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# Development of integrated evolutionary optimization algorithm and its application to optimum design of ship structures

Young-Mo Kong[1], Su-Hyun Choi[1], Bo-Suk Yang[2,*] and Byeong-Keun Choi[3]

[1]*Research Center, Daewoo Shipbuilding and Marine Engineering Ltd., 1 Aju-dong, Geoje, Gyungnam 656-714, South Korea*
[2]*School of Mechanical Engineering, Pukyong National University, San 100, Yongdang-dong, Nam-gu, Busan 608-793, South Korea*
[3]*School of Mechanical and Aerospace Engineering, The Institute of Marine Industry, Gyeongsang National University, 445 Inpyeong-dong, Tongyoung, Gyeongnam 650-160, South Korea*

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## Abstract

This paper proposes an integrated evolutionary optimization algorithm (IEOA) which is combined with genetic algorithm (GA), random tabu search method (TS) and response surface methodology (RSM). This algorithm, in order to improve the convergent speed that is thought to be the demerit of GA, uses RSM and the simplex method. Though mutation of GA offers random variety, systematic variety can be secured through the use of tabu-list. Efficiency of this method has been proven by applying traditional test functions and comparing the results to GA. And it is an evidence that the newly suggested algorithm can effectively find the global optimum solution by applying it to minimize the weight of fresh water tank that is placed in the rear of ship designed to avoid resonance. According to the results, GA's convergent speed in initial phase has been improved by using RSM. An optimized solution was calculated without the evaluation of additional actual objective function. Finally, it can be concluded that IEOA is a very useful global optimization algorithm from the viewpoint of convergent speed and global search ability.

*Keywords*: Evolutionary optimization algorithms; Genetic algorithm; Response surface methodology; Tabu search method; Simplex method; Fresh water tank

## 1. Introduction

The focus of many dynamic analyses is to find the maximum response and avoid the resonance in a given structure under all excitation forces. Usually, these features provide the basis of a design limit and are thus employed to determine the dynamic characteristics of a structure and its weight. For this reason, weight minimization for reducing the response and avoiding resonance has always been a major concern of design engineers.

Many classic optimization methods and practical software have been developed and most of them are very effective, especially to solve practical problems. However, finding a global optimum solution for the system is difficult. To overcome this disadvantage, many search algorithms have been developed for searching a global optimum solution. One of the most popular methods is the genetic algorithm (GA) [1, 2]. The GA is a technique in the field of evolutionary computation, and it is a powerful and general global optimization method, which does not require the strict continuity of classical search techniques; instead, it allows non-linearity and discontinuity to appear in the solution space. Due to the evolutionary characteristics, the GA can handle all kinds of objective functions and constraints defined on discrete, continuous, or mixed search spaces. However, the global access of the GA requires a computationally random search. So, the convergent speed to the exact solution is slow. Furthermore, the coding of the chromosome for a

*Corresponding author. Tel.: +82 51 629 6152, Fax.: +82 51 629 6150
E-mail address: bsyang@pknu.ac.kr
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large dimensional problem will be very long in order to get a more accurate solution. This results in a large search space and huge memory requirements for the computation. To overcome these demerits, many researchers have studied developing many hybrid genetic algorithms which combine the genetic algorithm with other ones [3-6]. These can save computation time and find the global solution as far as it goes. Therefore, the new algorithms are addressed to reach better accuracy and faster convergent speed to get an optimum solution in complicated and big structures like ships.

Response surface methodology (RSM) [7] is an optimization tool that was introduced by Box and Wilson [8]. It is a collection of statistical and mathematical techniques that are useful for developing, improving, and optimizing processes. These techniques are employed in order to estimate the optimization function and to find search directions to sub-regions of the domain with improved and hopefully optimal solutions. The simplex method (SM) is a derivative-free method of optimization that uses regular patterns of search involving simplexes [9]. This well known technique has proven to be popular for unconstrained objective functions. Tabu search (TS) is one of the recent metaheuristics originally developed for combinatorial optimization problems. Since the first presentation of Glover [10, 11], many studies have emerged in this area, such as TS with random moves for constrained optimization problems [12].

In this study, to search the optimum solution of multimodal function in high accuracy and high speed, a new hybrid evolutionary algorithm is suggested, which combines the merits of the popular algorithms such as GA, TS, RSM and SM. This algorithm, in order to improve the convergent speed that is thought to be the demerit of GA, uses RSM and SM. Though mutation of GA offers random variety, systematic variety can be secured through the use of a tabu list of TS. Especially, in the initial phase, GA's convergent speed can be improved by using RSM which is using the information on the objective function acquired through the GA process and then making response surface (approximate function) and optimizing this. The optimum solution was calculated without the evaluation of an additional actual objective function, and the GA's convergent speed could be improved. The efficiency of this method has been proven by applying traditional test functions and comparing the results to GA. It also confirmed that the global optimum solution is being searched efficiently by applying the proposed algorithm to weight minimization where avoiding resonance of the fresh water tank located on the rear of the ship was considered.

## 2. Integrated evolutionary optimization algorithm (IEOA)

### *2.1 Structure of IEOA*

The main idea is to reduce the number for evaluation of the objective function by using RSM which is one among the designed experiments to reduce the repetitive number, since it is one of the demerits of optimum design. The IEOA consists of four main parts: (i) GA for governing the general algorithm, (ii) tabu-list for systematic variety of solution, (iii) RSM for improving convergent speed for getting a candidate solution, and (iv) modified SM for local search. Figure 1 represents the flowchart of the IEOA. The left side of the flowchart shows global search region that is similar to the flowchart of standard GA, excluding the function assurance criterion (FAC), a set of history, tabu-list, and RSM. These parts offer candidate solutions, which are considered as initial search points in the local search region. The right side represents the local search region. This part finds the optimum solution by the modified SM, which uses the final solution by results of the global search as initial search point. Fig. 1-1~Fig. 1-3 show the detail process of Part A, B, and C in Fig. 1

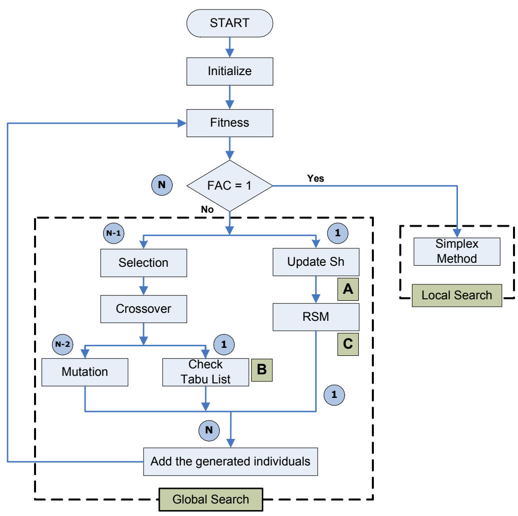



Fig. 1. Flowchart of proposed algorithm (IEOA).

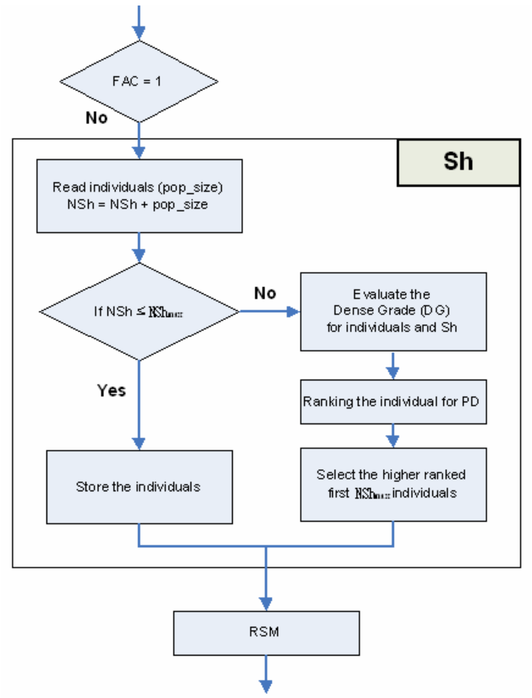



Fig. 1-1. Flowchart of Part A (update Sh).

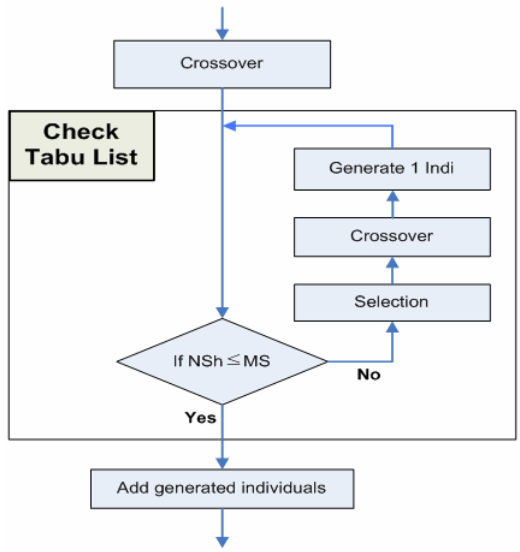



Fig. 1-2. Flowchart of Part B (check tabu list).

Part A shown in detail in Fig. 1-1 shows a set of history *Sh* region which provides the well distributed points to make a response surface. The *Sh* is constructed according to the following procedures:

*Step 1*: Read individuals from the current population

*Step 2*: $NSh = NSh + P_{size}$

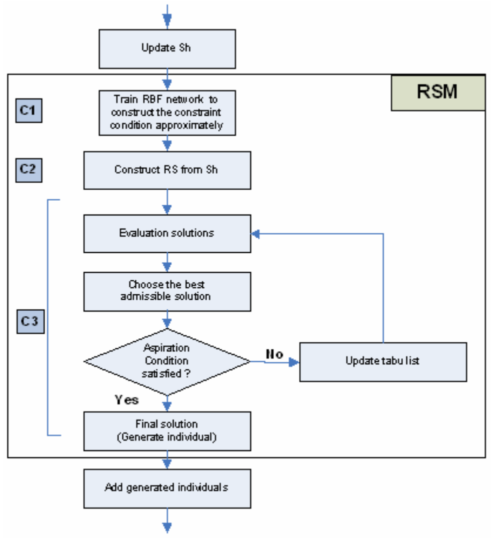



Fig. 1-3. Flowchart of Part C (RSM).

where $NSh$ and $P_{size}$ mean the size of a set of history and size of population, respectively.

*Step 3*: if $NSh \leq NSh_{\max}$, then go to step 7 where $NSh_{\max}$ means maximum size in *Sh*.

*Step 4*: Evaluate the dense grade $D_g$ for each individual.

$D_g = \max(d_{ik}) + \text{mean}(d_{ik})$

where $d_{ik}$ is Euclidian distance between $i$ and $k$;

$\left\| x^{(i)} - x^{(k)} \right\|, \quad i = 1, \ldots, NSh;\ i \neq k$

*Step 5*: Rank the individuals for $D_g$.

*Step 6*: Select the higher ranked first $NSh_{\max}$ individuals.

*Step 7*: Store the solutions in *Sh* and go out.

Part B shown detail in Fig. 1-2 represents checking the tabu-list to have a diversity of solution. The one individual which is selected in GA's individuals after crossover process is reviewed to ensure the diversity of solution. If the diversity of solution is ensured, the individual is selected and if not, the crossover process is repeated. That is, the individual is selected when it is located far away from the dense area. A dense grade criterion of solution and acceptance criteria of individual are $D \subset R^N$ for normalized domain and $V \subset R^N$ for a domain having the equally divided by $NSh_{\max}$ from $D$ where $N$ is number of design variables. Let $|V|$ is the size of $V$, then

$$|V| = \frac{l^N}{NSh_{\max}} \tag{1}$$

where $l$ is the one side length of domain $D$, $\delta\,(\in R)$ is the one side Euclidean length of hyper-polygon in $V$ defined as follows:

$$\delta = \sqrt[N]{|V|} = \frac{l}{\sqrt[N]{NSh_{\max}}} \tag{2}$$

An aspiration function for a given target design vector is represented to decide the acceptance of individual as follows:

$$f_a = 1 - \sum_{k=1}^{NSh} h(r) = 1 - \sum_{k=1}^{NSh} \exp\left(-\gamma \|X_k - X_i\|\right) \tag{3}$$

Let $h(r) = e^{-\gamma r}$, $r = \|X_k - X_i\|$, where $X_i$ is the position of target individual.

To set the $\gamma$, it is assumed that the ideal conditions are satisfied: (i) $Sh$ is full, and (ii) all members of $Sh$ are placed in the center of the $NSh_{\max}$ sub-domains which are supposed to have same hyper-volume and not to have any cross set of each other and to fit the domain $D$ absolutely. That is,

$$V_i \cap V_j = \phi, \quad i \neq j, \quad V_1 \cup V_2 \cup \cdots \cup V_{NSh_{\max}} = D \tag{4}$$

Then, set as $f_a = \beta$, where $\beta$ means the acceptance probability criterion.

$$f_a = \beta = 1 - \sum_{k=1}^{NSh} e^{-\gamma r} = 1 - \left(2N e^{-\gamma\delta} + R\right) \tag{5}$$

The second term on the right side corresponds to the closest member of $Sh$ to the target individual. The third term, $R$, is the residuals. The nature of $h(r)$, which is exponentially decreasing along with distances, makes $R$ be much smaller than the first term.

$$f_a = 1 - \left\{2N e^{-\gamma\delta} + 2N(N-1) e^{-\gamma\delta\sqrt{2}} + R_2\right\} \tag{6}$$

The aspiration criterion is as follows:

• If $rand > f_a$ then accept, where $rand = [0\ 1]$

• If trial number > maximum trial number, where, set 50

If the target individual is not satisfied with above aspiration criterion, one crossover is generated again and the process is repeated. The procedure is summarized as follows:

*Step 1*: Read $N-1$ individuals from selection process.

*Step 2*: Crossover $N-2$ individuals according to the crossover probability and go to step 5.

*Step 3*: One individual selected for tabu-list.

*Step 4*: If $rand > f_a$, then go to step 5, otherwise return to step 3.

*Step 5*: Add generated individuals.

Part C shown detail in Fig. 1-3 represents an RSM region. It is largely divided into 3 parts. First, considering the boundary condition in the response surface for optimization, the upper and lower values of design variables can be considered in this calculation process. However, the merits of this method are diminished when additional constraints like natural frequency are considered, because it has to evaluate the objective function to get the results from external calculations. To overcome this problem, this study used $Sh$ as the training data and inferred the satisfaction of constraint condition by using the radial basis function (RBF) neural network [13]. In this way, the calculation of actual problems could be avoided. Second, it makes a response surface from $Sh$ by using the least square method (LSM). Finally, the optimum solution of the response surface is calculated by using TS. The gradient-based algorithm can be used to increase the convergent speed for optimization. However, the solutions satisfying constraint conditions cannot be guaranteed since the constraint conditions are difficult to define precisely. Also, we adopt TS which has an excellent initial convergent speed, because the implementation of the response surface concept is to search for the approximate candidate solution. The generated final solution is added with other existing GA's individuals according to the sequence of Fig. 1 and the calculation of fitness is performed.

### *2.2 Implementation procedure of IEOA*

The procedure of the proposed algorithm can be summarized as follows:

*Step 1*: The parameters ($P_{size}$, $P_c$, $P_m$, $M_s$ and $M_c$) are set up.
where $P_c$, $P_m$ are crossover probability and mutation probability. $M_s$ and $M_c$ are selection and crossover method, respectively.

*Step 2*: Generate the initial chromosome $v_k$ ($k = 1, 2, \ldots, P_{size}$) randomly with $n$ elements.

$v_k = [x_{k1}, x_{k2}, \cdots, x_{kn}]$

When the chromosomes are generated, the element value range of each chromosome should be satisfied as $x_{kj}^L \le x_j \le x_{kj}^U$. Each chromosome satisfies all constraints $g_i(v_k) \ge 0$, $\forall i$. When a chromosome does not satisfy the conditions, then the chromosome has the lowest fitness. So it has a low possibility of selection to the next generation after all.

*Step 3*: Generate the initial solutions, and estimate constraint and set up a parameter range.

*Step 4*: Evaluate the fitness of individuals.

*Step 5*: Evaluate the *FAC*, if it is satisfied *FAC* = 1, go to step 12 otherwise go to step 6.

Each candidate for optimum solutions is decided by the *FAC* [14]. The *FAC* is a standard value to estimate the convergence of the initial candidate.

$$FAC = \frac{\left| f_{i-1}^T f_i \right|^2}{(f_{i-1}^T f_{i-1})(f_i^T f_i)}$$

where $f_i$ is the row vector, formed by the fitness values of the individuals at the *i*th generation and $f^T$ is the transpose of $f$.

The row size depends on the number of optimum solutions according to a designer's requirement. Theoretically the range of *FAC* is from 0 to 1.0. When the value is equal to 1, the convergence of optimization is completed. However, the value is difficult to converge to 1.0 considering the many candidate solutions to be evaluated. Therefore, in this study, the *FAC* is set to 0.9999.

*Step 6*: Update *Sh*: $Sh = \{ ( X_{Sh}, F) | X_{Sh} \in R^N, F \in R\}$, where $X_{Sh} = [x_1, x_2, \ldots, x_N]$.

*Step 7*: Perform selection and crossover, and check tabu-list.

*Step 8*: Construct the response surface from *Sh*:

$$f_{rs} = \alpha_0 + \sum_{i=1}^{N} \alpha_{ii} x_i + \sum_{i=1}^{N} \alpha_{ii} x_i^2 + \sum_{i=2}^{N} \sum_{j=1}^{i-1} \alpha_{ij} x_i x_j$$

where $\alpha_0$, $\alpha_{ii}$ and $\alpha_{ij}$ are coefficients calculated by LSM.

*Step 9*: Train the RBF network by *Sh* to construct the constraint conditions approximately.

*Step 10*: Calculate the optimum design on the response surface by TS and generate one individual based on $X^*$.

*Step 11*: Mutate and go to step 4.

*Step 12*: Search the optimum solutions by the local concentration search using modified SM for best candidate.

## 3. Numerical examples of function optimizations

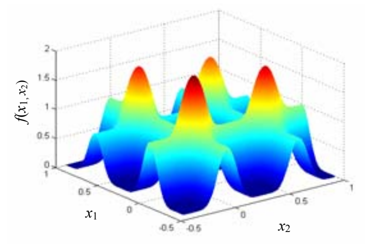
### 3.1 Test function

Three benchmark test functions are used to verify the efficiency of the proposed hybrid algorithm as shown in Fig. 2. These functions are often used to test optimization methods. The simulations are conducted for the 2-dimensional case. The first function is to be maximized, and the others are to be minimized.

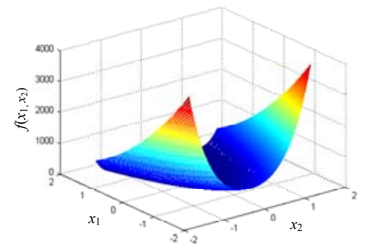
The first one is the four-peak function, which has one global optimum with three local optima and is defined as

$$f(x_1, x_2) = \exp\left( \log_{10}(0.25) \times \left( \frac{x_1 - 0.2}{0.8} \right)^2 \right) \cos^6(1.5\pi x_1) + \exp\left( \log_{10}(0.25) \times \left( \frac{x_2 - 0.1}{0.8} \right)^2 \right) \cos^6(1.5\pi x_2)$$

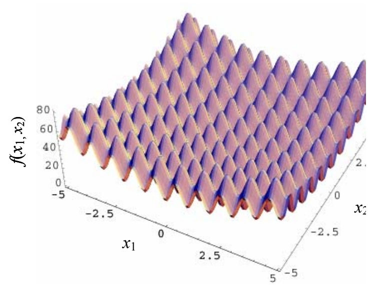
where $-0.4 \le x_1, x_2 \le 1$. This test function has a global optimum solution $f(\mathbf{x}) = 1.954342$ at $x_1 = 0$, $x_2 = 0$,




(a) Four-peak function




(b) Rosenbrock function




(c) Rastrigin function

Fig. 2. Test functions.

and three local optima solutions $f(\mathbf{x})$ = 1.807849, 1.705973 and 1.559480 as shown in Fig. 2(a). Conventional gradient based hill-climbing algorithms can be easily stuck to a local optimum because of their dependency on the start point, while the global search algorithm finds global optimum in general.

The Rosenbrock function is defined as

$$f(x_1, x_2) = 100(x_1 - x_2)^2 + (1 - x_1)^2$$

where $-2.0 \le x_1, x_2 \le 2.0$. This function is called a banana function [15] whose shape is presented in Fig. 2(b). The objective of this function is to find the variable **x**, which minimizes the objective function. This function has only one optimum solution $f(\mathbf{x}) = 0$ at $x_1$ = 1.0 and $x_2$ = 1.0. It is difficult to find an optimum solution because of an extremely deep valley along the parabola $x_1^2 = x_2$ that leads to the global minimum [16].

The Rastrigin function is defined as

$$f(\boldsymbol{x}) = 2 \times 10 + \sum_{i=1}^{2} \{x_i^2 - 10\cos(2\pi i)\}$$

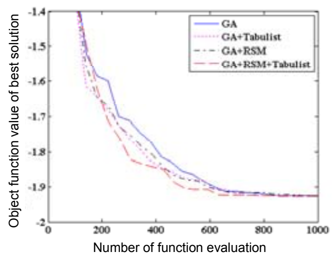
where $-5.0 \le x_1, x_2 \le 5.0$. This function is often used to evaluate the global search ability because there are many local minima around the global minimum as shown in Fig. 2(c). It is not easy to find a global minimum within a limited function call. This function has 220 local minima and one global minimum $f(\mathbf{x})$ = 0 at (0, 0).

### 3.2 Simulation results

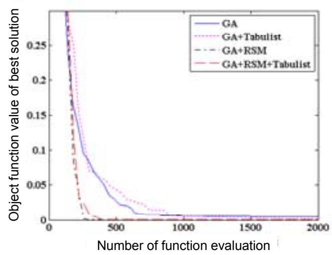
Fig. 3 shows the convergence trend of objective function for each test function. According to the results, GRSM (GA+RSM) and IEOA (GA+RSM+tabu list) algorithms which are based on RSM have faster convergent speed and more accurate solutions than standard GA, which validated the efficiency of RSM on the calculation. Also, the tabu list enables convergence to solutions quickly on the multimodal function due to the systematic diversity of solution. The setting parameters for each algorithm are listed in Table 1. Table 2 shows the comparison of optimization results for the above stated three test functions. The evaluation number means total evaluation number of the objective function used in optimization procedure, and it is directly proportional to the total calculation time. According to the results, for all test functions, IEOA can give better solutions than GA on accuracy and convergent speed. For the Rastrigin function, which is very useful to evaluate the global search ability because there are many local minima around the global minimum, IEOA found a global minimum with higher accuracy and less elapsed time compared to GA. According to these results, the proposed hybrid algorithm is a powerful global optimization algorithm from the view of convergent speed and global search ability.

Table 1. Set parameters for GA and IEOA.

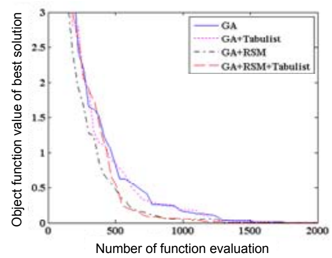
| Parameters | Value | Remarks |
|---|---|---|
| No. of generation | 100 | GA & IEOA |
| Population size, $P_{size}$ | 100 | |
| Crossover probability, $P_c$ | 0.5 | |
| Mutation probability, $P_m$ | 0.1 | |
| Size of $Sh$ for RSM, $NSh_{max}$ | 1000 | IEOA only |
| Step size for TS | 10 | |
| Count number for TS | 3 | |




(a) Four-peak function




(b) Rosenbrock function




(c) Rastrigin function

Fig. 3. Convergent trend of objective function.

Table 2. Comparison of optimization results.

| Test function | Exact solutions | Methods | Results | | No. of evaluation |
|---|---|---|---|---|---|
| | | | $f(\mathbf{x})$ | $x_1, x_2$ | |
| Four-peak function | $f(\mathbf{x}) = 1.9543$ | GA | 1.927 | $2.403\times10^{-3}$, $2.787\times10^{-3}$ | 2353 |
| | $x_1 = x_2 = 0.0$ | IEOA | 1.927 | $2.736\times10^{-3}$, $2.736\times10^{-3}$ | 459 |
| Rosen-brock function | $f(\mathbf{x}) = 0.0$ | GA | $1.640\times10^{-5}$ | 0.996, 0.996 | 1046 |
| | $x_1 = x_2 = 1.0$ | IEOA | 0.0 | 1.0, 1.0 | 419 |
| Rastrigin function | $f(\mathbf{x}) = 0.0$ | GA | $1.586\times10^{-4}$ | $1.408\times10^{-4}$, $8.15\times10^{-4}$ | 2109 |
| | $x_1 = x_2 = 0.0$ | IEOA | 0.0 | $-3.076\times10^{-9}$, $-7.747\times10^{-10}$ | 514 |

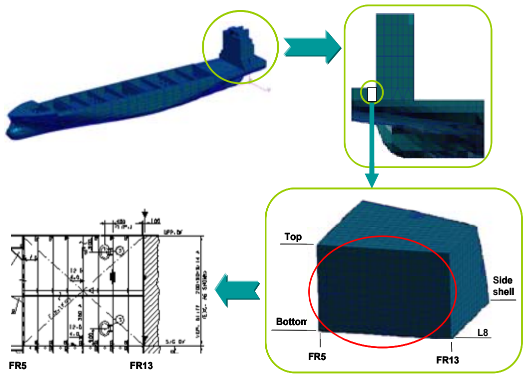


Fig. 4. Model and arrangement of fresh water tank.

## 4. Optimum design of fresh water tank of ship

In the engine room and the rear region of a ship, there are many tank structures that contact fresh and sea water or fuel and lubricating oil. Also, these are possibly subject to the excessive vibration during voyage because they are arranged around the main excitation sources of the ship such as the main engine and propeller. If problems occur, it takes a considerable cost, time and effort to improve the situation because the reinforcement work for emptying the fluid out of the tanks, additional welding and special painting and so on is required. It is very important to predict the precise vibration characteristics of the tank structures at the design stage. Optimum design needs to be applied. Especially when the structure is in contact with fluid, much analysis time must be taken. Therefore, a new optimization algorithm is required for getting a short analysis time and accurate solution. In this study, optimum design of a fresh water tank in an actual ship is carried out to verify the validity of the proposed algorithm (IEOA) and the results are compared to that of standard GA.

### *4.1 Vibration analysis of fresh water tank*

It is difficult to predict the vibration response of a local structure due to the complicated transfer mechanism of excitation force and the difficulty of assuming the damping ratio. Traditionally, therefore, a vibration analysis considering the design of avoiding resonance is conducted to prevent the local vibration.

In this study, the vibration analysis of the fresh water tank is carried out by using NASTRAN which is a commercial finite element program and widely used for big structures like ships. The analysis model and arrangement of the fresh water tank are shown in Fig. 4. Fig. 5 shows the design variables and boundary condition of the fresh water tank. Considering the precision of analysis and time-consuming modeling process, the range of modeling of fresh water tank is constrained to one side of the tank. The boundary conditions for the model are specified as follows: simple supports are used to the tank boundary area which is connected to the other bulkhead and deck. Table 3 shows the specification of main excitation sources.

In general, the design for avoiding local structure resonance in ships requires that the natural frequency of the structure must be two times higher than the blade passing frequency of the propeller under the maximum rpm of the main engine. In this study, the design target frequency is set as above 14.0Hz, which considers safety margins and twice blade passing frequency of the propeller (12.13Hz).

Fig. 6 shows the first three modes and natural frequencies of the fresh water tank by NASTRAN. These three modes frequently occur on the fresh water tank during a voyage. Especially, the 1st mode (8.60Hz) is a stiffener (stringer) mode which generates a strong vibration and much effect on the structure. In this model, the first natural frequency of the structure is also within the resonance region where the twice blade passing frequency of propeller is 12.13Hz. Therefore, the natural frequency of the structure is needed to be increased up to the target frequency under the condition that the tank is fully filled. The natural frequency of structure which is contacting fluid can be changed according to the water line of the tank. So, in order to design a safe structure, three modes of the fresh water tank are concerned in this study.

Table 3. Specification of main excitation sources.

| Excitation source | MCR | Excitation | |
|---|---|---|---|
| | | Order | Frequency |
| Main engine (6S 70MC-C) | 91 rpm | 3rd<br>4th<br>6th | 4.55 Hz<br>6.07 Hz<br>9.10 Hz |
| Propeller (Blade: 4ea) | | 1st<br>2nd | 6.07 Hz<br>12.13 Hz |

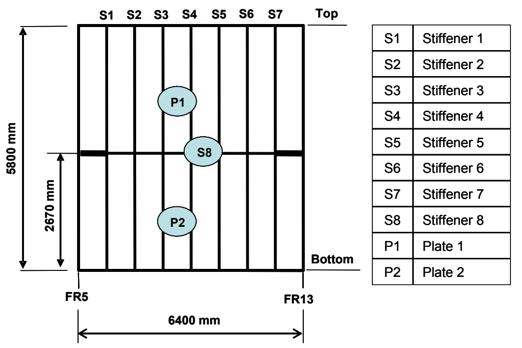
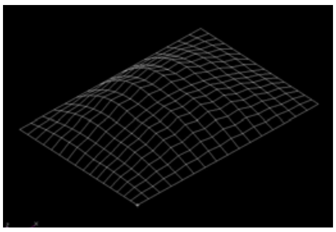
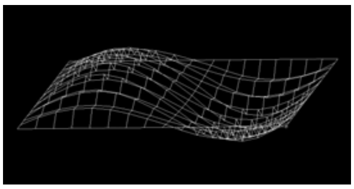


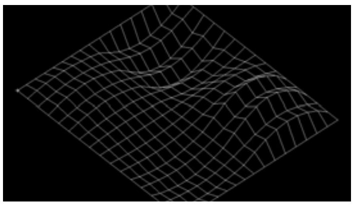

Fig. 5. Design variables and boundary conditions of fresh water tank.



(a) 1st mode (8.60Hz)



(b) 2nd mode (18.82Hz)



(c) 3rd mode (19.17Hz)

Fig. 6. Mode shapes of fresh water tank.

*4.2 Optimum design of fresh water tank*

The main vibration modes on the fresh water tank are stiffener modes in transverse direction. One of the most important factors is the stiffness of the stiffeners. In this study, the stiffener size and plate thickness of fresh water tank in Fig. 4 are defined as design variables in equation (7).

$$\mathbf{x} = \{S_1\ S_2\ S_3\ S_4\ S_5\ S_6\ S_7\ S_8\ P_1\ P_2\}^T \tag{7}$$

where $S$ and $P$ mean stiffener size and plate thickness, respectively.

The web length of stiffener $L_w$ is restricted as two categories such as Eq. (8) according to a shipyard's practice.

$$150 \le L_w \le 450 \text{ mm for stiffeners } (S_1 - S_7),\ 500 \le L_w \le 1000 \text{ mm for stringer } (S_8) \tag{8}$$

Also, the basic concept of local vibration design is the minimization of the response at each point. However, it is difficult to evaluate how much the excitation force influences the local structure. So, to avoid resonance, the first natural frequency of the structure is restricted as Eq. (9) which considers a safety margin of about 15% with twice blade passing frequency of the propeller (12.14Hz).

$$\omega_1 \ge 14.0\text{Hz} \tag{9}$$

The objective function combines linearly the weight of fresh water tank with natural frequency of structure like Eq. (10). The objective is to get an economic and sound structure to reduce the weight of stiffener $W$ and to increase the first natural frequency $\omega_1$.

$$\text{Minimize} \quad f(x) = \alpha\left(\frac{W_0}{W_t}\right) + \beta\left(\frac{\omega_{1t}}{\omega_{10}}\right) \tag{10}$$

where, subscript $t$ and 0 mean target and current values, respectively. $\alpha$ and $\beta$ are weighting factors and set $\alpha = 0.5, \beta = 0.5$ in this paper.

*4.3 Optimization results and discussion*

The optimum design was carried out to get an optimal size of stiffener and plate thickness on the fresh water tank to maintain its anti-vibration design. Table 4 shows the results of the design variables before and after optimization. It shows that the stringer $S_8$ is in-

Table 4. Comparison of original and optimal design variables.

| Design variable | Original design | Optimum design | | Remarks (IEOA) |
|---|---|---|---|---|
| | | GA | IEOA | |
| S1 | 200 | 214 | 207 | 4.0% |
| S2 | 200 | 320 | 223 | 12.0% |
| S3 | 200 | 253 | 285 | 43.0% |
| S4 | 200 | 325 | 283 | 42.0% |
| S5 | 200 | 328 | 303 | 52.0% |
| S6 | 200 | 277 | 251 | 26.0% |
| S7 | 200 | 281 | 230 | 15.0% |
| S8 | 550 | 893 | 947 | 72.0% |
| P1 | 11.0 | 10.7 | 10.3 | −6.36% |
| P2 | 11.0 | 10.6 | 10.0 | −9.09% |

Table 5. Comparison of results.

| Item | Original design | Optimum design | Remarks |
|---|---|---|---|
| Natural frequency | 8.60Hz | 14.02Hz | 163 % |
| Weight | 47.88kN | 45.62kN | −4.73 % |

Table 6. Comparison of optimization results.

| Item | Natural frequency | Weight | Objective function | No. of evaluation |
|---|---|---|---|---|
| GA | 14.04Hz | 49.04kN | 0.5547 | 1846 |
| IEOA | 14.02Hz | 45.62kN | 0.5167 | 1638 |

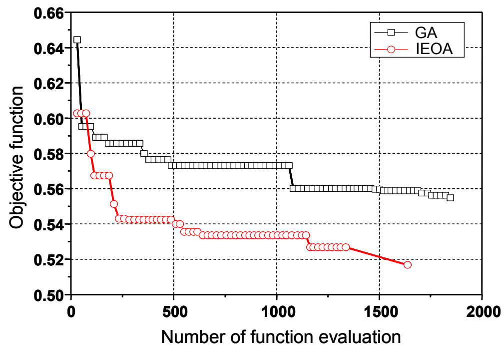



Fig. 7. Convergent trend of objective function.

increased by 72% and the others by 4.0-52%. This result indicates that the most reasonable modification method is to increase the stringer, which has an effect on decreasing the span of the vertical stiffeners. In this case, however, the plate thickness does not have any effect on the natural frequency of the structure. Table 5 shows the variation of natural frequency and weight of structure before and after optimization. According to the results, the first natural frequency increased by 163% from 8.6Hz to 14.02Hz, and the safety margin with twice passing frequency of the propeller correspondingly changed from -29.1% to 15.5%. Therefore, the structure is free from resonance. Moreover, the weights of stiffeners which are applied to the design variables also decreased in spite of the higher natural frequency. In summary, the local vibration problems which require avoidance of structure resonance through the movement of natural frequency without additional weight have been successfully solved by the proposed optimization method. Table 6 and Fig. 7 show the comparison of optimization results between GA and IEOA. The evaluation number means a total evaluation number of the objective function used in the optimization procedure, and is directly proportional to the total calculation time. According to the results, IEOA can give better solutions than GA on accuracy and convergent speed. These results lead us to draw the conclusion that the proposed new hybrid algorithm is a more powerful global optimization algorithm from the view of convergent speed and global search ability.

## 5. Conclusions

This paper proposes an integrated evolutionary optimization algorithm, as a new hybrid optimization algorithm that combines the merits of the popular algorithms such as GA, TS, SM and RSM. This algorithm, in order to improve the convergent speed that is thought to be the demerit of GA, uses RSM and SM. Though the mutation of GA offers random variety, systematic variety can be secured through the use of tabu-list. Especially, in initial phase, GA's convergent speed can be improved by using RSM which uses the information on objective function acquired through GA process and then making response surface (approximate function) and optimizing this. An optimized solution was calculated without the evaluation of additional actual objective function, and the GA's convergent speed could be improved. Efficiency and effectiveness of this method has been proven by applying popular test functions and comparing the results with GA. Also, the usefulness of newly suggested algorithm for finding the global optimum solution is proved by applying it to the weight minimization design where avoiding resonance of the fresh water tank located on the rear of the ship was considered.

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