Parametric Analysis of Nature Inspired Optimization Techniques

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ABSTRACT
There are large numbers of the optimization technique that have been used to optimize the thing in the field of computer science, transportation engineering, mechanical engineering, management and so on. But the traditional optimization techniques are replaced by nature inspired techniques. These technique involve directly or indirectly the participation of nature such as GA, ACO, BCO SA, SS. Such techniques provide an abstract way to solve the problem. Each technique is differing from the other technique but each technique having some similarity with other techniques. This paper provides the comparative analysis of Nature inspired optimization techniques in the tabular form.

KEYWORDS
Optimization, Techniques,
Stochastic, Population, Heuristic

1. INTRODUCTION

Optimization Techniques is a unique reference source of methods for achieving optimization i. e. to find the optimal solution. These techniques include both systems structures and computational methods. Commonly optimization techniques are used to find the optimal solution for the problems which have more than one solution. There are many optimization techniques available today such as numerical optimization technique, linear optimization, nonlinear optimization, constrained optimization, combinatorial optimization, Stochastic programming, EA, PSO, GA etc. Many techniques are appropriate only for certain types of problems. Thus, it is important to recognize the characteristics of a problem and to identify an appropriate technique in the context of given problem to find the optimal solution, such that for each class of problems there are different minimization methods, varying in computational requirements, convergence properties, and so on. Optimization problems are classified according to the mathematical characteristics of the objective function, the constraints and the control variables. The most important characteristic is the nature of the objective function. The relationship in between the control variables is of a particular form, such as linear, e.g.

$$f(x) = b^t x + c \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where b is a constant-valued vector and c is a constant, or quadratic, e.g.

$$f(x) = x^t A x \; b^t x + c \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where A is a constant-valued matrix, special methods exist that are guaranteed to locate the optimal solution very efficiently.
The optimization technique formulates the problem in given below steps:
1. Create a basic configuration

2. Identify the decision variables
3. Establish the objective function
4. Identify any constraints
5. Select and apply an optimization method

2. OPTIMIZATION TECHNIQUES

The various optimization techniques are given as:-

2.1 Particle Swarm Optimization (PSO)

PSO is a search method which utilizes a set of agents that move through the search space to find the global minimum of an objective function. The PSO was developed by Kennedy and Eberhart in 1995[50]. After its development, the simplicity and flexibility of the algorithm achieve a very efficient search of near optimal solutions for the problems with quite a tricky search space. This technique is developed from swarm intelligence and based on the research of bird and fish flock movement behavior [59]. While searching for food, the birds are either scattered or go together before they locate the place where they can find the food [60]. While the birds are searching for food from one place to another, there is always a bird that can smell the food very well, that is, the bird is perceptible of the place where the food can be found, having the better food resource information. Because they are transmitting the information, especially the good information at any time while searching the food from one place toanother, conducted by the good information, the birds will eventually flock to the place where food can be found [59].

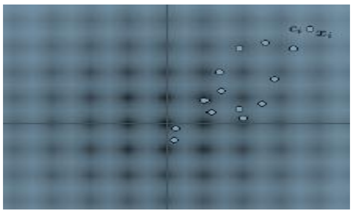

Fig. 1 Particle swarm in search with global minimum

2.2 Tabu Search (TS)

The roots of tabu search go back into to the 1970's. It was first presented in its present form by Glover in 1986. The basic ideas have also been sketched by Hansen in 1986. Additional efforts of formalization the tabu search are reported in 1990 [1]. Many computational experiments shown that tabu search has become an established optimization technique which can compete with almost all known techniques by its flexibility and also beat many classical procedures. Up to now, there is no formal explanation of this good behavior. The theoretical aspects of tabu search have been investigated Faigle & Kern 1992, Glover, 1992, Fox, 1993 [2]. The systematic use of memory is an essential feature of tabu search.

2.3 Simulated Annealing (SA)

In 1953, Metropolis et al. proposed an algorithm to simulate the behavior of physical systems in the presence of a heat bath. Thirty years later, Kirkpatrick et al. [8] applied the Metropolis algorithm to combinatorial optimization problems and named it by simulated annealing. In 1986, Bohachevsky et al. [55] applied the SA algorithm to solve continuous optimization problems. Since then, the SA algorithm has been subject to various modifications in order to improve its efficiency. The spread use of the SA algorithm is mainly due to the fact that it is easily implemented, it can be applied to any optimization problem, it does not use any derivative information, it does not require specific conditions on the objective function and it has been proved that the SA algorithm asymptotically converges to a global maximum.

2.4 Genetic Algorithm (GA)

Genetic algorithms (GA) have been successfully applied to optimization problems like routing, adaptive control, game playing, cognitive modeling, transportation, traveling salesman problems, optimal control problems, etc [11]. The genetic algorithm (GA) [16] transforms a population (set) of individual objects, each with an associated fitness value, into a new generation of the population using the Darwinian principle of reproduction and survival of the fittest and analogs of naturally occurring genetic operations such as crossover (sexual recombination) and mutation. Each individual in the population represents a possible solution to a given problem. The genetic algorithm attempts to find a very good (or best) solution to the problem by genetically breeding the population of individuals over a series of generations.

2.5 Evolutionary Algorithms (EA)

Evolutionary algorithms (EA) are a wide class of randomized problem solvers based on principles of biological evolution. They have been used successfully in many computational areas such as Optimization [56], Learning, Adaptation automatic programming, machine learning, operations research, bioinformatics and social systems. In many cases the mathematical function, which describes the problem is not known and the values at certain parameters are obtained from simulations. In contrast to many other optimization techniques an important advantage of evolutionary algorithms is they can cope with multi-modal functions [13]. Hence, there are lots of available experimental results concerning this class of algorithms, but compared to that amount, the theoretical knowledge of how they perform lags way behind. Indeed, the largest parts of the available research studies are of empirical nature. However, since the eighties when EA started to become popular, there have always been theoretical studies of this class of algorithms.

2.6 Scatter Search (SS)

Scatter search is an evolutionary method that has been successfully applied to hard optimization problems. The fundamental concepts and principles of the method were first proposed in the 1970s, based on formulations dating back to the 1960s for combining decision rules and problem constraints [22]. SS is a population based meta-heuristic that use a reference set to combine its individuals and obtain others. The method generates a reference set from a wider population of individuals. Then a subset is selected from this reference set. The selected individuals are combined to get new individuals to be used in improvement procedure. The individuals resulting from these improvements can motivate the updating of the reference set and even updating the population [21].

2.7 Ant Colony Optimization (ACO)

Marco Dorigo and his team provide the first ACO algorithms in the early 1990's [31]. The biological inspiration of ACO was the observation of ant colonies. Ants are social insects. They live in colonies and their behavior is governed by the goal of colony survival rather than being focused on the survival of individuals [32].The behavior that provided the inspiration for ACO is the ants' foraging behavior, and in particular, how ants can find shortest paths between food sources and their nest [32]. When searching for food, ants initially explore the area surrounding their nest in a random manner. While moving, ants leave a chemical pheromone trail on the ground. Ants can smell pheromone. When choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations [32]. ACO [32] is a class of algorithms, whose first member called Ant System. The ACO was initially proposed by Colorni, Dorigo and Maniezzo [57]. The main underlying idea, loosely inspired by the behavior of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. The collective behavior emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization problems.

2.8 Gradient Descent (GD)

Gradient descent is an optimization algorithm that approaches a local minimum of a function by taking steps proportional to the negative of the gradient (or the approximate gradient) of the function at the current point. If instead one takes steps proportional to the gradient, one approaches a local maximum of that function. The procedure is then known as gradient ascent. The idea behind gradient descent methods is to find the maximum or minimum of a response surface by following the gradient, either up or down [27]. One of the big advantages of such a method is that the nearest optimum can be found by only comparatively few calculations. However, gradient descent methods show several drawbacks. One of the most important points is that gradient descent methods do not necessarily find the global optimum [26]. As can be seen from the figure below, whether or not the global optimum is found depends on the starting point.

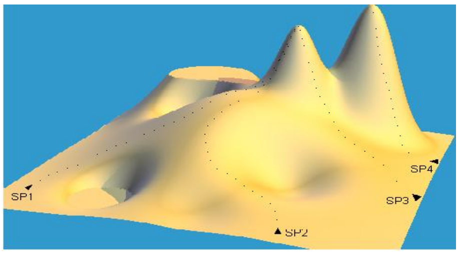

Fig.2 Finding global optimum using gradient descent

2.9 Bee Colony Optimization (BCO)

The Bee Colony Optimization (BCO) proposed in [34, 39] is a meta-heuristic, since it represents a general algorithmic framework applicable to various optimization problems in management, engineering, and control, and it should always be tailored for a specific problem. The BCO belongs to the class of population-based algorithms. The BCO is naturally inspired by real honey bee. The main idea behind this Bee Algorithm is the broadcasting ability of the bee to some neighborhood bees so they may know and follow a bee to chance upon the best source, locations, or routes to complete the optimization task. The detailed implementation will depend on the actual algorithms, and they may differ slightly and vary with different variants. The Bee Algorithm is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution [58].

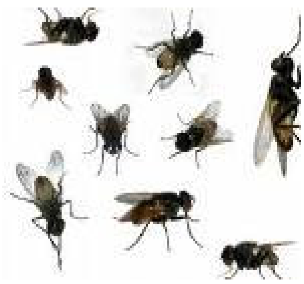

Fig. 3 Biological inspiration of BCO

2.10 Differential Evolution (DE)

Differential Evolution (DE) is a relatively new EA proposed by Price and Storn [45]. The algorithm is based on the use of a special crossover-mutation operator, based on the linear combination of three different individuals and one subject-to-replacement parent. The selection process is performed via deterministic tournament selection between the parent and the child created by it. However, as any other EA, DE lacks a mechanism to deal with constrained search spaces. In DE community [46], the individual trial solutions (which constitute a population) are called parameter vectors or genomes. DE operates through the same computational steps as employed by a standard EA. However, unlike traditional EA, DE employs difference of the parameter vectors to explore the objective function landscape.

3. PARAMETER

In this paper, the following parameters are used for comparison between above discussed optimization techniques.

- Methodology
- Inspiration
- Technique
- Dimension
- Developer
- Known Application area
- Efficiency
- Variants
- Constrained/Unconstrained
- Linear/Non Linear

The comparative analysis of the optimization technique is given in the form of table in Annexure – 1& 2 at the end of paper.

4. CONCLUSION

There are lots of optimization techniques available to solve the problem. But the each technique is distinguish from another i.e. applicability of technique to the problem and nature of the problem. Of course a problem can be solved by many optimization techniques i.e. more than one optimization techniques apply on the same problem. So in this situation, the complexity plays an important role. It also matter through which technique the best result is obtained whether that result is optimum or not.

Now, the different techniques have different complexity. Any problem must be solved with minimum complexity but also provide the optimal solution. So in terms of the complexity the gradient method provide the best result. But the complexity of the Tabu search and simulated annealing is almost same. The biological inspired techniques such as ACO, BCO, GA than SS, GD and DE are also present in the article. The complexity of ACO and BCO is quite similar but the difference is applicability of technique on the problem. Basically the ACO is 2D application and BCO is 3D application. Different problems can find optimal solution with different techniques. In the present paper various techniques are presented in an abstract way i.e. in the form of table so that user can choose the technique according to the problem.

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Comparative Analysis of Nature Inspired Optimization Techniques

Annexure - 1

S. No.	Parameter	Particle Swarm Optimization	Tabu Search	Simulated Annealing	Genetic Algorithm	Evolutionary Algorithm
1	Methodology	• Initialize each particle • Calculate fitness function for each particle. • Compare the fitness value with another calculated fitness value. The best value set as p Best. • Choose the particle with best fitness value to provide g best • Calculate particle velocity • Update particle position.	• Choose initial solution from a set S such as i€ S. • Create a candidate solution on the behalf of TB condition and aspiration condition. • Evaluate the solution and compare the previous one. • Update tabu and aspiration condition. • Stopping criteria.	• Initialize a finite set S. • Calculate cost function j €S. • For each i i. Find a set of neighbors to i. ii. Defined a +ve coefficient • Defined a cooling schedule. • Calculate the transition probability. • Stopping condition.	• Set of solution Called population • Defined a fitness function • Select a population • Produce another population • Compare with Criterion Function • Stopping condition.	• Generate initial population for individuals. • Evaluate fitness function of population. • Compare with criteria function • Generate new fitness function using ○ Selection ○ Recombination ○ Mutation • Find Best individual.
2	Inspiration	Behavior of Swarm in the nature such as bird, fish	Memory ability to use past experience. To improve current decision	Idea's come from paper published by Metropolis etc in 1953. (annealing in solids)	Theory of Evolution	Darwin Theory (Reproduction, Mutation, Recombination, Selection)
3	Technique	Population based stochastic optimization	Meta heuristic local descent based search	Probabilistic local descent based search	Global search heuristic method	Derative free optimization
4	Dimension	2D/3D	Multiple	2D/3D	2D/3D	2D/3D
5	Developer(s)/ Proposer(s)	Dr. Eberhert and Dr. Kennedy	Fred Glover	Kirkpatrick, Gelt and Vecchi	Johan Holland	
6	Year	1995	1986	1983	1975	Earlier in 1950
7	Known application area	• Function Optimization • Artificial NN • Fuzzy Control system	• Telecommunication • Network Design • Logic & AI • Real Time Decision Problem	• Network Design • Computer Aided & Circuit Design • Routing • Image Processing	• Automotive Design • Robotics • Biometric Invention • Finance and Investment • Evolvable H/W	• Robotics • Genetics • Bioinformatics • Automatic prog. • Transportation Engg.
8	Constrained/ Unconstrained	Constrained	Constrained	Both	Both	Both
9	Linear/Non Linear	Non linear	Both	Both	Both	Both
10	Efficiency	---------	PB Variant O(n) CB Variant O(nm)	O(n2), may be achieve O(n) depends upon the implementation	O(n log n)	O(nlogn)
11	Variants	Binary PSO, Real Valued PSO, Sequential PSO, Adaptive PSO, Canonical PSO, MINLP PSO,	Reactive TS, Canonical TS, Probabilistic TS, Multi Point TS,	Cooperative SA, Quantum SA, Adaptive SA, Parallel SA, Standard SA,	Parallel GA, Human Based GA, Breeding GA, Nested GA, Greedy GA, Chaotic GA, Adaptive GA	Co EA, Adaptive EA, Hybrid EA, Ranking Based EA, Neuro EA, Parallel EA, Organizational EA

S. No.	Parameter	Particle Swarm Optimization	Tabu Search	Simulated Annealing	Genetic Algorithm	Evolutionary Algorithm
		Hybrid PSO, 2D-OTsUPSO	Simplex Based TS	Constrained SA, Extended SA,SALO Variant		
12	References	[47], [48],[49], [50], [51], [52], [53], [54]	[1], [2], [3], [4], [5]	[6],[7], [8], [50], [55]	[9], [10], [11], [12], [16]	[13], [14], [15] ,[17], [46], [56]

Annexure – 2

S. No.	Parameter	Scatter Search	Gradient Descent	Ant Colony Optimization	Bee Colony Optimization	Differential Equation

1	Methodology	• Generate a starting set of solution vector that guarantee a critical level of diversity
		• Apply a heuristic process and design a best set of vectors to be a reference solution.
		• Create a new solution from reference solution.
		• Apply heuristic defined earlier.
		• Extract collection of best improved solutions from reference set and add into reference set.
		• Stopping condition.
			• Consider a starting point
			• Compute a search direction
			• Choose step length
			• Update the variable
				• Set parameter and initialize pheromone trials.
				• Construct Solution
				  ○ i. solution construction starts with an empty partial solution.
				• Local Search
				• improving the solutions
				• Constructed by the ants.
				• Update pheromone value.
				• Stopping criteria.
					• Initialize the population of the solution and select the feasible solution for the problem. It is the best initial solution.
					• For each Bee
					i. make a forward pass (Allows all bees from the hive and evaluate all possible moves. Choose one move using greedy selection process.)
					ii. make a backward pass (All bees are back to hive and evaluate the partial objective function value for each bee. Each bee decides randomly whether to continue its own exploration and become a recruiter or to become a follower. For each follower, choose a new solution from recruiters by the greedy method)
					• Evaluate all the feasible solution and find best one.
					• Stopping condition.
					• Provide the best solution for the problem.
						• Initialize random population, defined the parameter range and set generation number (initially G=0).
						• While the stopping Criteria is not satisfied. Do
						• Mutation Step
						i. generate a donor vector corresponding the ith target vector.
						• Crossover Step
						i. generates a trial vector for the ith target vector using.
						  • Binomial Crossover
						  • Exponential Crossover
						  • Arithmetic Crossover
						• Selection Step
						i. evaluate the trial vector
						• Increase the generation count.

2	Inspiration	Strategies for creating composite decision rule and surrogate constraint	A continuous function should decrease at least initially if one takes a step along the direction of –ve gradient.	Behavior of real ANT	Behavior of real bee	From generating trial parameters vector.
3	Technique	Population based meta heuristic	First order optimization	Meta heuristic algorithm	Population based search method	Population based stochastic optimization
4	Dimension	2D/3D	2D	2D	3D	D-Dimensional Space
5	Developer(s)/ Proposer(s)	Glover	Cauchy	Colorni, Dorigo and Maiezzo	Dervis Karaboga	Ken Price and Rainer Storn
6	Year	1998	1847	1991	2005	1995
7	Known application area	• Pattern Recognition • Bioinformatics • Forensic Anthropology • Computer Aided Design	• Designing of Component • Data Reduction • Engineering Analysis • Neural Network • Fuzzy Logic	• Bioinformatics & Biomedical • Protein Folding • Telecommunication N/W • Image processing • Data Mining • System Identification	• MANET & Ad Hoc Sensor N/W • Data Clustering • Image Analysis • Highway Traffic Congestion • Routing in Optical N/W • Train the NN	• Control System & Robotics • Multi sensor Data Fusion • Gene Regulatory N/W • Pattern Recognition & Image Processing • AI & NN Training
8	Constrained/ Unconstrained	Constrained	Both	With hybridization constrained	Unconstrained	Both
9	Linear/ Nonlinear	Both	Both	Both	-------------	Both
10	Efficiency	----------------	Less than Linear	$O(n^2)$	$O(n^2)$	$O(NP.D.G_{max})$

S. No .	Parameter	Scatter Search	Gradient Descent	Ant Colony Optimization	Bee Colony Optimization	Differential Equation
			search (O(n))			
11	Variants	Hybrid SS, Enhanced SS, Multi objective SS, Quantum SS, Parallel SS, Continuous SS, Hybrid Quantum SS	Stochastic GD, Threshold GD, Parallel GD, Chaotic GD, Approximate GD, Conjugate GD, Natural GD, Scaled GD	Modified ACO, Parallel ACO, Extend ACO, Multi Objective ACO, Simple Ant System, Rank ACO, Max Min Ant System, Beam ACO	Multi Objective Bee Colony, Hybrid ABC, Elitist ABC, Interactive ABC, Chaotic Bee Colony, Parallel ABC, Hybrid Simplex Bee Colony Algo.	Multi Objective DE, Parallel DE, Hybrid DE, Adaptive DE, Dynamic DE, Constrained DE, Self Adaptive DE
12	References	[19], [20], [21], [22], [23]	[24],[25], [26],[27] [28],	[29], [30][31], [32], [33], [56], [57]	[34], [35][36], [37], [38], [39], [58]	[40], [41],[42], [43], [44], [45], [46]