The Journal of Open Source Software

MF2: A Collection of Multi-Fidelity Benchmark Functions in Python

Sander van Rijn[1] **and Sebastian Schmitt**[2]

1 Leiden University, The Netherlands **2** Honda Research Institute Europe, Germany

DOI: 10.21105/joss.02049

Software

- Review
- Repository
- Archive

Editor: Melissa Weber Mendonça

Reviewers:

- @petroniocandido

Submitted: 17 January 2020
Published: 30 January 2020

Summary

The field of (evolutionary) optimization algorithms often works with expensive black-box optimization problems. However, for the development of novel algorithms and approaches, real-world problems are not feasible due to their high computational cost. Instead, benchmark functions such as Sphere, Rastrigin, and Ackley are typically used. These functions are not only fast to compute, but also have known properties which are very helpful when examining the performance of new algorithms.

As only a limited set of benchmark functions are typically used in literature, compiling a set of implementations for the most commonly used functions is warranted. This ensures correctness of the functions, makes any results directly comparable, and simply saves time from not having to implement the functions yourself. An example of a commonly used benchmark suite for optimizing continuous problems is the COCO BBOB software by Hansen et al. (2019).

As simulation-based problems in engineering are requiring increasingly more time and computation power, a new sub-field of *multi-fidelity* optimization has gained popularity. A multi-fidelity problem is characterised by having multiple versions of an evaluation function that differ in their accuracy of describing the real objective. A real-world example would be the aerodynamic efficiency of an airfoil: A *low-fidelity* simulation would use a coarse mesh, and give lower accuracy, but be fast to calculate, while a *high-fidelity* simulation would use a much finer mesh and therefore be more accurate while taking longer to calculate. Multi-fidelity methods aim to combine these multiple information sources to obtain better results in equal or less time compared to only using a single information source.

Because multi-fidelity problems are a new class of problems, the existing single-fidelity benchmark suites that exist cannot be used for this field. To this end, new multi-fidelity benchmark functions have been introduced in the literature and are being adopted by other researchers.

The `MF2` package provides a consistent Python implementation of a collection of these Multi-Fidelity Functions. It uses a standard interface that allows for querying single vectors or multiple row-vectors as a single matrix. It also offers a simple factory pattern interface for functions with parameters for e.g. correlation and dimensionality. At this moment, `MF2` has collected functions from the following previous works:

- Forrester, Sóbester, & Keane (2007) introduced a simple 1D bi-fidelity function for mostly illustrative purposes.
- Surjanovic & Bingham (2013) have previously collected a small collection of MATLAB/R implementations for the Borehole, Currin and Park91 A and B functions.
- Dong, Song, Wang, & Huang (2015) introduced bi-fidelity versions of the Bohachevsky, Booth, Branin, Himmelblau and Six-hump Camelback functions.
- Toal (2015) introduced correlation-adjustable multi-fidelity versions of the Branin, Paciorek, Hartmann3 and Trid functions.

This package is currently in use by the authors in their research on multi- fidelity hierarchical surrogate models.

Acknowledgements

This work is part of the research program DAMIOSO with project number 628.006.002, which is partly financed by the Netherlands Organisation for Scientific Research (NWO).

The first author would like to thank dr. Matthijs van Leeuwen, prof. dr. Thomas Bäck, and dr. Markus Olhofer for their supervision and involvement in the DAMIOSO project.

References

Dong, H., Song, B., Wang, P., & Huang, S. (2015). Multi-Fidelity Information Fusion Based on Prediction of Kriging. *Struct. Multidiscip. Optim.*, *51*(6), 1267–1280. doi:10.1007/s00158-014-1213-9

Forrester, A. I. J., Sóbester, A., & Keane, A. J. (2007). Multi-Fidelity Optimization via Surrogate Modelling. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *463*(2088), 3251–3269. doi:10.1098/rspa.2007.1900

Hansen, N., Brockhoff, D., Mersmann, O., Tusar, T., Tusar, D., ElHara, O. A., Sampaio, P. R., et al. (2019). *COmparing Continuous Optimizers: numbbo/COCO on Github*. Zenodo. doi:10.5281/zenodo.2594848

Surjanovic, S., & Bingham, D. (2013). Virtual library of simulation experiments: Test functions and datasets. Retrieved October 10, 2017, from http://www.sfu.ca/~ssurjano.

Toal, D. J. J. (2015). Some Considerations Regarding the Use of Multi-Fidelity Kriging in the Construction of Surrogate Models. *Structural and Multidisciplinary Optimization*, *51*(6), 1223–1245. doi:10.1007/s00158-014-1209-5