000)], [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2002)]. To increase the deducing strength the unary quality measures are usually used jointly, to cope of taking into account different aspects of the notion of "quality". Other methods are based on binary quality measures which assign numerical values to pairs of solutions, [Zitzler, Thiele (1998)], [Hansen, Jaszkiewicz (1998)].

Third group of evaluation methods, completely different in conceptual respect, is the method of attainment function,

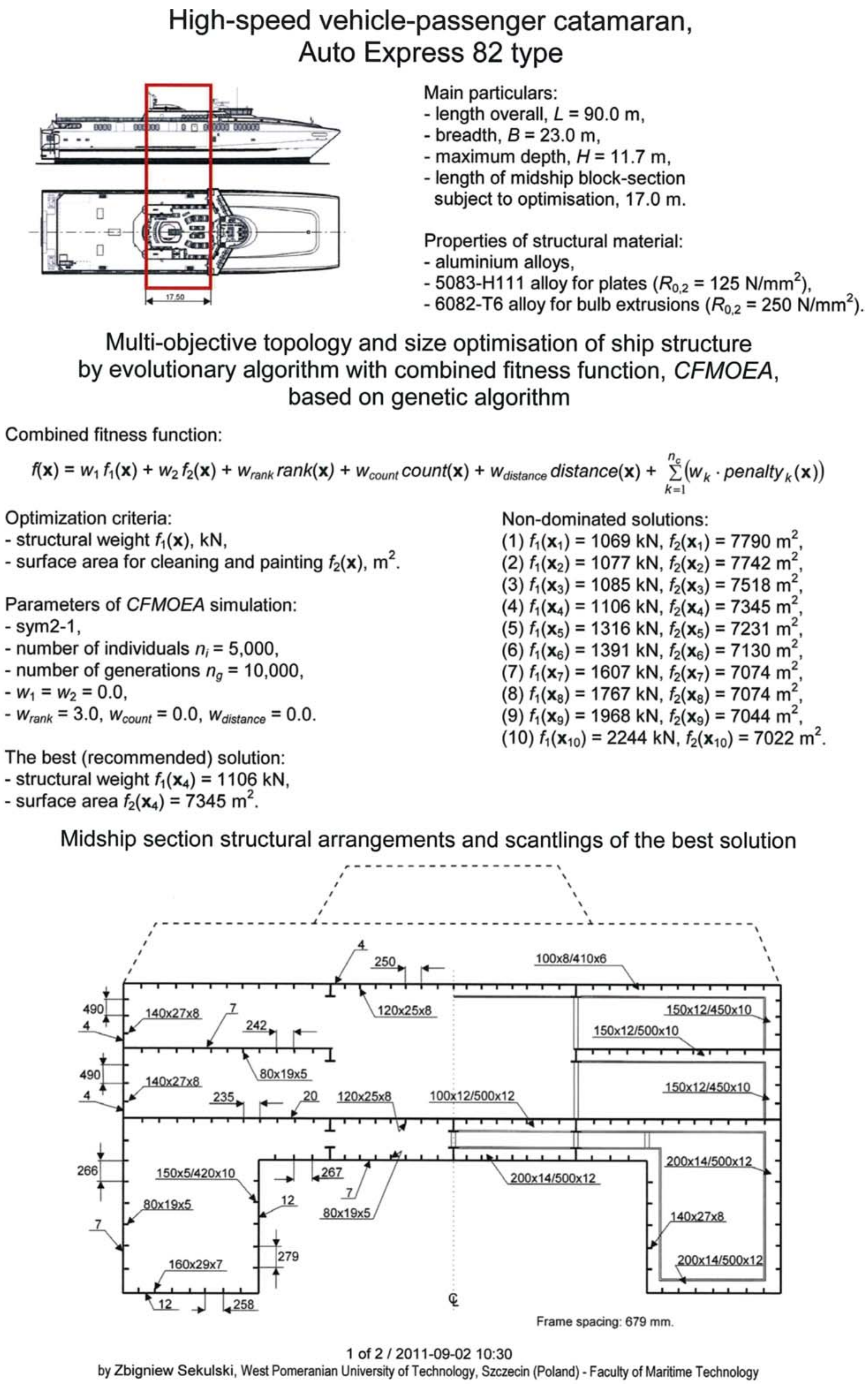

Fig. 41. *Result of the multi-objective evolutionary optimization of the ship structure with respect to the structural weight f_1 and surface area of structural members for maintenance (cleaning and painting) f_2 (sym2-1)*

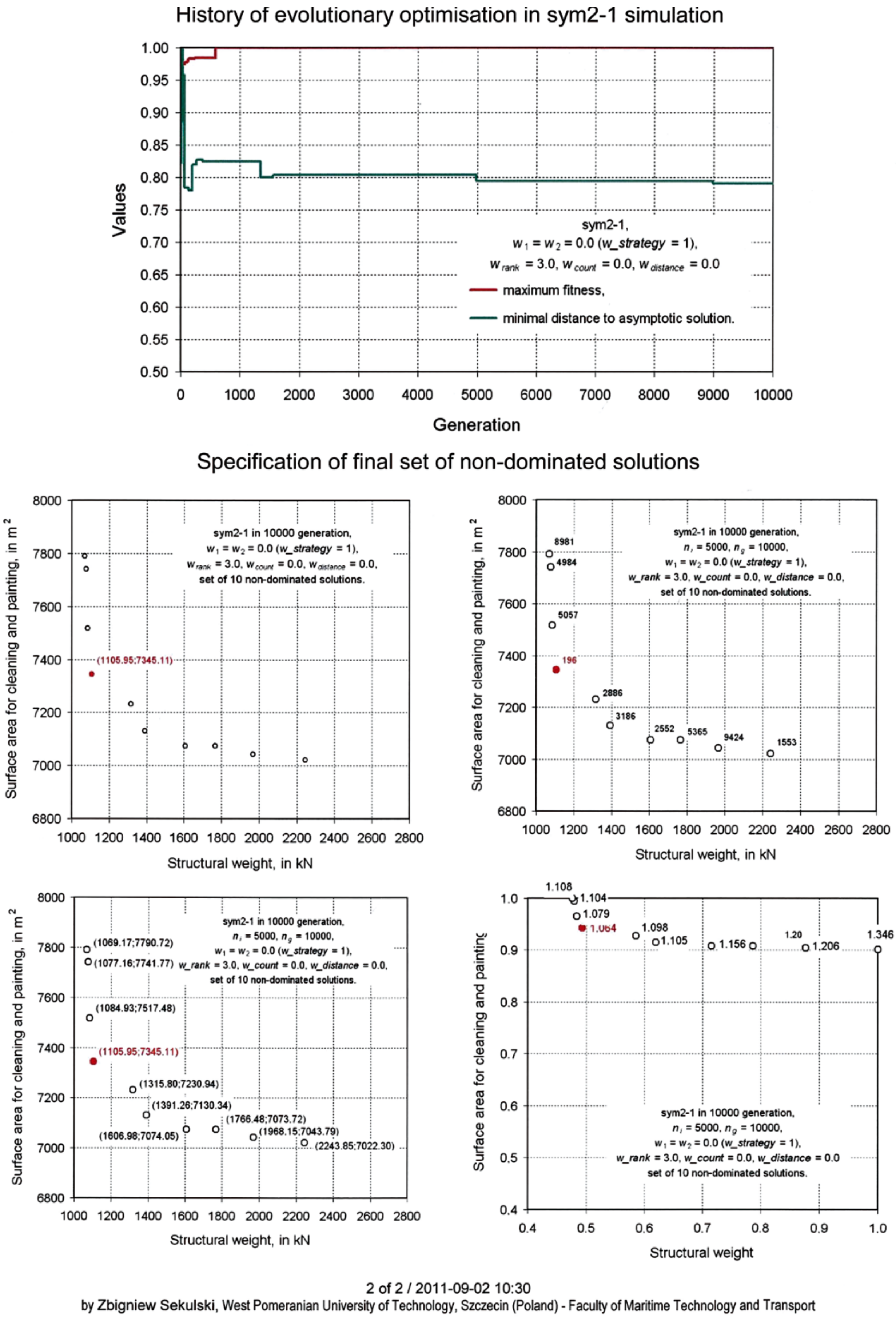

Fig. 41 cont. *Result of the multi-objective evolutionary optimization of the ship structure with respect to the structural weight f_1 and surface area of structural members for maintenance (cleaning and painting) f_2 (sym2-1), which contains: evolution of the highest value of fitness function and the lowest value of non-dominated solution distance from asymptotic one; structure of the set of non-dominated solutions; number of generations in which particular non-dominated solutions were found; detailed structure of the set of non-dominated solutions; structure of the set of non-dominated solutions in normalized objective space*

[Fonseca, Fleming (1996)], in which the probability of achieving any chosen objectives in evaluation space is assessed on the basis of the knowledge of many approximation sets.

Besides the above mentioned diversity of methods it is still unclear what mutual relations of certain quality measures are like (what is their mutual connection) and what their relative advantages and disadvantages are [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2002)]. In consequence there are no agreed opinions stating which quality measure or measures should be used in specific cases [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2002)].

To define a reliable evaluation methodology is very important for its application to algorithm validation. However, as far as the problem of multi-objective optimization is concerned there are several reasons due to which it is difficult to evaluate obtained results. Firstly, from evolutionary algorithms many solutions are obtained instead of only one, usually as many as possible solutions belonging to the set of non-dominated solutions, approximation set of Pareto-optimum solutions, are aimed at. Secondly, evolutionary algorithms are stochastic, therefore for effectiveness evaluation it is necessary to run many simulations and subject obtained results to statistical analysis; in this case drawn conclusions will also have stochastic characteristics. Thirdly, we may be interested in measuring different aspects of quality; for example, we may be more interested in possessing a robust, but slower, algorithm convergent to Pareto front practically in every case, than in a faster algorithm but convergent to Pareto front only occasionally (in case of specific types of tasks); we also may be interested in evaluating behaviour of evolutionary algorithm in the course of simulation, trying to determine its capability of maintaining diversity and gradual convergence to set of solutions close to Pareto front. This short discussion shows how difficult is to develop effectiveness measures for multi-objective optimization evolutionary algorithms.

The next problem in the discussion is the question: what should be measured? It is very important to determine what kind of results will be subjected to measurement, evaluation and analysis, and to define quality measures according to a task.

It is obvious that in the formulating of a good quality measure for multi-objective optimization evolutionary algorithm the following should be considered [Zitzler, Deb, Thiele (1999)]:

1. the minimizing of distance between approximation of Pareto front, obtained by the algorithm, and a real Pareto-optimum front of solutions, (of course if so is known, what in practice of optimizing engineering objects does not happen),
2. the maximizing of diversity of obtained non-dominated solutions, i.e. the arranging of non-dominated solutions in approximation set over empirical compromise area, as smoothly and homogeneously as possible,
3. the maximizing of number of solutions in the set which approximates the Pareto-optimum set. [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2002)], [Zitzler, Laumanns, Bleuler (2002)], [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2003)], [Fonseca, Knowles, Thiele, Zitzler (2005)], [Knowles, Thiele, Zitzler (2006)] presented the most extensive (in the author's opinion) review of problems related to evaluation of effectiveness of randomized multi-objective optimization algorithms. Assuming that a set of incomparable solutions (called an approximation set), is a result of operation of multi-objective optimization evolutionary algorithm, they proposed a mathematical basis for studying multi-objective optimization effectiveness algorithms.

In particular [Zitzler, Thiele, Laumanns, Fonseca, Grunert da Fonseca (2002)] showed that if we have two sets of solutions, a and B, which approximate Pareto-optimum set of solutions, then we cannot elaborate a finite set of quality measures, which can indicate if the approximation a of Pareto-optimum set is better that the approximation B, in every case. Elaborated quality measures may be applied only to specific aspects of the quality concept, therefore the only thing left to deduct is that the approximation a is not worse that the approximation B, which means that either the approximation a is better than the approximation B, or the approximations a and B are incomparable with regard to a specified quality measure. This statement cannot be generalized in a way indicating that the approximation a is always better than the approximation B. So if it is impossible to state in a close and exact quantitative way the supremacy of one approximation set over the other, therefore it is impossible to state the supremacy of one algorithm over the other. Choice of one of them is determined by the efficiency in every specific case it was used.

[Sarker, Coello Coello (2002)] made a review of propositions they considered the most important and enabling to measure the three above listed aspects of the notion „quality", subjected to evaluation. They also observed that there is no method that would allow to measure the three aspects with one value only. Unfortunately, attempts to elaborate a single measure for grasping them together have not been successful so far because they concern very different algorithm characteristics. That is why the attempts to reduce them to one measure may lead to misunderstandings. Therefore the using of different quality measures to estimate different aspects of algorithm behaviour seems more proper in practice[2)].

On the basis of visual assessment of approximating sets attained in particular simulations, Fig. 42, it can be stated that the best solutions, i.e. approximation sets, were obtained in the simulations: **sym**2-1 ($w_1 = w_2 = 0.0$, $w_{rank} = 3.0$, $w_{count} = 0.0$, $w_{distance} = 0.0$), sym1-2 (w_1, w_2 are random in the range [0, 1], $w_{rank} = 0.0$, $w_{count} = 0.0$, $w_{distance} = 0.0$) and sym2-3 ($w_1 = w_2 = 0.0$, $w_{rank} = 0.0$, $w_{count} = 0.0$, $w_{distance} = 3.0$). Solutions obtained from the simulations are arranged the most uniformly, hence they can be expected to be a good representation of searched Pareto-optimum front. In the case of the remaining simulations: sym1-1 ($w_1 = w_2 = 0.5$, $w_{rank} = 0.0$, $w_{count} = 0.0$, $w_{distance} = 0.0$), sym1-3 (w_1, w_2 are random 0 or 1, $w_{rank} = 0.0$, $w_{count} = 0.0$, $w_{distance} = 0.0$) and sym2-2 ($w_1 = w_2 = 0.0$, $w_{rank} = 0.0$, $w_{count} = 3.0$, $w_{distance} = 0.0$), the found solutions are arranged less uniformly, hence they represent Pareto-optimum front in a worse manner. Therefore it can be approximately stated that out of six conducted research simulations the following were found more effective: the simulation (1) that took into consideration influence of dominance attribute, i.e. dominance rank, the simulation (2) that took distance of the asymptotic solution into consideration, and the simulation in which the selection process is controlled only by optimization criteria. Less effective were found the simulations (4) and (5) in which selection process was controlled only by optimization criteria, the simulation (6) that took into consideration the influence of dominance attribute, i.e. dominance count. Thus in the group of more effective strategies there were two simulations which use the combined fitness and one simulation which realizes the strategy of random combination of objective function without

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2) Let's notice that fulfillment of mentioned algorithm quality aspects can be considered as multi-objective task of algorithm optimization (optimizer).

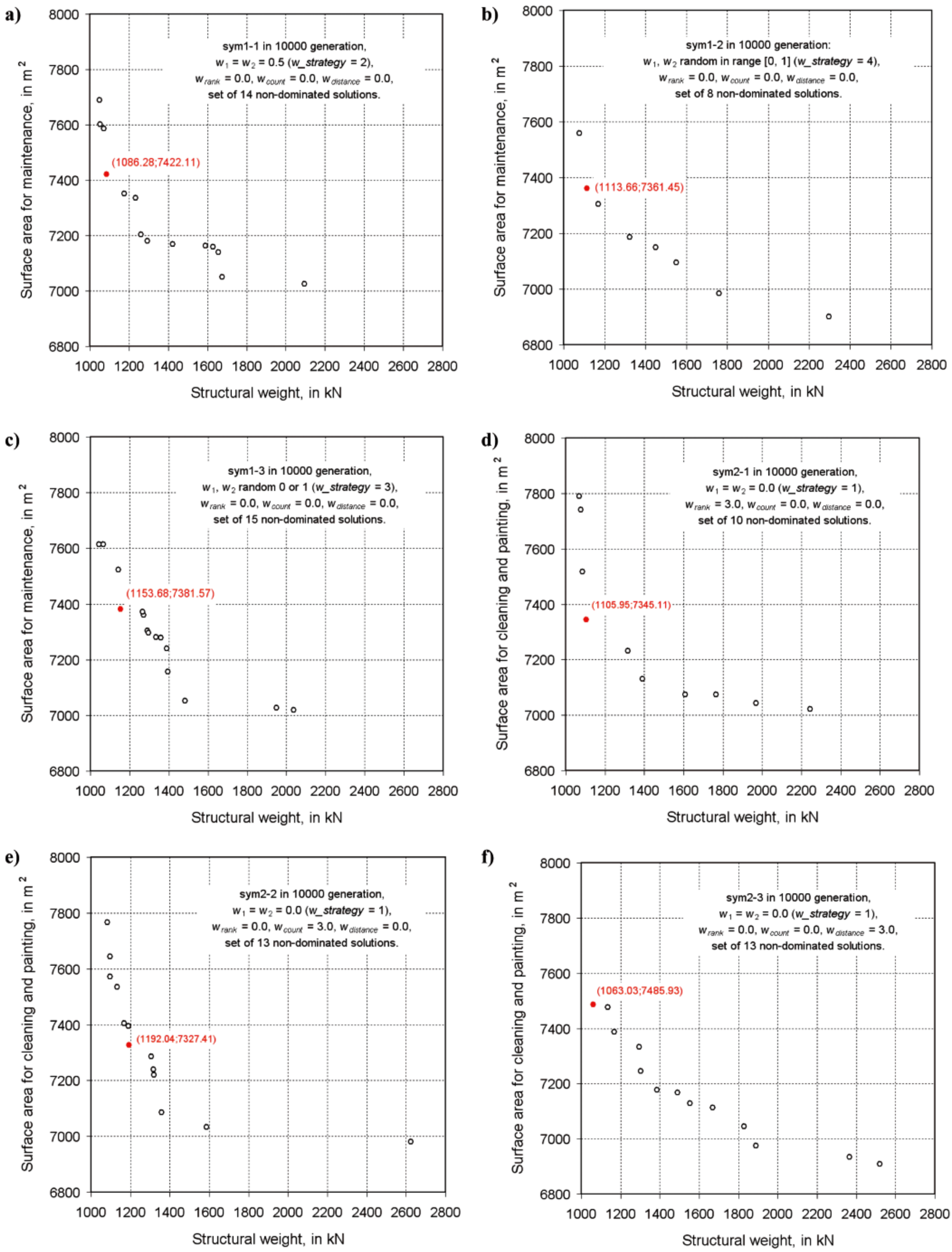

Fig. 42. *Specification of the sets of non-dominated solutions obtained during the performed genetic multi-objective optimization simulations of ship structure with respect to the structure weight f_1 and the surface area f_2; black circles represent non-dominated solutions, red dots represent non-dominated solutions closest to the asymptotic one*

taking into consideration domination attributes. On the basis of such superficial quality analysis can be proposed the statement that the combined fitness multi-objective optimization algorithm can be a more efficient strategy for multi-objective optimization of ship structure than scalarization of objective function strategy, without taking into consideration domination attributes in selection process.

The conducted series of computer simulations confirmed efficiency of the developed computational algorithm and computer program for solving the formulated unified problem of topology and optimization of ship structure dimensions. As a result of the calculations, were elaborated approximations of the set of Pareto-optimum solutions which in particular contain simulations of non-dominated solutions, from several to a dozen or somewhat more in number. The obtained results do not allow to unequivocally determine superiority of any examined strategies of fitness function evaluation. For formulating more detailed quantitative conclusions further systematic statistical studies performed on much larger number of samples, are necessary.

In the case of ship structure optimization the problem of efficiency assessment of elaborated algorithms is additionally complicated by the necessity of formulating many constraints and including them to the fitness function. In the task considered in this publication forty constraints were assumed. The constraint represented in optimization model in the form of proper components of penalty function, $n_c = 40$, very strongly limit solution space available for searching; this way they also distort image of influence of the assumed fitness function computing strategies on algorithm convergence and the quality of attained solutions and therefore on the efficiency of the studied algorithms.

From practical point of view it is interesting to notice which of the formulated constraints appears active in optimization process and which does not. In the first case to allocate large computational outlay to control them is justified. In the other case such outlay may appear useless from the point of view of effectiveness of optimization process and in some cases it is possible even to resign from controlling them. In the case of the optimization model used in this work the constraints in the form given by the inequality (21) concerning the required section moduli values of web frames in the three structural regions: side outboard region, bottom region and wet deck region, appeared active. In the case of the remaining constraints dealing first of all with the required thickness values of plates and dimensions of frames, the formulated constraints are satisfied with a large excess.

The final conclusion can be formulated as follows: one cannot formulate a finite number of quantitative measures which allow putting in order the set of Pareto-front approximating sets in relation to the quality, and therefore one cannot formulate objective quality/efficiency measures of the proposed multi-objective optimization evolutionary algorithms. Thus one cannot prove objectively and unequivocally the supremacy of one of the algorithms proposed and discussed in this work or realization strategies of one of them. It depends on a potential user whether he / she would consider the presented concept interesting, elaborate its computer realization and finally verify its efficiency in his / her specific case.

SUMMARY AND CONCLUSIONS

The problem of minimization of weight and total surface area of the complete three-dimensional midship block-section of the high- speed catamaran hull was presented and discussed in detail. The strength criteria for checking ship structure were taken from the selected classification rules. The calculation tool for solving the formulated unified problem of the multi-objective optimization of topology and scantlings of the sea-going ship hull structure was developed with the accuracy typical for the preliminary design stage.

The application of the genetic algorithm concept to solve the formulated optimization problem was presented. In the study it was proved that the genetic algorithm allows to include, in the multi-objective optimization model, a large number of design variables of real ship structure. The introducing of constraints related to strength, fabrication and standardization is not difficult and may cover a more representative set of criteria.

The aggregation method was proved effective even in the case of the fixed values of the weight coefficients since in the case of the constrained problem the components of the penalty function introduce a random influence to the fitness function. The method is thus closer to that based on the random weight coefficients of the optimization criteria.

This author has discussed crucial role of Pareto domination relation in process of evolution of feasible solutions for ship structure towards Pareto-front containing non-dominated variants of the ship structure. Using the concept of d omination in the set of feasible solutions this author has proposed his own definitions of the concept of domination rank as well as domination count, enabling this way to take into account relation between a feasible variant and other feasible variants. Basing on the ideas the author has proposed an evolutionary algorithm for solving the problem of topology-size multi-objective optimization of hull structure of sea-going ship, which uses, in selection process, the combined fitness function which allows taking into account, in selection process, the following items: (1) optimization criteria, (2) dominance attributes, (3) distance to the asymptotic solution as well as (4) penalty functions for violating assumed constraints. The computational program which makes it possible to perform ship structure multi-objective optimization with an accuracy appropriate for preliminary design stage, was elaborated. By using the tool and elaborated computational model of hull structure, series of computer simulations were conducted for the fast catamaran passenger-vehicle ferry of Auto Express 82 design. The results of the performed computations and subsequent discussion gave reasons for the statement that the elaborated algorithm may be considered an efficient tool for multi-objective optimization of ship structures in the preliminary design stage.

It should be remembered that the developed multi-objective optimization algorithm is based on the random processes therefore the obtained results should be interpreted in the statistical sense. It means that the simulations and their results may appear sometimes not representative. a slight change of the developed models or control parameters may result in a different course of simulation and lead to different results. In this context further systematic studies on algorithm efficiency controlled by a particular component of combined fitness function, are necessary.

Further systematic investigations of effectiveness of the proposed strategies, including repeated computations different to each other only by evolution history, aimed at statistical confirmation of the effectiveness, are deemed necessary.

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