AERODYNAMIC SHAPE OPTIMIZATION USING AN EVOLUTIONARY ALGORITHM

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Abstract

A method for aerodynamic shape optimization based on an evolutionary algorithm approach is presented and demonstrated. Results are presented for a number of model problems to access the effect of algorithm parameters on convergence efficiency and reliability. A transonic viscous airfoil optimization problem—both single and two-objective variations—is used as the basis for a preliminary comparison with an adjoint-gradient optimizer. The evolutionary algorithm is coupled with a transonic full potential flow solver and is used to optimize the inviscid flow about transonic wings including multi-objective and multi-discipline solutions that lead to the generation of pareto fronts. The results indicate that the evolutionary algorithm approach is easy to implement, flexible in application and extremely reliable.

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Seminar
California Institute of Technology

Department of Aeronautics
Pasadena, California
March 3, 2003

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PRESENTATION OUTLINE

- EVOLUTIONARY ALGORITHMS--GENERAL
- SINGLE OBJECTIVE RESULTS
- MULTI-OBJECTIVE ALGORITHM CHARACTERISTICS--PARETO FRONTS
- COMPARISON OF RESULTS FROM AN EVOLUTIONARY ALGORITHM AND AN ADJOINT GRADIENT BASED ALGORITHM
- ADDITIONAL COMPUTATIONAL RESULTS
- CONCLUSIONS

GENERAL CHARACTERISTICS:

SINGLE-OBJECTIVE EVOLUTIONARY ALGORITHMS

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EVOLUTIONARY ALGORITHMS—GENERAL

- EVOLUTIONARY ALGORITHMS (EA) are search algorithms based on natural selection. "*They combine survival of the fittest with structured yet randomized information exchange...*" GOLDBERG (1989)

- EA optimization has many advantages:
  - Simplicity
  - Robustness
  - Wide applicability
  - Embarrassingly parallel implementation

- EA optimization works for design spaces that are
  - Function discontinuous
  - Derivative discontinuous
  - Multi-modal
  - Multi-objective

- EAs typically require more function evaluations than other methods especially gradient-based methods

EVOLUTIONARY ALGORITHM CHARACTERISTICS

- ENCODING (DESIGN SPACE PARAMETERIZATION)
  - Each problem being optimized must be *representable* as a set of parameters called GENES, e.g., geometric parameters used in aerodynamic shape optimization. One set of genes is called a CHROMOSOME.
  - Chromosomes are constructed in one of two ways:
    - Bit strings
    - Real number strings

- FITNESS
  - A FITNESS FUNCTION is used to evaluate figure of merit for each chromosome, e.g., pressure integration to obtain lift

- SELECTION
  - SELECTION operation is used to determine which chromosomes will be carried forward to the next generation
  - More fit individuals are always favored in the selection process

EVOLUTIONARY ALGORITHM—SELECTION

▶TWO SELECTION ALGORITHMS HAVE BEEN STUDIED

● Multiple pass selection ("greedy selection")

- FIRST PASS: Select all chromosomes ranked 1
- SECOND PASS: Select all chromosomes ranked 1 and 2
- THIRD PASS: Select all chromosomes ranked 1, 2 and 3
- And so on until NC chromosomes have been selected

● Tournament selection

- Select the NOB chromosomes with the highest fitness in each objective
- Select three chromosomes at random and compare rankings
- Retain the highest ranking (in case of ties, retain the first selected)
- Repeat until NC chromosomes have been selected

EVOLUTIONARY ALGORITHM CHARACTERISTICS—CONT.

- ▶New Generation is Finalized Using Various Modification Operators
  - ▶ PASSTHROUGH (Controlled by P_1)
    - ▶Small number of chromosomes with highest rankings included without modification (ELITISM)
  - ▶ CROSSOVER (Controlled by P_2)
    - ▶Two chromosomes (PARENTS) are chosen at random from new generation
    - ▶Genes are combined using an averaging operator to produce a CHILD with shared characteristics from each PARENT
  - ▶ MUTATION
    - ▶Random gene chosen from random chromosome in new generation
    - ▶Using a small probability the chosen gene is randomly modified
    - ▶Two types of mutation used
      - ▶PERTURBATION MUTATION: Changes are small (Controlled by P_3)
      - ▶Standard MUTATION: Changes are large (Controlled by P_4)
  - ▶ MODIFICATION OPERATOR USAGE CONTROLED BY P-VECTOR--ΣP_i=1.0

❖CROSSOVER is generally viewed as most important operation for producing a rapid search or exploration.

❖MUTATION adds randomness, ensuring that no part of design space is neglected.

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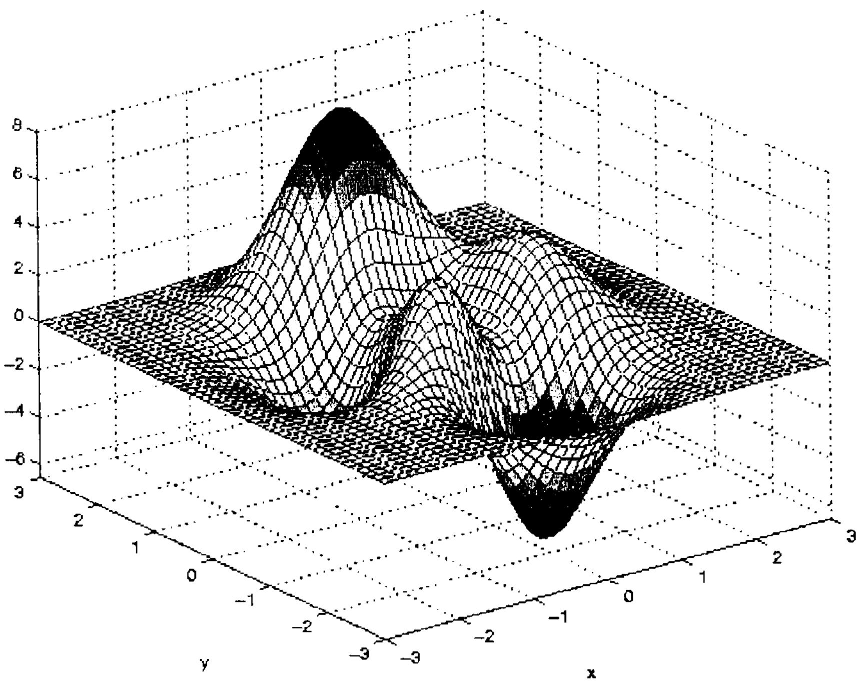
SAMPLE RESULTS--SINGLE OBJECTIVE

- ▶HILL CLIMBING PROBLEM
  - ▶TWO GENES
  - ▶MULTI-MODAL (MULTIPLE HILLS AND VALLEYS)

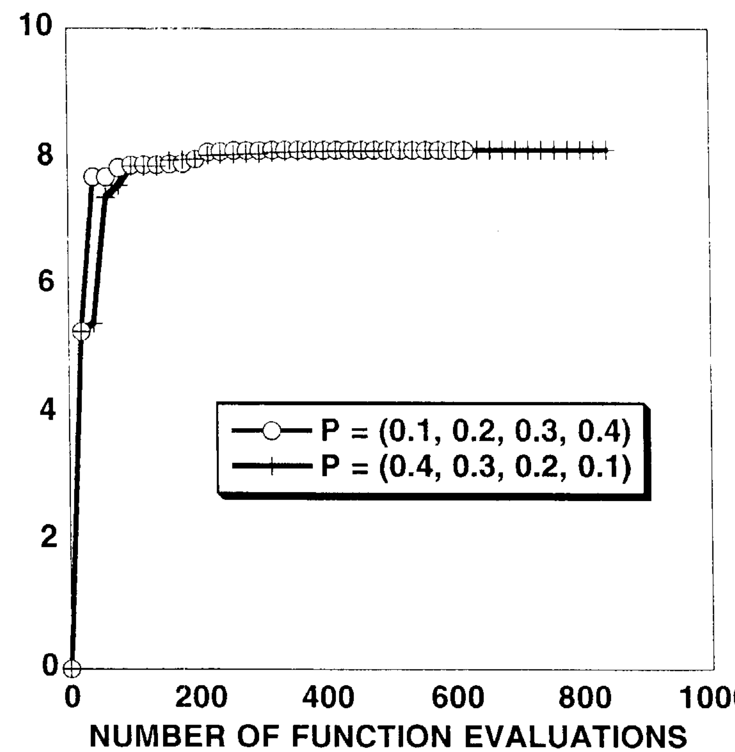
- ▶TRANSONIC WING OPTIMIZATION
  - ▶LIFT-TO-DRAG MAXIMIZATION
  - ▶AERODYANMIC FUNCTION EVALUATIONS
    - ▶TRANSONIC OVERSET POTENTIAL SOLVER (TOPS)
    - ▶CHIMERA ZONAL GRID APPROACH
    - ▶HYPGEN USED FOR WING VOLUME GRID GENERATION
  - ▶WING PARAMETERIZATION
    - ▶HICKS-HENNE BUMP FUNCTIONS USED (UPPER SURFACE ONLY)
    - ▶LEADING EDGE, TRAILING EDGE AND LOWER SURFARE FIXED
    - ▶FOUR BUMPS AT TWO STATIONS (ROOT AND TIP) + TWIST >> TEN GENES (GEOMETRIC DECISION VARIABLES)
    - ▶LINEAR LOFTING BETWEEN ROOT AND TIP
    - ▶FIXED PLANFORM

HILL CLIMBING PROBLEM

ISOMETRIC VIEW OF FUNCTION USED IN HILL CLIMBING PROBLEM



SAMPLE EA CONVERGENCE
β=0.01, CONV=10^{-5}, NC=20



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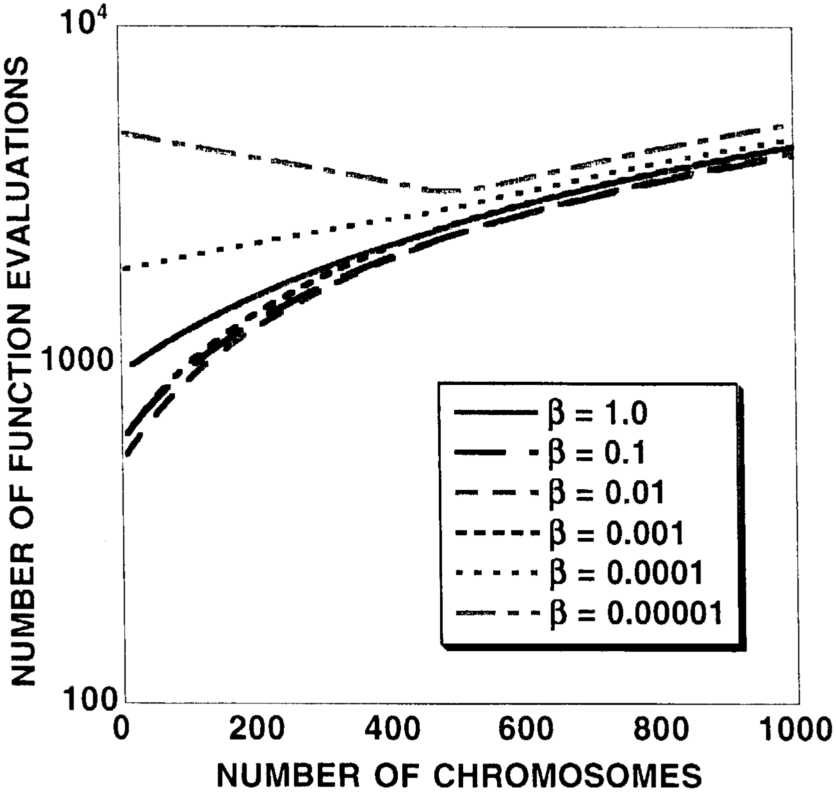
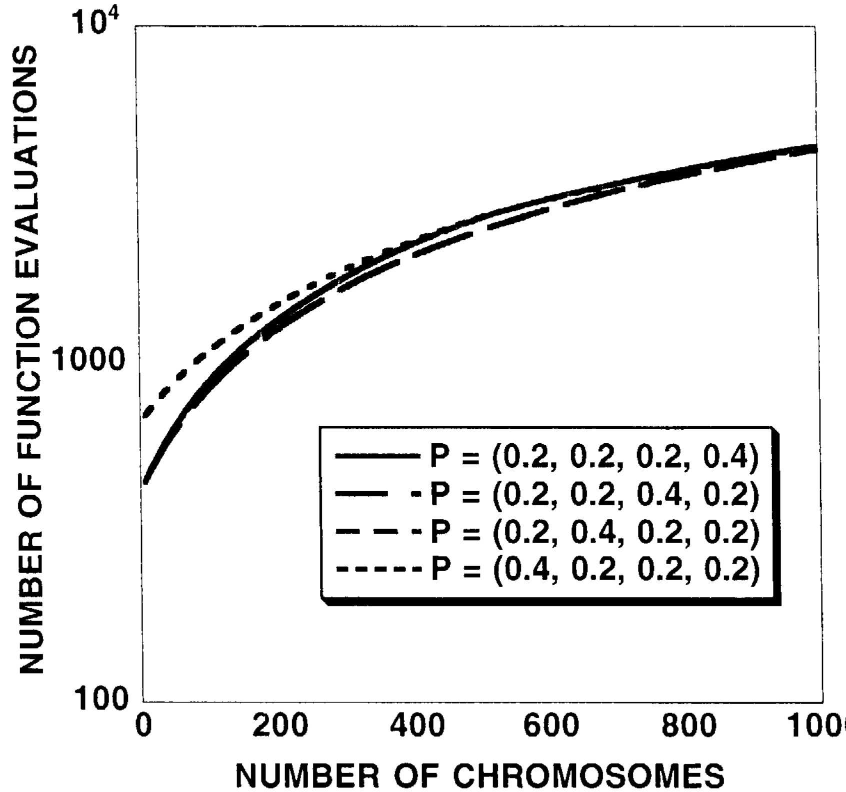
EA CONVERGENCE—HILL CLIMBING PROBLEM

EFFECT OF β ON CONVERGENCE
CONV = 10^{-5}, P = (0.1, 0.2, 0.3, 0.4)



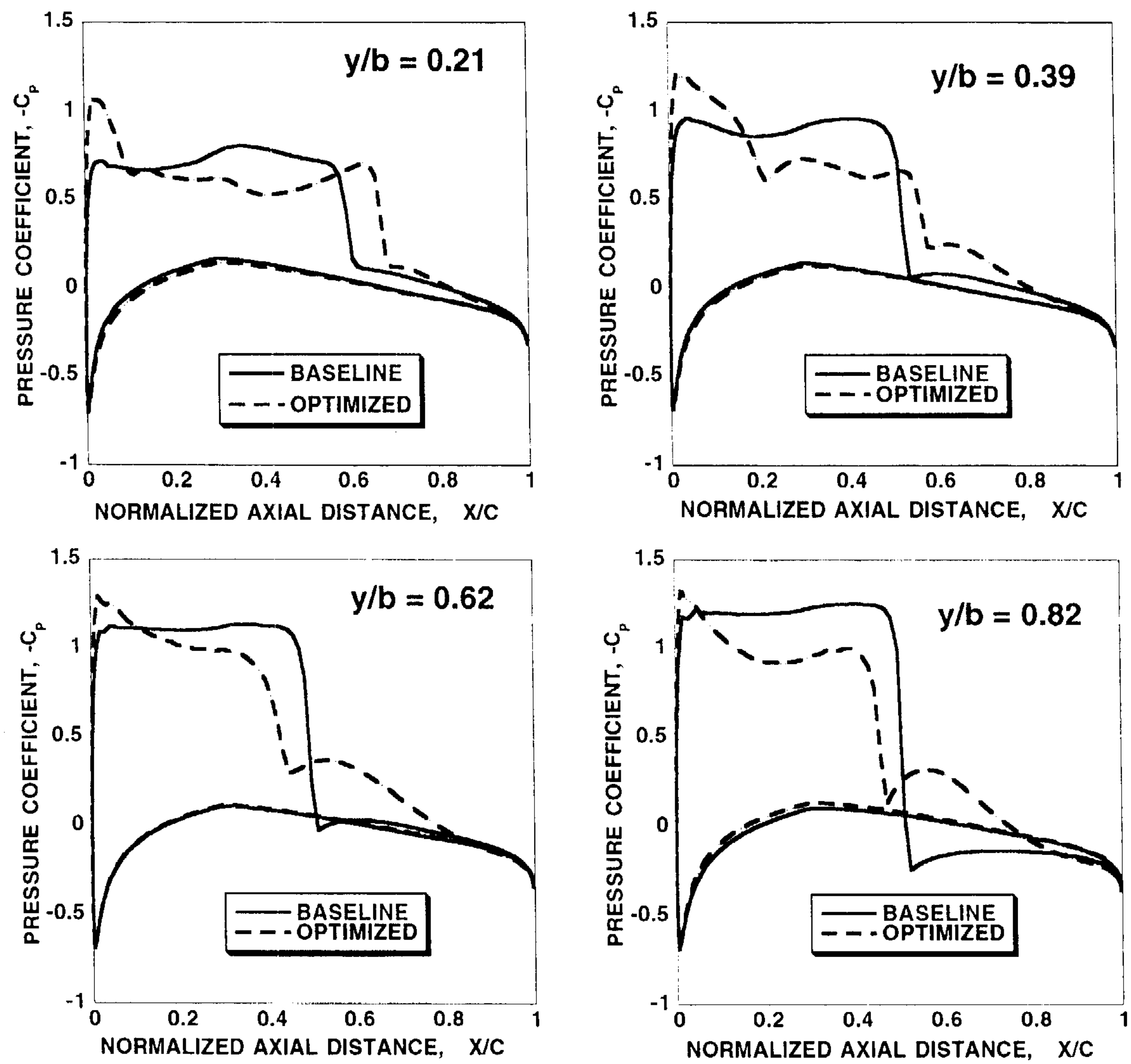
EFFECT OF P ON CONVERGENCE
CONV = 10^{-5}, β = 0.01



PRESSURE DISTRIBUTIONS—WING OPTIMIZATION

$M_\infty = 0.84$
$\alpha = 4°$
TR = 0.333
AR = 6.0
$\Lambda_{LE} = 36.65°$
RMAX < 10^{-6}
NG = 10
NC = 20
$\beta = 0.3$
P = (0.1, 0.2, 0.3, 0.4)

OBJ =
$1/(C_D/C_L+(C_L-0.45)^2)$

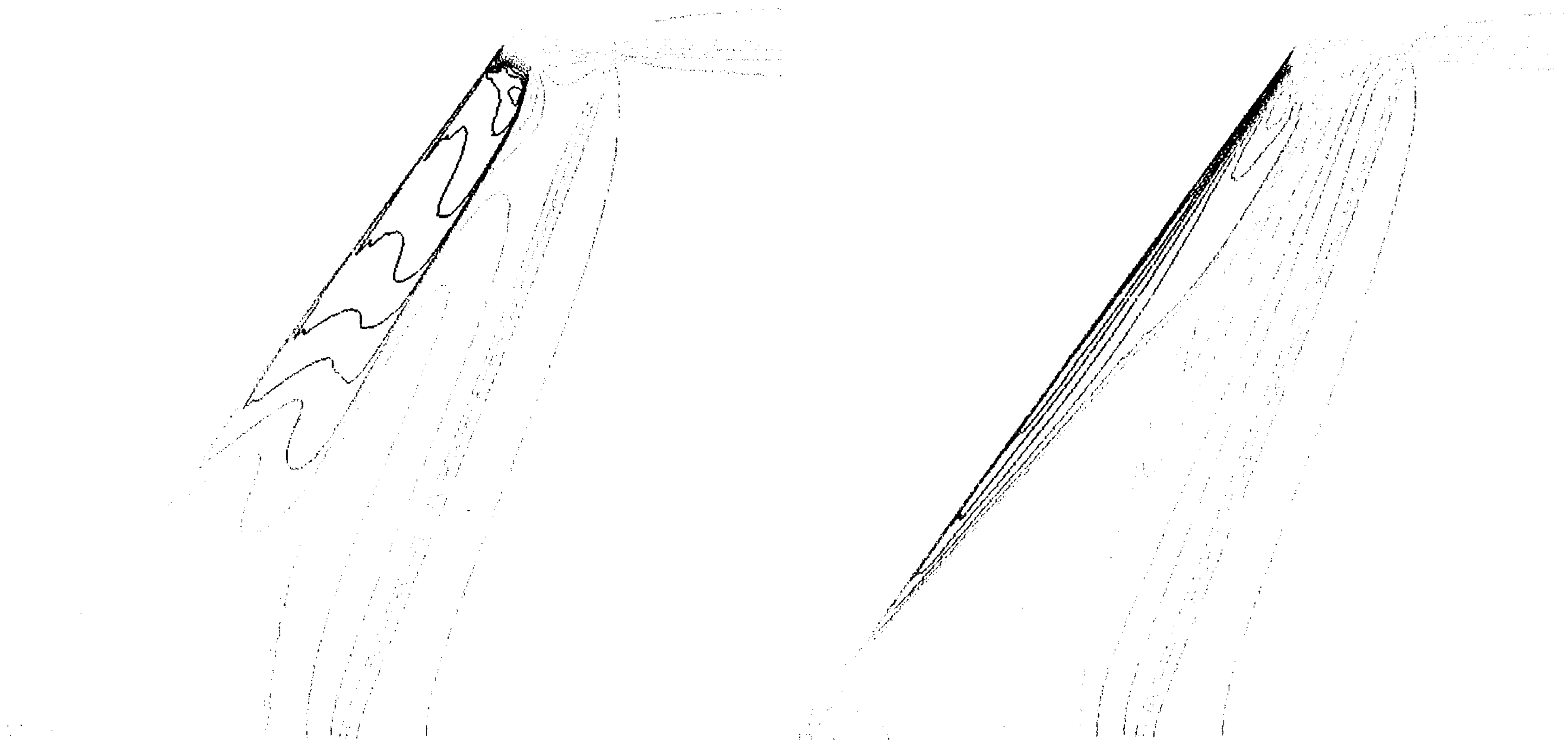


MACH NUMBER CONTOURS—WING OPTIMIZATION

$M_\infty = 0.84$, $\alpha = 4°$, $RMAX < 10^{-6}$, $NG = 10$, $\beta = 0.3$, $P = (0.1, 0.2, 0.3, 0.4)$

BASELINE SOLUTION

OPTIMIZED SOLUTION



EA CONVERGENCE—WING OPTIMIZATION

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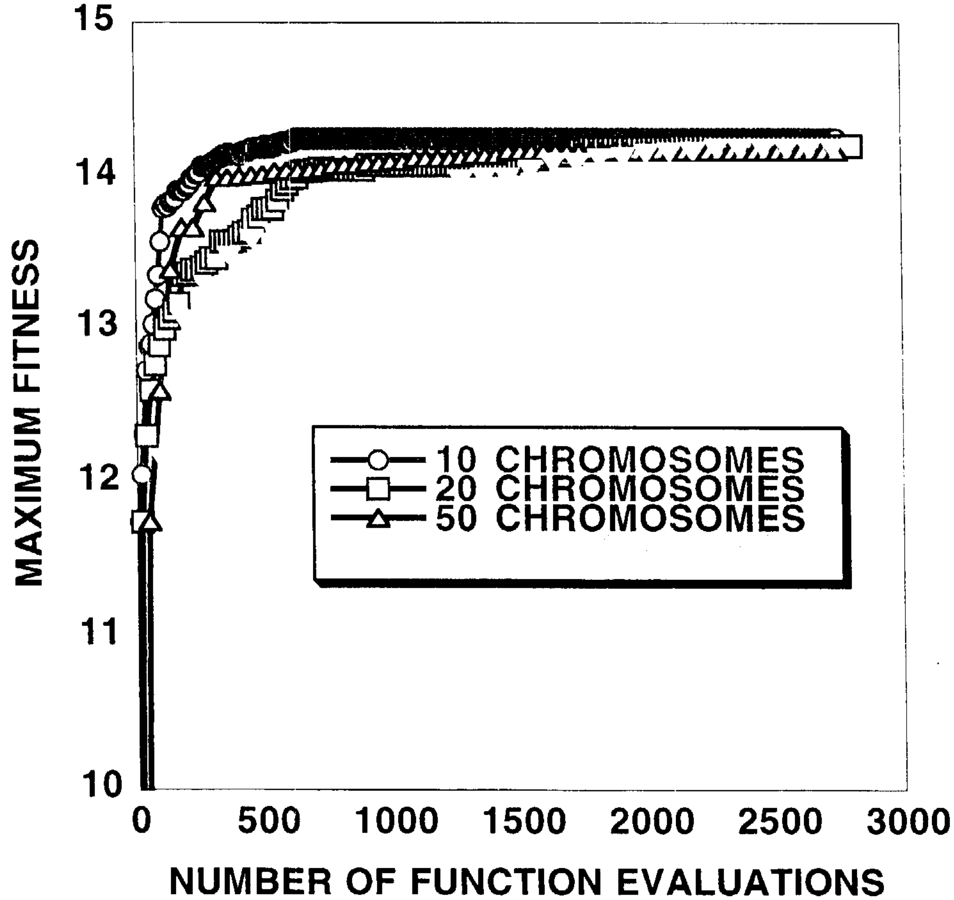
EFFECT OF POPULATION SIZE ON GA CONVERGENCE

$M_\infty = 0.82$, $\alpha = 4°$, $RMAX < 10^{-6}$, $NG = 55$, $\beta = 0.3$, $P = (0.1, 0.3, 0.4, 0.2)$



MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM CHARACTERISTICS

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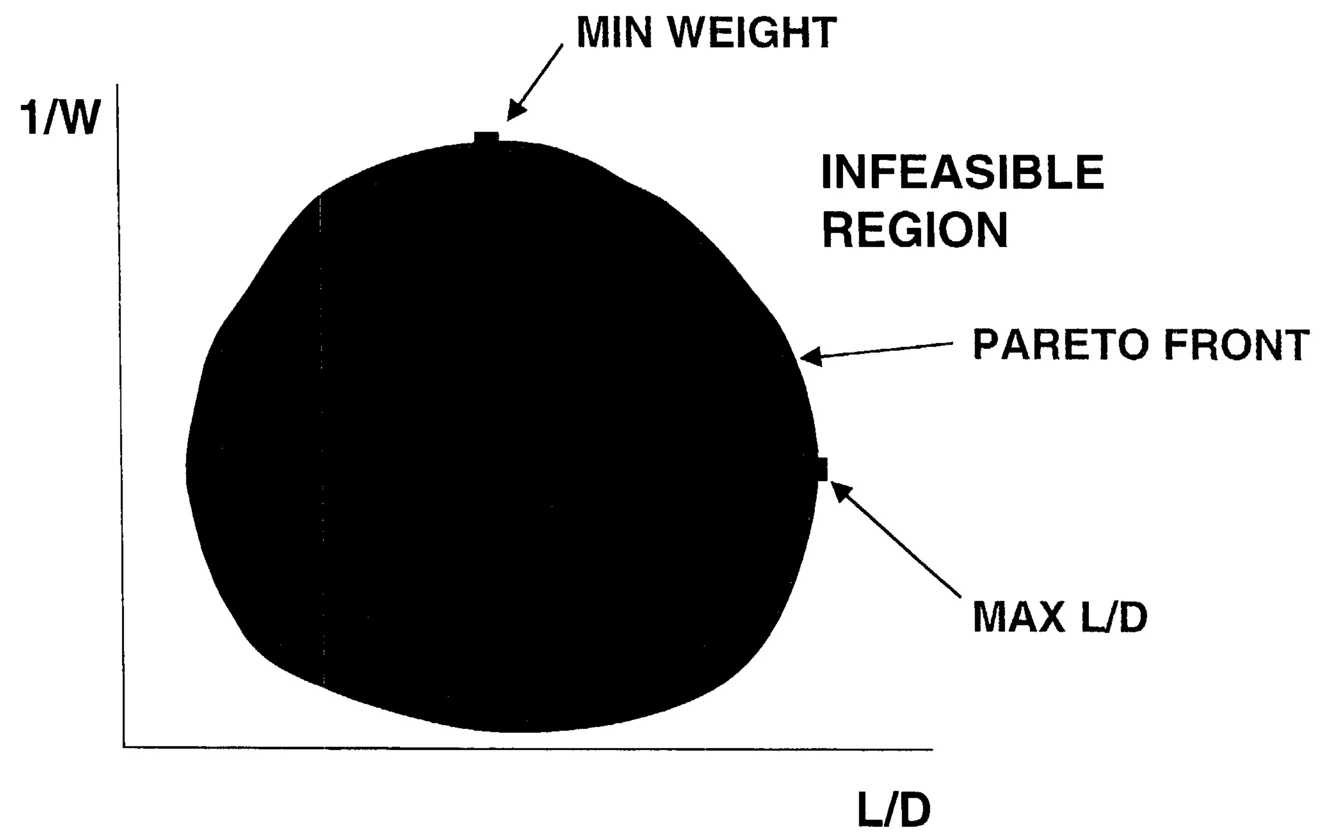
MULT-OBJECTIVE OPTIMIZATION--GENERAL

- EAs ARE USEFUL FOR MULTI-OBJECTIVE OPTIMIZATION, E.G., MAX L/D AND MIN WEIGHT



PRESENT EVOLUTIONARY ALGORITHM—NOTATION

▶ The ith gene in the jth chromosome of the nth EA generation is indicated by

$$x_{i,j}^{n}$$

▶ The jth chromosome within the nth generation composed of NG genes

$$\mathbf{X}_j^n = (x_{1,j}^n, x_{2,j}^n, \ldots, x_{i,j}^n, \ldots, x_{NG,j}^n)$$

▶ The fitness vector associated with the jth chromosome and the nth generation

$$\mathbf{F}_j^n = [f_1^n(\mathbf{X}_j^n), f_2^n(\mathbf{X}_j^n), \ldots, f_{NOB}^n(\mathbf{X}_j^n)]$$

where NOB is the number of objective functions.

MULTIPLE OBJECTIVE OPTIMIZATION
PARETO FRONT DEFINTIONS

- PARETO OPTIMAL SET or PARETO FRONT :
  - The optimal result of a multi-objective optimization

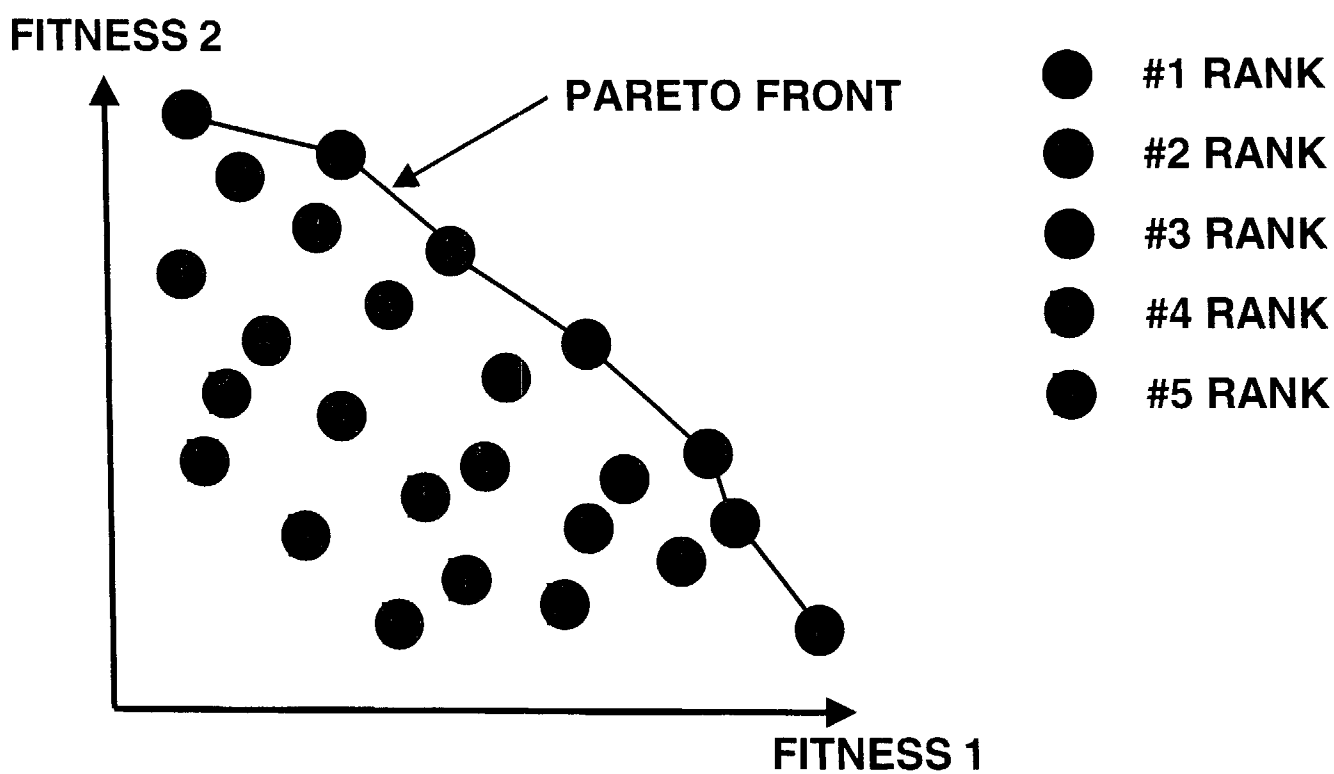
- Membership in the Pareto Optimal Set determined using the concept of DOMINANCE:

Chromosome X_a dominates chromosome X_b
iff $f_{a,k} \geq f_{b,k}$ for all k with $f_{a,k} > f_{b,k}$ for at least one k

- Chromosome rank tied to dominance.
  - Several ranking algorithms available:
    - Goldberg ranking
    - Fonseca and Fleming ranking
    - Others

MULTI-OBJECTIVE OPTIMIZATION RANKING

- Goldberg ranking using maximization for two objectives



MULTIPLE OBJECTIVE OPTIMIZATION ACTIVE AND ACCUMULATION FILES

- ACTIVE FILE:
  - Current collection of chromosomes (nth population)
- ACCUMULATION FILE:
  - Collection of all #1 ranked chromosomes discovered during EA iteration
- ACCUMULATION FILE development and use:
  - Add all newly discovered #1 ranked chromosomes
  - Cull old individuals that lose dominance
  - Increases in size with EA iteration
  - Used in active file ranking
  - Not used in the EA selection/crossover/mutation process (Some variations do use accumulation file in selection)

COMPARISON OF ADJOINT GRADIENT AND EVOLUTIONARY ALGORITHM APPROACHES

COMPARISON OF EVOLUTIONARY AND ADJOINT GRADIENT METHODS

- ADJOINT GRADIENT (AG) METHOD
  - ADJOINT METHOD USED TO DETERMINE DESIGN SPACE GRADIENTS
  - BFGS QUASI-NEWTON APPROACH USED FOR GRADIENT OPTIMIZATION
  - WEIGHTED OBJECTIVE FUNCTION (WOF) USED FOR "MULTI-OBJECTIVE" OPTIMIZATIONS, i.e., $OBJ^{NEW} = W*OBJ_1+(1-W)*OBJ_2$

- EVOLUTIONARY ALGORITHM (EA)
  - WOF AND DOMINANCE PARETO FRONT (DPF) APPROACHES BOTH USED

- MULTI-OBJECTIVE VISCOUS AIRFOIL OPTIMIZATION:
  - ALL FUNCTION EVALUATIONS PERFORMED USING ARC2D
    - STEADY STATE SOLUTIONS TO NAVIER-STOKES EQUATIONS
    - SPALART-ALMARAS TURBULENCE MODEL
  - B-SPLINE REPRESENTATION OF AIRFOIL USED
    - FIVE SPLINE KNOTS ON EACH SURFACE PLUS α -- TOTAL OF 11 GENES (DECISION VARIABLES)

- Details found in Pulliam, Nemec, Holst, Zingg, AIAA Paper 2003-0298.

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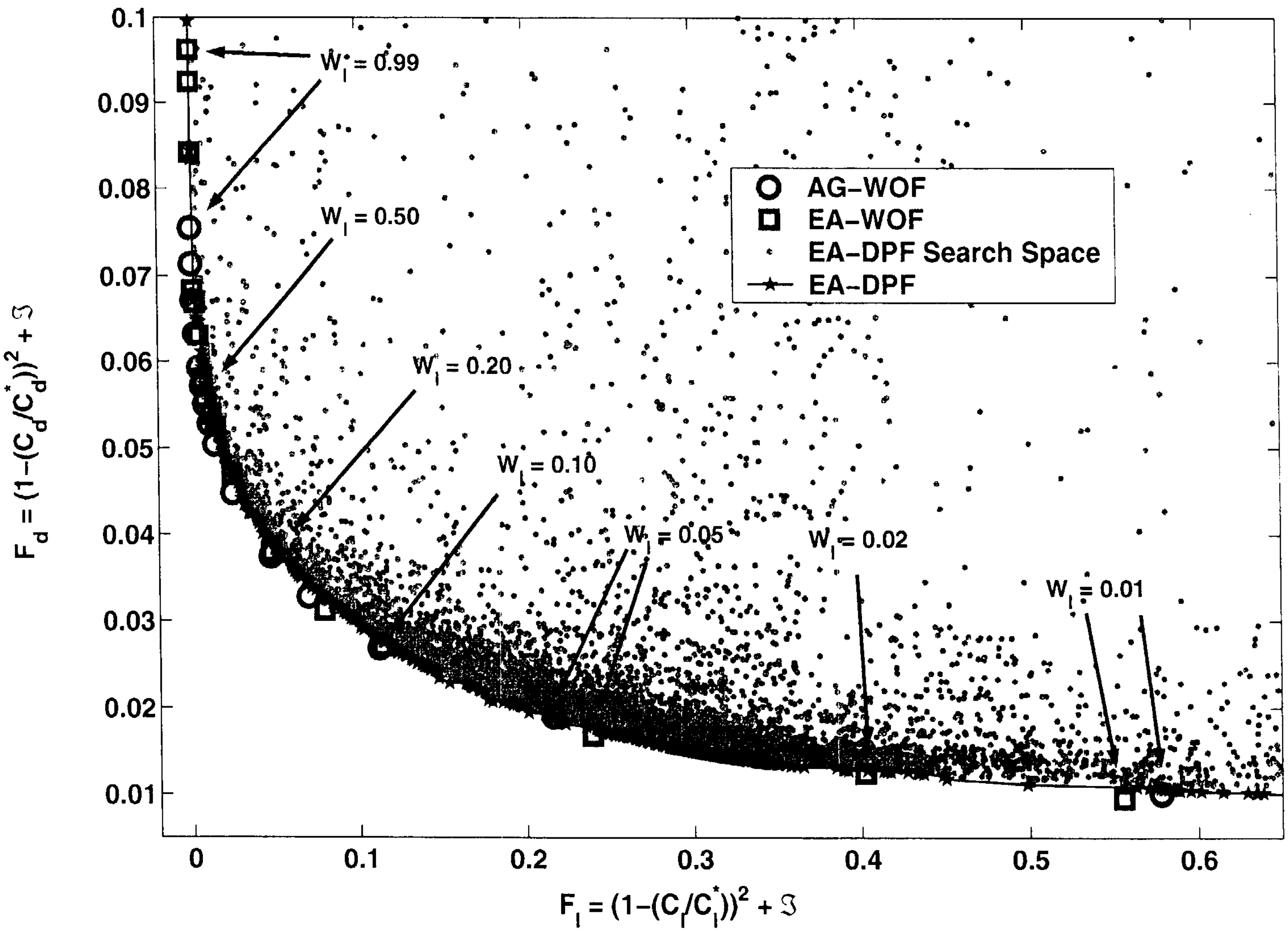
PARETO FRONT COMPARISONS

$M_\infty = 0.7$, $Re = 9X10^6$, $C_l^* = 0.55$, $C_d^* = 0.0095$



COMPARISON OF AG-WOF AND EA-DPF RESULTS

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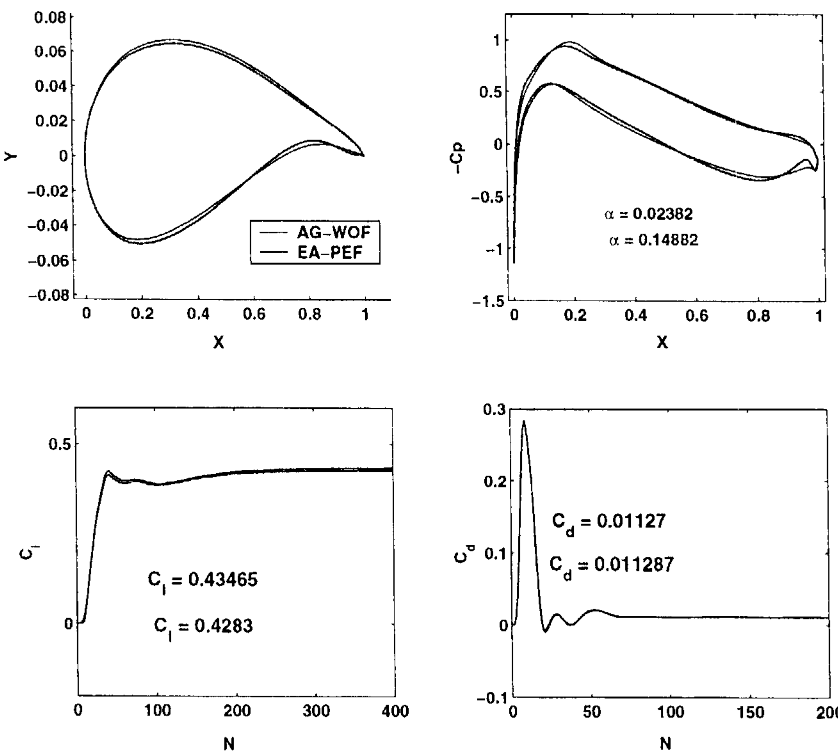
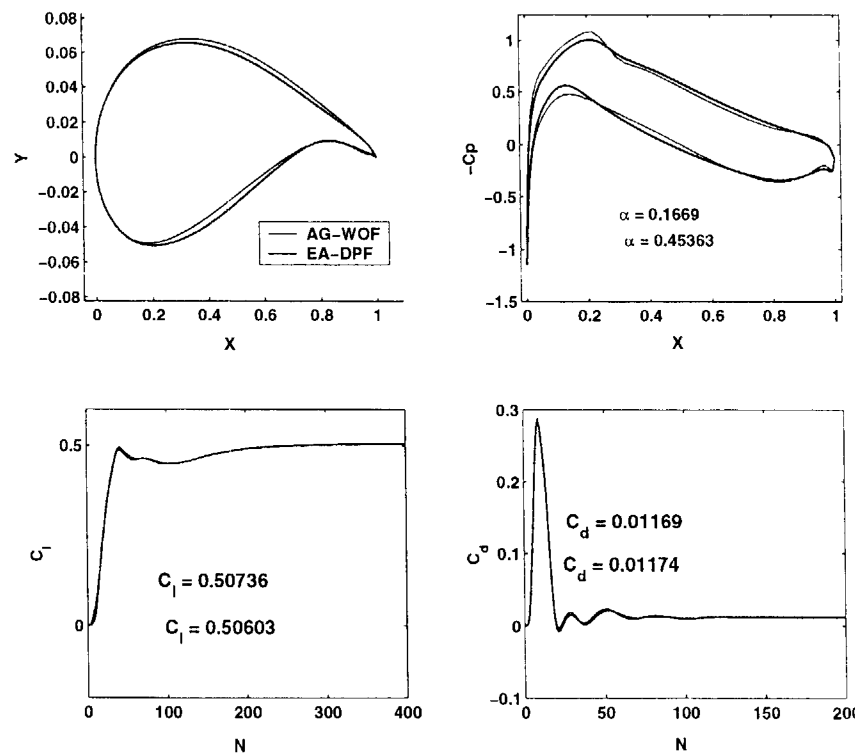
$M_\infty = 0.7$, $Re = 9X10^6$, $C_l^* = 0.55$, $C_d^* = 0.0095$

W = 0.2



W = 0.5



AG AND EA COMPARISON CONCLUSIONS

- ALL METHODS PRODUCED CONSISTENT PARETO FRONTS
- AG-WOF RESULTS ARE MORE TIGHTLY CONVERGED THAN EA-BASED RESULTS
- AG-WOF APPROACH INVOLVES A SIGNIFICANT AMOUNT OF CODING FOR EACH IMPLEMENTATION WHEREAS THE TWO EA APPROACHES DO NOT
- SPEED COMPARISONS:
  - AG-WOF ~ 30 TIMES FASTER THAN EA-WOF FOR SINGLE-OBJECTIVE OPTIMIZATION
  - AG-WOF ~ 4 TIMES FASTER THAN EA-DPF FOR TWO-OBJECTIVE OPTIMIZATION
    - AG-WOF 15 POINTS ON PARETO FRONT POINTS
    - EA-DPF 500 POINTS ON THE PARETO FRONT

EA RESULTS IN THREE DIMENSIONS

▶CASES PRESENTED

- ▶SINGLE-OBJECTIVE DRAG MINIMIZATION
- ▶TWO-OBJECTIVE SINGLE-DISCIPLINE MINIMIZATION
- ▶TWO-OBJECTIVE MULTI-DISCIPLINE MINIMIZATION

WING PARAMETERIZATION

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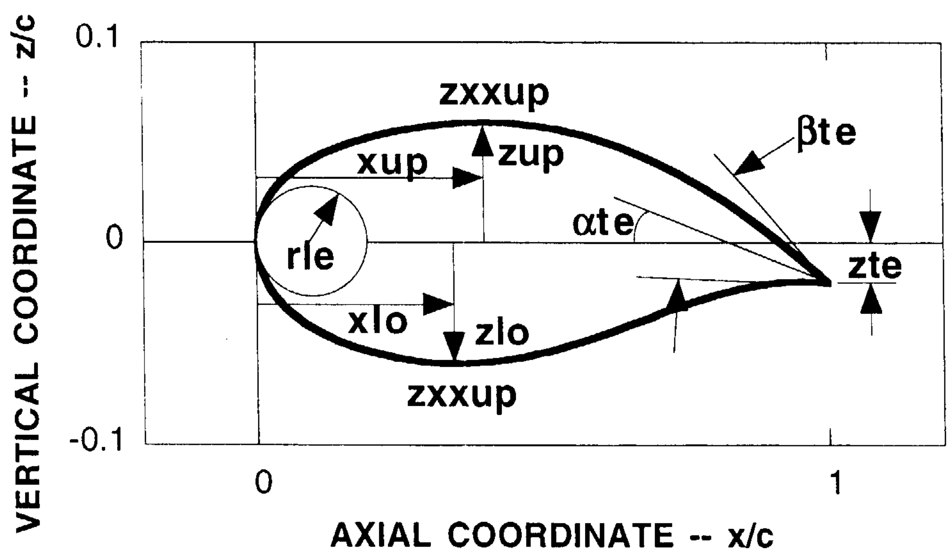
- Wing defined using N airfoil defining stations
- Each airfoil defined using Sobieczky parameterization (see definition below)
- Twist angle added to each defining station >> total number of parameters = 11N
- Linear lofting used between each defining station

$$z = \sum_{n=1}^{6} a_n \bullet x^{n-1/2}$$



FUNCTION EVALUATIONS

- AERODYNAMIC FUNCTION EVALUATIONS
  - TOPS (TRANSONIC OVERSET POTENTIAL SOLVER)
- TWO STATIONS (ROOT AND TIP) USED, I.E., NUMBER OF GENES (NG) IS 22
- WEIGHT FUNCTION EVALUATIONS
  - SIMPLE BOX BEAM MODEL
  - USES AERODYNAMIC LOADS TO ESTIMATE WEIGHT SO THAT MAX STRESS*FOS NOT EXCEEDED
  - SHEAR AND BENDING INCLUDED BUT NOT TORSION

SINGLE-OBJECTIVE WING OPTIMIZATION

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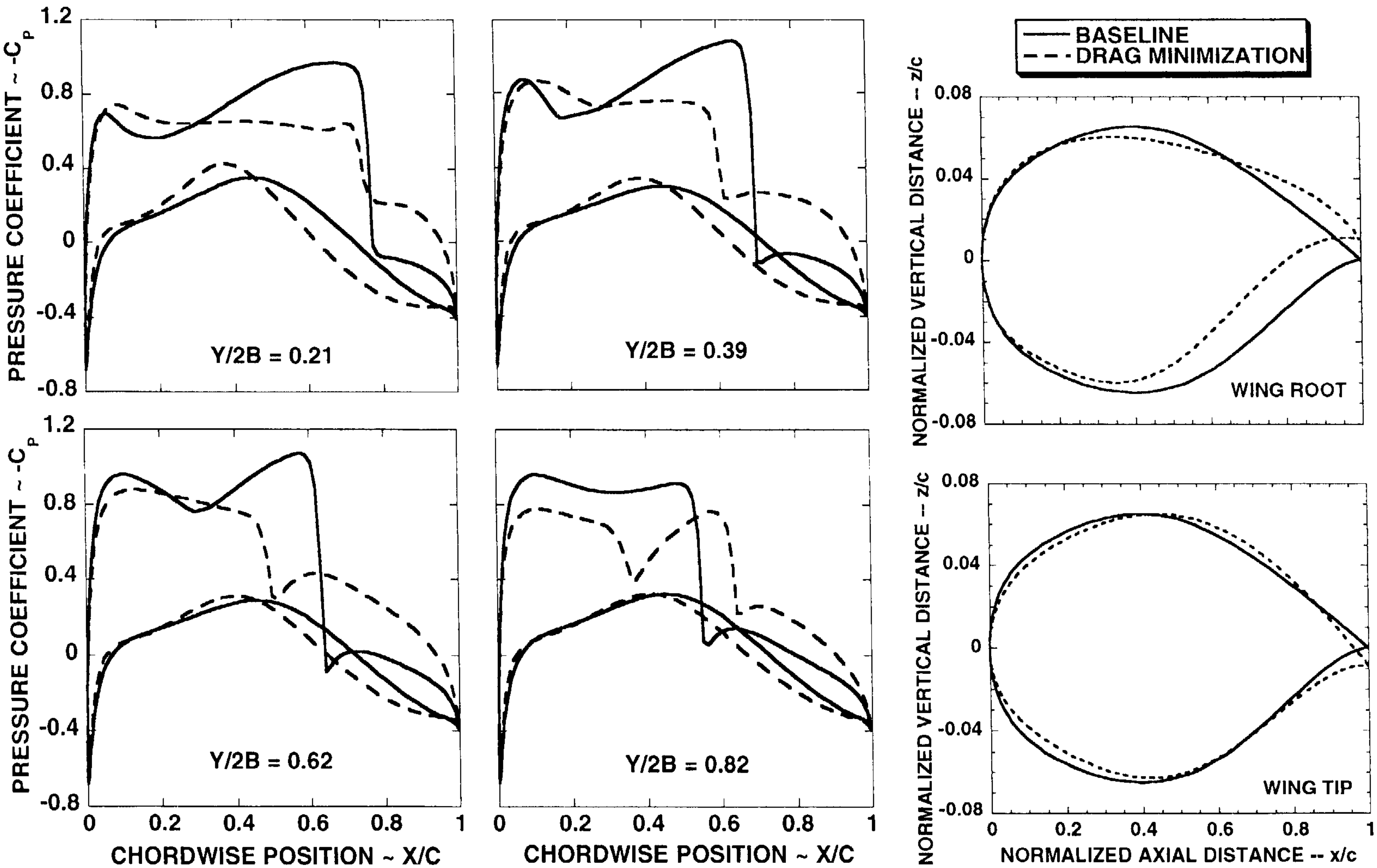
$M_\infty = 0.84$, $C_L = 0.45$, $RMAX < 10^{-6}$, $NG = 22$, $NC = 20$



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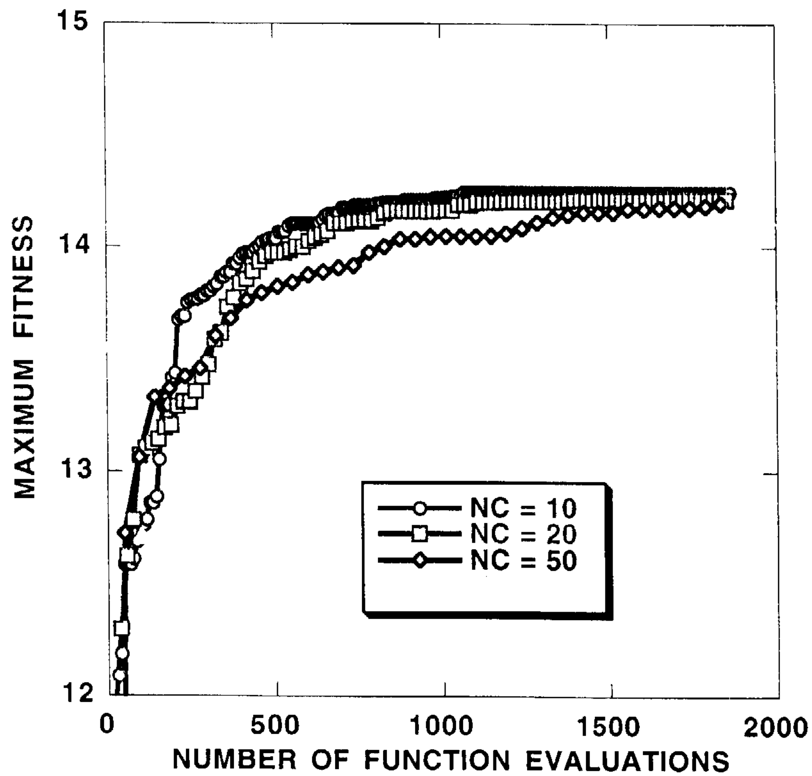
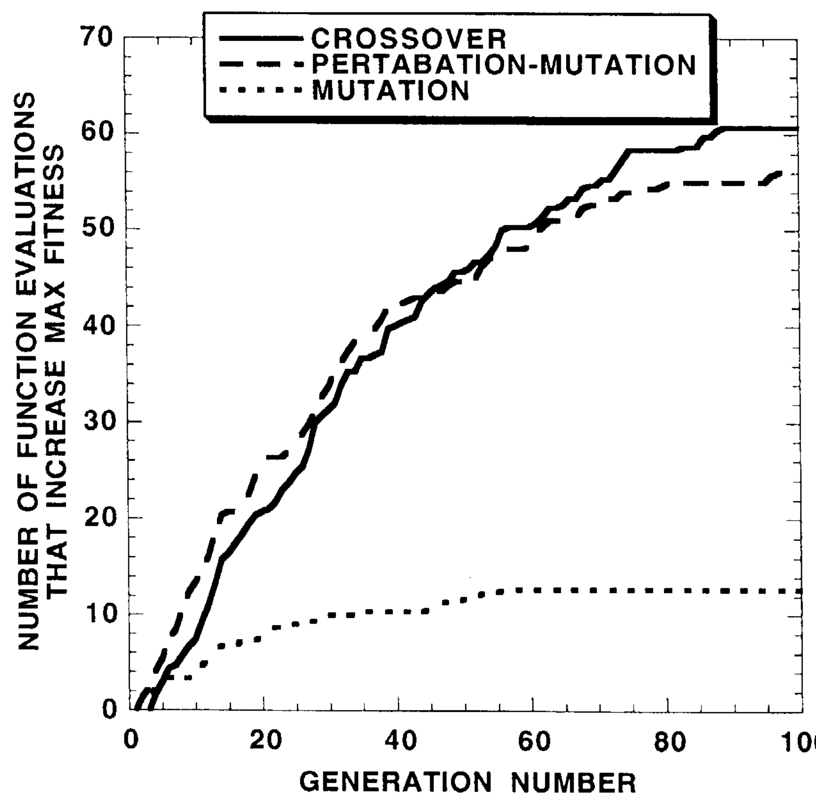
GA CONVERGENCE CHARACTERISTICS
DRAG MINIMIZATION

$M_\infty = 0.84$, $C_L = 0.45$, RMAX $< 10^{-6}$, NG = 22

EFFECT OF POPULATION SIZE ON GA CONVERGENCE



GA OPERATOR EFFECTIVENESS NC = 20



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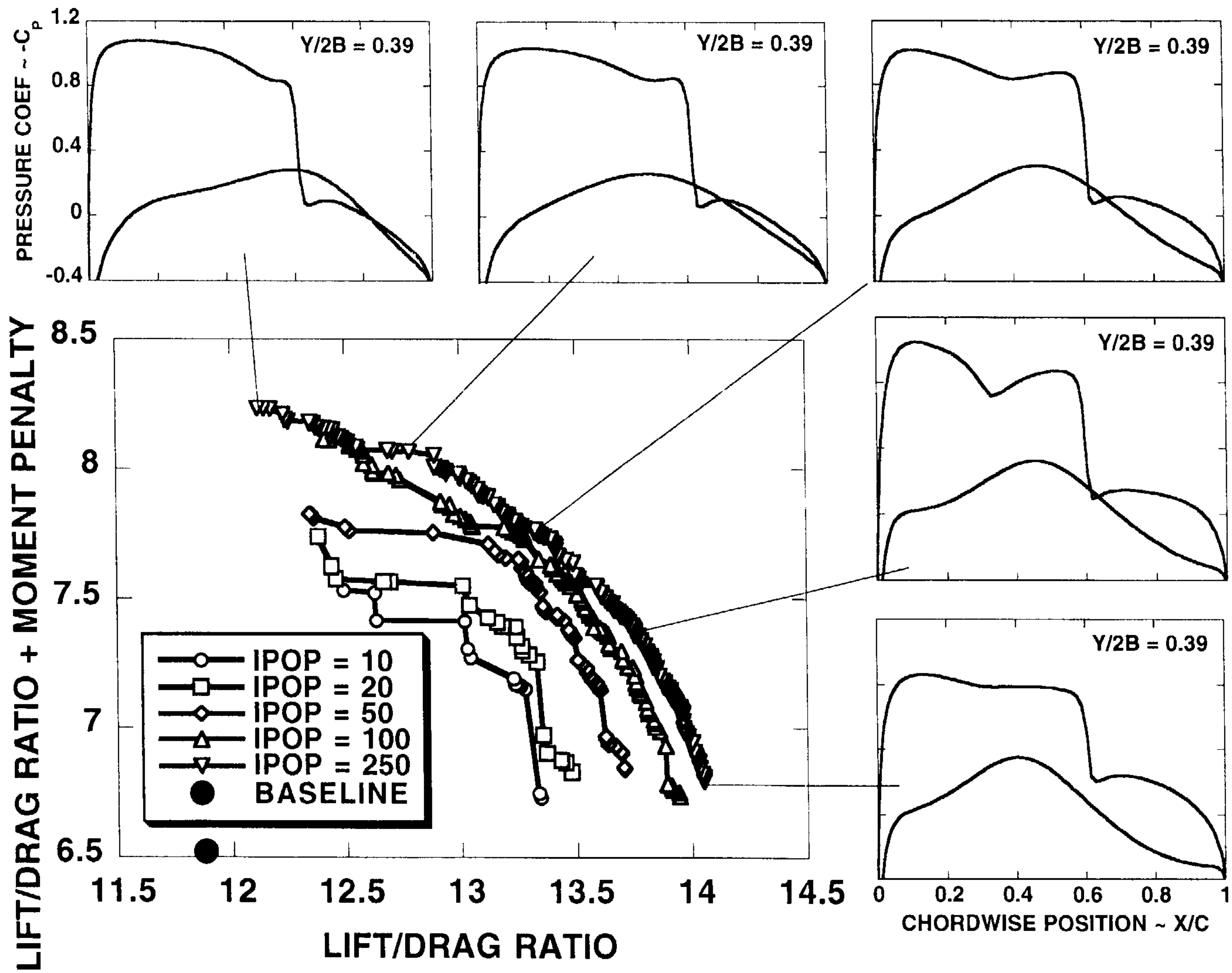
GA CONVERGENCE CHARACTERISTICS
TWO-OBJECTIVE, SINGLE DISCIPLINE OPTIMIZATION

$M_\infty = 0.84$, $C_L = 0.45$, RMAX < 10^{-6}, NG = 22



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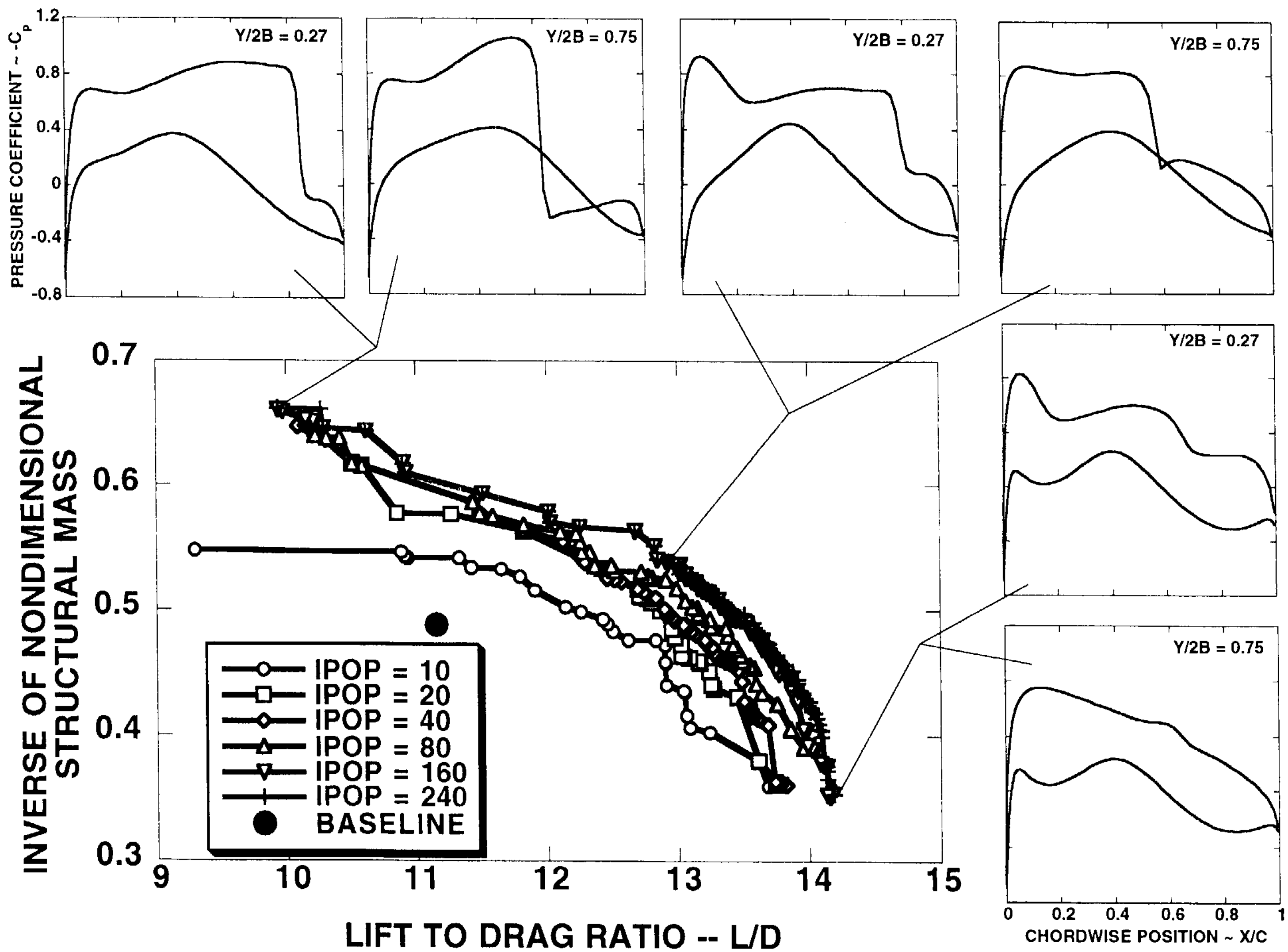
GA CONVERGENCE CHARACTERISTICS

TWO-OBJECTIVE, TWO-DISCIPLINE OPTIMIZATION

$M_\infty = 0.84$, $C_L = 0.45$, $RMAX < 10^{-6}$, $NG = 22$



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CONCLUDING REMARKS

EVOLUTIONARY ALGORITHMS REPRESENT AN ATTRACTIVE ALTERNATIVE FOR FINDING OPTIMAL SOLUTIONS IN ENGINEERING DESIGN

Strengths include:

- ▶ Robustness
- ▶ Flexibility
- ▶ Ease of implementation
- ▶ Embarrassingly parallel (ideal for heterogeneous distributed computing)
- ▶ Amenable to multi-modal design spaces
- ▶ Ability to work for multi-objective cases (pareto fronts)

Weaknesses include:

- ▶ Potentially expensive
- ▶ Difficult to know when convergence is reached

Future focus on:

- ▶ Efficiency improvements especially for multi-objective cases
- ▶ Parallel implementation (load balancing)
- ▶ Application to other problems