УДК 531.36, 629.7

Pioquinto J.G.Q., Moreno R.A.F.

METHODS FOR INCREASING THE EFFICIENCY OF THE DIFFERENTIAL EVOLUTION ALGORITHM FOR AERODYNAMIC SHAPE OPTIMIZATION APPLICATIONS

Introduction. Differential evolution (DE) is a simple and robust evolutionary strategy that has proven effective in determining the global optimum for several difficult optimization problems. Although DE offers several advantages over traditional (gradient-based) optimization approaches, its use in applications such as aerodynamic shape optimization where objective function evaluations are computationally expensive is limited by the large number of function evaluations that are often required. There are currently several approaches to improve the efficiency of DE for aerodynamic shape optimization applications, such as the use parameterization methods, evolutionary parameter control methods, population size reduction (PRS) methods, metamodeling techniques (the use of approximate models as surrogates for real objective functions), memetic methods (hybridization of gradient base algorithms with evolutionary algorithms), parallel computing strategies [1-3].

In the present work, 6 variants to the DE algorithm are presented, where different methods were implemented to improve efficiency in aerodynamic shape optimization processes, specifically in the optimization of the shape of airfoils.

Methodology. In the comparative analysis that was carried out, 6 different variants of the standard DED algorithm were evaluated, specifically it was based on the configuration proposed by Derksen (DE/current-to-best algorithm) [4] to be able to work with the Bezier-

PARSEC airfoil parameterization technique. Three of the proposed variants are based on the implementation of parallel computing strategies (PCS), and the other three on the implementation of multilayer perceptrons (MLP) as a surrogate model. The algorithms evaluated were:

1. DEp and DE-NN algorithms. Algorithms based entirely on the one proposed by Derksen [4]. DEp incorporates a PCS [5] to accelerate the computation process of the objective function, while DE-NN incorporates MLPs to obtain the value of the objective function.

2. CAPR-DEp and CAPR-DE-NN algorithms. The algorithms mentioned in the previous point were incorporated the Continuous Adaptive Population Reduction (CAPR) method, which is a PRS method [6]. This algorithm is a variant of the Successful History-Based Adaptive DE (SHADE).

3. CAPR-SHADEp and CAPR-SHADE-NN algorithms. These two variants, in addition to including the CAPR method, have the implementation of the adaptation strategy of the evolutionary parameters used by the Successful History-Based Adaptive for Differential Evolution (SHADE) algorithm [7].

To evaluate the performance of each of the algorithms, the following case study was proposed: minimizing the drag coefficient of a profile (c_d), maintaining a lift coefficient c_l=0.5, within an angle of attack (α) range of 0 to 3 degrees. In this case, a viscous, incompressible and non-turbulent flow was considered under Reynolds number Re=10^6.

$$\begin{aligned} \min \quad & c_d(x_{BP}, \alpha), \\ \text{such that} \quad & c_l(x_{BP}, \alpha)=0.5, \\ & \alpha \in [0, 3] \text{ deg}, \\ & x_{BP} \in \Omega_{BP}, \end{aligned}$$

where x_{BP} is the design vector of the profile and Ω_{BP} is the design region, both are delimited by the Bezier-PARSEC parameterization method in its variant BP3333. The details of the design space of the profile are taken from a previous work done by the author [8]. Having used the BP3333 parameters it was possible to omit the crossover operator in all the evaluated algorithms [4]. In all variants the XFOIL program was considered to solve the objective function. In the algorithms where MLPs were implemented, XFOIL was used for the training of these networks.

In order for the case to be solved by DE, it is necessary to convert it to a case of unconstrained optimization. This was solved by making use of an objective function penalty model [9].

$$\begin{aligned} \min \quad & L(x_{BP}, \alpha), \\ \text{such that} \quad & \alpha \in [0, 4] \text{ deg}, \\ & x_{BP} \in \Omega_{BP}. \end{aligned}$$

$L(x_{BP}, \alpha)$ is the penalty function to be minimized:

$$L(x_{BP}, \alpha) = \begin{cases} c_d(x_{BP}, \alpha), & if\ \psi(x_{BP}, \alpha) = 0, \\ \psi(x_{BP}, \alpha) + U_*, & if\ \psi(x_{BP}, \alpha) > 0\ \wedge c_d(x_{BP}, \alpha) \leq U_*, \\ \psi(x_{BP}, \alpha) + c_d(x_{BP}, \alpha), & if\ \psi(x_{BP}, \alpha) > 0\ \wedge c_d(x_{BP}, \alpha) > U_*, \end{cases} \quad (1)$$

where

$$\psi(x_{BP}, \alpha) = max\{0, |c_l(x_{BP}, \alpha) - 0.5| - \delta\} \quad (2)$$

U_* is an upper bound on the constrained global minimum value, which needs to be updated with the current best known function value at feasible points; δ it is a tolerance to the target value of the c_l.

Results. The results obtained in the optimization processes are shown in Table 1 and Fig. 1, considering an initial population of $10 \times D$ (D is number of design parameters). A stop condition $(L_{avg}\text{-}L_{opt}) < 5 \times 10^{-4}$ was considered in all of them. The results shown correspond to the median obtained after running each algorithm 10 times.

Table 1. **Network performance due to changes in hidden layers**

Algorithm	Computing time (s)	Number of Generations	Number of functions evaluated	c_d(α [°])	c_l(α [°])
DE/Derksen	9135.6	88	9680	0.00335(1)	0.5011(1)
DEp	1450.2	61	6710	0.00335(0.8)	0.5015(0.8)
DE-NN	46.1	53	5830	0.00337(1.2)	0.4991(1.2)
CAPR-DEp	1214.0	54	2378	0.00337(0.7)	0.5008(0.7)
CAPR-DE-NN	43.0	51	5324	0.00322(1.1)	0.4994(1.1)
CAPR-SHADEp	1469.1	80	7870	0.00335(0.6)	0.5015(0.6)
CAPR-SHADE-NN	126	114	9986	0.00317(1)	0.4991(1)

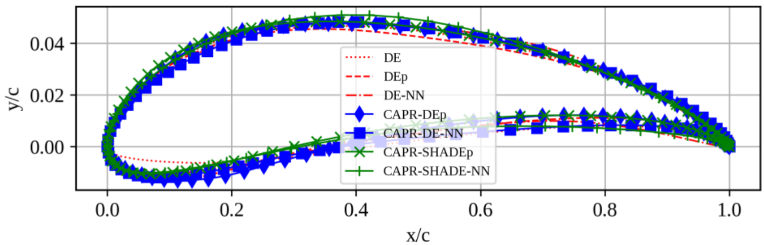

Fig. 1. Optimized airfoils

Conclusion. When viewing the results obtained, especially from the first three algorithms in Table 1, the relevance of using PCS (reducing up to 6 times the computing time) or MLP (reducing up to 205 times the computing time) is visualized. It is also important to mention that in most cases a trend was maintained in the optimal geometry of the profile. It is important to mention that two neural networks were implemented, whose determination coefficients were approximately 0.95, despite this, they managed to maintain a tendency to the optimal geometry to that obtained by the algorithms where XFOIL was used directly to calculate the objective function. In future works, the comparative analysis will be continued, mainly varying the initial population.

References

1. Chakraborty, S. Comparative performance analysis of differential evolution variants on engineering design problems / S. Chakraborty, A.K. Saha, S. Sharma, S.K. Sahoo, G. Pal // Journal of Bionic Engineering. – Vol. 19. – 2022. – pp. 1140–1160. doi: 10.1007/s42235-022-00190-4.
2. Madavan, N.K. On improving efficiency of differential evolution for aerodynamic shape optimization applications / N.K. Madavan // In 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference. – 2004. – pp. 4622.
3. Georgioudakis, M. A comparative study of differential evolution variants in constrained structural optimization / M. Georgioudakis, V. Plevris // Frontiers in Built Environment. – Vol. 6. – 2020. doi: 10.3389/fbuil.2020.00102.
4. Derksen, R.W. Bezier-PARSEC Parameterization for Airfoil Optimization / R.W. Derksen, T. Rogalsky // Canadian Aeronautics and Space Journal. – Vol. 55. – No. 3. – 2009. – pp. 163–174.
5. Joblib. Joblib: running Python functions as pipeline jobs //Joblib developers. – 2021. [Web Site]. Access mode: https://joblib.readthedocs.io (31.5.2023).
6. Wong, I. Continuous adaptative population reduction (CAPR) for differential evolution optimization /I. Wong, W. Liu, C.M. Ho, X. Ding // SLAS Technology. – Vol. 22. – No. 3. – 2017. – pp. 289–305. doi: 10.1177/2472630317690318
7. Tanabe, R. Success-history based parameter adaptation for differential evolution / R. Tanabe, A. Fukunaga // In 2013 IEEE Congress on Evolutionary Computation. IEEE. – 2013. – pp. 71–78.
8. Pioquinto, J.G.Q. Acceleration of Evolutionary Optimization for Airfoils Design with Population Size Reduction Methods / J.G.Q. Pioquinto, V.G. Shakhov // AviaSpace 2021: International Aviation and Cosmonautics Conference. – 2021.

9. Ali, M.M. A penalty function-based differential evolution algorithm for constrained global optimization / M.M. Ali, W.X. Zhu // Comput. Optim. Appl. – Vol. 54. – 2013. – pp. 707-739. doi: 10.1007/s10589-012-9498-3.

УДК 531.533

Степанов Р.П., Кусюмов А.Н.

О МОДЕЛИРОВАНИИ КОНЦЕВОГО ВИХРЯ КРЫЛА КОНЕЧНОГО РАЗМАХА

Выбор подходящего метода идентификации вихревых структур, сходящих с различных несущих поверхностей летательных аппаратов (ЛА), является важной задачей. Анализ ядра вихря, генерируемого несущей поверхностью, позволяет визуализировать вихревую структуру потока, определять значения циркуляции ядра вихря и его размеры в различных сечениях. Другим важным вопросом при исследовании вихревых структур является нахождение положения центра вихря для двумерного случая или оси вихря в трехмерном потоке. Оценка значения циркуляции ядра вихря и воспроизведение траектории вихря позволяют учитывать влияние вихрей на органы управления, расположенные в хвостовой части самолета. Важным вопросом также является оценка влияния концевых вихрей крыла на летящий сзади самолет.

В настоящее время анализ структуры течения и лётно-технические характеристики ЛА в основном определяются путём численного моделирования. Однако повышение точности численного моделирования обтекания ЛА требует значительных вычислительных мощностей. В случаях, когда необходимо провести численное моделирование вихревой структуры в среднем и дальнем поле, затрачиваемые