Review of Population Based Metahueristics in Multi-objective Optimization Problems

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***Abstract*—** Problems are a part of daily living, the solution to problems most times requires optimizing various alternative goals at the same time. For the case in question, the goals to be synchronised are usually in discord with each other and no single solution is feasible. A solution that takes into consideration only one objective can produce undesirable results for the other goals/objectives. A way of escape is to devise a set of solutions that satisfy all the objectives to a certain extent without being overwhelmed by any of other objectives. This paper gives an outline of multi-objective optimization through the use of Genetic Algorithm (GA) and Particle Swam Optimization (PSO).

***Keywords*—**Genetic Algorithm, Multi-criteria Optimization, Multi-objective Optimization, Particle Swarm Optimization.

I. INTRODUCTION

Multi-objective optimization is also known as multi-criteria or multi-attribute optimization. It is a process of optimizing several alternative goals at the same time, like reducing the cost of a product, increasing its quality, reducing the wastage of raw materials, maximizing the use of machinery and labour efficiency. These problems are characteristic of various sectors within an organisation: product and process design, finance, aircraft design, oil and gas, automotive design or any process, the optimization of which entails compromises occurring among diverse goals. The simultaneous increase in profit and the reduction of costs; maximum performance at minimum fuel consumption of a car; minimum weight and maximum strength, all exemplify the multi-objective optimization tasks [12].

Numerous objectives necessitate that several optimal solutions are provided. The optimal solutions that satisfy different objectives differ as do the objective functions which often contradict each other. This is why a solution that takes into consideration just one objective can produce undesirable results compared with the other goals/objectives.

Consequently, in such a case, obtaining a good solution might just entail considering a set of solutions that satisfy the given objectives to a certain extent without being overwhelmed by any of the other objectives. In this case, no single solution can be considered better than the others if all the objective functions are taken into account. Essentially, multi-objective problems need to be reformulated into single-objective ones before optimization takes place, this results in a single solution per run of the optimizer.

A minimization of multi-objective decision problem is defined as follows:

$$U = [U_1 U_2 U_3 ....U_n]$$

Where U is the vector of the control variable and n is the number of control variables.

Objective function is:

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

Subject to:

$$G_j(U) \leq 0,\ j = 1,2,3.......m$$

Optimization problems with more than one objective functions are commonplace and can be very often encountered in all spheres of knowledge [9].

Because of their opposing goals, no one solution can be proposed for such problems. What one can do is to try to find compromising solutions that offer the best trade-off among the competing goals [9]

In this paper, the multi-objective optimization techniques, like the GA and PSO have been summarised. Scientists began developing multi-objective optimization techniques with a general approach in which the multiple objective functions are merged into one composite objective function.

This composite objective function was then obtained by using the weighted sum method, utility theory etc. Applying this approach, one would need to be wary when scaling objectives due to the fact that small perturbations in weighing can bring about largely different solutions. To deal with this shortcoming, another approach was developed to determine the entire Pareto optimal set of solutions. When choosing a solution, one inevitably loses some of the results required for the other problems. This method can be best illustrated using a real life situation. The Multi-Objective Evolutionary Algorithms (MOEA) advanced a lot lately, particularly with regards to algorithms, known also as the Second Generation Multi-Objective Evolutionary Algorithms (SG-MOEA), the very best in the field. SG-MOEA allows the procurement of widespread and well distributed Pareto fronts for complex test

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functions and problems [5].

In the last decade, multi-objective optimization evolved a different perspective to solving problems through the use of radically new computing methods. As these problems need a number of optimal solutions, known as Pareto-optimal solutions, the Evolutionary Multi-objective Optimization (EMO) methods try to formulate a widely distributed set of solutions as close to the true Pareto-Optimal Front (POF) as possible in a single simulation run [7].

In this paper the multi-objective optimizations using GA and PSO have been considered. The remaining part of the paper is organized in the following way: Section II provides information on related studies done by various scientists in the domain of multi-objective optimization. Section III comprises the conclusion.

II. RELATED WORKS

Scientists commenced their studies in the field of multi-objective optimization first by using the GA followed by the PSO and finally the Bacterial Foraging Optimization (BFO). A few of the GA and PSO related research studies are reviewed.

Vasconcelos in [11] discussed multi-objective optimization problems as solved by evolutionary algorithms. The authors introduced the Non-dominated Sorting Genetic Algorithm (NSGA) to solve this class of problems, its application and effects were analysed in comparison with the results obtained from four other algorithms. The basic methodology of the NSGA is the ranking process, performed before the selection operation. This process selects non-dominated solutions in the population, by generation, to form non-dominated fronts based on the concept of non-dominance. The crossover, selection and mutation standard operators are performed. In this paper, the proposed non-dominated sorting genetic approach, by [7] was described and compared with four other algorithms with two test problems. In comparison, the NSGA performed better than the other four algorithms, thus proving that it can be vastly useful in finding multiple Pareto-optimal solutions. When applied to the SMES problem, it showed that it is reliable and can be used to solve multi- objective optimization in the field of electromagnetics.

In [10] the authors developed a Parallel Population Genetic Algorithm (PPGA) to find the best combination of selective groups that lead to the determination of the overall minimum variation in the assembly tolerance with a restricted number of generation cycles in the GA search process. Subsequently, the convergence and diversification process of the GA was sped up by keeping a larger number of concurrent parallel populations in the proposed methodology. This proved that the PPGA is quicker than the standard GA with a single population.

Moreover, the test results showed that the proposed PPGA performed better than the standard Genetic Algorithm (i.e. GA with a single population) in reaching the near optimal solution with the minimum number of GA cycles. The risk of reducing the speed of diversion and convergence of the PPGA by maintaining a larger number of concurrent populations was also examined in this publication. Trials showed that when the number of parallel populations is increased over two, the performance of the PPGA slows down as the search process is obstructed by the increase in diversification, caused by migration from many parallel populations. This shortcoming may be overcome by devising a more sophisticated migration and isolation policy.

The variations of the GA are studied by Abdullah in [1], and they are: Niched Pareto Genetic Algorithm (NPGA), Random Weighted Genetic Algorithm (RWGA), Non-dominated Sorting Genetic Algorithm (NSGA), Weight-Based Genetic Algorithm (WBGA), Strength Pareto Evolutionary Algorithm (SPEA), Dynamic Multi-objective Evolutionary Algorithm (DMOEA), Pareto Envelope-based Selection Algorithm (PESA). The variations also include Region-based Selection in Evolutionary Multi-objective Optimization (PESA-II), Multi- objective Evolutionary Algorithm (MEA), improved SPEA (SPEA2, Micro-GA, Rank-Density Based Genetic Algorithm (RDGA), fast Non-dominated Sorting Genetic Algorithm (NSGA-II), and Pareto-Archived Evolution Strategy (PAES). The author discussed the advantages and disadvantages of these variations of the GA. Overall, the multi-objective GA varies their fitness assignment procedure, elitism, or diversification approaches. However, this paper aims to introduce the variations of the multi-objective GA to researchers and practitioners with no experience in the process of multi-objective GA. Many scientists, applying the multi-objective GA prefer to develop their own personal algorithms by customizing strategies from various multi-objective GAs. This observation is another reason why this study focused on the introduction of the components of the multi-objective GA rather than on certain selected algorithms.

However, Eberhart in [3] reviews a Particle Swarm Optimization (PSO) algorithm for multi-objective optimization problems. A dynamic neighbourhood strategy of PSO was modified, one-dimensional optimization and new particle memory updating to produce a satisfying solution to the multiple objectives. The paper introduced a PSO for multi-objective optimization. Compared to the normal PSO, there are three modifications in this dynamic neighbourhood: version 1) Dynamic neighbours where each particle has different neighbours in each generation based on the fitness values. 2) New pBest updating strategy where the dominant solution of the current pBest will be counted. 3) One-dimension optimization where the search algorithm optimizes along one objective in every program run. The research study shows that dynamic neighbourhood PSO is a general method, which is efficient for the location of the Pareto front of the multi-objective optimization problems. The PSO approach excels in its ease of implementation and adjustment of few parameters.

Fieldsend in [4] compared a number of selection regimes for choosing the global best (gbest) and personal best (pbest) for swarm members in Multi-Objective Particle Swarm Optimization (MOPSO). Two separate gbest selection techniques exist in literature, one that does not restrict the selection of archive members and the other that has a `distance' based gbest selection technique. The paper discussed the theoretical justification of both of these approaches, in terms of the two types of searches that these methods apply; the potential risk of particle clumping in MOPSO was also explained. The popular pbest selection methods in literature were compared, and the effect of the recently introduced turbulence term was reviewed with respect to the additional search it implies, and across all parameter combinations. In the discussion, new paths for research in MOPSO were traced.

Coello, Pulido, and Lechuga in [2] offered an approach in which Pareto dominance is incorporated into Particle Swarm Optimization (PSO) in order to solve problems with several objective functions. Unlike the other recent attempts to extend PSO to solve multi-objective optimization problems, this algorithm uses a secondary (i.e. external) set of particles that are later used by other particles to guide their own flight. The researchers also introduce a special mutation operator that expands the exploratory powers of the algorithm. The approach proposed can be validated by use of certain test functions and metrics taken from popular literature on evolutionary multi-objective optimization. Results show the approach is a highly competitive and a viable alternative in solving multi-objective optimization problems.

New Multi-Objective Particle Swarm Optimization (MOPSO) was reviewed by [8]. The approach is for the generation of Pareto-optimal solutions for reservoir operation problems. In this method, a Particle Swarm Optimization (PSO) algorithm was integrated into Pareto dominance principles. In addition, a variable size external repository and an efficient Elitist Mutation (EM) operator were added. The new EM-MOPSO approach was first tested on problems extracted from existing literature and assessed with established performance measures. It was found that the EM-MOPSO suggests efficient solutions, giving a widespread with good convergence to true Pareto optimal solutions. After achieving good test results, the approach was tried on a real life case study of multi-objective reservoir operation problem in the Bhadra reservoir system, in India. The multiple goals to be achieved included minimization of irrigation deficit, maximization of hydropower and maximization of the satisfaction level of downstream water quality requirements.

Jiang Xiang and Jiang in [6] presented a Pareto Multi-Objective Particle Swarm Optimization (MOPSO) method, aimed at reducing the number of analyses in heuristic search methods. In this approach, the Pareto fitness function is used to select global extreme particles, then the solution accuracy and efficiency are balanced by the use of a special sequence approximate model. Research has proven that this method can ensure accuracy of calculation and at the same time reduce the number of accurate analyses.

III. Conclusion

In this paper, the existing techniques used to solve multi-objective optimization problems were examined. In particular, two multi-objective optimization techniques were studied, i.e. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). One can observe that the PSO is a better performer compared to the GA, in proffering solutions to multi-objective problems.

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