APPLICATION OF SIMULATED ANNEALING AND GENETIC ALGORITHM IN ENGINEERING APPLICATION

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ABSTRACT

Research on genetic algorithms (GAs) has shown that the initial proposals are incapable of solving hard problems in a robust and efficient way. Usually, for large-scale optimization problems, the execution time of first-generation GAs increases dramatically whereas solution quality decreases. The aim of this paper is to point out the main design issues in tailoring Simulated Annealing and GAs to large-scale optimization problems. In present paper, an objective function is defined with constraints and solved by both the technique i.e., SA and GA. The solution of this problem has shown the superior performance of SA as compared to GA in optimization technique. The problem considered in this paper is in general form and applicable to engineering applications with specific objective function and constraints depending upon the nature of problem to be optimized.

KEYWORDS
Simulated Annealing (SA), Genetic Algorithm (GA), Optimization, Real life problems

1. INTRODUCTION

Simulated annealing (SA) is one of the most flexible techniques available for solving hard combinatorial problems. The main advantage of SA is that it can be applied to large problems regardless of the conditions of differentiability, continuity, and convexity that are normally required in conventional optimization methods.

Annealing is the process of submitting a solid to high temperature, with subsequent cooling, so as to obtain high-quality crystals (i.e., crystals whose structure form perfect lattices) [1]. Simulated annealing emulates the physical process of annealing and was originally proposed in the domain of statistical mechanics as a means of modelling the natural process of solidification and formation of crystals. During the cooling process, it is assumed that thermal equilibrium (or quasi equilibrium) conditions are maintained. The cooling process ends when the material reaches a state of minimum energy, which, in principle, corresponds with a perfect crystal. It is known that defect-free crystals (i.e., solids with minimum energy) are more likely to be formed under a slow cooling process. The two main features of the simulated annealing process are: (1) the transition mechanism between states and (2) the cooling schedule. When applied to combinatorial optimization, simulated annealing aims to find an optimal configuration (or state with minimum "energy") of a complex problem. The objective function of an optimization problem corresponds with the free energy of the material. An optimal solution is associated with a perfect crystal, whereas a crystal with defects corresponds with a local optimal solution. The analogy is not complete, however, because in the annealing process there is a physical variable that is the temperature, which under proper control leads to the formation of a perfect crystal. When simulated annealing is used as an optimization technique, the "temperature" becomes simply a control parameter that has to be properly determined in order to achieve the desired results.

The original idea behind the simulated annealing algorithm is the Metropolis algorithm that models the microscopic behaviour of sets of large numbers of particles, as in a solid, by means of Monte Carlo simulation. In a material, the individual particles have different levels of energy, according to a certain statistical distribution. The possible lowest level of energy, known as the fundamental level, corresponds with the state where all particles stand still and occurs at temperature 0° K. For temperatures above that level, the particles will occupy different levels of energy, such that the number of particles in each level decreases as the energy level increases (i.e., the maximum number of particles is found in the fundamental level). The distribution of the particles in the various levels varies with the temperature; for T = 0 K, for example, all particles are in the fundamental level; as the temperature increases, more particles are found in higher energy levels but always as a decreasing function of the energy level.

The Metropolis algorithm generates a sequence of states of a solid as follows: giving a solid in state Si, with energy Ei, the next state Sj is generated by a transition mechanism that consists of a small perturbation with respect to the original state, obtained by moving one of the particles of a solid chosen by the Monte Carlo method. Let the energy of the resulting state, which also is found probabilistically, be Ej; if the difference Ej-Ei is less than or equal to zero, the new state Sj is accepted. Otherwise, in case the difference is greater than zero, the new state is accepted with probability.

$$\exp(\frac{Ei - Ej}{k_B T}),$$

Where, T is the temperature of the solid and $k_B$is the Boltzmann constant. This acceptance rule is also known as Metropolis criterion and the algorithm summarized above is the Metropolis algorithm [2]. The temperature is assumed to have a rate of variation such that thermodynamic equilibrium is reached for the current temperature level, before moving to the next level. This normally requires a large number of state transitions of the Metropolis algorithm. For a combinatorial optimization problem to be solved by simulated annealing, it is formulated as follows: let G be a finite, although perhaps very large, set of configurations and v the cost associated with each configuration of G. The solution to the combinatorial problem consists of searching the space of configurations for the pair (G, v) presenting the lowest cost. The SA algorithm starts with an initial configuration $G_o$and an initial "temperature" T_o and generates a sequence of configurations N =N_o. Then the temperature is decreased; the new number of steps to be performed at the temperature level is determined, and the process is then repeated. A candidate configuration is accepted if its cost is less than that of the current configuration. If the cost of the candidate configuration is bigger than the cost of the current configuration, it still can be accepted with a certain probability. This ability to perform uphill moves allows simulated annealing to escape from local optimal configurations. The entire process is controlled by a cooling schedule that determines how the temperature is decreased during the optimization process.

2. PROBLEM FORMULATION BY SA

The application of SA in optimization problem is formulated as an NLP problem, expressing the objective function and constraint functions in term of the specified independent variables. The objective function is expressed as

Optimize f(x)

Such that 'x' exists within the n-dimensional feasible region D:

X D, where

D = {x | x >=0, g_i(x) <=0, h_i(x) = 0, i=1 to n}

In the above equations, f(x), g_i(x) are real valued scalar functions and vector x comprises the n principal variables for which the optimization is to be performed .The function f(x) is called to be objective function, for which the optimal value of x result in the maximum value for f(x), and these optimal values satisfy the given constraints.

Algorithm:

```
Simulated Annealing
Begin
Initialize ($T_o$,$N_o$);
K: = 0;
Initial configuration $S_i$
Repeat procedure
Do L: =1 to Nk
Generate (Sj from Si);
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If f(Sj) ≤ f(Sj) do Si = Sj
Otherwise
If exp($\frac{f(Si)-f(Sj)}{Tk}$) >random [0,1] do Si = Sj;
End do;
K = K+1;
Calculation of the length (Nk);
Determine control parameter (Tk)
Stopping criterion
End;
```

From the current state Si with cost f(Si), a neighbor solution Sj, with cost f(Sj) is generated by the transition mechanism. The following probability is calculated in performing the acceptance test:

$$P_T\{\text{Accept Sj}\} = \{1 \quad if \quad f(S_j) \le f(S_i)\}$$

$$\text{or} \quad \{\exp(\frac{f(Si)-f(Sj)}{Tk}), \; if \quad f(S_j) > f(S_i)$$

3. STEP OF GENETIC ALGORITHM

A simple genetic algorithm process is illustrated in Figure1.1.[3]-[6]. After an initial population is randomly or heuristically produced, the fitness function of the pupation is evaluated and the genetic algorithm evolves the population through sequential and iterative application of three genetic operators: *parent selection*, *crossover*, and *mutation*. A new generation is formed at the end of each iteration [7]-[9].

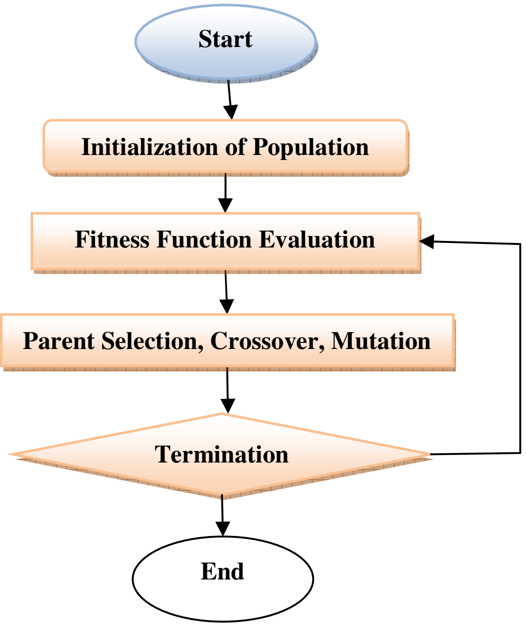
Start
Initialization of Population
Fitness Function Evaluation
Parent Selection, Crossover, Mutation
Termination
End

Figure 1.Flow Chart of Genetic Algorithm

4. RESULT AND DISCUSSION

Solve the following problem:

$$\min f(X1, X2) = \min_{X1,X2}\{X1.\sin[\sqrt{X1-(X2+9)}\,] -(X2+9).\sin[\sqrt{X2+0.5X1+9}]\}$$

Subject to (i) $-20 \le X1 \le 20$

(ii) $-20 \le X2 \le 20$

using the simulated annealing technique and binary genetic algorithm technique.

4.1. OPTIMIZATION RESULT BY SIMULATED ANNEALING TECHNIQUE

By using SA technique the optimum value of X1 is 19.999 and X2 is -19.69 and the objective function value is -19.3533.The best function value and the mean temperature which are obtained by SA technique are -19.69 and 0.0773719 respectively.

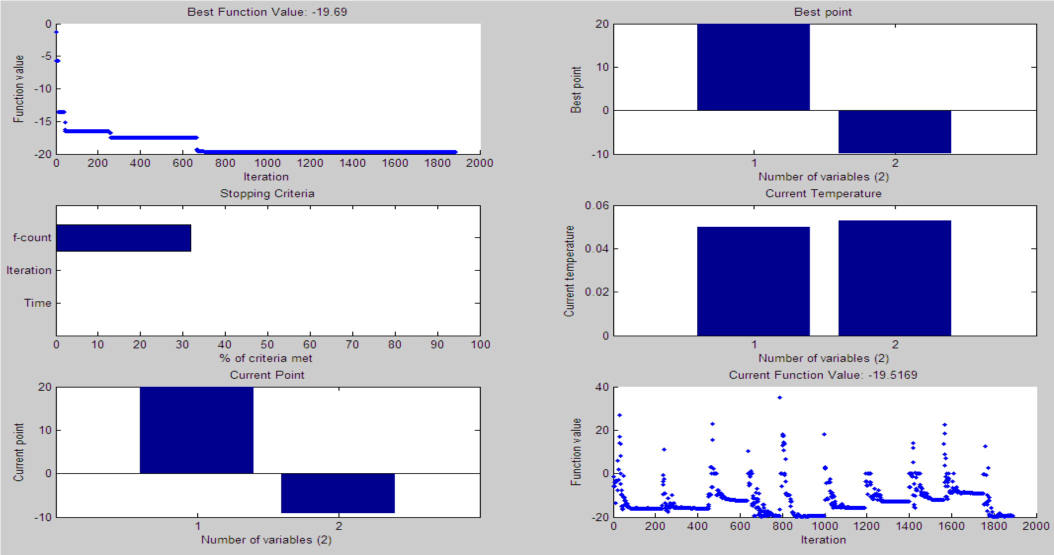

Figure 2. Prediction of Best function value, Best point, Stopping Criteria, Current Temperature, Current Point, Current function value in Simulated Annealing Process.

4.2. OPTIMIZATION RESULT BY GENETIC ALGORITHM

By conventional genetic algorithm method the optimum value of X1 is -14.5098 and X2 is -20 and the objective function value is -23.80 and by Mat-lab genetic algorithm programming method the optimum value of X1 , X2 and objective function value are 0 , 0.867 and -0.0042342 respectively.

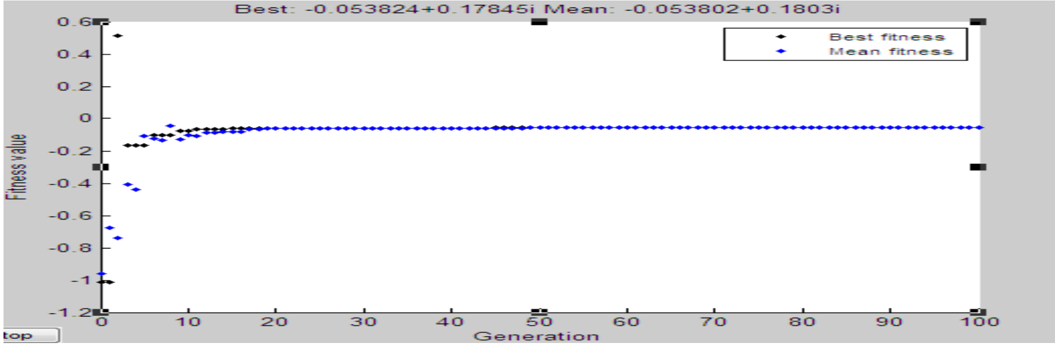

Figure 3. Prediction of Best Fitness Value with respect to Generation

5. CONCLUSIONS

The two optimization techniques namely SA and GA have been applied in this paper. By using Mat-lab genetic algorithm programming method the optimum value of X1 , X2 and objective function values comes out to be 0, 0.867 and -0.0042342, respectively.

By applying Simulated Annealing algorithm for the optimization of the same objective function with similar constraints, the optimum values of X1,X2 and objective function comes out to be 19.999, -9.928 and -19.690012, respectively. By using SA technique the optimum value of objective function has been reduced in comparison to GA technique. This proves that SA based design optimization is simple, robust and reliable for design optimization problem. Thus SA is a viable tool for obtaining optimal value in engineering optimization problem.

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BIOGRAPHIES

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