Latest advancements in software for interactive multiobjective optimization: introduction to DESDEO

Giovanni Misitano[1] Bhupinder Singh Saini[1]
giovanni.a.misitano@jyu.fi

[1]University of Jyväskylä (Finland), The Multiobjective Optimization Group

Presented during MCDM2022 in Portsmouth, England, on June 28, 2022.

Overview

1. Motivation
2. DESDEO
   - What is DESDEO?
   - The structure of DESDEO
   - Utilizing DESDEO
3. Some implemented methods
4. Hybridization
5. Call to action
6. Appendices

Motivation

1. Motivation
2. DESDEO
3. Some implemented methods
4. Hybridization
5. Call to action
6. Appendices

Why DESDEO?

- Implementations of interactive multiobjective optimization methods have been:
  - sporadic;
  - closed source, or otherwise with unavailable source code;
  - implemented in different programming languages;
  - repetitive;
  - not documented.
- Utilizing existing implementations is challenging.
- Comparing methods requires a lot of effort.
- DESDEO to address these issues.

Why DESDEO?

More:

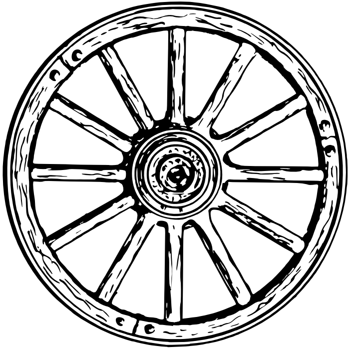
- Transparency
- Reutilization
- Documentation

Less:

- Hidden implementations
- Repetition
- Disposable code

Let us avoid...

...reinventing the wheel!



1 Motivation

2 DESDEO
- What is DESDEO?
- The structure of DESDEO
- Utilizing DESDEO

3 Some implemented methods

4 Hybridization

5 Call to action

6 Appendices

What is DESDEO?

DESDEO is:

- Open source
- Expandable
- Modular
- Implemented in Python
- The home of interactive methods (MCDM and EMO)

What is DESDEO?

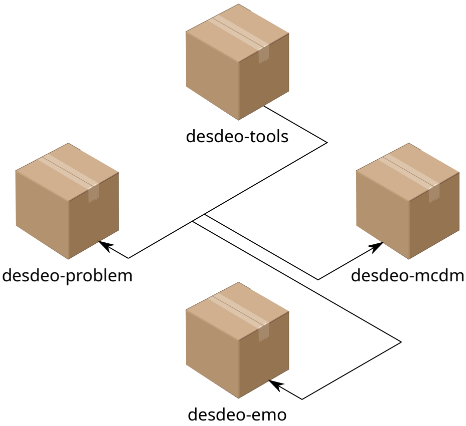
Therefore, DESDEO is an open source and modular Python framework for interactive multiobjective optimization[1].

[1] G. Misitano et al. “DESDEO: The Modular and Open Source Framework for Interactive Multiobjective Optimization”. In: *IEEE Access* 9 (2021), pp. 148277–148295. DOI: 10.1109/ACCESS.2021.3123825.

The structure of DESDEO

DESDEO consists of four **core packages**:

1. `desdeo-problem`
2. `desdeo-tools`
3. `desdeo-mcdm`
4. `desdeo-emo`



The structure of DESDEO

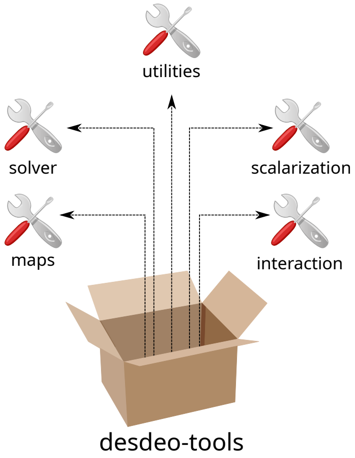
Each of the packages in DESDEO serve their own purpose:

- `desdeo-problem`
  - Modelling multiobjective optimization problems (continuous variables).
  - Test problems.
  - Surrogate problems.
- `desdeo-tools`
  - (Single-objective) optimization routines.
  - Scalarization of multiobjective optimization problems.
  - Miscellaneous utilities, such as indicators.
- `desdeo-emo`
  - Evolutionary multiobjective optimization methods.
  - Both interactive and non-interactive variants.
  - Evolutionary operators.
- `desdeo-mcdm`
  - Interactive methods based on scalarization.
    - Navigation methods.
    - Trade-off free methods.

The structure of DESDEO

Each package consists of **modules**. For instance, `desdeo-tools` contains:

1. `interaction`
2. `maps`
3. `scalarization`
4. `solver`
5. `utilities`



Utilizing DESDEO

One can mix and match the various packages and modules to fit one's needs:

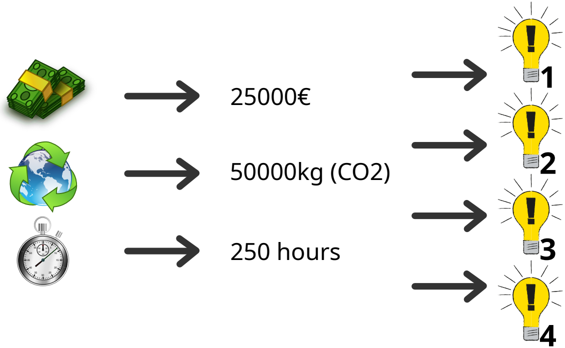
Example 1: defining a multiobjective optimization problem in DESDEO.

Some implemented methods

1 Motivation
2 DESDEO
3 Some implemented methods
4 Hybridization
5 Call to action
6 Appendices

The reference point method[2]

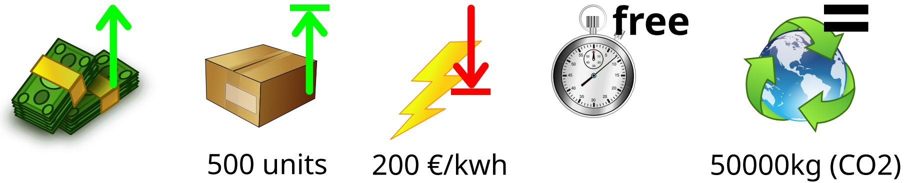
- The decision maker provides aspiration levels for each objective.
- $k+1$ new solutions are computed based on the aspiration levels.



[2] A. P. Wierzbicki. "The Use of Reference Objectives in Multiobjective Optimization". In: *Multiple Criteria Decision Making, Theory and Applications*. Ed. by G. Fandel and T. Gal. Berlin: Springer, 1980, pp. 468–486. DOI: 10.1007/978-3-642-48782-8_32.

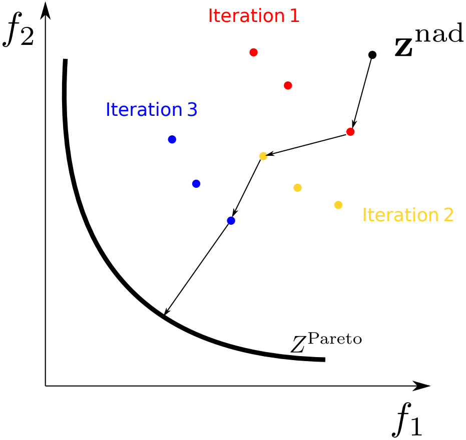
Synchronous NIMBUS[3]

- Classification of each objective of a Pareto optimal solution into five classes:
  1. Improve
  2. Improve until some value
  3. Worsen until some value
  4. Change freely
  5. Stay as it is
- New solutions computed based on classifications utilizing different scalarization functions.



[3] Kaisa Miettinen and Marko M. Mäkelä. "Synchronous approach in interactive multiobjective optimization". In: *European Journal of Operational Research* 170.3 (2006), pp. 909–922. DOI: 10.1016/j.ejor.2004.07.052.

E-NAUTILUS[4]



[4] Ana B. Ruiz et al. "E-NAUTILUS: A decision support system for complex multiobjective optimization problems based on the NAUTILUS method". In: *European Journal of Operational Research* 246.1 (2015), pp. 218–231. DOI: 10.1016/j.ejor.2015.04.027.

Interactive EMO methods

- Interactive versions of popular non-interactive EMO methods.
- Interactive RVEA[5] and NSGA-III[6].
    - Interactive? How? See[7].
- Interactive version of MOEA/D[8].
- IOPSIS[9]

[5] Ran Cheng et al. "A Reference Vector Guided Evolutionary Algorithm for Many-Objective Optimization". In: *IEEE Transactions on Evolutionary Computation* 20.5 (2016), pp. 773–791. DOI: 10.1109/TEVC.2016.2519378.

[6] Kalyanmoy Deb and Himanshu Jain. "An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints". In: *IEEE Transactions on Evolutionary Computation* 18.4 (2014), pp. 577–601. DOI: 10.1109/TEVC.2013.2281535.

[7] Jussi Hakanen et al. "Connections of reference vectors and different types of preference information in interactive multiobjective evolutionary algorithms". In: *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*. Athens, Greece: IEEE, 2016, pp. 1–8. DOI: 10.1109/SSCI.2016.7850220.

[8] Qingfu Zhang and Hui Li. "MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition". In: *IEEE Transactions on Evolutionary Computation* 11.6 (2007), pp. 712–731. DOI: 10.1109/TEVC.2007.892759.

[9] Bhupinder Singh Saini, Jussi Hakanen, and Kaisa Miettinen. "A New Paradigm in Interactive Evolutionary Multiobjective Optimization". In: *Parallel Problem Solving from Nature – PPSN XVI*. ed. by Thomas Bäck et al. Cham: Springer International Publishing, 2020, pp. 243–256.

Types of preferences supported for interactive EMO

- Supported preferences info in EMO methods:
  - reference points,
  - preferred solutions,
  - non-preferred solutions,
  - upper and lower bounds, and
  - classification.

Hybridization

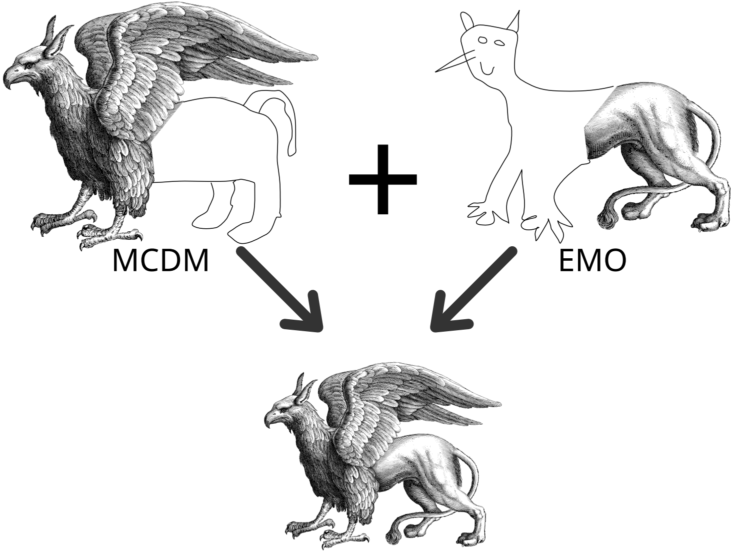
1. Motivation
2. DESDEO
3. Some implemented methods
4. Hybridization
5. Call to action
6. Appendices

Hybridization

Recall the main strengths and weknessess of MCDM and EMO methods:

- MCDM methods can compute accurate Pareto optimal solutions, but only one at a time.
- EMO methods can compute multiple solutions simultaneoulsy, but their Pareto optimality cannot be guaranteed.

Hybridization



Hybridization

- DESDEO allows for the hybridization of MCDM and EMO methods.
- Approximate the Pareto optimal front using an EMO method and use the front in an MCDM method.
  - E.g., use NSGA-III to calculate the front and then use the front in E-NAUTILUS.
  - The solution found by E-NAUTILUS can be *fine tuned* utilizing NIMBUS.
- Changing method between iterations. I.e., when the decision maker wishes to change the type of preference.

Example 2: switching methods, from EMO to MCDM.

Call to action

1. Motivation
2. DESDEO
3. Some implemented methods
4. Hybridization
5. Call to action
6. Appendices

Call to action

- DESDEO is completely open source and available on GitHub[10].
- Anybody is welcome to contribute.
- We want DESDEO to become a more collaborative project.
- DESDEO has also a webpage[11] where more information and news about DESDEO can be found.

[10] https://github.com/industrial-optimization-group/DESDEO

[11] https://desdeo.it.jyu.fi

Call to action

Try DESDEO if:

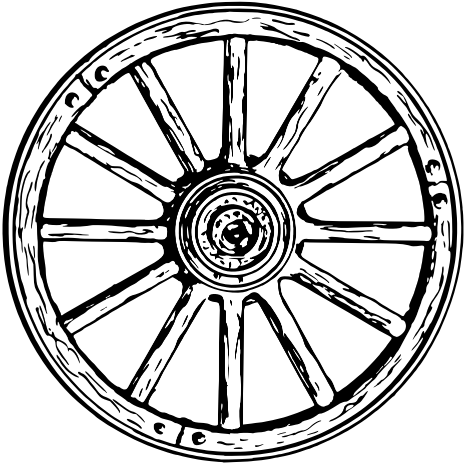
- You are interested in applying interactive multiobjective optimization methods.
- You would like to share your own interactive multiobjective optimization methods.
- You are interested in experimenting with and comparing interactive multiobjective optimization methods.
- You are interested in contributing to open source software and increase the visibility of your research.

Call to action

Try DESDEO and tell us what you think. Anybody is free to contribute and improve upon what we currently have. Join us in our efforts to make interactive multiobjective optimization available to practitioners and researchers alike.

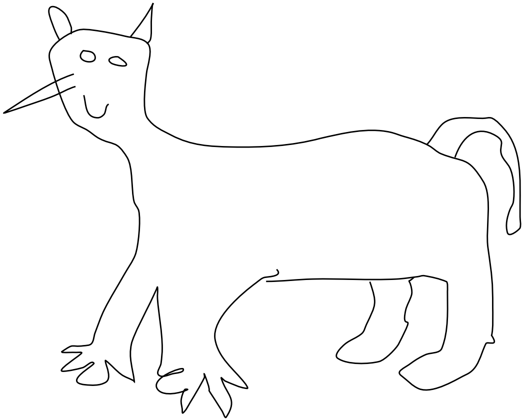
Call to action

The next time you come by interactive multiobjective optimization, remember DESDEO. Let us try to not reinvent the wheel...



Call to action

...and even more importantly, let us try to avoid whatever this symbolizes:



Appendices

1. Motivation
2. DESDEO
3. Some implemented methods
4. Hybridization
5. Call to action
6. Appendices

Aknowledgements

This work has been supported by the Academy of Finland (grant numbers 311877 and 322221) and the Vilho, Yrjö and Kalle Väisälä Foundation of the Finnish Academy of Science and Letters. This work is a part of the thematic research area Decision Analytics Utilizing Causal Models and Multiobjective Optimization (DEMO, jyu.fi/demo) at the University of Jyväskylä.

Links and resources

- DESDEO paper[1]
- DESDEO website[2]
- DESDEO on GitHub[3]
- Python notebook[4]

[1] G. Misitano et al. “DESDEO: The Modular and Open Source Framework for Interactive Multiobjective Optimization”. In: *IEEE Access* 9 (2021), pp. 148277–148295. DOI: 10.1109/ACCESS.2021.3123825

[2] https://desdeo.it.jyu.fi

[3] https://github.com/industrial-optimization-group/DESDEO

[4] https://desdeo.readthedocs.io/en/latest/notebooks/four_simple_use_cases.html

Bibliography I

[1] G. Misitano et al. "DESDEO: The Modular and Open Source Framework for Interactive Multiobjective Optimization". In: *IEEE Access* 9 (2021), pp. 148277–148295. DOI: 10.1109/ACCESS.2021.3123825.

[2] A. P. Wierzbicki. "The Use of Reference Objectives in Multiobjective Optimization". In: *Multiple Criteria Decision Making, Theory and Applications*. Ed. by G. Fandel and T. Gal. Berlin: Springer, 1980, pp. 468–486. DOI: 10.1007/978-3-642-48782-8_32.

[3] Kaisa Miettinen and Marko M. Mäkelä. "Synchronous approach in interactive multiobjective optimization". In: *European Journal of Operational Research* 170.3 (2006), pp. 909–922. DOI: 10.1016/j.ejor.2004.07.052.

[4] Ana B. Ruiz et al. "E-NAUTILUS: A decision support system for complex multiobjective optimization problems based on the NAUTILUS method". In: *European Journal of Operational Research* 246.1 (2015), pp. 218–231. DOI: 10.1016/j.ejor.2015.04.027.

Bibliography II

[5] Ran Cheng et al. "A Reference Vector Guided Evolutionary Algorithm for Many-Objective Optimization". In: *IEEE Transactions on Evolutionary Computation* 20.5 (2016), pp. 773–791. DOI: 10.1109/TEVC.2016.2519378.

[6] Kalyanmoy Deb and Himanshu Jain. "An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints". In: *IEEE Transactions on Evolutionary Computation* 18.4 (2014), pp. 577–601. DOI: 10.1109/TEVC.2013.2281535.

[7] Jussi Hakanen et al. "Connections of reference vectors and different types of preference information in interactive multiobjective evolutionary algorithms". In: *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*. Athens, Greece: IEEE, 2016, pp. 1–8. DOI: 10.1109/SSCI.2016.7850220.

Bibliography III

[8] Qingfu Zhang and Hui Li. "MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition". In: *IEEE Transactions on Evolutionary Computation* 11.6 (2007), pp. 712–731. DOI: 10.1109/TEVC.2007.892759.

[9] Bhupinder Singh Saini, Jussi Hakanen, and Kaisa Miettinen. "A New Paradigm in Interactive Evolutionary Multiobjective Optimization". In: *Parallel Problem Solving from Nature – PPSN XVI*. Ed. by Thomas Bäck et al. Cham: Springer International Publishing, 2020, pp. 243–256.