Aerodynamic Design Optimization with Evolutionary Algorithms

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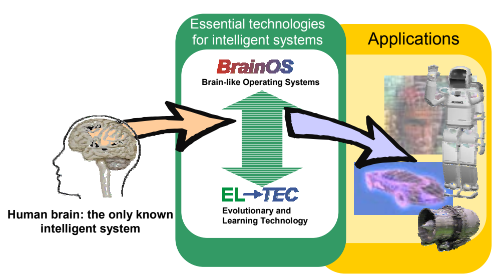
Outline of the Talk

- Introduction to Honda Research Institute
- Evolutionary Algorithms and Evolution Strategies
- Blade Optimization Using Evolution Strategies
  - 2D Shape representation
  - Problem coding
  - Quality criteria
  - Performance validation
  - Computing environments
  - Extension to 3D
- Major Theoretic Issues in Evolutionary Design Optimization
  - Adaptive representation and dynamic optimization
  - Use of meta-model for fast evaluations
  - Multi-objectivity in design optimization
  - Search for robust solutions

Honda Research Institute Europe

Principles of Biological Information Processing

- From theory to technology
- From analysis to applications
- Neural information processing models
- Evolutionary optimization of complex systems



Honda Research Network

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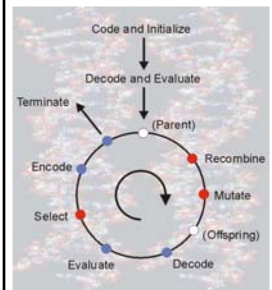
→ A diversity of

culture **competence** **expertise**

→ that produces high creativity

Evolution Strategies

Basics of Evolutionary Algorithms



- Evolution strategies:
  - real-valued coding
  - mutation as the primary variation operator
  - deterministic selection
  - self-adaptation
- Genetic algorithms:
  - binary / Gray coding
  - crossover believed to be the primary variation operator
  - stochastic selection

Evolution Strategies – Main Operators

- Mutation: add a random number drawn from a Gaussian distribution to the object parameter
- Recombination can also be used
  - discrete (parent-centric)
  - intermediate
  - multi-parent recombination (population-centric)
- Deterministic selection
  - Elitism: $(\mu + \lambda)$ selection
  - Non-elitism: (μ , λ) selection

Evolution Strategies – Self-Adaptation

Principle of self-adaptation

→ The variances σ_i^2 will evolved to adapt themselves to the fitness landscape

$$\boxed{\sigma_i(t) \;=\; \sigma_i(t-1)\exp(\tau' z)\;\exp(\tau z_i)}$$
$$\mathbf{x}(t) \;=\; \mathbf{x}(t-1) + \tilde{\mathbf{z}}$$
$$z_i, z \;\sim\; N(0,1)$$
$$\tilde{\mathbf{z}} \;\sim\; N(\mathbf{0}, \tilde{\sigma}(t)^2).$$

Different methods for adaptation of the search distribution:
- Generating set adaptation
- Rotation matrix adaptation
- Covariance matrix adaptation

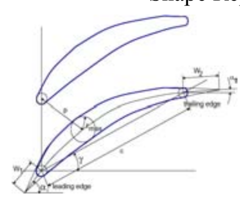
Advantages of Evolutionary Design

- In comparison of engineering approaches:
  - ➢ less constraints on search space
  - ➢ less constraints from engineering heuristics
- In comparison to traditional optimization techniques
  - ➢ no need of derivative information
  - ➢ population-based search
    - ❖ less sensitive to initialization
    - ❖ suited for parallelization
    - ❖ suited for multi-objective optimization
  - ➢ stochastic global search
  - ➢ need large number of performance evaluations

Evolutionary Blade Optimization

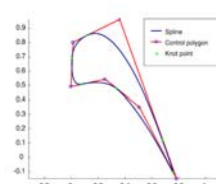
Design Optimization of Turbine Blade

Shape Representation



Parameterized representation

- Smaller number of parameters, lower search space
- Lower flexibility, less room for performance improvement

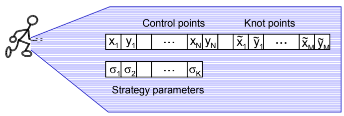


Non-uniform rational B-splines (NURBS)

- Larger number of parameters, higher flexibility, more room for “creative” design
- higher-dimensional search space

Problem Coding

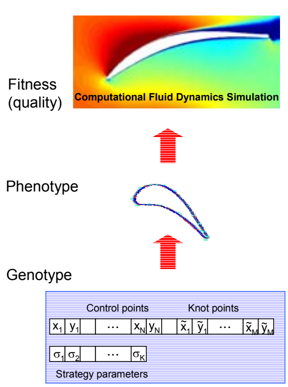
- Coordinates of the control points and knot points are coded in the first chromosome
- All strategy parameters, I.e., the standard deviation of the Gaussian distributions are coded in the second chromosome



General Design Criteria

- Aerodynamic
  - pressure loss
  - outflow angle
- Mechanical Integrity
  - stresses
  - eigen frequency
- Geometrical constraints
  - smoothness of the blade

Fitness Evaluations



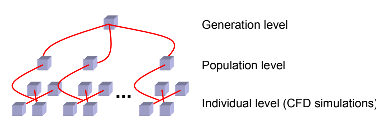
$f(x) = \eta_1 f_1(\omega) + \eta_2 f_2(\alpha_2) + \eta_3 f_3(x)$

- $f_1(\omega)$: pressure loss
- $f_2(\alpha_2)$: deviation of the outflow angle
- $f_3(x)$: mechanical constraints

Computing Environments

- PC clusters using Linux operation system of 152 knots
- Parallelization supported by PVM and MPI

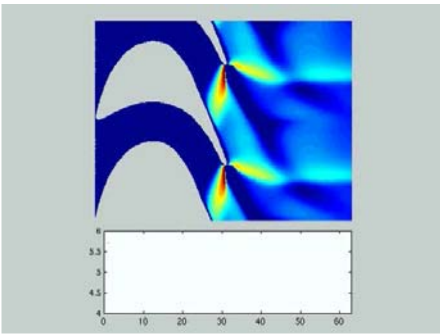
Master-slave architecture



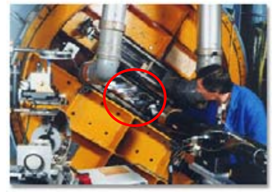
- Stability of the system (computing time of 3-4 weeks) is critical
- Maximal use of computing resource through grid computing techniques

Minimization of Pressure Loss – A Demo

Change of the flow dynamics during the optimization

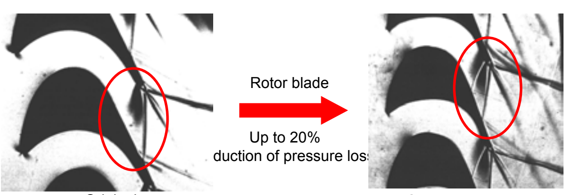


Performance Validation



- Validation through wind tunnel experiment
- No engineer will accept a design that cannot be explained properly
- A creative design can lead to new theoretical developments

2D Optimization Results



Original Optimized

(Schlieren photo taken in wind tunnel by DLR Göttingen)

Major Theoretic Issues in Evolutionary Design Optimization

Adaptive Representation (I)

Trade-off between flexibility and search efficiency exists in non-parameterized representation:

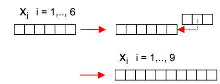
- The larger the number of parameters, the higher the capability to represent complex shapes
- A large number of free parameters results in a higher search space, which makes it difficult for an optimizer to find a good solution

started with 3 control points

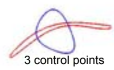
started with 10 control points

Adaptive Representation (II)

- Solution:
  Change (increase/decrease) number of parameters during optimization
- Implementation:
  Mutation of the coding structure



adaptive representation for design optimisation



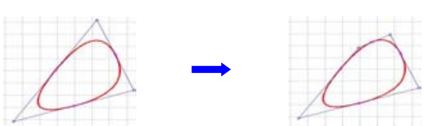
3 control points (initial)

starting with 10 points

final solution (10 points)

Adaptive Representation (III)

- Problem: Mutation of representation result in strong change in the phenotype and thus the fitness landscape, which is a typical dynamic optimization problems
  - ➢ could cause problem for self-adaptation
- Solution: neutral mutation
  - ➢ After insertion of new points, corresponding strategy parameters need to be initialized and included in the second chromosome too

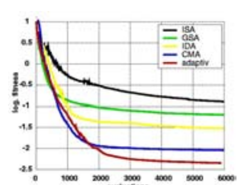


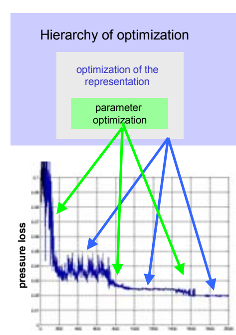
- Neutral mutation establishes a strong correlation between the current and new optima, which makes the search more efficient

Adaptive Representation (IV)

Comparison of different evolution strategies

- ISA
- Generative set adaptation (GSA)
- Covariance matrix adaptation (CMA)
- Adaptive representation



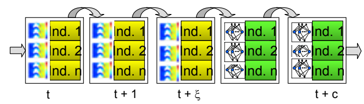


Use of Meta-models (I)

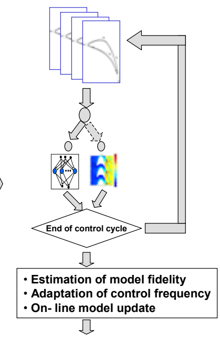
- Evolutionary algorithms need a large number of evaluations
- In aerodynamic design optimization, one singe evaluation using CFD simulation takes minutes to hours
- Meta-models can assist evolutionary algorithms to achieve a good solution in a shorter period of time
- Meta-models can also smoothen a rugged fitness landscape
- Polynomials (response surface methods), neural networks, Gaussian processes (Kriging) etc can serve as efficient models for approximating fitness landscape

Use of Meta-models (II)

- Generation-based model management
  - the meta-model is used together with the time-consuming CFD simulation
  - within a generation, only CFD simulation or meta-model will be used



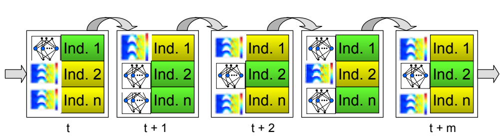
Frequency adaptation



Use of Meta-models (III)

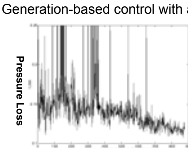
Individual-based model management

- CFD simulations and met-models are used together within a generation
- Different strategies can be used to "control" the evolution
  - choose individuals randomly
  - choose the best individuals according to the model
  - choose the individuals with most uncertain fitness estimation (exploration)

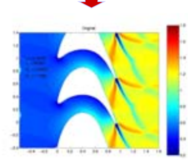


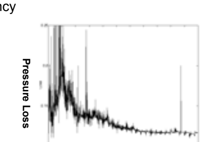
Use of Meta-models (IV)

- Evolution strategy
- Neural network as meta-model
- Generation-based control with adaptive frequency

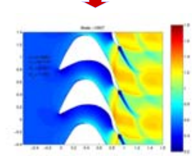


CFD evaluations



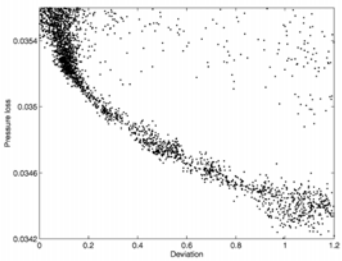


CFD + NN evaluations



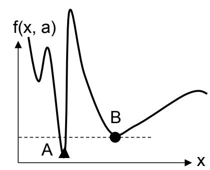
Multi-Objectivity in Blade Design

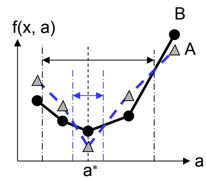
- Blade optimization is a multi-objective problem. The objectives are weighted aggregated in the previous designs
- The weights needs to be given beforehand and the objectives are could be conflicting



Search for Robust Solutions (I)

- Noise is unavoidable for many processes. In this case, noise must be taken into account in optimization
  - Robust to variations in design parameters (x)
  - Robust to variations in environmental parameters (a)





Search for Robust Solutions (II)

Search for robust solutions based on expected fitness function

- Averaging based approach:

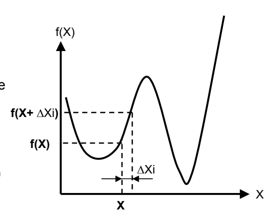
$$f(x) = \sum_i f(x+\Delta x_i),\ \Delta x_i \sim N(0,\sigma^2)$$

  - Need additional fitness evaluations
  - Use of approximate models could alleviate this difficulty

- Perturbation based approach:

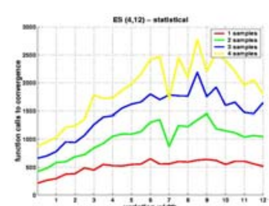
$$f(x) = f(x+ \Delta x(t)),\ \Delta x(t) \sim N(0,\sigma^2)$$

  - Approximation can be proved under the assumption of an infinite population size
  - No additional fitness evaluations needed



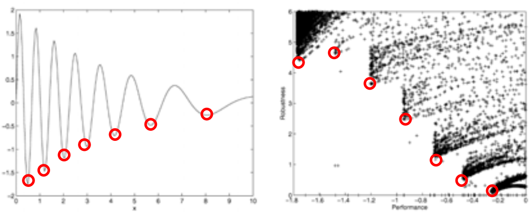
Search for Robust Solutions (III)

- In averaging based Two parameters need to be chosen:
  - number of averaging
  - the variation of the introduced noise
- Comparison of averaging and perturbation based approaches on a test problem by adding a uniformly distributed noise within a given variation width



Search for Robust Solutions (V)

- In averaging.based approach, many additional fitness evaluation is needed. To address alleviate this problem as much as possible, meta-model can be used
- Search for robust solutions turns out often a multi-objective problem



Partners & Activities

Partners

- Priv.Doz. Dr. H.-G. Beyer, University Dortmund, D
- Prof. Dr. C. Igel, Ruhr-University Bochum, D
- Prof. Dr. X. Yao, University Birmingham, UK
- Prof. Dr. Th. Bäck, Leiden University, NL, NuTech Solutions GmbH
- Prof. Dr. Schmeck, Dr. J. Branke, University of Karlsruhe, D
- Dr. Y.-S. Ong, Nanyang Technological University, Singapore

Activities

- involved in the organization of international conferences
- organization of special sessions and workshops at conference
- Lecture at Technical University of Darmstadt *Evolutionary Systems: From Biology to Technology*

Publications 2003

[1] Michael Hüsken, Yaochu Jin, and Bernhard Sendhoff. Structure optimization of neural networks for evolutionary design optimization. *Soft Computing Journal*, 2003. Accepted.

[2] Yaochu Jin. *Advanced Fuzzy Systems Design and Applications*. Physica/Springer, Heidelberg, January 2003.

[3] Yaochu Jin, Michael Hüsken, and Bernhard Sendhoff. Quality measures for approximate models in evolutionary computation. In Alwyn Barry, editor, *2003 Genetic and Evolutionary Computation Conference: Workshop Program*, pages 170-173, Chicago, July 2003.

[4] Yaochu Jin, Tatsuya Okabe, and Bernhard Sendhoff. Solving three objective optimization problems using evolutionary dynamic weighted aggregation: Results and analysis. In *Proceedings of the Genetic and Evolutionary Computation Conference*, LNCS, pages 636-637, Berlin, 2003. Springer.

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[12] Lars Willmes, Thomas Bäck, Yaochu Jin, and Bernhard Sendhoff. Comparing neural networks and kriging for fitness [illegible] omputation. In *Proceedings of IEEE Congress on Evolutionary Computation*. IEEE Press, 2003.

[13] Hans-Georg Beyer, Markus Olhofer, Bernhard Sendhoff. On the impact of systematic noise on the evolutionary op [illegible] a sphere model analysis. *Journal of Genetic Programming and Evolvable Machines*, 2003.

[14] Wei-Wei Chang, Chang-Jin Chung and Bernhard Sendhoff. Target Shape Design Optimization with Evolutionary Computation. In *Proceedings of IEEE Congress on Evolutionary Computation (CEC-2003)*. IEEE Press, 2003.

[15] Bernhard Sendhoff, Hans-Georg Beyer and Markus Olhofer. The influence of stochastic quality functions on evolutionary search. In K.C: Tan, et al. (Eds), *Recent Advances in Simulated Learning and Evolution 2003*, World Scientific. In print.

15 Publications in International Conferences and Journals

1 Book

3 Patents

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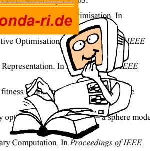

Summary and Conclusion

- Evolutionary algorithms have shown to be very promising in aerodynamic design
- Evolutionary aerodynamic design not only produced "creative" designs, but also helped to gain more understandings in flow dynamics
- Many interesting theoretic issues arise in evolutionary aerodynamic design, which need further investigations
- Theoretic work in evolutionary computation should pay more attention to real-world applications