

A Two-level Genetic Algorithm for Large Electromagnetic Optimization Problems

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Abstract— Many local two-level algorithms have been proposed for accelerating the electromagnetic optimization by stochastic algorithms. These algorithms use a combination of a coarse and a fine model in the optimization procedure. Despite of the good results, the global convergence properties represent an important drawback of these approaches. A global two-level algorithm has been proposed to deal with the convergence problems, but the requirement of refine the global surrogate model in each step remain as a point to be improved. This work introduces a global two-level genetic algorithm that uses single predefined coarse and fine surrogate models, which are defined as an artificial neural network non-linear regression of a preliminary set of finite element simulations. The problem dealing with the 8 parameters design of superconducting magnetic energy storage has been analyzed.

Index Terms— Genetic algorithms, Optimization methods, Metamodeling, Principal component analysis.

I. INTRODUCTION

The application of stochastic optimization algorithms, such as Genetic Algorithms (GA), to electromagnetic optimization problems is widespread. In general, the approaches are based on the construction of a surrogate model, which interpolate preliminary Finite Element simulations. In order to reach an optimal or near-optimal solution these algorithms usually require many model evaluations, demanding a reasonably computational time.

Many local two-level algorithms have been proposed for accelerating the electromagnetic optimization [1]-[3]. These algorithms use a combination of a coarse and a fine model in the optimization procedure. The coarse model is created based on some evaluations of the fine model and its accuracy strongly influences the convergence. Moreover, the local coarse model should be built in each iteration which represents an important drawback of these approaches.

A global two-level algorithm was proposed in [4] to deal with the convergence problems, but the requirement of refine the global surrogate model in each step remain as a point to be improved.

Therefore, we introduce a global two-level genetic algorithm that uses single predefined coarse and fine artificial neural network surrogate models. The fine surrogate model is defined as a non-linear regression of a preliminary set of simulations, which are performed according to an experimental central composite design [5]. The coarse model is build as an approximation of the five model in an appropriate subspace.

II. NEURAL NETWORK MODEL

An artificial neural network (ANN) consists of an artificial intelligence technique inspired by the structure and working of the human brain. An ANN is composed by interconnected elements, called artificial neurons, which are responsible for processing information [6]. The multi-layer perceptron (MLP), an ANN model widely known and used in pattern recognition tasks, is characterized by having, in addition to the input layer and output layer, one or more hidden layers that enable the network to map input patterns with similar structures for different outputs. To make this possible, the hidden layers act as feature detectors while the output layer has the function to receive the stimulus of the last hidden layer and build standard that will be the answer. Usually, for training MLP model, the supervised algorithm called back propagation is used. It is a learning algorithm based on error correction in which the training is performed in two phases: first, when a pattern is presented to the network through the input layer, the activation signal is propagated layer by layer, until the response is produced by the output layer. In the second phase, the obtained output is compared to desired output for this particular pattern producing an error signal. This error signal is then propagated from the output layer to input layer and the synaptic weights are being adjusted so that the response of the network approximates the desired response [6].

III. PRINCIPAL COMPONENTS SUBSPACE

The Principal Components Analysis (PCA) is a way of identifying patterns in data and expressing the data in a subspace by reducing the number of dimensions [7]. The method works as defined in the following steps:

Step 1: get some data - a set of design parameter e respective answers form the fine surrogate model.

Step 2: subtract the mean - subtract the average across each dimension in order to produce a data set whose mean is zero.

Step 3: calculate the covariance matrix.

Step 4: calculate the eigenvectors and eigenvalues of the covariance matrix.

Step 5: choosing the principal component - the eigenvectors with the highest eigenvalues have more significance. The notion of reduced dimensionality comes by ignoring the components of lesser significance.

Step 6: deriving the new data set - the projections of the original data on the principal components subspace.

IV. THE TWO-LEVEL GA

As in any multilevel approach some important ingredients should be defined:

Fine model: it is defined as a neural network non-linear regression model from a preliminary set of finite element simulations. The simulations were performed according to an appropriate experimental design in order to reduce the number of finite element runs.

Global coarse model: a set of design optimization parameters and the respective answers from the fine model is projected into the principal components subspace. The resulting new data set is used to training a coarse neural network model.

Prolongation and restrictions operators: the matrix formed by the principal components in the columns can be used to project the data in the subspace. The prolongation is accomplished just taken the transpose of the matrix and multiply it by the data to be transferred.

Fine and coarse optimization procedures: a combination of the usual GA is used here. After some iterations in the fine level the individuals are projected on the principal components subspace where a new GA search take place to find a approximation of the solution, which is refined in the fine level. This two-level procedure is illustrated in Fig. 1.

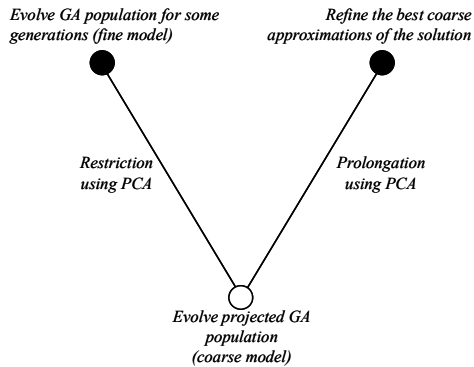


Fig. 1. Two-level optimization procedure

V. NUMERICAL PROBLEM

The problem analyzed in this work deals with the 8 parameters design of Superconducting Magnetic Energy Storage (SMES) as completely described in [8]. This is the well know benchmark TEAM Workshop problem 22.

The two objectives regarding to the energy and the stray field requirements are mapped into a single objective function and the constraints are handle by a penalty approach.

VI. INITIAL RESULTS

A. The Finite Element Simulations

The Ansys Maxwell finite element method analysis tool was used in the simulations. Since the problem has axial symmetry, the “Cylindrical about Z” magnetostatics solver was used. A parametric sweep with the required values was performed and the objective function calculated for each variation. For validation purposes, results were compared for optimal solution found in [8]. Additionally, another finite element analysis software (FEMM) was used in the validation

process, and the obtained results were coherent with those obtained with Ansys Maxwell.

Even though no permeable material is present in this application, it was assumed that the superconductor and the background material have relative permeability of around 1.0, allowing the finite element analysis to be executed [9]. The obtained flux lines are presented in Fig. 2.

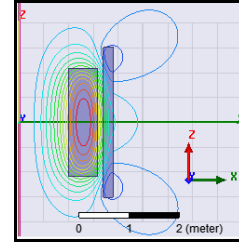


Fig. 2. Flux lines for the SMES arrangement

B. Neural network non-linear regression model

In order to ANN training we used a set of 8 inputs x_i (geometrical parameters) with their respective outputs y_i obtained from 200 real experiments. As our aim is to solve a problem of non-linear regression, a logistic activation functions in neurons of hidden layers and a single neuron in the output layer with a linear activation function have been used. The constructed ANN has 8 input neurons, 40 neurons in 5 hidden layers and 1 neuron in the output layer. In training was used 0.3 of learning rate. Furthermore, the traditional cross-validation technique has been used to validate the classifier performance [6]. The training error obtained for the built ANN is 1%.

C. Partial Conclusion and Comments

An appropriate experimental design can produce an accurate neural network model with a very small number of finite element simulations, in relation to the usual uniform grid approach. This is an important result for the application of the proposed two-level GA, which will be presented in the full paper.

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