Reference Point Based NSGA-III for Preferred Solutions

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Outline

- Motivation & Previous Work
- Proposed R-NSGA-III Algorithm
- Experimental Results
- Current & Future Work
- Conclusion

Motivation

Most EMO studies have concentrated on finding a representative set of the entire Pareto-optimal front and do not allow a DM to explicitly identify their preferred regions of interest.

1. Need a single preferred solution to implement in practice along with some knowledge of similar solutions.
    - Optimization process needs to be easier for a DM to understand, this is handled using reference point concept which has an intuitive meaning
2. Need an efficient preference-based optimization procedure that can be used to validate different parts of the trade-off frontier *i.e. gaps, holes.*

Previous Work: R-NSGA-II

- R-NSGA-II was proposed in 2006 and extended NSGA-II procedure
  - Allowed multiple preference conditions to be supplied simultaneously
  - Algorithm can be applied to any shape of pareto optimal frontier
  - For each reference point, solutions close to the provided point are target solutions

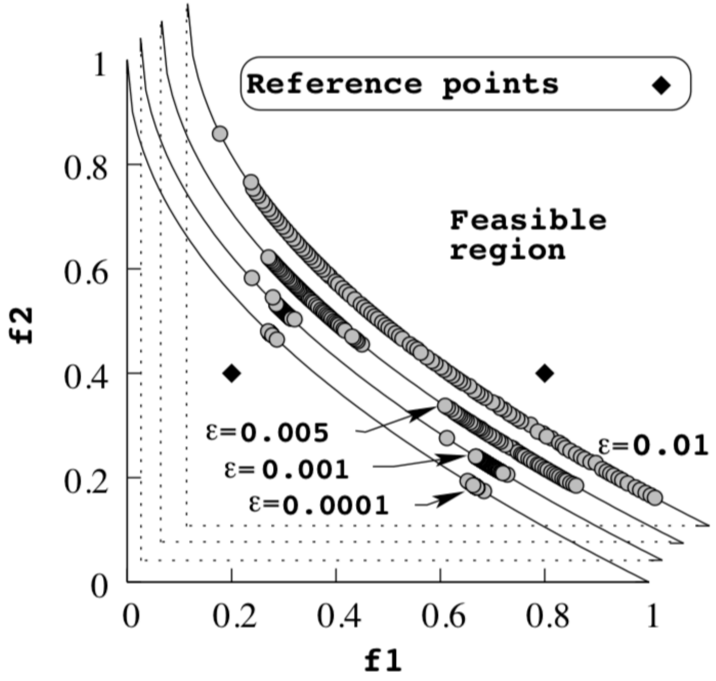
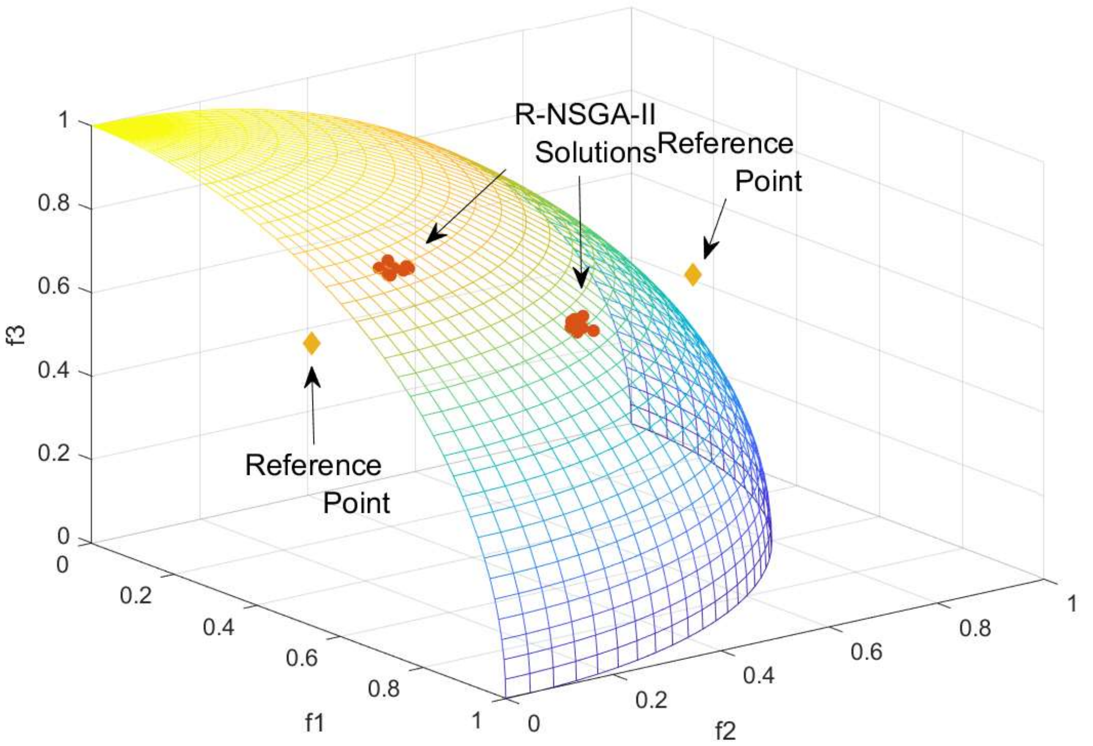


Figure. 2: Effect of ϵ in obtaining varying spread of preferred solutions on ZDT1.

Previous Work: R-NSGA-II

- Original study showed successful results in 2-3 dimensional problems and specific 5 and 10 dimensional problems
  - Outlier results may occur due to faulty normalization
- Solutions are not inherently structured - fails to find well distributed points



Design Principles

1. Algorithm should allow multiple preference regions to be targeted in a single run
2. Algorithm should be able to be used for any shape of pareto optimal frontier
3. Algorithm needs to be able to be used on many objective, large variable, and large constraint problems.
4. Algorithm should be computationally competitive with other state of the art algorithms.

Proposed R-NSGA-III : Reference NSGA-III

- The proposed R-NSGA-III extends NSGA-III for reference based optimization in higher dimensional problems
  - Here we modified the *Survival* operator in NSGA-III
- When no preference information is available DMs are expected to follow a two-step procedure:
  1. EMO algorithms should be applied first to find a representative set of Pareto-optimal points
  2. Then analyze representative points to focus on one or more regions of interest using reference based optimization

Proposed R-NSGA-III Algorithm

DM supplies aspiration points

Normalize aspiration points and current population

Calculate intercept with the unit hyperplane

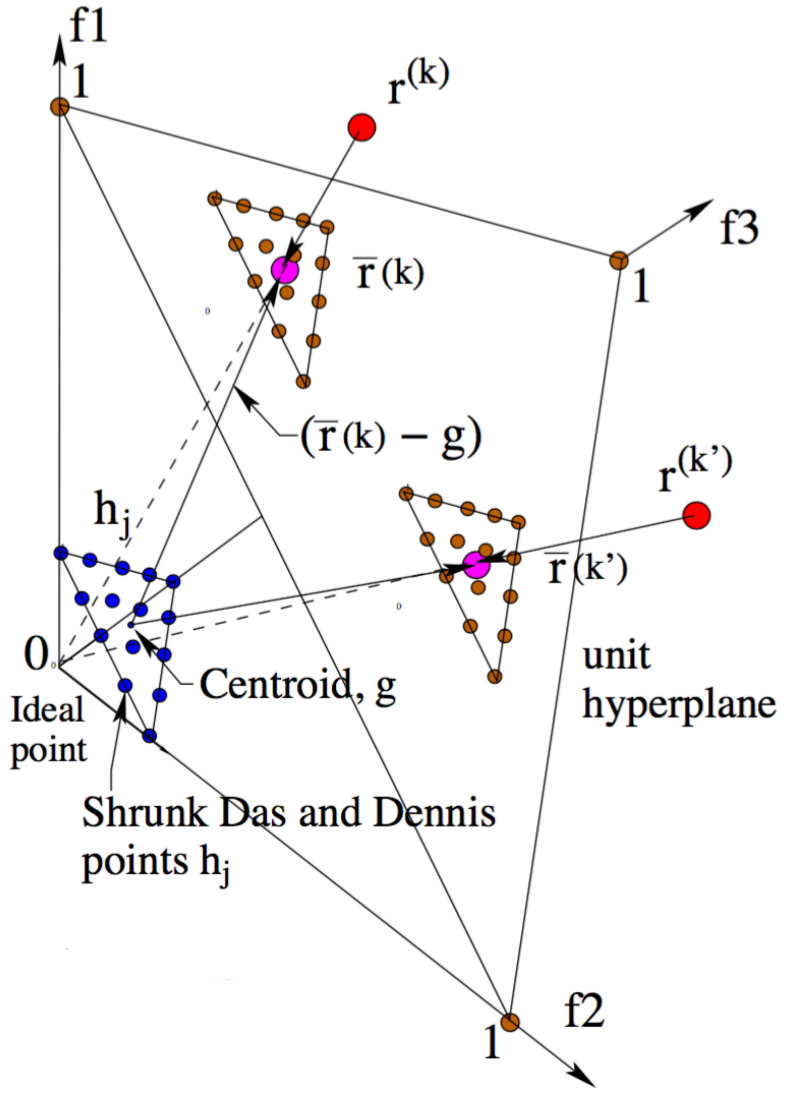
Create Das-Dennis points on unit hyperplane – called *H*

Shrink points *H* by parameter μ

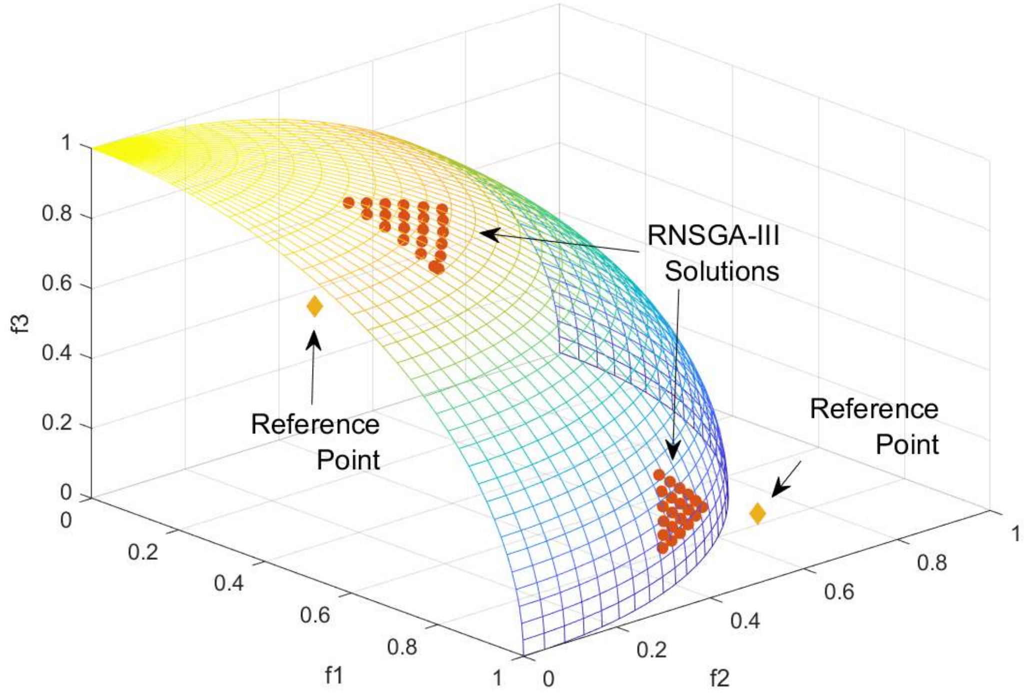
Shift shrunken points by centroid to intercepts

Add extreme points to set *H*

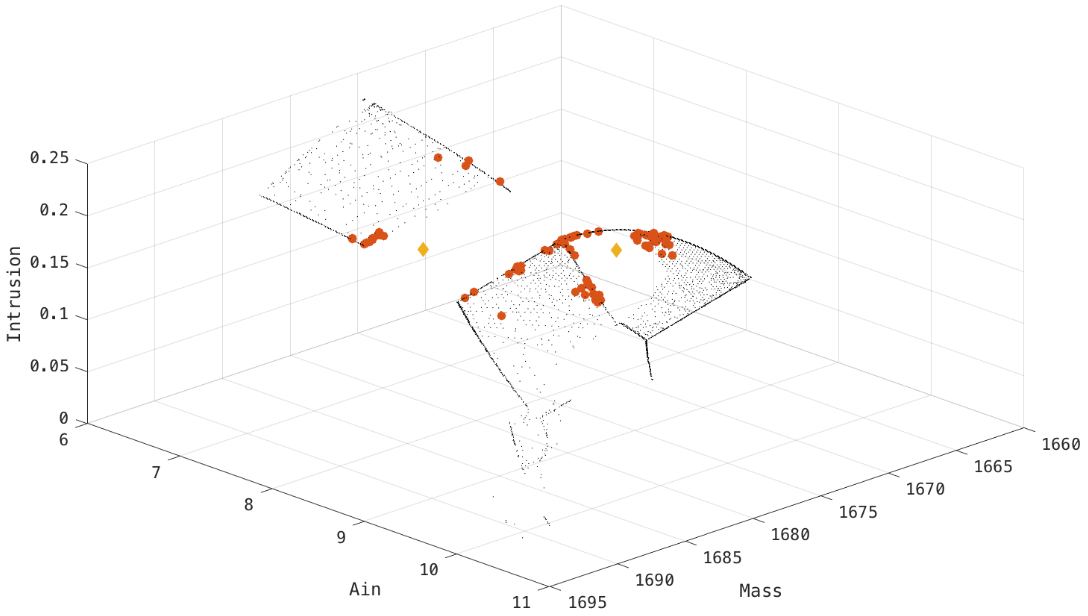
Remaining NSGA-III procedure



R-NSGA-III Results



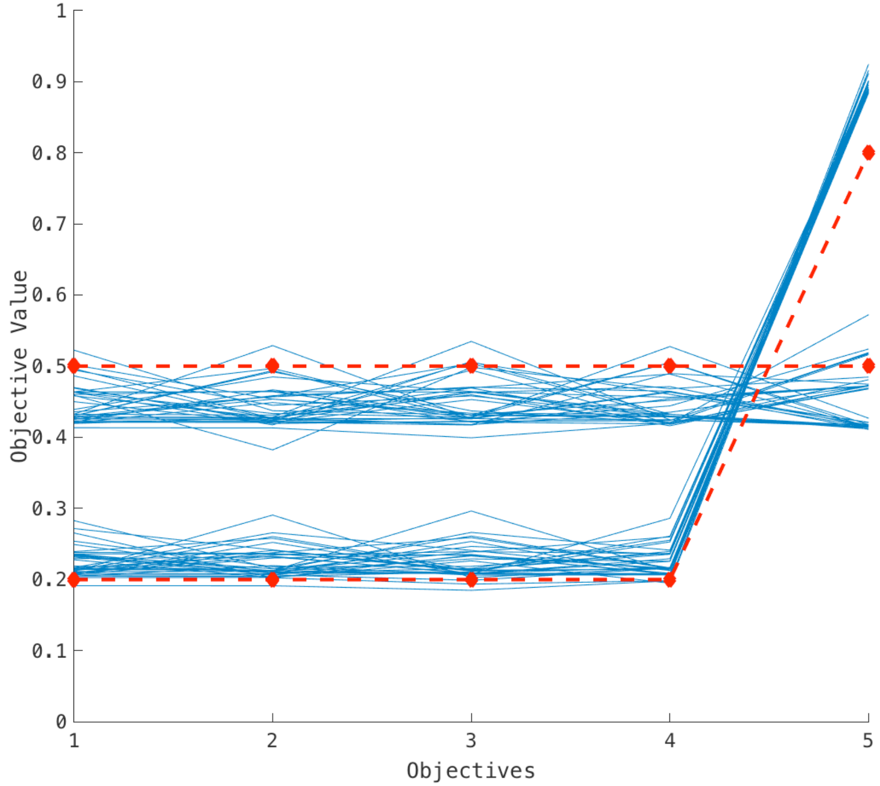
DTLZ2 - 3 Objective



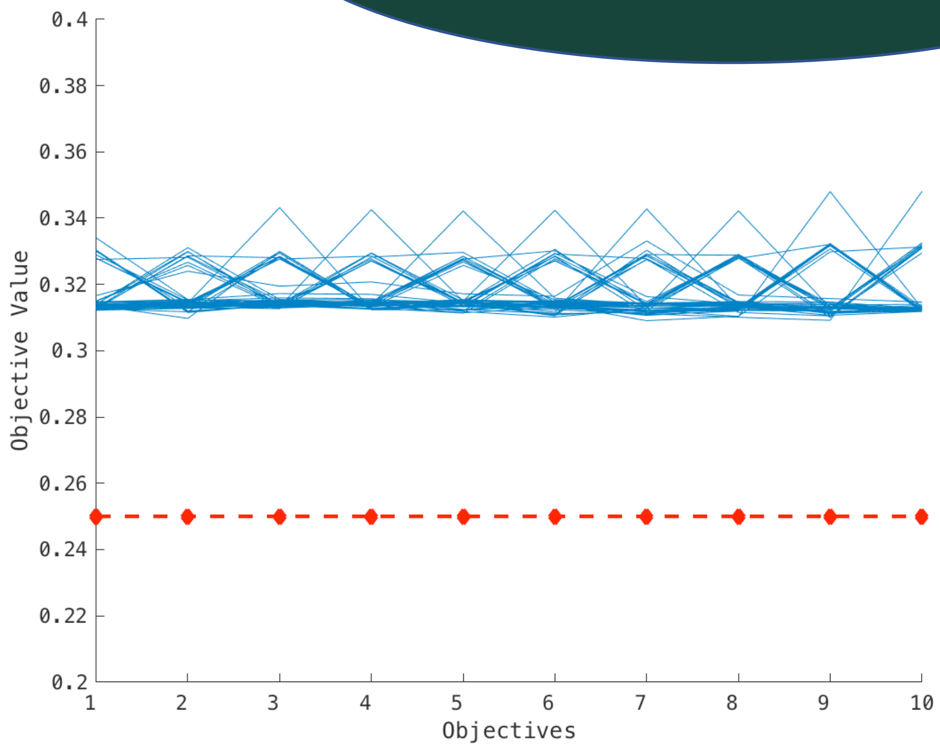
Crash Worthiness - 3 Objective

R-NSGA-III Results

DTLZ 2 & 4, WFG 5 & 6
1, 3, 5 Objectives



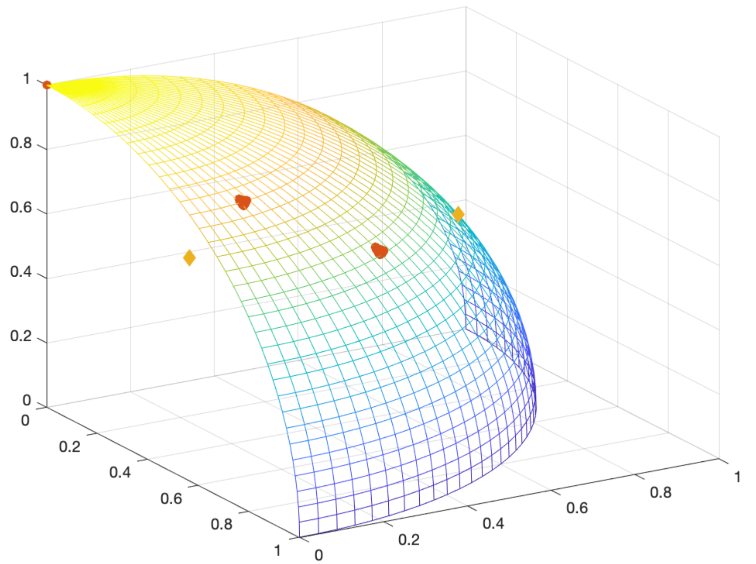
DTLZ2 - 5 Objective

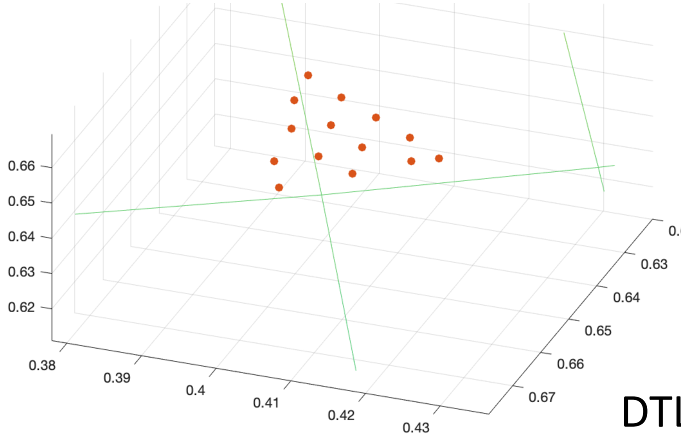


DTLZ2 - 10 Objective

Normalization & Hyperparameters

- New hyperparameter – μ is used to control the spread of the optimization task.
  - $0 < \mu \leq 1$
  - Similar to function of ε in R-NSGA-II that is used to denote minimum distance between solutions in the normalized space.
- Smaller μ values will result in a tighter set of solutions

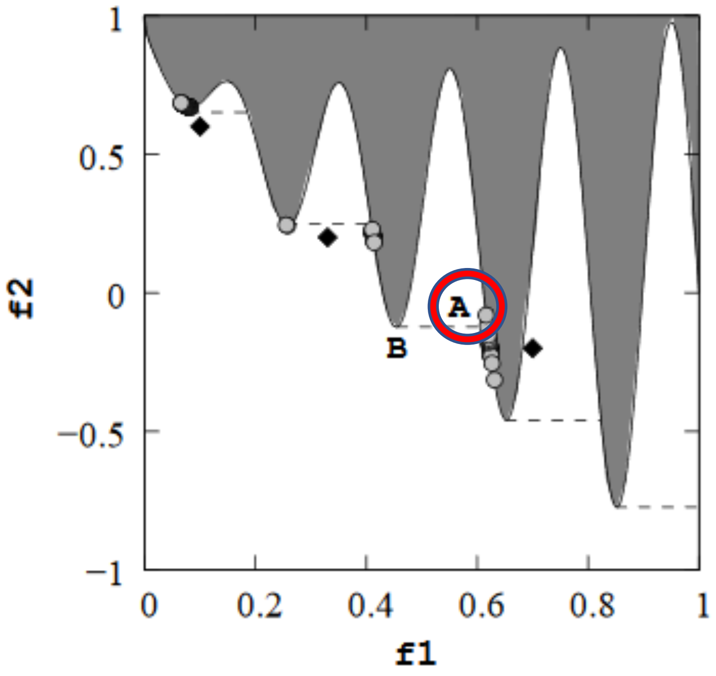




DTLZ2 – 3 Objective

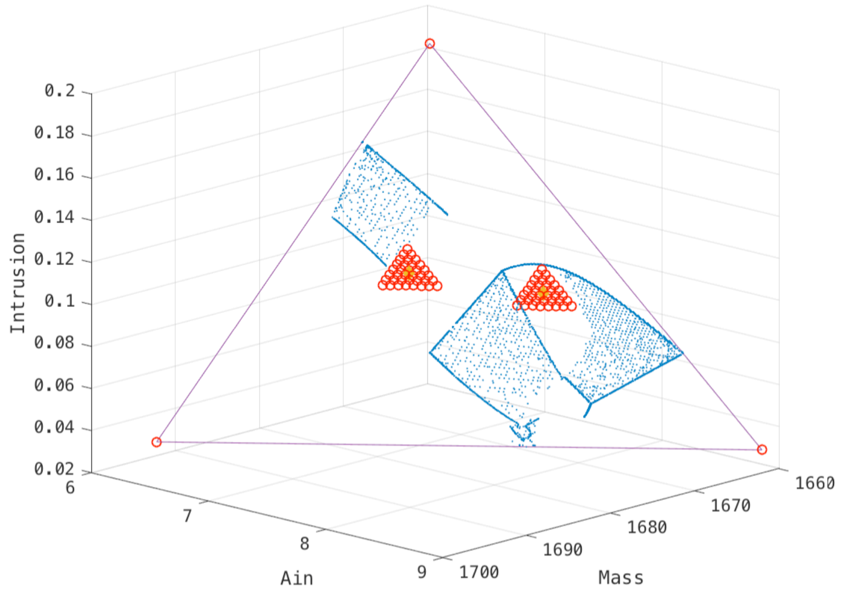
Current and Future Work

- How to avoid finding dominated solutions in a focused search



ZDT3 – R-NSGA-II run

- Dynamically updating aspiration points and μ to identify discontinuities



Crash Worthiness - 3 Objective Setup

Conclusions

- R-NSGA-III is designed on NSGA-III by changing the reference line generation procedure and aims to address many objective problems
- R-NSGA-III allows a decision maker to:
  1. Obtain their preferred solutions/preferred regions.
  2. Verify the shape of the pareto optimal front using structured solutions.

Code available at: https://github.com/msu-coinlab/pymoo

Questions?

References

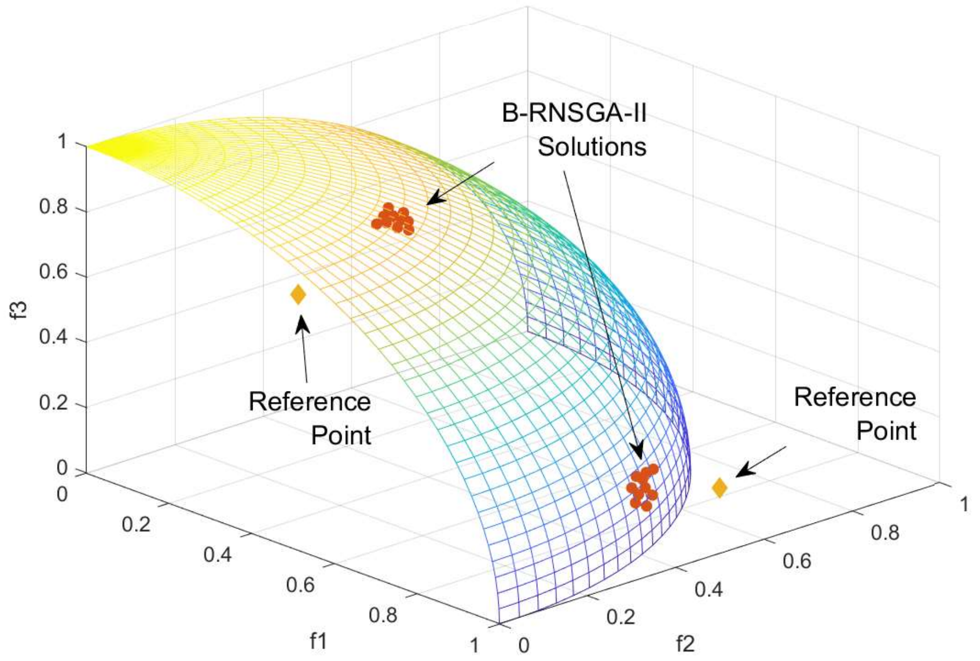
- K. Deb and J. Sundar, “Reference point based multi-objective optimization using evolutionary algorithms,” *Proceedings of the 8th annual conference on Genetic and evolutionary computation - GECCO 06*, 2006.
- Y. P. Vesikar, K. Deb, and J. Blank, “Reference Point Based NSGA-III for Preferred Solutions,” 2018. [Online]. Available: https://docs.wixstatic.com/ugd/0ffed2_289a3c4d23ec480abff5c5169b2a17a8.pdf.

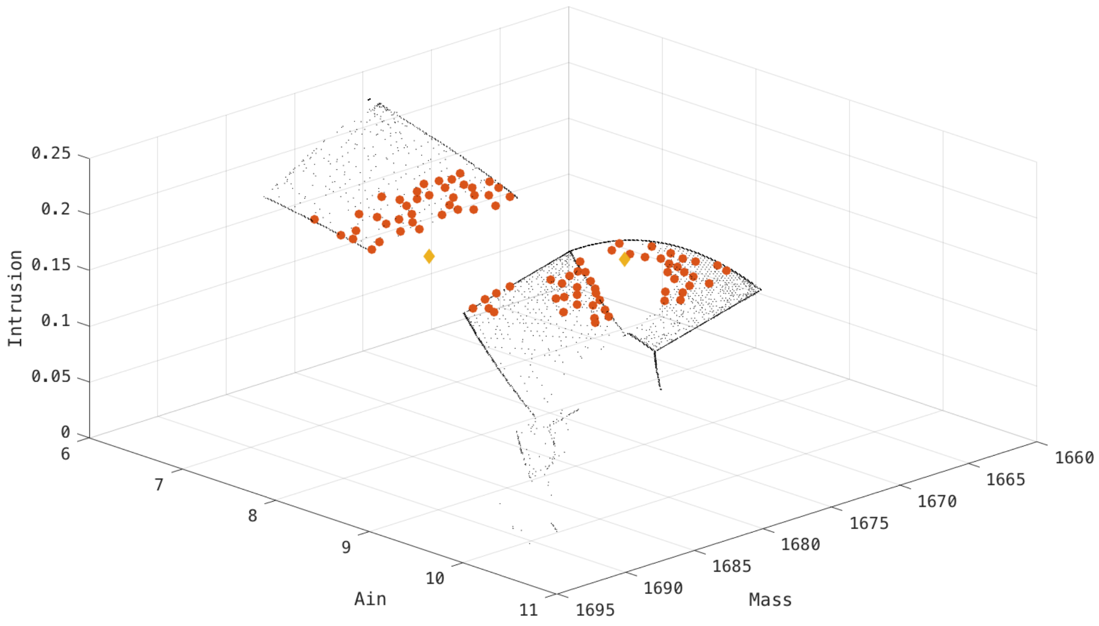
- K. Deb and J. Sundar, “Reference point based multi-objective optimization using evolutionary algorithms,” *Proceedings of the 8th annual conference on Genetic and evolutionary computation - GECCO 06*, 2006.

Proposed Balanced R-NSGA-II

- Modified R-NSGA-II procedure for a more balanced solution sets.
  - R-NSGA-II can find unequal numbers of solutions for multiple aspiration points.
- BR-NSGA-II Procedure
  - Execute traditional R-NSGA-II procedure until the last front.
  - for the last front, solutions closer to each aspiration point are chosen one at a time depending on the number of solutions previously accepted for the aspiration point.

BR-NSGA-II Results





Proposed R-NSGA-III Algorithm

- Updated survival selection operator.
  - Depends on DM supplied aspiration points.
- Algorithm:
  1. Normalize aspiration points to current population.
  2. Calculate the intercept with the unit hyperplane
  3. Create Das-Dennis points on the unit hyperplane
  4. Shrink the points by parameter μ
  5. Shift shrunken points by the centroid to intercepts
  6. Add extreme points to
  7. NSGA-III procedure, repeating every generation