GADO: A Genetic Algorithm for Design Optimization

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Presentation outline

- **Introduction**
- **Architecture of GADO**
- **Comparison to other methods**
- **Ongoing work**
  - Gnerating and using reduced models
  - Multi-objective optimization
- **Conclusion**

The engineering design optimization problem

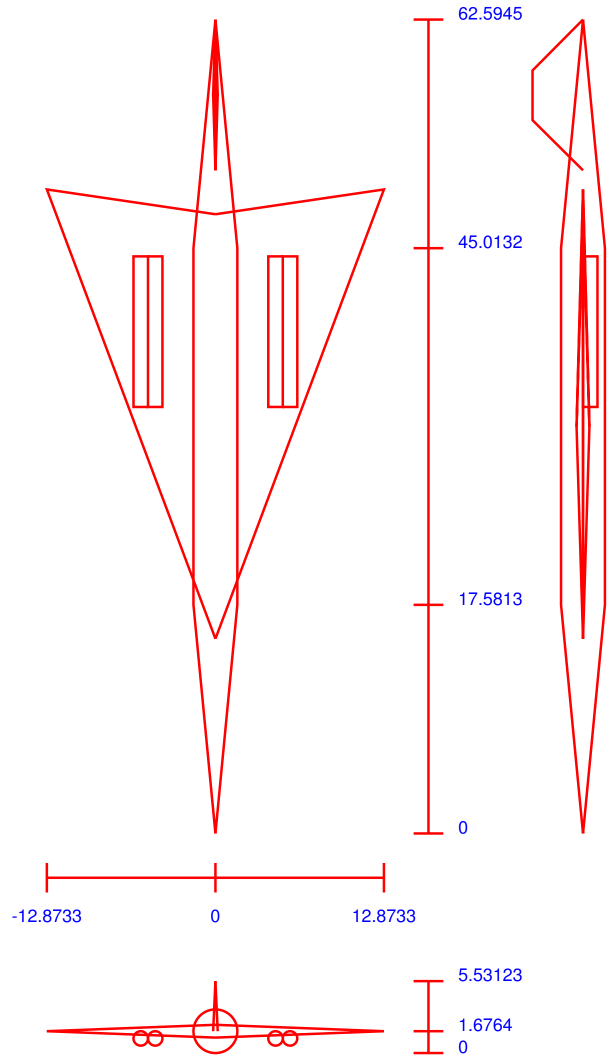
- **Objective**
  - Given a tool that evaluates designs, find the best design according to some measure of merit and subject to some constraints
  - Parametric design
- **Example**
  - Given an aircraft simulator
  - Design a supersonic aircraft capable of taking 70 passengers from Chicago to Paris in 3 hours
  - The aircraft should have the minimum takeoff mass (measure of merit)
  - The wings should be strong enough to hold the weight of the aircraft in all stages (constraint)

Objective: Optimization Method Tailored to Design

- **Properties of complex design domains:**
  - Many unevaluable points
    - Simulators are designed for use by humans
  - Many infeasible points
  - Expensive evaluation functions
  - Discontinuity of design space
  - Many local optima
    - Physical or numerical

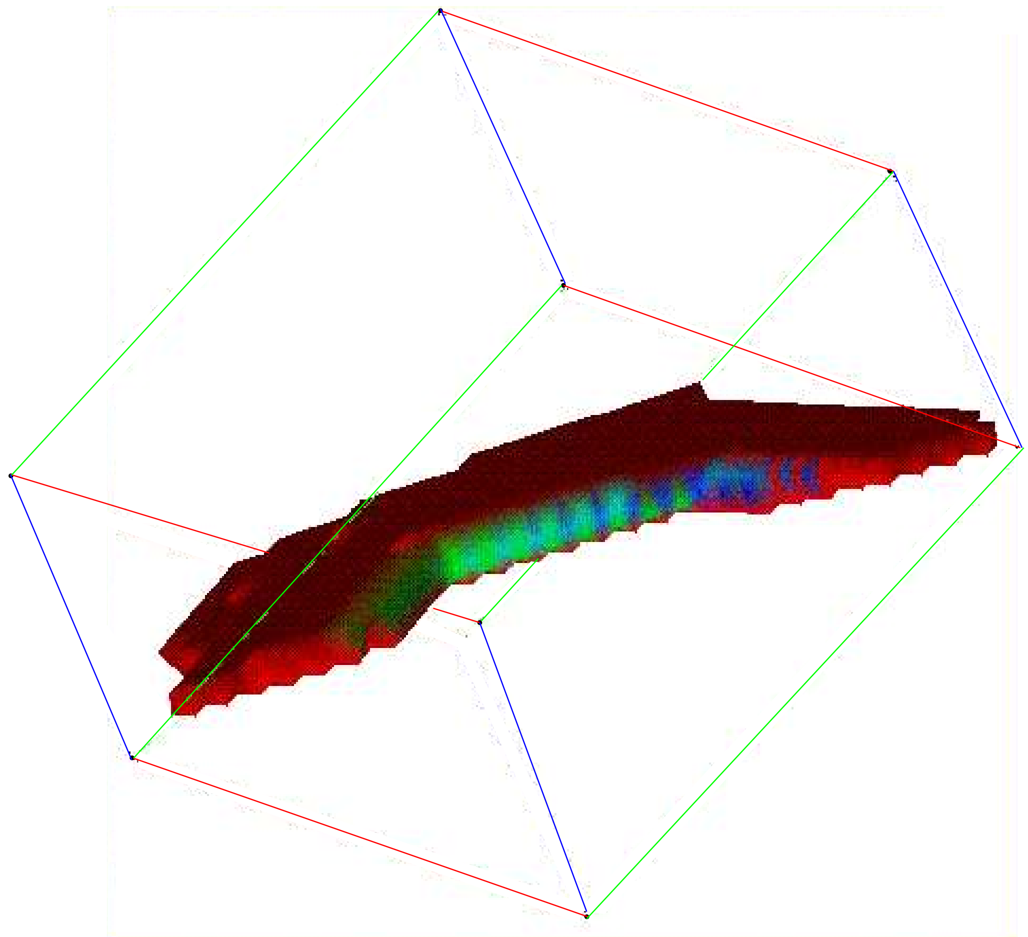
Domain 1: Supersonic aircraft design

- 12 parameters
- 37 inequality constraints
- 0.6% of the space is evaluable



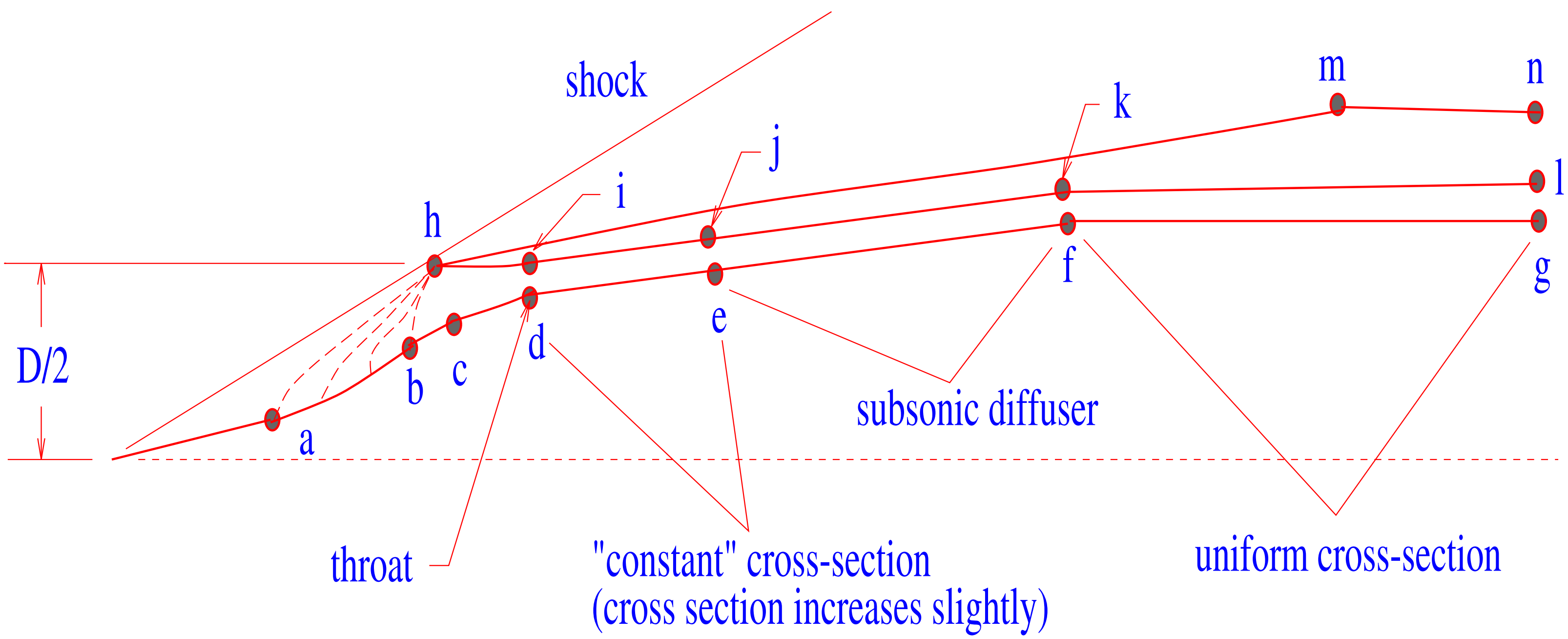
Aircraft search space cross section

Exhaust Nozzle Design: Isosurface Visualization

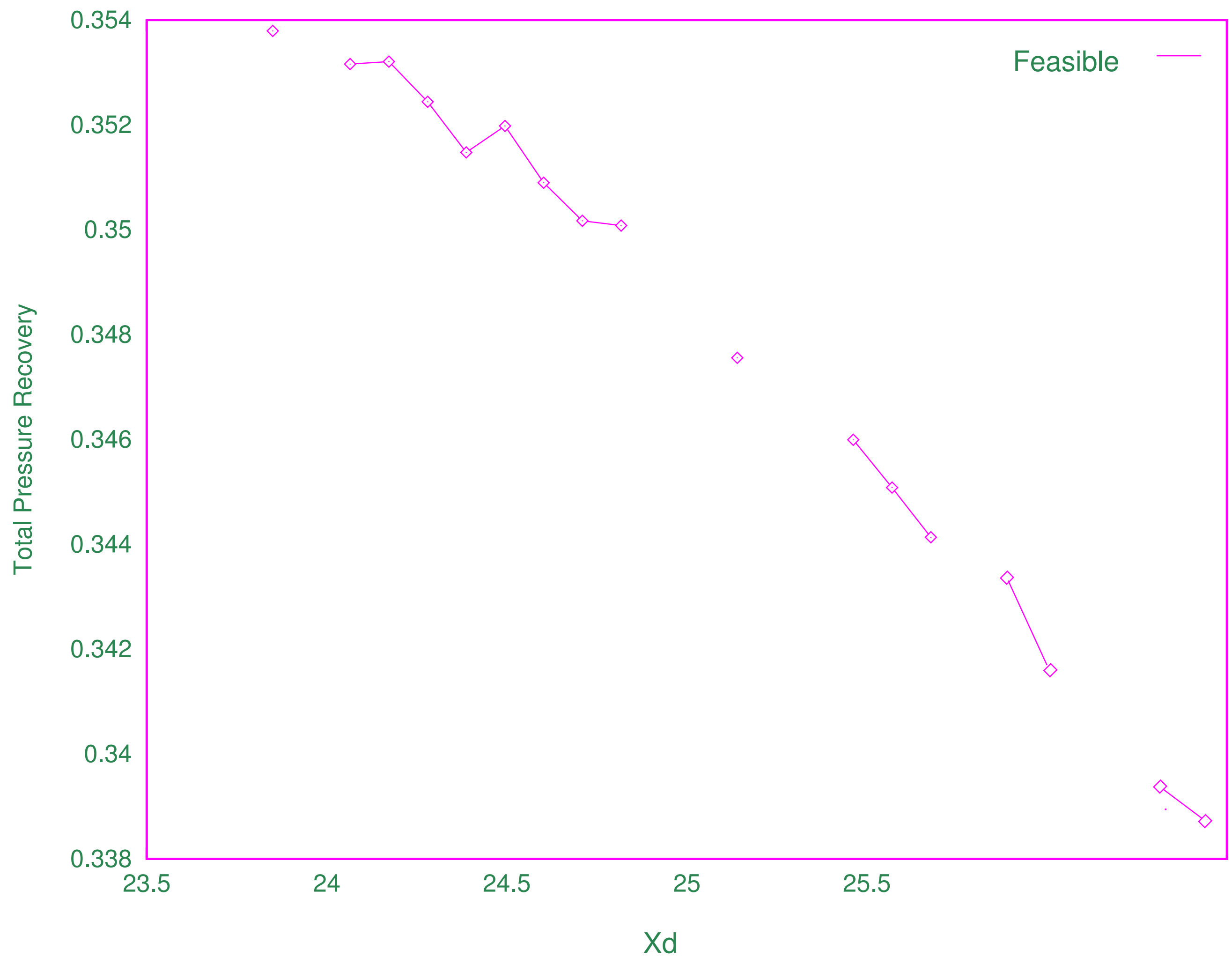


Domain 2: Missile inlet design (NIDA)

- **8 parameters**
- **20 inequality constraints**
- **3% evaluable, 0.147% feasible**



NIDA search space cross section

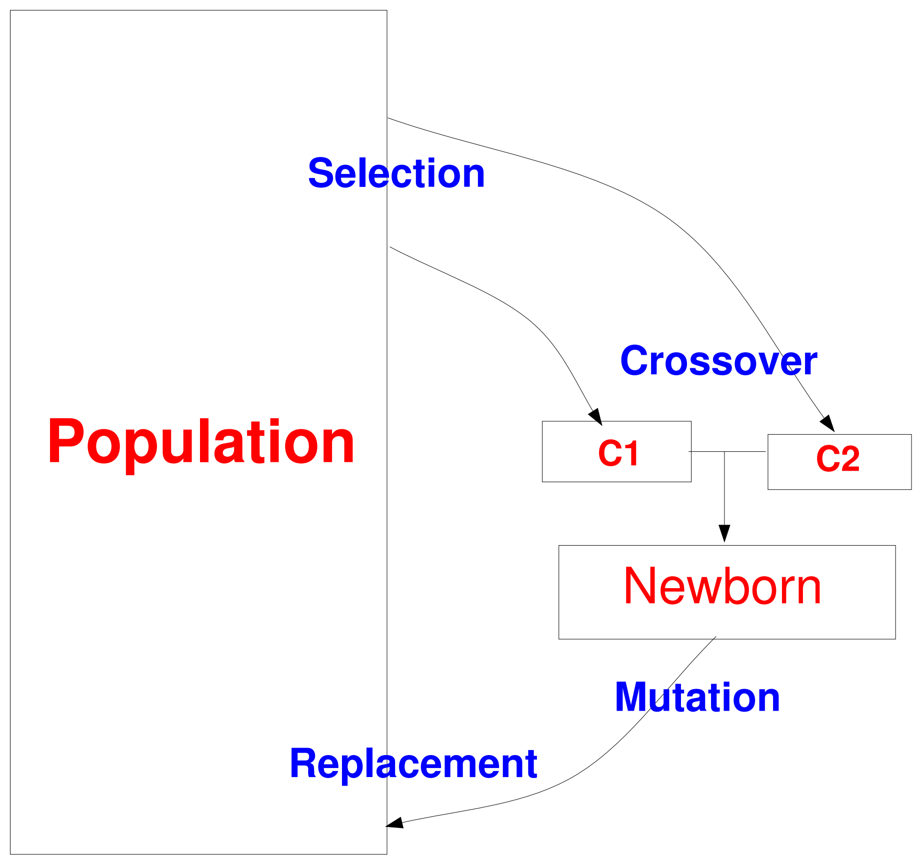


Genetic Algorithm Based Design Optimization

- **Maintains a population of potential designs (individuals)**
- **Better designs are generated using**
  - Crossover: 2 designs from the current population combine attributes
  - Mutation: 1 design changes attributes
- **Fitness of a design is based on measure of merit and constraint violation(penalty)**

Elements of a steady state genetic algorithm

- Representation
- Fitness function
- Initialization strategy
- Selection strategy
- Crossover operators
- Mutation operators
- replacement strategy



GADO: Genetic Algorithm for Design Optimization

Representation

Floating point

Fitness

Adaptive Penalty

Initialization

Repeated Random

Selection

Rank-Based

Crossover

Point
Line
Double Line
Uniform
Guided

Mutation

Uniform
Non-Uniform
Greedy
Shrinking-Window

Replacement

Crowding

Search-Control

Screening Module
Diversity Maintainance

GADO: Genetic Algorithm for Design Optimization

- **Most Novel ideas:**
  - Guided crossover
  - Screening module
  - Diversity maintenance module
  - Adaptive penalty functions

Guided Crossover

- **Method:**
  - Select one point
  - Find second point in "best" direction
  - Pick a point along the line connecting them
- **Motivation:**
  - Add gradient-like functionality without expense of computing gradients

Screening Module

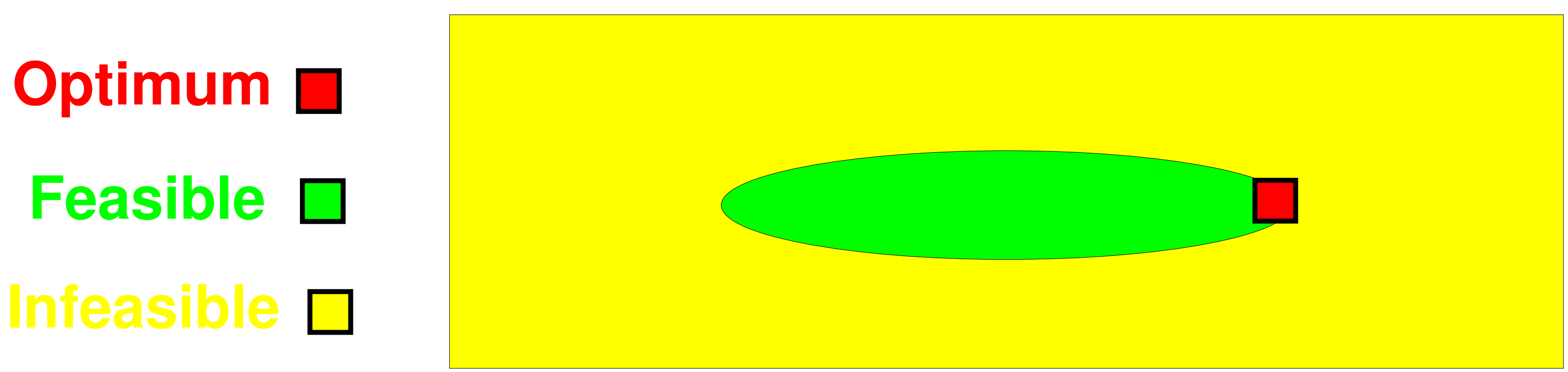
- **Method:**
  - Find k nearest neighbors
  - Discard if all k are below threshold
  - Threshold = Function of current population
- **Motivation:**
  - Decreases number of evaluations by avoiding unevaluable regions, as identified in past evaluations
  - Can eliminate >30% of evaluations
  - Negligible overhead

Diversity Maintenance Module

- **Method:**
  - At start compute inter-solution distances
  - If inter-solution distances are too small relative to this, reseed from earlier population elements
  - Reject points near past points
- **Motivation:**
  - Maintains diversity
  - Fewer evaluations

Adaptive Penalties

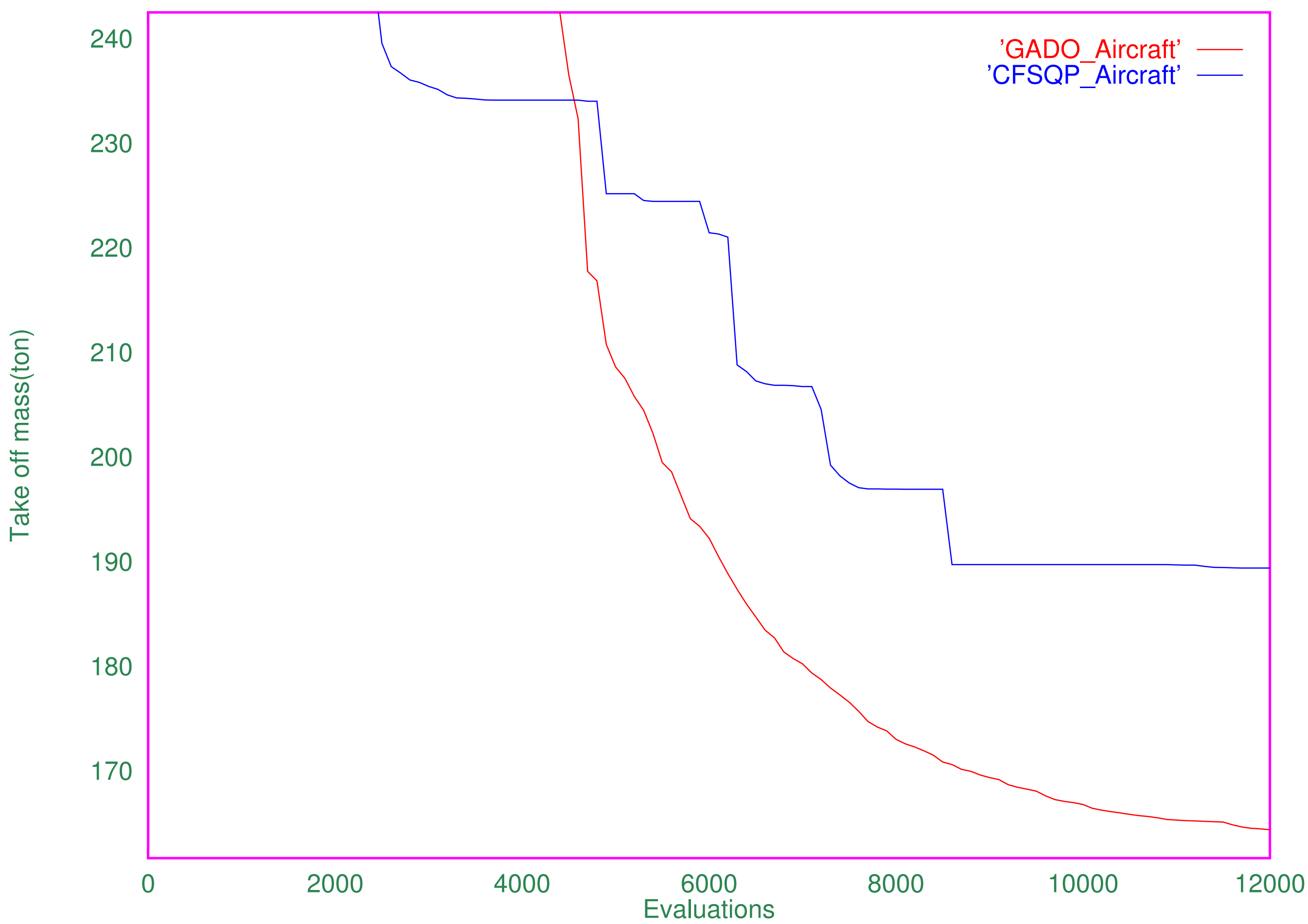
- **Method:**
  - Fitness = Measure of merit + Penalty
  - Penalty = $c(t) \times \sum$ constraint violations
  - $c(t)$ increases whenever the best element of the population does not have the least constraint violation
  - $c(t)$ can also decrease to inject "slightly" infeasible points into the population



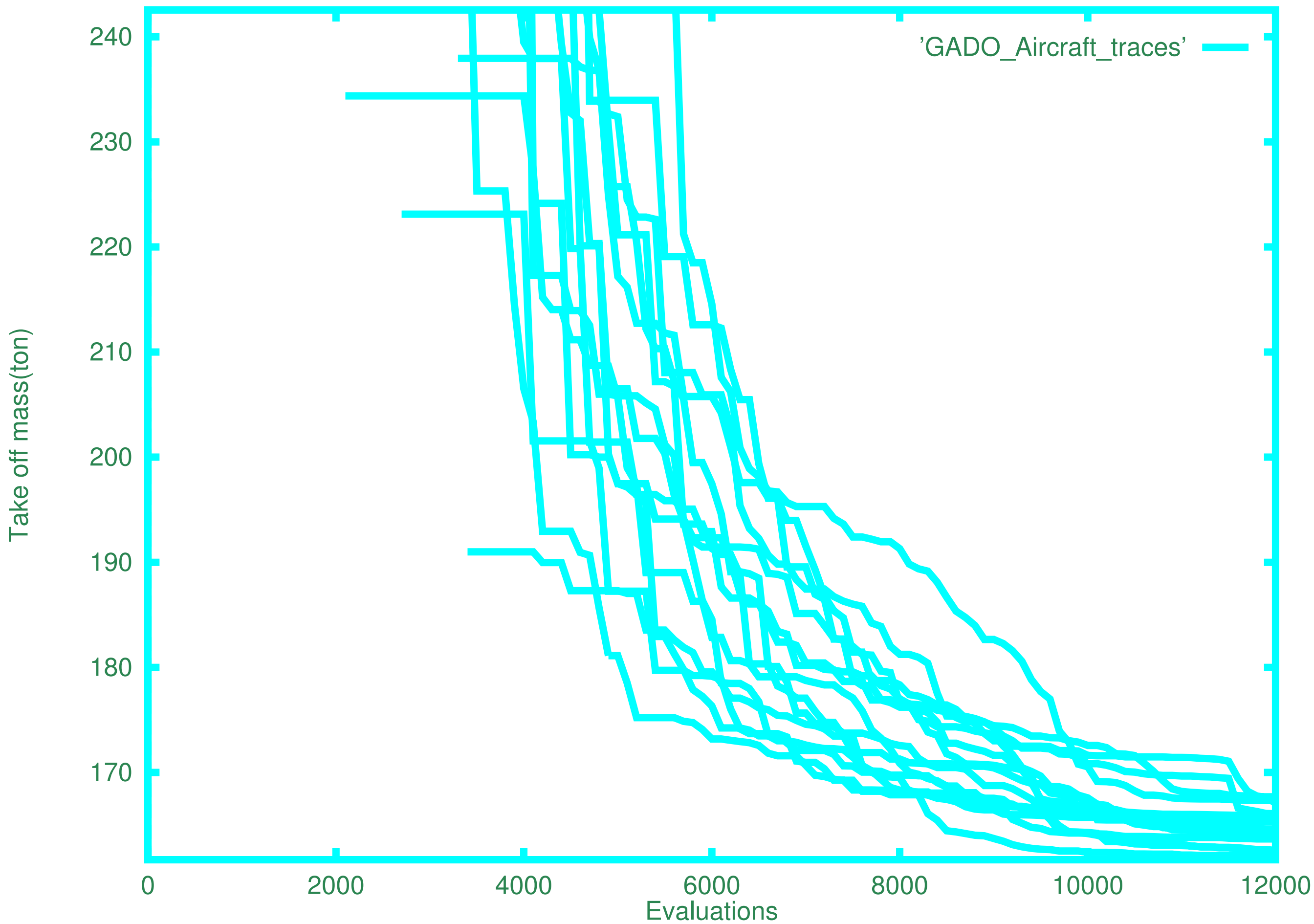
Comparison of methods: Conceptual Design of Aircraft

- **Random probes:**
  - No feasible points in 50,000 tries
- **Multistart CFSQP:**
  - Inferior on average
  - High variance in quality of solutions
- **Genocop III (GENetic algOrithm for Constrained OPtimization),**
- **ASA (Adaptive Simulated Annealing):**
  - Require feasible starting points
  - Inferior from "good" starting points

GADO vs. CFSQP in Aircraft design (domain 1)

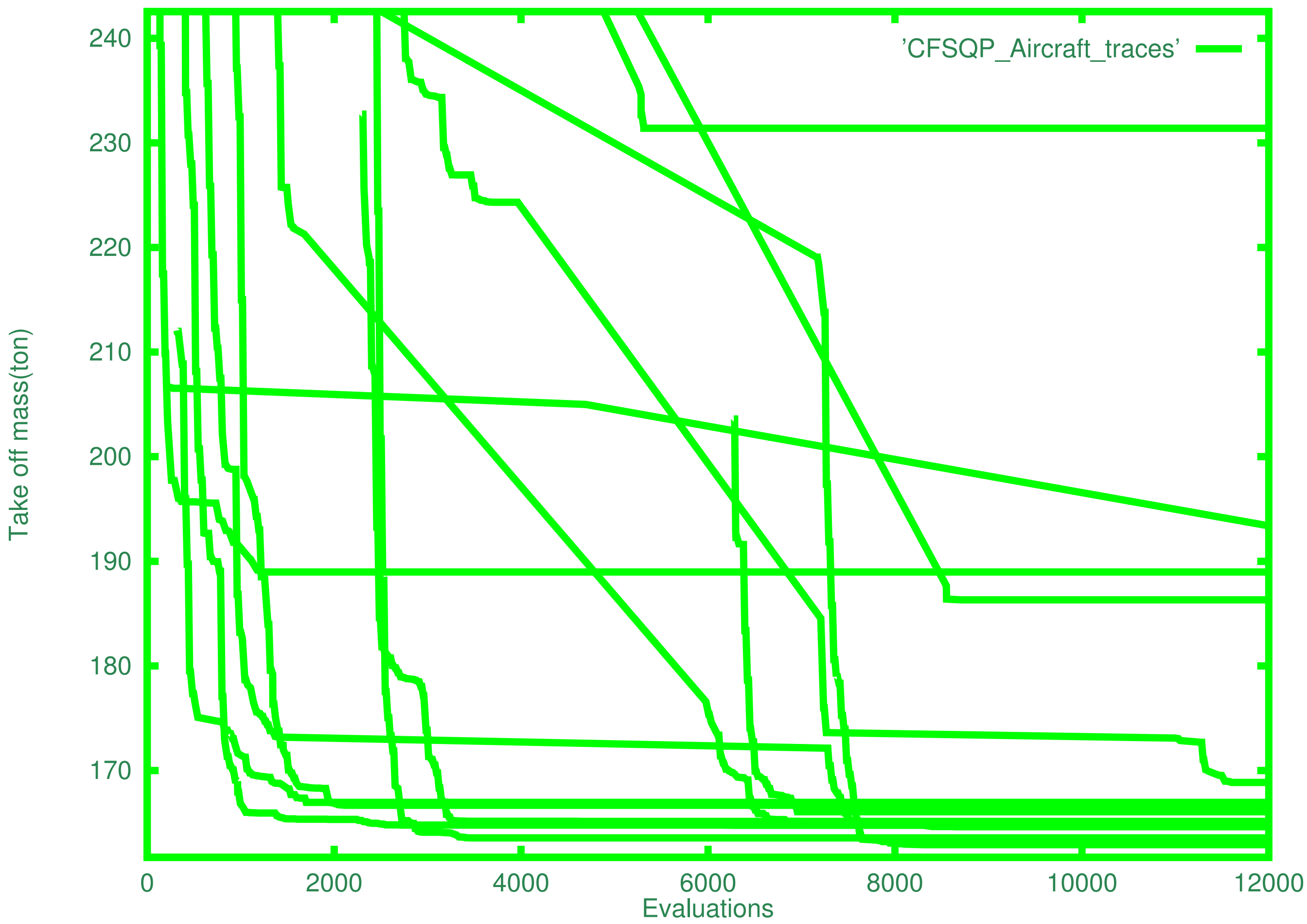


GADO runs

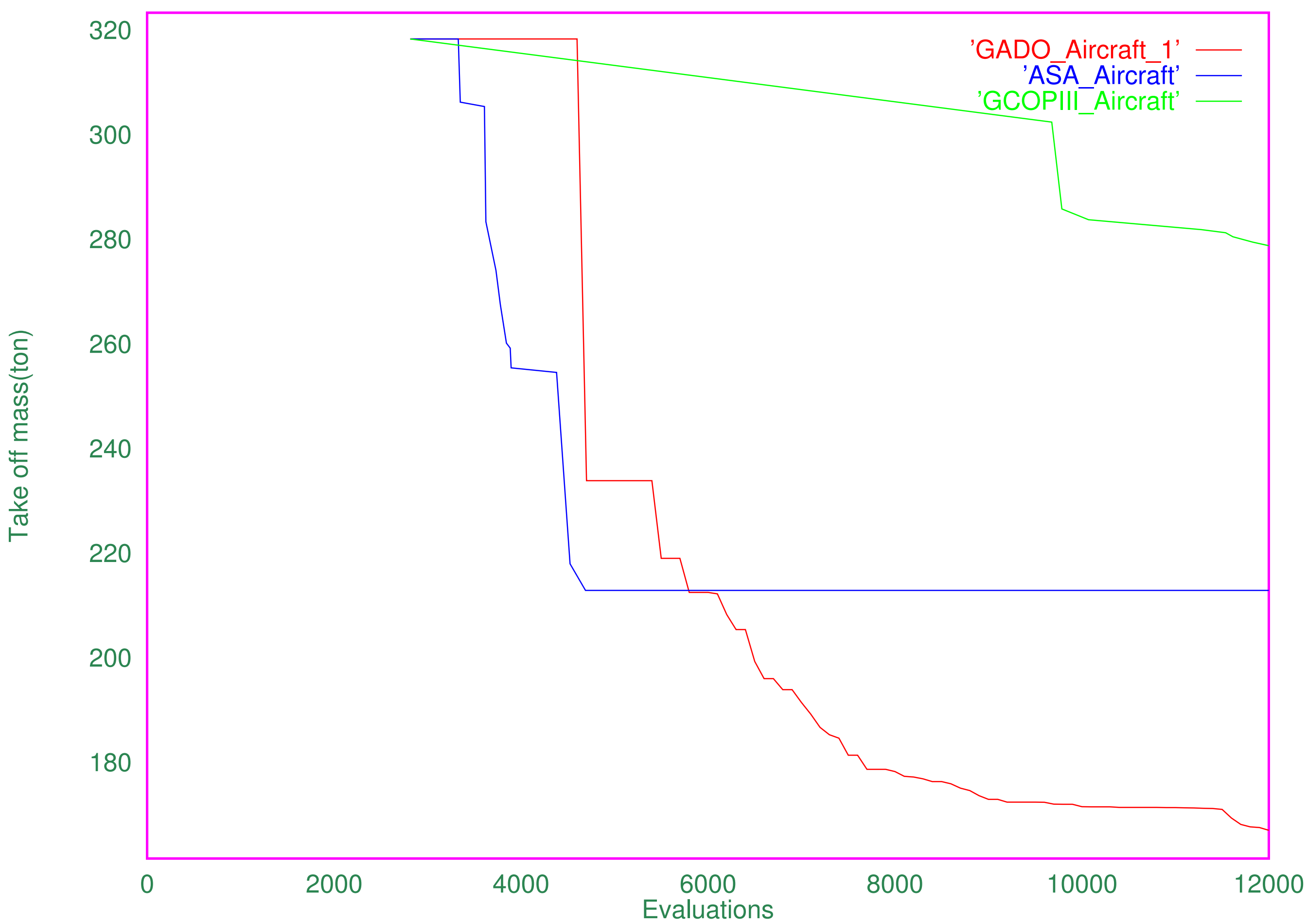


'GADO_Aircraft_traces'
240
230
220
210
200
190
180
170
Take off mass(ton)
0
2000
4000
6000
8000
10000
12000
Evaluations

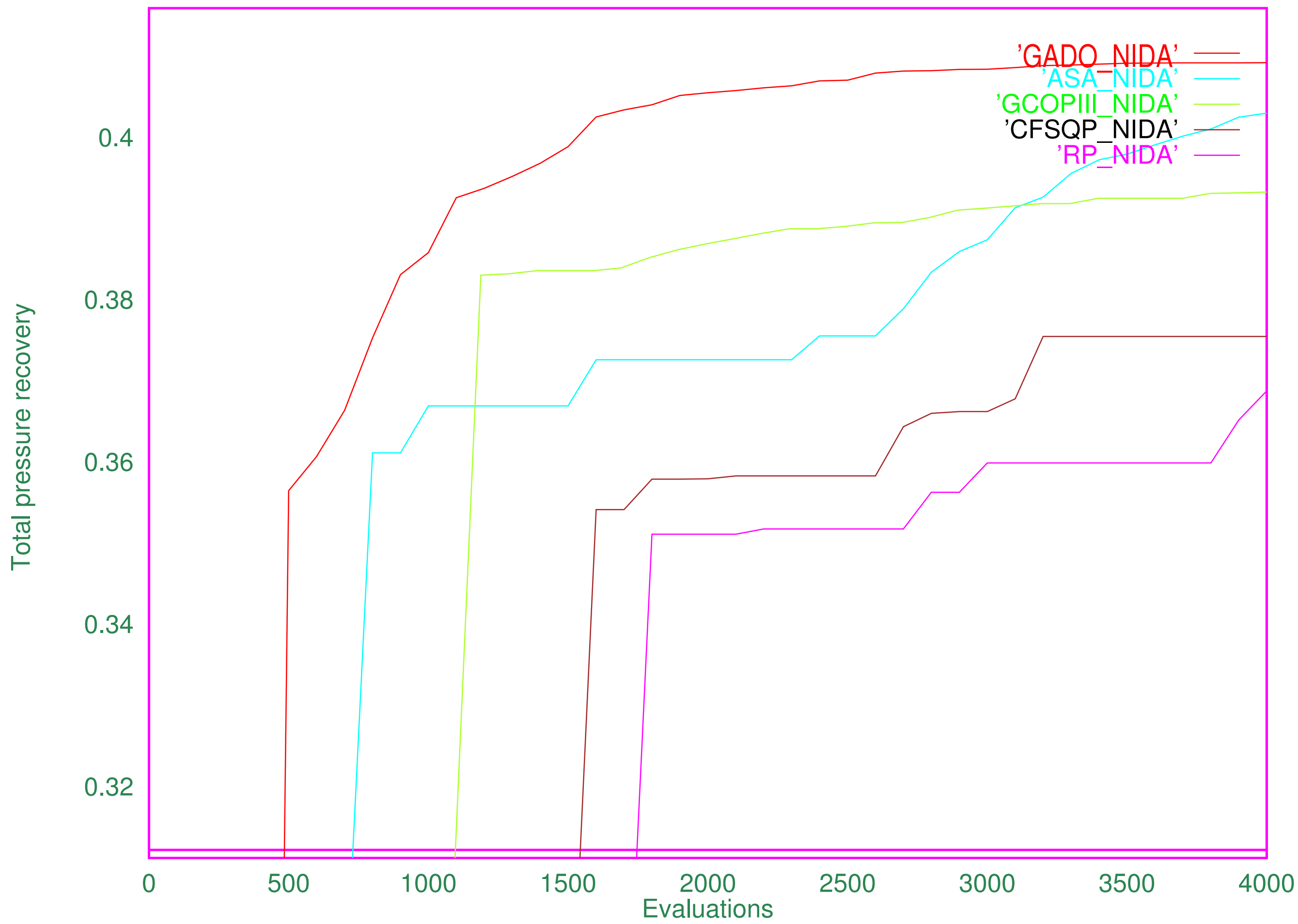
Multistart CFSQP runs



GADO vs. Genocop III and ASA in Aircraft design domain



Results in Missile Inlet Design (domain 2)



Case Study: Redesign of a two-dimensional supersonic inlet

- **Original designs by ITAM (Russia), redesign by Michael Blaize (Aérospatiale,France)**
- **First inlet**
  - ITAM design: Total pressure recovery=0.134
  - GADO: Total pressure recovery=0.194 (1.25 CPU hours)
  - CFSQP:
    - From GADO's optimum: no improvement
    - From original (ITAM) design: Total pressure recovery=0.160
    - Multistart: no better than the original design (1 CPU day)

GADO achieved

- Faster optimizations
- Better final designs
- lower variance in final design quality
- low sensitivity to internal parameters and setup

Ongoing research directions

- New application domains
- Using reduced models for speedup
- Multi-objective GADO

Generating and using reduced models for design optimization

- Reduced models and their sources
- Generation of reduced models
- Using reduced models through informed operators
- Future directions

Reduced models

- **Pre-existent:**
  - Simpler physical models
  - Coarse grids
- **Generated:**
  - Functional Approximations (Response Surfaces)
    - Least Squares
    - Neural Networks
    - Genetic Programming

Observation

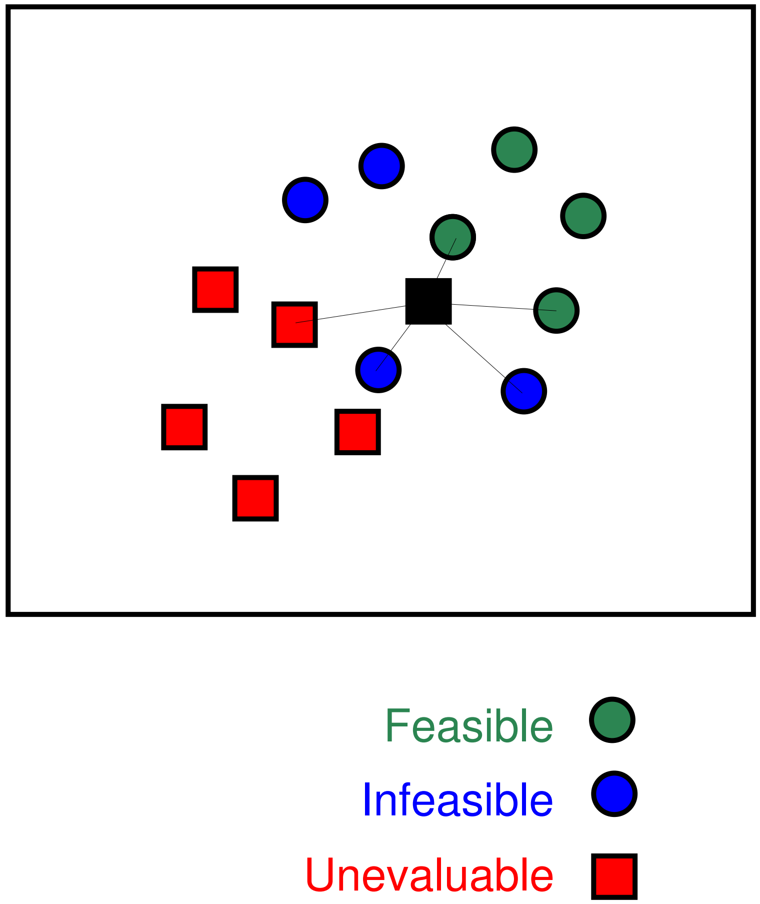
- **Previous methods do not take properties of design domains into consideration**
  - Unevaluable points
  - Numerical problems: discontinuity, high non-linearity
- **Some approaches make strong assumptions about reduced model accuracy**

Generating reduced models by incremental approximate clustering

- **Maintain previously encountered points divided into dynamic clusters**
- **Periodically introduce new clusters and refresh all clusters**
- **Periodically compute quadratic approximations**
  - Separate approximations for measure of merit and constraints
  - Global approximation: all points
  - Cluster approximations: large enough clusters

Approximate evaluation of a new point

- **If point's cluster has approximations, use them, otherwise use global approximations**
- **Two phase approach:**
  - Classify point using K nearest neighbors (feasible, infeasible, unevaluable)
  - Use classification and proper approximation functions to form fitness

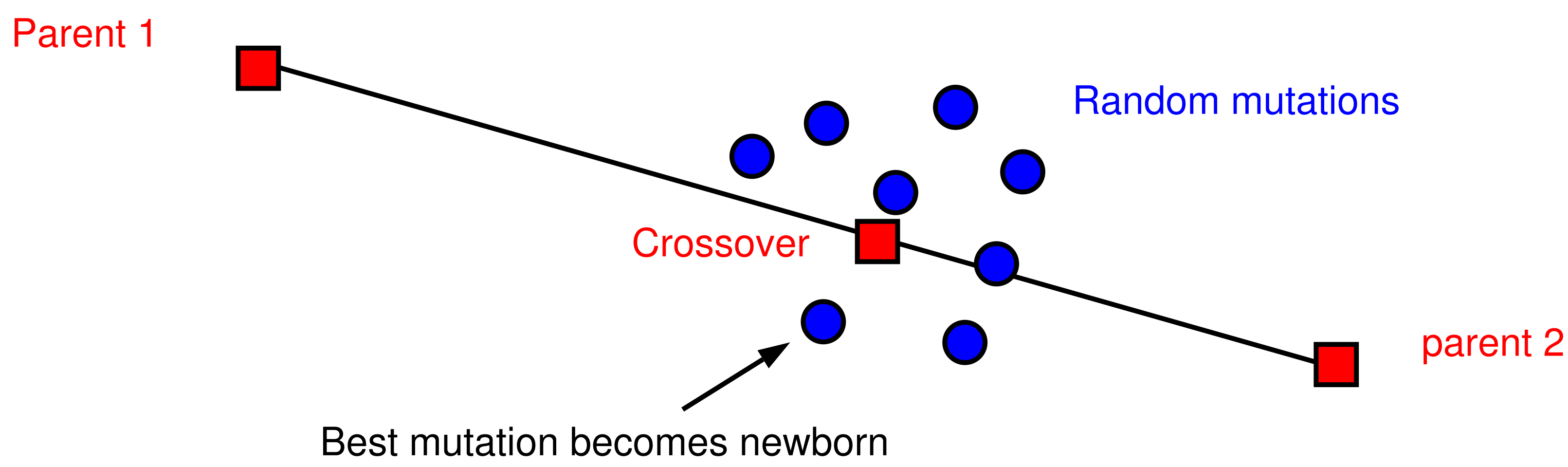


Informed operators

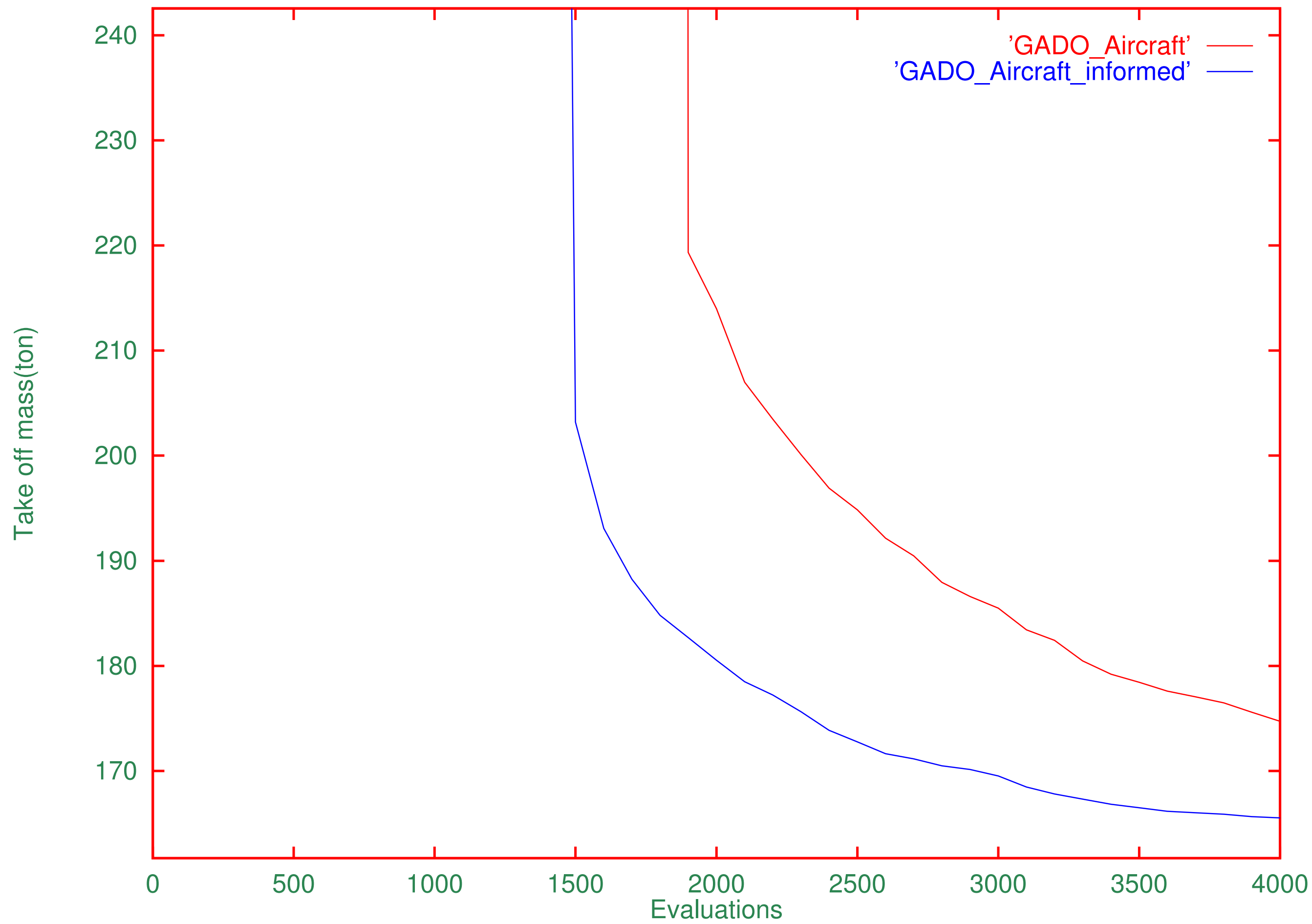
- **Idea: replace randomness with decisions informed by the reduced model**
- **Examples:**
  - Informed initialization
  - Informed crossover (parents,method)
  - informed mutation (type,amplitude)

Informed mutation

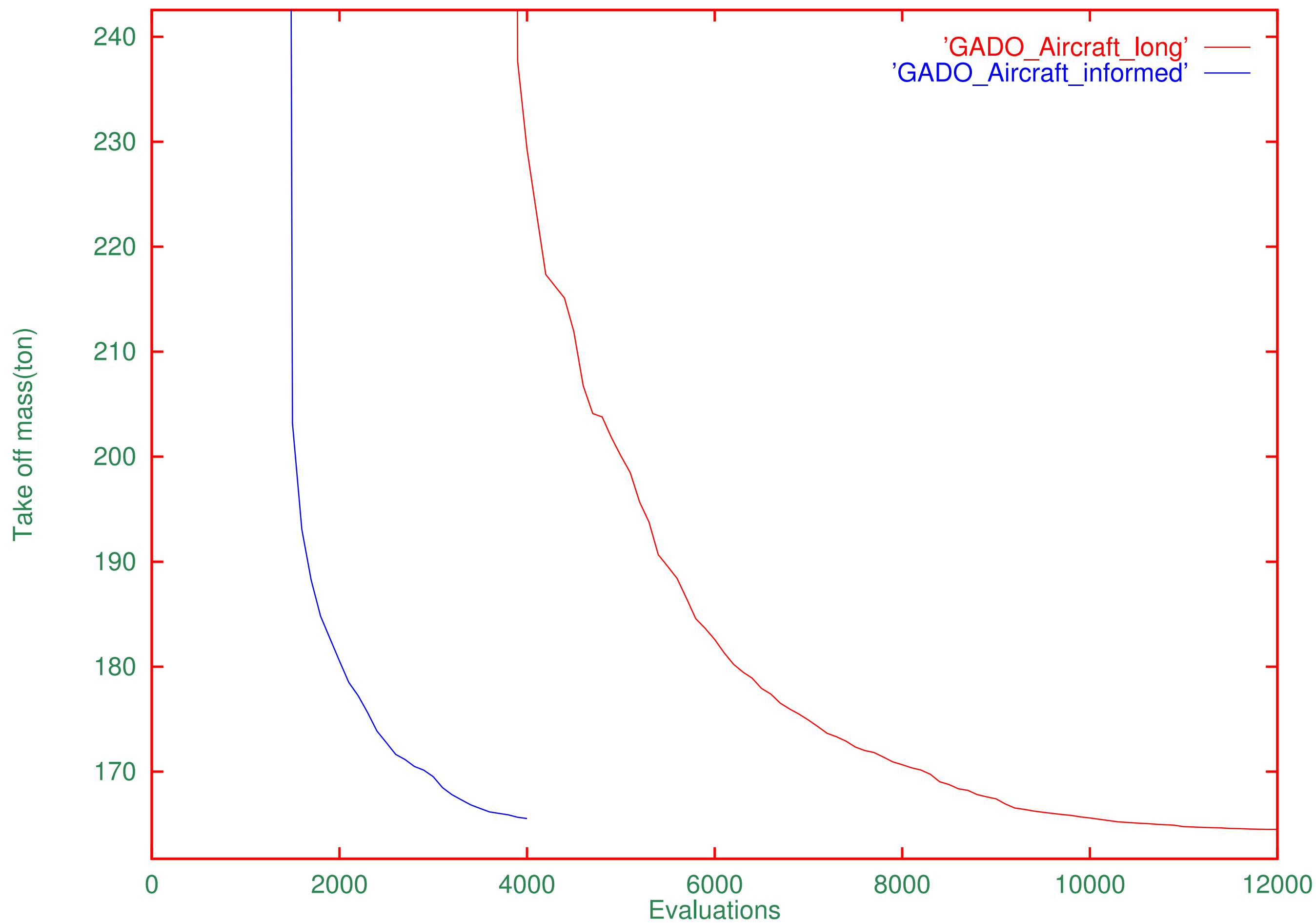
- Crossover done, followed by several random mutations
- Random mutations are evaluated using reduced model best becomes newborn



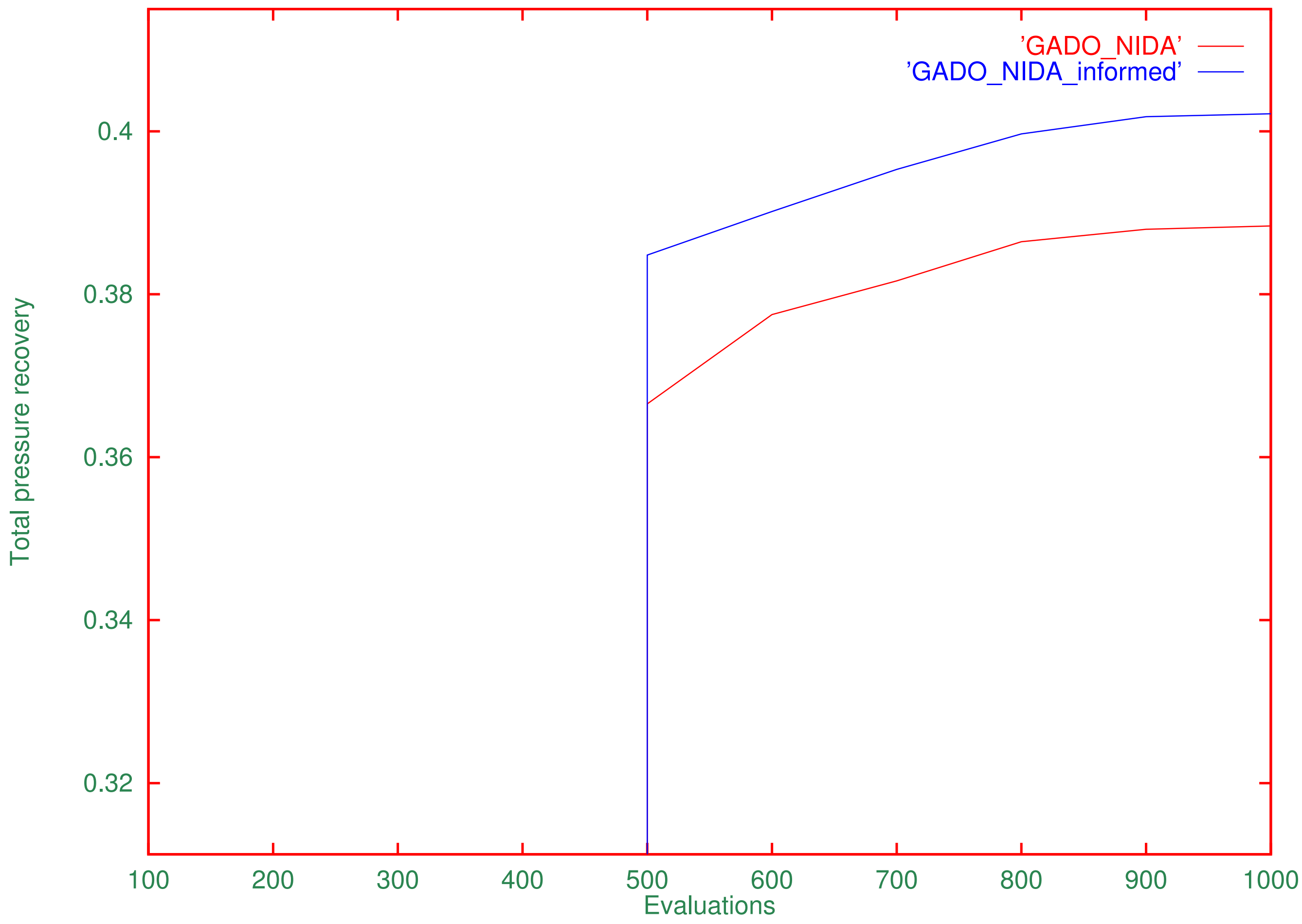
Utility of informed operators in aircraft design



Speedup with informed operators in aircraft design



Utility of informed operators in missile inlet design



Ongoing and future directions in Reduced Model Utilization

- **Dynamic adjustment of degree of reliance on the reduced model**
  - Cost
  - Recent accuracy
- **More systematic ways of using very cheap reduced models**
- **Use of decomposability and sensitivity information for speedup**
- **Other strategies (genetic engineering)**
- **Other approximation methods (NNs)**

Multi-objective optimization

- **Most realistic problems are multi-objective**
- **The goal is to sample the set of non-dominated solutions (Pareto front)**
  - A solution dominates another if it outperforms it in at least one objective and is not outperformed by it in any objective
  - On the Pareto front no solution is better than another when all objectives are considered simultaneously
- **A better multi-objective optimizer is one that provides a dense, well-spread, accurate sampling of the Pareto front**

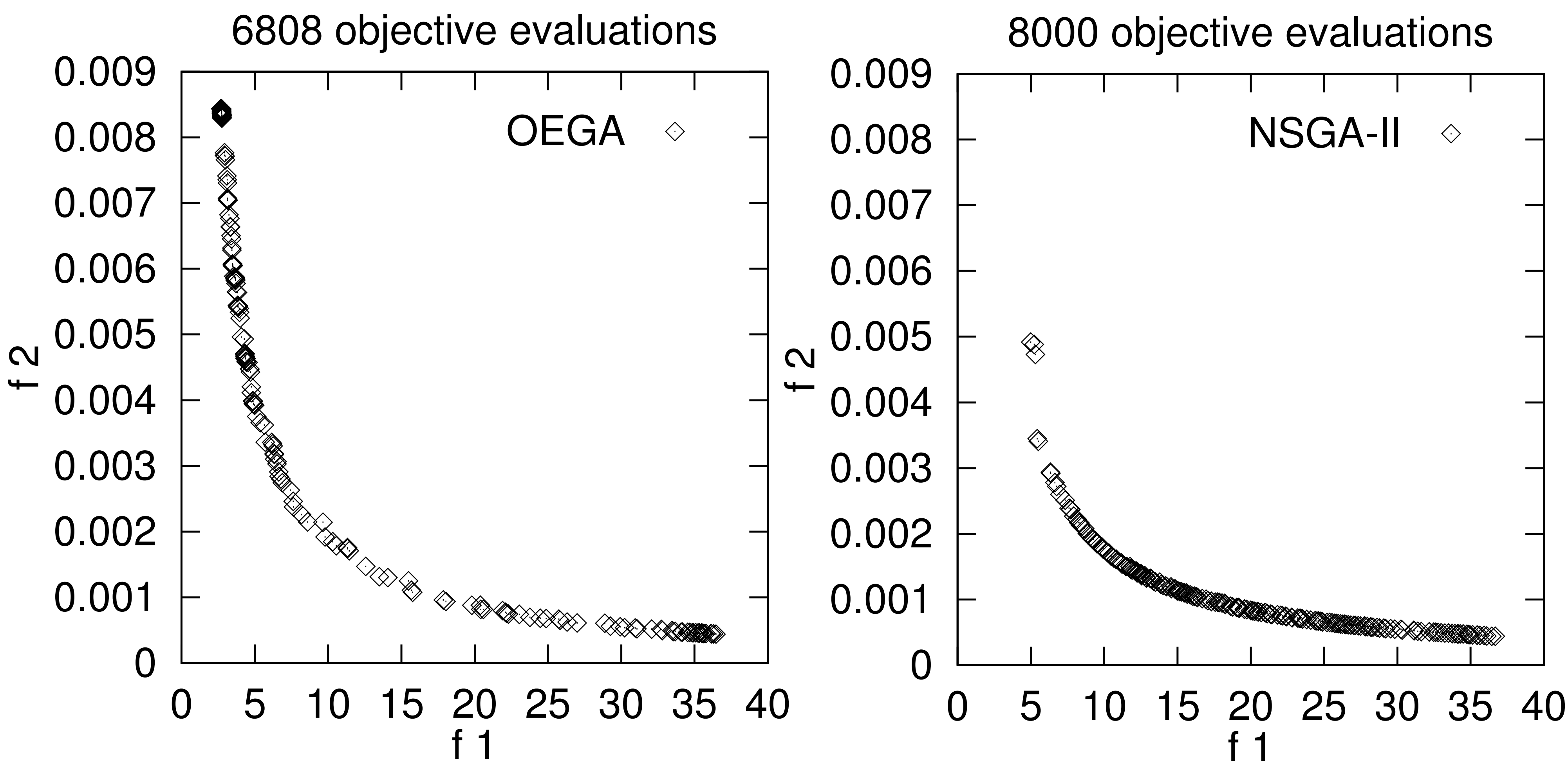
Genetic Algorithms for multi-objective optimization

- **A natural approach (population-based)**
- **Several methods exist in two basic categories**
  - Methods that evaluate all-objectives for each solution
  - Methods that evaluate only one objective for each solution
- **One of the best known methods is NSGA-II by Kalyanmoy Deb**

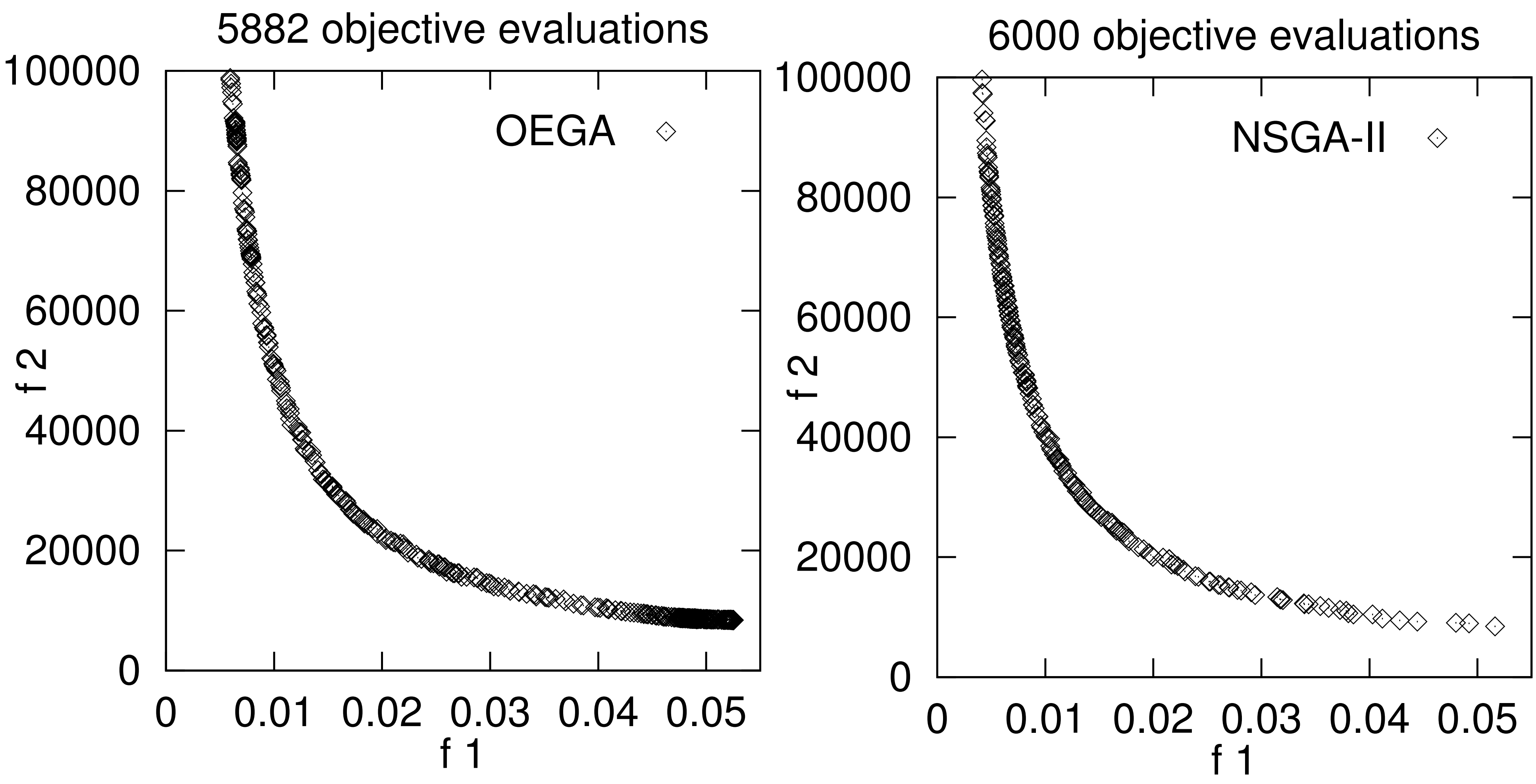
OEGADO for two objective optimization

- Idea: to use one GADO optimizer for each objective
- The optimizer of each objective forms a reduced model of it (native model)
- The optimizers exchange their reduced models at specified intervals
- Each optimizer uses the imported reduced model (instead of the native model) with informed operators

Comparison of methods in the Welded Beam design domain



Comparison of methods in the Truss design domain



Conclusion

- GADO is a GA tailored for design optimization
- Its merit was demonstrated in several realistic and benchmark domains
- Further improvement expected using reduced models
- Several extensions (example: OEGADO)