On the Use of a Multilayer Perceptron as an Aerodynamic Performance Approximator in Multi-Objective Transonic Airfoil Shape Optimization

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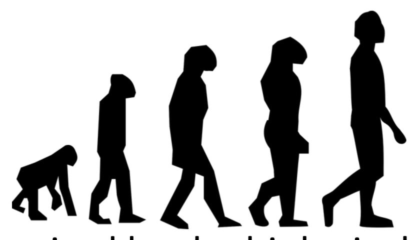
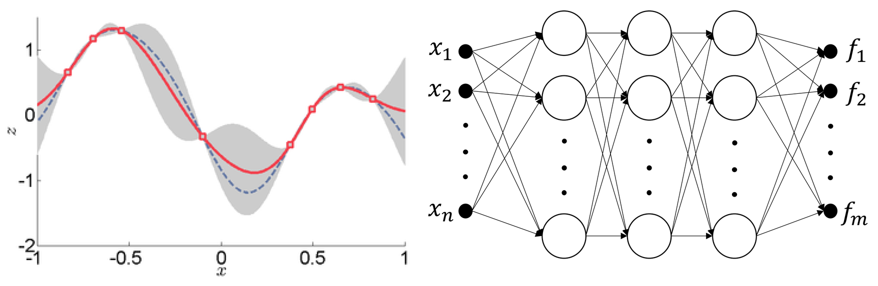
Background

- Aerodynamic shape optimization of transonic airfoils (ASO-TA) is **important.**
  - Most of commercial aircrafts today cruise at transonic speeds, near the speed of sound.
  - The shape of airfoil section strongly affects the aerodynamic characteristics.
- The aerodynamic shape optimization has used multi-objective evolutionary algorithms (MOEAs), e.g., **NSGA-II** [1].
  - NSGA-II requires numerous evaluations.
  - CFD evaluations are expensive!
  - CFD is replaced with a surrogate model.
- Multilayer perceptron (MLP) can do mapping between **many design variables** (input) and **multiple functions** (output) in **a single model.**
  - Kriging [2] is the most popular surrogates.
  - But, one Kriging can only map one function.
  - MLP has the potential to be used in high-dimensional problems

Boeing 737-800 cruises at M0.76
https://www.ana.co.jp/en/



EAs are inspired by the biological evolution



Kriging (left), Multilayer perceptron (right)

Objectives

- Develop a multilayer perceptron-assisted NSGA-II algorithm **(MLP+GA)**
  - MLP is used to assist the NSGA-II optimization process.
- Apply **MLP+GA** to multi-objective transonic airfoil shape optimization with low to moderate dimensionality
  - The use of MLP as an aerodynamic performance approximator is studied.
  - This describes a preliminary study before the MLP+GA is used in high dimensional problems.
- Compare the results with **NSGA-II algorithms without surrogates**
  - Standard NSGA-II with CFD as its true evaluation is carried out.
  - Investigate whether the use of MLP makes the NSGA-II optimization process more efficient.

Problem definition

Aerodynamic Shape Optimization of Transonic Airfoils (ASO-TA)

- **ASO-TA1** (2 objectives, 0 constraint, 9 variables)

minimize : C_d and $-C_l$
with respect to : PARSEC variables
subject to : -
flow conditions : Mach 0.73, Angle of Attack = 2°

- **ASO-TA2** (2 objectives, 0 constraint, 9 variables)

minimize : C_d and $-C_l$
with respect to : PARSEC variables
subject to : -
flow conditions : Mach 0.80, Angle of Attack = 2°

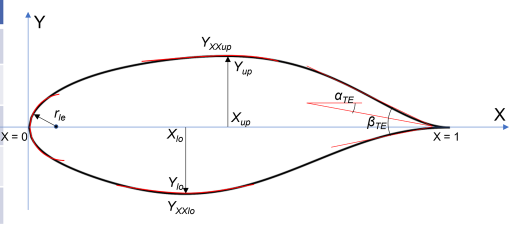
- **ASO-TA3** (2 objectives, 3 constraints, 18 variables)

minimize : C_d and $-C_l$
with respect to : B-Spline control points
subject to : $0.8 * A_{baseline} - A \leq 0$
$Y_1 - Y_{18} \leq 0$
$Y_2 - Y_{17} \leq 0$
flow conditions : Mach 0.73, Angle of Attack = 2°

Airfoil Parameterization

PARSEC

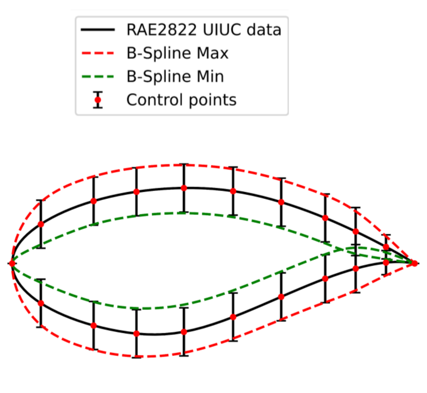
No	Var	L.B.	U.B.
1.	r_{LE}	0.0065	0.0092
2.	X_{up}	0.3466	0.5198
3.	Y_{up}	0.0503	0.0755
4.	Y_{XXup}	-0.5094	-0.3396
5.	X_{lo}	0.2894	0.4342
6.	Y_{lo}	-0.0707	-0.0471
7.	Y_{XXlo}	0.5655	0.8483
8.	α_{TE}	-0.1351	-0.0901
9.	β_{TE}	0.1317	0.1975



Note: The airfoils have a sharp trailing edge

B-Spline

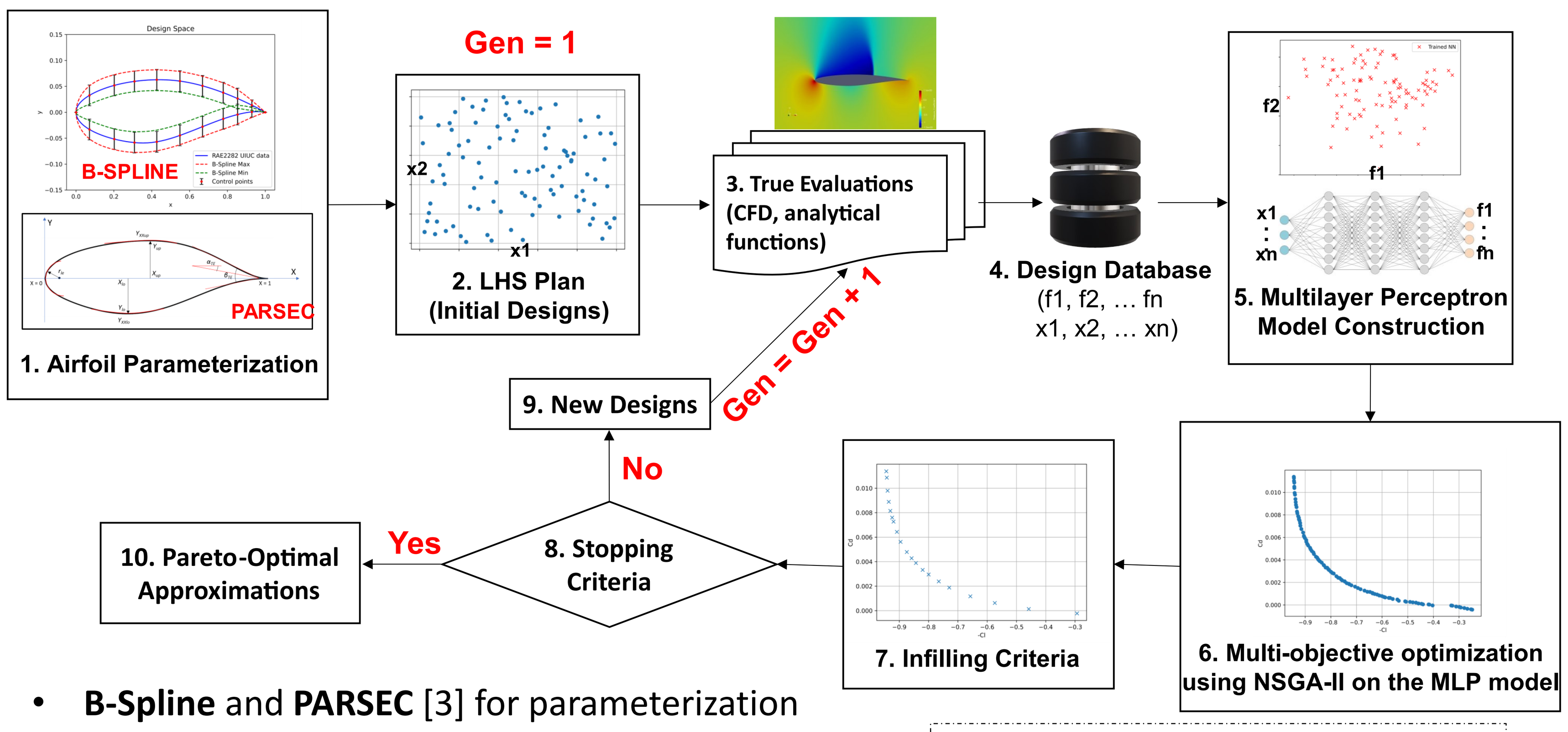
No	X	Var	L.B.	U.B.
1.	0.928864	Y_1	-0.009306	0.010694
2.	0.853553	Y_2	-0.024314	0.015686
3.	0.777785	Y_3	-0.032689	0.007310
4.	0.668445	Y_4	-0.048139	-0.007814
5.	0.549009	Y_5	-0.064642	-0.024642
6.	0.426635	Y_6	-0.076979	-0.036979
7.	0.308658	Y_7	-0.078459	-0.038459
8.	0.202150	Y_8	-0.071694	-0.031694
9.	0.071136	Y_9	-0.053169	-0.013169
10.	0.071136	Y_{10}	0.012644	0.052644
11.	0.202150	Y_{11}	0.031885	0.071885
12.	0.308658	Y_{12}	0.039629	0.079629
13.	0.426635	Y_{13}	0.042779	0.082779
14.	0.549009	Y_{14}	0.040194	0.080194
15.	0.668445	Y_{15}	0.030993	0.070993
16.	0.777785	Y_{16}	0.017847	0.057847
17.	0.853553	Y_{17}	0.065540	0.046554
18.	0.928864	Y_{18}	0.037689	0.023769



Note: ***Y*** is the control point y-coordinates. The baseline is **RAE2822 airfoil!**

Methodologies

MLP+GA (1st algo) applied to multi-objective transonic airfoil shape optimization



- **B-Spline** and **PARSEC** [3] for parameterization
- **Latin hypercube sampling** for initial designs
- Every algorithm starts with **100 initial designs**
- **Euler-based CFD** solved using **SU2** [4]
- **K-Means** algorithm as the infilling criteria (solutions closest to the centroids are chosen)

Number of CFD evaluations

MLP+GA : 100 + 20*5 = 200
NSGA-II 1st : 100 + 100*9 = 1000
NSGA-II 2nd : 100 + 20*10 = 300
NSGA-II 3rd : 100 + 20*10 = 300

NSGA-II with different settings (2nd, 3rd and 4th algo)

	2nd algo	3rd algo	4th algo
Pop size (P1, P2)	100	20	20
Pop size (P3)	100	10	10
n_{gen_max} (P1, P2)	10	11	11
n_{gen_max} (P3)	10	31	31
Crossover	$\eta_c = 15$ $rate = 0.9$	$\eta_c = 15$ $rate = 0.9$	$\eta_c = 15$ $rate = 0.9$
Mutation	$\eta_c = 20$ $r = 1/100$	$\eta_c = 20$ $r_{1,2} = 1/20$ $r_3 = 1/10$	$\eta_c = 20$ $r_{1,2} = 1/20$ $r_3 = 1/10$
Initial pop	LHS samples	K-Means on x	K-Means on f

Note: **P1, P2, P3 stand for problem 1, 2 and 3**

- The 3rd and 4th algorithm are done to make a fair comparison with MLP+GA with the same number of new designs per iteration.

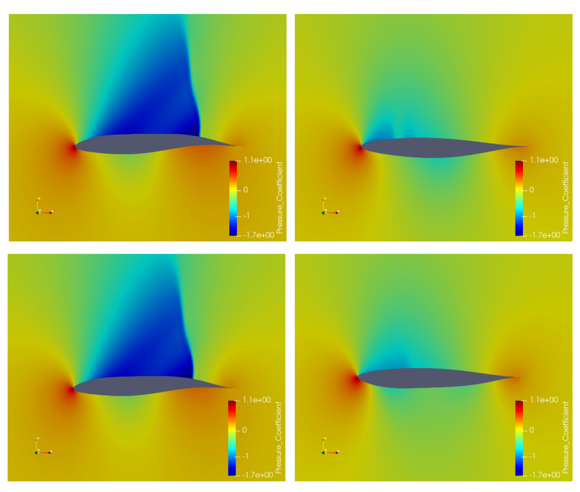
Optimization results

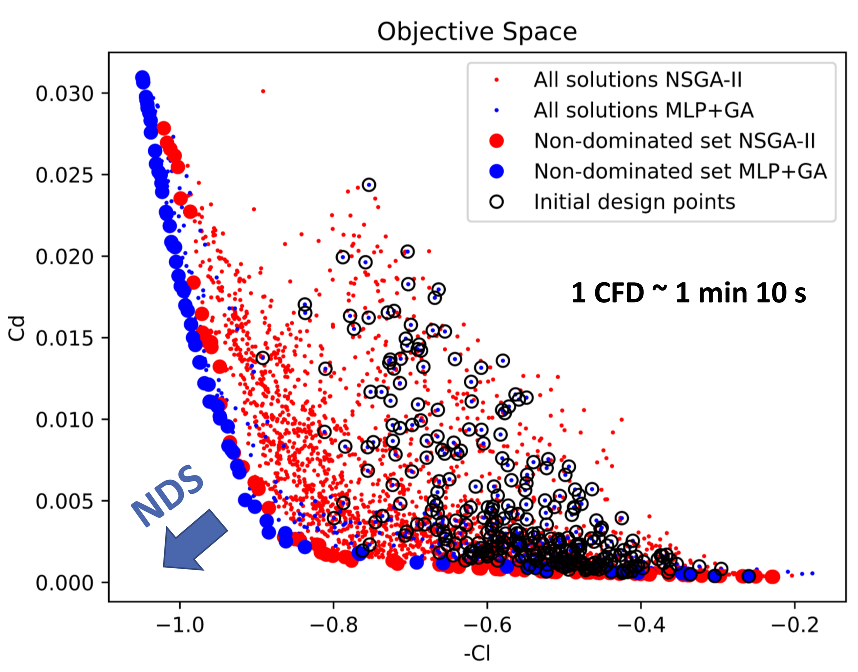
Note NDS: Non-dominated solutions
*The Euler CFD solvers are not realistic, however we focus on the algorithm performance comparison

ASO-TA1

- The initial designs are mostly located in the low Cd region (Cl between 0.4 and 0.6).
- MLP+GA is **48 hours faster** than NSGA-II

Extreme results by | High lift | Low drag
MLP+GA
NSGA-II

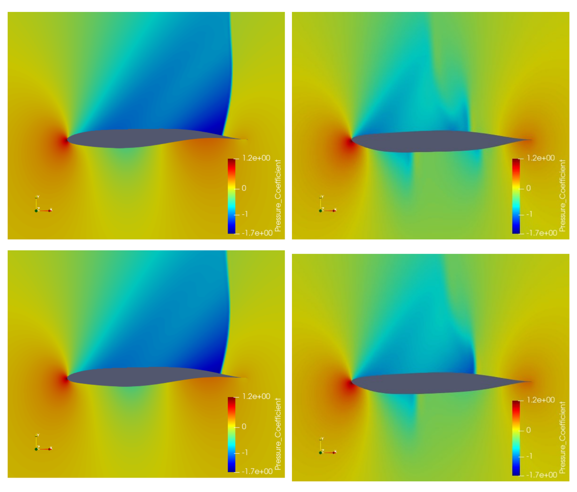


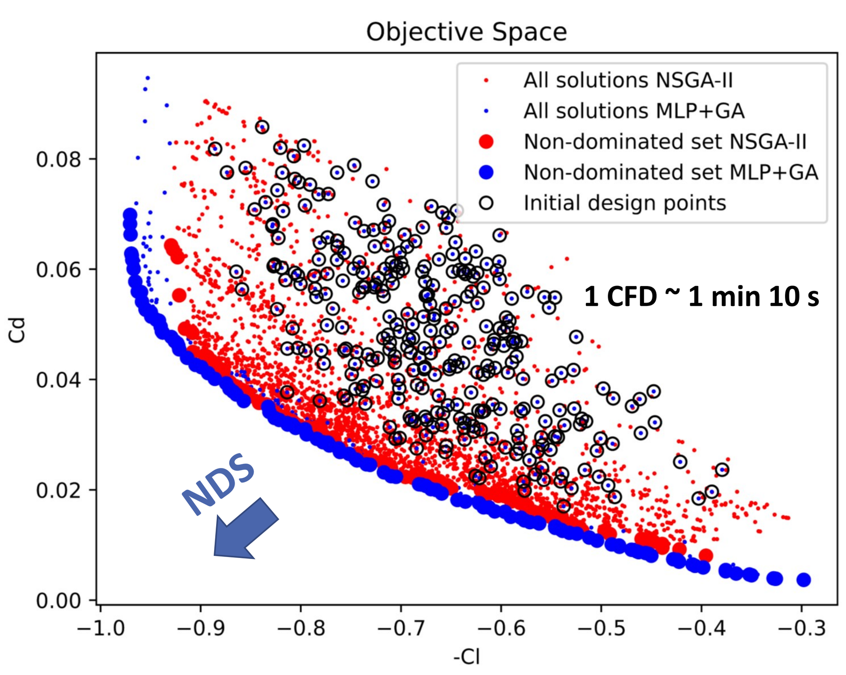


ASO-TA2

- The optimizer task is to find both extreme regions because the Mach number increases.
- MLP+GA is **48 hours faster** than NSGA-II

Extreme results by | High lift | Low drag
MLP+GA
NSGA-II

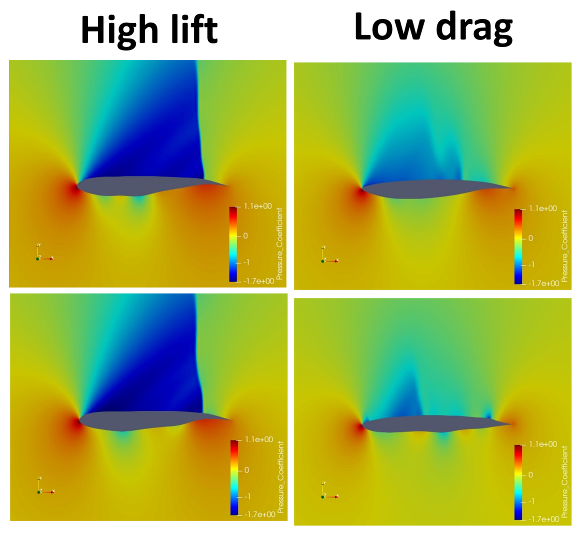


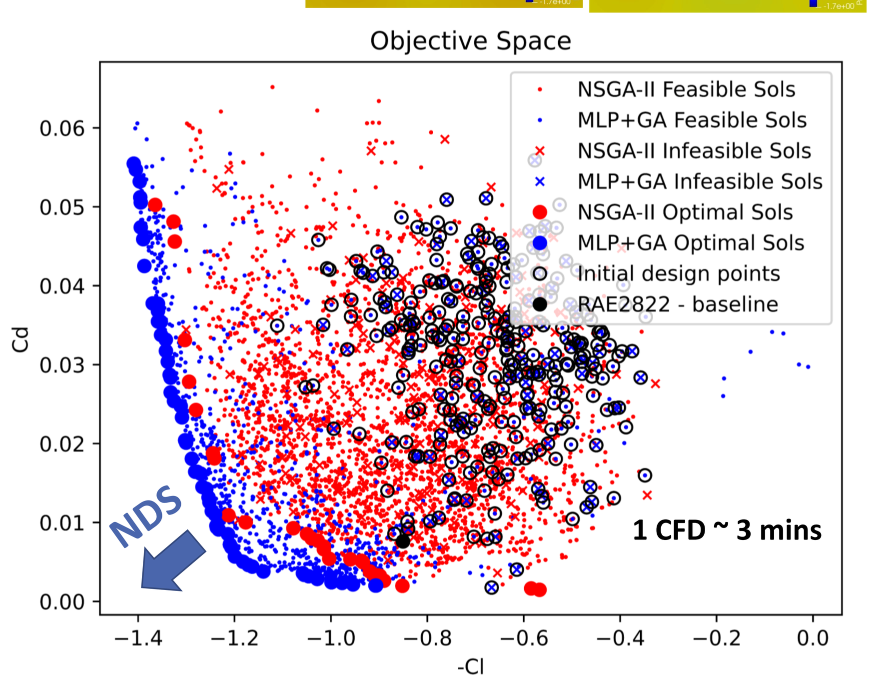


ASO-TA3

- The most complex problem with constraints
- Some solutions are infeasible.
- Both MLP+GA and NSGA-II can find better objectives than the baseline (RAE2822 airfoil)
- MLP+GA is **90 hours faster** than NSGA-II

Extreme results by | High lift | Low drag
MLP+GA
NSGA-II



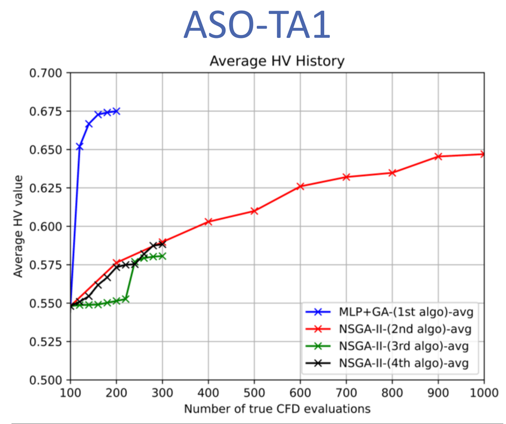


Performance comparison

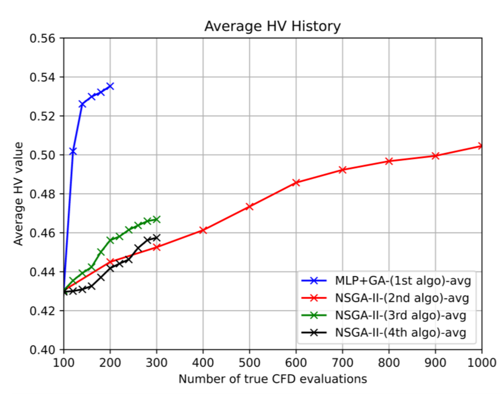
Hypervolume metric

- It measures proximity and diversity of non-dominated solutions
- *Higher HV, the better*
- HV is plotted vs the number of CFD evals

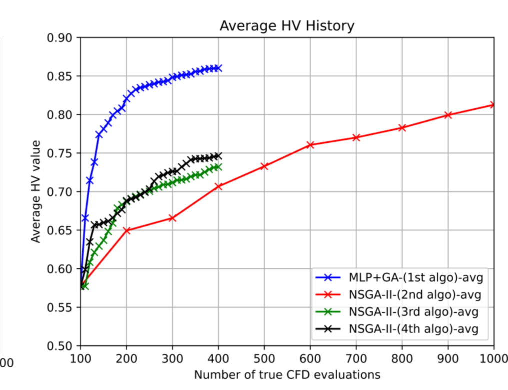
ASO-TA1



ASO-TA2



ASO-TA3



Conclusion and future works

- An optimization method called **MLP+GA** is proposed
- MLP+GA and NSGA-II with different settings **can find sets of non-dominated solutions.**
- MLP+GA can find **higher HV** solutions with significantly **fewer CFD** evaluations.
- MLP+GA **cuts the computational time**, indicating that the MLP is **sufficient as the aerodynamic performance approximator** and makes the genetic algorithm **more efficient**.
- MLP+GA has **the potential** to be applied to high dimensional design optimization problems with multiple objectives.

References

[1] K. Deb, et al., *IEEE TEC*, 6, (2002), 182-197.
[2] D. G. Krige, *JCMMSSA*, 52, (1951), 119-139.
[3] H. Sobieczky, *Recent Development of ADM*, (1999), 71-87.
[4] T. D. Economon, et al., *AIAA Journal*, 54, (2016), 828-846.