**Article information**

**Article title**

A Multi-Objective, Multi-Fidelity Materials Science Optimization Benchmark Dataset for Hard-Sphere Packing Simulations

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**Keywords**

adaptive design, physics-based, Lubachevsky–Stillinger, force-biased algorithms, particle packing, packing generation, transfer learning, size distribution

**Abstract**

Benchmarks are an essential driver of progress in scientific disciplines. The most effective benchmarks closely resemble real-world tasks, as an inadequate level of difficulty or relevance can hinder progress in the field. Benchmarks should also have sufficiently low computational overhead to promote accessibility and repeatability. The goal is then to win a “Turing test” of sorts by creating a surrogate model that is indistinguishable from the ground truth observation (at least within the dataset bounds that were explored), necessitating a large amount of data. This study captures several features that are characteristic of industry-relevant chemistry and materials science optimization tasks: high noise, multiple fidelities, multiple objectives, linear constraints, non-linear correlations, and failure regions. We performed 494498 random hard-sphere packing simulations representing 206 CPU days’ worth of computational overhead. Simulations required nine input parameters with linear constraints and two discrete fidelities each with continuous fidelity parameters. The results were logged in a free-tier shared MongoDB Atlas database, producing two core tabular datasets: a failure probability dataset and a regression dataset. The failure probability dataset maps unique input parameter sets to the estimated probabilities that the simulation will fail. The regression dataset maps input parameter sets (including repeats) to particle packing fractions and computational runtimes for each of the two steps. These two datasets were used to create a surrogate model as close as possible to running the actual simulations by incorporating simulation failure and heteroskedastic noise. For the regression dataset, percentile ranks were computed within each of the groups of identical parameter sets to enable capturing heteroskedastic noise, ensuring reliability and accurate results. This contrasts with a more traditional approach that imposes a-priori assumptions such as Gaussian noise, e.g., by providing a mean and standard deviation. A similar approach can be applied to other benchmark datasets to bridge the gap between optimization benchmarks with low computational overhead and realistically complex, real-world optimization scenarios.

**Specifications table**

|  |  |
| --- | --- |
| **Subject** | Computational materials science |
| **Specific subject area** | Physics-based geometric packing |
| **Type of data** | Table  Figure |
| **How the data were acquired** | Data was acquired by running compiled C software hosted at <https://github.com/VasiliBaranov/packing-generation> in a two-step process orchestrated using Python in <https://github.com/sparks-baird/matsci-opt-benchmarks/blob/main/scripts/particle_packing/packing_generation_submitit.py>. The Python code acted as a driver for the compiled packing generation executable and was run using the University of Utah’s Center for High-performance Computing (CHPC) resources. <https://github.com/facebookincubator/submitit> was used to send jobs to the SLURM scheduler and the MongoDB Data API was used to log results in JSON format. For a snapshot of the matsci-opt-benchmarks code used, see [https://github.com/sparks-baird/matsci-opt-benchmarks v0.2.0](https://github.com/sparks-baird/matsci-opt-benchmarks%20v0.2.0) (<https://zenodo.org/badge/latestdoi/577963870>). |
| **Data format** | Raw  Analyzed  Filtered |
| **Description of data collection** | Seven irreducible parameters plus number of particles and initial scaling factor were varied in a quasi-random Sobol sampling of 65536 parameter combinations using a constrained search space via the Ax Platform, with 15 repeats (total: 983040 simulations). Of these, 438371 ran to completion (279 CPU days) with 41228 unique sets. Failed simulations were recorded as NaN values with ratio of successful to total simulations tracked on a per parameter set basis (sobol\_probability\_filter.csv). Repeat simulations were grouped and ranked by percentile using the “dense” method with pct=True in pandas.core.groupby.GroupBy.rank (sobol\_regression.csv)1. Surrogate models were fitted for failure probability, packing fraction, and computational runtime for each of two particle packing algorithms, totaling six surrogate models. |
| **Data source location** | University of Utah, Salt Lake City UT USA |
| **Data accessibility** | Repository name: Zenodo  Data identification number: 7653759  Direct URL to data: [https:/dx.doi.org/10.5281/zenodo.7653759](https://dx.doi.org/10.5281/zenodo.7653759) |

**Value of the data**

* Valuable for adaptive design benchmarking
* Benefits optimization researchers and practitioners in the physical sciences
* Provides insight into packing behavior in powder-bed additive manufacturing, can be integrated with experimental data
* Provides an example for future datasets

**Objective**

In the fields of materials science and chemistry, industry-relevant optimization tasks are often hierarchical, noisy, multi-fidelity2,3, multi-objective4,5, high-dimensional6,7, and non-linearly correlated while exhibiting mixed numerical and categorical variables subject to linear8 and non-linear constraints. Existing benchmark datasets9–14, while very useful, ignore or simplify the influence of noise and ignore the fact that certain parameter combinations will result in failure. By incorporating simulation failure and heteroskedastic noise, we create a “Turing test” of sorts with the goal of creating a surrogate model that is indistinguishable from the ground truth simulation. This bridges the gap between cheap-to-evaluate surrogate functions based on benchmark datasets and high-cost, real-world objective function evaluations.

**Data description**

The failure probability dataset (sobol\_probability\_filter.csv) contains unique input parameter sets (nine variables) and the estimated probabilities that the simulation will fail at each of the two steps (force-biased algorithm and Lubachevsky–Stillinger).

The regression dataset (sobol\_regression.csv) contains input parameters (including repeats) spanning nine variables and corresponding particle packing fractions as well as computational runtimes for each of the two steps (force-biased algorithm and Lubachevsky–Stillinger).

There are six regression models (surrogate\_models.pkl) trained on all data meant for production use. These six models can be used together to create the benchmark function.

There are five cross-validation sets of six regression models (cross\_validation\_models\_0.pkl, cross\_validation\_models\_1.pkl, cross\_validation\_models\_2.pkl, cross\_validation\_models\_3.pkl, cross\_validation\_models\_4.pkl).

The model metadata (model\_metadata.json) contains the raw mean absolute error scores, the raw predictions, and the true values for each of the cross-validation folds.

Figure 1 contains a histogram for the number of successful repeats out of the 15 total requested repeats for each parameter combination.

Figure 2 contains the probability of a simulation failing for each of the two algorithms.

Figure 3 contains the histograms of observed particle packing fractions for each of the two algorithms.

Chart, histogram

Description automatically generated

Figure . Histogram of number of parameter groups vs. number of successful repeats within a given group. The lowest number of repeats for a parameter set is 3, with approximately 10 repeats on average.

Chart

Description automatically generated

Figure . Histogram of normalized simulation counts vs. the probability of a simulation failing for a given parameter set. On average, the force-biased algorithm or fba (blue) is more likely to succeed than the Lubachevsky–Stillinger or ls (red) algorithm.

Chart

Description automatically generated

Figure . Histogram of number of simulations vs. packing fraction for the force-biased algorithm or fba (blue) and Lubachevsky–Stillinger or ls algorithm (red). On average, the ls algorithm tends to have higher packing fractions with a more Gaussian-like distribution than fba.

**Experimental design, materials and methods**

In this study, 438371 hard-sphere packing simulations were conducted using a two-step process of a force-biased algorithm15,16 followed by the Lubachevsky–Stillinger algorithm17–19. The simulations were performed using mixtures of three different particle types, each characterized by two log-normal distribution parameters and three composition parameters. Two parameters (scale and shape) describe each of the three distributions, and three additional composition parameters describe the fractional share (e.g., in terms of volume) of each of the particle types. Additionally, the number of particles and an initial scaling factor were allowed to vary (see <https://github.com/sparks-baird/matsci-opt-benchmarks/blob/v0.2.0/scripts/particle_packing/packing_generation_submitit.py> for more details). With a greater number of particles, denser and more realistic packs can be generated at the expense of computational cost (i.e., the fidelity parameter). The initial scaling factor affects the computational stability of the simulation; with an adequate scaling factor, the simulation is more likely to be completed successfully. Quasi-random Sobol sampling was used to generate parameter combinations to obtain a more uniform sampling of the allowable parameter space. While there can be other uses, this dataset is primarily intended as a multi-fidelity benchmark dataset for constrained adaptive design experiments. To realistically capture the noise for this benchmark dataset, simulations were repeated for each of the quasi-random parameter combinations (most with at least 8 repeats). To maximize throughput and reduce latency, simulation parameters (including repeats) were shuffled and divided into batches and sent to a high-performance computing environment for asynchronous evaluation. Results were logged to a free-tier MongoDB Atlas database and then aggregated and prepared as machine-learning-ready datasets. For further implementation details, see <https://github.com/sparks-baird/matsci-opt-benchmarks/tree/v0.2.0/scripts/particle_packing> and <https://github.com/sparks-baird/matsci-opt-benchmarks/tree/v0.2.0/notebooks/particle_packing>. Instructions for model usage are available at <https://matsci-opt-benchmarks.readthedocs.io/>.

**Ethics statements**

There are no statements to declare.

**CRediT author statement**

**Sterling G. Baird**: Project administration, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Taylor D. Sparks**: Supervision, Funding acquisition

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**Declaration of interests**

x The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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