Multi-Concept Optimization: Challenges and Opportunities

Rounak Saha Niloy

School of Engineering and Technology
University of New South Wales, Canberra
r.niloy@unsw.edu.au

Outline

Exploring New Horizon in Design Optimization

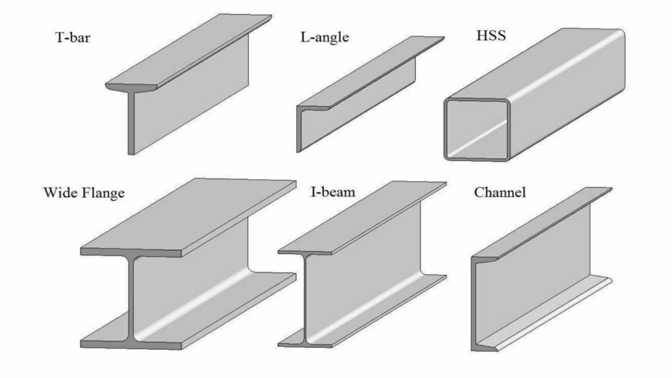


Figure: Optimization of a cantilever beam

Minimize

- Weight of beam
- Deflection at the free end

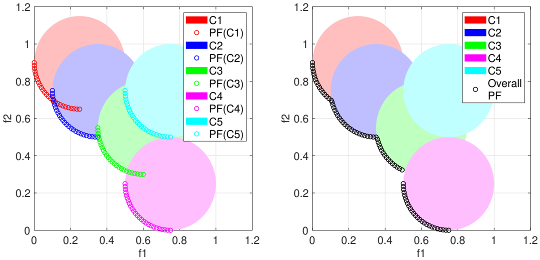
Exploring New Horizon in Design Optimization

- Traditional design optimization often limits itself to a single, pre-determined concept.
- This can miss out on innovative possibilities and lead to suboptimal solutions.
- Instead of fixing the cross-section, consider multiple options: *T-bar, L-angle, HSS, I-beam* and so on. Each shape represents a distinct concept, opening up a broader design space.

Introducing Multi-Concept Optimization (MCO)

- Concept selection is an inherent part of design optimization.
- Decisions made during the early phases of design, including concept selection and preliminary design, impact up to 70% of the overall product life-cycle costs [1], [2].
- MCO operates without the assumption of a pre-selected concept.
- It explores a set of concepts and their design space concurrently in order to identify the best concept and best design simultaneously [3].

Why MCO?



(a) (b)

Figure: (a) PF of individual concepts and (b) Overall PF for MCO problem.

Target of MCO:

- Not to achieve individual PF approximations (Fig. 2a).
- Focus on achieving an overall PF approximation across multiple concepts (Fig 2b).

Advantages of MCO:

- Uncovers a wider range of potential solutions
- Eliminates extensive individual iterations for each concept
- Saves computational resources

Existing MCO Algorithms

Sequential Non-evolutionary Approach [4]

- MOP reformulated as SOP with normal constraint approach
- Single-objective search conducted along multiple directions to find evenly distributed PF solutions
- Each concept's PF is sought independently
- PFs of different concepts plotted together

C_1-NSGA-II and C_2-NSGA-II [5]

- Solutions from different concepts are evolved simultaneously
- Customized operators e.g. *concept-based crowding sort*, *concept-based tournament selection*, *in-concept crossover*, *two regimes mutation* to undertake cross-comparison of solutions across multiple concepts

Existing MCO Algorithms

Cr1-NSGA-II [6]

- Uses adaptive concept-specific ε-domination to relax Pareto optimality
- Prevents premature elimination of marginally inferior concepts
- Identical search process as C_1-NSGA-II except for ε-domination ranking
- Performance depends on user-defined ε value

C-ε-MOEA [7]

- Introduced to address multi-modality in concept-based optimization
- Experimentally shown to outperform C_1-NSGA-II on multi-modal problems
- Significantly faster runtime compared to C_1-NSGA-II

Existing MCO Algorithms

Interactive Simultaneous Approaches in Multi-Concept Optimization

- Incorporate decision-maker (DM) preferences for specific concepts
- Avigad et al. [8]–[10]
  - Concept survival depends on estimated performance and DM preference
  - Solutions ranked using sorting, front-based sharing, and niching within concepts
  - Human preference incorporated through *human-machine fitness (HMF)*
- Avigad et al. [11]
  - Modified C_1-NSGA-II to IC-NSGA-II for interactive optimization
  - HMF replaces fitness for environmental selection and offspring generation

Existing MCO Algorithms

Multi-Concept Evolutionary Algorithm [12]

- Proposed three initial optimization strategies

Strategy 1	Equivalent to optimizing each concept sequentially
	Maintains a constant maximum number of function evaluations across all generations for each concept
Strategy 2	Allocates more computational resources to promising concepts at the expense of limiting resources for non-promising concepts
	Effectiveness impacted when the budget is repeatedly allocated to a concept with a reached PF

Existing MCO Algorithms

Multi-Concept Evolutionary Algorithm [12]

- Proposed three initial optimization strategies

Strategy 3	Allocates more computational resources to promising concepts at the expense of limiting resources for non-promising concepts (just like strategy 2)
	Monitors convergence of each concept at each generation using Inverted Generational Distance (IGD)
	If IGD difference is smaller than a user-defined threshold, allocates a minimum predefined number of evaluations to that concept in the next generation

Existing MCO Algorithms

Multi-Concept Evolutionary Algorithm [12] *(Contd.)*

- Proposed three initial optimization strategies
- Strategy 3 outperforms the other two strategies
- Strategies 1 and 2 yield fairly similar results in the bi-objective lattice structure optimization problem
- Strategy 3's performance may be influenced by the choice of the user-defined IGD difference threshold
- Two additional strategies involving approximation models were explored to expedite convergence

Challenges in MCO Algorithms

MCO can also be viewed as a union of several standard MOPs. Therefore, in addition to encountering challenges inherent in MOP algorithms, MCO algorithms confront specific issues related to:

- Allocating computational resources efficiently among different concepts
- Premature elimination of initially inferior performing concepts
- Achieving convergence for all concepts simultaneously is difficult, especially when some concepts converge faster than others
- Most of the existing studies are restricted to either a specific application case or a small set (often just 1-2) of simple benchmark test problems with little room to tune their difficulty
- They often involve user-defined parameters, and making incorrect choices can adversely affect the algorithm.

Limitations of Existing Test Problems[1]

- Problems are relatively straightforward with a small number of decision variables (usually 1-2).
- Constrained problems typically involve 1-2 constraints that are not highly nonlinear.
- PFs lack diversity and controllability in terms of shapes.
- Problems are not scalable in terms of the number of concepts, objective functions, decision variables and constraints.
- Most of the example problems with > 1 design variables have variable domains of identical magnitude.
- The magnitudes of trade-off ranges in each objective of existing test problems are often similar.

[1] R. S. Niloy, H. K. Singh, and T. Ray, "A brief review of multi-concept multi-objective optimization problems," in *IEEE Symposium Series on Computational Intelligence (SSCI)*, 2023, pp. 1511–1517.

Multi-Concept Multi-Objective Optimization Problems Suite[2]

- We proposed a general framework for generating multi-objective MCO test problems.
- The generator utilizes MOPs from existing well-known suites as concepts.
- The generator applies combination through scaling and translation to create problems with diverse features in terms of relative domination status between concepts, shapes of the PF, continuity, scale of objectives, etc.
- Leveraging the generator, we developed **Multi-Concept Multi-Objective Optimization Problems (MCMOP) Suite** having 25 bi-objective and 3 tri-objective problems.

[2] R. S. Niloy, H. K. Singh, and T. Ray, "A benchmark test suite for evolutionary multi-objective multi-concept optimization," *Swarm Evol. Comput.*, 2023. DOI: `10.1016/j.swevo.2023.101429`.

Premature Elimination of Concepts

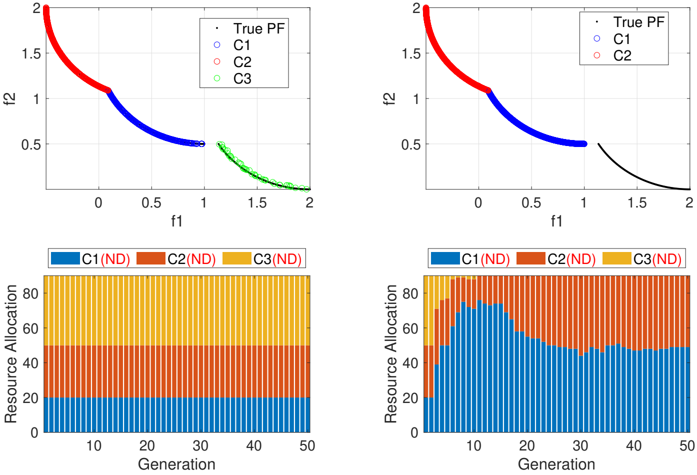
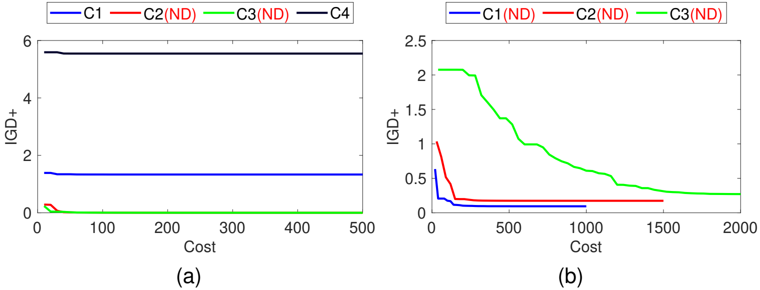


Figure: Premature elimination of nondominated C3 in ATP10: comparing overall PF (top) and concept-wise resource allocation (bottom) between sequential (left) and simultaneous (right) approaches.

Difficulty Level of Concepts



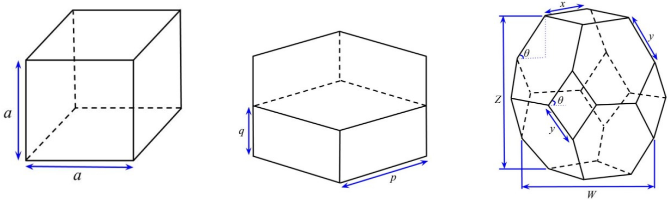
Problem Name	ATP 8	ATP 10
No. of Concepts	4	3
No. of Variables	1, 1, 1, 1	2, 3, 4

Figure: (a) Similar level of convergence difficulty among concepts of ATP8; (b) mixed level of convergence difficulty among concepts of ATP10.

Lattice Structure[3]

Objectives

- Minimize volume
- Minimize displacement
- Maximize surface area



(a) Cube (b) Hexagonal prism (c) Elongated tetrakaidecahedron

Figure: Three concepts for the unit cell of lattice structure

[3] B. Parker, H. K. Singh, and T. Ray, "Multi-objective optimization across multiple concepts: A case study on lattice structure design," in *Genetic and Evolutionary Computation Conference*, 2021, pp. 1035–1042. DOI: 10.1145/3449639.3459267.

Lattice Structure[4]

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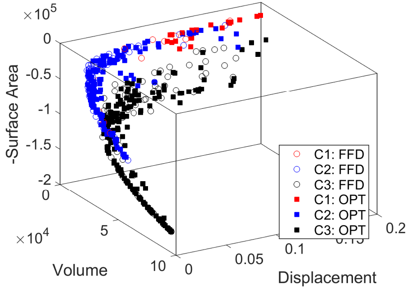

Figure: PF approximation of lattice structure design optimization problem

[4] B. Parker, H. K. Singh, and T. Ray, "Multi-objective optimization across multiple concepts: A case study on lattice structure design," in *Genetic and Evolutionary Computation Conference*, 2021, pp. 1035–1042. DOI: 10.1145/3449639.3459267.

Bicycle Derailleur[5]

Objectives

- Minimize mass
- Maximize actuation force
- Maximize safety factor

Initially, 28 derailleur configurations were assessed. Then, the four most promising configurations were further optimized.

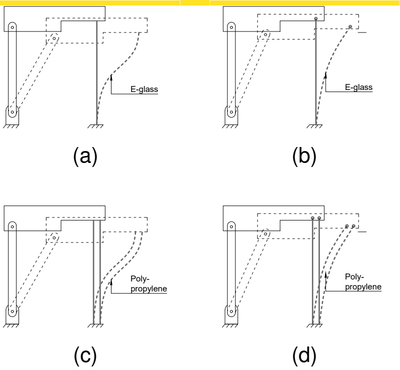

Figure: Four bicycle derailleur configurations

[5] C. A. Mattson, A. Mullur, and A. Messac, "Case studies in concept exploration and selection with s-Pareto frontiers," *Int. J. Prod. Dev.*, vol. 9, 2009. DOI: 10.1504/IJPD.2009.026173.

Bicycle Derailleur[6]

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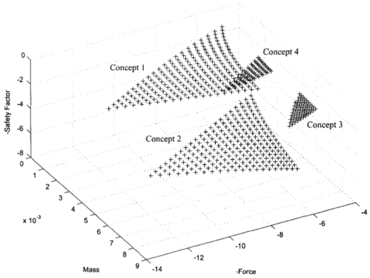

Figure: PF approximations of bicycle derailleur configurations

[6] C. A. Mattson, A. Mullur, and A. Messac, "Case studies in concept exploration and selection with s-Pareto frontiers," *Int. J. Prod. Dev.*, vol. 9, 2009. DOI: 10.1504/IJPD.2009.026173.

Battery Contact for Phone[7]

Objectives

- Maximize deflection
- Minimize bending stress

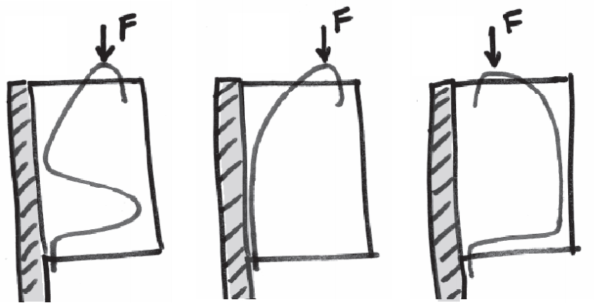

Figure: Conceptual sketches for three battery contact concepts

[7] C. A. Mattson, A. Mullur, and A. Messac, "Case studies in concept exploration and selection with s-Pareto frontiers," *Int. J. Prod. Dev.*, vol. 9, 2009. DOI: 10.1504/IJPD.2009.026173.

Battery Contact for Phone[8]

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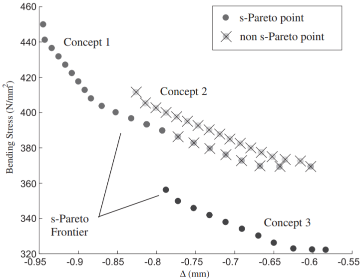


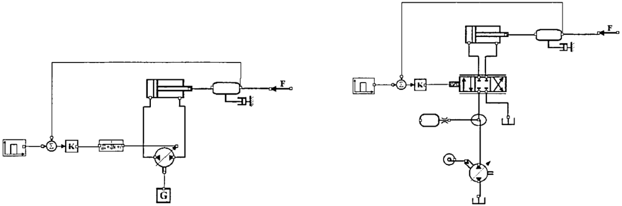
Figure: PF approximations of battery contact concepts

[8] C. A. Mattson, A. Mullur, and A. Messac, "Case studies in concept exploration and selection with s-Pareto frontiers," *Int. J. Prod. Dev.*, vol. 9, 2009. DOI: 10.1504/IJPD.2009.026173.

Hydraulic Actuation System Optimization[9]

Objectives

- Minimize control error
- Minimize energy consumption



(a) Servo pump (b) Servo valve

Figure: Two hydraulic actuation system concepts

[9] J. Andersson, P. Krus, and D. Wallace, "Multi-Objective Optimization of Hydraulic Actuation Systems," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, vol. 2, 2000, pp. 207–214. DOI: 10.1115/DETC2000/DAC-14512.

Hydraulic Actuation System Optimization[10]

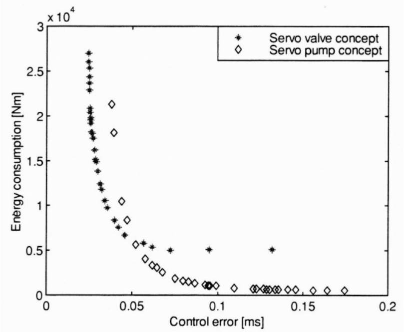


Figure: PF approximations of two hydraulic actuation system concepts

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Features of Real-World MCO Problems

- **Expensive to evaluate**
  - Complex simulations
  - Physical experiments
  - Computationally intensive models to evaluate the objective functions and/or constraints.

  Example: Rigidified inflatable structure [4], Lattice structure [12], Commuter aircraft [16]
- **Highly nonlinear and black-box constraints**
  Example: Rigidified inflatable structure [4]
- **Equality constraints**
  Example: Aegis UAV problem [17]

Future Works

- Development of benchmark problems.
- Development of efficient MCO algorithms.
    - Surrogate-assisted strategies
    - Machine learning techniques
    - Large-scale problems

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