Optimization Using Surrogates for Engineering Design

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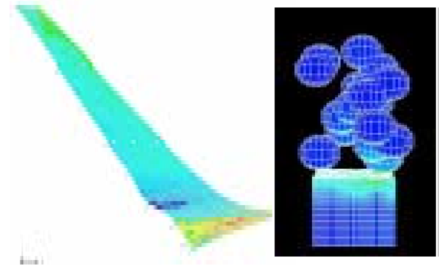
Thanks to: AFOSR, Boeing, LANL, SANDIA, ExxonMobil, NSF

Design Explorer Applications

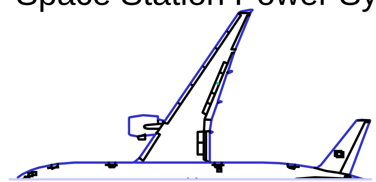
Helicopter Rotor Design

Space Station Power System



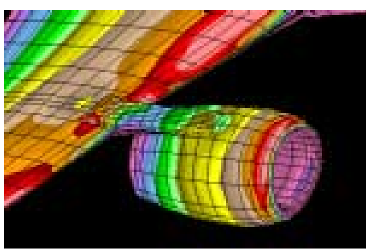
Shot peen forming of wing skins

Aerospike Nozzle



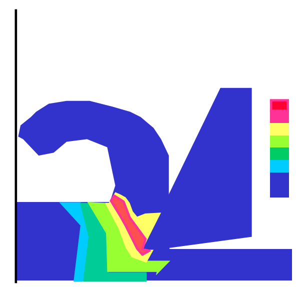
Multidisciplinary wing planform design

3-D Fighter Aerodynamics



Engine Nozzle Performance

777 Engine Duct Seals



Machining,riveting,and drilling database

A strawman surrogate approach

1. Choose surrogates s_f and S_C based on either:

(a) simplified physical models; or

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   But, what if no improvement was found?

Response surface global models

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- May be able to interpolate to gradients as well - Alexandrov

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Polynomials introduce extraneous extremes that trap strawman

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Correlation parameters for each site estimated by MLE.

Surrogate Management Framework

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2. Else if p_k is the only unfiltered point in P_k; Then set $x_{k+1} = x_k$ and $M_{k+1} = M_k/2$ and update the surrogates; Else return to 1

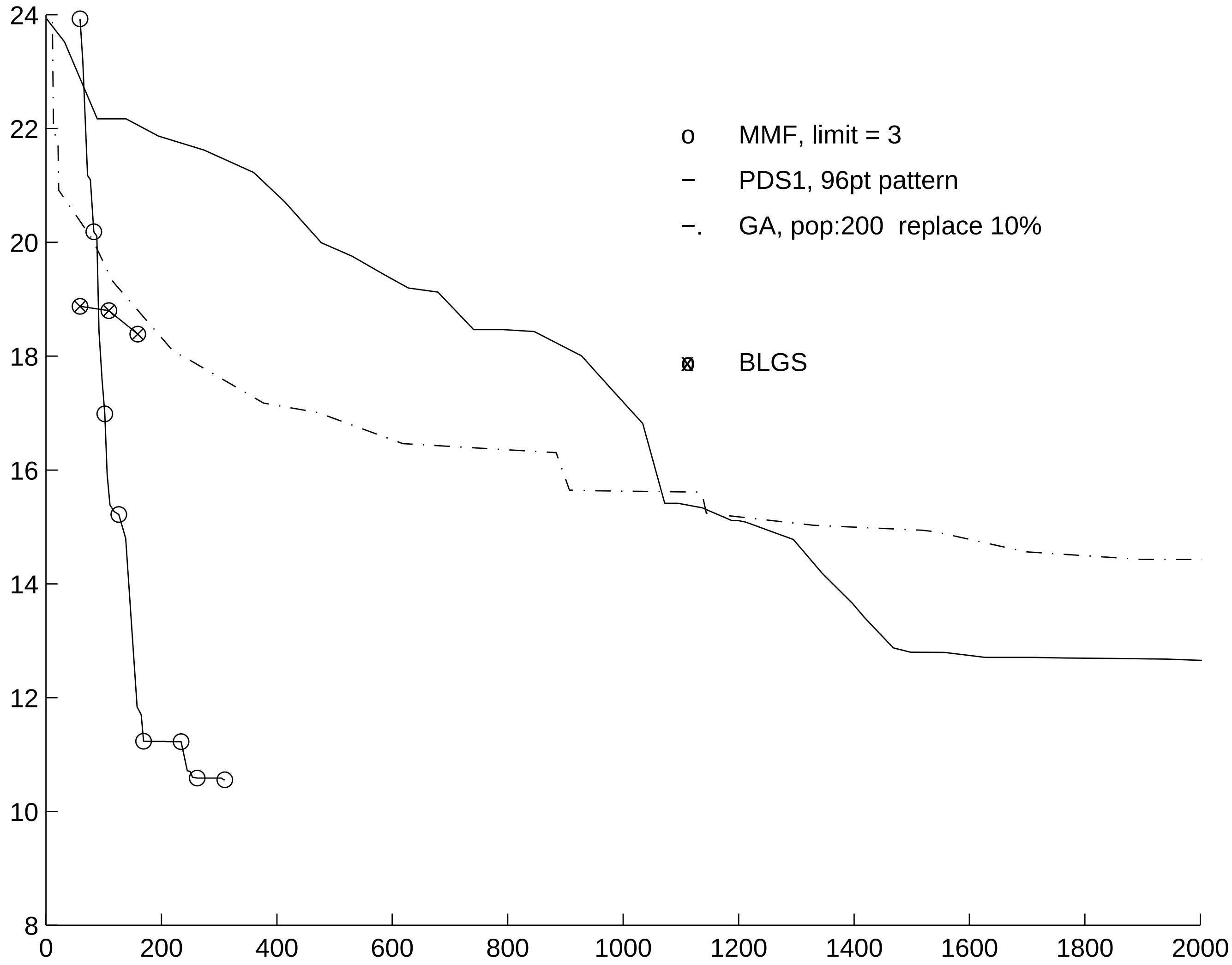
Just like FPS, but...

Poll step: Polling is done on the actual (barrier) functions, which guarantees convergence of the algorithm (through the sequence of unsuccessful poll steps).

Search step: Use surrogates s_f, S_C to find some promising candidates where f, C will be evaluated.

Update s_f, S_C with the new evaluations of f, C.

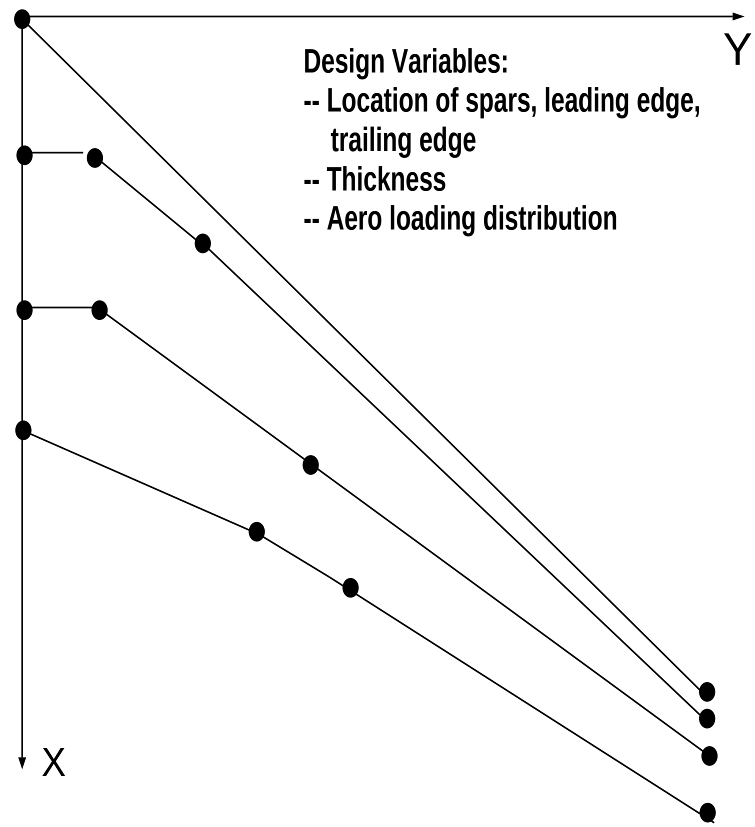
Comparisons on 31d helicopter example



Boeing wing planform design

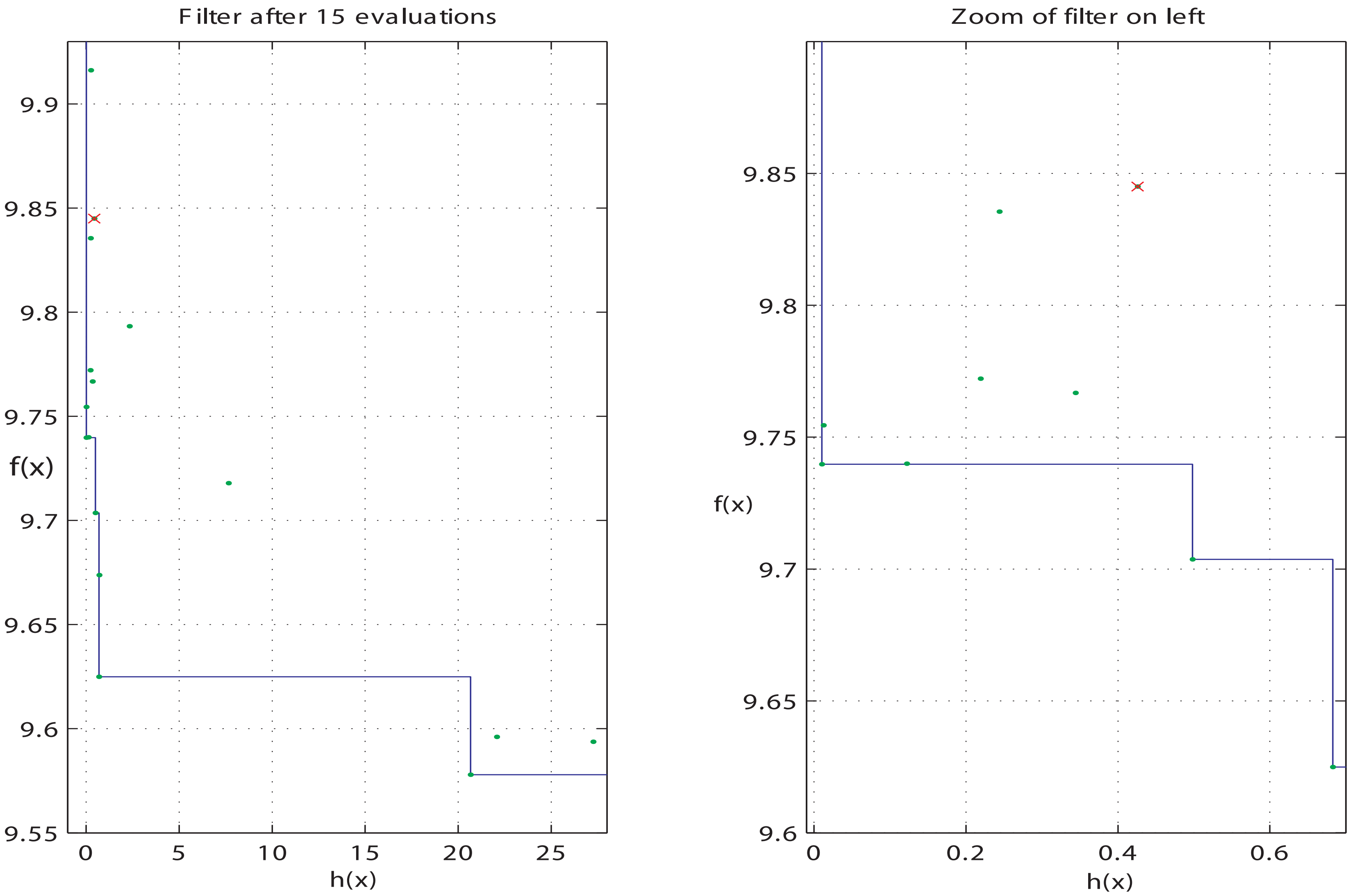
Infeasible baseline design.

	n	# of ctrs	# of fevals
A	15	11	304
B	15	11	292



New Boeing SonicCruiser planform

A planform filter



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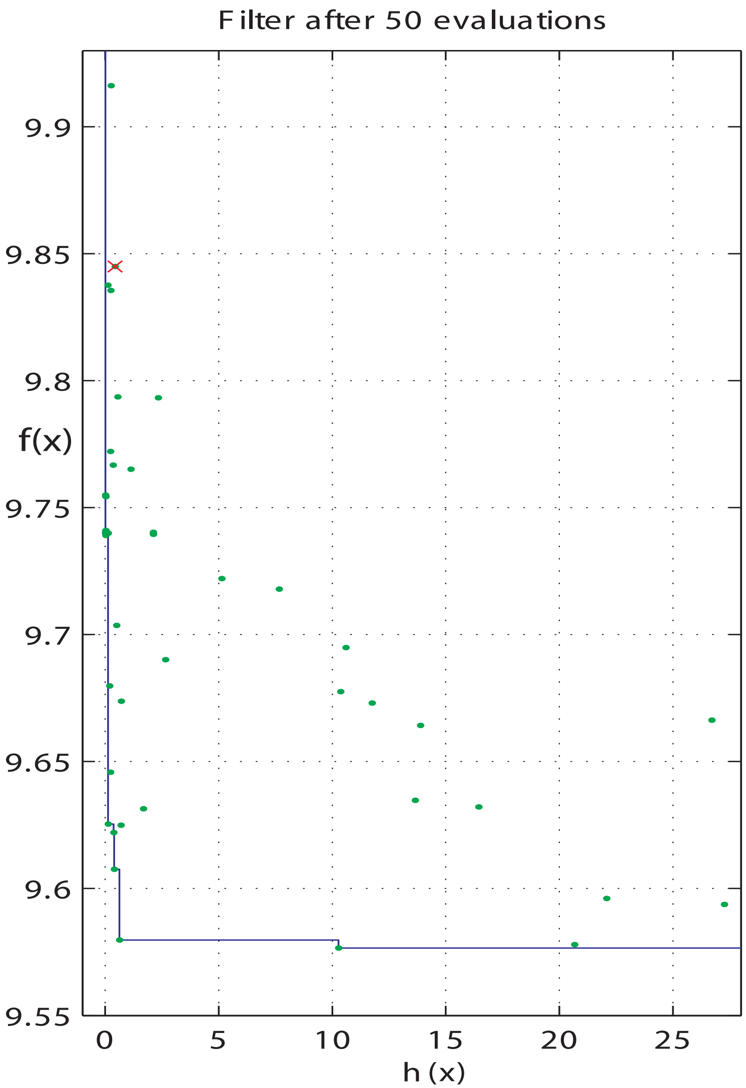

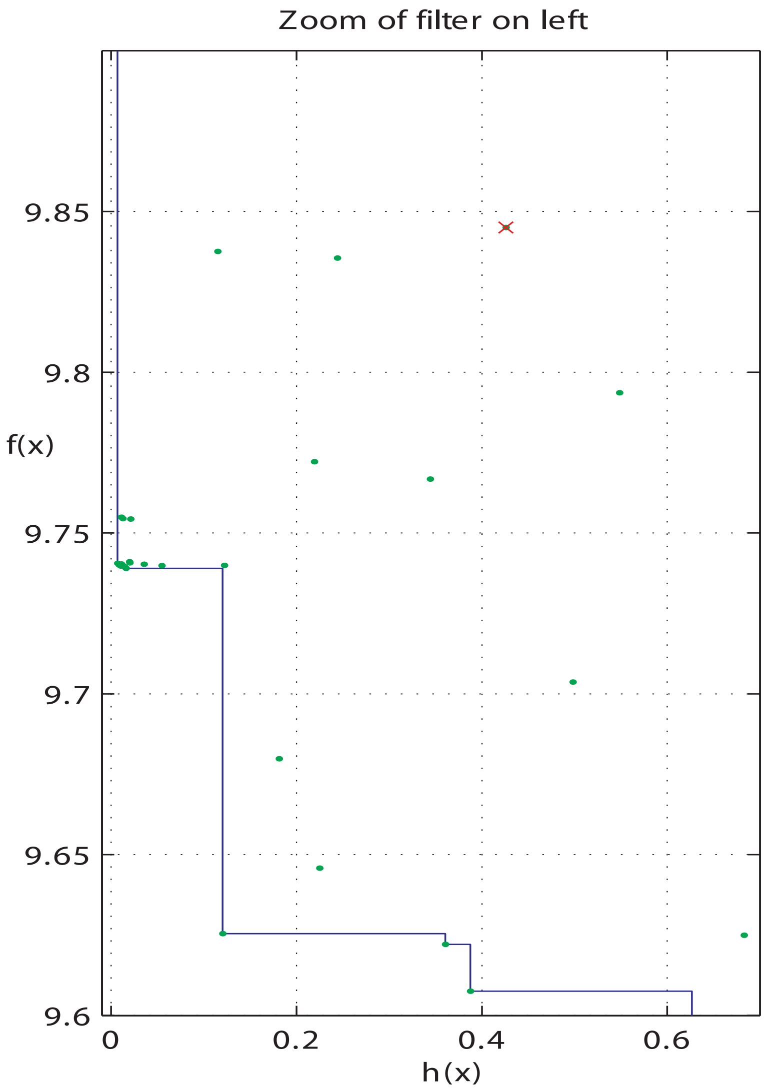

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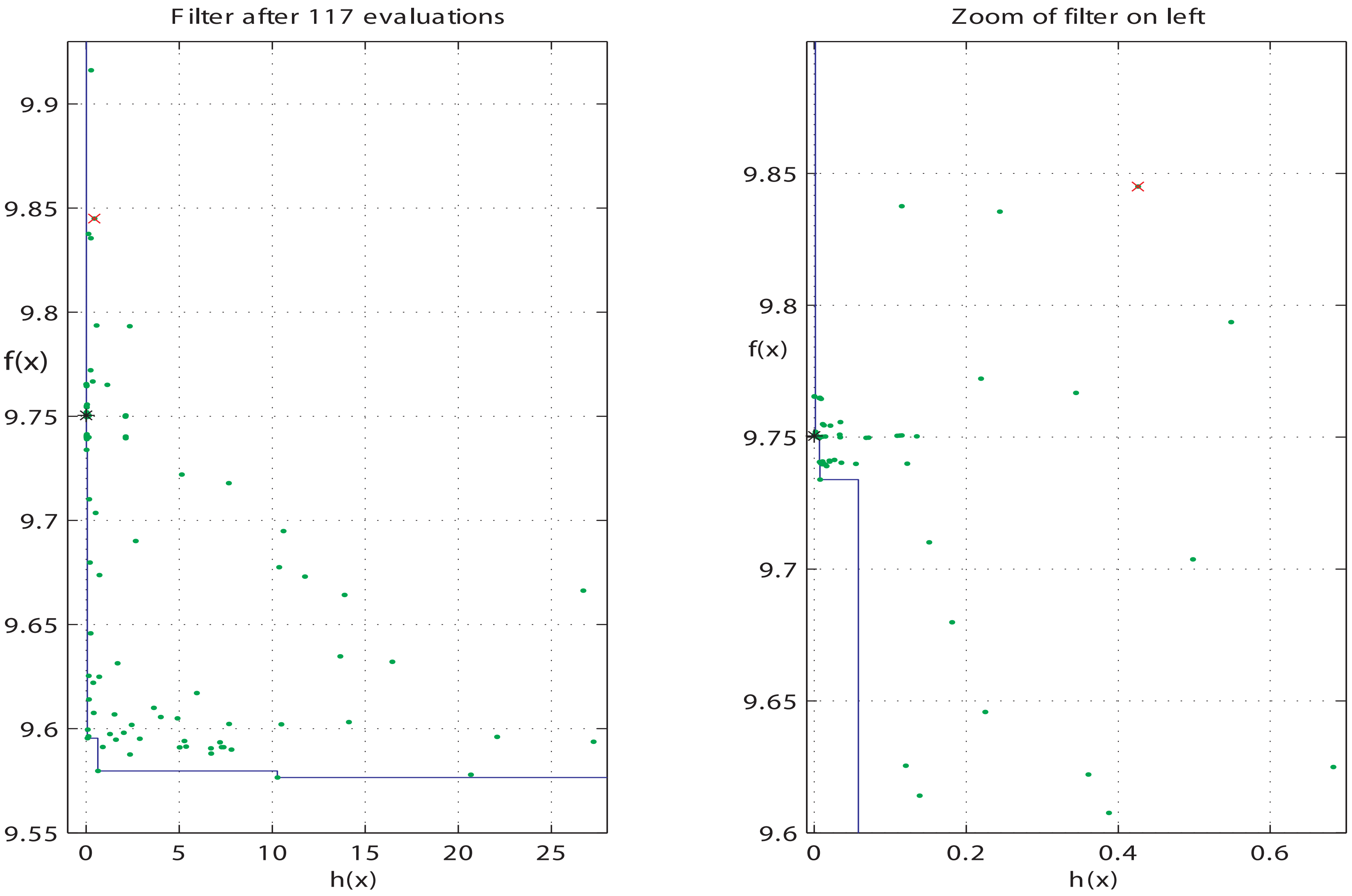
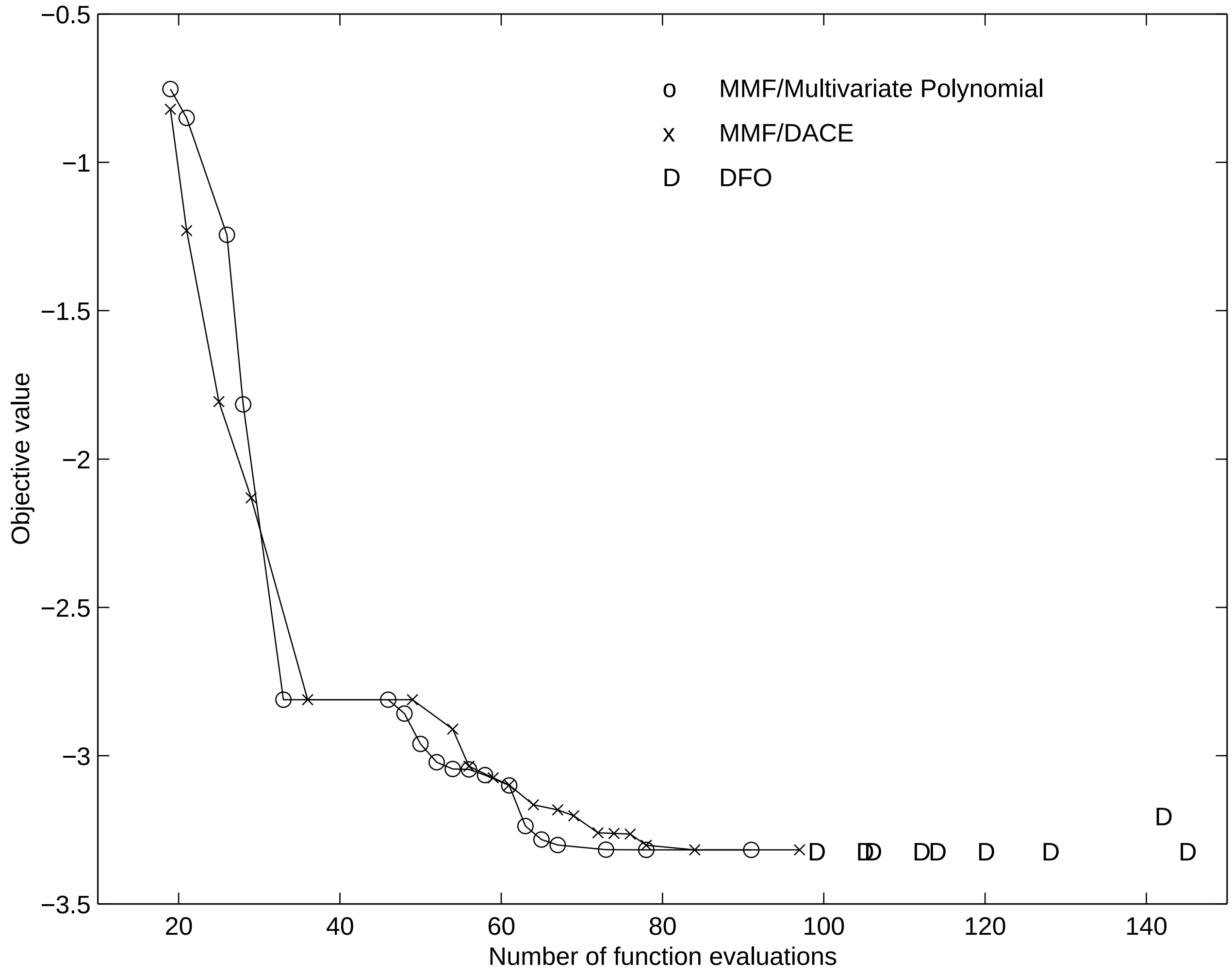
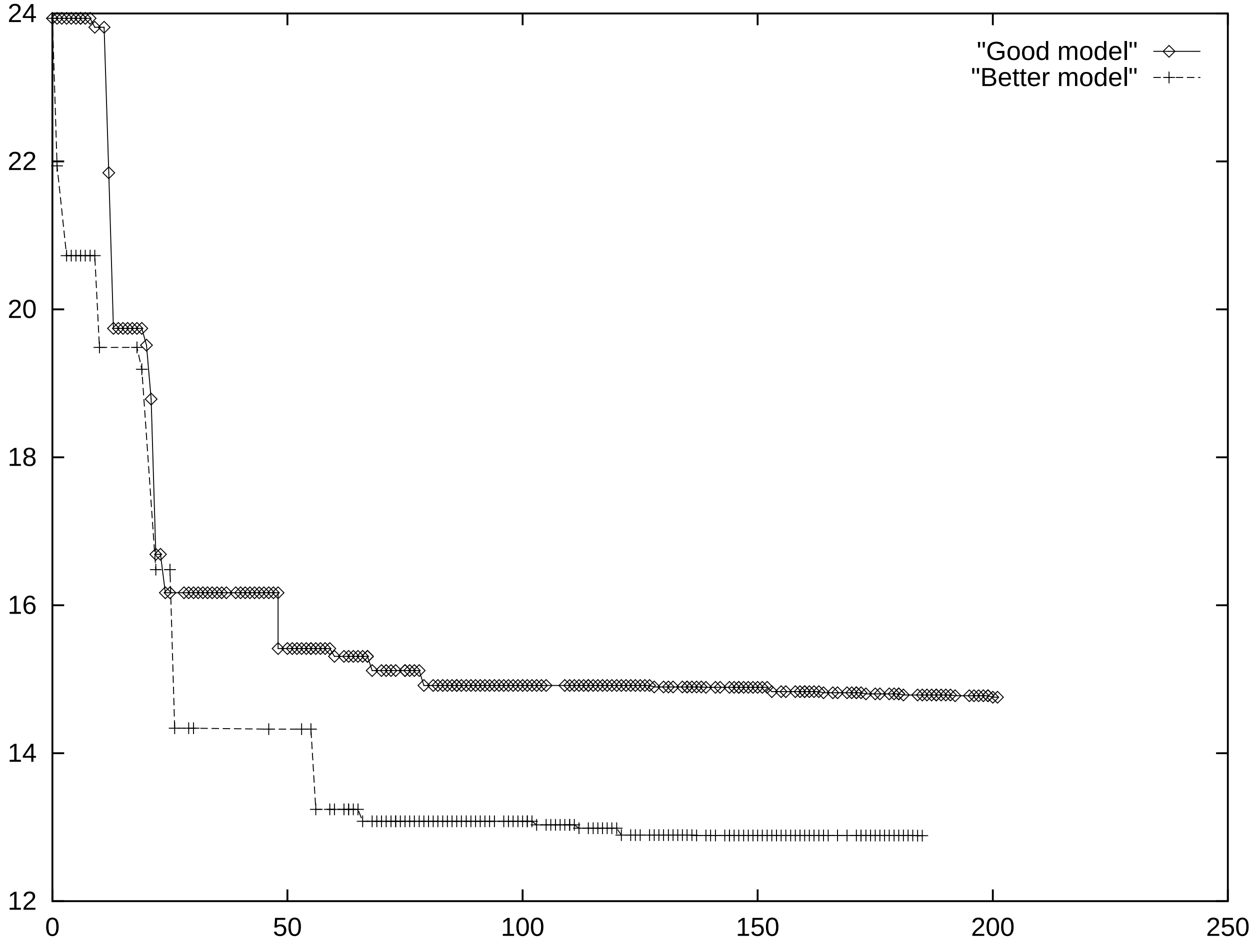


Polynomial vs DACE surrogates



Recovering from a bad surrogate



Software

- A simplified algorithm with local steps only is used 100k times each day in Boeing's commercialized 2NA parts nesting software

- Design Explorer is a Boeing proprietary implementation of our SMF with proprietary surrogates and a specialized search. Commercialization is underway

NOMAD

- Current NOMAD C++ implements the filter approach. Presently in production use at ExxonMobil. Available to beta users

- NOMADm is a downloadable MatLab implementation in production use at Seimens VDO for designing engine control laws

- Should handle uncertainty optimization models

Conclusions

- Clarke's nonsmooth analysis tools simplify, shorten, and strengthen the pattern search analysis
- Filters handle nonlinear constraints without using derivatives, Lagrange multipliers or penalty parameters
- SMF seamlessly incorporates user heuristic SEARCHES, and POLLING provides robustness and rigor
- SMF needs less accurate surrogates than designers want anyway

Plans

- Boeing and ExxonMobil want more design variables than present interpolatory surrogates can handle. Requires rethinking the surrogate/optimization interface. High payoff, high risk, high entertainment value

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- Put filter approach to categorical variables from NOMADm into NOMAD and test on pipe bending problems. Open ended, high entertainment value

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- Use NOMAD or Design Explorer to investigate various uncertainty formulations and explore tighter integration

Recommendations

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- Don't change the problem to fit the mathematics you know, develop the mathematics the problem needs

Finally

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Don't expect support up front. Remember, even meeting with you to formulate a joint project is support.