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Parametric optimization using genetic algorithm and neural network

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ABSTRACT

Genetic algorithms (GA) have became during last decades a popular stochastic global search method for structural optimization. GAs can compete successfully with the gradient-based approaches in many areas. GAs rely on the principle of the survival of fittest in natural selection. Improvement of global search can be done by incorporating in optimization procedure neural networks (NN) which can learn and adapt changes over the time.

In the paper the design optimization using FEA and both genetic algorithms and neural network approaches is discussed. The existing open source libraries, namely Galileo for GA, and ffnet for NN were used. The optimization procedure was implemented using Python language. FE modeling, analysis and post-processing were performed with the use of Abaqus Unified FEA suite from SIMULIA. The integration of GA and NN libraries with FEA tools was done by using the Abaqus Scripting Interface.

The first presented approach of optimization is based solely on GA. Evaluation of each individual can be performed by any tool which can return fitness value of a solution based on a chromosome, in this case Abaqus was used. The chromosomes created during genetic process compose a starting point of evaluation procedure. For each chromosome, a FEA model is built and then analysis is performed. The obtained results are interpreted according to a given objective function(s). The flow-chart of the applied algorithm is presented in Fig. 1. The described approach is general and can be used to optimization of any Abaqus FEA model. GAs are in general computationally expensive. Moreover, a random character of GAs require a multiple usage of optimization procedure. As a result of above, this approach of optimization can not be used for large design problems which require heavy computations.

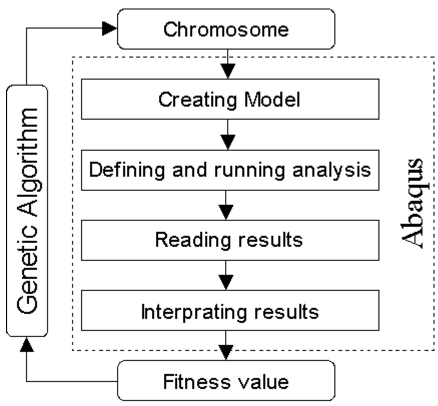

Fig. 1 Chromosome evaluation using Abaqus

The assumption that GA does not demand a precise solution for each chromosome is fundamental and a basis of modification. The crucial task of evaluation mechanism is extracting features of a chromosome which improve the quality of the individual. Thus, it is recommended to use an estimation tool which can rate the fitness less accurately but in a more faster way.

In the second presented approach of optimization it is proposed to replace the evaluation based on FE analysis with an estimation based on NN. In order to train NN, numerical analysis results for the selected and randomly generated chromosomes are used as a training set. After learning process terminated, an optimization attempt is carried out with the use of GA. This step corresponds to the first presented idea of optimization process with one exception; the evaluation procedure is done now with the use of NN. For each iteration of an optimization loop a training set is updated. A new training data consists of the result for the best individual obtained using GA and additionally, in the case of parallel computations, either results for random chromosomes or for created as a result of the best chromosome mutation. New training data verifies the GA solution in the first place and increases space of NN approximation on the other hand. As a result, the next GA optimal solution is calculated taking into consideration all previous attempts. The architecture of NN is changing simultaneously with the optimization process. The well-fitted architecture of NN is calculated according to a learning error. A flow-chart of the algorithm described above is presented in Fig. 2.

In the presented approach, each expensive FEA analysis is used for improving an estimation tool – NN. The greater number of analyses, the better estimation of individual is expected, however, in many cases NN is able to detect advantageous features even in a small number of training data.

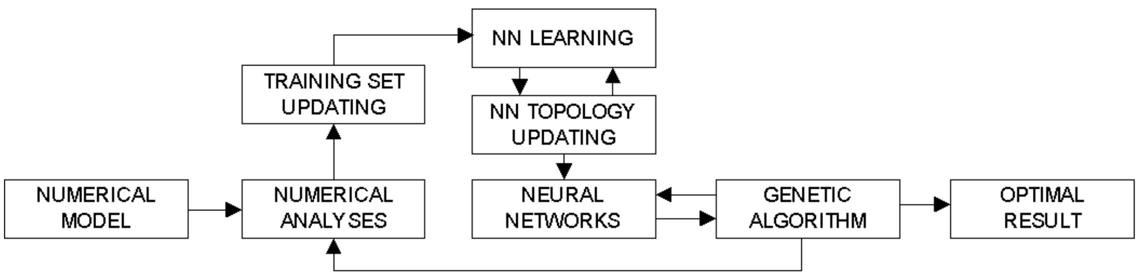

Fig. 2 Flow-chart of modified optimization procedure.

The presented algorithms were tested and verified for several problems, starting from very simple linear problems and complex nonlinear once as well.

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