# Adaptive Computing: Optimizing energy without breaking the bank

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## Introduction

Models are invaluable tools for energy and resource optimization. By simulating real-world conditions, we can test a variety of solutions without the costs and risks associated with materials and construction.

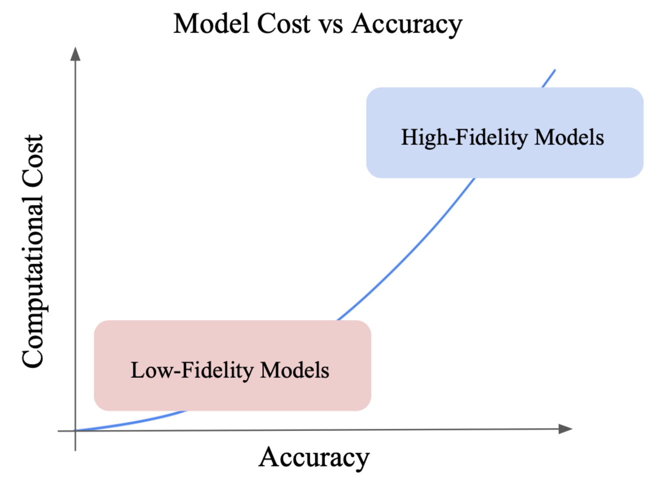


Figure 1. Tradeoffs of cost and accuracy for modeling. A **high-fidelity model (HFM)** is a complex, *highly accurate, computationally expensive* model. A **low-fidelity model (LFM)** is *computationally cheaper, yet less accurate.* A **multi-fidelity model (MFM)** takes information from both the LFM and HFM to create a *surrogate model* which yields *fast yet accurate* predictions.

*Our goals are to examine how we can improve the **effectiveness of MFMs for optimization purposes** by developing new **sampling strategies.***

*The contributions of this poster are as follows:*

- Analyzing the effects of LFM samples on finding the global minima of the HFM
- Comparing the effectiveness of various sampling strategies

## Sampling Strategies

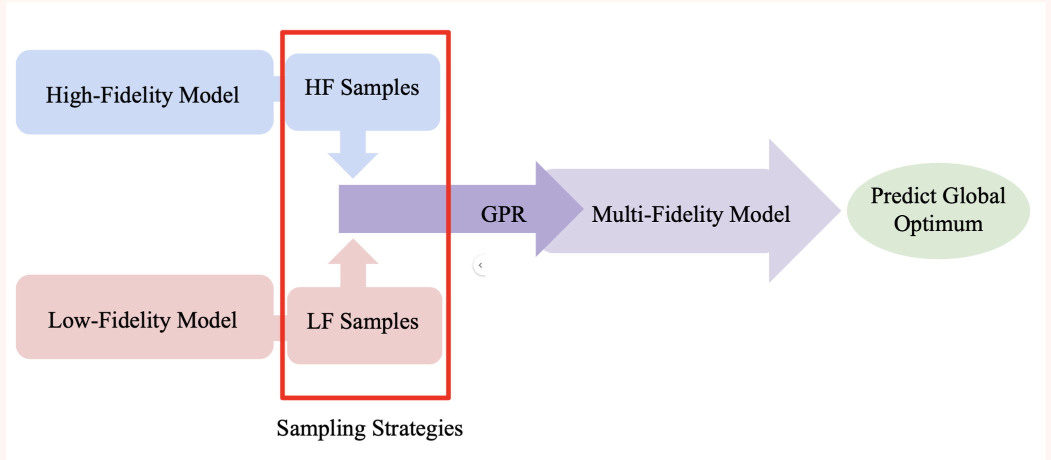


Figure 2. Flowchart of MFM training pipeline. Samples taken from an HFM and LFM are trained via Gaussian Process Regression (GPR) which produces an MFM.

Obtaining HFM model samples are expensive. Therefore, we are interested in strategies that minimize HFM sampling while preserving accuracy.

1. **Correlation-based sampling** samples HFM where LFM has low correlation values
2. **Iteration based sampling** prioritizes LFM samples at the beginning of GPR training and HFM samples at the end
3. **Uncertainty based sampling** samples HFM in areas of high prediction uncertainty
4. **Improvement based sampling** sample HFM when LFM samples do not change predicted minimum

## 1-Dimensional Demonstration

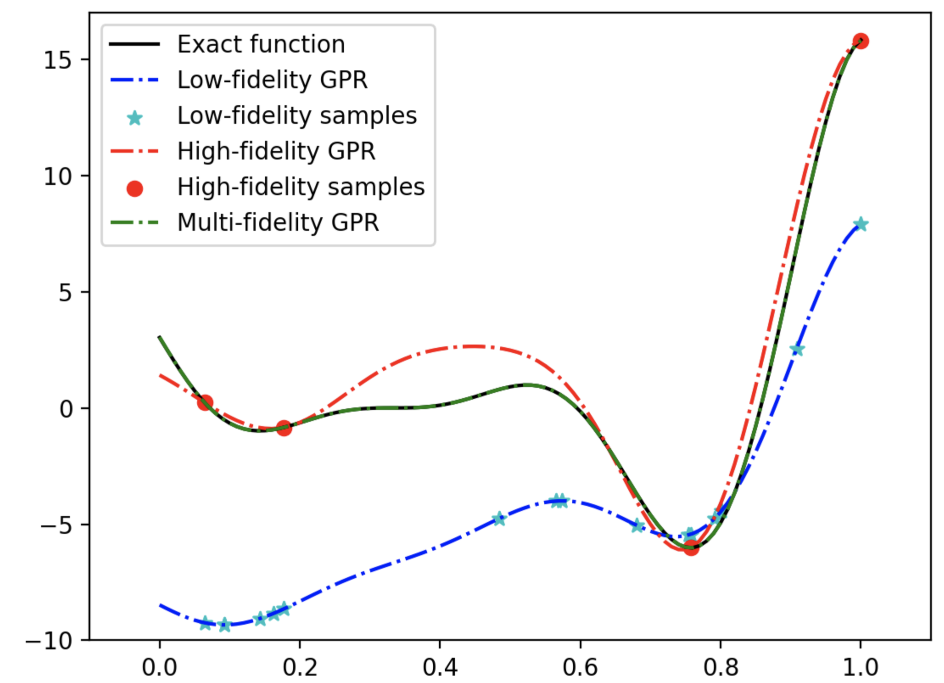


Figure 3. An MFM trained on a low correlation Forrester model. Multiple LFM samples were taken throughout the model. These initial samples were used to prompt an accurate HFM sample near the global minimum. The performance of 1-dimensional models tend to be most dependent on the iteration sampling strategy.

| Correlation | LF Samples | HF Samples | Error |
|---|---|---|---|
| Low Correlation | 6 | 4 | 1.48E-05* |
| | 3 | 4 | 1.06E-03 |
| | 7 | 2 | 4.50E-06 |
| | 13 | 2 | **5.00E-08** |
| Med Correlation | 8 | 2 | 3.66E-06* |
| | 2 | 3 | 2.77E+00 |
| | 5 | 2 | 2.87E-03 |
| | 10 | 1 | **9.20E-07** |
| High Correlation | 8 | 2 | 3.49E-06* |
| | 2 | 3 | 2.75E+00 |
| | 5 | 2 | 4.12E-03 |
| | 10 | 1 | **9.40E-07** |

Table 1. Performance of iteration sampling (2) strategies on 1-dimensional Forrester models for varying ratios of LF to HF samples. Bolded values are methods that were most accurate. Each group of models was run for a specific energy budget. Different methods sampled the LFM for 50, 25, or 10 percent of alloted energy budget. An energy budget was determined by minimum amount of energy required for control method* to converge. Error is absolute value between minimum HF sample of method and true global minima.

## Acknowledgements

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## 2-Dimensional Demonstration

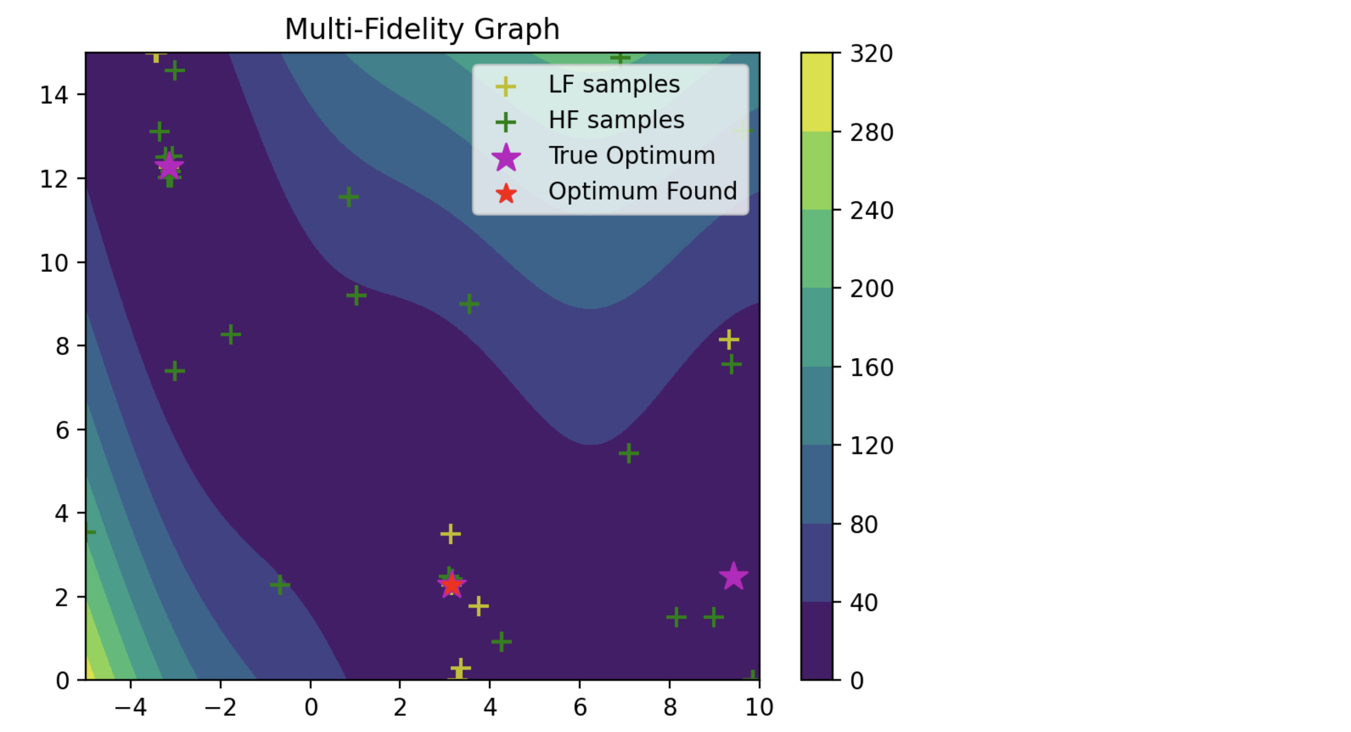


Figure 4. A contour graph of the Branin function using a combination of sampling strategies 1, 2, and 4. The HF samples tend to congregate around each of the three global optimums.

| Model | Sampling Strategy | LF Samples | HF Samples | Error |
|---|---|---|---|---|
| Branin | Control | 27 | 15 | 1.30E-02 |
| | 1 | 90 | 2 | 1 .14E+00 |
| | 2 | 25 | 15 | 2.49E-01 |
| | 3 | 95 | 1 | 4 .13E+00 |
| | 4 | 51 | 5 | 5.80E+00 |
| | 1, 2 | 20 | 15 | 8.18E-01 |
| | 2, 3 | 25 | 14 | 8.78E-03 |
| | **2, 4** | 15 | 14 | **2.29E-04** |
| | 1, 2, 4 | 10 | 5 | 6.77E-03 |
| | 2, 3, 4 | 4 | 10 | 5.80E+00 |

Table 2. Results of MFM prediction for Branin function using different sampling strategies. Sampling strategies (1) and (3) cannot be executed concurrently with the current framework.

## Conclusion

We evaluated the effects of correlation-based, iteration-based, uncertainty-based, and improvement-based sampling strategies for training MFMs to predict 1-dimensional and 2-dimensional global minima. For 1-dimensional models, *high numbers of initial LFM samples correlated to more efficient HFM sampling.* For 2-dimensional models, iteration-based sampling strategies were most independently effective. *The highest performing strategy utilized uncertainty-based and iteration-based strategies concurrently. The research suggests that iteration-based sampling will continue to be an effective method as dimensions increase.*

## References

[1] Stéphane Alarie, Charles Audet, Aïmen E. Gheribi, Michael Kokkolaras, and Sébastien Le Digabel. Two decades of blackbox optimization applications. *EURO Journal on Computational Optimization*, 9:100011, Jan 2021.[2] M. Giselle Fernández-Godino. Review of multi-fidelity models, 2023.