Advanced Computational Intelligence System for Inverse Aeronautical Design Optimisation

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***Abstract*—Computational Intelligence Systems (CIS) is one of advanced softwares. CIS has been important position for solving single-objective / reverse / inverse and multi-objective design problems in engineering. The paper hybridise a CIS for optimisation with the concept of Nash-Equilibrium as an optimisation pre-conditioner to accelerate the optimisation process. The hybridised CIS (Hybrid Intelligence System) coupled to the Finite Element Analysis (FEA) tool and one type of Computer Aided Design (CAD) system; GiD is applied to solve an inverse engineering design problem; reconstruction of High Lift Systems (HLS). Numerical results obtained by the hybridised CIS are compared to the results obtained by the original CIS. The benefits of using the concept of Nash-Equilibrium are clearly demonstrated in terms of solution accuracy and optimisation efficiency.**

Keywords-component; Computational Intelligence System, Reverse Engineering, Reconstruction/Inverse Design, Evolutionary Optimisation, Game-Strategies, Nash-Equilibrium.

I. INTRODUCTION

Computational Intelligence Systems (CIS) have been developed for solving single-objective/reverse/inverse and multi-objective design problems in engineering. CIS are intrinsically capable of dealing with imprecise context problems and producing a set of feasible solutions [1 -3]. However, due to the increment of design problem complexity in engineering, innovation of CIS is crucial for both solution accuracy and computational efficiency [4, 5] so it can be more reliable and flexible. One of alternative methods to make such improvement is Game Strategies which can save CPU usage while producing accurate solutions due to their efficiency in design optimisation [6 -8].

The paper investigates the application of an advanced CIS based on Genetic Algorithms (GA) coupled to Game strategies for the efficient reconstruction/inverse of aerodynamic shapes. For CIS, an optimisation tool; RMOP developed in CIMNE is considered. RMOP has two different CI engines; Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). In this paper, GA of RMOP is used and denoted as RMOGA. In addition, the concept of Hybrid-Game (Pareto and Nash-Game) [9] is applied to RMOGA to accelerate CIS process.

Lee et al. [9, 10] studied the concept of Hybrid-Game (Global/Pareto and Nash) coupled to advanced CIS software to solve complex engineering multi-objective and multidisciplinary design problems. Their research clearly shows that the Hybrid-Game improves the performance of current CIS.

Two CI systems are implemented and coupled to two different game strategies; the first approach RMOGA uses a standard Genetic Algorithm based on Global-Game and Pareto tournament [11, 12]. The second method uses RMOGA coupled to Nash-Game [8, 13, 14] approaches (denoted Hybrid-Game, HRMOGA). Hybrid-Game consists of one Global-Player and several Nash-players; Nash-players provide dynamic elite information (Nash-Equilibrium) to the Global algorithm and hence it can have faster convergence while producing high accurate solution simultaneously. It is shown in this paper how the Hybrid-Game can accelerate optimisation process to capture a desired design model using Nash-Game which acts as a pre-conditioner of the Global algorithm. Both CI systems are coupled to a Partial Differential Equations (PDEs) based FEA tool and a Computer Aided Design system; GiD and they are implemented to solve reconstruction of High Lift Systems (HLS) which requires high computational cost.

The rest of paper is organized as followed; Section II describes the CIS; RMOP and Hybrid-Game on RMOP. Mathematical benchmarks are considered in Section III. Section IV presents brief description of aerodynamic analysis tool and pre/post processor. Section V conducts real world design applications. Conclusions are presented in Section VI.

II. METHOLOGY

A. *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) [15]. As shown in Figure 1, RMOP consists of seven modules;

- ➢ EVAU is a module for evaluation and collecting results from analysis tools. It can handle Python script, pre-compiled analyser.

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- 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. It also provide high performance computation 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.
- SSOU is a searching module; selection, mutation, crossover for GA and also it produces velocity, positioning module for PSO.

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

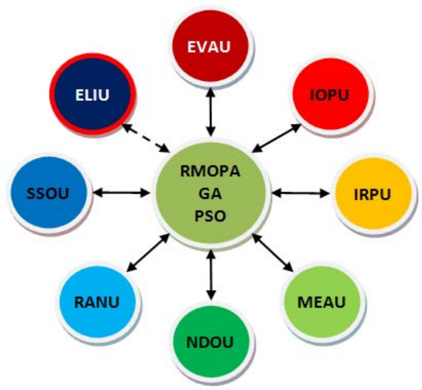

Figure 1. RMOP .

B. *Non-cooperative Game Strategy: Nash-Game*

In the Game strategies, each Nash player is in charge of one objective by using its own strategy set; a subset of design space. During the game, each player looks for the best strategy in its search space in order to improve its own objective while the set of design variables from other players are fixed. In other words, Nash-Game will decompose a problem into several simpler problems corresponding to the number of Nash-Players. The Nash-equilibrium is reached after a series of strategies tried by players in a rational set until no players can improve its objective by changing its own best strategy.

For instance, if the problem considers the objective function $f = \min(xy)$ as illustrated in Figure 2. The design variable x corresponds to the Nash Player 1 (P_1) and y to the Nash Player 2 (P_2). The P_1 is assigned for the optimization of x and the optimization of y to P_2. P_1 optimizes $f = \min(xy^*)$ by modifying x, while the elite design y^* is fixed by P_2. Symmetrically, P_2 optimizes $f = \min(x^*y)$ by modifying y while the elite design x^* is fixed by P_1. The Nash-equilibrium will be reached when both players P_1 and P_2 cannot improve their objective functions $f = \min(xy^*)$ and $f = \min(x^*y)$ respectively i.e. $f = \min(x^*y^*) \leq f = \min(x^*y)$ and $f = \min(x^*y)$. It can be seen that the Nash-Game decomposes a problem ($f = \min(xy)$) into two simpler problems, in this case two Nash-Players; P_1 ($f = \min(x^*y)$) and P_2 ($f = \min(xy^*)$) to create a competitive design environment for Nash-Game.

In this paper, Nash-Game is used to decompose complex design problems and also to be performed as a dynamic pre-conditioner incorporated to Global-Game.

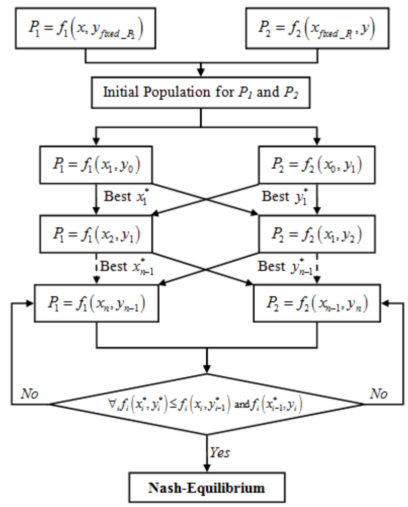

Figure 2. Nash-Game.

C. *Hybrid RMOGA (HRMOGA) Algorithm*

Traditionally, Global and Nash games are considered independently when solving a design problem. In this research, a Hybrid Nash –Global approach is considered and developed.

For example, if a problem considers $f = \min(xy)$ where design variables are x and y. A Hybrid-Game will consist of one Global Player and two Nash Players. The Global-Player will consider both design variables x and y to minimize f while Nash Player1 will only use x to minimize f and having design variable y^* fixed by Nash-Player2. Nash-Player2 will only use y to minimize f using x^* fixed by Nash-Player1. At every generation or at every predefined function evaluation, the best elite design variables (x^*, y^*) obtained by the Nash Players will be seeded to the population of Global Player. Thereby the Global Player can accelerate its searching speed to capture a global solution.

III. Mathematical Benchmark

In this section, one mathematical design problem is considered to compare optimisation efficiency of RMOGA and Hybridised RMOGA (HRMOGA) for single-objective design. The fitness function is shown (1). Two test cases are conducted with different number of design variables (n = 20, n = 30). The same random initial population is used for both RMOGA and HRMOGA. HRMOGA employs three players; one Global-Player (GlobalP) minimising (1) and two Nash-Players (NashP1, NashP2) misimising (2) and (3). The elite design

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obtained by Nash-Game will be seeded to the population of Global-Player at every generation. Table I describes crossover and mutation probabilities for RMOGA and HMOGA. The stopping criterion for RMOGA and HRMOGA is when the fitness value reaches lower than 1.0×10^{-6} i.e. f_{RMOGA} and $f_{HRMOGA} \leq 1.0 \times 10^{-6}$.

$$f_{Global-Player}\left(x_i\right) = \sum_{i=2}^{n}\left(x_i - 0.5\right)^2 \tag{1}$$

$$f_{Nash-Player1}\left(x_i, x_i^*\right) = \sum_{i=1}^{n_{NashP1}}\left(x_i - 0.5\right)^2 + \sum_{i=1}^{n_{NashP2}}\left(x_i^* - 0.5\right)^2 \tag{2}$$

$$f_{Nash-Player2}\left(x_i^*, x_i\right) = \sum_{i=1}^{n_{NashP1}}\left(x_i^* - 0.5\right)^2 + \sum_{i=1}^{n_{NashP2}}\left(x_i - 0.5\right)^2 \tag{3}$$

where n_{Global} = [20,30], n_{NashP1} = [10,15], n_{NashP2} = [10,15].
x_i* is an elite design obtained by the Nash-Player 1 and Nash-Player 2.

TABLE I. CROSSOVER AND MUTATION PROBABILITY FOR RMOGA AND HRMOGA

Optimiser	RMOGA	HRMOGA		
		GlobalP	NashP1	NashP2
CP, MP	0.9, 1/n	0.9, 1/n	1, 0.9, 1/n_{NP1}	1, 0.9, 1/n_{NP2}

Note: CP and MP represent crossover and mutation probability. GlobalP, NashP are Global-Player, Nash-Player. n is the total number of design variables and n_{NPi} is the number of design variables for Nash-Player.

Figures 3 and 4 compare the convergence history obtained by RMOGA and HRMOGA. It can be seen that HRMOGA has converged ($f \leq 1.0 \times 10^{-6}$) faster than RMOGA.

In design test case 1 (n_{Global} = 20), HRMOGA converged after 8 seconds (11,000 function evaluation) while the convergence of RMOGA occurs after 30 seconds (29,000 function evaluations). In design test case 2 (n_{Global} = 30), HRMOGA converged after 30 seconds (22,500 function evaluation) while the convergence of RMOGA occurs after 130 seconds (57,500 function evaluations). In other words, HRMOGA only needs to run 39% of RMOGA function evaluation with 25% of RMOGA computational cost for both test cases.

IV. 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 [5, 6] 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 RMOGA and HRMOGA, and PUMI evaluates an unstructured model and generates aerodynamic outputs in the format for GiD for post process.

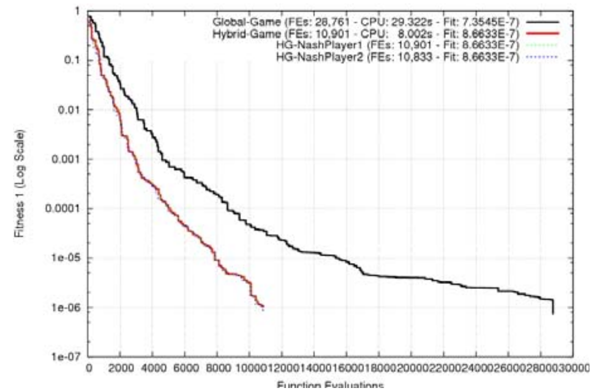

Figure 3. Convergence history obtained by RMOGA and HRMOGA for Test1 (n_{Global} = 20).

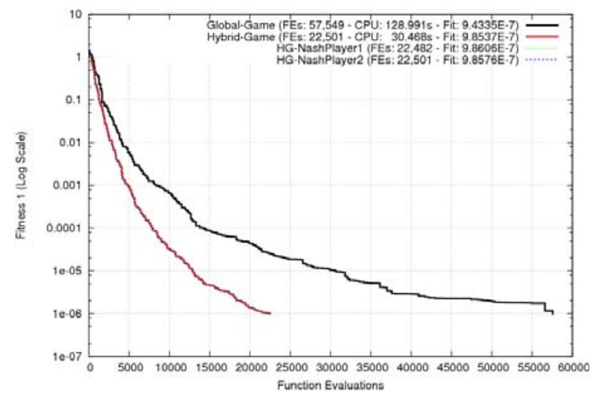

Figure 4. Convergence history obtained by RMOGA and HRMOGA for Test2 (n_{Global} = 30).

V. REAL WORLD DESIGN PROBLEMS

The reconstruction of pressure distribution on a High Lift Aircraft System using RMOGA and HRMOGA is considered. The results obtained by RMOGA and HRMOGA are compared in terms of computational cost and solutions quality.

A. Parameterisation of High Lift Systems

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.

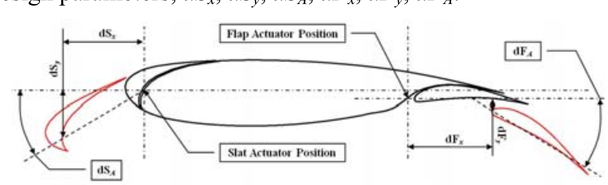

Figure 5. Slat and flap deployment parameters.

B. Fomulation of Design Problem

The baseline deployed configuration at take-off has the slat deployment of 22.5% and 10% of the chord in the x and y direction and deflects 22.5 degrees (dS_x = 22.5%c, dS_y = 10.0%c, dS_A = 22.5°) while the flap moves 20% and 2.5% of the chord in the x and y direction and 30 degrees deflection (dF_x = 20.0%c, dF_y = 2.5%c, dF_A = 30.0°). 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.

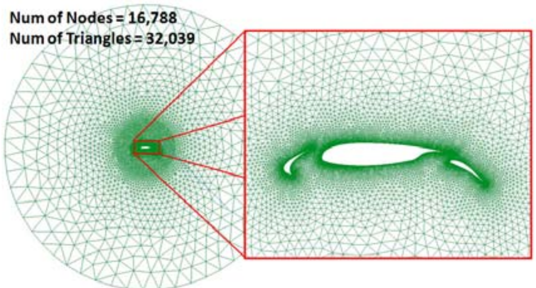

Figure 6. Mesh conditions for High Lift Systems obtained by GiD.

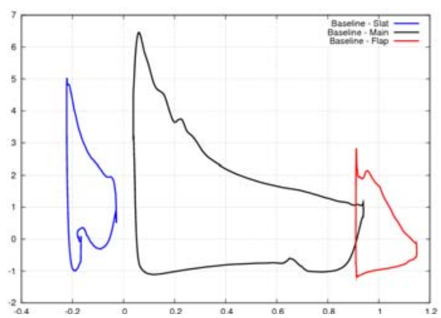

Figure 7. Pressure coefficient (Cp) obtained by the baseline design.

The upper and lower design bounds are shown in Table II. This design bounds will be considered for the both reconstructions of High Lift Systems at take-off conditions using RMOGA and HRMOGA.

TABLE II. DESIGN BOUNDS FOR RECONSTRUCTION OF HIGH LIFT SYSTEMS.

DVs	dS_x	dS_y	dS_A	dF_x	dF_y	dF_A
BD	22.5	10.0	22.5°	20.0	2.5	30°
Lower	15.0	5.0	15°	15.0	0.0	25°
Upper	25.0	15.0	25°	25.0	5.0	35°

Note: DVs and BD represent design variables and the baseline design. dS_x, dS_y, dF_x, dF_y are in the baseline chord length (%c) at cruise [0:1].

C. Reconstruction of High Lift System using RMOGA

1) Problem Definition

This test case considers the application of the method for single-objective reconstruction of high lift systems operating at M_∞= 0.2 and α = 15°. This reconstruction problem deals with minimising pressure error; the difference between a candidate pressures and the pressure distribution obtained by the baseline design deployed configuration shown in Figure 7. The fitness function is shown (4) and the optimisation is stopped after 50 hours.

$$f = \min\left(P_{Error}\right) \tag{4}$$

where
$$P_{Error}(\%) = \frac{1}{3}\left[\begin{array}{l} \dfrac{100}{S_{SP}}\sum_{i=0}^{n} abs\left(P_{T_i} - P_{C_i}\right)dx_i \\ +\dfrac{100}{S_{MP}}\sum_{j=0}^{m} abs\left(P_{T_j} - P_{C_j}\right)dx_j \\ +\dfrac{100}{S_{FP}}\sum_{k=0}^{l} abs\left(P_{T_k} - P_{C_k}\right)dx_k \end{array}\right],$$

P_T and P_C represent target and candidate pressure distribution; S_{SP}, S_{MP} and S_{FP} represent target pressure area for slat, main and flap; n, m and l represent the number of chord-wise pressure points on each aerofoil (n, m, l = 200).

2) Numerical Results

The RMOGA was allowed to run 1,532 function evolutions for 50 hours using two 4 × 2.5 GHz processors. The convergence history (fitness vs. function evaluation) is plotted in Figure 8. The optimal design produces a pressure error of 3.1 % when compared to the baseline design. It can be seen that there is good position agreement between the target deployed configuration and the optimal solution.

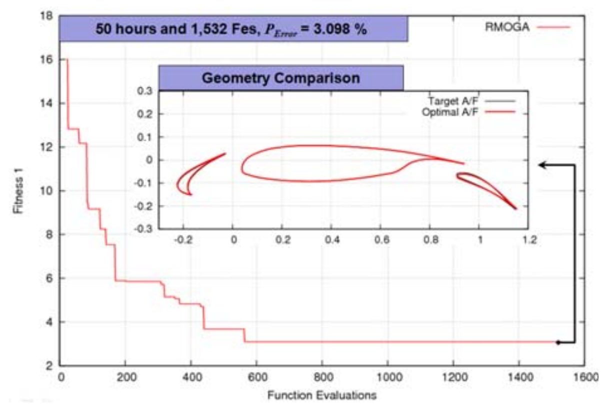

Figure 8. Convergence history obtained by RMOGA

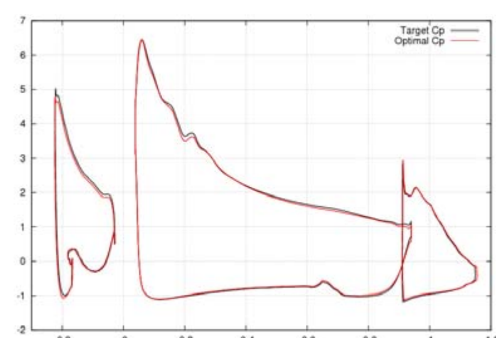

Figure 9. Cp distributions obtained by the baseline design (target) and the optimal solution.

Figure 9 compares the pressure coefficient (*Cp*) distribution obtained by the baseline design and the optimal solution. It can be seen that there is good *Cp* agreement between the target and the optimal solution.

D. Reconstruction of High Lift Systems usingHRMOGA

1) Problem Definition

This reconstruction problem deals with minimising the pressure error between computed pressures and pre-computed pressure (Figure 7) distributions using HRMOGA. HRMOGA employs three players (Global-Player and two Nash-Players); Global-Player optimises both slat and flap deployment (dS_x, dS_y, dS_A, dF_x, dF_y, dF_A). 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 Global and Nash players are shown (5) –(7) and the optimisation is stopped after 50 hours.

$$f_{Global-Player} = \min\left(P_{Error}\right) \tag{5}$$

$$f_{Nash-Player1} = \min\left(P_{Error}\right)\ with\ dF_x*, dF_y*, dF_A* \tag{6}$$

$$f_{Nash-Player2} = \min\left(P_{Error}\right)\ with\ dS_x*, dS_y*, dS_A* \tag{7}$$

where $P_{Error}(\%) = \frac{1}{3}\sum_{i=1}^{n}\left(\frac{100}{S_{P_i}}\sum_{j=1}^{m} abs\left(P_{T_{ij}} - P_{C_{ij}}\right)dx_{ij}\right)$,

*dS**, *dF** represent the elite designs obtained by Nash-Player 1 and Nash-Player 2,

P_T and P_C represent target and candidate pressure distribution,

S_P represents target pressure error,

n and *m* represent the number of aerofoils ($n = 3$) and chord-wise pressure points on each aerofoil ($m = 200$).

2) Numerical Results

The HRMOGA was allowed to run 547 function evolutions for 50 hours using two 4 × 2.5 GHz processors. The convergence history (fitness vs. function evaluation) is plotted in Figure 10. The optimal design produces a pressure error of 2.3 % when compared to the baseline design. It can be seen that there is good agreement between the target deployed configuration and the optimal solution.

Figure 11 compares convergence history obtained by RMOGA and HRMOGA. HRMOGA converged to P_{Error} of 2.29% which RMOGA cannot capture after 50 hours. To compare computational cost, two similar P_{Error} are selected; RMOGA - P_{Error} of 3.1% after 18.3 hours (564 function evaluations) and HRMOGA - P_{Error} of 3.0% after 7.4 hours (81 function evaluations), HRMOGA has capabilities to capture better design with only 37% computational cost of RMOGA.

Figure 12 compares pressure coefficient (*Cp*) distribution. It can be seen that there is good *Cp* agreement between the target and the optimal solution. The *Cp* contours obtained by the baseline design, the optimal solution from Section V.C and the current optimal solution are shown in Figures 13 -15.

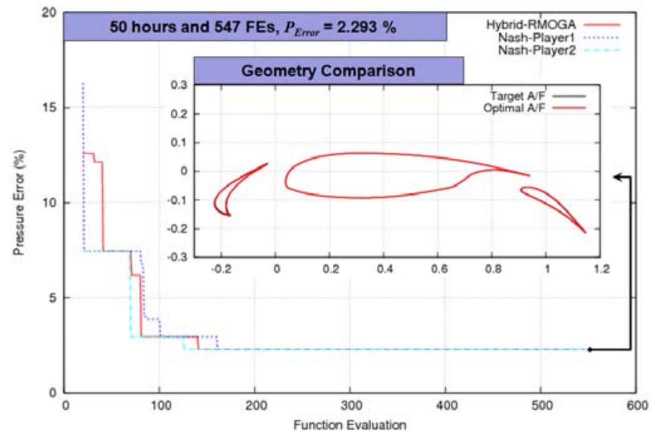

Figure 10. Convergence history obtained by HRMOGA.

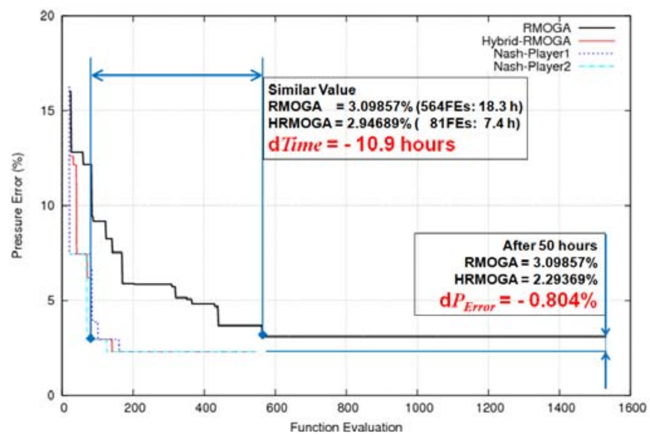

Figure 11. Comparison of convergence history obtained by RMOGA and HRMOGA.

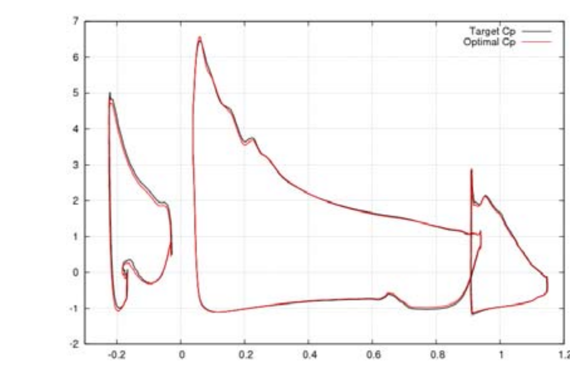

Figure 12. *Cp* distributions obtained by the baseline design (target) and the optimal solution.

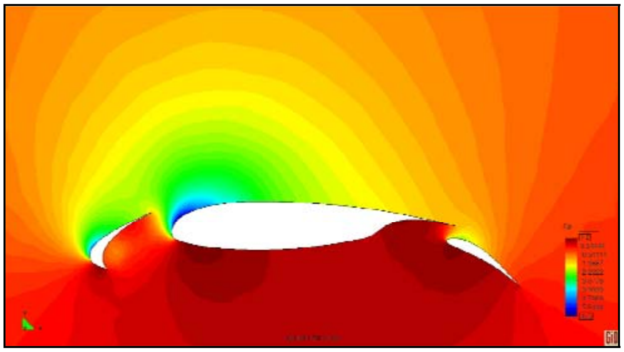

Figure 13. *Cp* contour obtained by the baseline design.

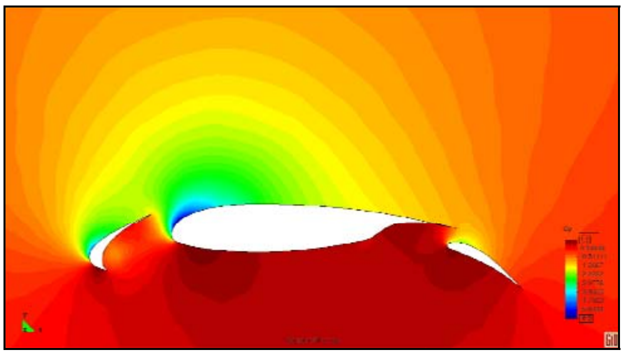

Figure 14. *Cp* contour obtained by the optimal solution of RMOGA.

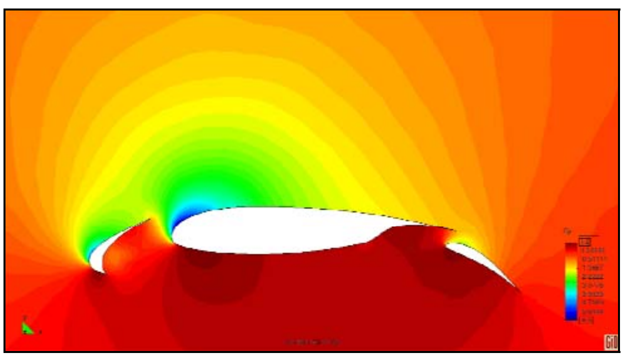

Figure 15. *Cp* contour obtained by the optimal solution of HRMOGA.

VI. CONCLUSION

Two Computational Intelligence Systems; RMOGA and HRMOGA are demonstrated and implemented to solve reconstruction of High Lift System design problems. Numerical results obtained by RMOGA and HRMOGA 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 HRMOGA and other conflicting game strategies such as hierarchical game, Stackelberg for distributed virtual or real games are presently under investigation.

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