

# Improved Modified Simulated Annealing Algorithm for Global Optimization

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## Abstract

This work presents an improved version of the Modified Simulated Annealing Algorithm (I-MSAA). Modified Simulated Annealing Algorithm (MSAA) was recently introduced for solving global optimization problems and is a newly improved version of the simulated annealing (SA) with three modifications: preliminary exploration, search step and probability of acceptance. The I-MSAA proposed here does not perform a preliminary exploration and reduces the probability of accepting worse solutions. I-MSAA was evaluated in benchmark functions (constrained and unconstrained) reported in the literature. The results indicated that I-MSAA is a good tool to optimize functions of high complexity.

**Keywords:** Modified simulated annealing algorithm, optimization, metaheuristics

## 1 Introduction

The practical problems of engineering are represented by functions that are highly modal, with several variables and with small feasible regions. Because of this, the deterministic methods, which depend on gradient information, are difficult to apply. Therefore, metaheuristics techniques can serve as appropriate alternatives of conventional methods because they do not require the gradient information or the convexity of the objective function and constraints, and they use probabilistic transition rules. They are based on stochastic search strategies that make them quite effective and versatile to counter the combinatorial explosion of the possibilities.

Several metaheuristics have been developed to solve global optimization problems, for example, Particle Swarm Optimization (PSO) [1], Genetics Algorithms (GA)

[2], Simulated Annealing (SA) [3], Harmony Search (HS) [4], Ant Colony Optimization (ACO) [5], Cuckoo Search (CS) [6], Colliding Bodies Optimization (CBO) [7], Water Wave Optimization [8], Big Bang–Big Crunch [9], Dolphin Echolocation (DE) [10], Ray Optimization (RO) [11], Charged System Search [12] among others.

Recently, the metaheuristic called Modified Simulated Annealing Algorithm (MSAA) [13–15] was introduced to solve global optimization and engineering problems. MSAA is a newly improved version of the simulated annealing (SA) with three modifications. Firstly, a preliminary exploration is realized to choose the starting point of search. Secondly, the transition from the start point to the new point is done by a search step. Thirdly, the range of probability of accepting a worse solution is reduced.

In this study an Improved Modified Simulated Annealing Algorithm (I-MSAA) is proposed with the aim of improving the quality of the solution and reducing search times. I-MSAA unlike the MSAA, does not reliably scan preliminary and reduces the probability of accepting a worse solution.

This study is structured as follows: Section 2 presents the methodology and the I-MSAA. Section 3 shows the results obtained with I-MSAA in the benchmark functions. Section 4 presents the conclusions of this study.

## **2 Methodology**

The algorithm proposed here (I-MSAA) was coded in MATLAB R2017a, and Windows platform using Intel(R) Core(TM) i5-3230M CPU@ 2.60 GHz processor speed with 8.00 GB RAM. I-MSAA was evaluated in 18 benchmark functions (5 unconstrained and 13 constrained) [13,16]. Figure 1 shows the 3D graphs of the unconstrained functions used. Every function was solved 100 times and the best value, worse value and standard deviation are reported in the tables.

I-MSAA is based on the SA. SA is a method developed from the statistical thermodynamics to simulate the behavior of atomic arrangements in liquid or solid materials during the annealing process. The difference between the algorithm proposed here and MSAA [13–15] is: i) reduction of probability of accepting worse solutions; ii) the starting point is chosen randomly and not by means of the preliminary exploration.

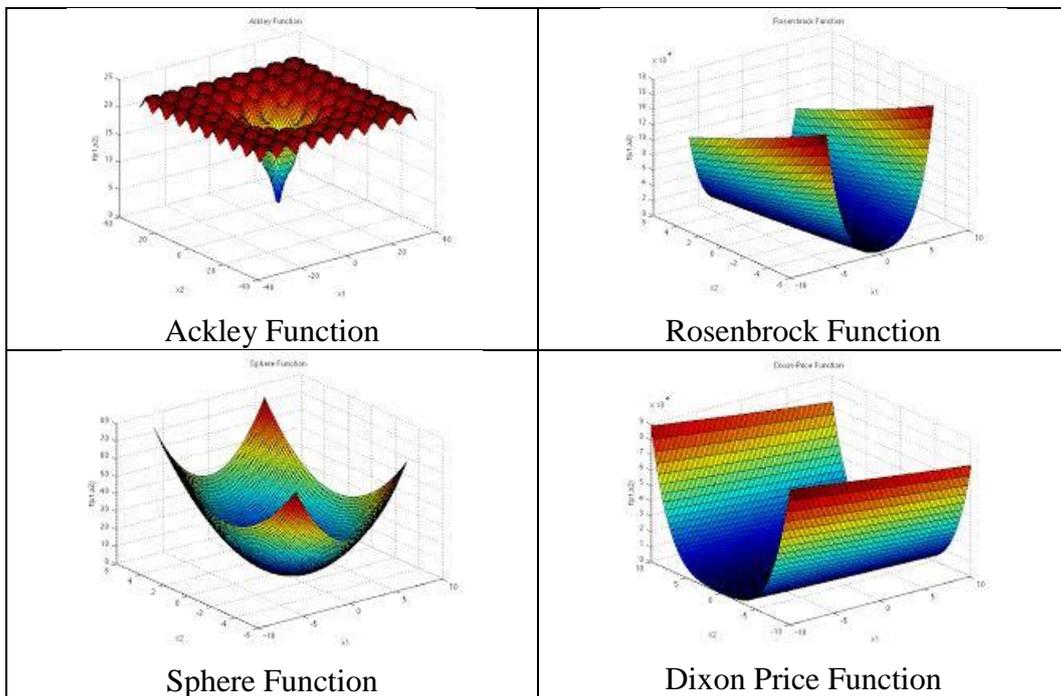


Figure 1. Unconstrained benchmark functions

The probability of acceptance of a worse solution is between 0 and 1/3 and is calculated by:

$$P = \frac{1}{1+2\exp(\Delta f/T)} \quad (1)$$

The Pseudo code of I-MSAA is as follow:

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Setting initial temperature ( $T_i$ )
Setting final temperature ( $T_f$ )
Setting maximum number of perturbations at the same temperature (npmax)
Generate Initial State (S) randomly
 $T=T_i$ 
While ( $T > T_f$ ) do //Temperature Cycle
For np=1 to npmax //Metropolis Cycle
Generate S' by search step
Obtain difference ( $\Delta f$ ) between S' and S
If ( $\Delta f \leq 0$ ) then
Accept S'
else
Boltzmann Probability =  $1/(1+2\exp(\Delta f/T))$ 
If (Boltzmann Probability > random(0, 1/3)) then
Accept S'
end if

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end if
end while
Decrease T by cooling function  $T_{k+1}=\alpha T_k$ 
end while
Shown best solution (Sbest)

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### 3 Results

Table 1 shows the comparison of the results obtained in the unconstrained functions between I-MSAA and SA. As seen, I-MSAA is a very stable algorithm, capable of obtaining consistent and reasonable results. In terms of robustness, the algorithm found the global optimum in all functions. Therefore, I-MSAA can be considered as a robust optimization algorithm. On the other hand, it can be said that ASAM shows a great capacity to escape from local optima when it comes to multimodal functions (Ackley). It also showed potential to handle difficult unimodal search functions to solve (Rosenbrock and Neumaier). Finally, it is observed that the basic SA is trapped in local optima, causing it to converge quickly and not find the minimum value of the function.

Table 1. Performance of SA and I-MSAA in unconstrained functions

Function	D	Optimal	SA			I-MSAA		
			Best	Worse	SD	Best	Worse	SD
Dixon Price	10	0.0	100.3	891.4	$1.9 \times 10^2$	0.0	0.0	$8.9 \times 10^{-8}$
Ackley	50	0.0	17.9	19.0	0.2	0.0	0.0	$2.3 \times 10^{-5}$
Neumaier	10	-210.0	764.8	$3.6 \times 10^3$	$6.4 \times 10^2$	-210.0	-210.0	$3.2 \times 10^{-9}$
Rosenbrock	50	0.0	$5.7 \times 10^5$	$9.4 \times 10^5$	$8.3 \times 10^4$	0.0	4.0	1.2
Sphere	50	0.0	186.4	249.4	12.8	0.0	0.0	$4.0 \times 10^{-8}$

Table 2 shows the results obtained with I-MSAA in the constrained functions. From this table, it can be seen that I-MSAA reaches the optimum in several problems and converges to the optimum in others. In addition, the proposed algorithm can deal with problems that contain moderate restrictions (g06); problems with a high number of restrictions (g01, g04); with low (g06, g08), moderate (g09) and high (g01, g02, g03, g07) dimensionality; with different types of restrictions and their combinations (linear, non-linear, equality and inequality); with feasible regions large (g02), very small (g05, g13) or disjunct (g12); and with problems where the global optimum is at the border of the feasible region (g01, g02, g04, g06, g07, g09). The 2 problems in which the algorithm had greater difficulty were g05 and g13, because they have very small feasibility zones and equality constraints, so finding solutions is a big step in the algorithm.

Table 2. Performance of I-MSAA in constrained functions

Function	Optimal	I-MSAA		
		Best	Worse	SD
g01	-15.00	-15.00	-14.99	$5.47 \times 10^{-4}$
g02	-0.80	-0.80	-0.75	0.01
g03	-1.00	-1.00	-1.00	$2.14 \times 10^{-6}$
g04	-30665.53	-30665.53	-30665.53	$4.86 \times 10^{-6}$
g05	5126.49	5081.21	5112.34	1.82
g06	-6961.81	-6961.81	-6961.80	$1.39 \times 10^{-3}$
g07	24.30	24.35	24.36	0.22
g08	-0.09	-0.09	-0.09	$6.43 \times 10^{-6}$
g09	680.63	680.63	680.63	$7.10 \times 10^{-4}$
g10	7049.33	7049.30	7068.21	3.34
g11	0.75	0.75	0.75	$6.59 \times 10^{-5}$
g12	-1.00	-1.00	-0.99	$5.67 \times 10^{-4}$
g13	0.05	0.05	0.53	0.21

## 4 Conclusions

In this work an Improved Modified Simulated Annealing Algorithm (I-MSAA) was introduced for the optimization of global optimization problems. The I-MSAA reduces the probability of acceptance a worse solution and does not perform preliminary exploration.

The performance of I-MSAA was evaluated in a total of 18 benchmark functions (unconstrained and constrained). In the 2 groups of functions studied the algorithm presented high precision, accuracy and robustness, as evidenced in Tables 1 and 2.

The I-MSAA is an excellent optimization algorithm that can be applied to practical engineering problems such as structural optimization, topological optimization, optimization of retaining walls.

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