ON NOVEL USAGE OF A HYBRID METHOD (ANN and GA) FOR FASTER 3-D AERODYNAMIC OPTIMIZATION

O. Ergüven VATANDAŞ

İstanbul Gelişim University
School of Applied Sciences,
Aviation Management Program,
İstanbul, Turkey
oevatandas@gelisim.edu.tr

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ABSTRACT

The purpose of this study is to offer a more efficient hybrid aerodynamic optimization method for 3-D wing configurations by using both genetic and artificial neural network. Artificial Neural Network (ANN) is used with a new approach in the aerodynamic optimization of a forward swept wing. The developed technique has been found much more robust than Genetic Algorithm (GA) only methods. For example, the new hybrid technique acquires the same fitness level as the one that GA only method can reach in 500 calculations, in about half time (about 250 calculations). The drag coefficient reduction is calculated %33 faster in the offered method. The neural network is embedded into the genetic algorithm along with augmented elitism to prevent possible bad members in the generations.

Keywords: *Hybrid optimization techniques, 3-D Aerodynamic optimization, Forward swept wings*

3-D AERODİNAMİK OPTİMİZASYON İÇİN HİBRİT BİR YÖNTEMİN (ANN ve GA) YENİ KULLANIMI ÜZERİNE

ÖZET

Bu çalışmanın amacı, genetik algoritma ve yapay sinir ağını kullanarak 3 boyutlu kanat konfigürasyonları için daha verimli ve etkin bir hibrid aerodinamik optimizasyon metodu sunmaktır. Yapay Sinir Ağı (ANN) ileri ok açılı kanadın aerodinamik optimizasyonunda yeni bir yaklaşımla kullanılmıştır. Geliştirilen tekniğin Genetik Algoritma (GA) yöntemlerinden çok daha etkin ve güçlü olduğu görülmüştür. Örneğin, yeni hibrid teknik, sadece GA kullanan yöntemin 500 akış çözümüyle ulaştığı seviyeye, yaklaşık yarı zamanda (250 hesaplamada) ulaşabilmektedir. Sürükleme katsayısında sağlanan azalma, önerilen yöntemde % 33 daha hızlı sağlanmaktadır. Yapay sinir ağı algoritması, olası kötü üyeleri önlemek için düzenlenmiş olan özel bir elitizm yöntemiyle birlikte GA içine eklenmiştir.

Anahtar Kelimeler: *Hibrid optimizasyon teknikleri, 3-B Aerodinamik optimizasyon, İleri ok açılı kanatlar*

1. INTRODUCTION

Genetic algorithm (GA) is a non-gradient optimization method that mimics the evolution process in nature. Initial population of design variable sets is analyzed with a predetermined, problem dependent cost function. Then, crossover and mutation methodologies are applied to the initial population where best solutions of the initial population survive to create a new population. This process continues until a global extremum is found [1].

For years now, several studies related to GA are reported in the literature. To name a few, Hacıoğlu and Özkol [2] have developed a new technique for 2-D airfoils design named as Vibrational Genetic Algorithm (VGA). Liu [3] proposed a new GA, to determine the best combination of design variables. Additionally, Hacıoğlu [4] proposed an Augmented Genetic Algorithm with Neural Network (AGANN), which increases the computational efficiency to a much higher level. He applied the technique to nozzle shape design problem and showed its effectiveness in the results.

Another new approach to the multi-objective constrained design of aerodynamic shapes is suggested by Epstein and Peigin [5]. The approach employs GA as an optimization tool in combination with a reduced-order-models method based on linked local databases obtained by full Navier–Stokes computations.

Qazi and Linshu [6] present a new procedure for efficient conceptual design of complex systems with multidisciplinary and computationally intensive analysis using large number of design variables. Ludwig et al. [7] introduced a new information-theoretic methodology for choosing variables and their time lags in a prediction setting, especially while the ANN is used in non-linear modeling. Kurtulus [8] investigated a neural network to model the unsteady aerodynamic force coefficients of flapping motion. The shape of the simulated force coefficients was in a good agreement with the numerical results. Huang et al [9] developed a robust optimization and applied to supercritical wing aerodynamic design. Their optimization design system consists of genetic optimization algorithm, improved back propagation (BP) neural network and deformation grid technology. Sun et al. [10] proposed an applicable airfoil / wing inverse design method by using Artifical Neural Network and airfoil / wing database, to fit the required aerodynamical features.

FORTRAN is selected as the programming language. FORTRAN's wide usage in aerospace industry for decades, performance and conventionality for writing technical formulas makes FORTRAN an ideal candidate for this study.

Onera M6, which is widely used in CFD applications, is modified as a Forward Swept Wing and used as the initial model. Afterwards, taper ratio and section of the wing are changed to create new members of generation. Finally, using Genetic Algorithm and Artificial Neural Networks, new alternatives and better members of population are obtained in order to optimize the wing.

In this study, an efficient hybrid aerodynamic optimization method for 3-D wing configurations by using both genetic and artificial neural network is investigated. Artificial Neural Network (ANN) is used with a new approach in the aerodynamic optimization of a forward swept wing. The developed technique has been found much more robust than Genetic Algorithm (GA) only methods.

2. ARTIFICIAL NEURAL NETWORK

In the hybrid technique used in this study, a trained ANN operator produces a candidate solution at each step of the GA process by using the target fitness values. Thus, a training set for the ANN uses FSW geometries and flow parameters calculated by the Euler flow solver [11]. At the beginning, the response surface obtained from the ANN is not expected to be close enough to the target solution, because the GA population (the set of training data for the ANN) is probably far from the target values. For this reason, at the initial generations, ANN produces unsuitable candidate solution with respect to the desired parameters. However, this candidate may have better fitness value than those produced by the GA. In this case, the member predicted by the ANN can make the GA faster in the exploration of better individuals. That is, even if ANN does not give the desired candidate, it may be able to provide a better individual for the population. On the other hand, as the GA progresses and the individuals (set of training data for the ANN) get closer to the target, ANN can produce better alternative candidates and eventually can achieve the desired solution. Consequently, this positive interaction between the ANN and the GA can lead to relatively faster selection of the desired solution.

In this research, as an ANN method, Radial Basis Function Networks (RBFN) technique is used. In the RBFN technique shown in Figure 1, training set made out of m samples as related to input data which have n parameters, is calculated by using the following equations.

$$u_i^k = \sum_{j=1}^{n} \left(x_j^k - x_j^i \right)^2 \quad \text{(i=1,m k=1,m)} \tag{1a}$$

$$h_i^k = \phi\left(u_i^k\right) \tag{1b}$$

$$[h]\{w\} = \{f\} \tag{1c}$$

At first m radial basis (h) are calculated for input data. Then weights wj are calculated between output layer and hidden layer based on output values (f). The number of individuals in training and the number of neurons in hidden phase are assumed the same.

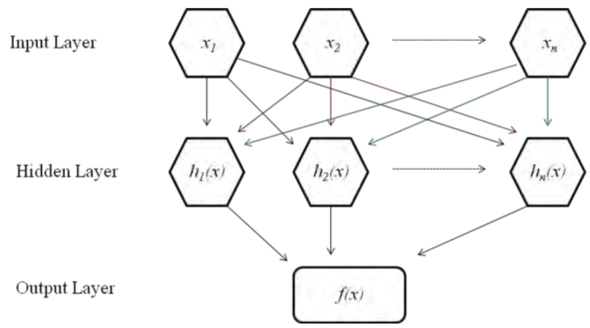

Figure 1. Layers of the RBFN technique as ANN

This means that the matrix [h] is m×m square matrix. The parameter ϕ in the equations 1 is the radial function. It may be taken in different forms. It is used as Gauss form in this study:

$$\phi(u) = e^{-\frac{u}{rs}} \tag{2}$$

Rs can be defined by user as real number. The weights wj are determined according to with the Equation 1c. Therefore it is possible to estimate output f(x) after determining u and h values by using the following formula:

$$f(x) = \sum_{j=1}^{m} w_j h_j \tag{3}$$

The training of the RBFN is performed based on individuals of the genetic algorithm population. Hence n chromosomes of each individual become the x parameters of the input layer. The fitness values of the GA optimization process will be f parameters of the output layer.

3. DEVELOPED HYBRID TECHNIQUE

The ANN method is embedded into the GA optimization process along with augmented elitism.
The augmented elitism is a precaution against the possibility of a bad member produced by the ANN procedure. In this case the best two members are taken from the previous population instead of the ANN member. However this is only a precaution and it is needed few times.

In this optimization, the main aim is to minimize the inviscid drag force. However it is not the unique target, while minimizing the drag, the lift force and the thickness ratio are aimed to be held fixed. The taper ratio and the wing sections are taken as design variables. The outlines of hybrid optimization of FSW are shown in Figure 2.

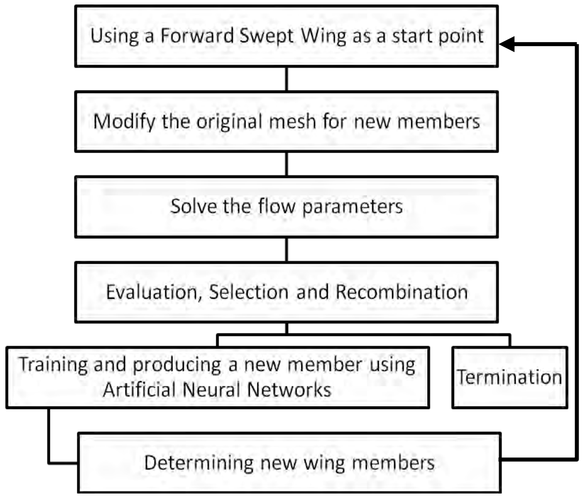

Figure 2 Main steps of the hybrid optimization process

The algorithm evaluates design variables depending on the design constraints. The initial (or starting) population is produced by changing the initial wing section and taper ratio. Afterwards, these initial candidates are subjected to hybrid optimization operations. All members in each population (or generation) are evaluated according to fitness values. Each member is then subjected to crossover process in accordance with the fitness values. The selection probability of each candidate depends on these fitness values. After this, the mutation process is applied to randomly alter some members. Maximum fitness values are calculated in Figure 3.

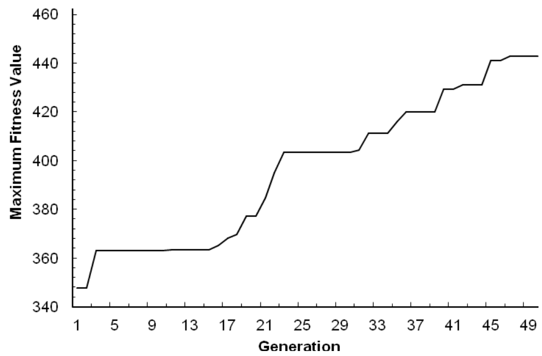

Figure 3 Maximum fitness values during the hybrid optimization.

Each generation consists of ten members and their surface plot is given in Figure 4. As it can be seen on the figure, fitness values increase with each generation and reach the peak at the final (50th) generation

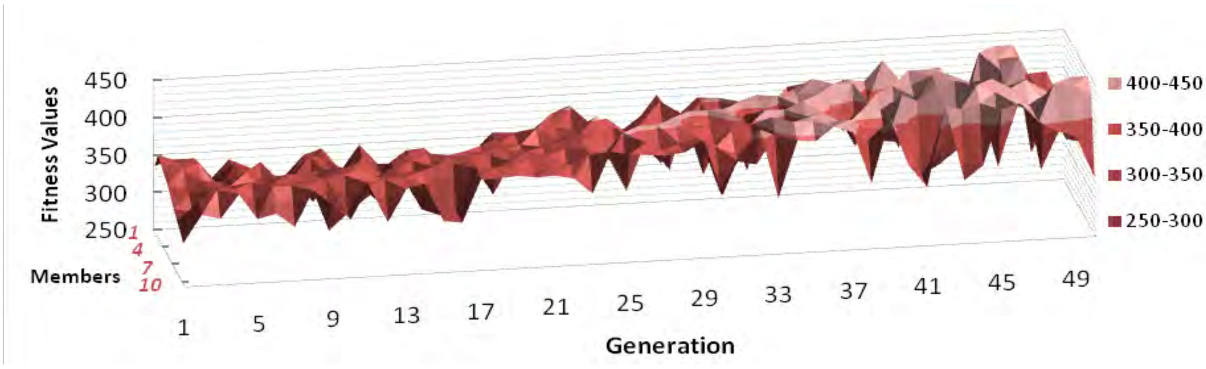

Figure 4 Fitness values within each generation during the hybrid optimization.

Because of elitism applied to genetic processes the maximum fitness value can not be less than previous step. So that the best member found in each generation can not be worse than the previous generation. Improvement in the drag coefficient is shown in the Figure 4.

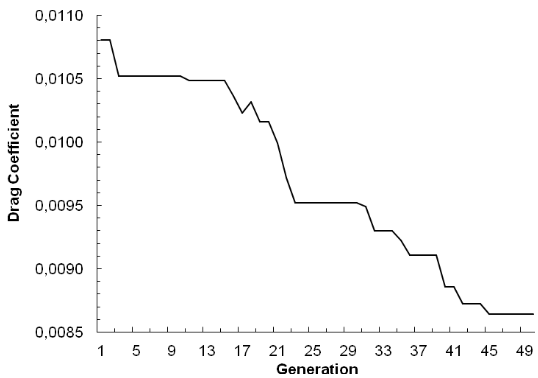

Figure 5 Development of the drag coefficient calculated for the best members in each generation.

As it can be seen from the graph, the inviscid drag calculated in each step has decreased around 20% without a significant change in the thickness and the lift values in 500 calculations. An Euler flow solver [11] is used to compute the flow parameters around FSWs.

In the Figure 6 pressure coefficient contours of the initial wing are shown on the left hand side, while the best wing obtained at the step 50 (50th generation) is seen on the right. The pressure coefficient distribution for the initial model is shown in Figure 7.

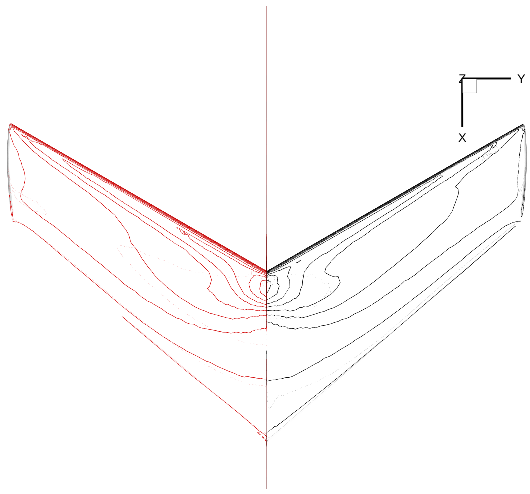

Figure 6 The coefficient of pressure contour starting forward swept wing (left) and the best wing at step 50 (right)

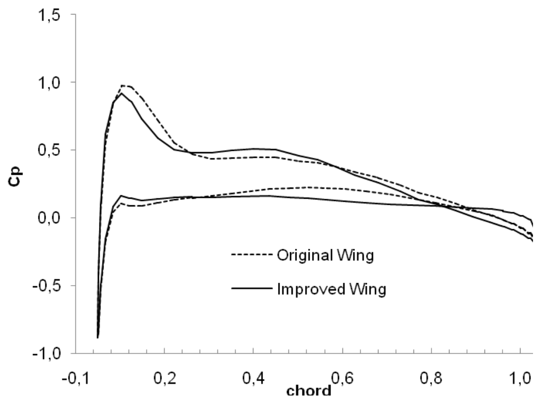

Figure 7 Pressure coefficient plot for the root sections.

The difference between wing sections is also very less because of the thickness ratio constraint. This fairly limits the variations in the genetic process. Initial and best wing sections are shown in the Figure 7.

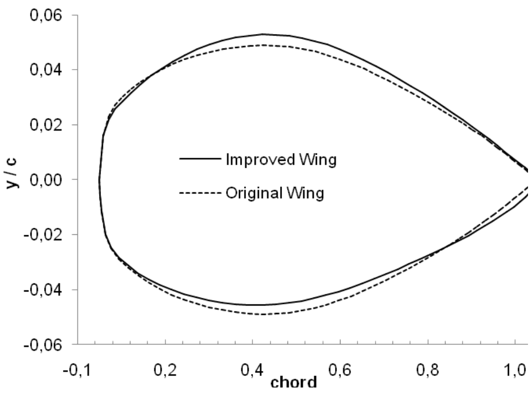

Figure 8 The airfoils of the starting and best FSW

4. COMPARISON OF HYBRID OPTIMIZATION TO THE PREVIOUS GENETIC OPTIMIZATION

In this section, some critical findings of the hybrid optimization technique are to be compared to the classical GA results [12-14]. This comparison gives relatively significant results. Comparison of maximum fitness value development of the hybrid (ANN-GA) and GA optimization processes is shown in Figure 9. As it can easily be seen on this Figure, increase rate in the maximum fitness value of hybrid optimization is greater than the GA optimization. The hybrid technique reaches the same value, in about half time. Because the optimized model in this study is 3 dimensional wing geometry, most of the calculation time is spent for the flow calculation. Each flow solution takes approximately half an hour or an hour depending on the mesh density and CPU capacity. There are 10 flow calculations in each generation. However the genetic optimization and ANN operations take maximum a few minutes. Because of this, instead of CPU time which depends on CPU type and mesh density, reduction in the number generations that GA reaches a high maximum fitness value, is preferred.

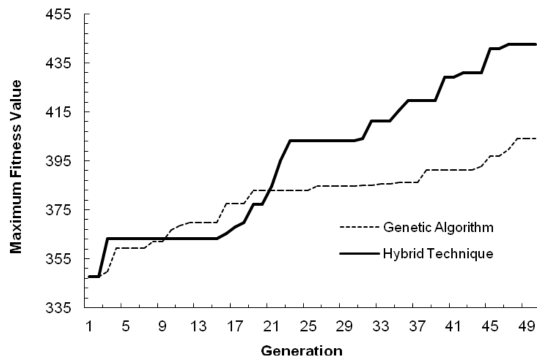

Figure 9 Maximum fitness value development comparison

Figure 10 shows the differences between drag coefficient progresses of ANN-GA and GA optimizations. Comparison of taper ratio developments in ANN-GA and GA optimizations is shown in Figure 11.

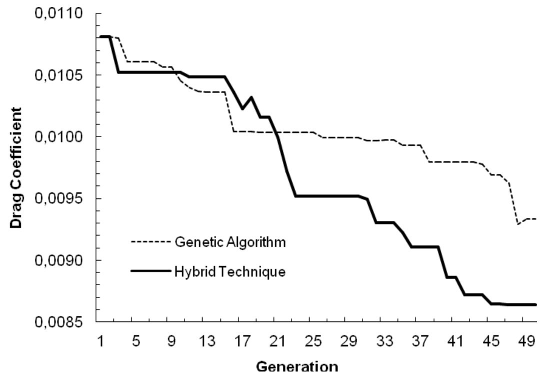

Figure 10 Drag coefficient calculated in each step

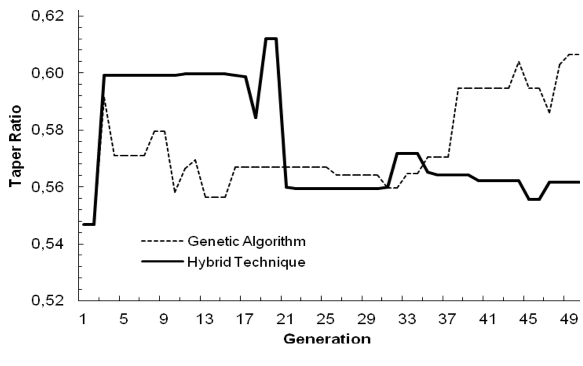

Figure 11 Taper ratio developments in GA and hybrid (ANNGA) optimizations

As it can be seen from the Figure 11, in the previous GA optimization, it has been observed that the taper ratio tries to increase. However in the hybrid method taper ratio stays almost at the same level.

5. CONCLUSION AND EVALUATION

By using the developed hybrid method, the drag coefficient reduction is performed 33% faster than the classical technique. While the hybrid technique reaches a specific fitness value in about 250 calculations, GA only method can obtain the same fitness value in 500 calculations.

Improvement in the drag force is realized without any significant change in the lift coefficient and the thickness ratio. After 50 generations, the fluctuations in the lift coefficient and in the thickness ratio are both about 3%. It is possible to keep these differences in a smaller margin by increasing the corresponding weighting constants in the fitness function. Nevertheless it should be noticed that large increment in these weighting constants would result in more calculation time.

The augmented elitism, which is used in this study, is a precaution against any possible bad member coming from the ANN operator. That is taking the best two members from the previous population instead of the ANN produced member.

The inviscid drag calculated in each step is decreased by 19% without a significant change in the wing thickness and the lift force values in 500 calculations. It has been found that this hybrid technique, developed in this study, is robust and converges faster. It has the capability of eliminating unsuitable wing geometries in the produced populations. The ANN method improves the classical GA, makes it go faster and capable of better selection.

This study has shown that the ANN technique is working in reducing the process time especially for the 3-D aerodynamic optimization. Normally the 3-D flow calculations take much time and the GA methods require many calculations for different 3-D geometries. From this point, the ANN techniques can be useful especially for 3-D genetic optimizations.

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