Review of Multi-objective Optimization using Genetic Algorithm and Particle Swarm Optimization

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ABSTRACT
Many real-world problems involve simultaneous optimization of multiple objectives that often are competing. In such problems, the objectives to be optimized are normally in conflict with respect to each other, which means that there is no single solution for these problems and optimizing a particular solution with respect to a single objective can result in unacceptable results with respect to the other objectives. So the solution to this problem is to find a set of solutions , each of which satisfies the objectives at an acceptable level without being affected by any other solution. This review paper presents an overview of multi-objective optimization using GA and PSO.

General Terms
Optimization, Multi-objective Optimization.

Keywords
GA (Genetic Algorithm), PSO (Particle Swarm Optimization).

1. INTRODUCTION
Multi-objective optimization is also called as multicriteria or multi attribute optimization. It is the process of simultaneously optimizing two or more conflicting objectives, which are subjected to certain constraints for example minimizing the cost of a product, maximizing the quality of a product, minimizing the wastage of raw material, maximizing the efficient use of machine and workers.Multi-objective optimization problems can be found in various fields: product and process design, finance, aircraft design, the oil and gas industry, automobile design, or wherever optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. Maximizing profit and minimizing the cost of a product; maximizing performance and minimizing fuel consumption of a vehicle; and minimizing weight while maximizing the strength of a particular component are examples of multi-objective optimization problems [1].

In Real-world applications, there are more than one objective functions, each of which may have a different individual optimal solution. Also the difference in the optimal solutions corresponding to different objectives because the objective functions are often conflicting to each other. So, optimizing with respect to a single objective often results in unacceptable results with respect to other objectives.

Therefore, a reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. So none of the solutions can be considered to be better than any other with respect to the all objective functions. In practice, multi-objective problems have to be re-formulated as single-objective prior to optimization, leading to the production of a single solution per run of the optimizer.

A minimization multi-objective decision problem can be defined as follows:

$U= [U_1\ U_2\ U_3 \ldots\ldots\ldots\ldots\ldots\ldots\ U_n]$

Where U is the control variable vector and 'n' is the no. of control variable.

Objective function is

$MIN/MAX= \{f_1(U),f_2(U),f_3(U)\ldots\ldots\ldots\ldots\ f_m(U)\}$

Subject to: $G_j(U) \leq 0 \qquad ,j=1,2,3\ldots\ldots\ldots\ldots m$

Optimization problems that have more than one objective functions are rather common in every field or area of knowledge [2].

Due to conflicting objectives, there is no single solution, which exits for these problems. Instead, the aim is to find good "trade-off" solutions that represent the best possible compromises among the objectives [2].

In this review paper we have reviewed the multi-objective optimization techniques like GA (Genetic Algorithm), PSO (Particle Swarm Optimization).In multi-objective optimization techniques, the researchers started their work with general approach, in which many multi-objective functions were combined into a single composite function. The determination of this composite objective function is possible with methods like weighted sum method, utility theory etc. But this approach had a major drawback that scaling among objectives is required and small perturbations in the weights can result in quite different solutions.So to overcome this drawback, the another approach was developed which determine the entire Pareto optimal set of solutions. Switching from one solution to other, there is always a certain amount of sacrifice in objectives to achieve required amount of gain in the others. This approach is more suitable for real life problems.In the last years the development of Multi-objective Evolutionary Algorithms (MOEA) experienced great advances especially in the algorithmic aspects, being the so called “second generation” (SG-MOEA) representative of the actual “State of the Art” on the matter. Using SG-MOEA it is possible to obtain very widespread and well distributed Pareto Fronts for many complicated test functions and problems [3].

Over the past decade or so, multi-objective optimization literature has witnessed a radically different perspective in solving the problems using evolutionary computing methods compared with the classical methods. Since these problems involve a multitude of optimal solutions, known as Pareto-optimal solutions, evolutionary multi-objective optimization (EMO) methods attempt to find a widely distributed set of solutions as close to the true Pareto-optimal front (POF) as possible in a single simulation run [4].

In this review paper we have reviewed the multi-objective optimization using GA and PSO. The remaining paper is organized as follows: section II gives some information about related work done by various researchers in the field of multi-objective optimization. Section III includes conclusion.

2. RELATED WORK

Researchers started their research for multi-objective optimization first by using GA, then using PSO and recently using BFO. We have reviewed some of the work related with GA and PSO discussed as follows:

In [5], Alexandre et.al have discussed multi-objective optimization problems solved by evolutionary algorithms. The authors have presented the nondominated sorting genetic algorithm (NSGA) to solve this class of problems and its performance is analyzed in comparing its results with those obtained with four others algorithms. The basic idea behind NSGA is the ranking process executed before the selection operation. This process identifies nondominated solutions in the population, at each generation, to form nondominated fronts based on the concept of nondominance criterion.

After this, the selection, crossover, and mutation usual operators are performed.

In this paper, a nondominated sorting genetic algorithm, proposed by K. Deb, is described and compared with four others algorithms using two test problems. In this comparison, the NSGA performs better than the others do, showing that it can be successfully used to find multiple Pareto-optimal solutions. Its application to the SMES problem shows that it is reliable to solve multi-objective optimization in electromagnetics.

In [6], S.G.Ponnambalam et. al have developed a Parallel Population Genetic Algorithm to find the best combination of selective groups which will lead to overall minimum variation in the assembly tolerance, with minimum number of generation cycles during the GA search process. An attempt is also made to further speed up the convergence and diversification process of the GA by maintaining more number of concurrent parallel populations in the proposed methodology. It is proved that the proposed Parallel Populations Genetic algorithm is much faster than the normal GA with single population.

In this paper the authors have developed, a parallelization scheme in order to speed up the search process of the GA called Parallel Populations Genetic Algorithm (PPGA). The experimentation results have proved that the proposed PPGA is performing much better than the normal Genetic Algorithm (that is GA with singe population) in terms of reaching the nearer-to-optimal solution with minimum number of GA cycles. Possibility of aggravating the speed of diversion and convergence of the PPGA through maintaining more number of concurrent populations is also attempted in this work. However, from the trials it is found that when the number of parallel population is increased beyond two, the performance of the PPGA slows down as the search process is getting retarded by the increase in diversification as a result of migration from many parallel populations. This problem may be overcome by designing a more sophisticated migration and isolation policy.

In [7], Abdullah Konak et. al have reviewed the various variations of GA that are Niched Pareto Genetic Algorithm (NPGA), Weight-based Genetic Algorithm (WBGA), Random Weighted Genetic Algorithm (RWGA), Nondominated Sorting Genetic Algorithm (NSGA), Strength Pareto Evolutionary Algorithm (SPEA), improved SPEA (SPEA2, Pareto-Archived Evolution Strategy (PAES), Pareto Envelope-based Selection Algorithm (PESA), Region-based Selection in Evolutionary Multi-objective Optimization (PESA-II), Fast Nondominated Sorting Genetic Algorithm (NSGA-II), Multi-objective Evolutionary Algorithm (MEA), Micro-GA, Rank-Density Based Genetic Algorithm (RDGA),and Dynamic Multi-objective Evolutionary Algorithm (DMOEA). Also the advantages and disadvantages of these variations of GA are discussed. Generally, multi-objective GA differ based on their fitness assignment procedure, elitism, or diversification approaches.

However, the discussion in this paper is aimed at introducing the components of multi-objective GA to researchers and practitioners without a background on the multi-objective GA. Many researchers that applied multi-objective GA to their problems have preferred to design their own customized algorithms by adapting strategies from various multi-objective GA. This observation is another motivation for introducing the components of multi-objective GA rather than focusing on several algorithms.

In [8], Xiaohui Hu et. al present a Particle Swarm Optimization (PSO) algorithm for multi-objective optimization problems. PSO is modified by using a dynamic neighborhood strategy, new particle memory updating, and one-dimension optimization to deal with multiple objectives.

This paper presents a particle swarm optimization algorithm for multi-objective optimization. Compared to the traditional PSO, there are three modifications in this dynamic neighborhood version:

1. Dynamic neighbors: Each particle has different neighbors in each generation based on the fitness values.

2. New pBest updating strategy: Only those solutions which dominate the currentpBest will be counted

3. One-dimension optimization: the algorithm only optimizes on one objective in each run.

It is demonstrated that dynamic neighborhood PSO is an efficient and general method to locate the Pareto front of multi-objective optimization problems. The advantage of the PSO method is that it is easy to implement and has few parameters that need to be adjusted.

In [9], Jonathan E. Fieldsend compares a number of selection regimes for the choosing of global best (gbest) and personal best (pbest) for swarm members in multi-objective particle swarm optimization (MOPSO). Two distinct gbest selection techniques are shown to exist in the literature, those that do not restrict the selection of archive members and those with `distance' based gbest selection techniques. Theoretical justification for both of these approaches is discussed, in terms of the two types of search that these methods promote, and the potential problem of particle clumping in MOPSO is described. The popular pbest selection methods in the literature are also compared, and the affect of the recently introduced turbulence term is viewed in terms of the additional search it promotes, across all parameter combinations. In light of the discussion, new avenues of MOPSO research are highlighted.

In [10], Carlos A. Coello Coello et. al present an approach in which Pareto dominance is incorporated into particle swarm optimization (PSO) in order to allow this heuristic to handle problems with several objective functions. Unlike other current proposals to extend PSO to solve multi-objective optimization problems, our algorithm uses a secondary (i.e., external) repository of particles that is later used by other particles to guide their own flight. The authors also incorporate a special mutation operator that enriches the exploratory capabilities of our algorithm. The proposed approach is validated using several test functions and metrics taken from the standard literature on evolutionary multi-objective optimization. Results indicate that the approach is highly competitive and that can be considered a viable alternative to solve multi-objective optimization problems.

In [11], M. Janga Reddy et. al described a multi-objective particle swarm optimization (MOPSO) approach for generating Pareto-optimal solutions for reservoir operation problems. This method is developed by integrating Pareto dominance principles into particle swarm optimization (PSO) algorithm. In addition, a variable size external repository and an efficient elitist-mutation (EM) operator are introduced. The proposed EM-MOPSO approach is first tested for few test problems taken from the literature and evaluated with standard performance measures. It is found that the EM-MOPSO yields efficient solutions in terms of giving a wide spread of solutions with good convergence to true Pareto optimal solutions. On achieving good results for test cases, the approach was applied to a case study of multi-objective reservoir operation problem, namely the Bhadra reservoir system in India. The multiple objectives involve minimization of irrigation deficit, maximization of hydropower and maximization of satisfaction level of downstream water quality requirements.

In [12], Zhan Si Jiang et. al present a pareto Multi-objective Particle Swarm Optimization (MOPSO) method in order to reduce the number of analysis of heuristic search methods. In this approach, pareto fitness function is used to select global extremum particles. And the solution accuracy and efficiency are balanced by adopting sequence approximate model. Research shows that the method can ensure the accuracy of calculation, at the same time help to reduce the number ofaccurate analysis.

3. CONCLUSION

In this paper, we have reviewed techniques to solve the multi-objective optimization problems. We have studied two multi-objective optimization techniques that are Genetic algorithm (GA) and Particle swarm optimization (PSO). As we have studied it is observed that performance of PSO is better as compared to GA for solving multi-objective problems.

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