Information Sciences 454–455 (2018) 255–274

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

A very optimistic method of minimization (VOMMI) for unconstrained problems

Vijaya Babu Vommi*, Rajkoti Vemula

Department of Mechanical Engineering, Andhra University, Visakhapatnam 530003, India

ARTICLE INFO

Article history:
Received 28 January 2017
Revised 10 April 2018
Accepted 13 April 2018
Available online 20 April 2018

Keywords:
Unconstrained optimization
Nontraditional optimization
Luck factor
Effort factor

ABSTRACT

Numerous nontraditional optimization techniques have been suggested in literature to solve highly complicated multimodal mathematical functions. The complexity involved in solving the functions increases with the increase in the number as well as the range of the variables. Most of the optimization algorithms involve much complexity in their understanding and implementation and this complexity is found to be proportional to the number of algorithm specific parameters. Hence, there is a need to find simple but effective algorithms with minimum number of algorithm specific parameters. The present work aims to introduce a novel and simple methodology for optimization without sacrificing the effectiveness. It relies on following the 'existing best practices' to achieve improvement. The algorithm employs two factors represented as luck and effort factors and solves many complex unconstrained optimization problems effectively. The proposed algorithm is found to be successful in providing better solutions than some popular algorithms for certain complicated problems, reported in literature.

1. Introduction

The optimization techniques that are based either on classical methods or on numerical methods fail more often to locate the global optimum when the objective function is a multimodal function. Real life complex problems could not be solved satisfactorily using the traditional optimization techniques [32]. This situation has led to the search for effective global optimization techniques. With the advent of high power computers, the nontraditional methods of optimization have become popular in solving complicated multimodal functions. Scientists, engineers and researchers in almost all fields are relying mostly on nontraditional optimization techniques to solve real life problems (e.g., [6,13,25,2]). All these nontraditional techniques lack any mathematical support to prove that they lead to global optimum. The supporting features for these optimization techniques are that they mimic the nature and are capable of reaching the near global optimum with high probability with empirical evidence. With the help of some complicated test functions [17], the performance of the suggested techniques could be evaluated. A good number of global optimization techniques have been suggested by the researchers in the recent past and no technique could be proved to be the best among all the existing. The difficulty associated with most of these techniques is that they need certain algorithm specific parameters to be controlled and a lot of effort has to be applied for fine tuning these parameters. The parameters suitable for minimizing a particular objective function may not be suitable to handle some other optimization problem even though the technique used is the same. Hence, the results can be considered to be sensitive to the parameters used in the technique adopted. This tendency has given rise to the idea

* Corresponding author.
E-mail address: vvijayababu.mech@auvsp.edu.in (V.B. Vommi).

https://doi.org/10.1016/j.ins.2018.04.046

of reducing the parameters required for the optimization technique, provided the solutions do not become inferior to other techniques using more parameters. Keeping the need to obtain a superior or an equally good solution with minimum or no algorithm specific parameters, the present method has been developed.

The proposed method is simply based on the idea that to grow or prosper in life, one has to study the life style of successful people and benchmark their attributes leading to success. In order to reach the performance of the successful people, the differences between the benchmarked attributes and the existing attributes have to be corrected in such a way that finally the performance may be on par or even better than the standard under consideration. To achieve the goal of reaching the attributes of the successful people, it is believed that two factors play an important role, namely, the effort applied and the luck. With these two factors affecting the success, a person would try to achieve the attributes of a successful person. The luck factor is represented by a random number and the effort factor by a real number.

The above analogy has been applied in optimizing the mathematical objective functions. Initially, N sets of variables (design vectors) are generated randomly from the feasible search space. The objective function values are calculated for the N initial solutions. The N initial solutions are sorted in the ascending order of their objective function values. The minimum value of the objective function is possessed by the first set of variables representing the best solution. The second best, third best and so on are available in the same order. The Nth solution is the worst or the weak solution in the first round of calculations. Hence, the Nth solution has a lot of scope for improvement with respect to the remaining. In this scenario, the solutions are divided equally into two halves. The first $N/2$ solutions are represented as strong solutions and the remaining $N/2$ solutions are treated as weak solutions. Keeping the strong (first) $N/2$ solutions unchanged, the remaining weak N/2 solutions are made to interact with the strong solutions in order to improve their attributes. This results in $N/2$ new solutions. A total of $[N+N/2]$ solutions are available after first iteration from which only N best solutions will be taken. They are further utilized in obtaining the optimum solution by using the proposed algorithm explained in the coming sections.

The present work is organized in the following manner: Section 2 reviews the pertinent literature. Section 3 describes the present method of minimization in detail with an illustration. Section 4 presents the experiments on certain difficult multimodal test functions, experiments on bench mark functions with higher dimensions and certain highlights about the performance of the proposed method. Section 5 is devoted to test the ability of the algorithm in tackling the dimensional complexity. Section 6 covers the comparison of the performance of the present algorithm with different variants of Particle Swarm Optimization algorithm. The final section gives the summary and concluding remarks on the present method of minimization.

2. Literature review

Inspired by the manner in which the metal crystals reconfigure and reach equilibria [28], Kirkpatrick et al. [24] proposed a method for optimization known as Simulated Annealing (SA). In an annealing process, the cooling of hot metals is done slowly to avoid defects. The optimization process starts with a single solution (design vector) and slowly proceeds toward the optimum. The results of SA depend on the initial temperatures and on the Boltzmann probability factors. Based on Darwin's theory of 'survival of the fittest', the first population based global optimization technique, popularly known as Genetic Algorithm (GA), was introduced for solving complex engineering and scientific problems [15,12]. The method starts with an initial population (a number of design vectors) and evolves after a number of generations. The new generations are obtained by using reproduction, crossover and mutation operators. Different probability values can be associated with crossover and mutation operations and also the crossover can have different forms like single point or multiple point crossovers. Tuning the parameters for different problems may result in different best values for population size, crossover points and probabilities of cross over and mutation. Kennedy and Eberhart [23] proposed the Particle Swarm Optimization (PSO) method. The particle here denotes either a bee or a bird in its own group. The position and the velocity of the particle play a major role in achieving the best solution. Apart from position and velocity, a parameter known as inertia (which varies linearly from0.9 to 0.4) has been introduced to improve the performance of the PSO algorithm [39].The ability of the ants to find the shortest distance between their nest and the food source has been used in developing the optimization algorithm known as Ant Colony Optimization (ACO) [7]. The number of ants and the pheromone decay rate are utilized in finding the optimum solutions. Storm and Price [41] introduced the Differential Evolution (DE) algorithm which uses mutation and cross over operations with certain differences compared to genetic algorithm. Karaboga [18] proposed the Artificial Bee Colony (ABC) algorithm in which three groups of bees namely, employed bees, onlooker bees and scout bees are utilized in finding the best solution. The number of food sources, the limit and the maximum cycle number are the three parameters that control the algorithm.

Apart from the above, a good number of optimization algorithms like artificial immune algorithm [9], harmony search algorithm [11], bio-mimicry of bacterial foraging algorithm [33], shuffled frog leaping algorithm [8], biogeography-based optimization algorithm [40], fire fly algorithm [42], cuckoo search algorithm [43], gravitational search algorithm [36], change system search algorithm [22], grenade explosion algorithm [1], teaching and learning based optimization algorithm [35],mine blast algorithm[37], artificial cooperative search algorithm [5], symbiotic organisms search algorithm [4], league championship algorithm[21], evolutionary membrane algorithm [14], heat transfer search algorithm [34],etc., have been reported in literature.