OPTIMIZATION OF DAMAGE STABILITY CHARACTERISTICS IN RO-RO PASSENGER SHIP DESIGN

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ABSTRACT

A procedure for optimization of Ro-Ro passenger ship damage stability characteristic has been developed based on probabilistic damage stability analysis and particle swarm algorithm. The main aim of the present study is to investigate the effectiveness of subdivison in Ro-Ro passenger ship design in the view of risk assessment to improve safety standards. The optimum arrangement is compared with initial structure and alternatives. The results and insights of present work are given in depth in the final part of the study.

Keywords: Ro-Ro passenger ship; Damage stability; Risk; Probabilistic assessment; Optimization

1. Introduction

In recent years, various approaches have been introduced to improve operational safety of ships. The risk assessment studies show that applied decisions in the design phase of ships have widespread impacts on operational safety of ships. One of these studies is SAFEDOR EU project which was completed in 2009 [1]. A risk-based regulatory framework was created as an output of that project.

Goal based/risk based design approach is particular design methodology to decrease operational risks in the design phase [2]. Ship design process has multidisciplinary and multi criteria decision environment. Stability one of the important disciplines in the design process about safety of ship. A ship can face with intact and damage situations during the operation. Ship stability calculations have been contained in time. Preliminary approaches for damage stability calculations had deterministic concepts but now, probabilistic calculations are developed based on deterministic concepts and these calculations are more inclusive and suitable for risk assessment, safety and design.

Subdivision of ship is the important design decision in the damage stability calculations. Arrangement of subdivisions allows to improve safety of ship in the damage condition. Making a decision for the most suitable subdivision is the one of the critical design problems in ship design. This is a kind of optimization problem and it can be solved by using design exploration framework.

Boulogouris, Papanikolaou and Zaraphonits tried to optimize the arrangements of Ro-Ro passanger ships by using genetic algorithm as one of the early examples in this area [3]. Turan and Cui improved the learning capacity of classical genetic algorithm by using a reinforcement learning based hybrid evolutionary algorithm [4]. This study reduced the runtime of optimization study effectively by using hybrid approach. Then, Puisa, Tsakalakis and Vassalos investigated the nature of functional dependency between the subdivison index and bulkhead position to reduce uncertainty and solution time in the subdivison optimization study [5].

The present paper is based on research work of STABRISK/GOALSOS research group within the preliminary studies and presents the results of the enhanced design exploration framework for the subdivision of Ro-Ro passanger ships. The framework includes probabilistic damage stability tool and particle swarm optimization algorithm, and also it achieves the minimization of capsize risk in damage condition by increasing attained index of probabilistic damage stability calculations. In this study, particle swarm algorithm is proved as a new approach for this subject.

In the following sections of paper the details of the damage stability calculations are given in Section 2. Mathematical background of the problem, framework set-up and optimization algorithm are presented and discussed in terms of risk based design in Section 3. Results of case study for the Ro-Ro passenger ship design are shared in Section 4. Finally the conclusions obtained from the study are included in Section 5.

2. Damage Stability

Damage stability calculations can be divided into two approaches as deterministic and probabilistic. For both approaches, the damage stability calculations normally are made according to the method of lost volume or lost buoyancy. Deterministic approach gives the floodable length after damage situation and it ignores numerous uncertainties such as damage location, loading conditions, environmental conditions etc. On the other hand, probabilistics approach assesses the probability of survival of a ship in the most dangerous flooding hazard by taking into account uncertainties simplifying to the worst case.

The current damage stability regulations are shared in Table 1. New harmonized rules, MSC.216(82) that entered into force on January 1st 2009.

Passenger vessels pre-2009	Deterministic
Safe return to port regulations	Deterministic
Damaged stability requirements - Type A/B vessels (pre-2009)	Deterministic
The Stockholm agreement	Probabilistic
SOLAS damaged stability rules post-2009	Probabilistic

Table 1. Stability regulations in use

	Probabilistic	**Deterministic**
Damage cases	Free	Fixed
Number of damaged spaces	Pre-determined	Fixed
Damage size	Variable	Fixed

Table 2. Probabilistic vs. deterministic comparison

The concept of probabilistic damage stability measures the probability that stability after flooding is sufficient to prevent capsize due to loss of stability and heeling moment. It contains contributions of all possible damage cases from a compartment to group of adjacent compartments. Attained subdivision index (A) for single compartment or group of adjacent compartments involves various probabilities shared below.

$$A_c = \sum_{1}^{i=t} p_i, s_i, v_i \tag{1}$$

- A_c – Attained index for particular loading condition
- i – Damage or damage zone under consideration
- t – Number of damages that has to ve investigated
- p - Probability that only the compartment or the group of compartments under consideration may be flooded, disregarding any horizontal subdivision.
- v - Probability that the damage will not exceed a given height above the waterline.
- s - Probability of survival after flooding the compartment or the group of compartments under consideration (IMO, 2006a).

Transverse, horizontal and longitudinal watertight subdivisions specifies the probability of flooding in the three-dimensional damage extension situation. Transverse and longitudinal extents of damages are limited to size of compartment and maximum vertical extent of damage above waterline is 12.5 m in the regulation.

Statistical part of damages originates from the study of Lutzen [6], and it gives the probabilistics effects of different damage parameters by utilizing cumulative distributions obtained from real worlds measurements.

Factor p_i can be calculated for one damaged zone only by using formula,

$$p_i = p(x_{1j}, x_{2j}) \cdot [r(x_{1j}, x_{2j}, b_k) - r(x_{1j}, x_{2j}, b_{k-1})] \tag{2}$$

Where

$$r(x_1, x_2, b_0) \tag{3}$$

while the symbols denoted represent:

j - the aft most damage zone number involved in the accident, starting with number 1 at the stern.

k - the number of a particular longitudinal bulkhead functioning as a barrier for transverse penetration, counted from the shell towards the centre line (k = 0 for the shell).

x_1 - distance from the aft end (terminal) of the ship to the aft end of the zone in question.

x_2 - distance from the aft end (terminal) of the ship to the forward end of the zone in question.

b - mean transverse distance in metres measured from the shell to the longitudinal barrier in question.

$p(x_1, x_2)$- accounts for the probability of the considered longitudinal damage extent. $r(x_1, x_2, b)$- a probability factor accounting for the transverse damage extent. IMO, 2006).

The reduction factor r was determined by the following formula:

$$r(x_1, x_2, b) = 1 - (1 - C) \cdot \left[1 - \frac{G}{p(x_1, x_2)}\right] \tag{4}$$

where:

$$C = 12 \cdot J_b \cdot (-45 \cdot J_b + 4) \tag{5}$$

$$J_b = \frac{b}{15B} \tag{6}$$

The factor s_i, probability of survival after flooding can be calculated by using formula;

$$s_i = minimum\{s_{intermediate,i} \ or \ s_{final,i} \cdot s_{mom,i}\} \tag{7}$$

$$s_{intermediate,i} = \left[\frac{GZ_{max}}{0.05} \cdot \frac{Range}{7}\right]^{1/4} \tag{8}$$

$$s_{final,i} = K \cdot \left[\frac{GZ_{max}}{0.12} \cdot \frac{Range}{16}\right]^{1/4} \tag{9}$$

$$K = \sqrt{\frac{\theta_{max} - \theta_e}{\theta_{max} - \theta_{min}}} \tag{10}$$

In 55th Session of the IMO SLF sub-Committee,the s factor was changed for the final equilibrium for damages involving the Ro-Ro deck.

$$s_{final,i} = K \cdot \left[\frac{GZ_{max}}{0.20} \cdot \frac{Range}{20}\right]^{1/4} \tag{11}$$

$$s_{mom,i} = \frac{(GZ_{max} - 0.04) \cdot Displacement}{M_{heel}} \tag{12}$$

The factor v_m shall be obtained from the formula;

$$v_m = v(H_{j,n,m}, d) - v(H_{j,n,m-1}, d) \tag{13}$$

where:

$(H_{j,n,m,d})$ is the least height above baseline, in metres

d is the draught..

Detailed explanation of formulas can be found in MSC.216(82).

Attained subdivision index, A (IMO, 2014) should be calculated as:

$$A = 0.4A_s + 0.4A_p + 0.2A_l \tag{14}$$

A_s – Attained index at depeest subdivison draught.
A_p – Attained index at partial subdivison draught.
A_l – Attained index at light service draught.

These calculations should be done for deepest, partial and light service condition. Each index is a sum of the contribution of all damage cases. This is the probabilistic concept of calculations. The partial indices are not to be less than 0.9R for passanger ships. R is the required index, and also total attained index should be higher than R.

$$A \geq R \tag{15}$$

IMO rules for passanger ships

Required index for passanger ships;

$$R = 1 - \frac{5000}{L_s + 2.5N + 15255} \tag{16}$$

where:

N = N1 + 2N2
N1 = number of persons for whom lifeboats are provided
N2 = number of persons (including officers and crew) the ship
is permitted to carry in excess of N1.

In summary, inputs of probabilistic damage calculations are;

- Loading conditions
- Subdivisions
- Openings and key points
- Zones set up
- Global settings related to formulas

And outputs are attained index of compartments, partial conditions and total.

3. Optimization procedure

3.1 Mathematical background

General purpose of an optimization problem is to find variables that give the maximum or minimum values of objective functions. Objective function represents the mathematical response of our purposes in the problem. The formulation of optimization problem can be defined:

$$\max\{f_1(x)\} \tag{17}$$

subject to,

$$g_j(x) \leq 0, \qquad j = 1, \dots, M \tag{18}$$

$$x = (x_1, x_2, \dots x_n) \tag{19}$$

The problem is a constrained single optimization problem. Also, Variables have lower and upper bounds.

3.2 Parametric model

Investigated framework was applied to Ro-Ro model which can be seen in Fig.1. Also, the ship's main particulars are given in table 1. A generic model was created for the internal watertight arrangement, based on 14 design variables in global x, y and z coordinates. The hull form of the vessel and draughts are kept constant during the optimization. Vertical position of double-bottom and decks are design variables so a proper relationship is defined between vertical center of gravity and design variable in z direction.

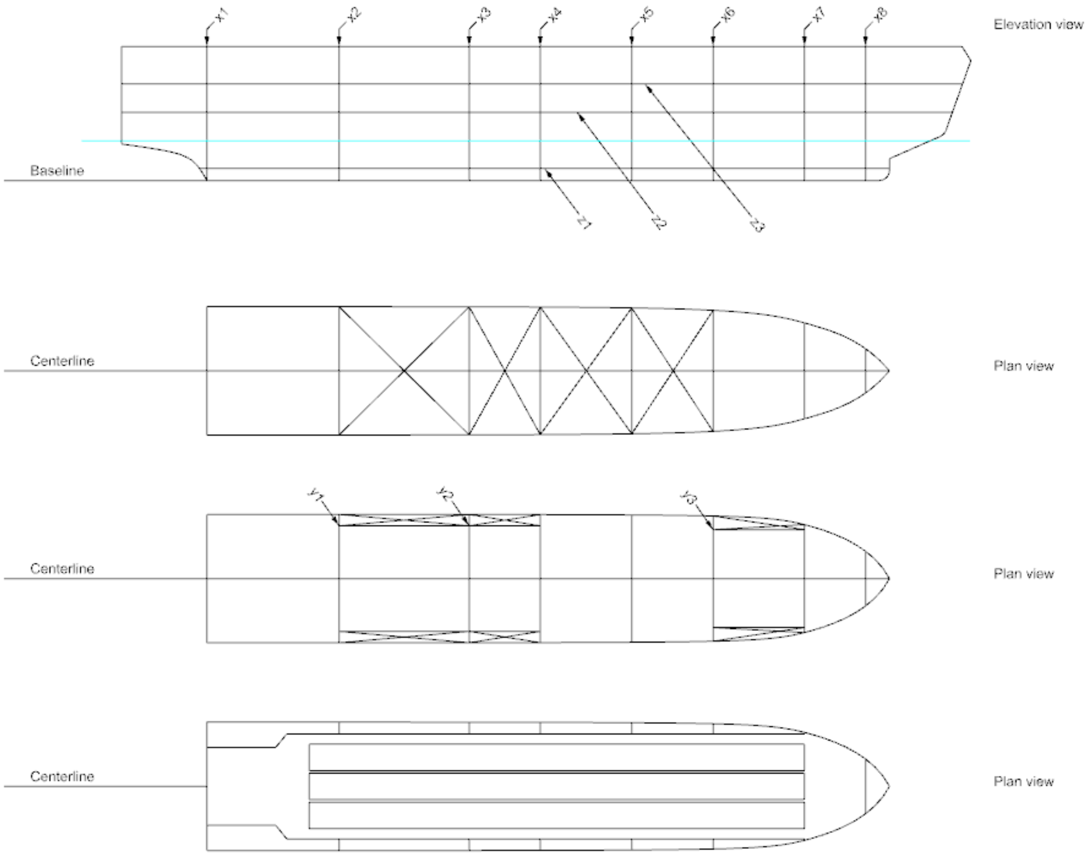
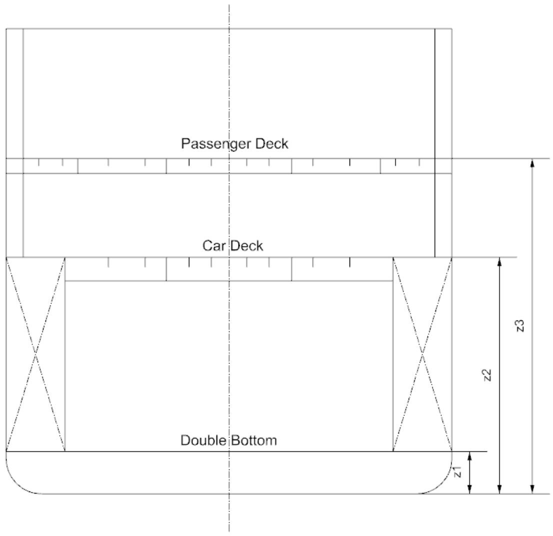


Figure 1. Ro-Ro general arrangement and parametric design variables



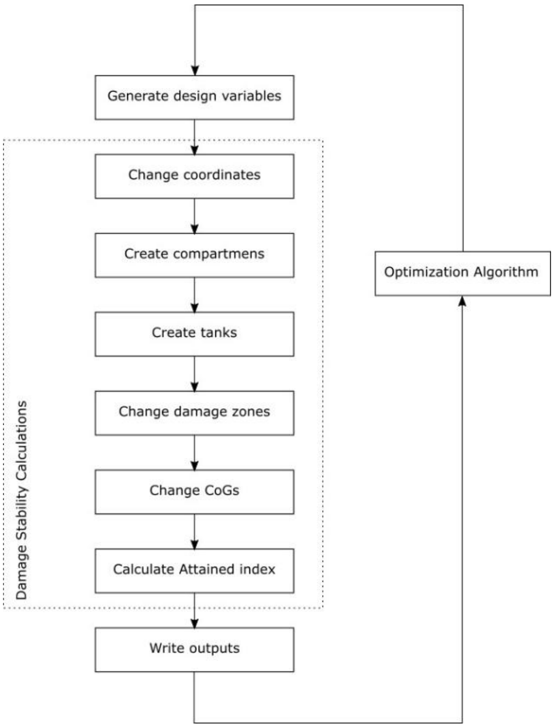


Figure 2. Typical mid-ship section and vertical design variables

Figure 3. Flowchart of optimization procedure

Number of bulkhead is kept constant so the structural weight variation is ignored because of low differences. Center of gravity is changed by using a weight function. No down-flooding openings are modeled in the study. The permeability of the machinery space is set equal to 0.85, for the accommodation spaces is 0.95 and the rest of the Ro-Ro compartments are set equal to 0.90.

3.3 Objective function

The main objective of this study is to enhanced survivability of the Ro-Ro vessel by maximizing the attained subdivision index. The design variables of objective function are global coordinates of watertight bulkheads. In the end, result of damage stability calculation is the value of objective function for the global optimization algorithm. The flowchart of the procedure that integrates global optimization algorithm and damage stability calculations is shown in Figure 3.

3.4 Particle swarm algorithm

The Particle Swarm Optimization algorithm (PSO) is a kind of population-based stochastic global search algorithms. The PSO algorithm is generally suitable for complex black-box non-linear optimization problems. The PSO algorithm was first introduced by Kennedy and Eberhart [7] and its basic idea was originally inspired by simulation of the social behavior of animals like bird flocking, fish schooling etc. Each member of population shares individual knowledge when population search food and it is the natural process of group communication. If any member can find out the food, the rest of population will follow inherently.

In PSO, each member of the population is called a particle and the population is called a swarm. Food means the finding of fitness function and the position of particles corresponds to design variables of fitness function. Particles search food randomly, and keep the knowledge the best previous positions of itself and its neighbors so they can adjust their own position and velocity by using the best position of swarm. Velocity update and position update are two primary operators of PSO algorithm. Iteratively, all particles try to find better and better positions the searching for optimum result of fitness function during until a minimum error or iteration number is achieved.

There are variations of PSO algorithm but all of them can be implemented easily. PSO algorithm does not use any gradient information so it is suitable for black-box optimization problems. Generally, PSO algorithm can be used to solve the non-linear, non-convex, continuous, discrete and integer variables type problems by modifying small portion of codes.

It requires low computer power by comparison with other heuristic algorithm and few lines of code are enough to setup algorithm so it is not complex to use.

Basic equations to calculate velocity and position of particles are share in below.

$$v_i^{k+1} = wv_i^k + c_1 r_1 \left(Xpb_i^k - x_i^k \right) + c_2 r_2 \left(Xsb^k - x_i^k \right) \tag{20}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{21}$$

Where x_i^k and v_i^k are the position and velocity vectors of i'th particle, respectively. k is the iteration number. $r_1$and $r_2$are two random numbers uniformly distributed in the range (1,0).

$$x_i = (x_1, x_2, x_3, \dots, x_d) \tag{22}$$

Where $x_d \in [l_d, u_d], d \in [1, D]$, l_d and u_d are the lower and upper bounds of the dth dimension of the D dimensional search space. Xpb_i^k is the best fitness value of particle and Xsb^k is the best fitness value of whole swarm so far. c_1 and c_2 are acceleration constants to control exploration tendency. When $c_1 = 0$ and $c_2 \neq 0$, PSO algorithm is the social only model and if $c_2 = 0$ and $c_1 \neq 0$, PSO becomes a cognition only model. w is the inertia weight which is offered by Shi and Eberhart [7] to bring about a balance between the exploration and exploitation characteristics of PSO. There are various inertia weight strategies discussed in the literature and these are classified in three main groups: constant, time-varying and adaptive in [8].

Particles move to optimum points mainly by using equation **Error! Reference source not found.** and **Error! Reference source not found.**. Also, there are alternative formulations for position and velocity vector for different PSO algorithms which can be seen in [9] but in this study basic forms are used. Movement illustration of particles is shared in Figure .

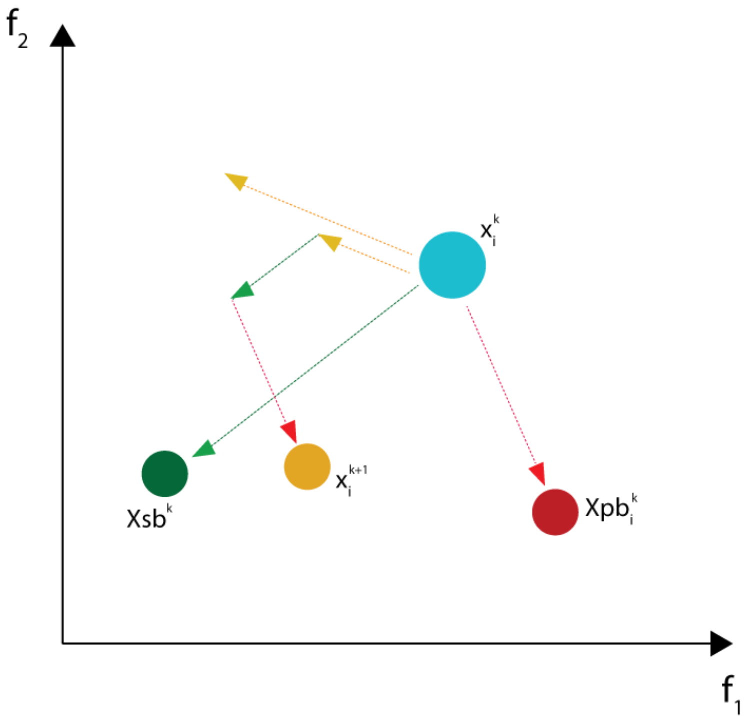


Figure 4. Particle movement scheme

Main part of PSO algorithm is the movement of particles by using position and velocity equations. Rest of the algorithm is quite similar to general recursive algorithms. The basic structure of PSO algorithm is as follows:

Initialize all particles with random positions (x_i^0) in search space and velocities (v_i^0).

Initialize best known positions of particles (Xpb_i^0) by using its initial positions.

Calculate the first best known position (Xsb^0) of swarm.

repeat

  for all Particle i in the swarm **do**

    Pick random numbers: r_p , r_g ϵ (0,1)

    Update the particle's velocity by using equation (2.1)

    Compute the particle's new position by using equation (2.2)

    if $fitness\left(x_i^{k+1}\right) > fitness\ (Xpb_i^k)$ **then**

      Update the particle's best known position: $Xpb_i^{k+1} = x_i^{k+1}$

    end if

    if $fitness\ \left(Xpb_i^{k+1}\right) > fitness\ (Xsb^k))$ **then**

      Update the swarm's best known position: $Xsb^{k+1} = Xpb_i^{k+1}$

    end if

  end for

until error criterion or iteration number is met

return

The general concept of particle swam algorithm can be also seen in Figure as the flowchart.

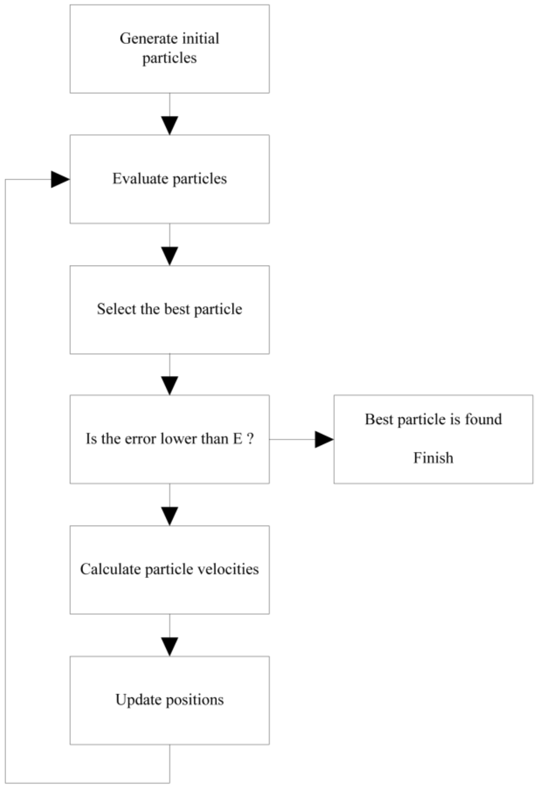


Figure 4. The basic scheme of particle swarm algorithm

There are different variations of particle swarm algorithm. The basic concept is implemented in this study.

PSO algorithm mainly has various parameters such as swam size (total number of particles), number of iteration, velocity components coefficients such as cognition and social behavior coefficients (c_1 and c_2), acceleration coefficients. Also, PSO algorithm can be improved by using extra parameters such as inertia weight, velocity clamping, velocity constriction etc. Number of iteration could be replaced with other termination criterion like error value, velocity etc. values of parameters could be fixed during the optimization process as an off-line strategy of values or they depend to optimization process as an online parameter tuning strategy. Optimal values of parameters are another optimization problem and in this study fixed values strategy is used. Basic parameters of algorithm are investigated below.

Swarm size
Swarm size is the number of particles in the population. A large number of particles can seek out the larger parts of the search space. On the other hand, this increases the computation time per iteration.

Iteration number
The number of iteration determines how many times swarm will be generated. The low number of iterations causes the early stopping before the optimum solution. The high number of iteration with appropriate stopping criteria is better for searching without unnecessary source usage.

Velocity Components
Particles velocity has three components which are inertia, cognitive, and social components. They generate the learning capacity of algorithm.

4. Case Study and Results

Investigated framework was applied to Ro-Ro model which can be seen in Fig.5. Also, the ship's main particulars are given in table 3.

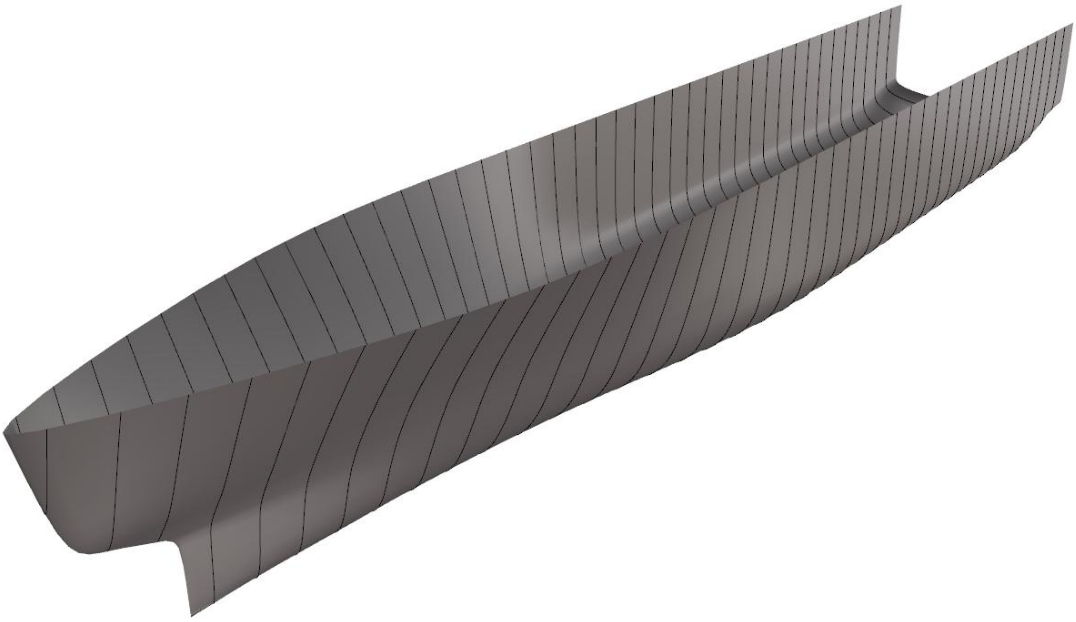


Figure 5. Ro-Ro 3D hull model

Main dimensions of Ro-Ro vessel are kept as fixed during the optimization study. Bulkheads and tanks coordinates are used as design variables. This approach decreased the number of parameters to find feasible solutions faster.

Table 3. Main dimensions of the vessel in case study.

Main Particulars		Units
Length overall (Loa)	82.910	[m]
Length waterline (Lwl)	79.233	[m]
Breadth molded (B)	12.700	[m]
Depth (D)	13.180	[m]

Full load draught (T)	4.120	[m]
Full load displacement	2304	[tonnes]
Full load VCG	3.698	[m]
Partial load draught (T)	3.93	[m]
Partial load displacement	2107	[tonnes]
Partial load VCG	3.784	[m]
Light service draught (T)	3.74	[m]
Light service displacement	1191	[tonnes]
Light service VCG	4.021	[m]
Max number of person on board	210	
Number of decks	5	

There are fourteen design variables which can be seen in table. Graphical illustration of design variables can be seen in Fig.1 in 3.2 Parametric model section. Double bottom design variable is limited with MSC.216(82) regulation 9. Height of double bottom should not be less than B/20. Also, this value should be between 760 mm and 2000 mm.

Car deck height is limited with a car design dimensions. Height of car deck affects the performance of the ship including stability, seakeeping etc. and therefore, they are restricted with boundaries.

Wing tank design variables are beneficial to increase stability in damage condition but this might reduce the car capacity. These variables are limited for three or four lines cars. All the design variables are also shared in table 4 with lower and upper boundaries.

Table 4. Optimization variables with their types and bounds

No	Symbol	Variables	Original design	Bounds	
				Lower	Upper
1	x_1	Aft peak Bulkhead	8.40	8.20	8.60
2	x_2	Machinery space Bulkhead	21.40	20.00	23.00
3	x_3	Transverse Bulkhead 01	34.20	30.00	36.00
4	x_4	Transverse Bulkhead 02	41.20	40.00	43.00
5	x_5	Transverse Bulkhead 03	50.20	50.00	52.00
6	x_6	Transverse Bulkhead 04	58.20	55.00	60.00
7	x_7	Transverse Bulkhead 05	67.20	65.00	70.00
8	x_8	Collision Bulkhead	76.20	0.05L from FP	0.08L from FP
9	y_1	Wing Tank	1.13	0.50	2.00
10	y_2	Wing Tank	1.13	0.50	2.00
11	y_3	Wing Tank	1.13	0.50	2.00
12	z_1	Double Bottom	1.20	0.76	2.00
13	z_2	Car Deck	6.70	6.50	7.00
14	z_3	Passenger Deck	9.50	9.50	10.50

Number of constraints are used to generate practicable designs. First set is required heights for decks. Engine room should have suitable volume to arrange engine and equipment and therefore, a constraint is used to limit minimum length of engine room. Also, required volumes for liquid tanks are used as constraint to arrange bulkheads locations. Last constraint is that attained index should be bigger than required index. This constraint filters the valid designs for damage stability. All constraints are also shared in table 5.

Table 5. Constraints

No	Formula	Definition
1	$h_{deck}^{min} - \lvert z_1 - 0 \rvert \leq 0$	Required heights for decks
2	$h_{deck}^{min} - \lvert z_2 - z_1 \rvert \leq 0$	
3	$h_{deck}^{min} - \lvert D - z_3 \rvert \leq 0$	
4	$l_{ER}^{min} - \lvert x_2 - x_1 \rvert \leq 0$	Required length for the engine room
5	$V_{FOT}^{min} - V_{FOT} \leq 0$	Required volumes for liquid tanks
6	$V_{FOT} - V_{FOT}^{max} \leq 0$	
7	$V_{FWT}^{min} - V_{FWT} \leq 0$	
8	$V_{FWT} - V_{FWT}^{max} \leq 0$	
9	$V_{FBT}^{min} - V_{FBT} \leq 0$	
10	$V_{FBT} - V_{FBT}^{max} \leq 0$	
11	$V_{LOT}^{min} - V_{LOT} \leq 0$	
12	$V_{LOT} - V_{LOT}^{max} \leq 0$	
13	$A \geq R$	Attained index should be bigger than required

In this study, particle swarm optimization algorithm is used to search design space with bounds and constraints for selected objectives. In section 3.4, details of used PSO algorithm are investigated. PSO algorithm has various main settings like swarm size, iteration number, termination criteria and velocity settings. These are shared in Table 6. Effect of these settings should be utilized within the scope of studied problem.

Table 6. The parameters setting of PSO

Swarm size	20
Iteration number	5
Termination criteria	Solution error / total iteration number
Inertia	0.729
Cognitive component	1.65
Social component	1.65

The calculation is preformed up to the 5 adjacent zones and part of the results for pi, vi, ri is given in the following table 3.

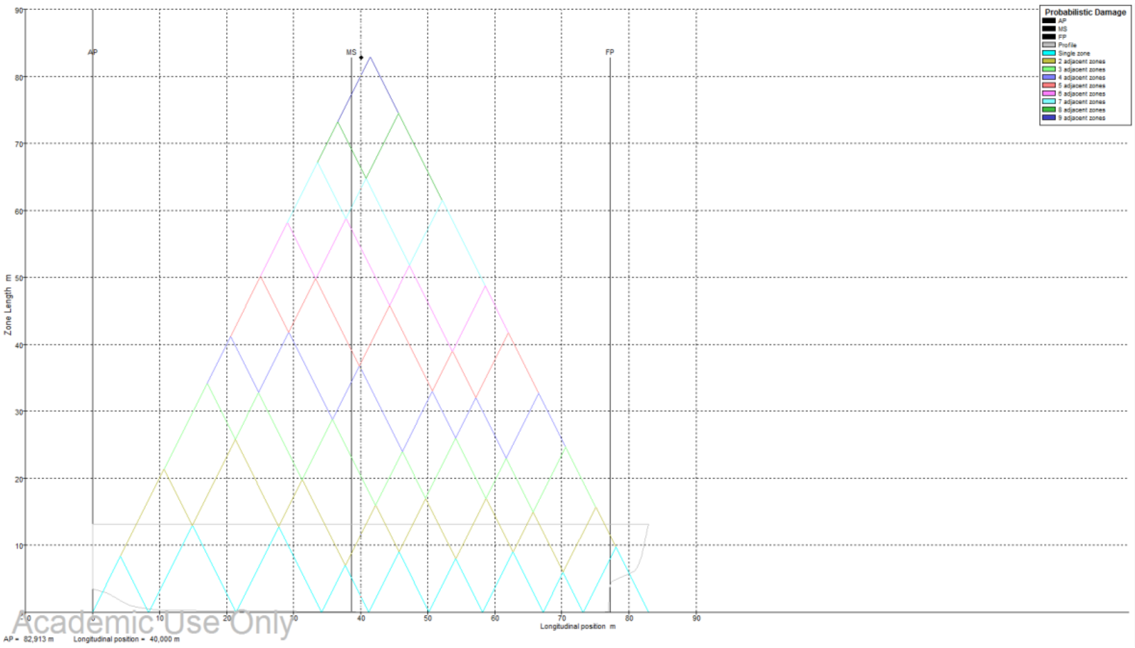


Figure 6. Possible single and adjacent damage zones up to 9.

The eleven-zone division of a ship where the bottom line triangles indicate single-zone damages, while the parallelograms indicate multi-zone damages is illustrated in figure 6.

Design variables, bounds and constraints of optimization problem are shared above. Defined problem, algorithm and parametric model are combined in the created framework properly. Good decision making environment requires well defined structure. Fig.7 illustrates flowchart of the framework.

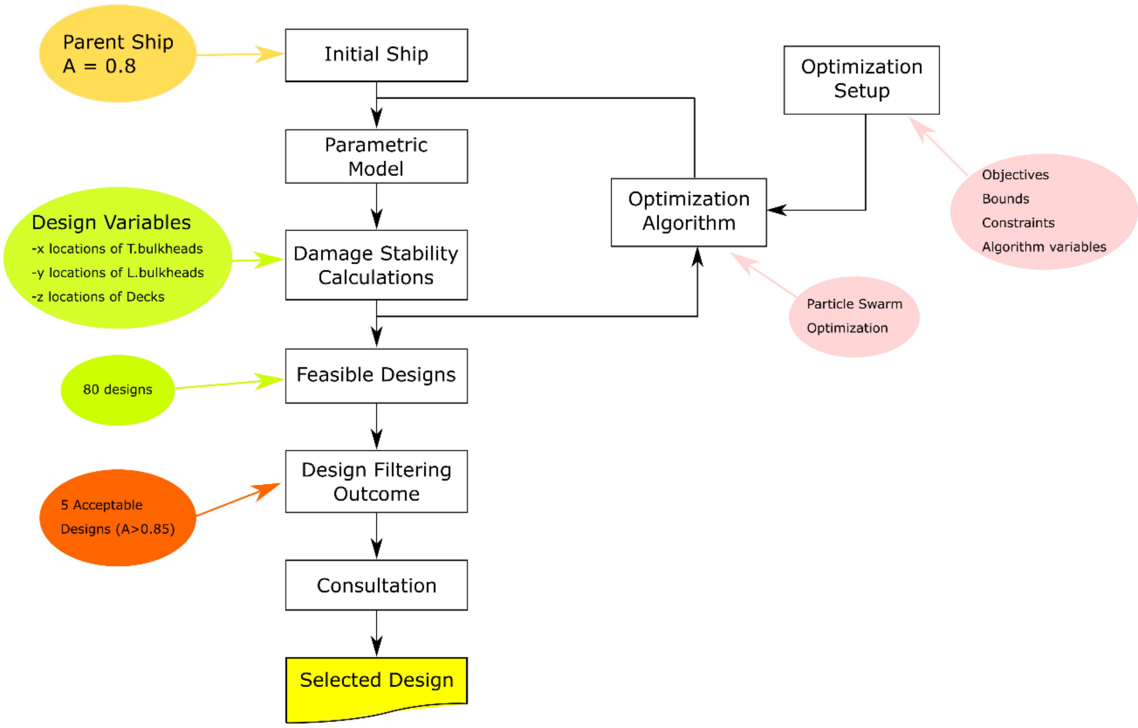


Figure 7. Flowchart of the created framework

Defined optimization problem is solved by using created framework. Various designs are generated during the solution. Some of them are infeasible and they eliminated by using constraints. Rest of feasible designs are filtered by using a threshold value for attained index. A sample of the optimization problem outcome is shared in Table 7.

Table 7. Comparison of original and optimized designs.

No	Symbol	Variables	Original design	Optimum design
1	x_1	Aft peak Bulkhead	8.40	8.60
2	x_2	Machinery space Bulkhead	21.40	22.00
3	x_3	Transverse Bulkhead 01	34.20	32.25
4	x_4	Transverse Bulkhead 02	41.20	41.00
5	x_5	Transverse Bulkhead 03	50.20	51.10
6	x_6	Transverse Bulkhead 04	58.20	60.00
7	x_7	Transverse Bulkhead 05	67.20	66.00
8	x_8	Collision Bulkhead	76.20	77.00
9	y_1	Wing Tank	1.13	1.25
10	y_2	Wing Tank	1.13	1.25
11	y_3	Wing Tank	1.13	1.25
12	z_1	Double Bottom	1.20	0.85
13	z_2	Car Deck	6.70	6.55
14	z_3	Passenger Deck	9.50	9.50
Optimization Object				
1		Index A	0.855	0.923

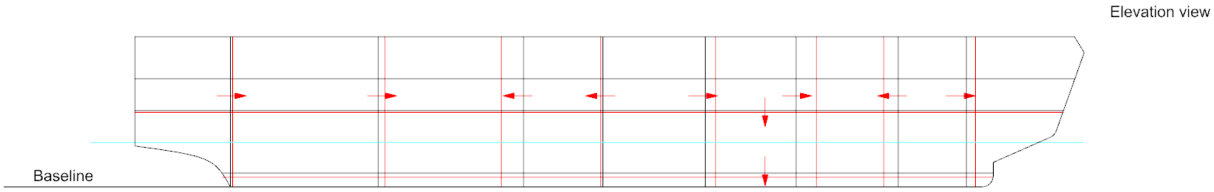


Figure 8. Original vs. optimized design (GAs)

5. Discussion and Conclusion

The optimization method based on probabilistic damage stability to increase safety is applied to a Ro-Ro passenger ship. Subdivision of ship is used a tool to minimize risk after damage condition. More reliable subdivision is searched by using particle swarm optimization algorihm. In this study, a framework is created by combining paramatric model, damage stability calculation tool and optimization algorithm. Objective of optimization problem is attained index of PDS calculation. The goal of problem is improved 7% in comparison with original design by rearranging subdivisons in x, y, z coordinates. Based on the work presented in the foregoing, the following concluding remarks may be drawn. Design space exploration is suitable method to analyze safety status of ship based on arrangement. Height of decks are more sensitive to increase attained index than location of transverse bulkheads. Also, locations of transverse bulkheads should be in aggrement with the longitudinal probability distribution of damage cases. Created framework provedes good results in terms of design objectives. This framework has potential to apply similar ship degin optimization problem. Future work will focus on integration of other design calculation into framework.

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