IV International Conference on Computational Methods for Coupled Problems in Science and Engineering
COUPLED PROBLEMS 2011
M. Papadrakakis, E. Oñate and B. Schrefler (Eds)

COUPLING HYBRID-GAME STRATEGIES WITH PARTICLE SWARM OPTIMISATION FOR MULTI-OBJECTIVE HIGH LIFT SYSTEMS DESIGN OPTIMISATION

D. S. LEE*, J. PERIAUX*, L. F. GONZALEZ†, AND E. ONATE*

* International Center for Numerical Methods in Engineering (CIMNE)
Universidad Politécnica de Cataluña
Campus Norte UPC, 08034 Barcelona, Spain
e-mail: dslee@cimne.upc.edu, jperiaux@gmail.com, onate@cimne.upc.edu, www.cimne.com

† Australian Research Center Aerospace Automation (ARCAA)
Queensland University of Technology, Brisbane, Australia
email: felipe.gonzalez@qut.edu.au

Key words: Multi-objective, Evolutionary Algorithms, Game Strategies, Nash-Game, High Lift Systems (HLSs).

Abstract. This paper investigates the High Lift System (HLS) application of complex aerodynamic design problem using Particle Swarm Optimisation (PSO) coupled to Game strategies. Two types of optimization methods are used; the first method is a standard PSO based on Pareto dominance and the second method hybridises PSO with a well-known Nash Game strategies named Hybrid-PSO. These optimization techniques are coupled to a pre/post processor GiD providing unstructured meshes during the optimisation procedure and a transonic analysis software PUMI. The computational efficiency and quality design obtained by PSO and Hybrid-PSO are compared. The numerical results for the multi-objective HLS design optimisation clearly shows the benefits of hybridising a PSO with the Nash game and makes promising the above methodology for solving other more complex multi-physics optimisation problems in Aeronautics.

1 INTRODUCTION

With increasing complexity in engineering design problems, research in Computational Intelligence System (CIS) for Multi-Objective (MO) and Multidisciplinary Design Optimization (MDO) faces the need for developing robust and efficient optimisation methods and produce higher quality designs [1, 2] without paying expensive computational cost. Game strategies including Nash and Pareto Strategies are Game Theory tools [3, 4] which can be used to save CPU usage and to produce useful Pareto non-dominated solutions due to their efficiency in engineering design optimisation. In this paper, two game strategies are implemented and coupled to a Particle Swarm Opimisation (PSO) [5]; the first optimisation method uses a Pareto optimality based PSO while the second method uses a dynamic combination of Nash-equilibrium [3, 7] and Pareto optimality approaches (denoted as Hybrid Game). Hybrid-Game consists of one Pareto-Player and several Nash-players providing dynamic elite information to the Pareto Game and hence it can produce a Nash-equilibrium and Pareto non-dominated solutions simultaneously [7]. It is shown in this paper how a Nash-game performances as a pre-conditioner of the Pareto algorithm to accelerate the optimisation process to capture Pareto front. This new approach is implemented successfully to solve complex robust MO/MDO problems which require expensive computational cost such as the detailed design of a High Lift Systems.

The rest of paper is organised as follows; Section 2 describes methodology. Mathematical benchmarks are considered in Section 3. Section 4 presents brief description of aerodynamic analysis tool and pre-post processor. Section 5 conducts two real world design problems using RMO-PSO and HRMO-PSO. Section 6 concludes overall numerical results and presents future research avenues.

2 METHODOLOGY

2.1 Multi-Objective Design Optimisation

Engineering design problems require a simultaneous optimisation of conflicting objectives and an associated number of constraints. Unlike single objective optimisation problems, the solution is a set of points known as Pareto optimal set [8, 9]. Solutions are compared to other solutions using the concept of Pareto dominance. A multi-criteria optimisation problem can be formulated as:

$$\textit{Maximise/Minimise}\ f_i(x_j) \quad i = 1,\ldots,N \tag{1}$$

$$\text{Subject to}$$

$$g_k(x_j) = 0 \quad j = 1,\ldots\ldots,M \quad \text{and} \quad h_l(x_j) \leq 0 \quad k = 1,\ldots\ldots,P$$

where f_i, g_j, h_k are, respectively, the objective functions, the equality and the inequality constraints. N is the number of objective functions and x is an n - dimensional vector where its arguments are the decision variables. For a minimisation problem, a vector x_1 is said partially less than vector x_2 if:

$$\forall_i f_i(x_1) \leq f_i(x_2) \text{ and } \exists_i f_i(x_1) \leq f_i(x_2)$$

In this case the solution x_1 dominates the solution x_2.

As Particle Swarm Optimisation (PSO) evaluates multiple swarms/populations of particles/individuals, they are capable of finding a number of solutions in a Pareto set. Pareto selection ranks the population and selects the non-dominated individuals for the Pareto fronts. A Pareto optimality based PSO that has capabilities for multi-objective optimisation is termed Multi-Objective PSO (MOPSO).

2.2 Robust Multi-objective Optimisation Platform (RMOP)

RMOP is a computational intelligence framework which is a collection of population based algorithms including Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) [5, 8]. In this paper, a PSO searching method in RMOP is used (denoted as RMO-PSO). RMO-PSO uses the Pareto tournament selection operator which ensures that the new individual is not dominated by any other solutions in the tournament.

As shown in Figure 1, RMOP originally consists of seven modules;

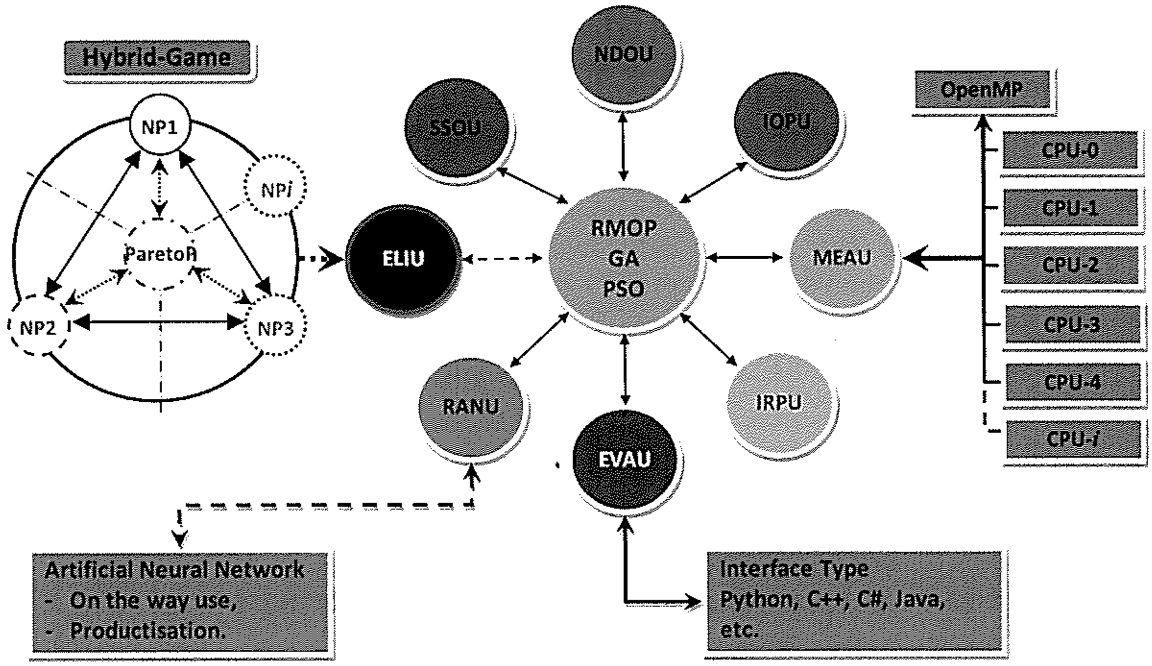


Figure 1: RMOP.

- ELIU is an elite module for game strategies especially for dynamic Nash-Game. This module forces to link between Pareto and Nash Game to solve complex single and multi-objective design problems.
- EVAU is a module for evaluation and collecting results from analysis tools. It is also capable to handle other language-based interfaces.
- IOPU is a module for handling input, output data and also plotting convergence history, initial population (with/without buffer population), total populations, Pareto optimal front.
- IRPU is an initial random population module.
- MEAU is a module for allocating/dis-allocating memory for population and it provide Parallel/Distributed optimisation environment.
- NDOU is a module for computing Pareto-tournament, non-dominated sorting solutions from population.
- RANU is a module for generating pseudo random number module and Artificial Neural Network (ANN).
- SSOU is a searching module; selection, mutation, crossover for GA and also it produces velocity, positioning module for PSO.

In this paper, RMOP uses PSO searching method and also a module; ELIU is developed and added to hybridise RMO-PSO with a non-cooperative Game Strategy; Nash-Game. ELIU produces elite information from Nash-Game and seeds Nash elite design information to Pareto-Game population.

RMOP is easily coupled to any analysis tools such as Computation Fluid Dynamic (CFD), Finite Element Analysis (FEA) and/or Computer Aided Design (CAD) systems. In addition, it is capable to solve any engineering design application [10, 11].

2.3 Particle Swarm Optimisation

Particle Swarm Optimisation (PSO) proposed by Kennedy and Spears [5] is a robust stochastic optimisation technique that a population of individuals adapts to its environment by moving towards to promising regions which can be captured by Equation (2). In numerical interpretation, a particle represents the individual and a swarm refers to the population. This environment adaptation is a stochastic process that depends on the both individual best and global best solutions as shown in Equation (2). In other words the adaptation is based on the best knowledge obtained by the population.

$$\begin{aligned} x_{k+1}^{i} &= x_{k}^{i} + v_{k+1}^{i} \\ v_{k+1}^{i} &= \omega v_{k}^{i} + c_1 r_1 \left(p_{k}^{i} - x_{k}^{i}\right) + c_2 r_2 \left(p_{k}^{g} - x_{k}^{i}\right) \end{aligned} \tag{2}$$

where i represents i^{th} particle/individual,
k represents k^{th} swarm/population,
v_k^i is the velocity at i^{th} particle in k^{th} swarm,
x_k^i is the position at i^{th} particle in k^{th} swarm,
p_k^i is the best position obtained by the i^{th} particle in k^{th} swarm so far,
p_k^g is the best position obtained in k^{th} swarm so far,
r_1 and r_2 represent random numbers between 0 and 1,
c_1 and c_2 represent acceleration constants,
or confidence numbers in individual (c_1) and swarm (c_2).

In this paper, Pareto optimality based Particle Swarm Optimisation (denoted as RMO-PSO) is used to solve a multi-objective design problems. It is also hybridised with a dynamic Game-Strategy; Nash-Game to find a better individual for each objective during the optimisation (denoted as HRMO-PSO). Traditionally, Pareto and Nash games are considered independently when solving a design problem. In this research, a Hybrid Nash-Pareto approach is considered and developed.

3 MATHEMATICAL BENCHMARKS USING RMO-PSO

Three complex multi-objective mathematical design problems including ZDT1, ZDT3, ZDT4 are considered and solved by using RMO-PSO [12].

ZDT1 – Convex Pareto Optimal Problem

$$f_1(x_1)=x_1 \quad \text{and} \quad f_2(g,h)=gh \tag{3}$$

$$g(x_i)=1+9\left(\sum_{i=2}^{n}x_i\right)\Big/(n-1),\ h(f_1,g)=1-\sqrt{f_1/g},\ n=30, x_i\in[0:1],$$

Stopping criteria: Gen ≤ 100

ZDT3 – Discontinuous Pareto Optimal Problem

$$f_1(x_1)=x_1 \quad \text{and} \quad f_2(g,h)=gh \tag{4}$$

$$g(x_i)=1+9\left(\sum_{i=2}^{n}x_i\right)\Big/(n-1),\ h(f_1,g)=1-\sqrt{f_1/g}-\frac{f_1}{g}\sin(10\pi f_1),\ n=30, x_i\in[0:1]$$

Stopping criteria: Gen ≤ 100

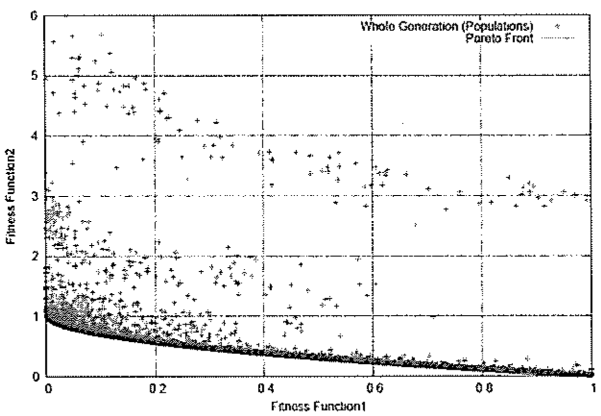
ZDT4 – Multimodality Pareto Optimal Problem

$$f_1(x_1)=x_1 \quad \text{and} \quad f_2(g,h)=gh \tag{5}$$

$$g(x_i)=1+10(n-1)+\sum_{i=1}^{n}\left(x_i^2-10\cos(4\pi x_i)\right),\ h(f_1,g)=1-\sqrt{f_1/g},$$

$n=10, x_1\in[0:1], x_{2-10}\in[-5:5]$, Stopping criteria: Gen ≤ 200

Figures 2 and 3 show that RMO-PSO has no difficulty to find true Pareto optimal front for complex multi-objective mathematical design problems; ZDT1, ZDT3 and ZDT4. Therefore RMO-PSO is applied to solve a multi-objective High Lift Systems (HLSs) design optimisation with confidence.



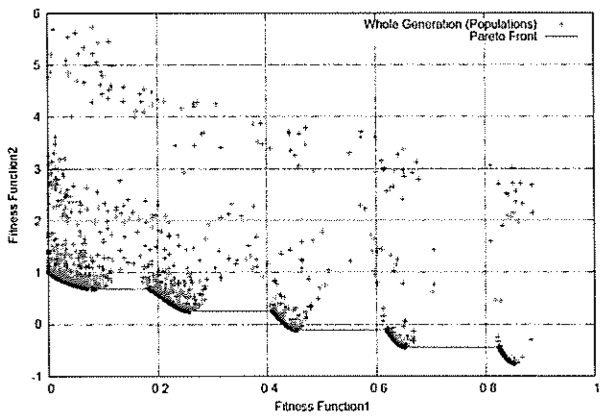


Figure 2: True Pareto optimal front for ZDT1 (left) and ZDT3 (right) obtained by .

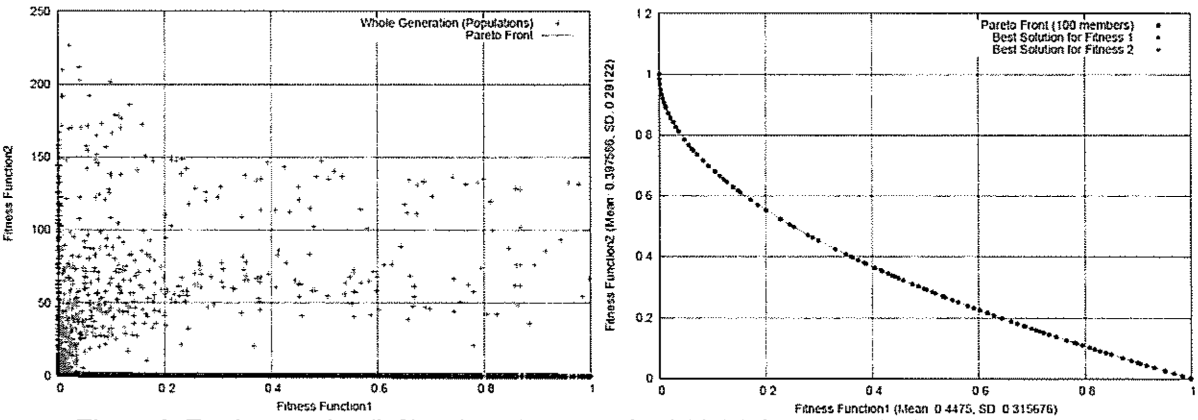


Figure 3: Total generation (left) and true Pareto optimal (right) for ZDT4 obtained by RMO-PSO.

4 AERODYNAMIC ANALYSIS TOOL AND PRE-POST PROCESSOR

In this paper, the GiD and PUMI are utilized as a pre/post CAD processor and an unstructured finite Euler solver [13, 14] respectively. They are developed in International Center for Numerical Methods for Engineering (CIMNE). GiD can generate a mesh for finite element, finite volume or finite difference analysis and write the information for a numerical simulation program in its desired format. PUMI uses finite element approach with Galerkin approximation method. The validation of PUMI can be found in Reference [15]. GiD generates unstructured mesh/grid for candidate's model based on the design parameters obtained by the RMO-PSO and HRMO-PSO, and PUMI evaluates an unstructured model and generates aerodynamic outputs in the format for GiD for post process as shown in Figure 4.

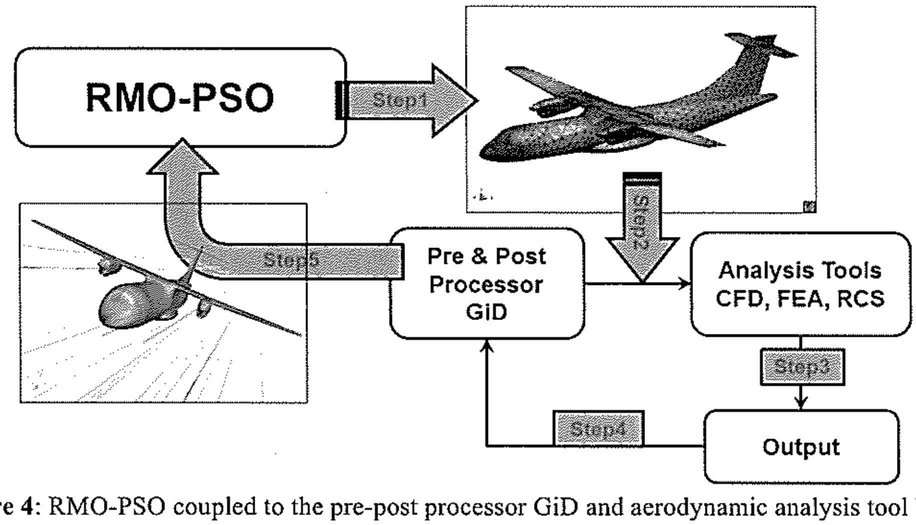


Figure 4: RMO-PSO coupled to the pre-post processor GiD and aerodynamic analysis tool PUMI.

5 HIGH LIFT SYSTEMS DESIGN OPTIMISATION

The multi-objective design optimisation for a High Lift Aircraft System using RMO-PSO and HRMO-PSO is considered. The results obtained by RMO-PSO and HRMO-PSO are compared in terms of computational cost and solutions quality.

5.1 Parameterisation of Design Problems

The High Lift Systems (HLS) consist of multi-element airfoil; slat, main, flap as shown in Figure 5. The size of the slat and flap considered in this test are 25% and 28% of the chord of multi-element aerofoil.

The deployment of slat and flap can be defined by six design parameters; dS_x, dS_y, dS_A, dF_x, dF_y, dF_A as shown in Figure 5.

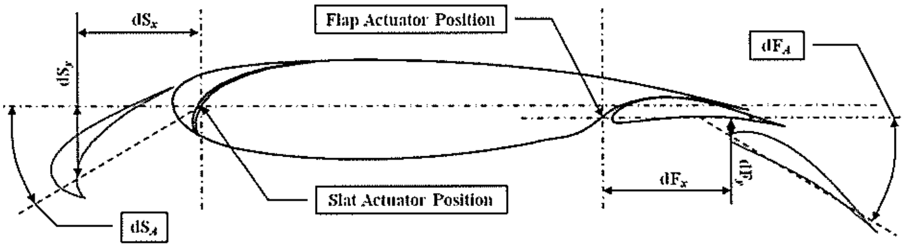


Figure 5: Control parameters for High Lift System.

Figure 6 shows the computational mesh of 16,788 vertexes and 32,039 triangles. The mesh is generated by using GiD and the model is evaluated by PUMI. The coefficient of pressure (Cp) distribution obtained by the baseline design is shown in Figure 7.

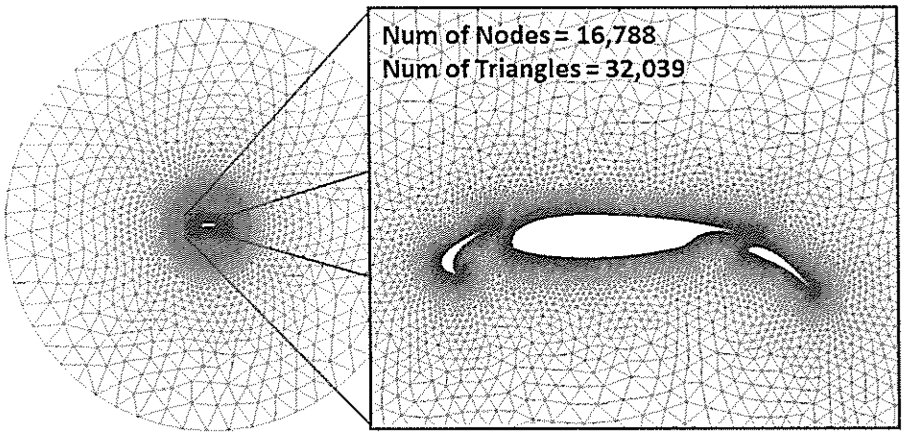


Figure 6: Mesh conditions obtained by GiD.

5.2 Formulation of Design Problem

Two deployment configurations are considered for the baseline design at take-off (M_∞ = 0.20, α = 15.0°) and landing (M_∞ = 0.12, α = 17.18°) flight conditions as shown in Figure 7.

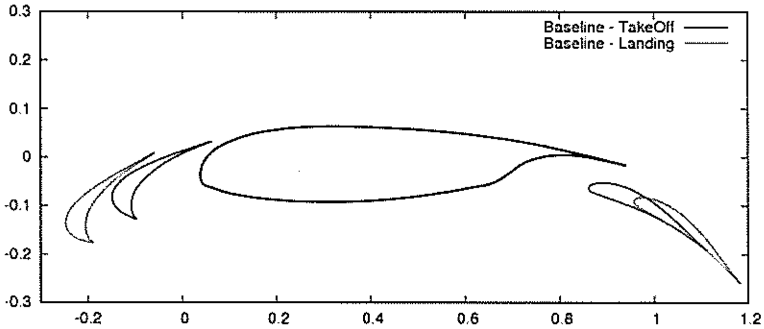


Figure 7: High lift systems eployment configurations for take-off and landing.

The slat and flap configuration at take-off are -15.0% and -7.5% of the chord in the x and y direction and deflects 15.0 degrees (dS_x = -15.0%c, dS_y = -7.5%c, dS_A = -15.0°) while the flap moves +15.0% and -2.5% of the chord in the x and y direction and 25.0 degrees deflection (dF_x = +15.0%c, dF_y = -2.5%c, dF_A = +25.0°). During the landing, the baseline design will have the slat deployment (dS_x = -25.0%c, dS_y = -12.5%c, dS_A = -25.0°) and the flap deployment (dF_x = +25.0%c, dF_y = -5.0%c, dF_A = +35.0°).

The upper and lower design bounds are shown in Table 1. This design bounds will be considered for High Lift Systems at take-off and landing conditions using RMO-PSO and HRMO-PSO.

Table 1: Design bounds for High Lift System at take-off and landing.

Design Variables	dS_x	dS_y	dS_A	dF_x	dF_y	dF_A
Lower bound	-15.0	-5.0	-15.0°	+15.0	-0.0	+25.0°
Upper bound	-25.0	-15.0	-25.0°	+25.0	-5.0	+35.0°

Note: dS_x, dS_y, dF_x, dF_y are in the percentages of the chord.

5.3 Multi-objective HLS Design Optimisation using RMO-PSO

Problem Definition

This test case considers the application of the method for multi-objective design optimisation for high lift systems. This problem deals with maximising lift coefficients at take-off (M_∞ = 0.20, α = 15.0°) and landing (M_∞ = 0.12, α = 17.18°) flight conditions. The fitness functions are shown in Equation (6) and the optimisation is stopped after 100 hours.

$$f_1 = \min\left(1/Cl_{TakeOff}\right) \text{ and } f_2 = \min\left(1/Cl_{Landing}\right) \quad (6)$$

$$\text{at Take-off } \left(M_\infty = 0.20, \alpha = 15.0°\right) \text{ and Landing } \left(M_\infty = 0.12, \alpha = 17.2°\right)$$

Stopping criteria: Elapsed time ≤ 100 hours

Numerical Results

The RMO-PSO was allowed to run 1,532 function evolutions for 100 hours using single 4 × 2.5 GHz processor. The Pareto optimal front obtained by RMO-PSO is plotted in Figure 8. It can be seen that Pareto member 1 (best solution for fitness function 1) improves take-off lift coefficient by 7.5% while Pareto member 7 (best solution for fitness function 2) improves landing lift coefficient by 13.2 %. Pareto members 1, 2 and 7 are selected and they are compared to the baseline design. Table 2 compares the fitness values obtained by the baseline design and Pareto members 1, 2 and 7.

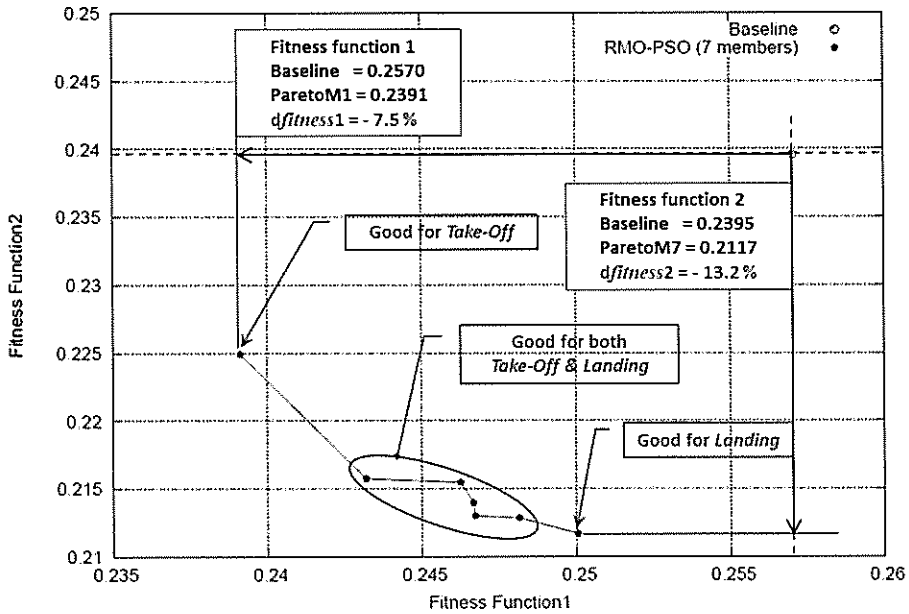


Figure 8: Pareto optimal front obtained by RMO-PSO.

Table 2: Comparison of fitness values obtained by the baseline design and Pareto optimal solutions.

Models	*Cl* at take-off	*Cl* at landing
Baseline Design	3.89025	4.17380
Pareto Member 1	4.18197 (+ 7.5%)	4.44630 (+ 6.5%)
Pareto Member 2	*4.11202 (+ 5.7%)*	*4.63498 (+ 11.0%)*
Pareto Member 7	3.99925 (+ 2.8%)	4.72380 (+ 13.2%)

Figures 9 and 10 compare the *Cp* contours obtained by the baseline design and Pareto member 2 at take-off and landing conditions.

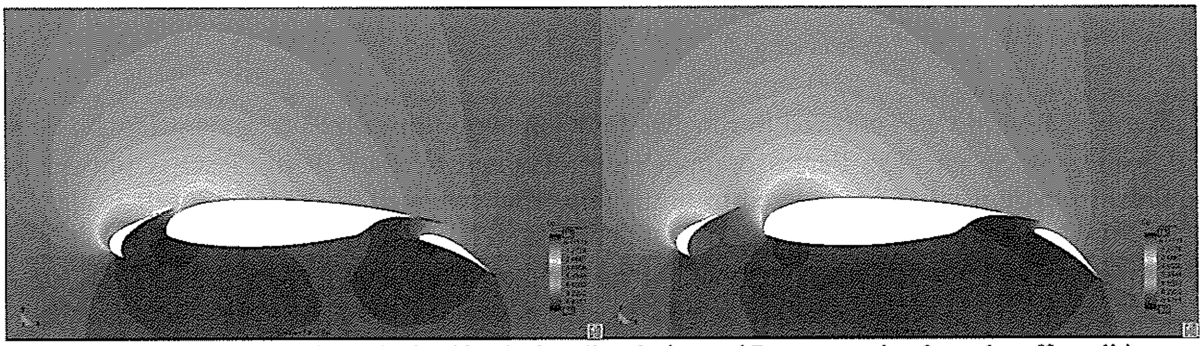


Figure 9: *Cp* distributions obtained by the baseline design and Pareto member 2 at take-off condition.

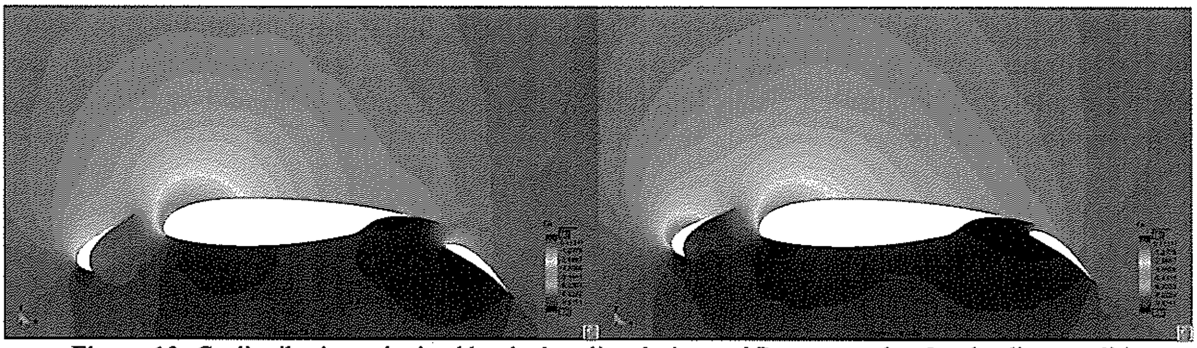


Figure 10: *Cp* distributions obtained by the baseline design and Pareto member 2 at landing condition.

5.4 Multi-objective HLS Design Optimisation using HRMO-PSO

Problem Definition

This problem considers a multi-objective design optimisation for high lift systems using HRMO-PSO at take-off (M_∞ = 0.20, α = 15.0°) and landing (M_∞ = 0.12, α = 17.18°) flight conditions. HRMO-PSO is a hybridised version of RMO-PSO using Nash-Game (ELIU module mentioned in Section 2). HRMO-PSO employs three players (Pareto-Player and two Nash-Players); Pareto-Player optimises both slat and flap deployment (dS_x, dS_y, dS_A, dF_x, dF_y, dF_A) to maximise lift coefficients at take-off and landing flight conditions. Nash-Player1 only optimises the slat deployment (dS_x, dS_y, dS_A) with the elite design for flap deployment (dF_x*, dF_y*, dF_A*) obtained by the Nash-Player2 while Nash-Player2 only optimises the flap deployment (dF_x, dF_y, dF_A) with the elite design for slat deployment (dS_x*, dS_y*, dS_A*) obtained by the Nash-Player1. The fitness functions for Pareto and Nash players are shown (7) and (8) and the optimisation is stopped after 100 hours.

$$Pareto-Player: f_1 = \min\left(1/Cl_{TakeOff}\right) \text{ and } f_2 = \min\left(1/Cl_{Landing}\right) \quad (7)$$

$$Nash-Player1: f_1\left(dS_x, dS_y, dS_A, dF_x^*, dF_y^*, dF_A^*\right) = \min\left(\overline{1/Cl_{TakeOff\&Landing}}\right) \quad (8)$$

$$Nash-Player2: f_1\left(dS_x^*, dS_y^*, dS_A^*, dF_x, dF_y, dF_A\right) = \min\left(\overline{1/Cl_{TakeOff\&Landing}}\right)$$

$$\text{at Take-off } \left(M_\infty = 0.20, \alpha = 15.0°\right) \text{ and Landing } \left(M_\infty = 0.12, \alpha = 17.2°\right)$$

Stopping criteria: Elapsed time ≤ 100 hours

Numerical Results

The HRMO-PSO was allowed to run 552 function evolutions for 100 hours using single 4 × 2.5 GHz processor. The Pareto optimal front obtained by the HRMO-PSO is plotted in Figure 11 where it is also compared to the Pareto front obtained by RMO-PSO. It is clearly shown that the Pareto optimal solutions obtained by HRMO-PSO have lower values for the fitness functions 1 and 2 when compared to the Pareto solutions obtained by RMO-PSO.

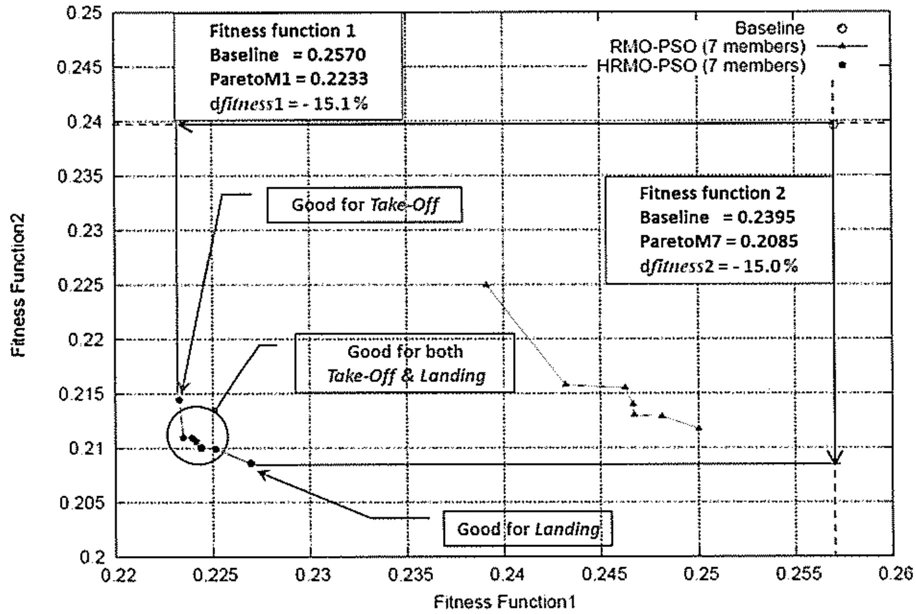


Figure 11: Pareto optimal front obtained by RMO-PSO.

Pareto member 1 (best solution for fitness function 1) improves take-off lift coefficient by 15.1% while Pareto member 7 (best solution for fitness function 2) improves landing lift coefficient by 15.0 %. Pareto members 1, 2 and 7 obtained by HRMO-PSO are selected and they are compared to the baseline design. Table 2 compares the fitness values obtained by the baseline design and Pareto members 1, 2 and 7. Figures 12 and 13 compare the *Cp* contours obtained by the baseline design and Pareto member 2 at take-off and landing conditions.

Table 3: Comparison of fitness values obtained by the baseline design and Pareto optimal solutions.

Models	*Cl* at take-off	*Cl* at landing
Baseline Design	3.89025	4.17380
Pareto Member 1	4.47787 (+ 15.1%)	4.66334 (+ 11.7%)
Pareto Member 2	*4.47395 (+ 15.0%)*	*4.74011 (+ 13.6%)*
Pareto Member 7	4.40573 (+ 13.3%)	4.79389 (+ 15.0%)

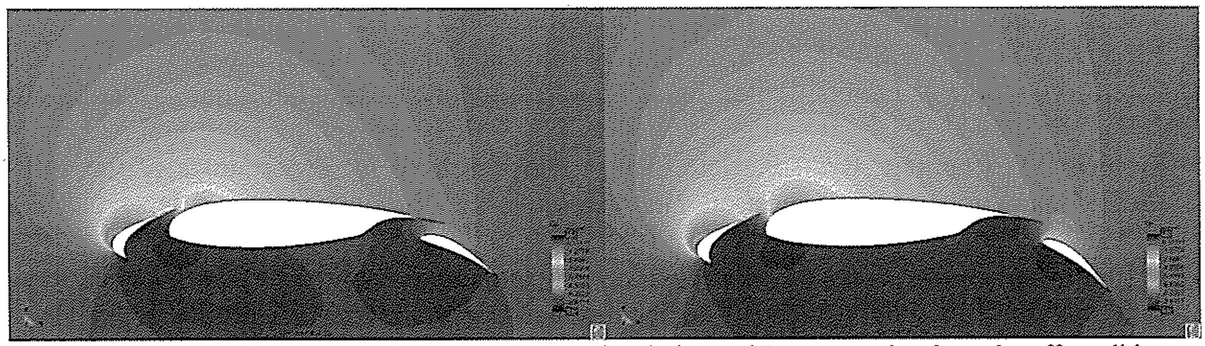


Figure 12: *Cp* distributions obtained by the baseline design and Pareto member 2 at take-off condition.

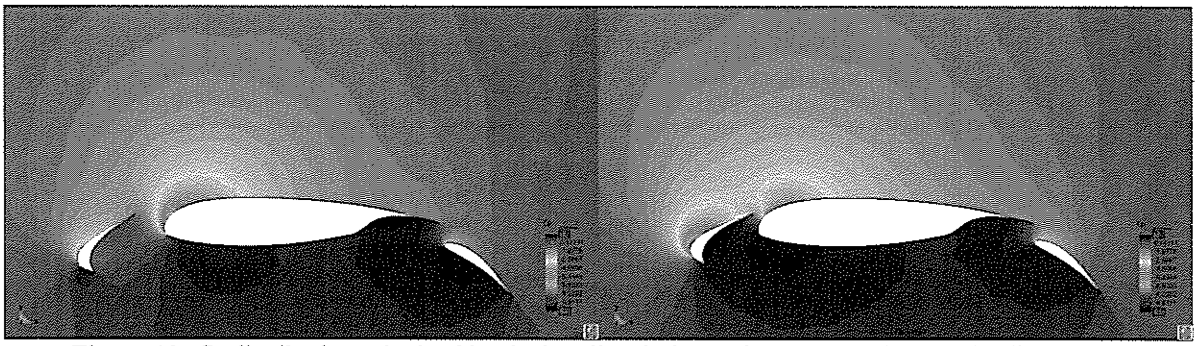


Figure 13: *Cp* distributions obtained by the baseline design and Pareto member 2 at landing condition.

6 CONCLUSIONS

Two Computational Intelligence Systems (CIS); RMO-PSO and HRMO-PSO are demonstrated and implemented to solve multi-objective of High Lift System design problems. Numerical results obtained by RMO-PSO and HRMO-PSO optimisation approaches are compared in terms of efficiency and model quality. The paper clearly shows the benefits of using Hybrid-Game in CIS which produces more accurate solution while reducing computational cost when compared to the original CIS. Current research focus on direct design problems and multi-objective design problems using HRMO-PSO and other conflicting game strategies such as hierarchical game, Stackelberg for distributed virtual or real games are presently under investigation.

ACKNOWLEDGEMENT

The authors would like to thank E. Tercero in GiD team, and Dr. R. Flores and E. Ortega at CIMNE for their support and fruitful discussion on GiD and PUMI.

REFERENCES

[1] Lee, D.S., Gonzalez L.F., Srinivas K., Periaux, J., *Robust Evolutionary Algorithms for UAV/UCAV Aerodynamic and RCS Design Optimisation*, An International Journal Computers and Fluids. Vol 37. Issue 5, pages 547-564, ISSN 0045-7930. 2008.

[2] Lee, D.S., Gonzalez L.F., Srinivas K., Periaux, J., *Robust Design Optimisation using Multi-Objective Evolutionary Algorithms*, An International Journal Computers and Fluids. Vol 37. Issue 5, pages 565-583, ISSN 0045-7930. 2008.

[3] Nash, J., *Non-cooperative Games*. The Annals of Mathematics 54. pg 286-295.

[4] Pareto, V., Cours d' Economie Politique, Technical report, Rouge, Lausanne, Switzerland, 1896.

[5] Kennedy, J., Eberhart, R.C.: Particle Swarm Optimization. In: Proceedings of the 1995 IEEE International Conference on Neural Networks, Piscataway, New Jersey, IEEE Service Center pp. 1942–1948 (1995).

[6] Sefrioui, M., and Periaux, J., Nash Genetic Algorithms: Examples and Applications. Proceedings of the 2000 Congress on Evolutionary Computation CEC00, IEEE Press, La Jolla Marriott Hotel La Jolla, California, USA, ISBN:0-7803-6375-2, pg :509-516, 2000.

[7] Lee, D.S., Uncertainty Based Multiobjective and Multidisciplinary Design Optimization in Aerospace Engineering, The Univ. of Sydney, Sydney, NSW, Australia, section 10.7,

p.p. 348-370 (2008)

[8] Deb, K., *Multi-objective optimization using evolutionary algorithms*. Chichester, UK: Wiley, (2001)

[9] Koza, J., *Genetic Programming II*. Massachusetts Institute of Technology, 1994.

[10] Lee, D.S., Periaux, J., Onate, E., Gonzalez, L.F., Advanced Computational Intelligence System for Inverse Aeronautical Design Optimisation, The 2011 Future Technology Research Association International (FTRA) - International Conference on Advanced Software Engineering (ICASE-11), Busan, Korea, 26-28 May, 2011.

[11] Lee, D.S., Periaux, J., Bugeda, G., Onate, E., Multi-Objective High Lift System s Design Optimisation using Hybridised Evolutionary Algorithm with Nash-Game. 9th World Congress on Structural and Multidisciplinary Optimization (WCSMO9), Shizuoka Japan, 13-17 June, 2011

[12] Zitzler, E., Deb, K., and Thiele, L., Comparison of multiobjective evolutionary algorithms: Empirical results. *Evolutionary Computation*, 8(2):173–195, 2000.

[13] Ribo, R., de Riera, M., Tercero, E., Ronda, J., Sans, A., Ribera, A., and Horcas, S., GiD Reference Manual, Ed. CIMNE, Spain, 2008.

[14] Flores, R. and Ortega, E., PUMI: An Explicit 3D Unstructured Finite Element Solver For The Euler Equations, Technical Report. CIMNE, Spain, 2008.

[15] Lee, D.S., Gonzalez, L.F., Periaux, J., and Onate, E., Efficient Shape Reconstruction of a Bi-NACA Aerofoil using Advanced Evolutionary Algorithms coupled to Game Strategies. Int. Conf. on Computation Methods for Coupled Problems in Science and Engineering, COUPLED PROBLEMS 2009, Eds. B. Schrefler, E. Onate, and M. Papadrakakis, ISBN 978-84-96736-65-8, Ischia Island, Italy, 8-10 June 2009.