ECCM 2010
IV European Conference on Computational Mechanics
Palais des Congrès, Paris, France, May 16-21, 2010

A Comparison of Particle Swarm Optimization and Genetic Algorithms for the Optimum Design of Steel Truss Structures

V. Plevris[1], L. Poufos[1], M. Papadrakakis[1]

[1] *National Technical University of Athens, Athens, Greece, vplevris@central.ntua.gr, loucas_p@yahoo.gr, mpapadra@central.ntua.gr*

In the past two decades, a number of optimization algorithms have been used in structural design optimization, ranging from gradient-based mathematical algorithms to non-gradient probabilistic-based search algorithms, for addressing global non-convex optimization problems. Many important probabilistic-based algorithms have been inspired by natural phenomena, such as Evolutionary Programming (EP), Genetic Algorithms (GA), Evolution Strategies (ES), among others.

The Genetic Algorithm (GA) is based on the biological principle of natural selection and the survival of the fittest, as dictated by the theory of evolution. First, a population of random solutions is generated and ranked according to their fitness by an evaluation (objective) function. Each candidate solution is called an individual and the aspects of each solution are its chromosomes. Some of the individuals are stochastically selected for reproduction, where a higher fitness ranking increases the chance of an individual being selected. The offspring of the next generation of individuals come from recombination (cross-over) of the parents and therefore carry their chromosomes, while in every generation there is also a small chance that mutation in some of the chromosomes of the individuals will occur, in order to increase the diversity of the initial genetic pool. The offspring and some of the parents will form the next generation which in turn will be ranked by the evaluation function and reproduce.

Recently, a family of optimization methods has been developed based on the simulation of social interactions among members of a specific species looking for food or resources in general. One of these methods is the Particle Swarm Optimization (PSO) method [1, 2] that is based on the behaviour reflected in flocks of birds, bees and fish that adjust their physical movements to avoid predators and seek for food. A swarm of birds or insects or a school of fish searches for food, resources or protection in a very typical manner. If a member of the swarm discovers a desirable path to go, the rest of the swarm will follow quickly. Every member searches for the best in its locality, learns from its own experience as well as from the others, typically from the best performer among them. Even human beings show a tendency to behave in this way as they learn from their own experience, their immediate neighbours and the ideal performers in the society. The PSO method mimics the behaviour described above. The method has been given considerable attention in recent years among the optimization research community. As in GA, in PSO a population of potential solutions is considered and utilized to search within the design space. However, the members of this population do not reproduce but rather communicate with each other their knowledge of solutions in order to reach the optimum. Each member of the population, or “particle”, “flies” through the multi-dimensional design space with a certain velocity vector for each step (iteration). It conducts a search in its vicinity for an optimum position, specified by the evaluation function, and after each iteration it adjusts its movement according to its previous velocity, its own experience of the best position (personal best) as well as the experience of whole swarm or the members of the its neighbourhood (global best).

The Genetic Algorithm and the Particle Swarm Optimization method have a lot of similarities and share a number of common characteristics. Both methods are stochastic, derivative-free, population-based iterative methods which rely on an external evaluation function to rate the respective individual solutions within each iteration and find the optimum. For both methods the initial population of candidate solutions is created randomly and scattered across the design space, a fitness value evaluates the candidate solutions, a probabilistic process governs the creation of the state of the next generation and no certainty is provided that the final solution is the global optimum. The conceptual difference of the two methods lies in their definition, which in PSO is given in a social context, instead of the biological context for the GA case. Unlike the GA, PSO has no genetic operators such as crossover and mutation, as the particles improve their fitness by altering their physical position in the solution space, according to a velocity vector updated in each iteration.

The objective of this study is to examine the behaviour of the two optimization methods in optimization problems of steel structures and compare them to each other. Their respective strengths and weaknesses are analyzed and their general efficiency is examined in comparison to various other optimization methods. The two methods are applied in single-objective, continuous, constrained structural engineering optimization problems. The aim is to minimize the weight of the structure under the constraints of maximum allowable nodal displacements and maximum allowable values of stresses. The constraints are checked by performing a Finite Element analysis for every candidate optimum design. In particular, two steel truss structures are considered as benchmark test examples for the two methods. The first test example is a ten-bar plane truss and the second is a 25-bar space truss. A number of parametric studies are conducted for each method, in order to apprehend their general behaviour until convergence. The performance, the functionality and the effect of different setting parameters are studied. In the process, the values of these parameters which improve convergence on the two examples are selected. After this fine tuning of the two methods, their respective results are compared to each other as well as to results obtained by other methods from the literature. The comparison is done with regard to the speed of convergence in terms of number of function evaluations and accuracy of the solution.

References

[1] Kennedy, J. and R. Eberhart, *Swarm Intelligence*. 2001, San Francisco, USA: Morgan Kaufmann Publishers.

[2] Kennedy, J. and R. Eberhart, *Particle swarm optimization*, in *IEEE International Conference on Neural Networks*. 1995: Piscataway, NJ, USA. p. 1942–1948.