Adaptive Surrogate Modeling Strategy for Expensive CAE Analyses Utilizing Computing Power of HPC Clusters for Concurrent Evaluations

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Design optimization that involves CAE (FEA/CFD) analysis can be very computationally expensive and time consuming, and quite non-linear. The surrogate-based modeling technique is becoming more popular and practical because it can quickly predict the design performance, can be easily understood and manageable to create. Besides, it can be used to perform design optimization studies in a timely fashion, and is often used by design engineering teams to conduct what-if analysis.

However, quite often the accuracy of the predicted outcome from surrogate-based models is not sufficient. Traditionally a well distributed sampling based on Design of Experiment (DOE) algorithm is used to create design samples for which CAE analysis is run, and the resulting data is used to train a surrogate model (Neural Network or Radial Basis Function etc). Efficiency of such approach may still be questionable because the CAE problem could be constrained where data is not useful, could be highly non-linear in some regions while less non-linear elsewhere. Therefore, a more efficient way to improve surrogate model accuracy is to find the relatively critical and non-linear regions in the solution space and selectively sample these regions for CAE evaluation. Furthermore, since CAE analyses like external aerodynamics CFD analysis are extremely computationally expensive; the only way to practically build and utilize a good surrogate model for optimization and trade-off analysis is to evaluate the design samples concurrently over High Performance Computing (HPC) cluster.

This paper presents a three-step surrogate modeling strategy of using DOE, followed by Modified Multivariate Adaptive Cross-validation Kriging (MMACK) algorithm, and then Lipschitz Sampling to concurrently and efficiently increase the number of design samples to achieve high accuracy surrogate models. In step 1, Uniform Latin Hypercube (ULH) DOE algorithm is used to get initial design sampling of the design space; in step 2, the MMACK algorithm trains the surrogate model using Kriging on existing design samples while a genetic algorithm is used to find the optimal scaling parameter in Kriging, then multiple critical locations in the design space are identified by maximizing the related cross validation of Mean Squared Error (MSE). To maximize the MSE, Sequential Quadratic Programming (SQP) runs are used concurrently at multiple initial starting points. The local and global maxima points are then ranked, checked for redundancy, and evaluated with actual CAE simulations concurrently as the next generation of design samples to improve the overall surrogate model quality. The entire procedure of step 2 is repeated until the maximum allowed number of design samples for this step is reached. In the final step, the Lipschitz Sampling Algorithm adds new design samples in the most non-linear regions which are indicated by local Lipschitz constants.

The above strategy will be explained in detail in the final paper. The final paper will also show it's application to Extendable Rosenbrock function for 5, 10, 30, and 50 dimensions as proof of concept. Initial test results have shown that the strategy is promising and proving more effective and efficient than performing pure ULH sampling for surrogate mode building. The same strategy will also be applied to build a surrogate model of drag coefficient as a function of 10 to 30 shape variables for a passenger car. CFD simulations to predict drag coefficient for such model range from 10 – 20 hours per simulation on a HPC cluster. The final paper will include the data and results.

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