Black-Box Optimization Revisited: Improving Algorithm Selection Wizards through Massive Benchmarking

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Abstract

Existing studies in black-box optimization suffer from low generalizability, caused by a typically selective choice of problem instances used for training and testing different optimization algorithms. Among other issues, this practice promotes overfitting and poor-performing user guidelines. To address this shortcoming, we propose in this work a benchmark suite which covers a broad range of black-box optimization problems, ranging from academic benchmarks to real-world optimization problems, from discrete over numerical to mixed-integer problems, from small to very large-scale problems, from noisy over dynamic to static problems, etc. We demonstrate the advantages of such a broad collection by deriving from it NGOpt8, a general-purpose algorithm selection wizard. Using three different types of algorithm selection techniques, NGOpt8 achieves competitive performance on all benchmark suites. It significantly outperforms previous state of the art on some of them, including the MuJoCo collection, YABBOB, and LSGO. A single algorithm therefore performed best on these three important benchmarks, without any task-specific parametrization. The benchmark collection, the wizard, its low-level solvers, as well as all experimental data are fully reproducible and open source. They are made available as a fork of Nevergrad, termed OptimSuite.

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1 Introduction: State of the Art

Many real-world optimization challenges are black-box problems; i.e., instead of having an explicit problem formulation, they can only be accessed through the evaluation of solution candidates, often requiring simulations or even physical experiments. Black-box optimization methods are particularly widespread in machine learning (Salimans et al., 2016; Wang et al., 2020), to the point that it is considered a key research area of artificial intelligence. Black-box optimization algorithms are typically easy to implement and easy to adjust to different problem types. To achieve peak performance, however, proper algorithm selection and configuration are key, since black-box optimization algorithms have complementary strengths and weaknesses (Rice, 1976; Smith-Miles, 2009; Kotthoff, 2014; Bischl et al., 2016; Kerschke & Trautmann, 2018; Kerschke et al., 2018). But whereas automated algorithm selection has become standard in SAT solving (Xu et al., 2008) and AI planning (Vallati et al., 2015), a manual selection and configuration of the algorithms is still predominant in the broader black-box optimization context. To reduce the bias inherent to such manual choices, and to support the automation of algorithm selection and configuration, sound comparisons of the different black-box optimization approaches are needed. Existing benchmarking suites, however, are rather selective in the problems they cover. This leads to specialized algorithm frameworks whose performance suffer from poor generalizability. Addressing this flaw in black-box optimization, we present a unified benchmark collection which covers a previously unseen breadth of problem instances. We use this collection to develop a high-performing algorithm selection and configuration wizard, NGOpt8. NGOpt8 uses high-level problem characteristics to select one or several algorithms, which are run for the allocated budget of function evaluations. Originally derived from a subset of the available benchmark collection, in particular YABBOB, the excellent performance of NGOpt8 generalizes across all settings of our broad benchmark suite. Implemented as a fork of Nevergrad (Rapin & Teytaud, 2018), the benchmark collection, the wizard, and all performance data are open source. The algorithms are automatically rerun at certain time intervals and all data is exported to the public dashboard (Rapin & Teytaud, 2020). All code is available at https://dl.fbaipublicfiles.com/nevergrad/all.

In summary, our contributions are as follows.

(1) OptimSuite Benchmark Collection: OptimSuite combines several contributions that recently led to improved reliability and generalizability of black-box optimization benchmarking, among them LSGO (Li et al., 2013), YABBOB (Hansen et al., 2009a; Liu et al., 2020; Meunier et al., 2020b), Pyomo (Hart et al., 2017; Meunier et al., 2020b), MLDA (Gallagher & Salem, 2018), and MuJoCo (Todorov et al., 2012; Mania et al., 2018).

(2) Algorithm Selection Wizard NGOpt8: Our algorithm selection technique, NGOpt8, can be seen as an extension of the Shiwa wizard presented in Liu et al. (2020). It uses three types of selection techniques: passive algorithm selection (choosing an algorithm as a function of a priori available features (Baskiotis & Sebag, 2004; Liu et al., 2020)), active algorithm selection
Algorithm 1 High-level overview of NGOpt8. Selection rules are followed in this order, first match applied. $d =$ dimension, budget $b =$ number of evaluations. Details in (Meunier et al., 2020b).

| Case | Choice |
|------|--------|
| Discrete decision variables only | Genetic algorithm mixed with bandits (Heidrich-Meisner & Igel, 2009) |
| Noisy optimization with categorical variables | Adaptive (1 + 1)-Evolutionary Alg. (Doerr et al., 2019) |
| alphabets of size $< 10$, sequential evaluations | Convert to the continuous case using SoftMax as in (Liu et al., 2020) and apply CMandAS2 (Rapin et al., 2019) |
| alphabets of size $< 10$, parallel case | FastGA (Doerr et al., 2017) |
| Other discrete cases with finite alphabets | (1 + 1)-Evolutionary Alg. with linearly decreasing stepsize |
| Presence of infinite discrete domains | |

| Numerical decision variables only, evaluations are subject to noise | |
|---|---|
| $d > 100$ | progressive optimization as in (Berthier, 2016) |
| $d \leq 30$ | TBPSA (Hellwig & Beyer, 2016) |
| $b > 100$ | sequential quadratic programming |
| Other cases | TBPSA (Hellwig & Beyer, 2016) |

| Numerical decision variables only, high degree of parallelism | |
|---|---|
| Parallelism $> b/2$ or $b < d$ | MetaTuneRecentering (Meunier et al., 2020a) |
| Parallelism $> b/5$, $d < 5$, and $b < 100$ | DiagonalCMA (Ros & Hansen, 2008) |
| Parallelism $> b/5$, $d < 5$, and $b < 500$ | CMA+meta-model (Auger et al., 2005) |
| Parallelism $> b/5$, other cases | NaiveTBPSA as in (Cauwet & Teytaud, 2020) |

| Numerical decision variables only, sequential evaluations | |
|---|---|
| $b > 6000$ and $d > 7$ | Chaining of CMA and Powell, half budget each. |
| $b \leq 30d$ and $d > 30$ | (1+1)-Evol. Strategy w/ 1/5-th rule (Rechenberg, 1973) |
| $d < 5$ and $b < 30d$ | CMA-ES + meta-model (Auger et al., 2005) |
| $b \leq 30d$ and $d > 30$ | Cobyla (Powell, 1994) |

For all other cases, please refer to the source code. (a bet-and-run strategy which runs several algorithms for some time and stops all but the strongest (Mersmann et al., 2011; Pitzer & Affenzeller, 2012; Fischetti & Monaci, 2014; Malan & Engelbrecht, 2013; Muñoz Acosta et al., 2015; Cauwet et al., 2016; Kerschke et al., 2018), and chaining (running several algorithms in turn, in an a priori defined order (Molina et al., 2009)). Our wizard combines, among others, algorithms suggested in (Virtanen et al., 2019; Hansen & Ostermeier, 2003; Storn & Price, 1997; Powell, 1964, 1994; Liu et al., 2020; Hellwig & Beyer, 2016; Artelys, 2015; Doerr et al., 2017, 2019; Dang & Lehre, 2016). Another core contribution of our work is a sound comparison of our wizard to Shiwa, and to the long list of algorithms available in Nevergrad.
Table 1: Properties of selected benchmark collections. “+” means that the feature is present, “-” that the feature is missing, and an empty case that it is not applicable. Far-optimum refers to problems with optimum far from the center or on the side of the domain; such benchmarks test the ability of optimization algorithms to answer promptly to a bad initialization (Chotard et al., 2012). “Translations” applies only to artificial benchmarks. “Multimodal” (resp. “symmetrization”, “real-world”) do not imply that all test functions are multimodal (resp. symmetrized, real-world). “Open sourced” refers to open access to most algorithms involved in the published comparison; here, “-” refers to license issues for the benchmark itself.

2 Sound Black-Box Optimization Benchmarking

We summarize desirable features and common shortcomings of black-box optimization benchmarks and discuss how OptimSuite addresses these.

Generalization. The most obvious issue in terms of generalization is the statistical one: we need sufficiently many experiments for conducting valid statistical tests and for evaluating the robustness of algorithms’ performance. This, however, is probably not the main issue. A biased benchmark, excluding large parts of the industrial needs, leads to biased conclusions, no matter how many experiments we perform. Inspired by (Recht et al., 2018) in the case of image classification, and similar to the spirit of cross-validation for supervised learning, we use a much broader collection of benchmark problems for evaluating algorithms in an unbiased manner. Another subtle issue in terms of generalization is the case of instance-based choices of (hyper-)parameters: an experimenter modifying the algorithm or its parameters specifically for each instance can easily improve results by a vast margin. In this paper, we consider that only the following problem properties are known in advance (and can hence be used for algorithm selection and configuration): the dimension of the domain, the type and range of each variable, their order, the presence of noise (but not its intensity), the budget, the degree of parallelism (i.e., number of solution candidates that can be evaluated simultaneously). To mitigate the common risk of over-tuning, we evaluate algorithms on a broad range of problems, from academic
**Figure 1:** YABBOB and some extensions. Other variants include parallel, differences of budgets and combinations of those variants, with excellent results for NGOpt8 (see Nevergrad’s dashboard [https://dl.fbaipublicfiles.com/nevergrad/allxps/list.html](https://dl.fbaipublicfiles.com/nevergrad/allxps/list.html), publicly visible, for the part of our code which is already merged there).

benchmark problems to real-world applications. Each algorithm runs on all benchmarks without any change or task-specific tuning.

**Use the ask, tell, and recommend pattern.** Formalizing the concept of numerical optimization is typically made through the formalism of oracles or parallel oracles (Rogers, 1987). A recent trend is the adoption of the ask-and-tell format (Collette et al., 2010). The bandit literature pointed out that we should distinguish ask, tell, and recommend: the way we choose a point for gathering more information is not necessarily close to the way we choose an approximation of the optimum (Bubeck et al., 2011; Coulom, 2012). We adopt the following framework: given an objective function $f$ and an optimizer, for $i \in \{1, \ldots, T\}$, do $x \leftarrow \text{optimizer.ask}$ and $\text{optimizer.tell}(x, f(x))$. Then, evaluate the performance with $f(\text{optimizer.recommend})$. The requirement of a recommend method distinct from the ask is critical in noisy optimization. A debate pointed out some shortcomings in the noisy counterpart of BBOB (Hansen et al., 2009b) which was assuming that ask = recommend: (Beyer, 2012a,b; Coulom, 2012a) have shown that in the noisy case, this difference was particularly critical, and a framework should allow algorithms to “recommend” differently than they “ask”. A related issue is that a run with budget $T$ is not necessarily close to the truncation of a run in budget $10T$.

**Translation-invariance.** Zero frequently plays a special role in optimization. For example, complexity penalizations often “push” towards zero. In control, numbers far from zero are often more likely to lead to bang-bang so-
AllDEs \((d \in \{5, 20, 100\})\). HDBO \((d \in \{20, 2000\})\).

Bayesian optimization, often exploring boundaries first, is outperformed in high dimension (Wang et al., 2020).

Figure 2: NGOpt8 vs specific families of optimization algorithms (DE, and BO in the high-dimensional case). Not all run algorithms are mentioned, for short.

Rotation and symmetrization. Some optimization methods may perform well on separable objective functions but degrade significantly in optimizing non-separable functions. If the dimension of a separable objective function is \(d\), these methods can reduce the objective function into \(d\) one-dimensional optimization processes (Salomon, 1996). Therefore, Hansen et al. (2009a, 2011) have insisted that objective functions should be rotated to generate more difficult non-separable objective functions. However, Bousquet et al. (2017) pointed out the importance of dummy variables, which are not invariant per rotation;
and (Holland, 1975) and more generally the genetic algorithms literature insist that rotation does not always make sense — we lose some properties of a real-world objective function, and in some real-world scenarios rotating would e.g. mix temperature, distance and electric intensity. Permutating the order of variables is also risky, as their order is sometimes critical - k-point crossovers a la Holland (Holland, 1975) typically assume some order of variables, which would be broken. Also, users sometimes rank variables with the most important first — and some optimization methods do take care of this (Cauwet et al., 2019). We do include rotations, but include both cases, rotated or not. For composite functions which use various objective functions on various subsets of variables, we consider the case with rotations – without excluding the non-rotated case. A possibly better form of symmetrization, which makes sense for replicating an objective function without exact identity, consists in symmetrizing some variables: for example, if the $i^{th}$ variable has range $[a, b]$, we can replace $x_i$ by $b + a - x_i$. Applying this on various subsets of variables leads to $2^d$ symmetries of an objective function, if the dimension is $d$. This variation can reduce the bias toward symmetric search operations (Li et al., 2013).

**Benchmarking in OptimSuite.** We summarize in Table 1 some existing benchmark collections and their (desirable) properties. We inherited various advantages from Nevergrad, namely the automatic rerun of experiments and reproducibility in one-line. Our fork includes PBT (a small scale ver-
sion of Population-Based Training [Jaderberg et al. (2017)], Pyomo [Hart et al. (2017)], Photonics (problems related to optical properties and nanometric materials), YABBOB and variants, LSGO [Li et al. (2013)], MLDA [Gallagher & Saleem (2018)], Rocket, PowerSystems, FastGames, 007, Rocket, SimpleTSP, Realworld [Liu et al. (2020)], and others including a (currently small) benchmark of hyperparameters of Scikit-Learn [Pedregosa et al., 2011], all of those being visible at the above-mentioned URL. We note that, at present, we do not reproduce the extreme black-box nature of Loshchilov & Glasmachers (2017).

3 A New Algorithm Selection Wizard: NGOpt8

Black-box optimization is sometimes dominated by evolutionary computation. Evolution strategies [Beyer & Schwefel, 2002; Beyer, 2001; Rechenberg, 1973] have been particularly dominant in the continuous case, in experimental comparisons based on the Black-Box Optimization Benchmark BBOB (Hansen et al., 2009a) or variants thereof. Parallelization advantages [Salimans et al., 2016] are particularly appreciated in the machine learning context. However, differential evolution [Storn & Price, 1997] is a key component of all winning algorithms in competitions based on variants of Large Scale Global Optimization (LSGO [Li et al., 2013]), suggesting a significant difference between these benchmarks. In particular, LSGO is more based on correctly identifying a partial decomposition and scaling to $\geq 1000$ variables, whereas BBOB focuses (mostly, except (Varelas et al., 2018)) on $\leq 40$ variables. Mathematical programming techniques [Powell, 1964, 1994; Nelder & Mead, 1965; Artelys, 2015] are rarely used in the evolutionary computation world, but they sometimes won competitions [Artelys, 2015] and significantly improved evolution strategies through memetic methods [Radcliffe & Surry, 1994]. The wide literature in algorithm selection [Rice, 1976; Smith-Miles, 2009; Kotthoff, 2014; Bischl et al., 2016; Kerschke & Trautmann, 2018; Kerschke et al., 2018] was applied to continuous black-box optimization and in a public platform in [Liu et al., 2020]: their optimization algorithm combines many optimization methods and outperforms each of them when averaged over diverse test functions. Closer to machine learning, efficient global optimization [Jones et al., 1998] is widely used, though it suffers from the curse of dimensionality more than other methods [Snoek et al., 2012]; [Wang et al., 2020] presented a state-of-the-art algorithm in black-box optimization on MuJoCo, i.e. control of various realistic robots [Todorov et al., 2012]. We propose NGOpt8, which extends [Liu et al., 2020] by the following features: (1) Better use of chaining [Molina et al., 2009] and more intensive use of mathematical programming techniques for the last part of the optimization run, i.e., the local convergence, thanks to Meta-Models (in the parallel case) and more time spent in Powell’s method (in the sequential case). This explains the improvement visible in Section 4.1. (2) Better performance in discrete optimization, using additional codes recently introduced in OptimSuite, in particular adaptive step-sizes. (3) Better segmentation of the different cases of continuous optimization. The obtained algorithm selection wizard, NGOpt8,
Table 2: State-of-the-art results from Wang et al. (2020) and references therein, compared to results from NGOpt8. “ioa” = iterations on average for reaching the target loss. “ooN” = out of N runs. “iter” = “iterations for target reached for half runs”. “*” refer to problem for which the target was never reached in previous (black-box) papers: then BR means ”best result”. NGOpt8 reaches the target for Humanoid and Ant whereas previous (black-box) papers did not; we get nearly the same ioa for Hopper and HalfCheetah (Nevergrad computed the expected loss instead of computing the ioa, so we cannot compare exactly; see Fig. 5 for the curves). We were slower than LA-MCTS on Swimmer. Note that we keep the same method for all benchmarks and, just by adding a rule switching to DiagonalCMA for $d < 200$ in continuous domains (as well as Wang et al. 2020 switched to a different method for the three easy cases) we could solve Swimmer faster than LA-MCTS. We also point out that on HDMULTIMODAL, NGOpt8 performs better than LA-MCTS, as detailed in the text, and as confirmed in Wang et al. 2020, which acknowledges the poor results of LA-MCTS for high-dimensional Ackley and Rosenbrock.

### 4 Experimental Results

When presenting results on a single benchmark function, we present the usual average loss for different budget values. When a collection comprises multiple benchmark problems, we present our aggregated experimental results with two distinct types of plots: (1) Average normalized loss for each budget, averaged over all problems. The normalized loss is the loss linearly rescaled to $[0, 1]$. (2) Heatmaps, showing for each pair $(x, y)$ of optimization algorithms the frequency at which Algorithm $x$ outperforms Algorithm $y$. Algorithms are ranked by average winning frequency. Benchmarks in Sections 4.1-4.2 are included in our experiments.
4.1 Benchmarks in OptimSuite Used for Designing NGOpt8

**YABBOB** (Yet Another Black-Box Optimization Benchmark (Rapin et al., 2019)), is an adaptation of BBOB (Hansen et al., 2009a), with extensions such as parallelism and noise management. It contains many variants, including noise, parallelism, high-dimension (BBOB was limited to dimension $< 50$). Several extensions, for the high-dimensional, the parallel or the large budget case, have been developed: we present results in Fig. 1. The high-dimensional one is inspired by Li et al. (2013), the noisy one is related to the noisy counterpart of BBOB but correctly implements the difference between ask and recommend as discussed in Section 2. The parallel one generalizes YABBOB to settings in which several evaluations can be executed in parallel. Results on PARAMULTIMODAL are presented in Fig. 3 (left). In addition, NGOpt8 was run on ILLCONDI & ILLCONDIPARA (ill conditionned functions), HDMULTIMODAL (a multimodal case focusing on high-dimension), NOISY & RANKNOISY (two noisy continuous testbeds), YAWIDEBBOB (a broad range of functions including discrete cases and cases with constraints).

**AllDEs and Hdbo** are benchmark collections specifically designed to compare DE variants (AllDEs) and high-dimensional Bayesian Optimization (Hdbo), respectively (Meunier et al., 2020b). These benchmark functions are similar to the ones used in YABBOB. Many variants of DE (resp. BO) are considered. Results are presented in Fig. 2. They show that the performance of NGOpt8, relatively to DE or BO, is consistent over a wide range of parametrizations of DE or BO, at least in their most classical variants. All these variants are publicly visible in Nevergrad and/or in our branch.

**Realworld**: A test of NGOpt8 is performed on the Realworld optimization benchmark suite proposed in (Rapin & Teytaud, 2018). This suite includes testbeds from MLDA (Gallagher & Saleem, 2018) and from Liu et al. (2020). Results for this suite, presented in Fig. 3, confirm that NGOpt8 performs well also on benchmarks that were not explicitly used for its design - however, this benchmark was used for designing Shiwa, which was the basis of our NGOpt8. A rigorous cross-validation, on benchmarks totally independent from the design of Shiwa, is provided in next sections.

4.2 New Benchmarks in OptimSuite Used Only for Evaluating NGOpt8

**Pyomo** is a modeling language (Hart et al., 2017) in Python for optimization problems. It is popular and has been adopted in formulating large models for complex and real-world systems, including energy systems and networked resource systems. We implemented an interface to Pyomo for Nevergrad and enriched our benchmark problems (Meunier et al., 2020b), which include discrete variables and constraints. Experimental results are shown in Fig. 4. They show that NGOpt8 also performs decently in discrete settings and in constrained cases.
Additional new artificial and real-world functions: LSGO (large scale global optimization) combines various functions into an aggregated difficult testbed including composite highly multimodal functions. Correctly decomposing the problem is essential. Various implementations of LSGO exist; in particular we believe that some of them do not match exactly. Our implementation follows \cite{Li2013}, which introduces functions with subcomponents (i.e., groups of decision variables) having non-uniform sizes and non-uniform, even conflicting, contributions to the objective function. Furthermore, we present here experimental results on SequentialFastgames from the Nevergrad benchmarks, and three newly introduced benchmarks, namely Rocket, SimpleTsp (a set of traveling salesman problems), power systems (unit commitment problems \cite{Padhy2004}). Experimental results are presented in Fig. 4. They show that NGOpt8 performs well on new benchmarks, never used for its design nor for that of the low-level heuristics used inside NGOpt8.

MuJoCo: \cite{Todorov2012, Wang2020, Mania2018} proposed the MuJoCo testbeds in the black-box setting. MuJoCo tasks correspond to control problems. Defined in \cite{Wang2020, Mania2018}, the objective is to learn a linear mapping from states to actions. It turned out that the scaling is critical \cite{Mania2018}; for reasons mentioned in Section 2, solutions are close to 0. We chose to scale all algorithms at the power of 0.1 the closest to 1.2/d, for all methods run in Fig. 5. Refer to the comparison shown in Table 2 and Fig. 5: we see that NGOpt8 and Shiwa perform well, including comparatively to gradient-based methods in some cases, while having the ability to work when the gradient is not available. Black-box methods, when the gradient is available, have, in addition, the advantage of saving up the computational cost of the gradient. The algorithm performing best in \cite{Wang2020} is LA-MCTS. Results from NGOpt8 are comparable to, and usually better than (for the 3 hardest problems), results from LA-MCTS, while NGOpt8 is entirely reproducible and the same method is run for all benchmarks and was not optimized for the task. In contrast to NGOpt8, \cite{Wang2020} uses different underlying regression methods and sampling methods depending on the Mujoco task, and is not run on other benchmarks except a part of HDMULTIMODAL. NGOpt8 performances are significantly better for Ackley and Rosenbrock in dimension 100 (expected results around 100 and 10^{-8} after 10k iterations for Rosenbrock and Ackley respectively for NGOpt8, vs 0.5 and 500 in \cite{Wang2020}). From the curves in \cite{Wang2020} and in the present work, we expect LA-MCTS to perform well with an adapted choice of parametrization and with a low budget, for tasks related to MuJoCo, whereas NGOpt8 is adapted for a wide range of tasks.

5 Conclusions

This paper proposes OptimSuite, a very broad benchmark suite composed of real-world and of artificial benchmark problems. OptimSuite is implemented as a fork of Nevergrad \cite{Rapin2018}, from which it inherits a strong
Figure 5: Results on the MuJoCo testbeds. Dashed lines show the standard deviation. Compared to the state of the art in (Wang et al., 2020), with an algorithm adapted manually for the different tasks, we get overall better results for Humanoid, Ant, Walker, worse for Swimmer (could match if we had modified our code for the 3 easier tasks as done in (Wang et al., 2020)), similar for Hopper and Cheetah: we reach the target for 5 of the 6 problems, whereas previous black-box algorithms solved 3 tasks at best.

reproducibility: our (Python) code is open source (Meunier et al., 2020b), tests are rerun periodically, and up-to-date results are available in the public dashboard (Rapin & Teytaud, 2020). A whole experiment can be done as a one-liner. OptimSuite fixes issues common in existing benchmarking environments. The suite subsumes MuJoCo, Pyomo, LSGO, YABBOB, MLDA, and several new real-world problems. We also propose NGOpt8, an improved algorithm selection wizard. Despite its simplicity, NGOpt8 shows very promising performance across the whole benchmark suite, often outperforming the previous state-of-the-art, problem-specific solvers: (a) NGOpt8 outperforms LA-MCTS on MuJoCo, despite LA-MCTS being strongly specialized on that particular benchmark, solving 5 out of 6 benchmarks including 2 which were never previously solved by black-box methods (b) NGOpt8 outperforms Shiwa on YABBOB and its variants, which were the benchmark used for creating Shiwa in the first place (c) NGOpt8 outperforms all methods from Nevergrad in LSGO except one specific variant of DE (d) NGOpt8 is also the best-performing algorithm or among the best on almost all other benchmarks.

Further work. OptimSuite subsumes most of the desirable features outlined in Section 2 with one notable exception, the true black-box setting, which other benchmark environments have implemented through a client-server interaction (Loshchilov & Glasmachers, 2017). A possible combination between our platform and such a challenge, using the dashboard to publish the results, could be useful, to offer a meaningful way for cross-validation. Further improving NGOpt8 is on the roadmap. In particular, we are experimenting with the
automation of the still hand-crafted selection rules. Note, though, that it is important to us to maintain a high level of interpretability, which we consider key for a wide acceptance of the wizard. Another avenue for future work is a proper configuration of the low-level heuristics subsumed by NGOpt8; as of today, some of them are merely textbook implementations, some room for improvement can therefore be expected. We also plan on extending OptimSuite further, both through interfacing existing benchmark collections/problems, and by designing new benchmark problems.

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