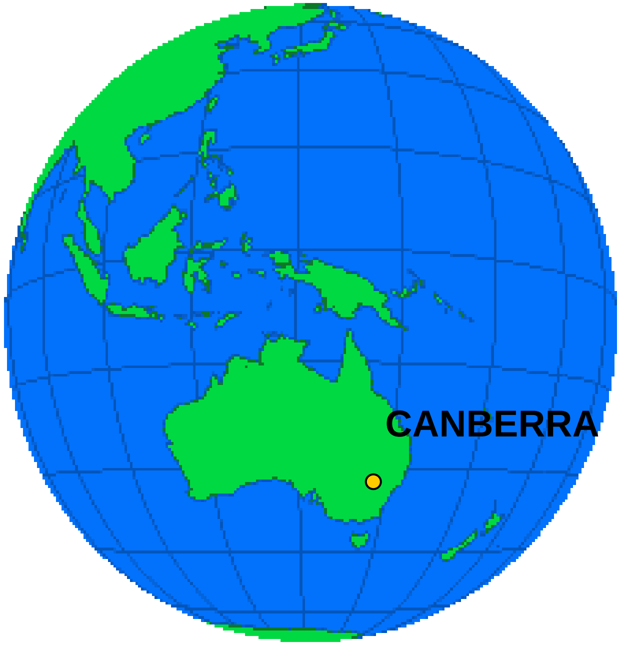
Part 1: Overview of Multidisciplinary Design Optimization Research at the University of New South Wales, Australian Defence Force Academy.

Part 2: Surrogate Assisted Optimization.



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Leader of the Multidisciplinary Design Optimization Research Group.
Email: t.ray@adfa.edu.au

INTRODUCTION

UNSW@ADFA: Sort of a satellite campus of University of New South Wales. Undergraduate students are from Defence only. Postgraduates students may or may not be from Defence. Predominantly International Students. It has 5 schools (ITEE, ACME, HASS, PEMS and Business).

School of Aerospace, Civil and Mechanical Engineering: The School has 33 Full Time Academic Staffs and 45 Full Time PhD students. There are about 20 Part Time PhD and Full/Part Time ME students. On an average there are about 8-10 Practicum students at any point in time.

About me: I obtained my B.Tech. (Hons.), M.Tech and PhD all from Indian Institute of Technology Kharagpur, India. After my PhD, I moved to Singapore and since then worked in various capacities with Information Technology Institute, Singapore, Institute of High Performance Computing, Singapore and Temasek Labs, National University Singapore. In Dec 2004,I moved to Canberra to join UNSW@ADFA.

PRESENTATION PLAN

MDO GROUP AND ITS FOCUS

AREAS UNDER INVESTIGATION

APPLICATION SNAPSHOTS

SURROGATE ASSISTED OPTIMIZATION

PROGRESS AND UPDATES ON ONGOING DEVELOPMENTS

RECENT CHALLENGING PROBLEMS

BROAD INTERESTS OF THE GROUP

- Develop Optimization Algorithms to Solve Multidisciplinary Design Optimization Problems.
- Focus is on both Development of Optimization Algorithms and their Applications to Engineering Design Problems.
- Problems are Multiobjective, Computationally Expensive, Involves Highly Nonlinear Constraints and Objective Functions (Black Box Form) and Mixed Variables.

PARTICULAR INTERESTS OF THE GROUP

Areas

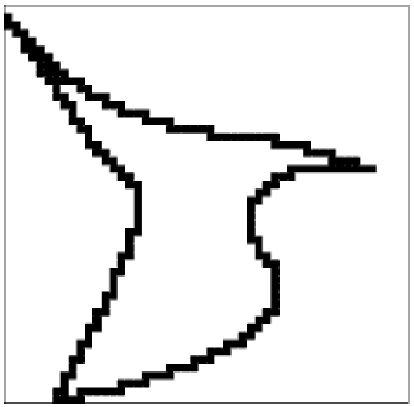
- Multiobjective Optimization
- Constrained Optimization
- Robust Design and Constrained Robust Design
- Dynamic Multiobjective Optimization
- Shape and Topology Representation
- Surrogate Assisted Optimization Models
- Preserving Infeasible Solutions forTradeoff and Convergence
- Evolutionary Algorithms, Memetic Algorithms, Simulated Annealing, Particle Swarms,Cultural Algorithms and Fast Evolutionary Programming.
- Many Objective Optimization
- Trans-dimensional Optimization
- Spatial Prediction Models
- Realistic Transportation Models
- Flexible Manufacturing System Models
- Co-evolution and Ensembles

Applications

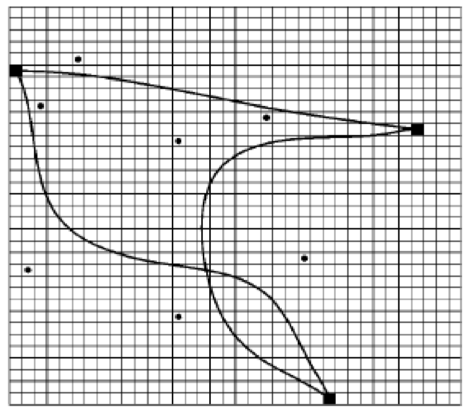
- Antenna Design, Dielectric Filter Design
- Aircraft Concept Design
- Optimal Identification of Parameters for Metal Forming
- Optimal Parameter Identification for Biochemical Kinetics.
- Topology Optimization of Compliant Mechanisms
- Optimal Design of Launch Vehicle
- Nose Cone Design
- Online Controller Design for UAV Models.
- Optimal Gas Injection Volumes for Oil Extraction
- UAV Path Planning
- Ship Hull Form Design
- Formula SAE Car Chassis Design
- Inlets for Hypersonic Flow
- Optimal Parameters for Flapping Wings

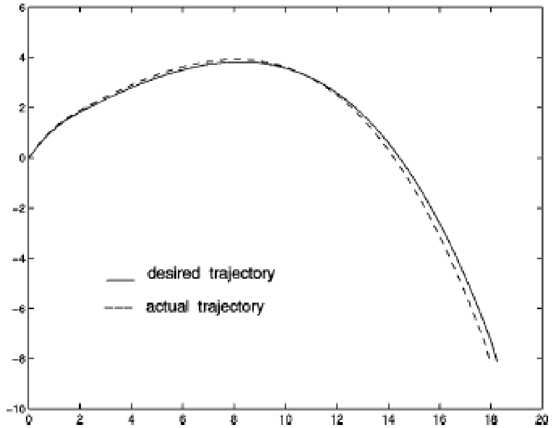
TOPLOGY OPTIMIZATION OF COMPLIANT MECHANISMS

Aim: Evolve the Topology of Compliant Mechanisms



gen.80 , obj.=4.85





Generate a Topology of the Mechanism such that the tip in the right follows the desired path.
EA coupled with ABAQUS.

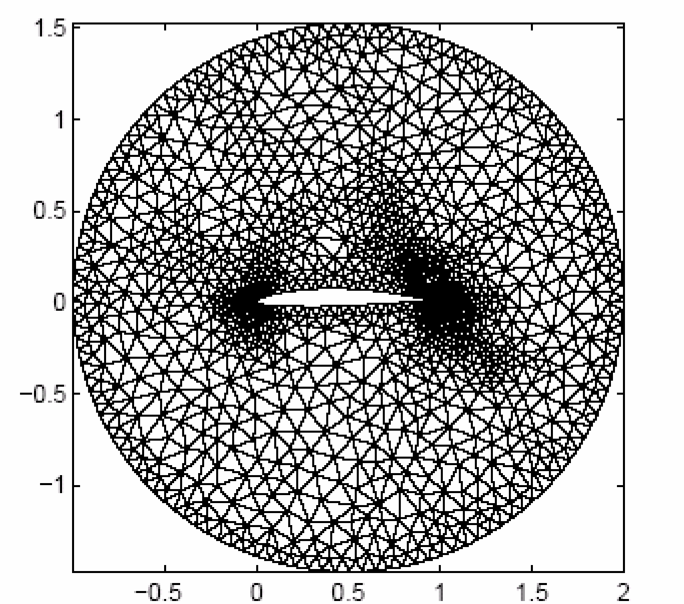
Kang, T., Guang, Y. C. and Ray, T. (2002). Design Synthesis of Path Generating Compliant Mechanisms by Evolutionary Optimization of Topology and Shape, *ASME Transactions, Journal of Mechanical Design*, Vol. 124, September 2002, pp. 492-500.

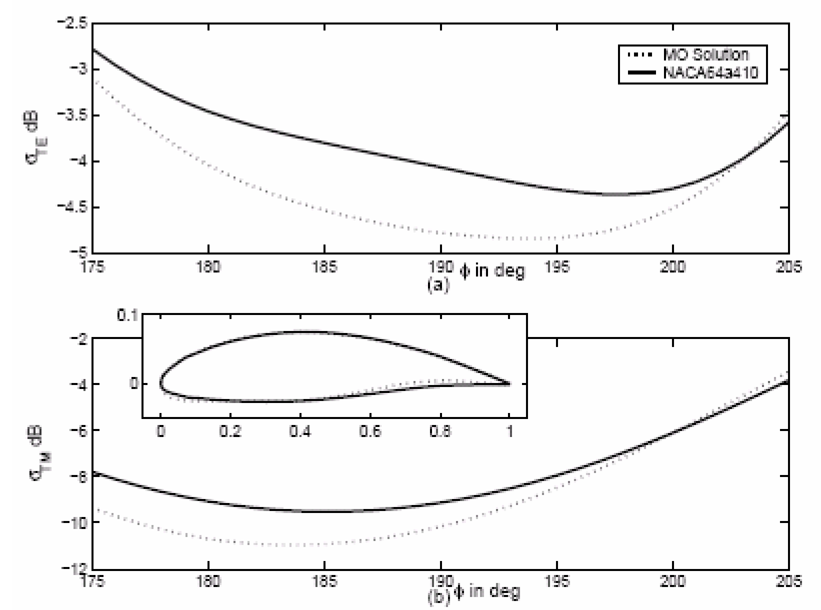
AIRFOIL DESIGN WITH CFD & CEM CONSIDERATIONS

Aim: Minimize RCS and CD

- Minimize F_{CEM}
- Minimize $F_{CFD} = c_d$
- Subject to
  - $c_l = 0.576$
  - $-1^\circ \leq \alpha \leq 1^\circ$

$$F_{CEM} = \max_{\phi \in [180^\circ, 200^\circ]} \{\sigma_{TE}(\phi), \sigma_{TM}(\phi)\}$$





1dB Reduction in Bistatic RCS as compared to NACA64A410

Venkatarayalu, N. and Ray, T. Application of Multi-objective Optimization in Electromagnetic Design*, Real World Multi-objective Systems Engineering: Methodology and Applications*, Eds. Nedjah, N., Nova Science, NY, 2005.

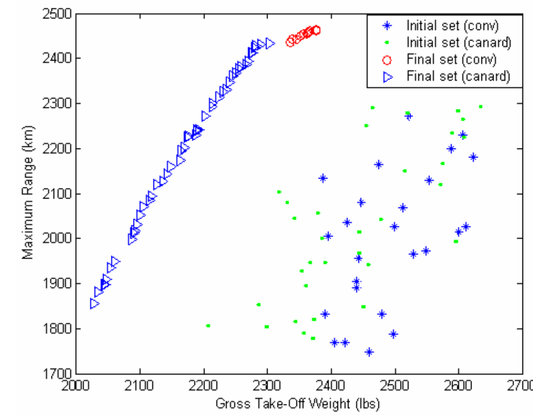
AIRCRAFT CONCEPT DESIGN

Aim: Find the Geometry for Various MO Formulations

Geometry defined using NURBS.

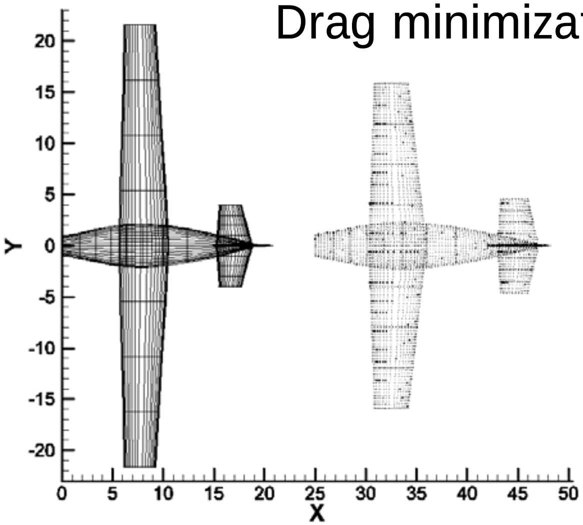
Disciplines: Aerodynamics, Propulsion, Structures & Weights, Stability & Control

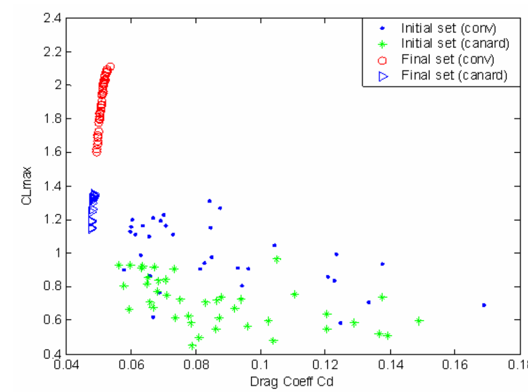
Multiple single and multi-objective problems have been solved.



Maximize Range & Minimize To Weight

Drag minimization



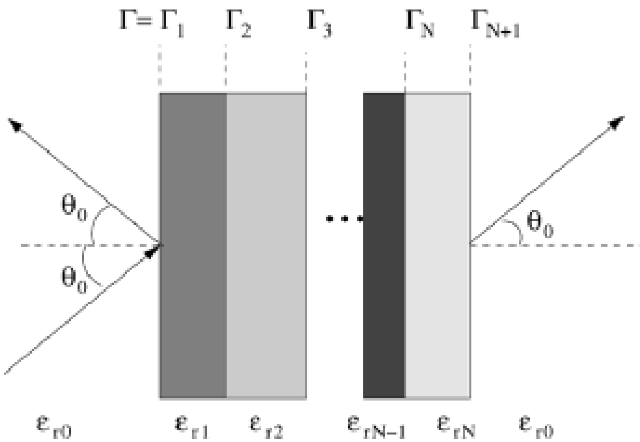


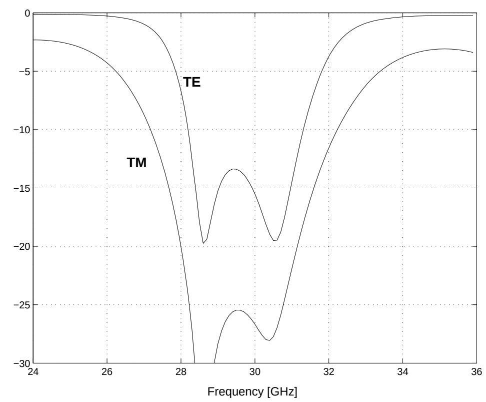
Maximize Lift & Minimize Drag during cruise

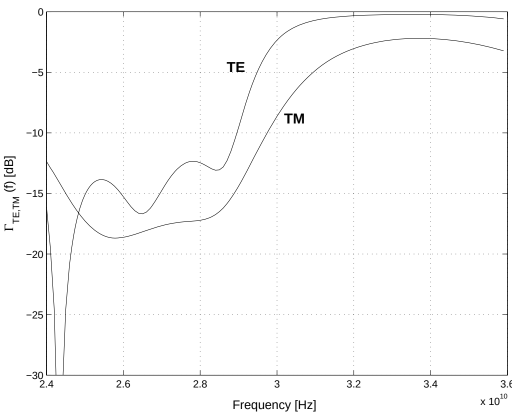
Rao, C.S., Tsai, H.M., and Ray, T. Aircraft Configuration Design Using a Multidisciplinary Optimization Approach., *42nd AIAA Aerospace Sciences Meeting*, Reno, Nevada, USA, 5-8 January 2004.

DIELECTRIC FILTER DESIGN

Aim: Identify the Layer Properties and Thickness







Bandpass Filter Design: Lower cutoff at 28 GHz and Upper cutoff at 32GHZ. Reflection coefficient is greater tha -5dB in stopband and less than -10dB in the passband. & layered dielectric.

Lowpass Filter Design: Cutoff frequency of 30GHZ.

Maximum of 15000 Design Evaluations.

Venkatarayalu, N., Ray, T. and Gan, Y.B., (2005). Multilayer Dielectric Filter Design Using a Multi-objective Evolutionary Algorithm, *IEEE Trans. On Antennas and Propagation*, Vol. 53, No. 11, pp. 3625-3632, 2005.

YAGI UDA ANTENNA DESIGN

Aim: Identify the Element Lengths and their Spacing for Maximum Gain

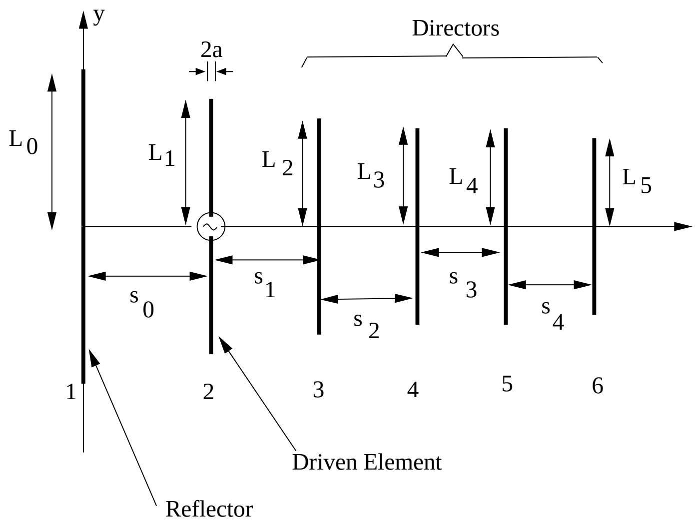


TABLE II

15-ELEMENT YAGI–UDA ANTENNA DESIGNS OBTAINED USING (a) GA FROM [7] AND (b) CI ALGORITHM

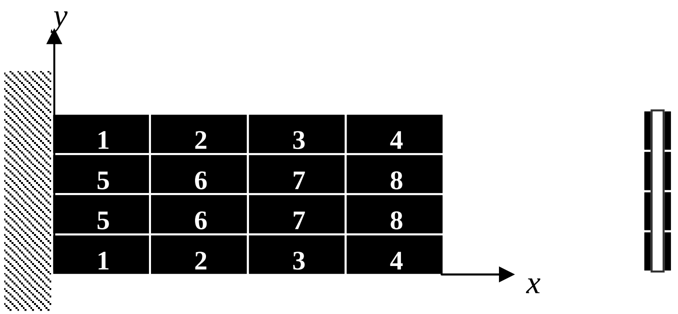
	GA optimized [7]		CI optimized	
Elements	Length, L_n	Spacing, S_n	Length, L_n	Spacing, S_n
1	0.236λ	-	0.235λ	-
2	0.230λ	0.249λ	0.227λ	0.196λ
3	0.221λ	0.155λ	0.224λ	0.238λ
4	0.205λ	0.185λ	0.215λ	0.142λ
5	0.216λ	0.191λ	0.204λ	0.231λ
6	0.210λ	0.252λ	0.212λ	0.447λ
7	0.210λ	0.442λ	0.206λ	0.395λ
8	0.189λ	0.431λ	0.203λ	0.371λ
9	0.191λ	0.362λ	0.201λ	0.441λ
10	0.200λ	0.205λ	0.202λ	0.433λ
11	0.204λ	0.268λ	0.206λ	0.445λ
12	0.215λ	0.414λ	0.196λ	0.365λ
13	0.174λ	0.197λ	0.189λ	0.359λ
14	0.199λ	0.130λ	0.203λ	0.429λ
15	0.204λ	0.362λ	0.196λ	0.390λ
Gain(dBi)	15.41		16.66	
Z (Ω)	50..64 – j 5.08		45.42 – j 5.74	

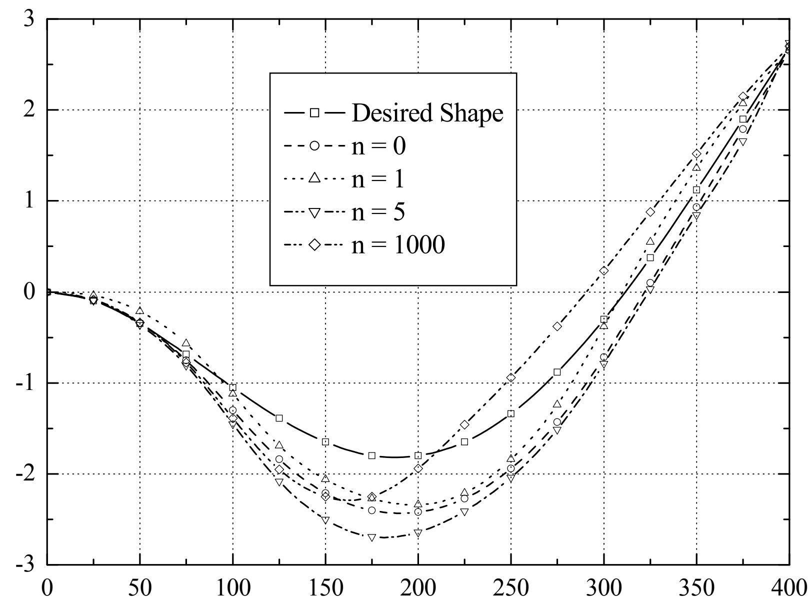
More than 1dBi improvement

Venkatarayalu, N. and Ray, T. (2004). Optimum Design of Yagi-Uda Antennas Using Computational Intelligence, *IEEE Trans. On Antennas and Propagation*, Vol. 52, No. 7, pp. 1811- 1818, 2004.

OPTIMAL GAIN OF PIEZOELECTRIC PATCHES

Aim: Identify the Gains of Piezoelectric Patches





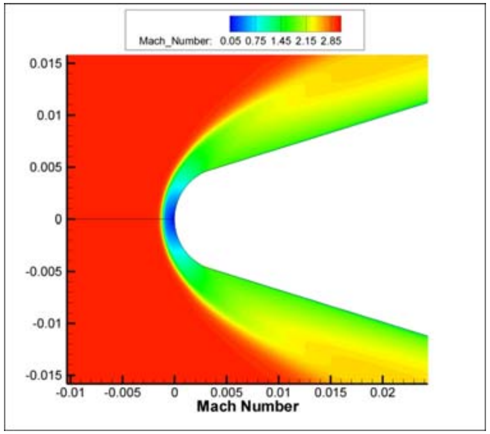
Liew, K.M., He, X.Q, and Ray, T. (2004). Computational Intelligence in Optimal Shape Control of Functionally Graded Smart Plates, *Computer Methods in Applied Mechanics and Engineering*, Vol. 193, Issues 42-44, pp. 4475-4492, 2004.

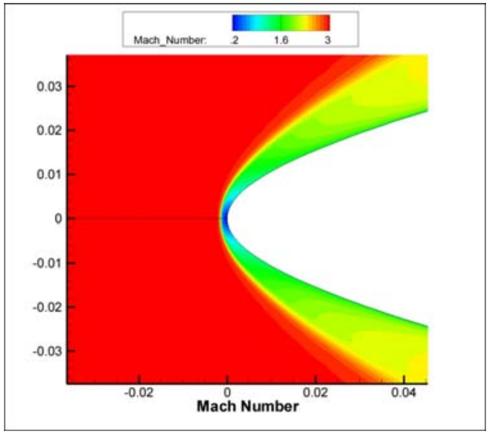
NOSE CONE DESIGN

Aim: Minimization of Total Drag

Approach: With and without surrogates

	M = 3.02	M = 8.04
Base Design	0.2601	0.3001
Without Surrogate	0.2565 (1.39%)	0.2942 (1.96%)
With Surrogate	0.2569 (1.21%)	0.2977 (0.80%)
Computational Saving	18%	11%

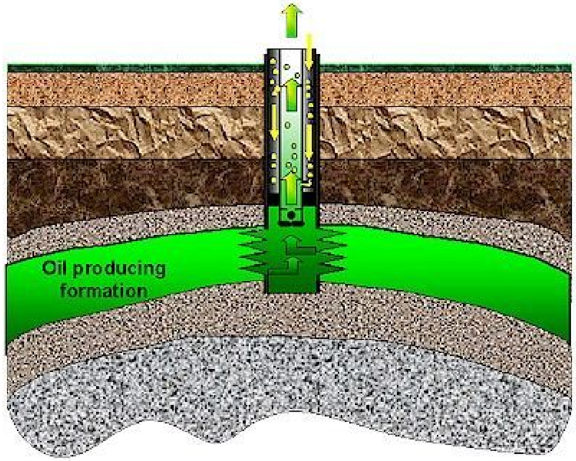




Deepak, R., Ray. T. and Boyce, R. Evolutionary Algorithm Shape Optimization of a Hypersonic Flight Experiment Nose Cone, Journal of Spacecrafts and Rockets, 45 (3), pp. 428-437,2008.

OPTIMAL GAS INJECTION VOLUME

Aim: Identify Optimal Gas injection Volumes to the Oil Wells for Maximum Extraction



Six Well		Fifty Six Well	
Buitrago et al.	3629.00	Buitrago et al.	21789.9
Best EA	3663.99	Best EA	22033.4
Worst EA	3653.90	Worst EA	21222.4
Average EA	3660.20	Average EA	21622.3
Median EA	3660.77	Median EA	21651.2

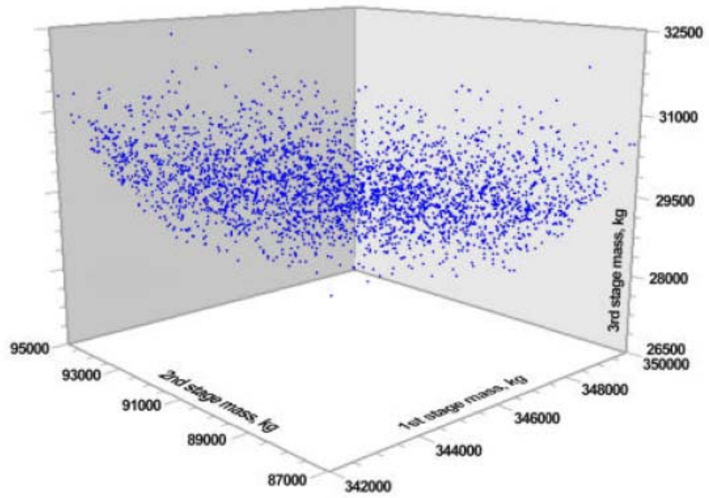
An Increase of 243 Barrels per Day for 56 Oil Well Problem (Benchmark Problem)

Ray,T. and Sarker, R. Genetic Algorithm for Solving a Gas Lift Optimization Problem, *Journal of Petroleum Science and Engineering,* Vol. 59, pp. 84-96, 2007.

Ray,T. and Sarker,R., Evolutionary Algorithms Deliver Promising Results to Gas Lift Optimization Problems, World Oil, April 229 (4), pp. 141-142, 2008.

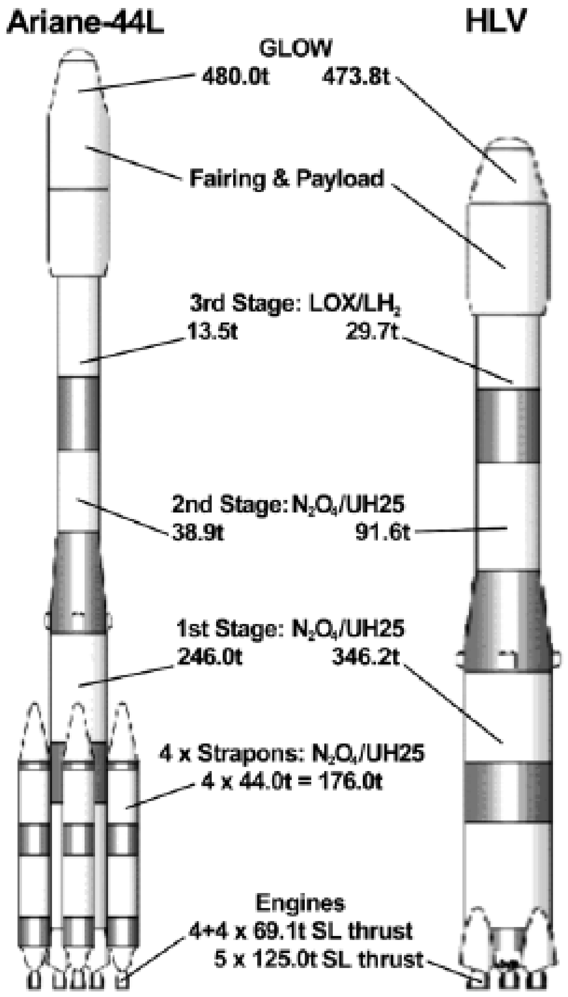
LAUNCH VEHICLE DESIGN

Aim: Identify Stage Masses of a Launch Vehicle



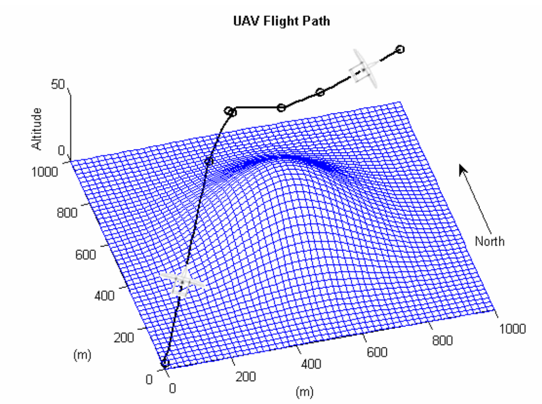
47 Kg Reduction in Total Stage Masses

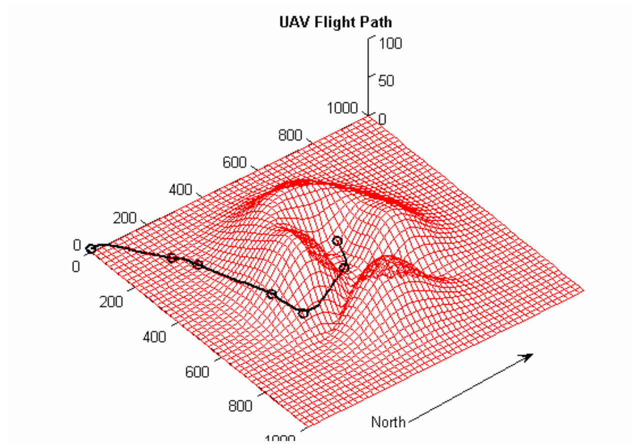
Briggs, G.P., Ray, T. and Milthorpe, J.(2007). Optimal Design of an Australian Medium Launch Vehicle, *Innovations in Systems and Software Engineering*, (A NASA Journal), Springer. Vol. 3, pp. 105-116,2007.

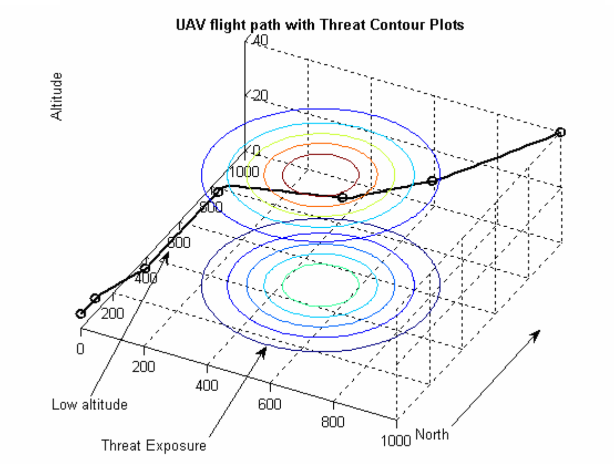


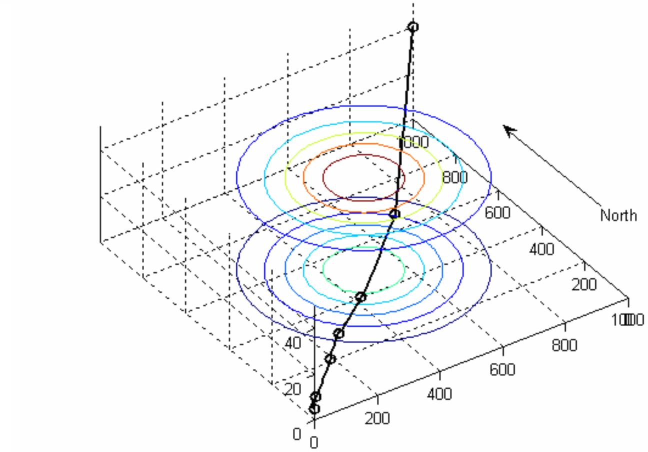
UAV PATH PLANNING

Aim: Identify Optimal Paths for Minimal Threat and Distance Traveled





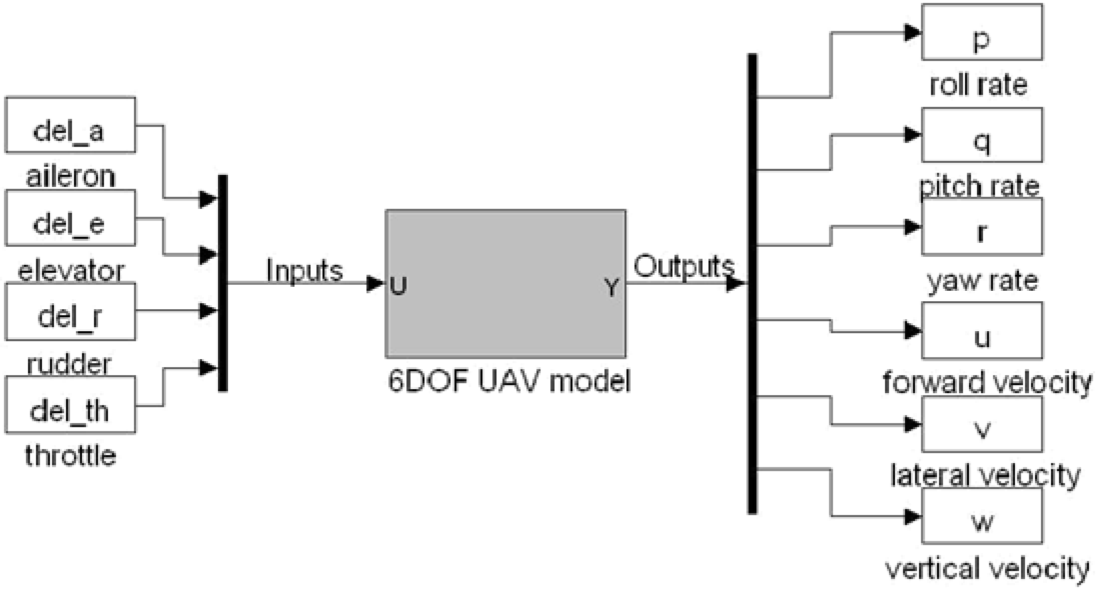




Sanders, G. and Ray, T. Optimal Offline Path Planning of a Fixed Wing Unmanned Aerial Vehicle (UAV) using an Evolutionary Algorithm, *IEEE Congress on Evolutionary Computation* CEC-2007, Singapore, September, pp. 4410-4416, 2007.

DYNAMIC MO FOR UAV LONGITUNUDAL CONTROL (1 of 2)

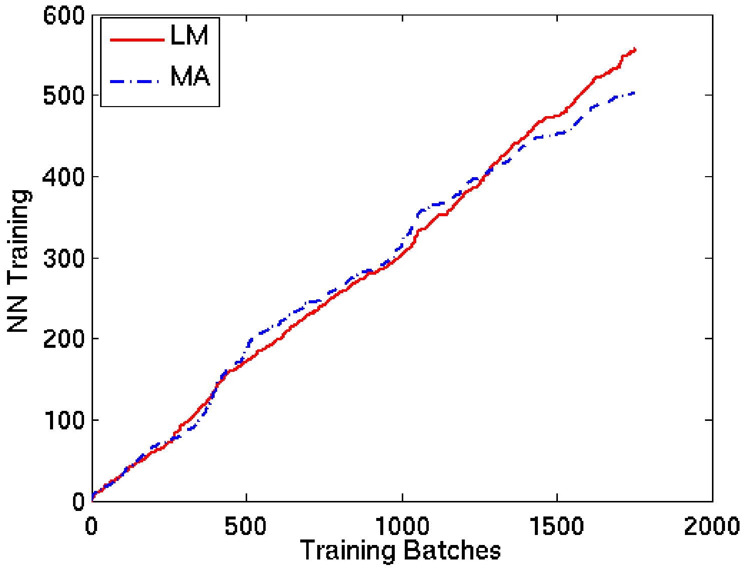
Aim: Train NN Controllers Minimum Number of Times



UAV platform	Wingspan	Engine Size	Payload	Total Weight
Megasoar	2.42m	29cc Glow	2kg	8.5kg

DYNAMIC MO FOR UAV LONGITUNUDAL CONTROL (2 of 2)

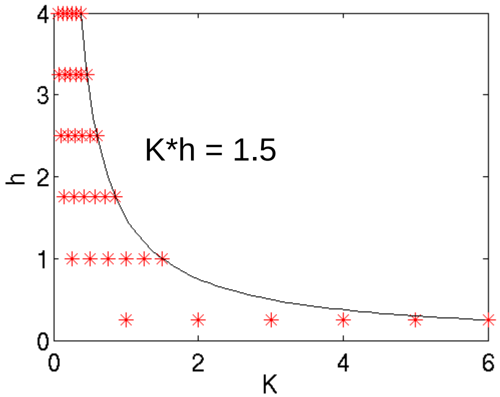
- Test Setup
  - Flight Data (1751 mini-batches)
  - LM method (single objective)
  - MA method (bi-objective)
- NN Training Cycles
  - LM – 550
  - MA – 502



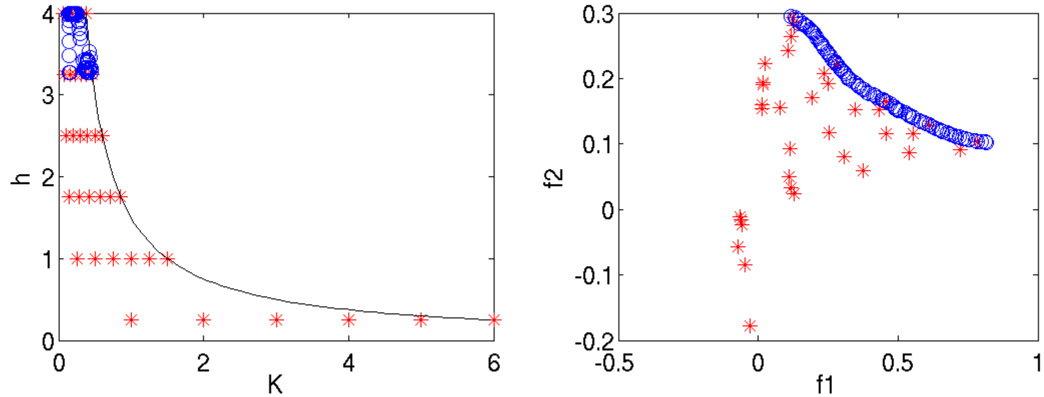
Isaacs, A., Puttige, V., Ray, T., Smith, W., and Sreenatha, A., Development of a Memetic Algorithm for Dynamic Multi-objective Optimization and its Application to Online System Identification, *Proceedings of IEEE World Congress on Computational Intelligence (WCCI),* Hong Kong, 2008.

FLAPPING WING DESIGN (1 of 2)

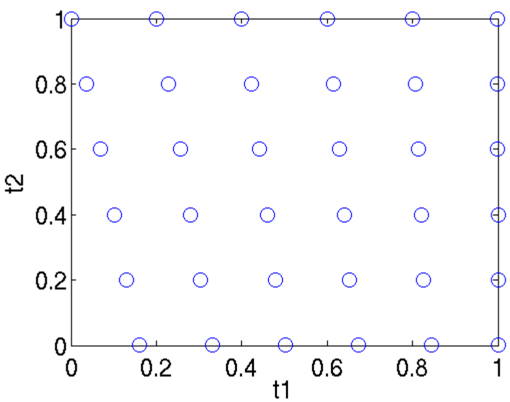
Aim: Find wing parameters (frequency & amplitude) to Maximize Thrust and Efficiency



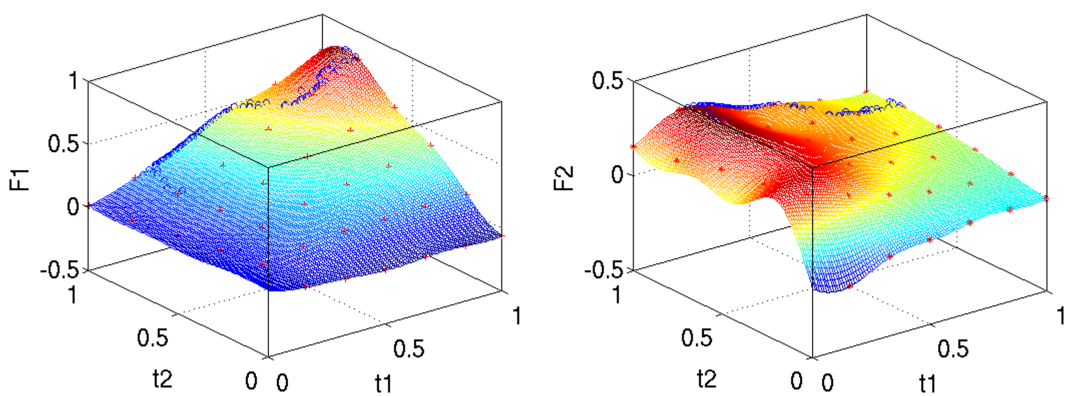
DOE based sampling



Non-dominated solutions in x-space and f-space



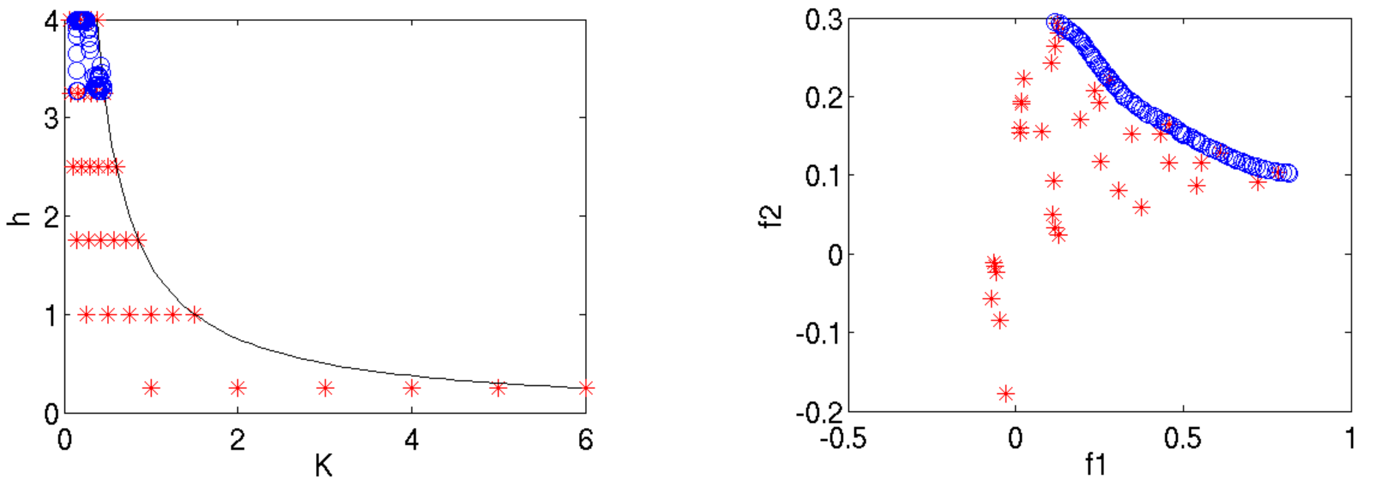
Transformation to parameter space



Surrogate models for f1 and f2 as function of parameters

FLAPPING WING DESIGN (2of 2)

Aim: Find wing parameters (frequency & amplitude) to Maximize Thrust and Efficiency



Non-dominated solutions in x-space and f-space

Parameters		Predicted		Calculated	
Frequency	Amplitude	Thrust	Efficiency	Thrust	Efficiency
3.545	0.4321	0.7896	0.0997	0.7538	0.0972
3.034	0.1403	0.0863	0.305	0.0845	0.287
3.2728	0.1484	0.1176	0.2971	0.1171	0.2963

SURROGATE ASSISTED OPTIMIZATION

PROGRESS IN SURROGATE ASSISTED OPTIMIZATION

BACKGROUND

Problems that we deal with are computationally expensive. Ranges from 30 minutes to 8 hours on a Single CPU.

Analysis Tools are Commercial Codes and we have Limited Licenses.

Concept Development Phase Codes are in MATLAB. Some Computationally Cheap Applications are directly coupled with MATLAB codes. More serious ones coupled with optimization codes in MPIC++.

We have our own MDO Linux cluster with 8 CPU’s for code development and benchmarking. CFD Applications are either run on Fluids Linux Cluster with 20 CPU’s and extensively on APAC.

SURROGATE ASSISTED OPTIMIZATION

FUNDAMENTAL QUESTIONS

1. Do we know which Surrogate Model to use ?
2. Should we Train our Surrogate Model once and use it over and over again in lieu of actual computation within an Optimization Framework ? If not how frequently should we train ?
3. How many Data sets should we use to train our Surrogate Model ?
4. How to choose a Training Set and a Validation Set ?
5. Should we use a Single Global Surrogate Model or Multiple Local Ones ?
6. If we want Multiple Surrogate Models, How many ?
7. Should we use Multiple Surrogate Models of One Type or should we use Multiple Surrogate Models of Multiple Types ?
8. Should we rely on our Surrogate Model to predict performance of a solution even if its neighborhood is under-sampled ?

BOTTOM LINE

We are free to use any amount of time for model building, sampling, checking as long the algorithm delivers better solutions with fewer actual analysis.

INVOLVEMENT IN SURROGATE ASSISTED OPTIMIZATION

1994: Multiple MLP Models Coupled with Optimization for Concept Design of Ships.

1998: Springback Minimization (ANSYS-LSDYNA Analysis), MLP trained once and used subsequently throughout the optimization run, SO

2002: Multifidelity Models for Airfoil Design, SO

2003: RBF with Model Management, Test Function up to 20D, SO

2004: Kriging / Cokriging, DOE, Model Management Test Function 50D, SO. Number of Clusters Varying.

2006: MO, RBF, Periodic Retraining, ZDT and Engineering Design Optimization Problems.

2007: MO RBF Chemical Engineering Problems

2007: Spatially Distributed Surrogates with Neighborhood Checks, SO and MO Test Functions, Engineering Design Optimization Problems.

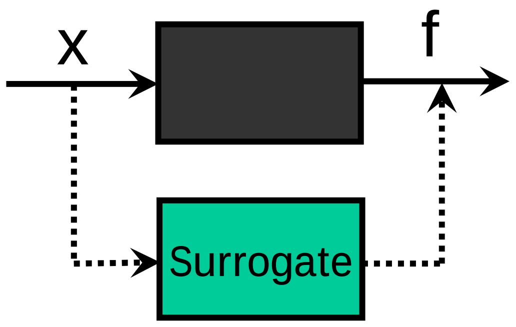
2007: Surrogate Assisted Crossovers

2008: Multiple Spatially Distributed Surrogates of Multiple Types with Neighborhood Checks.

2008: Surrogate Ensembles

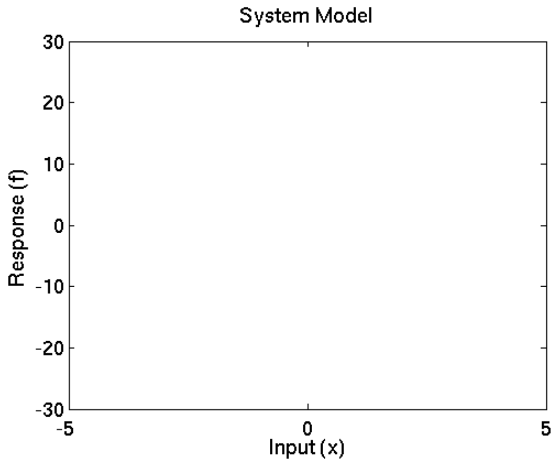
2008: Flow-field Approximation

PROGRESS IN SURROGATE ASSISTED OPTIMIZATION

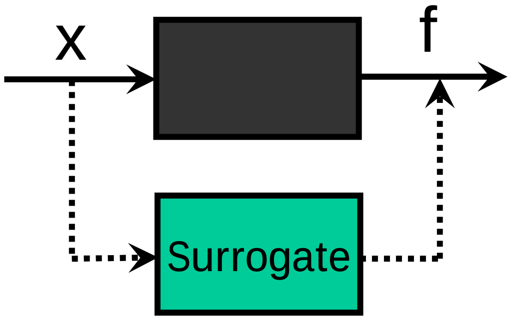


System model to be approximated

PROGRESS IN SURROGATE ASSISTED OPTIMIZATION

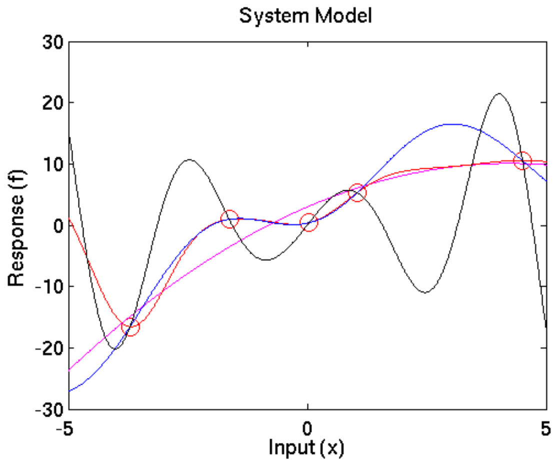


Different types of Surrogate Models

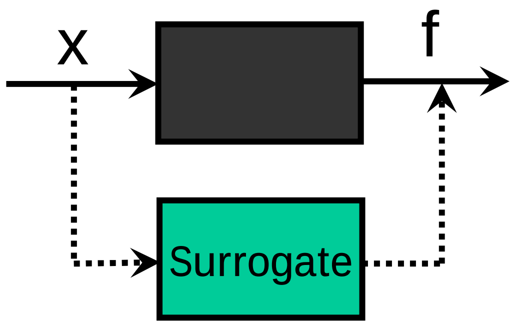


System model to be approximated

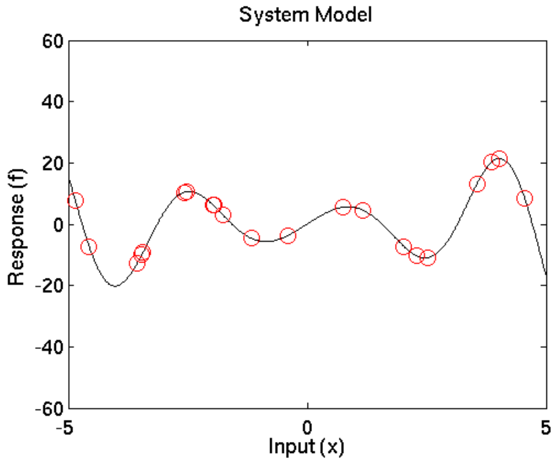
PROGRESS IN SURROGATE ASSISTED OPTIMIZATION



Different types of Surrogate Models

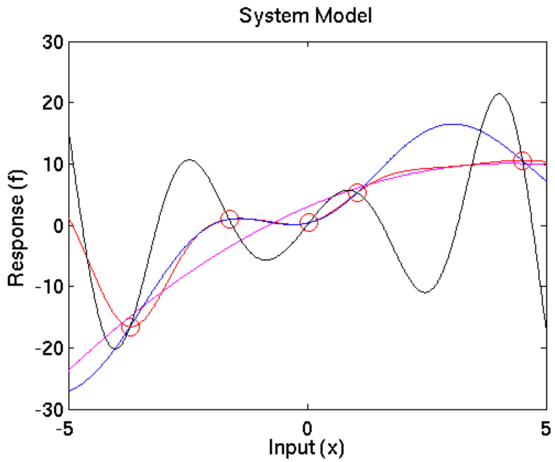


System model to be approximated

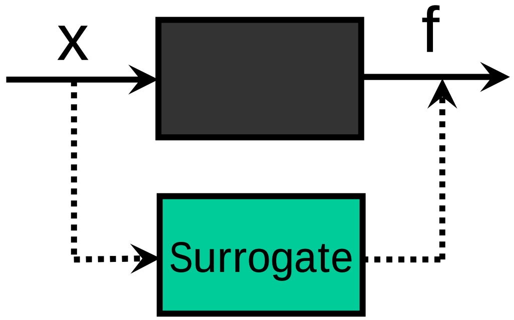


Different number of Surrogate Models

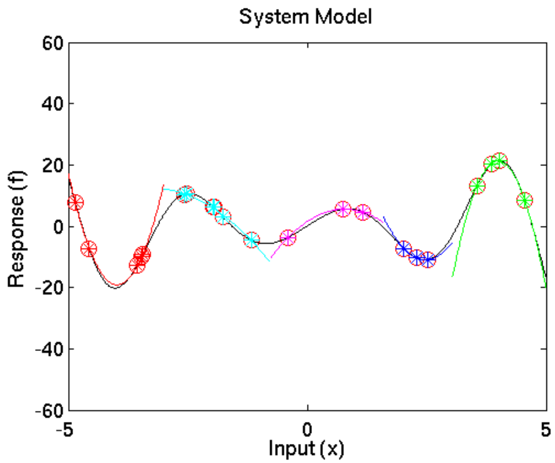
PROGRESS IN SURROGATE ASSISTED OPTIMIZATION



Different types of Surrogate Models



System model to be approximated



Different number of Surrogate Models

- Single Surrogate
  - Multiple Models
- Spatially Distributed Surrogates
  - Fixed
  - Multiple Adaptive
- Surrogate Ensembles

SPATIALLY DISTRIBUTED SURROGATE MODELS

Require: NG > 1 {Number of Generation}

Require: M > 1 {Population Size}

Require: K > 1 {Number of Partitions}

Require: $I_{TRAIN} > 0$ {Periodic Surrogate Training Interval}

1: A = Φ {Archive of the Solutions}

2: P_1 = Initialize{}

3: Evaluate {P_1}

4: A = AddToArchive (A,P_1)

5: S = BuildSurrogates (A,K)

6: for i=2 to NG do

7: if modulo (i, I_{TRAIN})==0 then

8: Evaluate (P_{i-1}) { Evaluate Parent population using Actual Analysis}

9: A = AddToArchive (A,P_{i-1})

10: S = BuildSurrogates (A,K)

11: end if

12: Ci-1 = Evolve(P_{i-1},S)

13: EvaluateSurrogate(C_{i-1},S)

14: P_i= Reduce(P_{i-1} + C_{i-1})

15: end for

- Initialize (p)
- Evaluate (p)
- Repeat
  - cp = Evolve (p)
  - Evaluate (cp)
  - Sort (p + cp)
  - p = Reduce (p + cp)
- Stop

Require: A {Archive of actual evaluations}

Require: K { Number of partitions}

Require: m {Number of objectives}

Require: $p \geq 0$ {Number of constraints}

1: $A_1,\ldots,A_K$ = KMeans (A,K)

2: for i = 1 to K do

3: for j = 1 to m do

4 $S_i f_j$ = SurrogateTrain (A_i, f_j)

5. end for

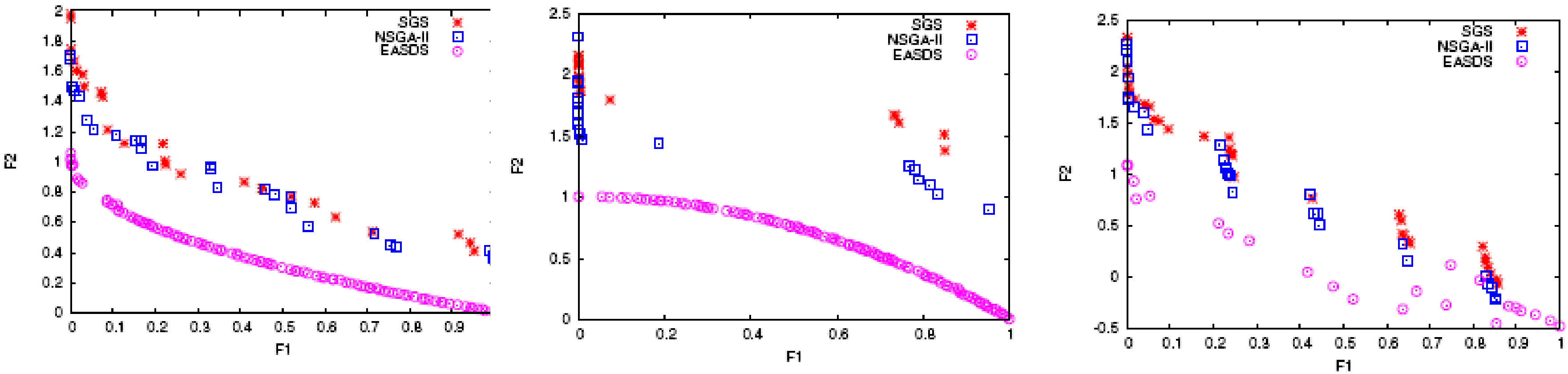
6. for j = 1 to p do

7. $S_i g_j$ = = SurrogateTrain (A_i,g_j)

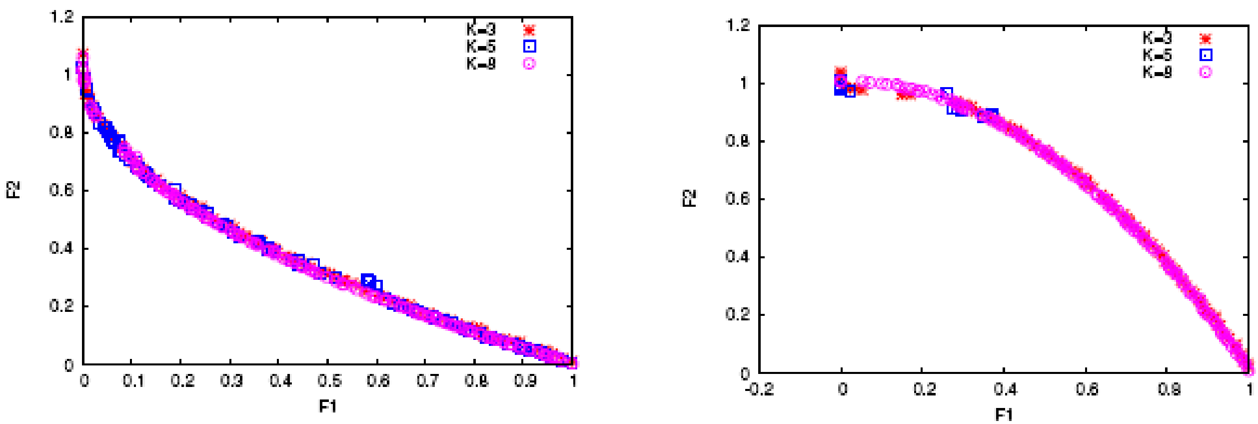
8. end for

9. end for

SOME RESULTS : SINGLE, MULTIPLE AND EA



ZDT1, ZDT2 and ZDT3: Same number of function evaluations, Same starting population, 2100 evaluations.



ZDT1 and ZDT2: Effect of Number of Clusters

SOME RESULTS : SINGLE, MULTIPLE AND EA

RBF with Model Management, CEC 2004

Function evaluations required for same Tolerance (5-D)

Test Function	Tolerance	Regular GA (Actual function evaluations)	Proposed Algorithm (Actual function evaluations)	Proposed Algorithm (Approx. function evaluations)
Spherical	4.2524×10^{-56}	**49050**	**21450**	205440
Ellipsoidal	1.8985×10^{-50}	**49050**	**21051**	201600
Schwefel	4.0729×10^{-38}	**49050**	**25951**	248640
Rosenbrock	0.2703	**17500**	**7201**	68640
Rastrigin	3.9037	**16270**	**4601**	43680

Our Algorithm typically requires 50% evaluations to reach the Same Accuracy.

SOME RESULTS : SINGLE, MULTIPLE AND EA

RBF with Model Management, CEC 2004

Function evaluations required for same Tolerance (10-D)

Test Function	Tolerance	Regular GA (Actual function evaluations)	Proposed Algorithm (Actual function evaluations)	Proposed Algorithm (Approx. function evaluations)
Spherical	1.6114×10^{-35}	**99100**	**77567**	759174
Ellipsoidal	9.0924×10^{-26}	**99100**	**84334**	825487
Schwefel	9.9169×10^{-17}	**99100**	**53834**	526587
Rosenbrock	5.3030	**16500**	**7001**	67620
Rastrigin	8.3438	**17120**	**7100**	68600

SOME RESULTS : SINGLE, MULTIPLE AND EA

RBF with Model Management, CEC 2004

Function evaluations required for same Tolerance (20-D)

Test Function	Tolerance	Regular GA (Actual function evaluations)	Proposed Algorithm (Actual function evaluations)	Proposed Algorithm (Approx. function evaluations)
Spherical	2.9952×10^{-21}	**199200**	**110467**	1091640
Ellipsoidal	4.7247×10^{-8}	**199200**	**81534**	805200
Schwefel	2.0129×10^{-5}	**199200**	**144267**	1426260
Rosenbrock	17.6649	**70447**	**21201**	207900
Rastrigin	22.0698	**101650**	**28020**	213040

SOME RESULTS : SINGLE, MULTIPLE AND EA

RBF with Model Management, CEC 2004

Summary of Computational Efforts using Actual Evaluations

	5-D	**10-D**	**20-D**
Number of actual function evaluations	49050	99100	199200
Total time for actual function evaluations	1.943 s	4.079	37.311 s
Total elapsed time (Wall clock time)	41.971 s	120.814 s	420.315 s

Summary of Computational Efforts using Approximations

	5-D	**10-D**	**20-D**
Number of actual function evaluations	5050	10100	20201
Number of approximate function evaluations	48000	98000	198000
Total time for training of RBF	5.543 s	17.336 s	77.363 s
Total time for RBF approximations	23.357 s	95.224 s	416.851 s
Total time for actual function evaluations	0.210 s	0.41 s	3.643 s
Total elapsed time (Wall clock time)	69.120 s	230.772 s	887.537 s

SOME RESULTS : SINGLE, MULTIPLE AND EA

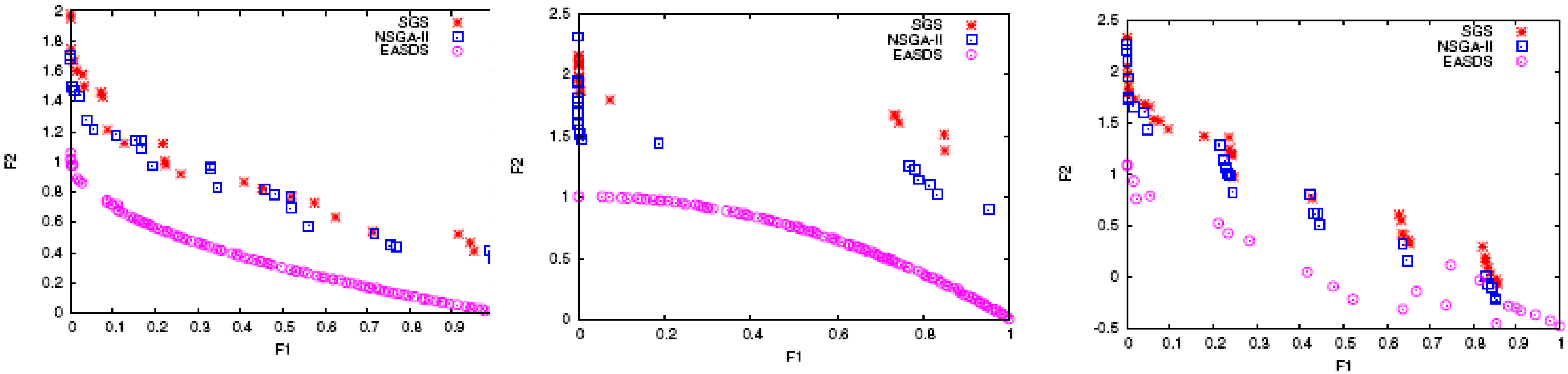
RBF with Model Management, CEC 2004

Comparison with Previous Studies

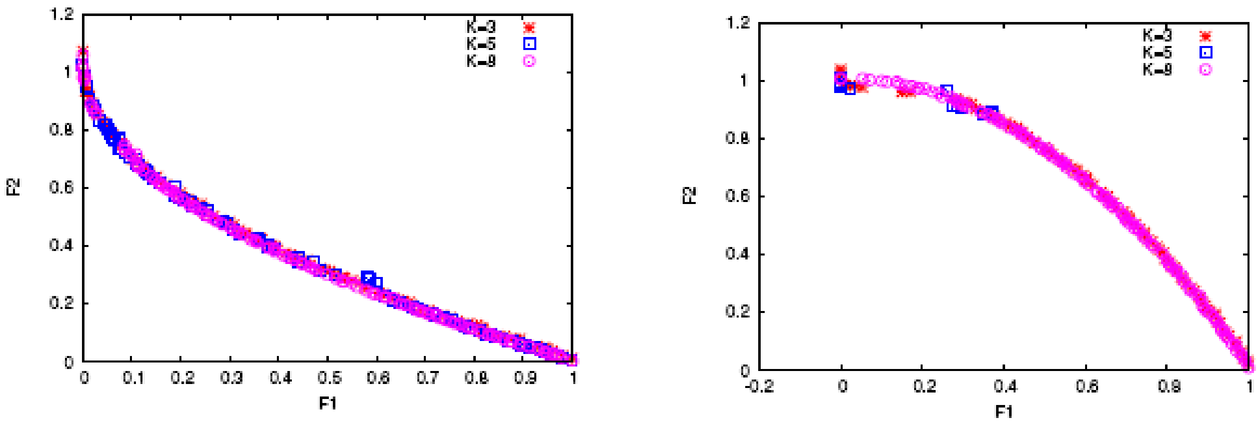
	Test Functions		Tolerance	
	Spherical	Schwefel		
Proposed Model	5×10^{3}	5×10^{3}	8.27×10^{-58}	1.38×10^{-19}
Sakuma & Kobayashi (2000)	1×10^{5}	5.6×10^{5}	1×10^{-10}	1×10^{-10}

	Rosenbrock	Rastrigin	Tolerance	
Proposed Model	5×10^{3}	5×10^{3}	1.3574	4.0865
Ono et al. (1999)	1.5×10^{5}	3.7×10^{6}	1×10^{-10}	1×10^{-6}

SOME RESULTS : SINGLE, MULTIPLE AND EA



ZDT1, ZDT2 and ZDT3: Same number of function evaluations, Same starting population, 2100 evaluations.



ZDT1 and ZDT2: Effect of Number of Clusters

ENHANCEMENTS

STRATEGY 1: Identify P points closest to the solution under consideration. Use Q points out of this P to create various types of Surrogate Models. If there are no points in the Archive within a threshold distance to this solution under consideration, go and do an Actual computation. Choose the best surrogate model among different types by their MSE on the validation set which is P-Q. Q is selected from P via KMeans clustering.

Advantages:

- Stop predicting in regions if they have not been sampled via actual analysis.
- Some functions might be better approximated by a type of surrogate.
- No hassles in determining periodic training interval.

Possibilities exist for alternative strategies for choosing the best surrogate. (Ongoing)

Surrogate Models that are currently being used are Quadratic RSM, Kriging, MLP and RBF.

SURROGATE ASSISTED RECOMBINATION

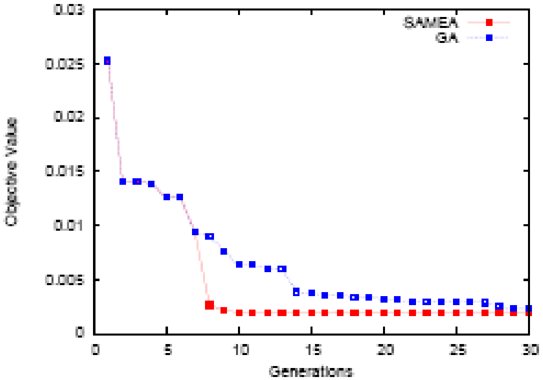
Why do most surrogate assisted models evaluate a solution generated out of recombination ?

What's wrong in running a SQP on a Surrogate Model and Perform an Actual Analysis on it ?

Total number of evaluations 1200, population of 40. Comparison with NSGA-II

Table 3: Results for problems g01, g04, g06, g07, g10

		g01	g04	g06	g07	g10
Best	GA	-10.2	-30492.5	-6869.45	114.19	-
	SAMEA	**-15**	**-30665.5**	**-6920.15**	**62.18**	**10036**
Worst	GA	-3.14	-29443	-1309.08	1185.37	-
	SAMEA	-11.3	-29197	-1647.44	1185.37	16197.1
Average	GA	-7.14	-29981.75	-4244.66	447.12	-
	SAMEA	-13.64	-30111.06	-5285.37	300.92	12167.2
Median	GA	-7.36	-29916.75	-5116.03	301.61	-
	SAMEA	-13.8	-29920.75	-5923.97	222.56	11498.8
Std.Dev.	GA	1.98	316.86	2097.27	305.86	-
	SAMEA	0.79	454.49	1668.04	258.2	2150.76



Airfoil Design

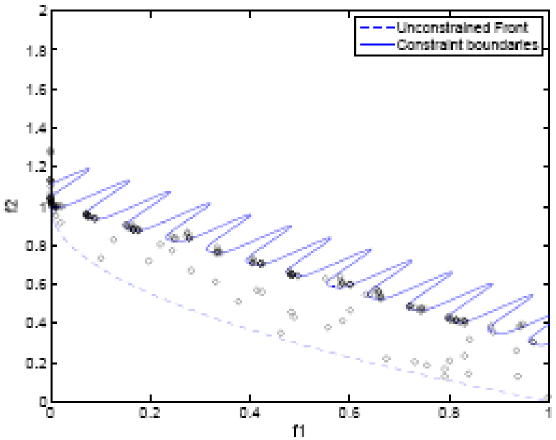
PUBLICATIONS ON SURROGATES

- Ray, T., Isaacs, A., and Smith, W., Surrogate Assisted Evolutionary Algorithm for Multi-objective Optimization, *Multi-Objective Techniques and Applications in Chemical Engineering*, Eds. Rangaiah, G.P. World Scientific. In Press
- Isaacs, A., Ray, T. and Tsai, H.M.(2008), Constrained Aerodynamic Shape Optimization using an Evolutionary Algorithm with Spatially Distributed Surrogates, AIAA-2008-6225, *Applied Aerodynamics Conference*, 2008.
- Isaacs, A., Ray, T., and Smith W.(2008), Multi-objective Design Optimization With Multiple Adaptive Spatially Distributed Surrogates, *International Journal of Product Design.* 2008
- Isaacs, A., Ray, T., and Smith W.,(2007). An Evolutionary Algorithm With Spatially Distributed Surrogates For Multi-objective Optimization, *Proceedings of Artificial Life* Gold Coast, Australia, Dec. 2007, *Lecture Notes in Computer Science*, Springer, Vol. 4828, pp. 257-268, 2007.
- Ray, T.(2006), A Neural Network Assisted Optimization Framework and its Use for Optimum Process Parameter Identification in Sheet Metal Forming, *Artificial Neural Networks in Finance and Manufacturing*, Eds. Kamruzzaman, J., Begg., R., and Sarker, R., Idea Group, USA,(2006).
- Ray, T. and Smith, W. (2006). A Surrogate Assisted Parallel Multi-objective Evolutionary Algorithm for Robust Engineering Design, *Engineering Optimization,* Vol. 38, No.9, pp. 997-1011, 2006.
- Won, K.S and Ray, T. (2005). A Framework for Design Optimization Using Surrogates, *Engineering Optimization* , Vol. 37, No.7,pp. 685-703, 2005.
- Liew, K. M., Ray, T., Tan, H. and Tan, M. J. (2004). Optimal Process Design of Sheet Metal Forming for Minimum Spring-back via an Integrated Neural Network Evolutionary Algorithm, *Structural and Multidisciplinary Optimization*, Volume 26, No. 3-4, February, pp. 284-294, 2004.
- Won, K.S., and Ray, T. (2004), Performance of Kriging and Cokriging based Surrogate Models within the Unified Framework for Surrogate Assisted Optimization, *IEEE Congress on Evolutionary Computation*, Portland, pp. 1577- 1585, 2004.
- Won, K.S., Ray,T., and Kang, T.(2003). A Framework for Optimization Using Approximate Functions, *IEEE Congress on Evolutionary Computation*, Canberra, Australia, 6-8 December, pp. 1520-1527, 2003.
- Liew, K. M., Ray, T., Tan, H. and Tan, M. J. (2002). Evolutionary Optimization and use of Neural Network for Optimum Stamping Process Design for Minimum Spring-back, *Transactions of ASME Journal of Computing and Information Science in Engineering*, Vol. 2, pp. 38-44.
- Ray, T., Tsai, H. M and Tan, C. M. (2002). Effects of Solver Fidelity on the Performance of a Stochastic Parallel Search for Airfoil Shape Optimization, Proceedings of the *9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, Atlanta, Georgia, 4-6 September, 2002.
- Liew, K.M., Tan, H., Ray, T. and Tan, M.J. (2001). Evolutionary Algorithm for Optimal Process Design in Sheet Metal Forming for Minimum Spring-back, *6th US National Congress of Computational Mechanics*, Michigan, August 2001.
- Sha, O. P, Ray, T., and Gokarn, R. P.,(1994). An Artificial Neural Network model for Preliminary Ship Design, Proceedings of the International Conference on Computer Applications in Shipbuilding, ICCAS 1994, Bremen, Germany, August 1994.

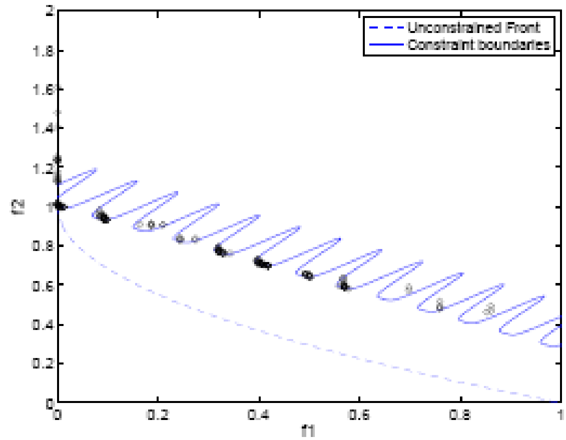
CURRENT EFFORTS

INFEASIBILITY-FEASIBLITY WAR : EA vs IDEA

IDEA: Infeasibility Driven Evolutionary Algorithm



(c) 50 generations



(c) 50 generations

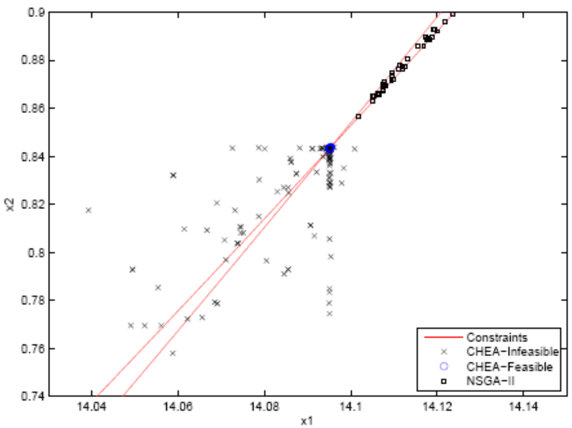
Progress of population for test problem CTP2

Why rank a Feasible solution better than an Infeasible one ? A marginal Infeasible solution is better than a poor Feasible solution.

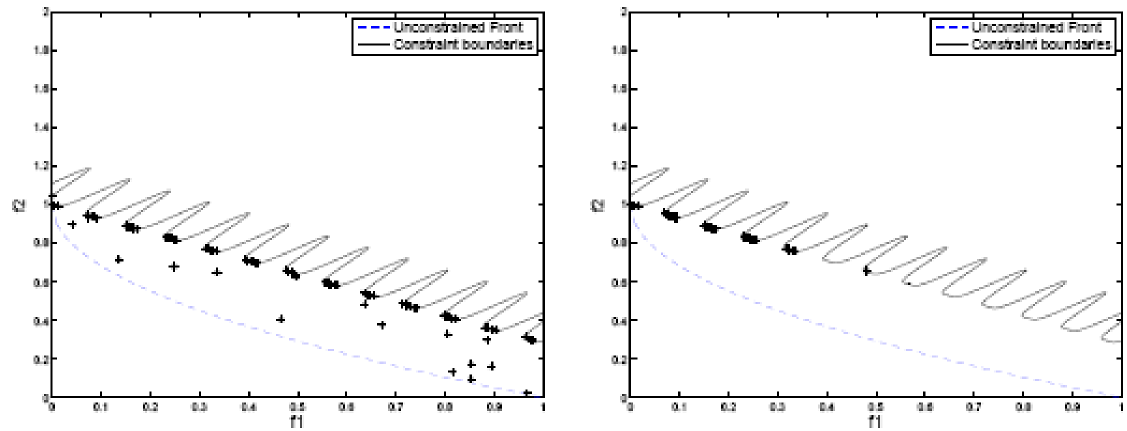
Singh, H.K., Isaacs, A., Ray, T. and Smith, W., Infeasibility Driven Evolutionary Algorithm (IDEA) for Engineering Design Optimization*, 21st Australasian Joint Conference on Artificial Intelligence (AI-08)*, December 2008, New Zealand,

INFEASIBILITY-FEASIBLITY WAR : WHY IDEA ?

IDEA: Infeasibility Driven Evolutionary Algorithm



Final Population of G6



(a) IDEA

(b) NSGA-II

CTP2 Behavior with IDEA AND NSGA-II

Take Note that the results are for smaller number of generations

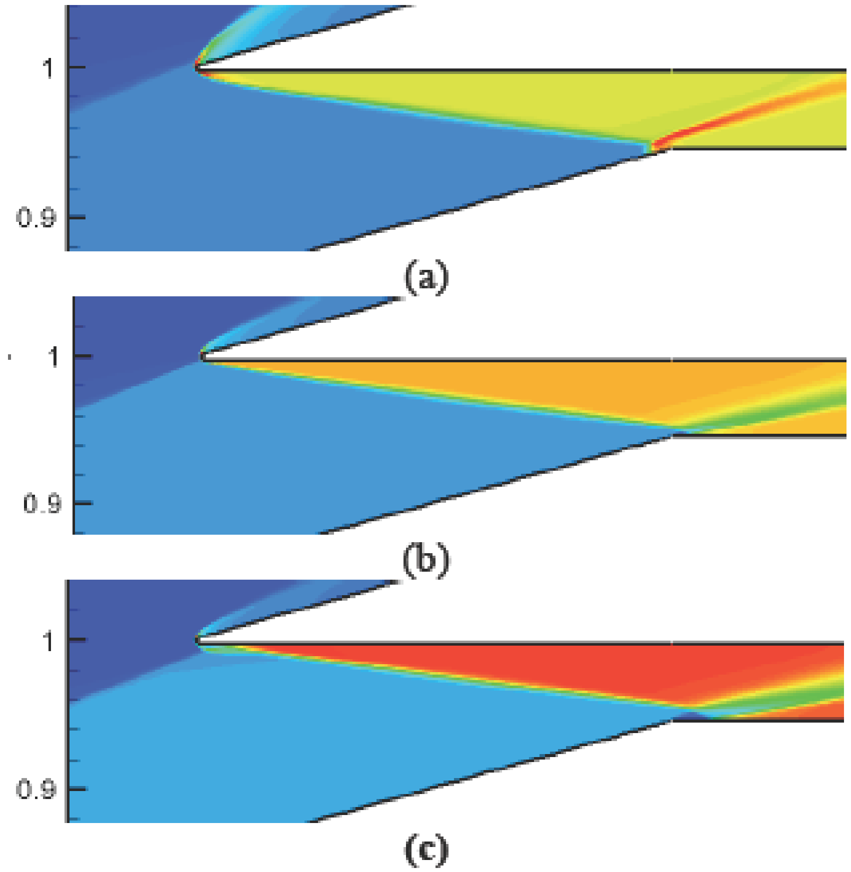
Ray, T., Singh, H.K., Isaacs, A., and Smith, W., Infeasibility Driven Evolutionary Algorithm for Constrained Optimization, *Constraint-Handling in Evolutionary Optimization*, *Studies in Computational Intelligence Series*, Eds, Efrén Mezura-Montes, Springer, 2008. In Press.

PREDICTION OF A FLOWFIELD

Aim: Given a set of Flow-fields for different inflow conditions, can we predict the entire Flow-field ?

Did some studies using Dimensionality Reduction in 2007 at Temasek Labs, National University of Singapore. Able to predict pressure distribution of airfoils at subsonic speeds. Need to develop further to optimize design of inlets.

Just started working with support from Defence Science and Technology Organization and University of Queensland.

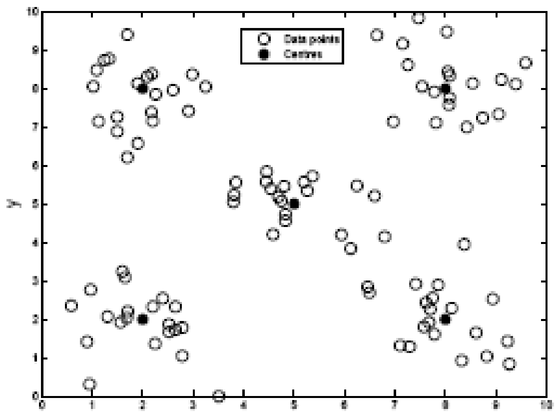


TRANSDIMENSIONAL OPTIMIZATION

Aim: Identify the Number of Variables and their Values

Clustering Problem: 100 points, Xie Beni Index as Cluster Quality Measure

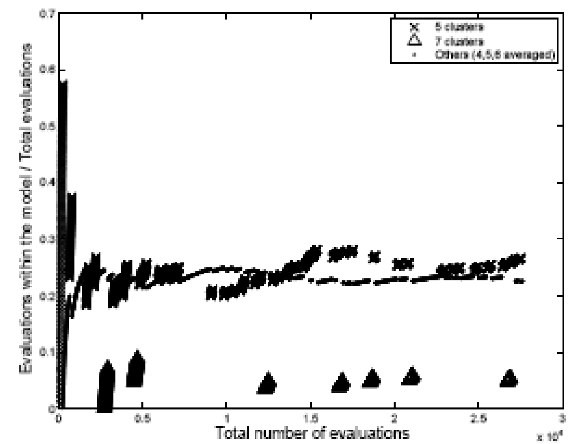
Model	TDSA Mean	TDSA Best	TDSA Worst	NSGA-II Mean	NSGA-II Best	NSGA-II Worst
μ_1 (3 centers)	0.1078	0.1062	0.1108	0.1080	0.1060	0.1102
μ_2 (4 centers)	0.0828	0.0779	0.0977	0.0805	0.0775	0.0961
μ_3 (5 centers)	**0.0759**	**0.0626**	0.1885	**0.0641**	**0.0608**	0.0882
μ_4 (6 centers)	0.0940	0.0739	0.1467	0.0782	0.0710	0.1071
μ_5 (7 centers)	0.1402	0.0886	0.2848	0.0963	0.0792	0.1234



Warehouse Location and Capacity Planning

- K locations with specific demands.
- Demands to be catered through N warehouses, to be set up at any of these K locations.
- Distance chart (km):

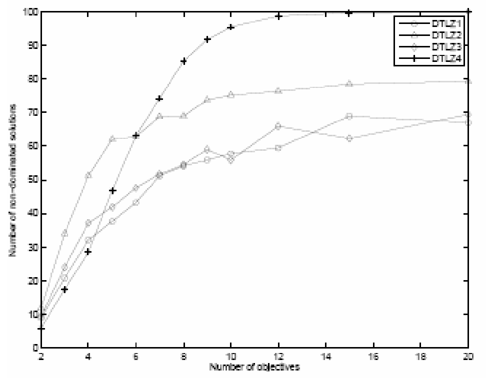
	Canberra	Sydney	Melbourne	Brisbane
Canberra	5	246.99	466.35	940.61
Sydney	246.99	5	713.33	728.83
Melbourne	466.35	713.33	5	1371.06
Brisbane	940.61	728.83	1371.06	5

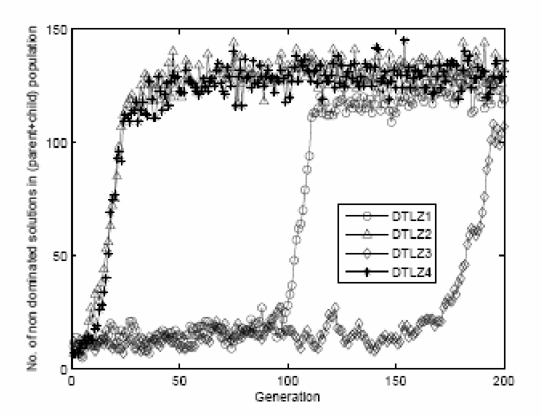


Singh, H.K., Isaacs, A., Ray, T. and Smith, W., A Simulated Annealing Algorithm for Single Objective Trans-Dimensional Optimization Problems, *Hybrid Intelligent Systems (HIS)*, Barcelona, September 2008.

MANY OBJECTIVE OPTIMIZATION

Aim: Develop Optimization Algorithms to Solve Many Objective Optimization Problems





Why Non-dominance does not work ?

Have we just been lucky ?

Should we scrap the existing practice of comparing existing algorithms based on its final population ? What's wrong if ones archive is better than another although the final population is not as good.

Singh, H.K., Isaacs, A., Ray, T. and Smith, W. A Study on the Performance of Substitute Distance Based Approaches for Evolutionary Many Objective Optimization,*Simulated Evolution and Learning (SEAL 2008)*, December 2008, Melbourne.

TOPLOGY OPTIMIZATION OF FSAE CAR CHASSIS

Aim: Evolve the Topology of the FSAE Car Chassis

WS02

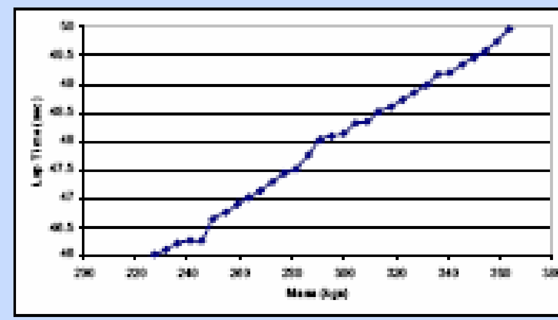
WS03

Why Save weight?

Lap time of the winning car for SAE-A 2006 is **48.084 sec.** and for the second car is **48.517 sec.**

Lap time difference of 0.5 sec corresponds to a weight reduction of approx. 20 Kgs as seen from the graph[2].

The mass of the winning car[3] was 190 kg, while that of ADFA car WS03 was 260 kg.



Evolve a structure that meets the strength requirements while minimizing its weight and other handling qualities. The structure should adhere to the constraints posed by operational conditions:

- unobtrusive sitting arrangement of the driver
- roll hoops for the driver safety
- location of suspension points
- Placement of cockpit equipment