Multi-Objective Optimization Evolutionary Algorithm

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1 Introduction

A multi-objective optimization problem (MOOP) entails more than one objective to be optimized, often conflicting objectives, and has a parento optimal set of solutions. Multi-Objective Evolutionary Algorithms (MOEAs) seek to approximate the pareto front of the MOOP in a single run, by evolving a population of solutions, inspired from the biological evolution using selection, reproduction, recombination and mutation.

The research focuses on developing a new and more efficient evolutionary algorithm to solve constrained multi-objective optimization problem, and compare its performance with existing MOEAs like *Non-dominated Sorting Genetic Algorithm-II* (NSGA-II), etc.

2 Research Progress

In the initial phase of my work, under the literature of evolutionary algorithms (EAs), the general structure of a genetic algorithm (GA) was studied and how they are implemented to solve an optimization problem, may it be a single-objective problem or a multi-objective problem. To understand the run of an EA on an optimization problem, the "*Travelling Salesman Problem*" (TSP) was chosen. A plain single-objective GA was implemented on a TSP with a single salesman. The one and only objective function to optimize in this particular problem was the length of the tour. Hence, the plain GA was run on a sample test problem to optimize (note that in this case, by "optimizing", we are interested in "minimizing") the tour length.

Different selection operators, like *tournament selection* and *fitness proportionate selection* were implemented in order to select parent individuals who will be participating in the crossover to produce child individuals. It was observed that the algorithm using tournament selection method converges faster and in earlier generations than fitness proportionate method, as shown in Figure 1. Considering the hypothesis that how good an optimization algorithm is depends upon how fast can it converge to its optimal solution, it was reported that the tournament selection method outperforms the fitness proportionate method. With this execution and testing of a plain GA, a concrete notion was developed about GAs to solve optimization problem.

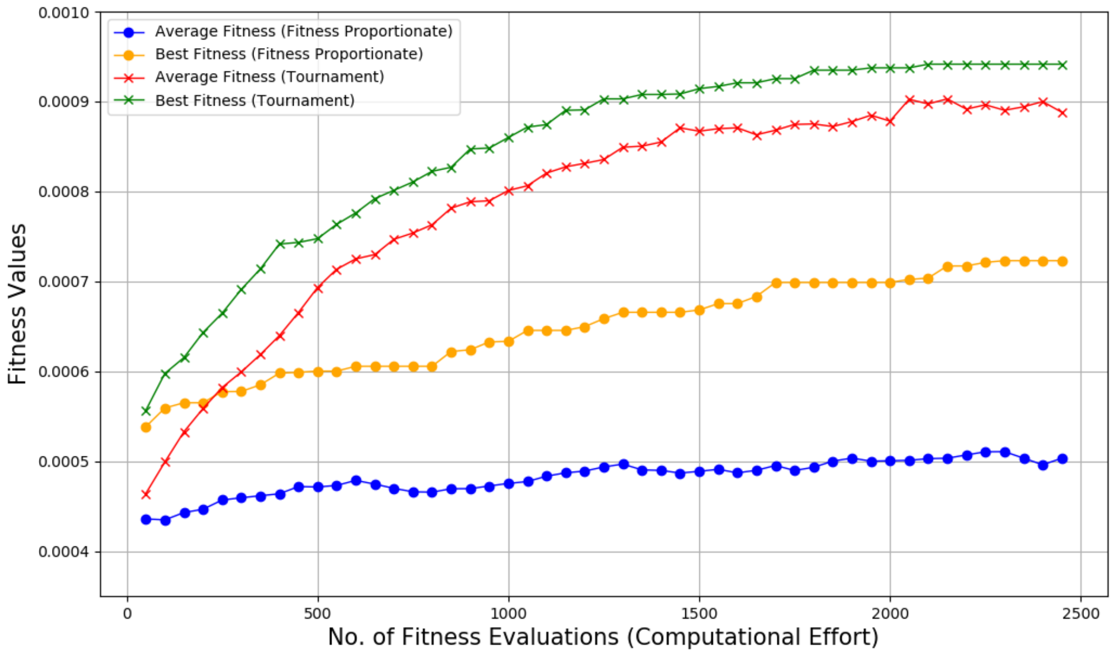

Figure 1: *Population Size = 50, No. of generations evolved = 50, Total no. of runs of algorithm = 5*

In the next phase of my work, the research focus shifted to implementing a MOEA. An existing elitist MOEA, particularly known as NSGA-II, was studied and implemented on a two-objective optimization problem (here, we took a *minimisation* problem). The two objective functions considered for the minimisation problem were x^2 and $(x-2)^2$, where the decision variable space : $x \in (-\infty, +\infty)$. It is evident that the pareto front of this problem would be $x \in [0, 2]$, hence we would expect the algorithm to converge to the aforementioned pareto front (non-dominated solutions) after sufficient number of generations are evolved. For the specific run of NSGA-II on this optimization problem:-

Population Size = 40
Generations Evolved = 200
Mutation Rate = 0.2
Weighted crossover used :- $Child = weight * Parent_1 + (1 - weight) * Parent_2$

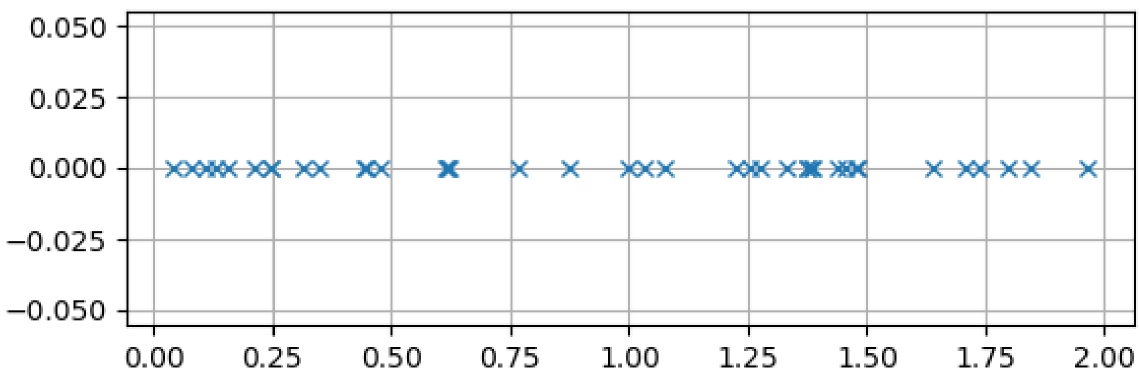

Figure 2: *Visualization of Decision Variable Space (or, Data Space)*

In Figure 2, each of the *crosses* denote one individual in the final population the algorithm outputs, which is evidently close to the pareto front, i.e. $x \in [0, 2]$.

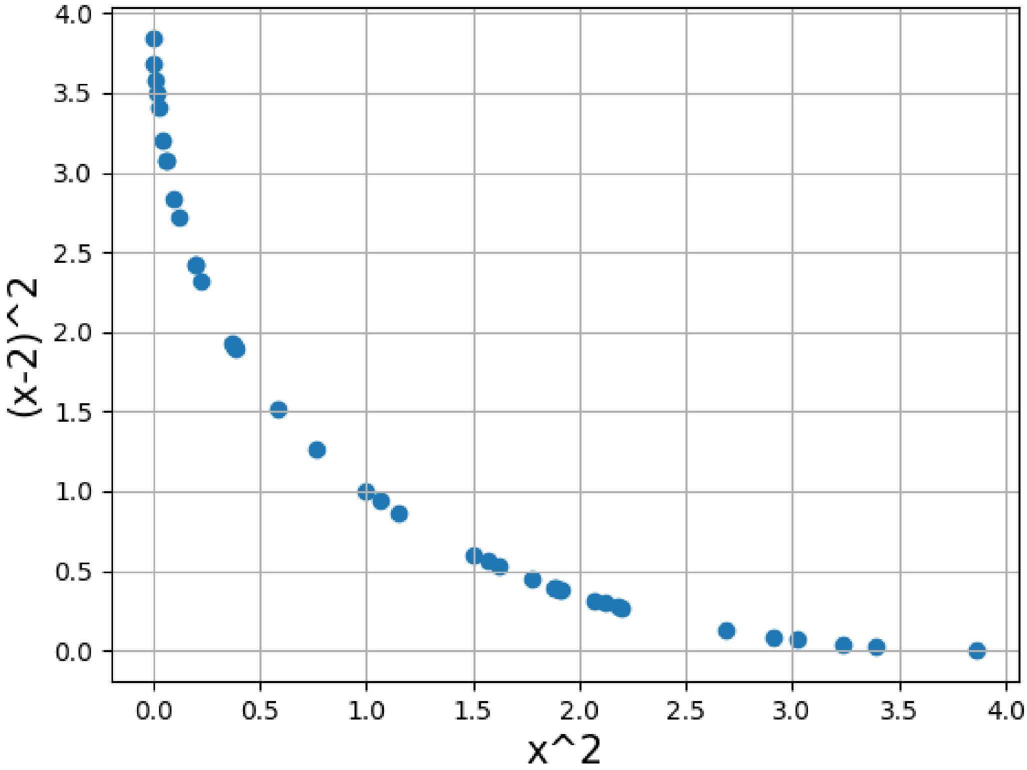

Figure 3: *Visualization of Objective Space*

In Figure 3, a reasonably *good approximation* to the pareto front was obtained in the objective space. It should be noted that the non-dominated set of solutions obtained in the final population converged to the expected pareto front and showed a reasonable diversity, as NSGA-II takes care of the diversity in objective space along with convergence to the pareto front. Hence, the run of NSGA-II was successful on this particular MOOP. With this successful execution of NSGA-II, a concrete understanding was developed about the working of MOEAs.

3 Future Work

Moving ahead, it should be noted that the NSGA-II doesn't take into account the diversity in data space, but only in objective space. This motivates the further research to modify NSGA-II to consider the diversity in both, *data space* and *objective space*. Some more ideas were discussed to incorporate in NSGA-II like keeping an *archive* to store the "elite" solutions. I plan to study and implement yet another existing EA, known as Evolutionary Multi Objective Crowding Algorithm (EMOCA), followed by formulating improvement ideas and incorporating them in EMOCA. At the end, a new MOEA is expected whose performance will be compared with NSGA-II, EMOCA, etc. and hopefully it would outperform existing MOEAs. Further, the algorithm would be refined to handle *"constrained"* MOOPs.

References

[1] K. Deb, *Multiobjective Optimization Using Evolutionary Algorithms*. Chichester, U.K.: Wiley, 2001.

[2] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "*A fast and elitist multi-objective genetic algorithm: NSGA-II*", Proc. Parallel Problem Solving from Nature VI, 2000