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OPTIMAL DESIGN OF HYDROFOIL AND MARINE PROPELLER USING MICRO-GENETIC ALGORITHM (μGA)

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Abstract

This paper presents results from the application of the genetic algorithm (GA) technique to the design optimization of hydrofoil and marine propeller incorporating potential based boundary element method (BEM). Although, larger population size as implemented by simple genetic algorithm (SGA) could find the optimal individual after a fewer number of generations than smaller population size, it is penalized by a longer amount of time to evaluate fitness in every generation. An investigation is, therefore, conducted in this research to implement micro genetic algorithm (μGA) with a very small population, and with simple genetic parameters, in order to achieve faster convergence to better solution from generation to generation. The technique is applied here to optimize hydrofoils of different plan forms, e.g., rectangular, elliptical, trapezoidal etc. Firstly, the hydrofoil design parameters, such as, angle of incidence, maximum thickness and camber ratios, aspect ratio, taper ratio, angle of sweep etc. are initialized randomly and the generated hydrofoil is analyzed by potential based boundary element method. GA then updates the design parameters over generation after generation and finally, finds an improved hydrofoil of maximum lift-drag ratio or minimum drag coefficient satisfying some design constraints. An improved blade or hydrofoil section is also designed by GA satisfying some design constraints. Finally, the technique is applied to the optimum design of marine propeller. In this study, μGA is found useful and prospective tool for the design optimization of hydrofoil and marine propeller due to its faster convergence.

Keywords: Genetic algorithm, boundary element method, hydrofoil, propeller, design optimization

NOMENCLATUER

C_D	Drag coefficient	P_C	Probability of crossover
C_L	Lift coefficient	S	Span
C_{Pmin}	Minimum pressure coefficient	t_0/C	Maximum thickness ratio
C_r, C_t	Root and tip chord respectively	y	Co-ordinate in vertical direction (2-D section), Co-ordinate in spanwise direction (3-D hydrofoil)
$f(x)$	Objective function		
$F(x)$	Constrained objective function		
f_0/C	Maximum camber ratio	α	Angle of incidence
$I_j(x)$	*i*-th inequality constraint	β	Angle of sweep
K_T	Thrust coefficient	η_o	Open water effciency
K_Q	Torque coeffcient	δ_i	Penalty coefficients
L/D	Lift-drag ratio	$\phi_i(x)$	Penalty term
N_P	Population size	λ	Taper ratio
N_C	Total number of constraints	Λ	Aspect ratio

1. Introduction

Genetic algorithm (GA) has been introduced firstly by Holland (1975) expressing its two main features: 1) the string representation of complex structures, and 2) the power of simple transformations acting on the strings to improve these structures. Goldberg (1989) has made further developments introducing fitness functions. In fact, GAs are advantageous because of their robustness and simplicity. They can cope easily with discontinuous, rough, or multimodal functions, and make an interesting tradeoff between diversification, i.e., exploration of the search space and intensification, i.e., exploitation of the results. Application of simple genetic algorithm (Goldberg, 1989; Michalewicz, 1996; Haupt & Haupt, 1998 and Man *et al*, 1999) has been implemented by Karim and Ikehata (2000a) for the optimal design of rectangular hydrofoil using polynomial expressions of boundary element analysis results and also for the optimal design of systematic series propeller (Karim and Ikehata, 2000b). Though it is easier and less time consuming for finding optimum results, error may arise due to the regression equations, developed from analysis or experimental results, which are also valid only within the specific ranges. For this reason, boundary element analysis has been incorporated in this study directly with the optimization algorithm. Using gradient-based optimization technique, it is difficult to find gradient from the analysis results if those are not approximated by interpolation or some polynomial functions for which the accuracy of the results may be lost. Moreover, polynomial expression is suitable for few numbers of variables but it is computationally expensive for a large number of variables. As for example, if we use six variables and at least 4 points for each variable Mishima and Kinnas (1996), then total number of analysis runs needed for this case is 4^6, i.e., 4096. But the present method can find the optimum with less than 600 analysis runs as will be found later.

The advantage of GA is that it does not need to find gradient and accuracy will be as it is obtained by the analysis method. However, the drawback of the SGA including direct analysis method is time penalty required in evaluating fitness for large populations, over generation after generation. So an investigation is conducted here to implement micro-genetic algorithm (μGA) with a very small population, and with simple genetic parameters, in order to achieve fast turn around time from generation to generation evolution.

An extensive study of different genetic algorithm techniques from SGA to μGA with different GA parameters has been done by Carroll (1996). According to his study, larger populations should find the optimal individual for the environment in few numbers of generations than smaller populations. But, at the same time, larger populations take a longer amount of time to compute their progress at each generation. Therefore, he recommended μGA for the problem which requires longer amount of time (more than 30 CPU sec.) for function evaluations since total run time for many generations can be between a day and more than a week depending upon the population size.

Currently, many SGA users use population ranging in size from 30 to 200. The usual choice is based on earlier studies by De Jong (1981), in which, suggestions for optimal population choices based on parametric studies are presented. An investigation carried out by Goldberg (1998) showed that for serial implementation of binary coded GA the optimal population size is small. This result was obtained from optimizing for effective real-time schema processing in a given population. Goldberg also points out that simply taking a small population size and letting them converge is certainly not very useful, and proceeds to outline a scheme by which small population GA can be implemented. This research will apply this small population (coined as **Micro Genetic Algorithm-μGA**) approach for solving optimization problem. As implemented by SGA, the usual choice of population size is based on the concept that bigger population relates to better schema processing, less chance of premature convergence, and better optimal results. However, the population size should be as little as possible for less time requirement in evaluating fitness if direct analysis is incorporated for this search technique.

Micro-genetic algorithms are small-population GAs with reinitialization. Krishnakumar (1989) utilizes population size, $N_P = 5$, crossover rate, $P_C = 1$, and mutation rate, $P_m = 0$, along with an elitist selection strategy that always advances the best string of the current population to the next generation. Krishnakumar compares his μGA to SGA with typical parameter settings ($N_P = 50$, $P_C = 0.6$, and $P_m = 0.001$). He reports faster and better results with the μGA on two simple stationary functions and on a real-world, engineering control problem. μGAs have also been applied to the optimization of an air-injected hydrocyclone (Karr, 1991a), to the design of fuzzy logic controllers (Karr, 1991b), to the solution of the k-queens problem (Dozier *et al*, 1994) and to the optimization of chemical oxygen-iodine laser (Carrol, 1996).

2. Boundary Element Method

The boundary element method (BEM) or more commonly surface panel method (Hess and Smith, 1996; Hess, 1990; Kerwin *et al*, 1987 and Suciu and Morino, 1976) analyzes numerically the potential flow around lifting body as exactly as possible. In this method, the boundary surface of the body is represented by hyperboloidal quadrilateral panels with a constant source and doublet distributions and the trailing vortex wake is also represented by hyperboloidal panels with a constant doublet distribution. The complete solution for potential flow is obtained by simultaneously satisfying a condition of zero normal velocity at a control point on each panel of the body together with equal pressure Kutta condition at each trailing edge panel. The effect of viscosity has been added to the potential solution using Prandtl-Schlichting's formula.

Using this method, the results for rectangular and trapezoidal hydrofoils are compared with experimental results (Karim *et al*, 2000a). Here the same method is used to analyze all of the hydrofoils and marine propeller. The panel arrangement of elliptical hydrofoil (only half span is considered) including coordinate axes has been shown in Fig. 1. The lift and drag coefficients computed by BEM for the elliptical hydrofoil of aspect ratio 3.0 with NACA 0012 section (Abbott and Doenhoff, 1959) are compared with the experimental results from University of Tokyo (Takasugi *et al*, 1992) as shown in Fig. 2. From the figure, it is clear that computed lift coefficient agrees well with experimental results up to angle of incidence of 8 degrees and then it becomes lower than the experimental values. The drag coefficient is always higher than the experimental values but satisfactory within our design range. For more accuracy, viscous flow solver can be incorporated, but it will be computationally expensive.

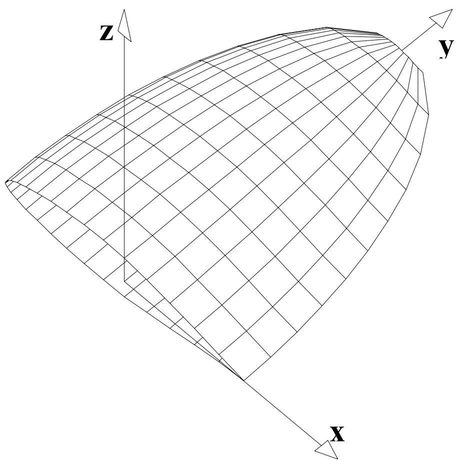

Fig. 1: Panel arrangement of elliptical hydrofoil (only half span is shown)

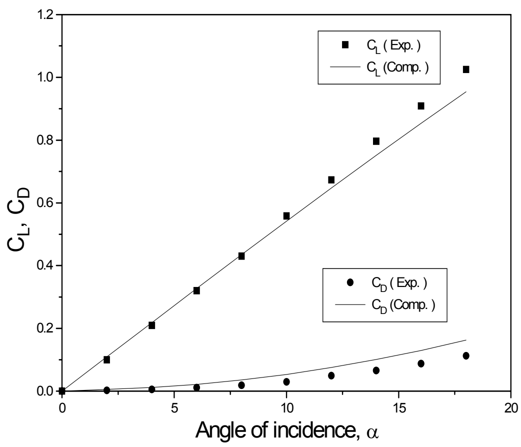

Fig. 2: Comparison of lift and drag coefficient with experiment for elliptical hydrofoil of aspect ratio 3.0

3. Optimization Problem

The objective is to find the design variables x to minimize or maximize the objective function $f(x)$, i.e.,

min or max $f(x)$ **(1)**
subject to $I_j(x) \leq 0$; $j=1,2,\ldots\ldots,m$
$E_k(x)=0$; $k=1,2,\ldots\ldots,n$

Where x is the solution vector, $I_1(x) \leq 0$, $I_2(x) \leq 0,\ldots\ldots,I_m \leq 0$ are inequality constraints and $E_1(x)=0$, $E_2(x)=0,\ldots\ldots,E_n(x)$ are equality constraints.

In the present study, the objective is to minimize drag coefficient, C_D in case of rectangular hydrofoil and to maximize lift/drag ratio, L/D in case of elliptical and trapezoidal hydrofoil. The design constraints to be considered are:
-Lower limit of lift due to a minimum payload requirement,
-Minimum foil section thickness for structural requirement,

-Negative minimum pressure coefficient for avoiding cavitation inception.

At first this constraint problem is converted to an unconstrained one associating penalty for any constraint violation. Thus Equation (1) is transformed into the following function:

$$F(x) = f(X) + \sum_{i=1}^{N_C} \delta_i \phi_i(X) \qquad (2)$$

where, N_C is the total number of constraints, δ_i is the penalty coefficients for constraint i, $\phi_i(X)$ is a penalty term related to the i-th constraint.

4. Application of Genetic Algorithm

An initial population of size, N_P is generated from random selections of the parameters in the parameter space. Each parameter set represents the individual chromosomes. Each of the individuals is assigned a fitness value after evaluation with boundary element analysis. There are then three genetic operations, such as, selection, crossover and mutation to produce the next generation. Fit individuals are selected for mating to create offspring, whereas, weak individuals die off. The process of mating and production is continued until an entirely new population of size, N_P is generated with the hope that strong parents will create a fitter generation of offspring. The fitness of each of the offspring is determined and the process of selection/crossover/mating is repeated. Successive generations are created until very fit individuals are obtained.

4.1 Micro genetic algorithm (μGA)

The μGA can be viewed as a diversification method because it promotes diversity across runs. Over multiple runs, selection pressure rises and falls, but selection noise drops due to redundancy. Just as in the SGA, the μGA works with binary coded populations and is implemented serially. The major difference of SGA and μGA comes in the population choice. In the μGA structure as proposed by Krishnakumar (1989), the population size is fixed at $N_P = 5$. It is known fact that GA generally does poor with very small population due to insufficient information processing and early convergence to non-optimal results. The key to success with small population was outlined by Goldberg (1988) as follows:

1. Randomly generate a small population.
2. Perform genetic operations until nominal convergence (as measured by bit wise convergence or some other reasonable measure).
3. Generate a new population by transferring the best individuals of the converged population to the new population and then generating the remaining individuals randomly.
4. Go to step 2 and repeat.

Based on this approach, a step-by-step procedure for the μGA implementation can be summarized as follows (Krishnakumar, 1989):

In the first step [See Fig.3], a population of size 5 either randomly or 4 randomly and 1 good string from any previous search is selected. In the second step, fitness is evaluated and the best string is determined. It is labeled as string 5 and carried it to the next generation (elitist strategy). In this way there is a guarantee that the information about good schema are not lost. The remaining four strings are chosen for reproduction (the best string also competes for a copy in the reproduction) based on a deterministic tournament selection strategy. The population is so small that the law of averages does not hold good and the selection strategy is kept purely deterministic.

In the tournament selection strategy, the strings are grouped randomly and adjacent pairs are made to compete for the final four (Care should be taken to avoid two copies of the same string mating for the next generation). Crossover is applied with crossover rate, $P_C = 1.0$. This is done to facilitate high order of schema processing. The mutation rate is kept to zero as it is clear that enough diversity is introduced after every convergence through new population of strings. The final step is to check for nominal convergence (reasonable measure based on either genotype convergence or phenotype convergence). It goes to the second step and repeats the cycle up to convergence. After convergence it restarts from beginning (first step) and the whole cycle is repeated until the number of generation exceeds the maximum number of generation as specified.

In the case of μGA, the "start and restart" procedure helps in avoiding premature convergence and the μGA is always looking for better strings. In implementing μGA, the intention is purely to find the optimum as quickly as possible and not in the average behavior of the population. In other words, the performance measure for μGA is based on the best-so-far string, rather than on any average performance. Population convergence for this study is defined to occur when less than 5% of the bits of the other individuals are different from the best individual as suggested by Carroll (1996). He also studied μGA with different population sizes of 3 and 10 and concluded that N_P equal to 5 is the optimum value.

5. Results and Discussions

The combination of NACA 66 modified thickness form and NACA a = 0.8 camber form (Koyama, 1993) is used for all of the hydrofoils. The results of genetic algorithm for rectangular, elliptical, trapezoidal hydrofoil and marine propeller have been described elaborately in the following subsections.

5.1 Rectangular hydrofoil

In the case of rectangular hydrofoil, the objective is to minimize drag coefficient, C_D satisfying following design constraints:

$C_L \geq 0.3$, $t_0/c \geq 0.07$ and $|C_{Pmin}| \leq 0.45$

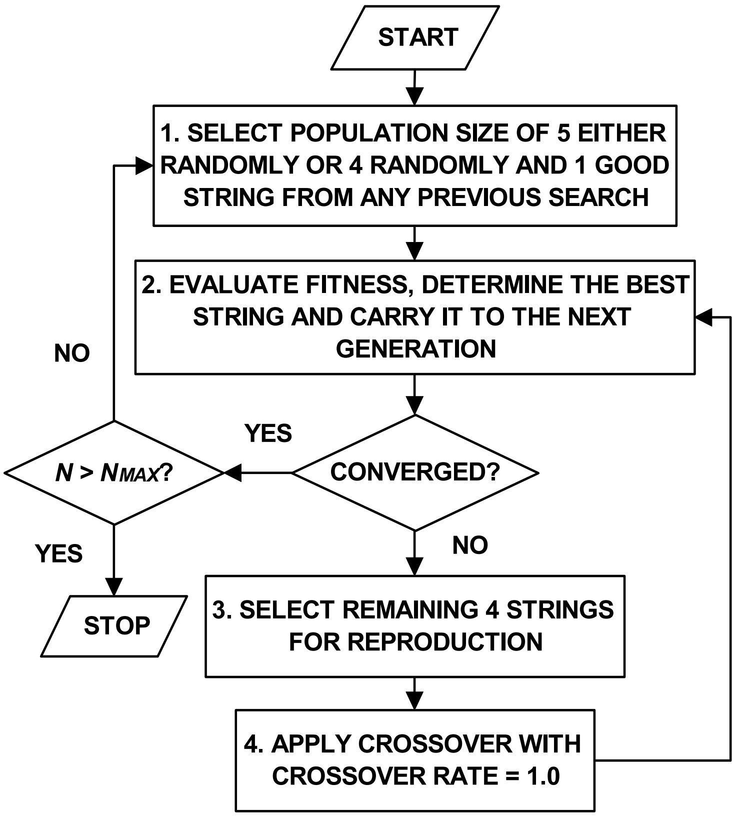

Fig. 3: Cycle of μ-genetic algorithm

The absolute value of minimum pressure coefficient equal to 0.45 corresponds to the maximum speed of about 45 knots without cavitation inception (Eppler and Shen, 1979). In this case, four design variables, such as, angle of incidence, α, maximum thickness ratio, t_0/c, maximum camber ratio, f_0/c

and aspect ratio, Λ are chosen. These parameters are descretized and translated into a binary string of length 26 as shown in Table 1. There are 2^{26}, i.e., approximately 6.7 million possible permutations of this parameter space. The successful use of GA technique for searching this large parameter space to design optimal hydrofoil was demonstrated by Karim *et al* (2000a). In that case, however, polynomial expressions obtained from the least square method based on boundary element analysis results were used. In the present case, direct boundary element method has been incorporated to analyze all of the hydrofoils.

Table 1: GA parameter search space for rectangular hydrofoil

Parameter	Range	Increment	# of possibilities	# of binary digits
α (deg.)	1.00-5.00	0.01600	256	8
t_0/c	0.06-0.12	0.00095	64	6
f_0/c	0.00-0.03	0.00048	64	6
Λ	6.00-8.00	0.03200	64	6

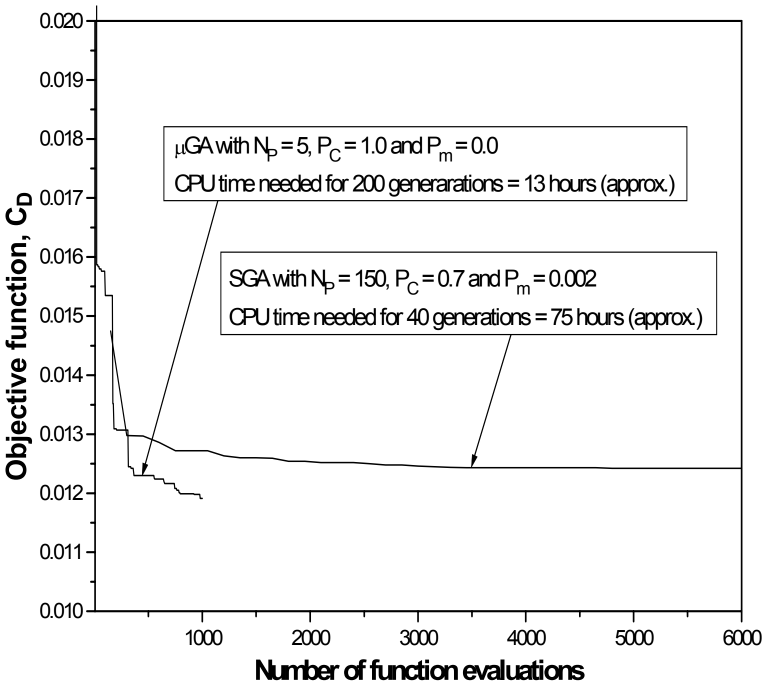

Fig. 4: Comparison of progress of μGA with that of SGA

The results of GA are shown in Table 2. The results of SGA with direct analysis are almost similar to those with polynomial expression. However, the value of C_D is slightly higher in the latter case. This difference is due to the error occurred by polynomial approximation. The problem has been also solved using μGA and the progress of μGA has been compared with that of SGA as shown in Figure 5. From this figure, it is clear that after 40 generations with population size of 150, i.e., 6000 analysis runs, SGA did not find the minimum value of C_D that has been found by μGA after 200 generations with population size of 5, i.e., 1000 analysis runs. However, the difference is very small. The principal advantage of μGA is that it requires about 13 hours of CPU time for 200 generations, whereas, SGA requires about 75 hours of CPU time for 40 generations on a personal computer (*PC*) with *CPU* speed of 500MHz. The performance of μGA is better than SGA since it converges faster than that.

Table 2: Results of GA for rectangular hydrofoil

Variable	α (deg.)	t_0/c	f_0/c	Λ	C_D	CPU time (approx.)
SGA using polynomial approximation	1.8235	0.0700	0.0300	8.0	0.013697	3.5 hours
SGA using direct analysis	1.8321	0.0713	0.0277	8.0	0.011648	75 hours
μGA using direct analysis	1.7686	0.0705	0.0286	8.0	0.011641	13 hours

5.2 Elliptical hydrofoil

In the case of elliptical hydrofoil, five parameters, such as, angle of incidence, maximum thickness & camber ratios, aspect ratio and angle of sweep have been used and each parameter is coded by less number of binary digits for faster convergence of optimum results; since the accuracy after two decimal points is not considered so much important in this study. Table 3 shows the GA parameter search spaces used in this study. However, taper ratio is not considered here; since it is fixed by elliptical chord distribution. So the total number of possibilities is then 2^{14}, i.e., 16384. Lift-to-drag ratio (*L/D*) is used as the objective function and the constraints similar to rectangular hydrofoil are used in this case. μGA found near optimal *L/D* ratio (27.48424) at 33 generations and optimal *L/D* ratio (27.48491) at 108 generations. The results obtained by μGA have been shown in Table 4. GA found the upper bound of camber ratio and aspect ratio as the optimum values. In fact *L/D* increases with camber and aspect ratio. But camber is restricted by minimum value of C_P constraint and aspect ratio by maximum permissible span, weight etc.; though they are not considered in this case. Optimum maximum thickness ratio is found as minimum value set by structural constraints. Optimum angle of sweep is found as its lower bound.

Table 3: GA parameter search space for elliptical and trapezoidal hydrofoils

Parameter	Range	Increment	# of possibilities	# of binary digits
α **(deg.)**	1.25-3.0	0.25	8	3
t_0/c	0.05-0.12	0.01	8	3
f_0/c	0.0-0.03	0.01	4	2
Λ	6.5-8.0	0.50	4	2
β **(deg.)**	1.25-5.0	0.25	16	4
λ	0.1-0.8	0.10	8	3

Table 4: Results of GA for elliptical hydrofoil

α (deg.)	t_0/c	f_0/c	Λ	β (deg.)	*L/D*	C_L	$-C_{Pmin}$
2.5	0.07	0.03	8.0	1.25	27.4849	0.3692	0.4069

5.3 Trapezoidal hydrofoil

The plan form view of the trapezoidal hydrofoil has been shown in Fig. 5, where b, C_r, C_t, β are the half span, root chord, tip chord and the angle of sweep respectively. The taper ratio is defined as the ratio of tip chord to root chord, i.e., $\lambda = C_t / C_r$. Six variables such as angle of incidence, maximum thickness and camber ratios, aspect ratio, angle of sweep and taper ratio are chosen for the optimal design of trapezoidal hydrofoil. The objective function and design constraints similar to elliptical hydrofoil are considered here. The design parameter search spaces are shown in Table 3. With total 17 bits, the total number of possibilities is 2^{17}, i.e., 131072. In this case, μGA found near optimal *L/D* ratio (27.53500) at 82 generations and optimal *L/D* ratio (27.53568) at 113 generations. The results obtained by μGA have been shown in Table 5.

The taper ratio and angle of incidence take the intermediate values as the optimum values. The lift-drag ratio is also improved slightly in this case. To check the results, effect of two design variables, such as, angle of incidence and taper ratio on the *L/D* ratio is studied keeping the values of other design variables fixed. The contour plot of *L/D* ratio has been shown in Fig. 6, from which it is clear that GA has successfully found the king of the hill.

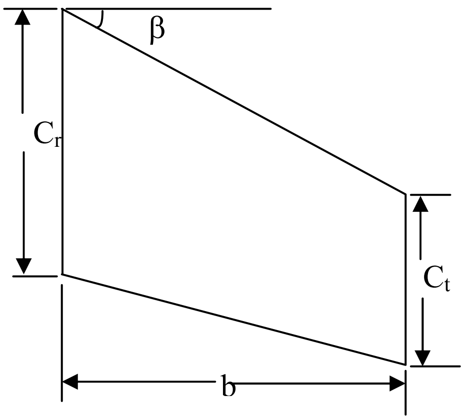

Fig. 5: Plan form view of the trapezoidal hydrofoil

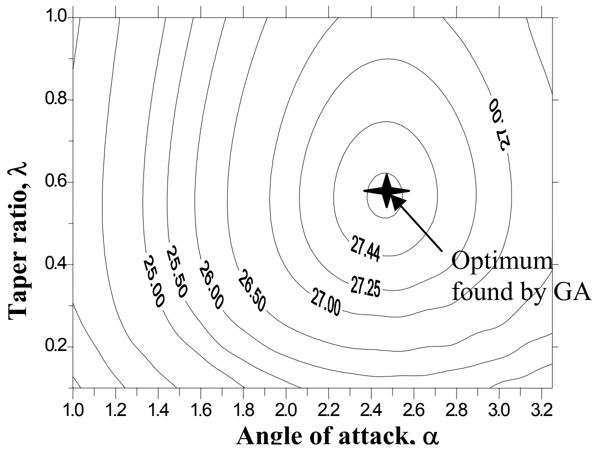

Fig. 6: Contour of *L/D* ratio for trapezoidal hydrofoil ($t_0/c = 0.07, f_0/c = 0.03, \Lambda = 8.0, \beta = 2.5$)

The variation of *L/D* ratio with angle of sweep is shown in Fig. 7. According to the figure, the *L/D* ratio increases with increase in angle of sweep, reaches the maximum at angle of sweep of 2.5 and then decreases. However, the variation is very small and not so much improvement is found with angle of sweep. The main advantage of angle of sweep is that if the length of the span is restricted, it is possible to increase the aspect ratio as well as *L/D* ratio by increasing the angle of sweep since *L/D* ratio increase with increase in aspect ratio.

The variations of *L/D* ratio with angle of incidence for different maximum thickness and camber ratios are shown in Fig. 8 and 9 respectively. From Figure 11, it is found that the values of *L/D* ratio for smaller value of maximum thickness ratio are higher than those for larger value of maximum thickness ratio at each angle of incidence. This is due to the fact that viscous drag is increased by the increase in maximum thickness ratio. For this reason, optimum value of maximum thickness ratio tries to approach the lower bound. In the present case, however, it is restricted by minimum value assigned for the structural reason.

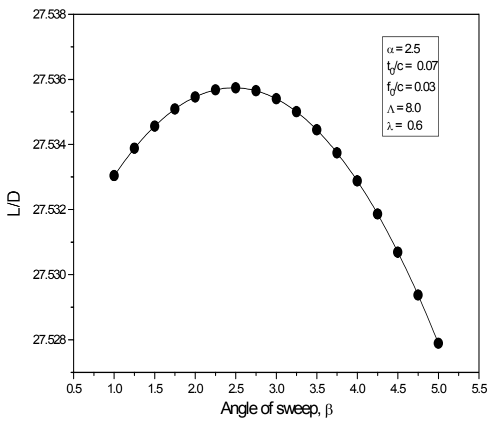

Fig. 7: Variation of *L/D* ratio with angle of sweep, β for trapezoidal hydrofoil.

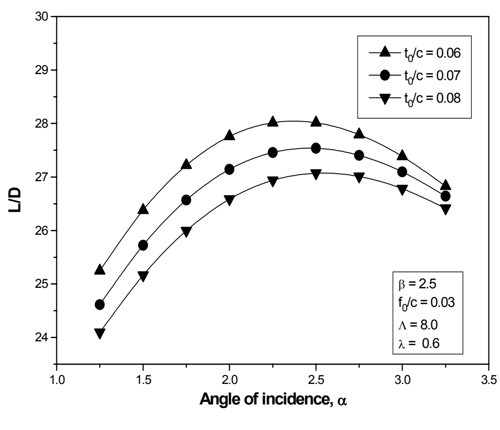

Fig. 8: Variation of *L/D* ratio with angle of incidence in case of trapezoidal hydrofoil

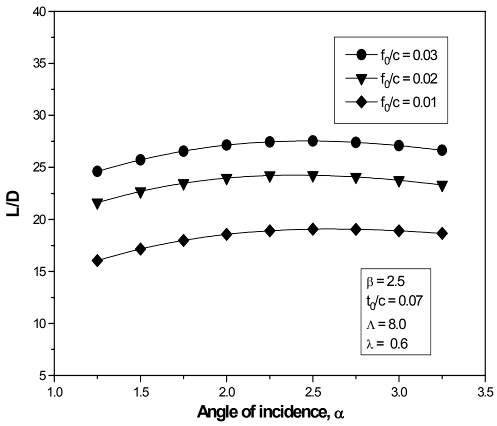

Fig. 9: Variation of *L/D* ratio with angle of incidence for different maximum camber ratios *(f_0/c)* in case of trapezoidal hydrofoil

From Fig. 9, it is clear that the values of *L/D* ratio for larger value of maximum camber ratio are always higher than those for smaller value of maximum camber ratio. This is why optimum value of maximum camber ratio approached to the upper bound where it does not violate the constraint of minimum C_P value. It is interesting to note that for optimum value of maximum thickness and camber ratios, the *L/D* ratio reaches maximum at optimum angle of incidence found by GA.

Rectangular hydrofoil is the special case of trapezoidal hydrofoil when taper ratio is equal to 1.0 and angle of sweep is equal to zero. Since GA found optimum value of taper ratio as 0.6 and angle of sweep as 2.5 degrees, we can conclude that the performance of trapezoidal hydrofoil is better than rectangular hydrofoil. Again the value of *L/D* ratio for optimum trapezoidal hydrofoil is higher than that for optimum elliptical hydrofoil. So the performance of trapezoidal hydrofoil is found better than any other hydrofoil for the present design case.

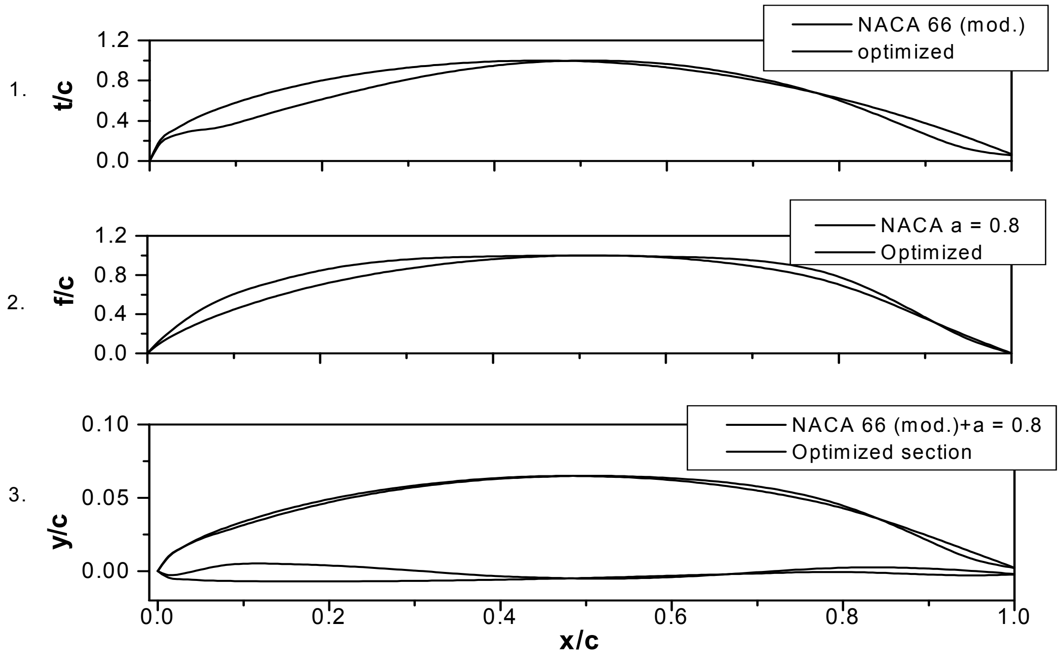

Fig. 10: Comparison of optimized section with the original NACA section (1. Thickness distribution, 2. Camber distribution, and 3. 2-D section)

Table 5: Results of GA for trapezoidal hydrofoil

α (deg.)	t_0/c	f_0/c	*Λ*	*β* (deg.)	*λ*	*L/D*	C_L	$-C_{Pmin}$
2.5	0.07	0.03	8.0	2. 5	0.6	27.53568	0.3688	0.4194

5.4 Two-dimensional section design

Many researchers studied two-dimensional section design but all of their methods are based on two-dimensional analysis ignoring three-dimensional effect. In the present study, however, two-dimensional section with NACA 66 (mod.) thickness distribution and NACA a = 0.8 camber distribution are fitted

with B-spline polygon vertices (9 for the former and 7 for the latter). Then the shape of the section is varied by shifting B-spline polygon vertices vertically and using this generated section, trapezoidal hydrofoil (aspect ratio, 8.0, taper ratio, 0.6, maximum thickness ratio, 0.07, maximum camber ratio, 0.03, angle of incidence, 2.5 deg. and angle of sweep, 2.5 deg.) is analyzed by 3-D boundary element method. GA then updates the section shape by shifting the 5 polygon vertices for thickness and 5 for camber distribution and finally, the optimum section is found for which hydrofoil attains maximum *L/D* ratio satisfying following design constraints:
$C_L \geq 0.3$; $t_0/c = 0.07$; $f_0/c = 0.03$; and $C_{Pmin} \leq 0.45$

GA has found the optimum section for trapezoidal hydrofoil after 204. In Fig. 10, the optimum section is compared with the original NACA section including thickness and camber distributions. The chord wise pressure distributions for the optimum section are compared with those for the original NACA section at different span wise positions as shown in Fig. 11. The hydrodynamic coefficients of optimized section have been compared with NACA standard section in Table 6. It is interesting to note that *L/D* ratio is increased by 35% $((L/D_{Opt}-L/D_{NACA})/L/D_{NACA})$ with respect to the original NACA section.

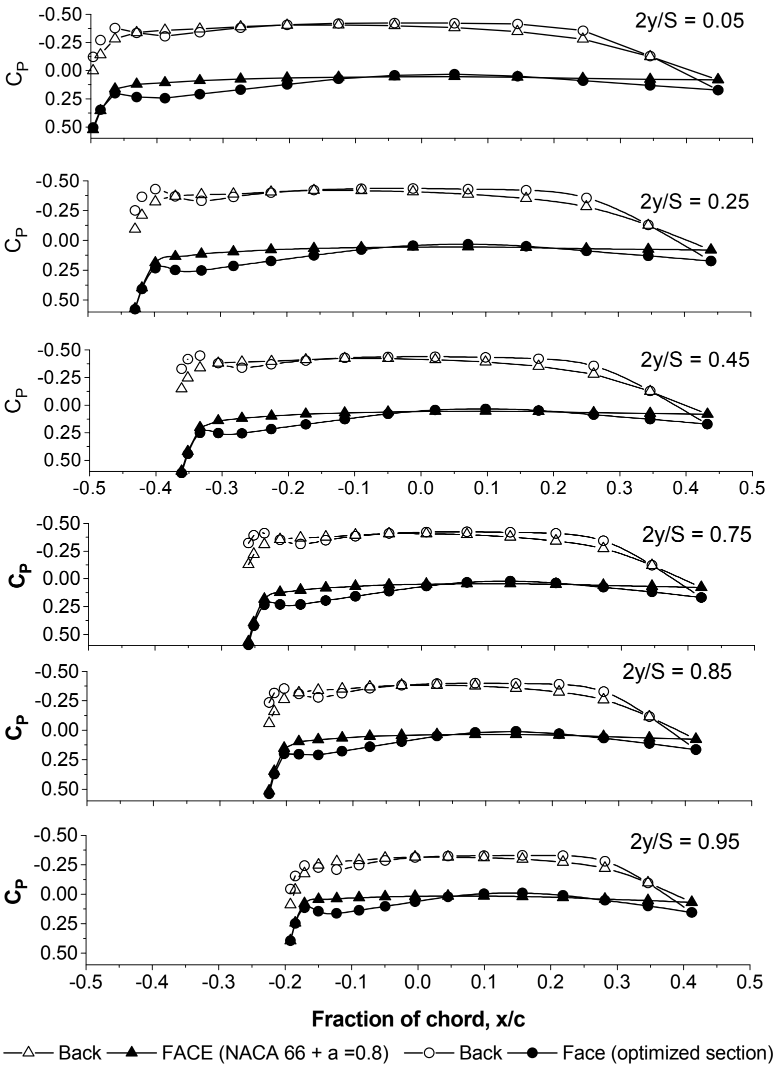

Fig. 11: Comparison of pressure coefficients between NACA and optimized section

Table 7: Comparison of hydrodynamic coefficients of optimized section with those of NACA original section.

	C_L	C_D	L/D	$-C_{Pmin}$
Original NACA section	0.36884	0.01339	27.53568	0.4194
Optimized section	0.42232	0.01137	37.13586	0.449843

5.5 Design of marine propeller

In this study, a marine propeller is designed using micro genetic algorithm (μGA). At first, span wise chord distribution, pitch distribution, maximum thickness and camber distributions of DTRC 4119 propeller are fitted with 5 B-spline polygon vertices. GA then updates these geometric characteristics by shifting 3 vertices vertically without changing end 2 vertices. Using these characteristics, the generated propeller is analyzed by Boundary Element Method and improved propeller of efficiency higher than DTRC 4119 propeller is found by GA with small amount of change from the original propeller. The constraints used here are as follows:

$K_T \geq$ **0.12;** $K_Q \leq$ **0.03 and** $C_{Pmin} \leq$ **0.7**

Fig. 12 shows the comparison of span wise chord distribution between the improved and original DTRC 4119 propeller. The chord distribution of improved propeller is almost constant up to 90% radial position. The comparison of pitch angle between the improved and original propellers is shown in Fig. 13. The curve of pitch angle of improved propeller is under that of original propeller. The thickness and camber ratios of improved propeller are compared with those of original propeller in Figs. 14 and 15. The thickness of improved propeller increases with respect to original propeller. The camber distribution of improved propeller is almost mirror image of original propeller, i.e., loading is shifted from root to tip in case of improved propeller.

The open water characteristics of improved propeller are compared with those of original propeller in Table 7. From this table it is clear that the efficiency is increased by about 5%. However, if we draw the open water characteristics at off design conditions, we can see that performance of the improved propeller is better than the original propeller as shown in Fig. 16, but unfortunately the improved propeller has maximum efficiency at the design advance coefficient of original propeller. From the design point of view, design advance coefficient should be a little bit left from the peak of the efficiency curve. So if we choose design advance coefficient for improved propeller a little bit left, the range of the operating condition of the propeller will be reduced and the improvement over the original propeller will not be more than 1 or 2%.

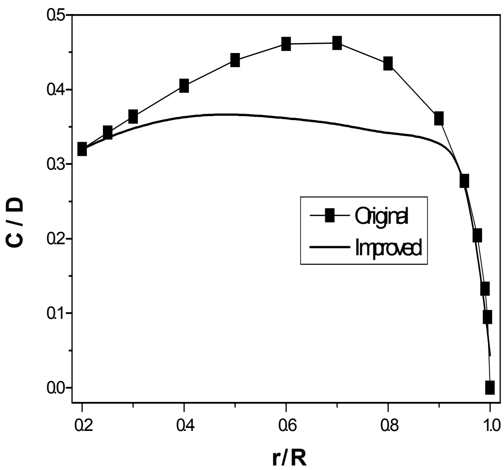

Fig. 12: Comparison of span wise chord distribution of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.833$)

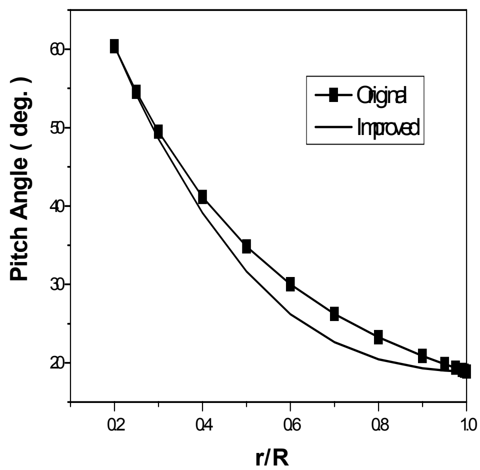

Fig. 13: Comparison of pitch angle of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.833$)

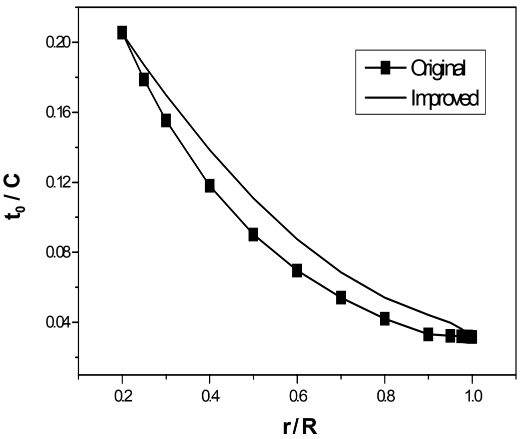

Fig. 14: Comparison of maximum thickness ratio (t_0/C) of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.833$)

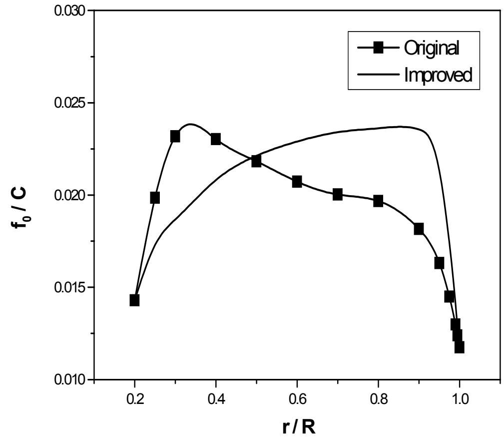

Fig. 15: Comparison of maximum camber ratio (f_0/C) of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.833$)

To overcome this problem, GA is applied to optimize propeller at advance coefficient, a little bit higher than the design advance coefficient, as for example, at $J = 0.9$. The constraint of minimum pressure coefficient is relaxed by a small amount. In the previous case, the first point of distribution is fixed, but now this condition is released. The propeller distributions are shown in Figs 7-10. The open water characteristics at advance coefficient, $J = 0.833$ are shown in Table 7. In the present case thrust coefficient has been increased and performance of the improved propeller is better than the previous case. Moreover, it is clear from Fig. 21, the present improved propeller may have the same design advance coefficient as the original propeller.

Table 7: Comparison of open water characteristics of improved propeller and those of DTRC 4119 propeller at design advance ratio, $J = 0.833$

Type of Propeller	K_T	K_Q	η_0
DTRC 4119	0.1657	0.0297	0.7406
Improved	0.123	0.0207	0.7898

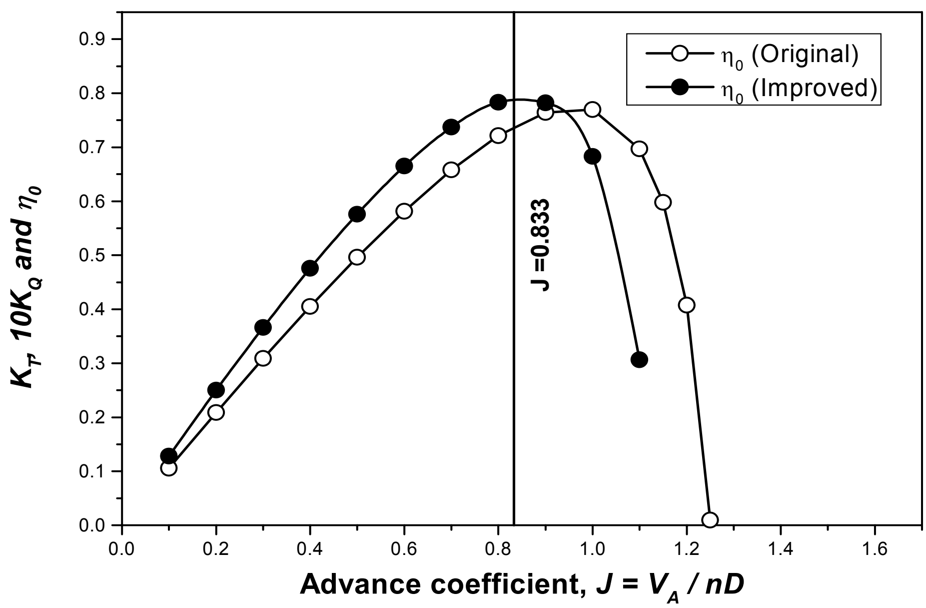

Fig. 16: Comparison of open water characteristics of improved propeller with that of DTRC 4119 propeller at off-design conditions (Optimized at $J = 0.833$)

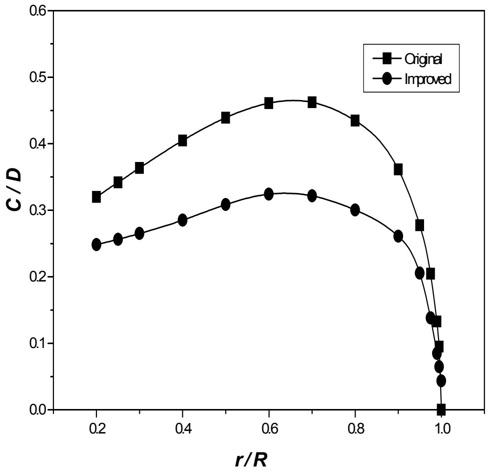

Fig. 17: Comparison of span wise chord distribution of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.9$)

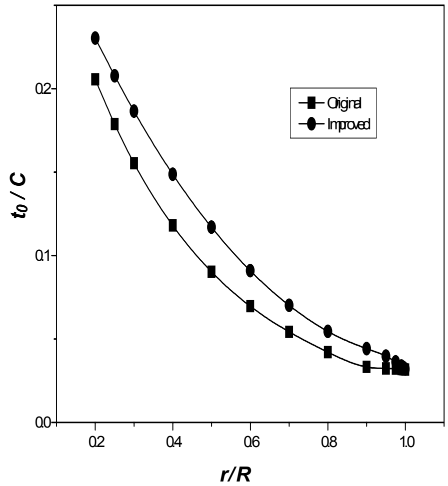

Fig. 19: Comparison of maximum thickness ratio (t_0/C) of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.9$)

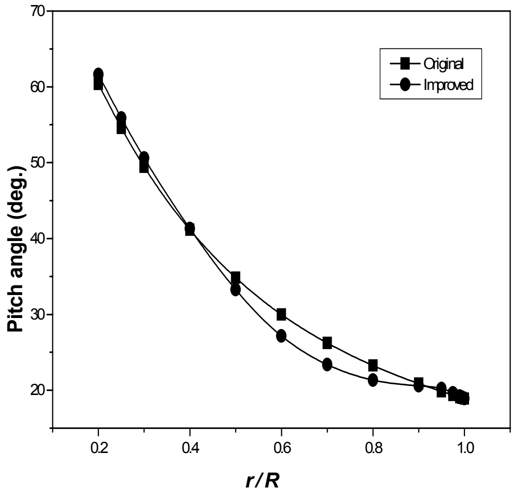

Fig. 18: Comparison of pitch angle of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.9$)

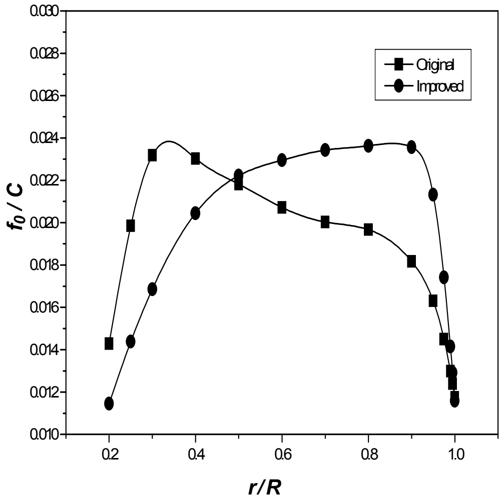

Fig. 20: Comparison of maximum camber ratio (f_0/C) of improved propeller with that of DTRC 4119 propeller (Optimized at $J = 0.9$)

Table 8: Comparison of open water characteristics of improved propeller and those of DTRC 4119 propeller at design advance ratio, $J = 0.833$

Type of Propeller	K_T	K_Q	η_0
DTRC 4119	0.1657	0.0297	0.7406
Improved (previous)	0.123	0.0207	0.7898
Improved (present)	0.1413	0.0236	0.7926

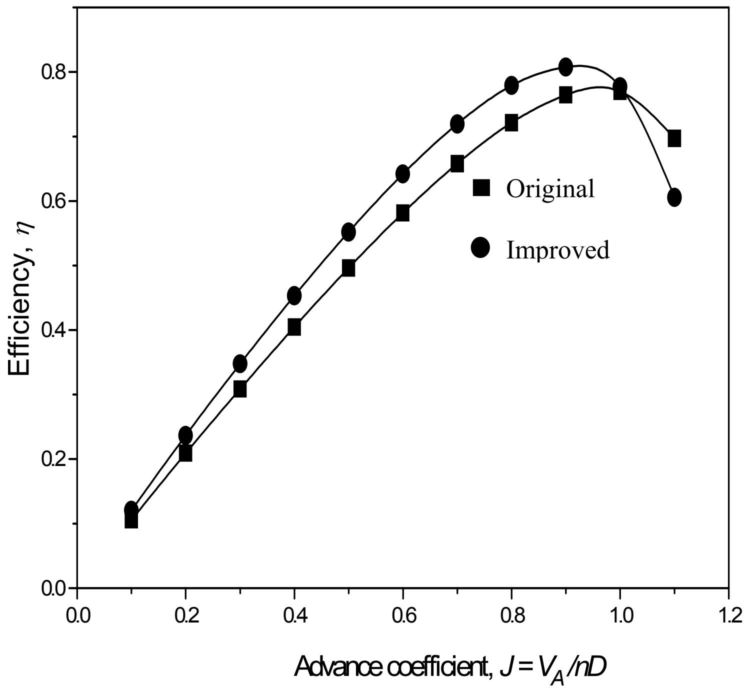

Fig. 21: Comparison of open water performance of improved propeller with that DTRC 4119 propeller (Optimized at $J = 0.9$)

6. Conclusion

A genetic algorithm based optimization technique has been successfully applied to the design of hydrofoil of different plan forms and marine propeller incorporating boundary element method. From the abovementioned study, the following conclusions can be drawn:

1. Genetic algorithm is successful for the design optimization of non-cavitating rectangular, elliptical and trapezoidal hydrofoils satisfying some design constraints. They are also useful for the two-dimensional section design taking three-dimensional effect into account.
2. The method is also applicable to the design of marine propeller.
3. The performance of micro-genetic algorithm is better than simple genetic algorithm for its faster convergence.
4. Direct implementation of boundary element method with GA instead of regression equations increased the accuracy of the analysis results.

GA has been restricted here only to optimize non-cavitating hydrofoils and propeller, however, it can be extended to cavitating hydrofoils or other lifting bodies, e.g. rudder etc.

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