Structuring the Space of Opportunities

Representations in Evolutionary Design Optimization

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Cooperative Intelligence

Artificial intelligence is the ability to use optimally limited resources – including time – to achieve goals in complex environments.


Cooperative Intelligence is Artificial Intelligence embedded in a Social Context.
Agenda

- HRI Overview
- Examples for applications of evolutionary design optimization
  - Energy management optimization
  - Engineering design optimization
- Representations
  - Shape deformations
  - Shape morphing: Comparison of different shape deformation methods
  - Shape morphing: Evolvability for set-up of control volumes
  - Multi-objective optimization for exploration vs. exploitation
- Summary and Outlook
EC Applications – Energy Management Optimization
Many Objective Optimization for Building Energy Systems
provided by Dr. Tobias Rodemann, HRI-EU

Optimization of investment into new devices (battery, Photo-Voltaic, heat storage...):
Minimum investment costs, annual costs, CO2 emissions and maximum resilience (emergency power supply), battery lifetime [10 design parameters, 5 objectives]

Scientific Question and Approach
- Handling of large variations in objective values (10^1-10^6) → Desirabilities
- Large number of potential MOEA algorithms (>100) → Performance comparison
- Visualization of solutions and comparison to baseline → Parallel coordinate plot, histograms

![Diagram of optimization process](image-url)
Comparing best found solutions

Boxplot of 10 well-known MOEAs (10 runs each)

Baseline solution is dominated

Identify reasonable values

IBEA, PICEAg & Two_Arch2 performed best

Annual cost and emissions are strongly correlated

References:
Dynamic Pricing for EV Charging Considering Fairness


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Application

- Controlled charging to increase profit of operators of public charging stations
- Increase flexibility provided by customers through dynamic pricing
  → Deadline differentiated pricing

Scientific Question and Approach

- Issue: Dynamic prices might be perceived as unfair with negative consequences for the charging station operator
  → Investigated setting: Optimization of price offers considering the operator’s profit and price fairness
- Unfairness: unfair\text{day} - Customers with similar arrival times and similar energy requirements should get similar price offers (per kWh)

- Optimization of price offers in each interval w/ evolutionary algorithms
  - Approximation of expected profit via Monte Carlo simulation since exact preferences of customers not known
  - Single-objective optimization via self-developed EA
  - Multi-objective optimization via NSGA-II

- Experimental evaluation w/ different variances $\delta_P$ (0-3) in electricity prices
Experimental Results

• Results single-objective only w.r.t. expected profit:
  ➢ High unfairness, increasing with increasing variance in operating costs

• Results single-obj. with constraint of $\text{unfair}^{\text{day}} = 0$:
  ➢ High reduction of profit

• Results multi-obj. with choosing solutions with highest profit from Pareto fronts
  ➢ Significantly reduces unfairness without impact on profit

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EC Applications – Engineering Design Optimization
**Common Principles**

- **regularity**
  no solutions should be favoured solely by the representation

- **strong causality**
  the variation induced neighbourhood relation in both spaces should be conserved under the genotype – phenotype mapping

- **completeness**
  all feasible solutions should be reachable with the representation

*High-quality shape representations strongly influence the success of optimizations*
Representations: Shape Morphing

- **Free-form deformation (FFD)**
- **Cage deformation**
- **Space deformation (RBF)**
- **Shell based deformation**
Background

- GE Honda develops turbofan engine HF120 for HondaJet
- Many components need to be optimized during design process
  - Improve aerodynamic efficiency of fan blade
- Accurate CFD simulations with realistic conditions are very resource consuming

Problems

- Only few optimization runs can be done
  - How representative/reproducible are obtained results
- What representation for geometry changes?
  - Number of parameters
    - Expected tradeoff between achievable efficiency and number of parameters:
      - More parameters ⇔ higher flexibility ⇔ potentially better improvement ⇔ but more evaluations necessary: true?!?
- Which optimization algorithm?

Target

- Get better understanding of fitness landscape for real-world turbo-fan optimization problem
- How much variation exists when running same or similar optimizations multiple times:
  - in performance (efficiency)? in actual design/geometry?
CFD Simulation setup
• Flow in fan rotor passage
  • Trans-sonic compressible flow
  • OpenFOAM setup (~ 96 cpu-hours for one evaluation)
  • Cruise operating condition (rpm, mass flow rate)

Optimization setup
• Fitness function (minimized)
  \[ f = 1 - \frac{\eta_{cruise}}{\eta_{base,cruise}} + \text{Penalties} \]
  Penalty term ensures converged flow

Blade deformation representation
• Three deformable sections: hub, mid-span, shroud
  (other sections are interpolated)
• Deform sections with Hicks-Henne shape functions
• Also move and rotate sections
• Number of shape functions per section \( N_{HH/\text{section}} \in [3,12] \)
  \[ \Rightarrow \text{Dimensionality of representation:} \]
  \[ D = 3 \left( N_{HH/\text{section}} + 3 \right) \in [18,45] \]
Influence of optimization algorithm
- More explorative search in PSO: step-size and initialization
- Similar efficiency improvements
  - PSO: $\Delta \eta_{\text{rel}} = 3.42\%$
  - CMA-ES: $\Delta \eta_{\text{rel}} = 3.45\%$
- Geometries: qualitative differences in aerodynamically sensitive regions

Influence of random initialization
- Similar efficiencies
  - Seed 1: $\Delta \eta_{\text{rel}} = 3.97\%$, Seed 2: $\Delta \eta_{\text{rel}} = 3.91\%$
  - Seed 3: $\Delta \eta_{\text{rel}} = 4.05\%$
- Geometries: qualitative differences in aerodynamically sensitive regions

Influence of dimensionality of representation
- No clear trend in optimization progress
- No clear trend for achievable efficiency improvement
- Geometries: qualitative differences in aerodynamically sensitive regions

Conclusions
- All the tested variants achieve comparable improvements
- Optimized geometries showed substantial variation over the complete blade geometry
- Even minor changes lead to very different geometries
- Fitness landscape is highly multi-modal with many local minima and small basins of attractions
Representations – Shape Morphing
**Shape Morphing - Challenges**

**Shape Morphing**
- Operation to transform an initial design to a deformed design
- Mapping of discretized surface by spline functions or RBF kernels (i.e. many surface points are reduced to a lower number of parameters)
- For EC: Optimal trade-off needs to be found for minimum parameters with maximal shape flexibility
- For EC: Shape morphing allows online adaptation of parameter number for more local deformations
- [For CFD/FE simulations: simultaneous deformation of design and numerical grid]

**2-level Challenge**
- Higher level: Comparison of different deformation types
- Lower level: Optimal number and distribution of initial control points or RBF kernels

→ „The Value of Evolvability“
Potential Definitions

- Evolvability is an evolved quality and is specified as the ability of the configuration space (in this case, the space of genotypes and phenotypes) to produce an endless supply of viable configurations with remarkably few obvious dead-ends

- Evolvability is considered in the sense of the capacity of a system to produce favorable phenotypic variations of a design within a moderate number of generations while avoiding non-feasible mutations

- Produce favorable solutions → Performance increase
- Moderate number of generations → Time
- Avoid non-feasible mutations → Search space and direction
Comparison of Deformation Types

**Computational Performance**

![Computational Performance Chart](chart.png)

**Quality**

- **DMFFD**
  - mesh smoothness based on mean curvature visualizations
- **RBF**
  - aliasing artifacts

**Adaptivity**

![Adaptivity Graph](graph.png)

**Mesh Quality**

- **RBF**
  - Quality
- **DM-FFD**
  - Quality

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Comparison of Deformation Types

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Mesh Quality (cont.)  OpenFOAM CFD solver mesh check

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Summary

“Evolvability perspective”

- RBF deformations comprise the highest potential to successfully generate valid designs within the mutation step of an evolutionary design optimization
- FFD is a recommended method if fast and simple conceptual design exploration should be robustly achieved
**Engineering Design Optimization**

- Initial deformation set-up: minimum parameter number w/ max. flexibility
- Initial deformation set-up: strong influence on search efficiency

**Challenges**

- Human set-up: time consuming process, typically shape feature based (less surprising)
- Development of computational set-up method which integrates historic data

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**Initial idea and early experiments**

- Simplified FFD control volume

![Control volume diagram](image)

Modify CP1 and CP2 and count the number of unmodified POI

**Experimental results (Evolutionary target matching optimization)**

Control volumes w/ higher evolvability converge faster; better fitness after fixed number of iterations

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Optimal Deformation Set-Up

**Generalization**

- Linear Deformation Representations: \( M' = M + U_p \)
- Deformation Matrix: \( U \)

A Computational Method for Deformation Set-up

- Multi-objective optimization for “Variability” (Infill distance) and “Improvement potential” (gradient information): Exploration vs. exploitation
- Gradient information options:
  - Initial information based on shape information (human heuristics)
  - Initial information based on existing historic data
  - Online adaptation of set-up while gathering information during optimization

- Optimal convergence speed: “Regularity” by orthogonalization

**Regularity**
- Defined as condition number of deformation matrix
- Force $R = 1$ by orthogonalization

\[ R(M) = 1 \]
\[ \kappa^{-1}(M) = \frac{\sigma_{\text{min}}}{\sigma_{\text{max}}} = 1 \]
\[ \sigma_{\text{min}} = \sigma_1 = \cdots = \sigma_n = \sigma_{\text{max}} = 1 \]

**Example: Evolutionary Face Matching Optimization**
- Uniform set-up: fast but worse fitness
- Adapted set-up: slow but better fitness
- Adapted + orthogonal: fast and good fitness!

- Orthogonalization speeds up convergence
- Disadvantage: Unintuitive for a human-based opt.
Summary and Outlook
Summary

• Evolvability criteria provide potential characteristics for developing computational methods to find optimal representations
• Optimal representations allow efficient evolutionary search
• Shape morphing methods:
  • High level comparisons favor RBF deformations for practical applications; FFD is promising for initial robust trials to learn about the shape and performance
  • Deformation set-ups can be computed using a multi-objective optimization for an optimal trade-off between exploration and exploitation
  • Orthogonalization of deformation matrix increases convergence speed

Outlook

• Evaluation of shape morphing set-up in aerodynamic optimization
• Evaluation of shape morphing set-up for Hicks-Henne splines
• Evaluation of shape morphing set-up in dynamic optimization problems using online learning
Thank you for your attention