25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

# An Efficient Multi-Objective Optimization Strategy Using the Self-Organizing Maps for Airfoil Shape Designs

**Octávio Regeni Silva**
**SungKi Jung**
**Luiz de Siqueira Martins Filho**
Universidade Federal do ABC, Centro de Engenharia, Modelagem e Ciências Sociais Aplicadas, Santo André, São Paulo 09210-580, Brazil.
sungki.jung@ufabc.edu.br

***Abstract.*** *In this study, an efficient multi-objective optimization strategy is presented to circumvent a time-consuming problem of the optimization, which is combined with the evolutionary algorithm and the computational fluid dynamics (CFD). The strategy is based on the two approaches; a readjustment of initially designed ranges of parameters and construction of the rapid response model replacing the CFD calculations. The self-organizing map method and the generalized regression neural networks are employed for the readjustment of the design ranges and the response model, respectively. For the multi-objective optimization, the adaptive range multi-objective genetic algorithm was used. Lastly, present approaches are tested to design the airfoil shapes, which have a better aerodynamic performance than a reference airfoil in terms of a maximum lift coefficient and a lift-to-drag ratio.*

***Keywords:*** *self-organizing map, generalized regression neural networks, adaptive range multi-objective genetic algorithm, PARSEC method, computational fluid dynamics*

## 1. INTRODUCTION

An evolutionary algorithm in general needs the population-based search algorithm. One of the representatives is a genetic algorithm, which is inspired by biological evolution, such as reproduction, mutation, recombination, and selection. This algorithm can deal almost of all types of objective functions (linear/non-linear and continuous/dis-continuous equations), it however requires a lot of computations for evaluations of the populations. In particular, its real application for the computational fluid dynamics (CFD)-based aircraft design contains a time-consuming issue, which remains as a challengeable topic.

An optimization for the airfoil shape design has been enormously studied for the single- or multi-objectives using the genetic algorithm combined with the CFD method. Lian and Liou (2005) applied the evolutionary algorithm to the multi-objective optimization of transonic compressor blade. Yang *et al.* (2012) adopted the single-objective evolutionary algorithm to maximize the range of a canard-controlled missile. Choi *et al.* (2015) developed the multidisciplinary design optimization system to take into account the fluid-induced structural deformation for a flexible wing and propose the better design concept for the wing. We have also studied the evolutionary algorithm to reduce the shock wave strength on the upper surface of the airfoil in the transonic regime (Jung *et al.*, 2009) and to maximize the lift coefficient and lift-to-drag ratio (Jung and Kim, 2013). In addition, a relationship between the design parameters and corresponding objectives was analyzed by the self-organizing map (SOM) (Jung *et al.*, 2016). The SOM is one of neural network models, and the SOM can serve as a cluster analysis tool for high-dimensional data. Obayashi and Sasaki (2002) applied the SOM to analyze 766 Pareto solutions of the supersonic wing obtained from the evolutionary algorithm. Jeong *et al.* (2005) employed the SOM as a purpose of the data mining for an aerodynamic design space. Parashar *et al.* (2008) utilized the SOM for the design selection from the Pareto data obtained via the multi-objective design exploration of airfoil. Besides, the surrogate model has been employed for a rapid response to circumvent the time-consuming issues of the CFD computations. The spline interpolations, kriging, and neural networks are representative methods for the models. In particular, the generalized regression neural networks (GRNN) (Li *et al.*, 2014) represents an improved technique in the neural networks based on the nonparametric regression.

In this study, an efficient and relatively accurate strategy is presented by employing the SOM for a range adaption of design parameters and the GRNN for a surrogate model replacing the CFD calculations. Further, an architecture for the optimization is established on the adaptive range multi-objective genetic algorithm (ARMOGA), which is a real-coded search algorithm towards the Pareto front (Jung *et al.*, 2016). For the airfoil shape design, the PARSEC method (Sovieczky, 1998) was used and the objectives pursue to increase the maximum lift coefficient and the lift-to-drag ratio.

## 2. AN INTEGRATED OPTIMIZATION SYSTEM

Figure 1 shows the optimization system. Initial ranges of design variables are readjusted by the SOM analysis. The readjusted ranges play a key role to efficiently search the Pareto front and reduce the error of GRNN predictions at given populations. Then, the GRNN is constructed based on the design variables and corresponding objectives obtained by the iterative process of the ARMOGA. As generations increase, the accuracy of the GRNN is enhanced. If an average error of GRNN predictions is less than the certain criteria, the CFD calculations are replaced to the GRNN solutions. For the CFD calculations, the compressible Navier-Stokes equations are used to simulate the maximum lift coefficient and the lift-to-drag ratio at the low Mach number and the transonic regime for the takeoff and the cruise, respectively.

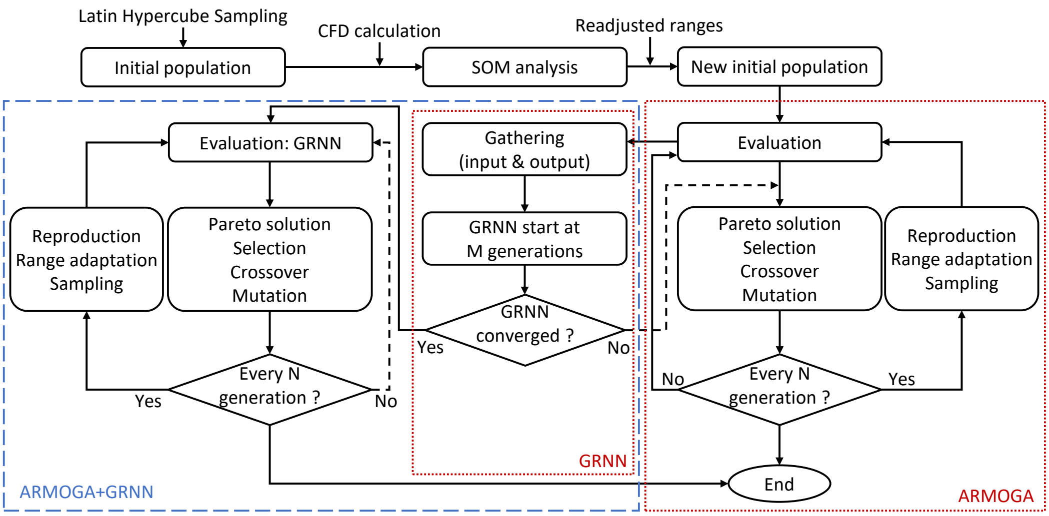


Figure 1: Flowchart of the integrated system for the efficient multi-object optimization.

### 2.1 Readjustment of design ranges via the Self-Organizing Map

Initial design ranges affect the efficient search of optimum solutions. Thus, proper design ranges can play a role to enhance the efficiency of the search algorithms. The SOM, which can provide a relationship between the objectives and design variables, fulfills the readjustment of initial design rages by mapping from the high dimension onto the two dimension. To identify the proper design ranges via the SOM method, the samples are chosen by the Latin Hypercube Sampling (LHS) method. The readjusted ranges are imposed as the initial design ranges of the search algorithm, that is, adaptive range multi-objective genetic algorithm.

### 2.2 Search algorithm for the multiple objectives and surrogate model

The adaptive range multi-objective genetic algorithm is used for an exploration of the Pareto front moving toward the optimum. The algorithm has been already developed and successfully worked in our previous works. To reduce the computational time due to CFD calculations, the GRNN, which provides a fast convergence in comparisons with other neural networks, is employed. Figure 2 shows the Pareto front of the ARMOGA with the GRNN predictions for the following test function,

$$minimize: \quad \mathbf{F} = [f_1(x_1, x_2), f_2(x_2)]\,, \tag{1}$$

where, $f_1(x_1, x_2) = (1 + x_1)/x_2$, $f_2(x_2) = x_2$, and $1 \leq x_1 \leq 5$, $0.1 \leq x_2 \leq 1$. As the populations increase, the solutions of the ARMOGA with the GRNN are closer to the exact solutions. In addition, the ARMOGA with the GRNN shows a drastic efficiency in comparisons with a direct application of the ARMOGA. After three generations, the GRNN provided accurate predictions, and total computation time was reduced to over than 90 percents.

### 2.3 Aerodynamic forces and airfoil generator

In this study, the objectives are to increase the maximum lift coefficient at the subsonic regime and the lift-to-drag ratio at the transonic regime. These objectives need a high-fidelity tool for predicting the flow behavior around the airfoil, because the flow separations and shock waves, which contain the viscous and compressible effects, affect the maximum lift coefficient and lift-to-drag ratio, respectively. Thus, the CFD method that enable the flow simulations for both regimes is employed. Also, the PARSEC was used to generate the airfoil shapes. The CFD approaches and the PARSEC method have been successfully validated and developed in previous works.

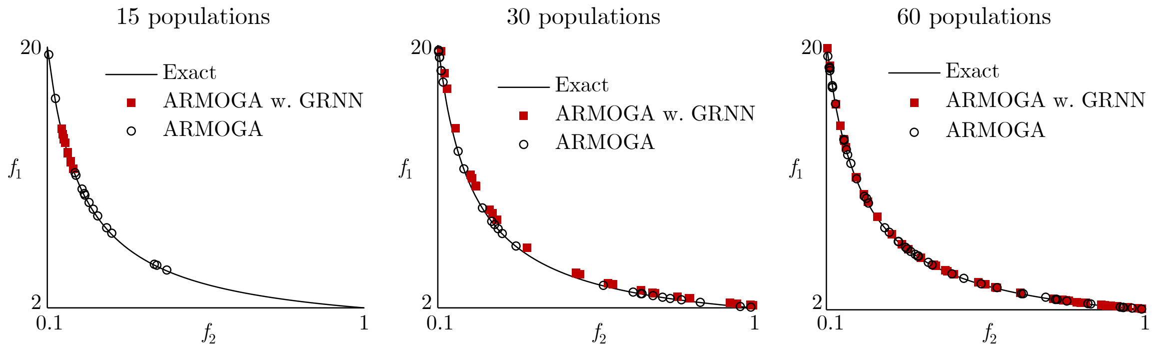


Figure 2: Assessments of the evolution algorithm with the surrogate model at 300 generations.

## 3. APPLICATIONS AND DISCUSSIONS

The integrated system is applied to design the airfoil having better aerodynamic performances than the RAE2822 airfoil, which is commonly used to the CFD-based optimization problem as the reference airfoil. The objectives are to increase the maximum lift coefficient and lift-to-drag ratio at given Mach numbers (M) and angles of attack ($\alpha$), M=0.729 and $\alpha$=2.31 for the transonic regime and M=0.2 and $\alpha$=14.0 for the subsonic regime, respectively. The Mach numbers and angles of attack were identified by a lift curve of the RAE2822 airfoil and literature survey, Initial design ranges of PARSEC parameters are set up as $\pm 20$ percents of the PARSEC parameters for the RAE2822 airfoil and readjusted by the SOM analysis. Figure 3 shows the readjusted design ranges of ten design variables. Each design range shows an irregularity and some variables contain partial fragments. Thus, the bounds for readjusted ranges were determined at the maximum and minimum points of the each variable.

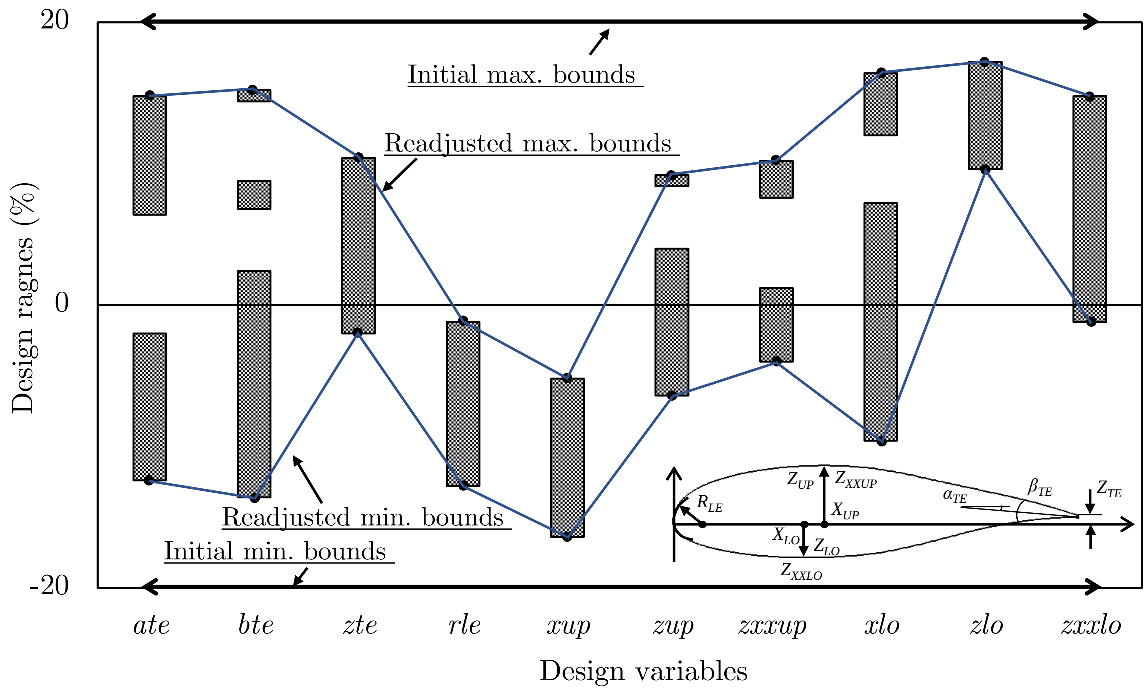


Figure 3: Readjusted design ranges of the PARSEC parameters via the SOM analysis.

Based on the readjusted design ranges, an accuracy of the GRNN can be enhanced by short distances among the populations of the ARMOGA. Further, the object functions adopt weight factors for efficiently search the optimum shapes. The following equation show the object function,

$$maximize: \quad \mathbf{F} = [f_1(M_1, \alpha_1), f_2(M_2, \alpha_2)] \tag{2}$$

where, $f_1(M_1 = 0.729, \alpha_1 = 2.31) = C_D$, and $f_2(M_2 = 0.2, \alpha_2 = 14.0) = C_L$. $C_D$ and $C_L$ are the drag coefficient and maximum lift coefficient of the RAE2822 airfoil at given Mach numbers and angles of attack. Equations 2 serves as the min-max function. For this study, 21 generations and 30 populations were used for the ARMOGA, and the CFD calculations play a role to provide the objectives for 11 generations only. The other objectives are estimated by the GRNN.

Hence, the current strategy enabled to save computational costs, approximately 50 percents, then a direct simulation via the CFD for optimization. Figure 4 shows all candidates, and the lift and drag coefficients of RAE2822 airfoil is shown as a blue dot. The red dots indicate the final candidates that shows better aerodynamic performances than the RAE2822 airfoil.

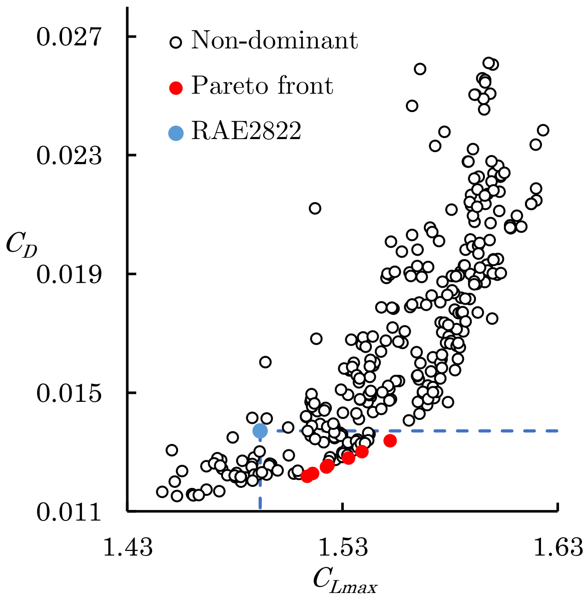


Figure 4: The multi-object solutions of all candidates during the optimization.

Figure 5 shows comparisons of airfoil shapes among the candidates and the RAE2822 airfoil. Lastly, table 1 is given to compare the aerodynamic performances. As a result, the current strategy showed a great efficiency with robust solutions that can avoid a drawback of the surrogate model involving the accuracy issues.

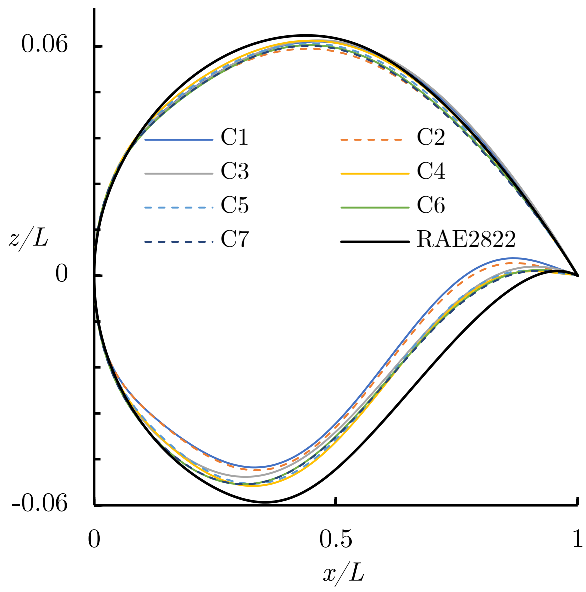


Figure 5: Comparisons of airfoil shapes among the RAE2822 and the candidates.

Table 1: Comparisons of lift and drag coefficients among the RAE2822 and the candidates.

| | RAE2822 | *C1* | *C2* | *C3* | *C4* | *C5* | *C6* | *C7* |
|---|---|---|---|---|---|---|---|---|
| *CL* | 1.4917 | 1.5522 | 1.5391 | 1.5328 | 1.5233 | 1.5225 | 1.5162 | 1.5136 |
| *CD* | 0.0137 | 0.0134 | 0.0130 | 0.0128 | 0.0125 | 0.0125 | 0.0123 | 0.0122 |

## 4. REFERENCES

Choi, W., Park, C.W., Jung, S.K. and Park, H.B., 2015. "Multi-objective optimization of flexible wing using multidisciplinary design optimization system of aero-non linear structure interaction based on support vector regression". *Journal of the Korean Society for Aeronautical & Space Sciences*, Vol. 43, No. 7, pp. 601–608.

Jeong, S., Chiba, K. and Obayashi, S., 2005. "Data mining for aerodynamic design space". *Journal Aerospace Compting Information and Communication*, Vol. 2, No. 11, pp. 452–469.

Jung, S.K., Choi, W., Martins Filho, L.S. and Madeira, F., 2016. "An implementation of self organizing maps for airfoil design exploration via the multi-objective optimization technique". *Journal of Aerospace Technology and Management*, Vol. 8, No. 2, pp. 193–202.

Jung, S.K. and Kim, J.H., 2013. "A study on real-coded adaptive range multi-objective genetic algorithm for airfoil shape design". *Journal of the Korean Society for Aeronautical & Space Sciences*, Vol. 41, No. 7, pp. 509–515.

Jung, S.K., Myong, R.S. and Cho, T.H., 2009. "An efficient global optimization method for reducing the wave drag in transonic regime". *Journal of the Korean Society for Aeronautical & Space Sciences*, Vol. 37, No. 3, pp. 248–254.

Li, X., Zecchin, A.C. and Maier, H.R., 2014. "Selection of smoothing parameter estimators for general regression neural networks: Applications to hydrological and water resources modelling". *Environmental Modelling and Software*, Vol. 59, pp. 162–186.

Lian, Y. and Liou, M.S., 2005. "Multi-objective optimization of transonic compressor blade using evolutionary algorithm". *Journal of Propulsion and Power*, Vol. 21, pp. 979–987.

Obayashi, S. and Sasaki, D., 2002. "Self-organizing map of pareto solutions obtained from multiobjective supersonic wing design". In *40th AIAA Aerospace Sciences Meeting & Exhibit*. Reno, NV, U.S.A.

Parashar, S., Pediroda, V. and Poloni, C., 2008. "Self organizing maps for design selection in robust multi-objective design of aerofoil". In *46th AIAA Aerospace Sciences Meeting & Exhibit*. Reno, NV, U.S.A.

Sovieczky, H., 1998. "Parametric airfoils and wings". Notes on Numerical Fluid Mechanics.

Yang, Y.R., Jung, S.K., Cho, T.H. and Myong, R.S., 2012. "Aerodynamic shape optimization system of a canard-controlled missile using trajectory-dependent aerodynamic coefficients". *Journal of Spacecraft and Rockets*, Vol. 49, No. 2, pp. 243–249.