

# Bayesian Neural Network Surrogates for Efficient Global Optimization of an Airfoil Geometry

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Aerodynamic shape optimization is a computationally demanding process, particularly when directly employing high-fidelity simulations to evaluate complex, real-world geometries such as airfoils. Efficient global optimization (EGO) techniques, traditionally relying on Gaussian Process (GP) [1] surrogates to model expensive black-box functions, offer a powerful solution for reducing this cost. However, the choice of surrogate model can greatly influence optimization performance. This presentation explores the potential of Bayesian Neural Networks (BNNs) as surrogate models within the EGO framework. BNNs offer several compelling advantages over traditional GPs. Their architecture provides greater flexibility for representing complex relationships, potentially leading to improved approximation accuracy. This could also lead to potential benefits in the robust design, when using a distributionally robust optimization (DRO) framework [2]. Furthermore, BNNs inherently quantify predictive uncertainty, which is crucial for the EGO's acquisition function that guides the selection of promising new sample points. This study aims to improve both the accuracy and efficiency of the optimization process compared to GP-based methods.

## REFERENCES

- [1] C.E. Rasmussen and C.K.I. Williams, *Gaussian Processes for Machine Learning*, The MIT Press, 2005.
- [2] L. Chen, J. Rottmayer, L. Kusch, N.R. Gauger and Y. Ye, *Data-driven aerodynamic shape design with distributionally robust optimization approaches*. arXiv:2310.08931, 2023.