Numerical Global Optimization Competition on GNBG-II Generated Test Suite

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Abstract

This paper presents an extended abstract for our competition on GNBG-II. For GECCO 2025 competitions, we introduce GNBG-II consisting of 24 box-constrained problem instances derived from the Global Numerical Benchmark Generator (GNBG), providing a diverse and challenging test suite for optimization algorithms. Although the core design of GNBG-II remains the same as in the 2024 competitions, the current version introduces additional complexities to further increase the difficulty of the benchmark problems. We invite authors to test and evaluate their algorithms on GNBG-II, the details are available at: **https://dsmlossf.github.io/GNBG-Competition-2025/**

CCS Concepts

• **Theory of computation → Bio-inspired optimization**.

Keywords

GNBG-II, Numerical Optimization, Performance Evaluation

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1 Introduction

Global Numerical Benchmark Generator (GNBG) was introduced in 2024 for the Genetic and Evolutionary Computation Conference (GECCO) and IEEE Congress on Evolutionary Computation (CEC) competitions [1]. Following the success of the last year's events, we propose to host the GNBG-II competition at GECCO and CEC 2025. This competition aims to provide a comprehensive and configurable benchmark environment for continuous numerical optimization, enabling researchers to rigorously evaluate the performance of their optimization algorithms in diverse sets of problems.

GNBG-II problem instances use the same single baseline function as in case of GNBG, but both differ in their complexity, design, and level of difficulty. Although GNBG targets general-purpose research and provides a customizable framework, GNBG-II limits customization. A key focus of GNBG-II is the inclusion of advanced deceptive and asymmetric problem landscape scenarios that commonly trap optimization algorithms in local optima. In addition, the benchmark covers a broad spectrum of conditioning, from well-conditioned to highly ill-conditioned problems, facilitating a comprehensive assessment of an algorithm's robustness and numerical stability. The GNBG-II search space is composed of diverse landscapes formed by the aggregation of multiple components, each corresponding to a unique basin of attraction. These components share the same dimensional structure, but differ in complexity and difficulty, offering varied optimization challenges.

The primary focus of this benchmark suite is to evaluate eight key characteristics of an algorithm, including symmetry, modality, ruggedness, separability, variable interactions, ill-conditioning, deceptiveness, and basin linearity. Although GNBG provides a flexible platform for custom benchmark generation aimed at general-purpose research, GNBG-II is geared toward standardized evaluations and robust comparative analysis, making it particularly valuable for competitions and advanced algorithm testing.

In comparison to other well-known benchmarks such as Black-Box Optimization Benchmarking (BBOB) [2] and IEEE Congress on Evolutionary Computation (CEC) [3], GNBG-II is a much more challenging framework. CEC focuses on separability and modality, and BBOB on smoothness and noise; whereas GNBG-II incorporates additional features such as variable interactions, non-linear transformations, and others. It also has deceptive instances to simulate the most challenging problem landscapes.

The extended abstract is divided into four sections. Apart from the introduction, section 2 provides details on the GNBG-II problem instances, section 3 highlights the evaluation criteria for the 2025 competition, and section 4 presents the conclusion.

2 Problem Instances for GNBG-II Competition

Here we present 24 well-designed problem instances, labeled f_1 to f_{24}, formulated using the GNBG framework [1]. GNBG-II retains key features of 2024 competition such as ruggedness, modality, deceptiveness, variable interactions, linearity, ill-conditioning, among others, while incorporating additional complexities, such as challenging terrains, variable multicomponents, and partially connected landscapes, to increase difficulty and create more challenging problem instances. The problem instances are classified as:

- f_1 to f_6: Unimodal instances;
- f_7 to f_{15}: Single component multimodal instances;
- f_{16} to f_{24}: Multi-component multimodal instances;

All problem instances are defined within $[-100, 100]^D$, where $D = 30$ is the dimension size. Table 1 provides a summary of the characteristics of the GNBG-II problem instances. The aim of the competition is to analyze and understand the behavior of an algorithm

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Table 1: General Overview of 24 problem instances of GNBG-II Benchmark Suite

Characteristic	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}	f_{23}	f_{24}
Modality	Unimodal						Multimodal with single component									Multimodal with multiple competing components								
Basin local optima	×	×	×	×	×	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Separability	$\mathcal{F}$	$\mathcal{F}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{F}$	$\mathcal{F}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{P}$	$\mathcal{F}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$	$\mathcal{N}$
Varying variable interactions	×	×	✓	✓	✓	✓	×	×	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓
Symmetry	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{S}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$	$\mathcal{A}$
Ill-conditioning	×	×	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓
Basin linearity	$\mathcal{E}$	L	$\mathcal{L}$	$\mathcal{L}$	$\mathcal{E}$	$\mathcal{L}$	L	$\mathcal{L}$	$\mathcal{L}$	$\mathcal{E}$	$\mathcal{E}$	L	$\mathcal{L}$	$\mathcal{E}$	$\mathcal{E}$	L	L	$\mathcal{L}$	$\mathcal{L}$	$\mathcal{E}$	$\mathcal{L}$	$\mathcal{L}$	$\mathcal{L}$	$\mathcal{L}$
Deceptive	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	✓	✓	✓	✓	✓	✓	✓	✓

• Existence of local optima within the basin of each component.
† $\mathcal{F}$, $\mathcal{N}$ and $\mathcal{P}$ stand for fully separable, non-separable, and partially separable, respectively.
‡ $\mathcal{S}$ and $\mathcal{A}$ stand for symmetric and asymmetric, respectively.
* $\mathcal{E}$, $\mathcal{L}$, and L stand for super-linear, sub-linear, and linear, respectively.

to diverse problem landscapes, spanning from simple unimodal surfaces to highly intricate and rugged multi-modal terrains.

3 Evaluation Criteria

The competition is open to all practitioners and researchers in the field of continuous numerical optimization, and participants can use newly proposed or previously published algorithms. All the problem instances are black box and must be used in the exact format as provided. In the event of a competition win, the source code of the algorithm must be provided to ensure the reproducibility and verification of the results.

Three performance indicators are used to assess the performance of the optimization algorithm. These are

- **Average absolute error:**
  Mean and standard deviation of 31 runs.
- **Function Evaluations (FEs) to Acceptance Threshold:**
  Mean number of FEs required by an algorithm to find a solution with absolute error smaller than 10^{-8}.
- **Success rate:**
  As a percentage of runs, where the algorithm finds the acceptance threshold successfully.

Note that the stopping criteria are $500,000$ FEs for f_1 to f_{15} and $1,000,000$ FEs for f_{16} to f_{24}.

4 Conclusion

In this extended abstract, we provide details on the GNBG-II benchmark suite introduced for the GECCO and CEC 2025 competitions. It consists of 24 challenging problems that incorporate simple unimodal instances to highly deceptive, ill-conditioned, asymmetric multimodal instances. In general, GNBG-II provides a standardized and challenging benchmark environment for the rigorous evaluation of continuous optimization algorithms. Its focus on controlled problem characteristics and diverse landscape features makes it a valuable tool for both algorithm development and competitive benchmarking.

References

[1] Yazdani Danial, Mohammad Nabi Omidvar, Yazdani Delaram, Deb Kalyanmoy, and H Gandomi Amir. 2023. GNBG: A generalized and configurable benchmark generator for continuous numerical optimization. (2023). arXiv:2312.07083

[2] Nikolaus Hansen, Anne Auger, Raymond Ros, Steffen Finck, and Petr Pošík. 2010. Comparing results of 31 algorithms from the black-box optimization benchmarking BBOB-2009. In *Proceedings of the 12th annual conference companion on Genetic and evolutionary computation*. 1689–1696.

[3] Guohua Wu, Rammohan Mallipeddi, and Ponnuthurai Nagaratnam Suganthan. 2017. Problem definitions and evaluation criteria for the CEC 2017 competition on constrained real-parameter optimization. *National University of Defense Technology, Changsha, Hunan, PR China and Kyungpook National University, Daegu, South Korea and Nanyang Technological University, Singapore, Technical Report* (2017).