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An Efficient Aerodynamic Optimization Method using a Genetic Algorithm and a Surrogate Model

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Abstract

A reliable method is presented for robust estimation of the expensive objective functions in single objective optimization algorithm. Multi Layer Perceptron Neural Net (NN) is successfully implemented for evaluating computationally expensive aerodynamic objective functions while the normal distribution concept is applied to determine the parts of the design space which are trained to the NN. Detecting these parts, NN is successfully implemented for evaluating computationally expensive aerodynamic objective functions in design optimization of airfoil shape at viscous transonic flow conditions. This approach, results in more precise NN estimation while decreasing the NN requirements. The accuracy and efficiency of the method is validated with simple Genetic Algorithm. The total number of flow solver calling is noticeably reduced through using this technique, which in turn reduces the total time without deteriorating the optimization algorithm.

Introduction

Among different methods for aerodynamic optimization, Genetic Algorithms are known to possess unique capabilities compared to other methods. The fundamental aspects of Genetic Algorithms are described in reference [12]. One of the key features of a GA is that it searches the design space from a population of points and not from one special point resulting in a greater likelihood of finding the global optimized point. Another advantage of using a GA is that it uses only the objective function and does not require its derivatives. These features and some other features made GAs attractive to practical engineering applications such as aerodynamic shape optimization [17, 19, 15]. However, a GA has the disadvantage of being computationally time-consuming in aerodynamic optimization problems. Several attempts have been made such as parallel processing [13, 3] or adaptive GA [14] in order to decrease the time required by GA but considerable work is yet to be done.

The increasing amount of available information from successive generations during the optimization process has encouraged researchers to introduce a new field in fitness function approximation. Many fitness function approximation models (surrogate models) are introduced until now which approximate the expensive objective functions. These models are trained using the existing set of evaluated solutions and can search for promising solutions. A literature survey reveals that many of the new approaches of GA utilize these methods to reduce the total time associated with optimization process. Chung, et al. applied merit Functions to supersonic Business Jet drag minimization problem and showed that Response Surface model can be used in a global optimization problem [1]. Interesting fitness approximation techniques can be found in [6].

Among different surrogate models, NN are particularly suitable for the representing objective functions that incorporate several design variables. Since most design problems in Aerodynamics involve lots of parameters, NN seem to be a suitable choice for these cases. Karakasis and Giannakoglou used Radial Basis Function Net Works in transonic aerodynamic multi-objective optimization of airfoil shape [9]. In another research, Giannakoglou et al. utilized gradient-assisted NN in several aerodynamic optimization problems [10].

Despite their wide usage, there are many important subjects that require careful tuning when incorporating NN in the evolutionary algorithms. Among them are the number of generations which should run using GA, in order to provide a rich training set for NN and the number of patterns needed to train the surrogate model [10].

To cover these problems, the normal distribution concept is used in this research. To improve the application of Neural Networks (NN) in evaluating computationally expensive aerodynamic objective functions**,** the normal distribution is applied to determine that part of the design space which is trained to the NN. Detecting these parts, the NN is successfully implemented for evaluating computationally expensive aerodynamic objective functions in evolutionary optimization of airfoil shape at transonic high Reynolds number flight conditions.

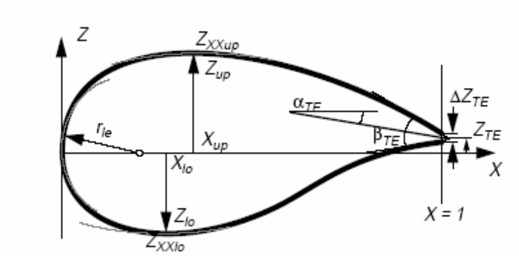

Figure 1. PARSEC method for airfoil parameterization

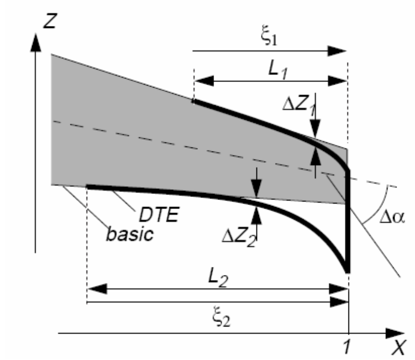

Figure 2. Parameters used for TE modelling

Aerodynamic Optimization Using GA

Genetic Algorithms are attractive for aerodynamic design optimization since they are more likely to find a global optimum. GA utilizes the three operators of reproduction, cross over and mutation. More information about GA can be found in [9]. In the present study simple Genetic algorithm is applied to the optimization of a transonic airfoil. Thus, fitness, chromosomes and genes are corresponding to the objective function, design candidates and design variables, respectively. There are twenty individuals in each generation. Selected airfoil shapes comprise the initial population for comparison purposes. Then, the population is optimized according to the objective function value (fitness) through the Genetic Algorithm which is considered to be the ratio of the lift coefficient to drag coefficient (C_l/C_d). The overall process consists of evaluation, selection, crossover and mutation.

Selection is a process in which chromosomes are copied in mating pool according to their fitness. In this work the tournament operator [2] is used with an elitist strategy where the best chromosome in each generation is transferred into the next generation without any changes.

The crossover operator exchanges the chromosomes of the selected parents randomly. A simple one-point crossover operator is used with an 80% probability of combination, as the use of smaller values was observed to deteriorate the GA performance.

Mutation is carried out by randomly selecting genes of each chromosome and changing their values by an arbitrary amount within prescribed ranges. In this work the mutation probability is set to 10% and then adds a random disturbance to the parameter about 15% of design space that defined for each chromosome's gen. Optimization is then accomplished by a conventional GA.

Design parameters are a combination of PARSEC and a new method for trailing edge modelling introduced in [18] these parameters are shown in Figures 1 and 2. ΔZ the trailing edge is computed using the following equations.

$$\Delta Z_{lower} = \frac{L_{lower} \tan\Delta\alpha}{\mu.n}[1-\mu.\xi^n-(1-\xi^n)^\mu] \tag{1}$$

$$\Delta Z_{upper} = \frac{L_{upper} \tan\Delta\alpha}{\mu.n}[1+\eta.\xi^n-(1-\xi^n)^\mu] \tag{2}$$

The considered values for μ , η and n are 1.3, 0.8 and 6, respectively. Trailing edge coordinate (Z_{TE}) and thickness parameters of PARSEC method are considered equal to zero thus they can be omitted from the list of design variables. Therefore the total number of design variables is increased to 10 which include leading edge radius (r_{LE}), upper and lower crest location $(X_{UP}, Z_{UP}, X_{LO}, Z_{LO})$ and curvature (Z_{xxUP}, Z_{xxLO}), trailing edge direction (α_{TE}) and wedge angel (β_{TE}) from PARSEC method and $\Delta\alpha_{TE}$ from new method for trailing edge modelling. The total number of the design parameters applied in this method is ten.

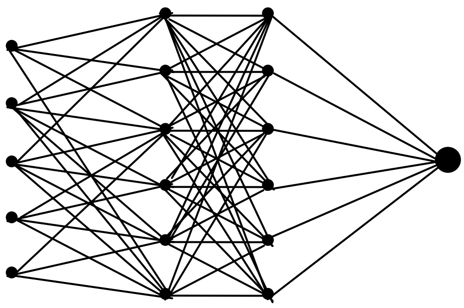

Figure 3. Multi layer Perceptron with two layers

Flow Solver

The huge numbers of airfoil shapes that are generated by the Genetic Algorithm are evaluated based on numerical simulation of viscous flows governed by Navier-Stokes equations using a finite-volume cell-centred scheme. To decrease the computational time, an implicit method is used in the present work. The method is a dual time implicit method that follows the work of Jahangirian and Hadidoolabi for unstructured grids [4]. Further details of the method can be obtained from the above reference.

The computational field is discretized utilizing triangular unstructured grids. A successive refinement method is used for unstructured grid generation [5]. During the design process, the mesh is continuously updated as the shape of the geometry changes. In the present work, the primary mesh generated around initial airfoil is moved to be fitted to the new generated airfoil using spring analogy.

Application of Neural Nets in Optimization Algorithm

One of the main concerns in the aerodynamic optimization with GA is the required computational effort. One idea to deal with this problem is using the parallel computing, which is highly compatible with the evolutionary algorithms. Despite its efficiency in reducing the time consumed by GA, the required hardware is sometimes expensive and time consuming in practice. The other idea, which is followed in this work, is utilizing the approximate methods in order to estimate the objective function values. These approximate methods use surrogate models to predict the time consuming objective functions. According to what mentioned in the introduction section, several surrogate method have been used in literature [6, 7, 9]. Among all fitness function approximation methods, Neural Network (NN) is widely used in the estimation of the costly objective functions [10, 11, 16]. The most common Neural Network models are the Radial Basis Function Net work (RBFN) and the Feed-forward Multi-Layer Perceptron (MLP). MLP, which is utilized in this research, is illustrated in Figure 3.This type of Neural Network is known as supervised NN because it requires a desirable output in order to learn. One of the most popular methods for NN training is Back Propagation method (BP) which is utilized in this paper. More information about Multilayer Perceptron and Back Propagation can be found in [6]. The goal of this type of Neural Network is to create a model that correctly maps the input to output using the training data. This model can then be utilized to produce the output when the related function is unknown or expensive to use.

Fitness Function approximation Using Neural Net and Normal Distribution Concept

Regarding its application in GA, Neural Network can be trained either off-line or on-line. In the off-line approach, the NN model is trained using the data which are built during a specified generation in the optimization process. Once such a NN has been trained, it is used to evaluate the fitness values in the optimization algorithm. The most important problem associated with this method of learning is that the trained data set may not cover the entire design space. Therefore NN is not able to provide the acceptable values for the fitness function. During the on-line learning in NN, data can be added to the NN without any change to the previous results or revaluations. Therefore this approach is much more reliable than the off-line learning but the efficiency of the method highly depends on the method. More detailed discussion about on-line and off-line training can be found in [9]. The on-line learning process updates the training set through the evolution. Different methods of training about on-line learning process are studied in [11].

Once a Neural Net has been trained, it is used to evaluate candidate solutions generated by GA. However the discrepancy between the fitness obtained from the exact solution and NN should be controlled and limited to avoid converging to incorrect optimum during the optimization process.

The Neural Network structure used here is based on a two hidden layer Feed-forward Perceptron network. The Neural Network inputs at first layer include the values of genes for each chromosome and the output is the fitness value of the same

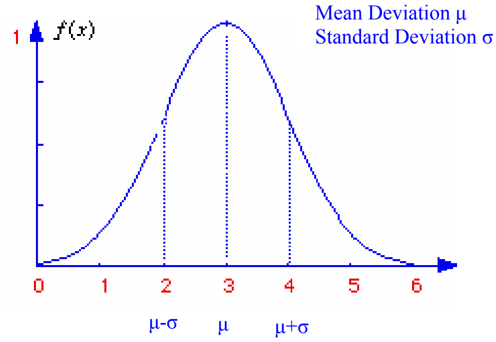

Figure 4. Normal distribution curve

chromosome at output layer. The hidden layers have 10 neurons. Training data consist of chromosome's genes and fitness values at a specified generation.
To improve the reliability of the fitness values computed in the NN, a new method is used to determine the capability of NN in providing a suitable guess for fitness value. Similar to the previous method, a training data set is prepared after pacing some generations. This data set is then trained to NN. To determine the scattering of the data, normal distribution of the training data set is calculated. The normal distribution curve is a continuous, bell-shape, symmetric distribution. It is shown in Figure 4 for a sample data. Normal distribution in this figure is gained utilizing normal distribution function. Normal distribution function shows the distribution of the probabilities and is calculated using the following equation.

$$f(X) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(X-\mu)^2}{2\sigma^2}\right) \qquad (3)$$

μ and σ, are the mean value and the standard deviation which are obtained through the following equations.

$$\mu = \frac{\sum_{i=1}^{n} X_i}{N} \qquad (4)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \mu)^2}{N}} \qquad (5)$$

In the equations above, X_i is the *i*th data and *N* is the number of data. The mean deviation represents the central point of the distribution, while the standard deviation describes the width of the distribution. The higher the standard deviation, the wider the normal curve will be. Mean and standard deviations of a sample data are shown in Figure 4.
The specified range in Figure 4, i.e. the range between $\mu-\sigma$ and $\mu+\sigma$ is the most populated part of the population distribution. Therefore, determining the normal distribution, it is decided whether a specific individual is in the part of design space which is trained to NN, i.e. the most populated region in the train set or not. The NN used here applies an on-line training method, i.e. if it was decided to use flow slower for evaluation of objective function according to the above criteria, the information related to this individual are added to the training set for the next generation.

Results

To show the efficiency of the proposed approach, it is utilized in the aerodynamic optimization of a viscous transonic airfoil shape.

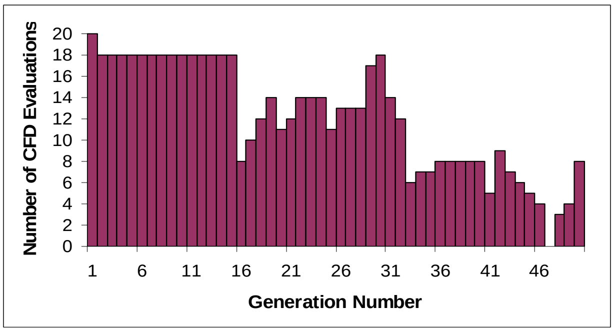

Figure 5. Number of flow solver calls in each generation

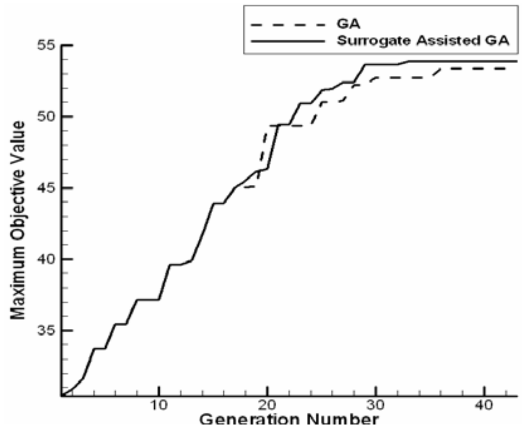

Figure 6. Convergence history of the maximum objective function

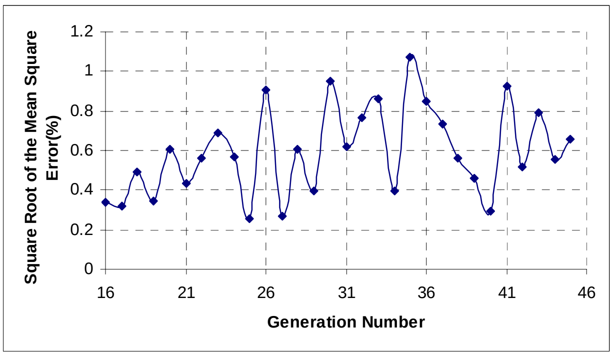

Figure 7. Average error of NN estimation

The optimization is carried out at transonic flight conditions of Mach Number 0.75 and incidence angle of 2.79 degrees and Re=6.5 million. Initial airfoil is RAE 2822.
The objective function is lift coefficient to drag coefficient (C_l/C_d) and twenty individuals are considered in each generation. NN is applied after 16 generations when enough data are generated for training.
Figure 5 shows the number of the CFD runs during the optimization process using the suggested approach. The total number of the CFD runs in NN assisted GA is 603 which provides 33.15% decrease in flow solver calls when compared with GA.
Figure 6 shows the convergence history for both simple GA and surrogate assisted GA. According to this figure, both methods follow similar curves. The maximum objective value gained by surrogate assisted GA is very close to the one obtained by GA.
Figure 7 shows the square root of the mean square error of NN estimation for each generation. The maximum error is related to 35^{th} generation and is 1.07% which is an acceptable value.

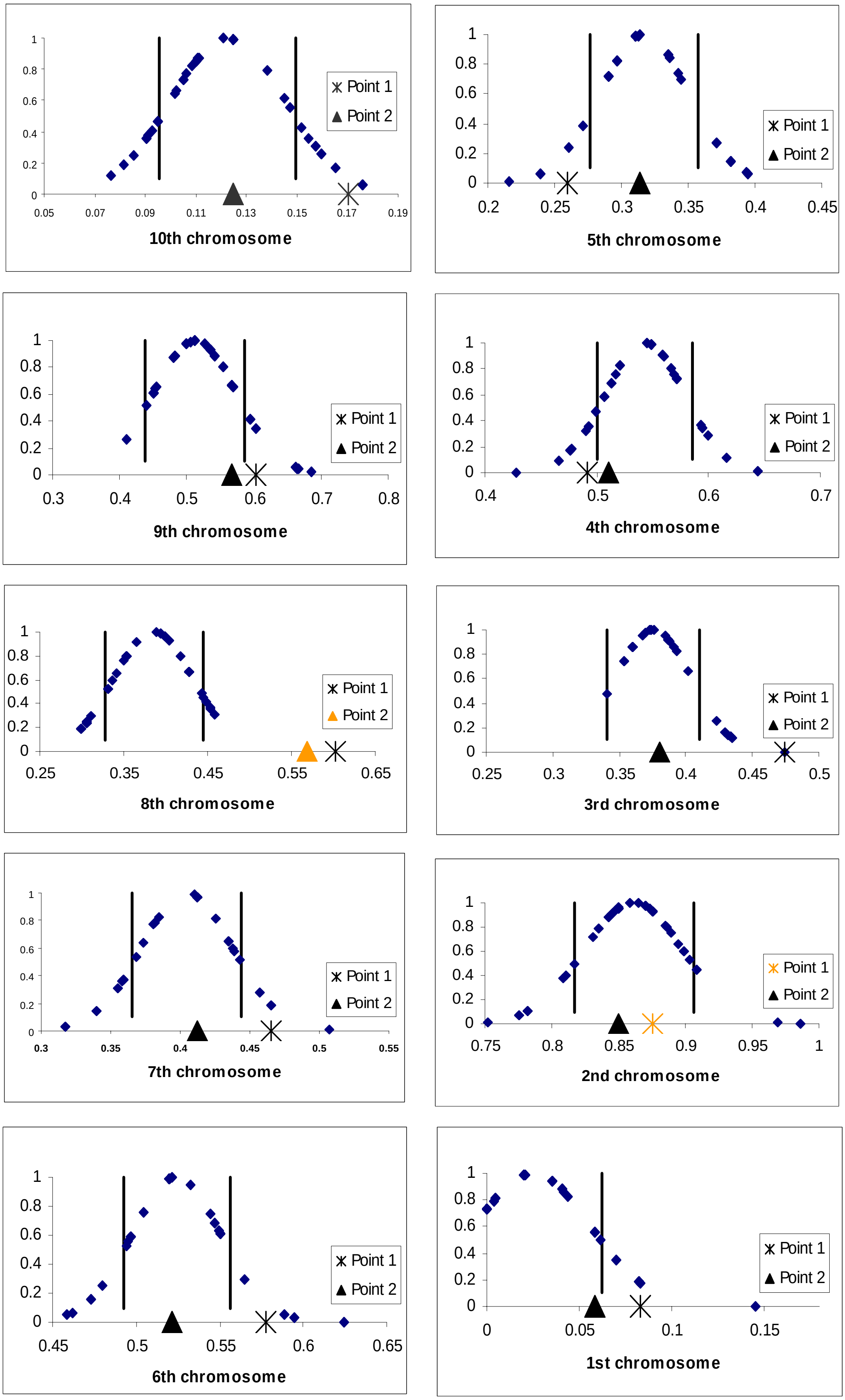

Figure 8. Normal function distribution and range specification of the sixteenth generation

The number of the CFD runs in each generation, is quite random, depending on the location of the individuals in the normal distribution curve. Figure 8 shows the normal distribution and the range between $\mu - \sigma$ and $\mu + \sigma$ for ten chromosomes representing the design variables generated during the first fifteen generations in the Genetic Algorithm. Two individual of the sixteenth generation are also selected randomly and their positions are shown in this figure in order to decide about the method that should be applied for computing their objective values. It is illustrated in the picture that in the case of the first individual, the chromosomes fell outside the specified ranges except for the second chromosome of the first individual. Therefore the objective function for this individual is computed using flow solver. However, in the case of the second individual, chromosomes are within the ranges excluding the eighth chromosome. The objective function of this individual is estimated using NN. This method is used for the entire individuals of each population.

Figure 9 illustrates unstructured grids around initial airfoil. Figures 10 and 11 compare the results of the optimized airfoil shapes from a Genetic Algorithm and the combination of the Genetic Algorithm and the described NN. These figures confirm that optimum airfoil shape resulting from proposed surrogate model is very similar to the optimum shape obtained though GA.

Artificial Neural Network was successfully implemented in evaluation of costly aerodynamic objective functions. Normal distribution of the trained data set was determined in order to specify weather the NN is able to provide an accurate estimation for a special individual and training data set was updated at the end of each generation. The results obtained were compared with simple GA to show the capability of the surrogate method in providing precise guess for aerodynamic objective functions. The comparison show that there is negligible difference between simple GA and proposed surrogate assisted GA, making the proposed method practicality more applicable for optimization problems

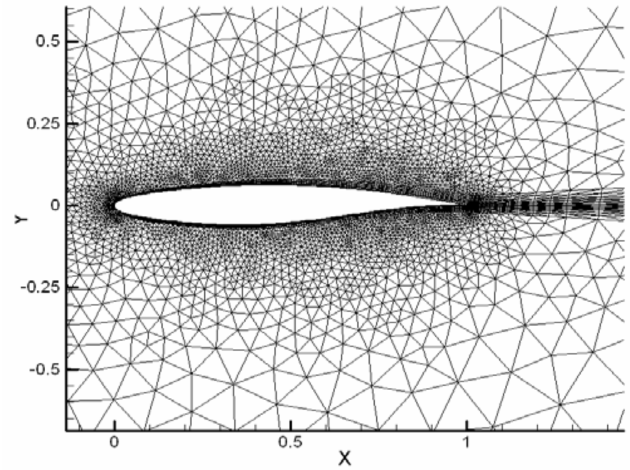

Figure 9. Unstructured grids around RAE 2822 airfoil

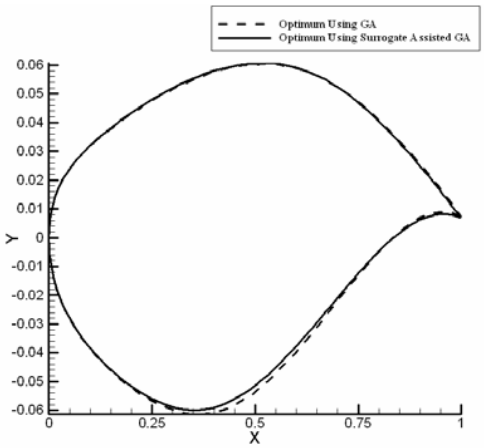

Figure 10. Optimum airfoils using GA and surrogate assisted GA

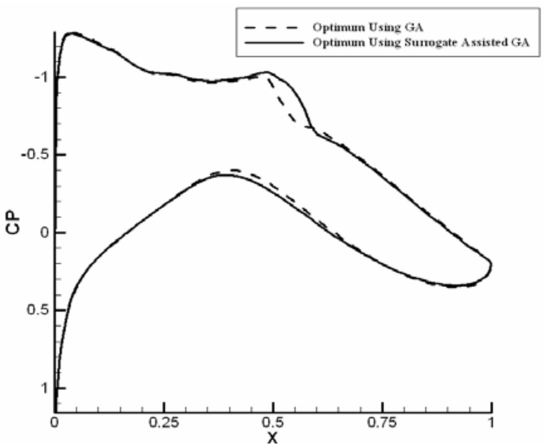

Figure 11. Pressure distributions of optimum airfoils using GA and surrogate assisted GA

Conclusions

Artificial Neural Network was successfully implemented in evaluation of costly aerodynamic objective functions. Normal distribution of the trained data set was determined in order to specify weather the NN is able to provide an accurate estimation for a special individual and training data set was updated at the end of each generation. The results obtained were compared with simple GA to show the capability of the surrogate method in providing precise guess for aerodynamic objective functions. The comparison show that there is negligible difference between simple GA and proposed surrogate assisted GA, making the proposed method practicality more applicable for optimization problems.

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