DESIGN FOR SAFETY WITH MINIMUM LIFE-CYCLE COST

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ABSTRACT

The paper outlines an approach to multidisciplinary ship design via a software platform maintaining a holistic view on the overall ship quality. The platform integrates design and first-principles design evaluation tools that estimate performance indices of risk, costs, earnings and ship functionality. The platform has built-in mechanisms that determine dominant design parameters, derive parametric models and perform gradual optimisation of constantly updated response surfaces, thus guiding designers towards cost-effective design solutions. The applications aspects and results of the platform are also presented here.

Keywords: *cost, design, holistic, platform, risk, multi-disciplinary, multi-objective, integration*

1. BACKGROUND

Traditionally, ship design has not purely been engineering endeavour but it has also involved comprehensive business, economical and social studies, among others prompting in the process, intense consultations between all stake holders of a future vessel. The latter sets design requirements and constraints representing the input to the technical side of the ship design iterations also referred to as the design “spiral” (Gale, 2003) .

In the ship design “spiral” the ship designers move through the design process in a number of steps, each dealing with a particular synthesis or analysis task. After all the steps have been completed, the design is unlikely to be balanced (or even feasible). Thus, a second cycle begins and all the steps are repeated. Typically, a number of cycles (design iterations) is required to arrive at a satisfactory solution. This process is not sequential, unless the design is entirely developed by one person.

Although modern design methods are capable of producing very good designs, these designs are unlikely to be optimal. This is because the actual process requires a great deal of design time and thus designers are unable to explore the complete design solution space. Moreover, without being able to recognise the effects of slight modifications on the design all at once, designers may adversely affect other design requirements while concentrating on a particular design aspect. Lastly and more importantly, with safety being treated as a constraint rather than a design objective, meeting safety requirements cost-effectively is left to chance. The implications of this are twofold:

- The safety level of the vessel might not be as expected; the level of safety associated with most of prescriptive regulations is largely unknown (explicitly)
- The safety of the vessel might have costed more than it should, have the right trade-offs taken place, this in turn might have led to reduced earnings and to a less competitive design

These are particularly true for new design concepts or design concepts incorporating innovative features for which operational experience is very limited or does not exist at all. Attaining safety objectives cost effectively and the potential for increased profitability have led to the introduction and implementation of risk-based design. In simple terms, risk-based design (RBD) is a goal-based design process incorporating multi-disciplinary, multi-objective performance verification in which explicit safety criteria are among the design goals. Hence, the intuitively appealing approach to RBD has been a software platform that integrates design and design evaluation tools under one umbrella, allowing to instantly reflect design changes in all design objectives considered.

The current market offers a number of such platforms of which most distinctive are VIP (Wu, Duffy et al., 2007), ANSYS EKM[1], NOESIS OPTIMUS[2] and ENGINEOUS iSIGHT[3]. These integration platforms have primarily focused on tool integration, which is the only prerequisite for formal design optimisation. Hence these platforms are rather optimisation platforms of which structure of the integrated process (e.g., no. of design parameters) is predetermined. However in practice this structure is dynamic because design describing information grows with iterations, Figure 1.

Therefore, the design process must be regarded as a *dynamic optimisation problem* that should be readdressed every time when new design data becomes available. This should not be confused with *dynamic programming* but seen as a *greedy algorithm* (Black, 2005) that follows the methodology (see Subsection 2.2) of making the locally optimal choice at each design stage in order to gradually converge to some satisfactory solution.

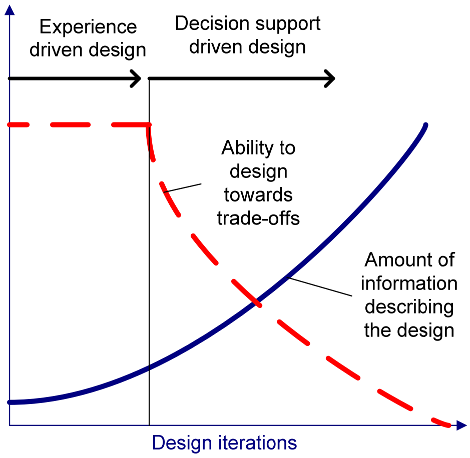


Figure 1. Design complexity vs. ability to deliver trade-off solutions.

It is worth noting that design by experience is efficient and effective only until a point when the design complexity is still manageable by a group of designers, see Figure 1. In this context the term *manageable* refers to a situation when design spiral iterations lead to trade-off solutions. With increasing number of design parameters the degree of freedom of a designed object raises exponentially, according to S^N law. Here S corresponds to the number of states a design parameter has (for continuous parameters S is theoretically infinity) while N stands for the actual number of design parameters. Thus for example, an introduction of two additional discrete parameters (e.g., size of two circular openings) with five options coming from a manufacture, will multiply the total degree of freedom by 5^2 and rise design complexity by an order of magnitude. In this context the term *degree of freedom* refers to the number of design variants that can be produced by altering states of design variables.

[1] *www.ansys.com/Products/ekm.asp*
[2] *www.noesissolutions.com*
[3] *www.engineous.com/products.cfm*

Bearing in mind the above, SAFEDOR has developed an integrated design platform for risk-based design, setting a primary focus on a design environment as such and making sure that tool integration and design facilitation are addressed. The following subsections give an overview of key features of the SAFEDOR platform (SP), skipping those pertaining to tools integration that are common to other platforms.

2. CONCEPT

2.1 Achieving holism

In simple terms, the holism is achieved by providing an interface for monitoring the reflection of any design changes in resultant variations of all design objectives. Figure 2 illustrates the principle of holism, indicating that a design change made in design tools (e.g., NAPA) is propagated down to design evaluation tools that produce safety, costs, earnings and functionality measures. Additionally, links amongst design objectives (state parameters) are also maintained, thus helping to understand and make use of the correlation between them (see Subsection 3.2).

In summary, the SAFEDOR platform implements holism by

- integrating tools, maintaining data transfer and process control,
- publishing design and state parameters and
- visualising design iterations and providing access to associated data.

Tool integration. The implementation of tool integration, data management and process control derives from the earlier work in VIP (Wu, Duffy et al., 2007) and brings in new features like management of dynamic input/output. A mechanism for preparation of simple scripts takes care of it. This allows maintaining links amongst tools of which input/output is changing over time. CFD codes of which output content is based on convergence characteristics of internal algorithms is a case in point. Such CFD codes are used for functionality or safety (e.g., fire simulation) analysis.

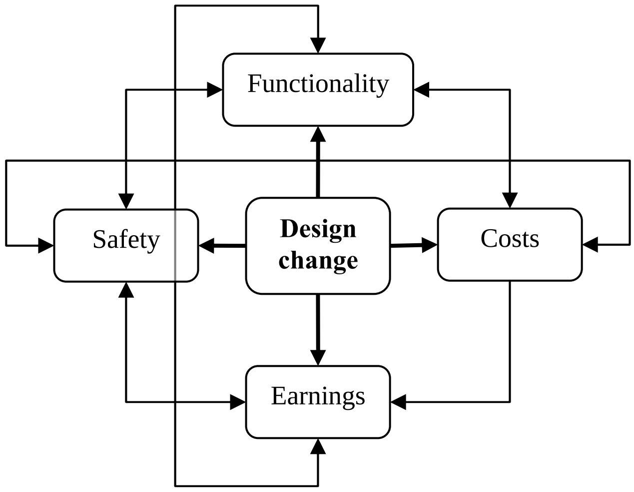


Figure 2. Interpretation of the holistic view.

Parameter publishing. Tools integration allows performing design spiral activities and hence generating design data. The publishing of this data for further manipulation in the SAFEDOR platform is called *parameter publishing*. In simple terms, the platform automates the access to design data, brining them in one place whereat they can be easy analysed and manipulated. The automated and scripting-based implementations of parameter publishing are available.

Visualisation. Data, usually quantitative, generated over design iterations and then published for further analysis are typically strongly scattered and difficult to use for comparison of different design variants or any other qualitative analysis. Therefore, they must be mapped into another level and presented in a more lucid way. Figure 3 exemplifies the way of comparing design variants in terms of tree design objectives. These design variants are all Pareto optimal solutions, hence equal in terms of these three design criteria. Additionally, a user can instantly access data (e.g., first-principles analysis files) associated with any design version. Other graph types are also available with the platform.

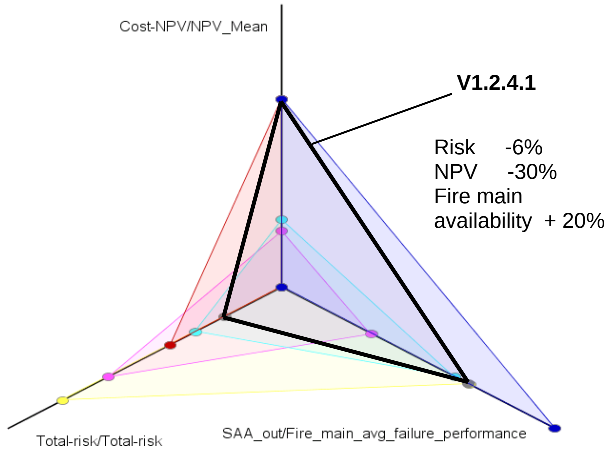


Figure 3. Example trade-off design variants. The highlighted design is compared to the initial design.

2.2 Design towards trade-offs

The features outlined in the preceding sub-section are prerequisite for monitoring the design process and, by comparing various design variants, ensuring that the actual design is a best compromise. The question of how to achieve that compromise is answered in this subsection.

As shown in Figure 1, the exponentially increasing design complexity indicates that the design by experience become ineffective. Instead, data analysis and decision making support mechanisms are necessary. To this end, the platform implements the following

- suggestion of a right direction towards improvement in all design objectives,
- sensitivity analysis towards determination of dominant/critical design parameters,
- derivation of response surfaces and
- gradual multi-objective optimisation of response surfaces.

Estimation of the right direction. The technique analyses previous design iterations and estimates the next design change that would potentially lead in the direction of desired design objective values. This technique is practical when there is no much data about the design sensitivity to design variables yet. This contrasts with statistical methods discussed in the following paragraphs as they are effective only when there is enough data to derive correlation trends from.

The right design direction (a vector) is expressed as needed changes in design parameters. Specifically, the design direction $\Delta\mathbf{x}$ is expressed as

$$\Delta\mathbf{x} = \mathbf{x}_i - \mathbf{x}_j = \begin{Bmatrix} x_{1i} - x_{1j} \\ x_{2i} - x_{2j} \\ \vdots \\ x_{ni} - x_{nj} \end{Bmatrix} \quad (1)$$

where n is the total number of design variables published, $i, j = 1, 2, 3, \dots K$ for $i \neq j$ and K as the number of design iterations/versions made so far. The problem here is to find such i and j that make $\Delta\mathbf{x}$ lead towards pre-set design goals and not diverge from them. This is done by analysing all the combinations of i and j and choose the one that maximises the following dot product

$$\max_{i,j}\left[(\boldsymbol{\phi} - \mathbf{c}) \cdot \left(\mathbf{f}(\mathbf{x}_i) - \mathbf{f}(\mathbf{x}_j)\right)\right] \quad (2)$$

where $\boldsymbol{\phi} = \left(f_1^*, f_2^*, f_3^*, \dots, f_m^*\right)^T$ is a point/vector of specific target values for all design objectives, $\mathbf{c} = \left(f_1(\mathbf{x}_c), f_2(\mathbf{x}_c), \dots, f_m(\mathbf{x}_c)\right)^T$ is a current design solution to be advanced towards $\boldsymbol{\phi}$ in terms of objective values f_i, for $i = 1, 2, \dots, m$. The right side of the dot product in (2) yields the difference between $\mathbf{x}_i$ and $\mathbf{x}_j$ in terms of design objectives. Graphically the presented technique is shown in Figure 4.

Figure 4 shows a case of five design variants of which the third one is considered as a starting point for next iterations. The two design objectives, risk and cost, are minimised towards pre-set target values, which can be expressed as percentages of initial values. The fifth and first design variants are the solution for (2) and hence if we apply $\Delta\mathbf{x}$ (1) to the third variant we may move towards the target in the direction shown as the grey arrow (potential move). The grey arrows connecting design variants with each other indicate the search algorithm goes through all point pairs until the one maximising (2) is found[4].

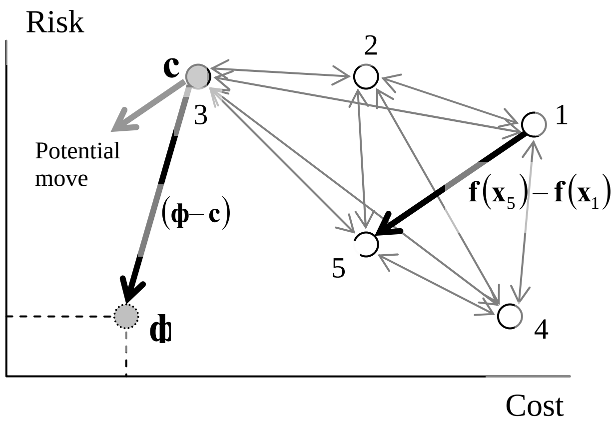


Figure 4. Illustration of the search for the right change in design parameters.

Sensitivity analysis. The purpose of sensitivity analysis (SA) is to determine dominant or critical design variables with respect to resultant variations in design objectives considered. It is rather obvious that this kind of analysis is crucial because its outcome is often not intuitive, provided the number of parameters describing a ship concept.

In the SAFEDOR platform implements the sampling-based SA (Helton and Johnson et al., 2006) where the sampling per se is performed (1) manually by designers while altering design parameters or (2) automatically by running design of experiments. Then each design variant corresponds to a sample (an observation) containing unique design variables and related design objective values. This allows applying statistical techniques measuring the strength and significance of correlation amongst parameters. Currently, partial Spearman correlation coefficients are calculated, following by tests on statistical significance against the null hypothesis of no correlation. The significance level is chosen arbitrary, although $\alpha = 0.05 - 0.1$ has been used.

Dominant design parameters are determined automatically, reflecting new changes in the design. The actual procedure of statistical analysis has been implemented as an external script written in language R. Language R is a scripting approach to R Project for Statistical Computing[5]

Response surface analysis. The determination of dominant design parameters sets a basis for further statistical analysis of the design problem at hand. In particular, the multivariate regression analysis or response surface analysis is of great interest to expressing relationships as closed form equations.

As with determination of dominant parameters, response surfaces for selected state variables are derived on the fly. Users of the platform can also choose when the response surfaces are to be updated. The procedure of response surface derivation has also been implemented as an external script written in language R.

Gradual optimisation. Once response surfaces have been updated they are composed into a multi-objective optimisation problem. An optimisation result is a set of Pareto designs that are candidate solutions and should be further analysed against their feasibility.

Figure 5 demonstrates the concept of gradual optimisation that delivers solutions of which closeness to the real optimum is stipulated by amount of design data available. As derivation of response surfaces follows some saturation points (P_i in Figure 5) in terms of new design data, then the response surface optimisation delivers corresponding local

[4] $\sum_{i=1}^{K-1} 2(K-i)$ - the number of combinations.

[5] http://www.r-project.org/

optima, $\mathbf{x}_1^*, \mathbf{x}_2^*, \ldots \mathbf{x}_k^*$, to be considered by designers. It is intuitive that as k grows, the closer becomes $\mathbf{x}_k^*$ to some real optimal solution $\mathbf{x}^*$. Formally,

$$\lim_{k\to\infty} \mathbf{x}_k^* \cong \mathbf{x}^*. \qquad (3)$$

An illustration of the gradual optimisation is shown in Figure 6. The figures illustrates a case of two design objectives, flooding risk and building cost, varied over the number of bulkheads. The optimal solution for these two objectives problem is denoted as $\mathbf{x}^*$ and it is close to the intersection of the two curves.

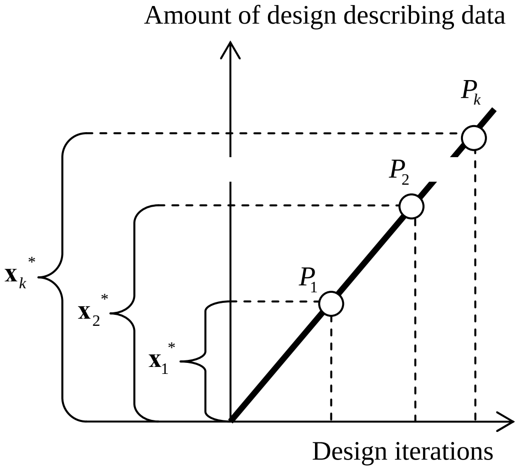


Figure 5. Solutions of gradual local optimisation.

Note, the both risk and cost curves are not real curves although exhibit typical shapes when estimating the cost and flooding risk for variable number of transversal bulkheads.

Initially there is a situation when only two initial points, $\mathbf{x}_1$ and $\mathbf{x}_2$, (two variants of the number of bulkheads) are known. Then linear response surface, $f(\mathbf{x}_1, \mathbf{x}_2)$, is derived based on these points to represent the variation of flooding risk; a response surface for the cost has the same shape as the linear cost curve and hence not shown here.

Optimisation of response surface $f(\mathbf{x}_1, \mathbf{x}_2)$ yields first optimum $\mathbf{x}_1^*$, which corresponds to $\mathbf{x}_3'$—a local optimal number of bulkheads. Then the second optimal solution $\mathbf{x}_2^*$ for the number of bulkheads is found, based on the response surface $f(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3)$ (linear form, again) enriched with new data.

The new local optimum corresponds to $\mathbf{x}_4'$ and has additionally advanced towards global optimum $\mathbf{x}^*$. The gradual optimisation procedure is so repeated until a found local optimum is satisfactory enough.

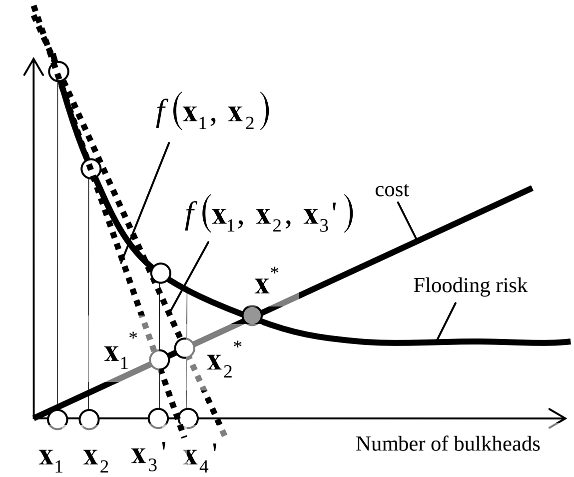


Figure 6. Cost vs. flooding risk optimisation with two local solutions.

The technique of gradual optimisation of response surfaces has analogy with *stochastic approximation methods* (Robbins, and Monro, 1951) that attempt to find zeroes or extrema of functions which cannot be computed directly due to lack of data. The comparison of the both methods is a subject of future work.

2.3 Design Methodology

The features implemented in the SAFEDOR imply a design methodology to be followed when working with the platform. Figure 7 outlines such a methodology, indicating the decision support options that have been introduced.

The presented decision support options have their own user graphical interfaces that ease their application. The next section presents a case study of platform application, outlining results achieved for subdivision design.

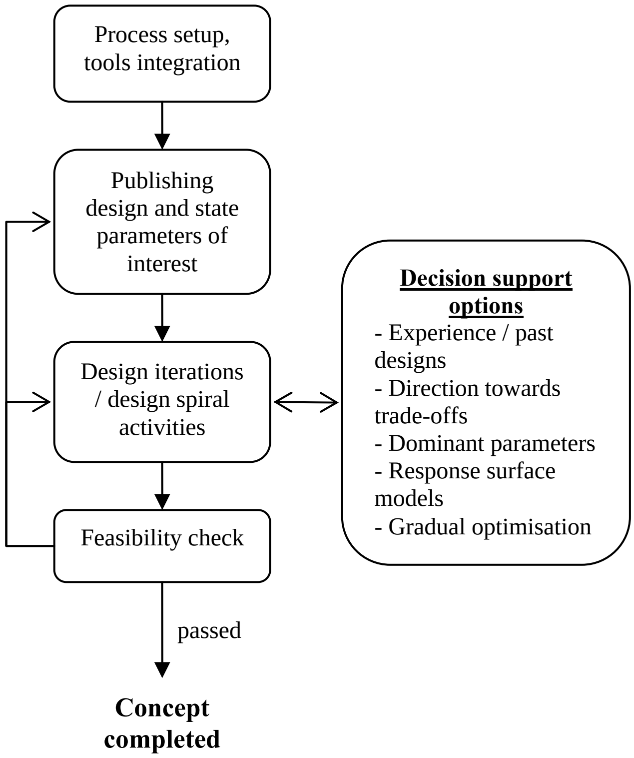


Figure 7. Summary of decision support options available with the SAFEDOR platform.

3. CASE STUDY

The case study outlined below concerns about subdivision design of a cruise liner. The study case is not exhaustive, aiming at demonstrating the sensibility of the gradual optimisation technique (see Subsection 2.2) in the first place.

3.1 Problem statement

Design of watertight subdivision is driven by three design objectives:

- building cost,
- total risk (safety level) and
- failure performance of the fire main system.

Building cost is estimated using an approximate cost model developed at SSRC. The cost model is a function of main particulars, number of bulkheads (N_{BT}) and openings, spaces areas etc., as shown in (4). In principle, the cost is a linear function of its parameters.

$$C = f\left(L_{BP}, D, B, C_B, \ldots, N_{BT}, N_O, A_i \ldots\right) \quad (4)$$

The total risk is estimated according to the methodology by Jasionowski and Vassalos (2006) and stands for the expected number of fatalities from flooding and fire accidents. The risk from flooding is estimated by combining simulation of passenger evacuation by HELIOS (Majumder, Vassalos et al., 2005) and first-principles flooding simulation by Proteus3 (Jasionowski, 2001). The expected number of fatalities from a fire accident is estimated by zone model-based simulations of fire, followed by evacuation simulation in HELIOS. The methodology is comprehensively presented by Guarin et al. (2004).

The failure performance of the fire main system, Figure 8, is implicitly estimated by post-accident systems availability analysis software HELIOS-SAVANT (Vassalos et al., 2009), developed by SSRC under SAFEDOR.

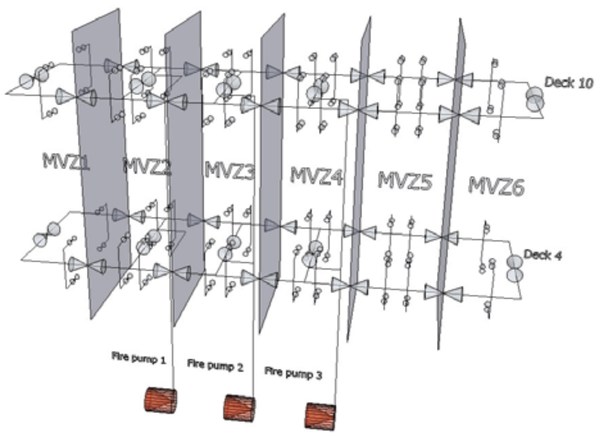


Figure 8. Schematic representation of the fire main system.

The failure performance is derived from calculation results shown in Figure 9 and expressed as

$$F_{FM} = 2 \cdot \max\left(P_{MZ,i}\right) - \min\left(P_{MZ,i}\right) \qquad (5)$$

where $P_{MZ,i}$ is failure probability within main vertical zone i, for $i = 1, 2, \ldots, 6$. By seeking a minimum of (5) the independence of fire main components installed in different zones is increased, while simultaneously reducing the failure probability of the whole system.

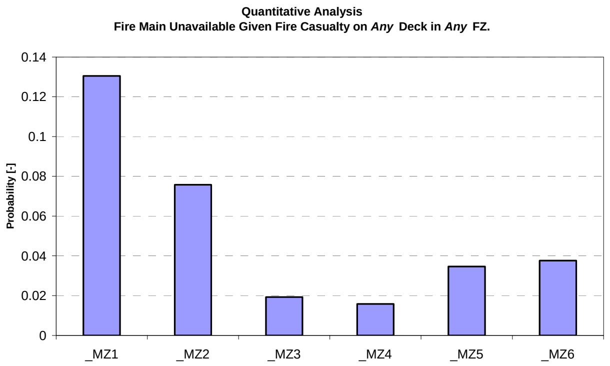
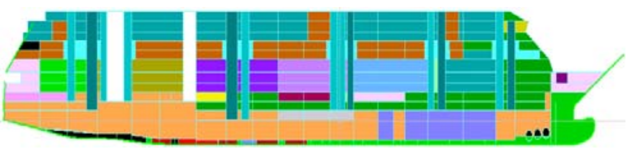


Figure 9. Fire main failure probabilities give a fire accident within any A-class compartment (Vassalos et al., 2009). The abscise axis stands for main vertical zones, the ordinate axis shows the corresponding failure probabilities.

The naval architecture tool NAPA[6] has been used to develop a ship model that included a subdivision and a superstructure with deck layouts, Figure 10. The ship model is a copy of an operating cruise liner of which details are not further disclosed, due to confidentiality reasons.



100,000 GT
3,500 pax
Lbp 266.23 m
Loa 298.816 m
Beam 32.2 m
Draft 8 m

Figure 10. Used cruise model and its main particulars.

[6] *www.napa.fi*

The design process began by arbitrary placing transversal bulkheads and further moving them forward and back to arrive at an initial subdivision index “A” of 0.733. Each variation of bulkhead positions has been stored as a separate design variant within a database linked to the SAFEDOR platform.

The variation of design parameters was automatically propagated down to integrated design evaluation tools that delivered total risk, building cost (4) and fire main failure performance (5) values for each variation. This formed an initial data set that has further been used for sensitivity analysis, derivation of response surfaces and gradual local optimisation. The next subsection discusses the outcome of this design exercise.

3.2 Application results

The application results are presented graphically as variation curves for all three design objectives, preceding by corresponding variation of index “A” in Figure 11.

In total, eleven design iterations have been performed of which one, V-1.2.4.1, is based on optimisation results of response surfaces. The response surfaces of linear form were derived based on seven points generate arbitrary, they correspond to designs V-1 to V-1.2.4.

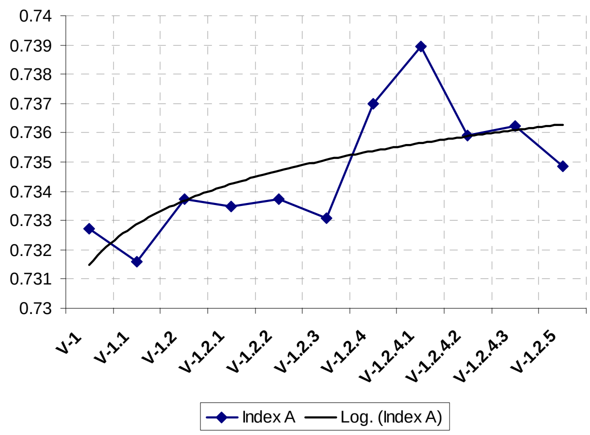


Figure 11. Variation of attained subdivision index “A” over design iterations.

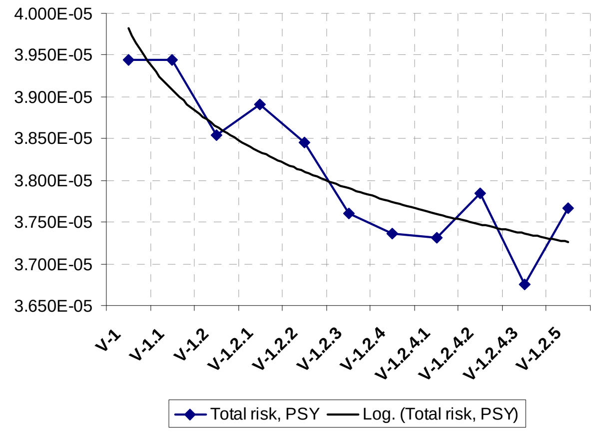


Figure 12. Variation of total risk (per ship year) over design iterations.

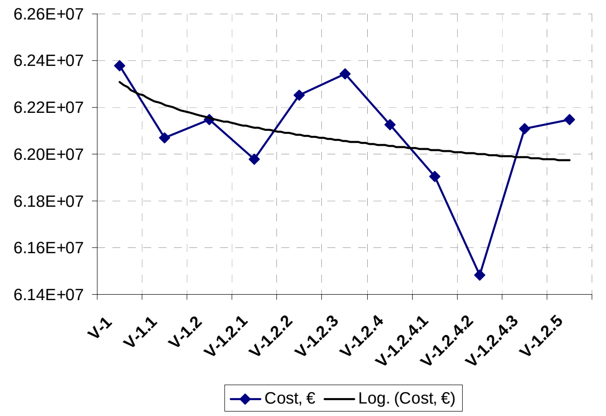


Figure 13. Variation of building cost (€) over design iterations.

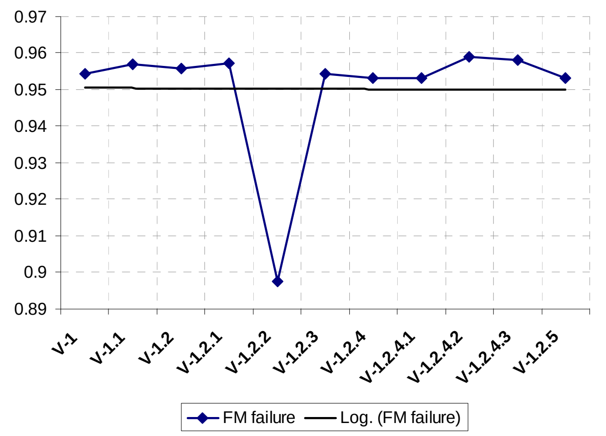


Figure 14. Variation of failure performance of the fire main system over design iterations.

The trends in Figure 12 and Figure 13 show that risk and cost are creeping down while the failure performance of the fire main system is only slightly affected. The solution of optimisation, V-1.2.4.1, causes a peak in index "A" as well as descents in all three design objectives.

It is worth noticing the strong correlation between index "A" and the total risk, as shown Figure 15. Hence by optimising either of them independently, the other is also improved. This is at least true locally, provided that the total risk includes the flooding risk component.

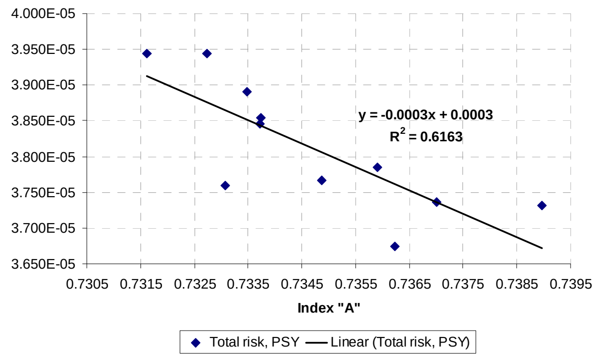


Figure 15. Correlation between index "A" and the total risk (per ship year).

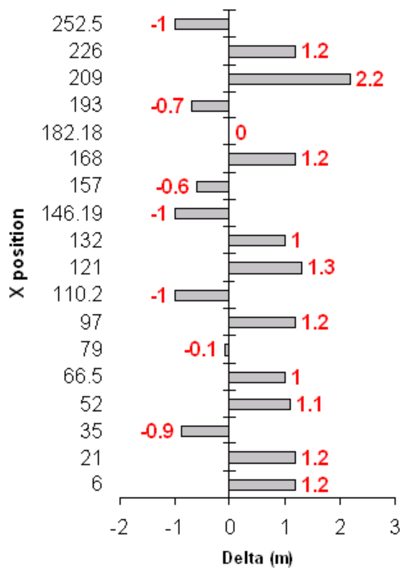


Figure 16. Changes in transversal bulkhead positions needed to migrate from version V-1 to version V-1.2.4.1.

All performed design iterations, except V-1.2, are Pareto optimal solutions and it is up to a designer to decide which one is to be a starting point for next iterations. In the actual case we have chosen the design obtained through optimisation of response surfaces, that is V-1.2.4.1 as it has the highest index "A" value as well as favourable rates for the design objectives, in view of initial design V-1. Figure 16 compares design variables, positions of transversal bulkheads, of initial and new designs.

4. CONCLUDING REMARKS

The presented SAFEDOR platform is a multi-disciplinary design tool on its own. It possesses features of optimisation platforms (e.g., modeFRONTIER7, OPTI-SLANG8) and brings in innovative functionally that captures the dynamics of a design process. As a result, incremental improvements through design optimisation becomes a secondary purpose of the platform, while the primary one is design from scratch towards trade-offs or cost-effective concepts.

The platform provides design decision support, which is based on statistical data analysis and gradual local optimisation of response surfaces. This allows making sure that majority of design iterations lead to improvement in all design objectives.

Gradual optimisation of response surface proves effective for design of subdivision, deck layouts and functional elements. However, this approach is resultant only at later design stages, when there is enough data to derive parameter correlations from. Therefore, another technique that suggests a design direction potentially improving all design objectives should be used initially.

The model of Risk Control Option (RCO) has not been implemented explicitly. Instead, due to the possibility to compare design variants in terms of cost/risk ratio, design changes that lower the ratio can be considered as RCOs therefore.

The platform has a flexible architecture enabling new data mining and design decision support modules to be accommodated in the near future.

[7] *www.esteco.com*
[8] *www.cadfem.de*

5. ACKNOWLEDMENTS

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