



Chapter XIII

A Neural-Network-Assisted Optimization Framework and Its Use for Optimum-Parameter Identification

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Abstract

Surrogate-assisted optimization frameworks are of great use in solving practical computationally expensive process-design-optimization problems. In this chapter, a framework for design optimization is introduced that makes use of neural-network-based surrogates in lieu of actual analysis to arrive at optimum process parameters. The performance of the algorithm is studied using a number of mathematical benchmarks to instill confidence on its performance before reporting the results of a springback minimization problem. The results clearly indicate that the framework is able to report optimum designs with a substantially low computational cost while maintaining an acceptable level of accuracy.

Introduction

There are numerous problems in the area of process design in which a designer is faced with the challenge to identify optimum process parameters that maximize one or more performance measures while satisfying constraints posed by statutory requirements, physical laws, and resource limitations. Currently, a vast majority of such applications are guided by trial and error and user experience. Such problems are nontrivial to solve as there are a large number of parameters that could be varied; the performance function is highly nonlinear and computationally expensive as it often involves calculations based on finite element methods (FEM), computational fluid dynamics (CFD), and so on.

Population-based, stochastic optimization methods like Genetic Algorithm (GA), Evolutionary Algorithm (EA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) methods have been quite successful in solving highly nonlinear, mixed-variable optimization problems. However, all the aforementioned methods are known to be computationally expensive, as they need to sample numerous candidate solutions and hence cannot be used outright to deal with optimum process-parameter-identification problems involving computationally expensive simulations. In order to contain the computational time within affordable limits, two schemes are usually adopted within a population based stochastic algorithm, namely (a) use of multiple processors to evaluate different candidate solutions and (b) use of approximations (surrogate models) in lieu of actual expensive simulations.

In order to use approximations and surrogate models within an optimization framework, one needs to decide on the following: (a) representation accuracy of the surrogate model and (b) choice of a particular surrogate model. Surrogate models often have large approximation errors and can introduce false optima (Jin, Olhofer, & Sendhoff, 2002). Introduction of these false optima is a particularly serious problem when used in conjunction with stochastic optimization methods like GAs and EAs as they could converge incorrectly, referred to as ill-validation (Jin, Olhofer, & Sendhoff, 2000). The problem of ill-validation is seldom addressed in the literature, and most reported applications using approximate functions tend to use a once-for-all approximation function throughout the course of optimization without even a check on the validity of approximation at different stages of optimization (Jin et al., 2000). A naïve application of the approximate model repeatedly without retraining may thus lead to incongruity between the original and surrogate search spaces. Ratle (1998) suggested a heuristic convergence criterion used to determine the retraining frequency based on the convergence stability and the correlation between the actual and approximate function spaces.

The second issue relates to the choice of a surrogate model. The choice could range from Quadratic Response Surfaces, artificial-neural-network- (ANN-) based approximators like Multilayer Perceptrons (MLPs), Radial Basis Function Networks (RBFs), or geostatistical methods like Kriging and Cokriging. ANN-based approximators, that is MLPs and RBFs are particularly well suited for the present purpose as they are able to capture nonlinear relationships and known to be universal function approximators (Hornik, Stinchcombe, & White, 1989; Poggio & Girosi, 1989). An extensive discussion of these two networks can be found in Haykin (1999).

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