Meta-heuristic Approaches to Solving Next Release Problem

Akshay Kumar Chaluvadi
Computer Science Department
North Carolina State University
Raleigh, NC, 27606, USA
achaluv@ncsu.edu

Pritesh Ranjan
Computer Science Department
North Carolina State University
Raleigh, NC, 27606, USA
pranjan@ncsu.edu

Raghav Potluri
Computer Science Department
North Carolina State University
Raleigh, NC, 27606, USA
rpotlur@ncsu.edu

1. Abstract

Companies developing and maintaining software need to determine which feature should be added as a part of their next release. They wish to select the features to ensure the satisfaction of customer is high and cost of releasing the feature is within the allocated budget. This situation is modelled as a NP hard problem. The use of various modern optimizers to find a near optimal solution is theme of the project. We used Ant Colony Optimizer, Differential Evolution and Genetic Algorithm to compare the results against. Our results show how Differential Evolution outclassed the other optimizers in terms of results.

2. Introduction

To understand the Optimizers one should clearly understand the model being used. The Next Release problem can be described as: Given a software package, there is a set, C, of m customers whose requirements must be considered in the development of the next release of this system. There is also a set, R, of n requirements to complete. To meet each requirement, it is needed to expend a certain amount of resources, which can be transformed into an economical cost: the cost of satisfying the requirement. Additionally, different clients have different interests in the implementation of each requirement. The first component of the objective function expresses the weighted overall satisfaction of the stakeholders. The other component deals with risk management, expressing those requirements with higher risk should be implemented earlier. Finally, the two restrictions will, respectively, limit the implementation cost of requirements in each release and guarantee that the precedence among requirements will be respected.

In the following sections we will be discussing our approach to dealing with MO-NRP problem. We have implemented Genetic algorithm, Differential Evolution and Ant Colony Optimization in our project work. In **section 3,** we describe the dataset we worked with. In **section 4** presents a note on two methods to determine Pareto Dominance – Binary Dominance (BDOM) and Continuous Dominance (CDOM). In **section 5**, we describe generating population and random solutions to the problem. **Section 6,** describes the GA algorithm. **Section 7**, describes the Differential Evolution approach that we employed. In **section 8,** we describe a way to **tune the 'extrapolate amount' variable** f for DE using Simulated Annealing and comment on the values of f generated for different initial population size for DE. We also present a comparison of the results (spread and Inter Generation Distance) with different values of f. Finally, in **section 9** we describe an implementation of Ant Colony Optimization, and the results we obtained for NRP.

3. The Dataset:

We have generated artificial dataset for our NRP model. The parameter for the model were as follows:
Requirements: Number of Requirements = 30
The range of cost for requirements is from 1 to 200. A 200 means the requirement is associated with high risk & cost of implementation, while a 0 means that an intern can be assigned this job.
Requirements table: *R*

r0	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20	r21	r22	r23	r24	r25	r26	r27	r28	r29
47	47	44	92	58	5	168	112	129	38	199	172	25	67	145	143	188	85	167	135	61	118	177	170	102	118	7	49	160	83

Clients: Number of clients $(n) = 20$

The range for clients is integer value from 1 to 10. A 10 means the software company will do anything to keep this client happy, while a 1 means, the company doesn't mind loosing this client.

Clients table: C

c0	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19
9	5	8	1	5	8	3	10	10	1	1	6	10	4	3	5	1	3	5	5

Budget: 1000

The importance matrix: Number of Clients by Number of Requirements. Each cell $[i, j]$ represents the importance a $client[i]$ gave for a $requirement[j]$.

The range for importance is integer values from 0 to 100. A 100 means that the particular client desperately wants that feature, while 0 means the client doesn't care.

	r0	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20	r21	r22	r23	r24	r25	r26	r27	r28	r29
c0	17	55	71	68	37	44	51	78	52	39	49	2	4	71	99	59	39	17	50	99	77	54	86	23	51	96	58	46	27	55
c1	96	0	79	82	89	74	81	52	56	43	5	87	57	20	50	48	36	34	54	62	61	46	2	23	17	59	86	80	80	82
c2	25	85	67	8	1	1	76	25	11	63	34	7	16	53	16	27	71	45	32	47	2	39	42	18	10	90	51	21	61	82
c3	2	1	14	72	16	71	68	55	22	98	80	52	22	65	39	58	32	63	5	30	97	88	30	86	31	94	75	42	25	0
c4	88	3	82	97	57	17	87	98	71	51	38	35	20	68	43	19	10	67	29	50	32	88	90	1	20	33	99	79	34	21
c5	68	84	94	34	89	69	48	99	23	73	8	17	92	21	76	60	84	37	34	29	87	61	96	89	13	55	10	3	7	87
c6	79	83	34	62	78	38	57	22	8	26	89	57	93	46	27	79	83	1	67	9	11	89	4	24	99	42	11	16	24	75
c7	10	91	38	97	91	29	25	48	10	65	4	1	99	29	60	45	31	6	92	97	97	11	21	62	98	54	69	66	26	54
c8	31	24	8	28	99	45	65	64	95	39	30	33	31	85	90	30	33	54	58	60	24	2	24	7	55	7	7	64	29	80
c9	49	87	15	50	80	7	95	17	78	99	82	32	10	51	92	29	90	14	91	3	31	91	81	91	84	75	69	17	43	15
c10	72	67	25	6	97	81	55	54	85	45	39	34	26	2	65	42	57	6	35	13	12	26	83	40	40	61	23	0	53	50
c11	65	44	69	73	24	50	48	22	41	56	91	92	27	65	4	7	51	88	16	77	89	31	69	85	37	70	74	60	86	90
c12	96	57	17	25	21	57	76	5	68	72	35	52	16	73	4	99	81	63	27	92	96	14	78	85	66	70	44	93	98	38
c13	81	43	16	32	12	91	96	12	60	41	11	29	25	75	0	19	44	2	63	61	84	20	28	54	27	59	25	69	79	81
c14	98	55	49	86	77	57	38	28	10	81	11	75	55	97	76	98	13	50	57	31	50	36	53	0	44	45	30	40	79	69
c15	49	65	38	20	0	28	60	89	83	51	99	46	84	41	75	99	30	17	62	53	36	0	39	43	40	86	59	74	90	75
c16	49	75	64	65	63	41	63	64	94	79	85	77	82	61	35	26	71	88	54	15	84	48	47	4	51	75	42	35	66	1
c17	51	95	69	40	69	61	21	20	89	27	7	83	52	37	51	74	17	65	72	82	27	61	23	56	17	79	87	33	22	97
c18	71	85	3	90	62	31	43	76	79	19	63	16	98	44	92	73	61	26	53	14	13	72	36	75	24	72	72	30	10	40
c19	49	10	18	5	60	89	21	3	71	82	97	61	34	84	11	69	9	40	49	38	17	23	82	46	58	21	72	33	59	91

Note: Different dataset can be generated with different seed to random function.

The objective was to maximize total client satisfaction: [1]

$$maximize\ satisfaction\ (f_1) = \sum_{i=1}^{n} c_i \sum_{r_i \epsilon R} v_{ij}$$

While minimizing the total cost. (Secret, we are maximizing negative of cost.) [1]

$$minimize\ cost\ (f_2) = \sum_{r_i \epsilon R} r_i$$

As it can be readily observed the two objectives compete with each other, improving on one naturally means making the other worse. Hence, our goal is to find a set of solution that are on the Pareto frontier and let the software company decide exactly which solution they would want to go with.

4. Pareto Dominance – Binary Dominance and Continuous Dominance.

In order to compare two candidate solutions, we evaluate the candidates and then compare the objective values to determine which candidate is better. But, in case of multi-objective problems, one candidate can perform better in one dimension while losing on other. In such cases, we can use the concept of *Binary Dominance* (BDOM). According to BDOM a solution u dominates another solution v, if solution u's objectives are never worse than solution v and at least one objective in solution u is better than its counterpart in v [2].

While BDOM works well when number of objectives is less – ideally 2 – it doesn't tell how good is the solution. Continuous Dominance (CDOM) – defined in [3] – sums the total improvement of solution u over other solutions.

We will be showing that with our problem – even with 2 objectives – using CDOM substantially outperformed BDOM. We adapted CDOM code from here [5].

5. Generating candidates and population:

In evolutionary algorithms we need a candidate which is one of the possible solutions. Multiple such candidates put together is called a population. During subsequent runs of an evolutionary algorithm (called iteration) the quality of the population should increase. In our case a candidate is represented by a list of length equal to the number of requirements. The value in the list represents whether the requirement shall be implemented or not. A sample candidate:

r0	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20	r21	r22	r23	r24	r25	r26	r27	r28	r29
-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-1	0	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1

-1 represents that the particular requirement should not be implemented, while 0 means it should be implemented in this particular release.

To generate a population of given size, we first generate a candidate, check if the candidate satisfies all the constraints and add to the population set if it is not already there. We repeat this until the size of population set becomes equal to the specified population size.

The solutions generated (at random) in the previous step is a result of random search. This is the bottom-line result which must be outperformed by our meta-heuristic solutions. A plot of the objectives (cost – on X axis and Satisfaction – on Y axis) is shown in Figure 1.

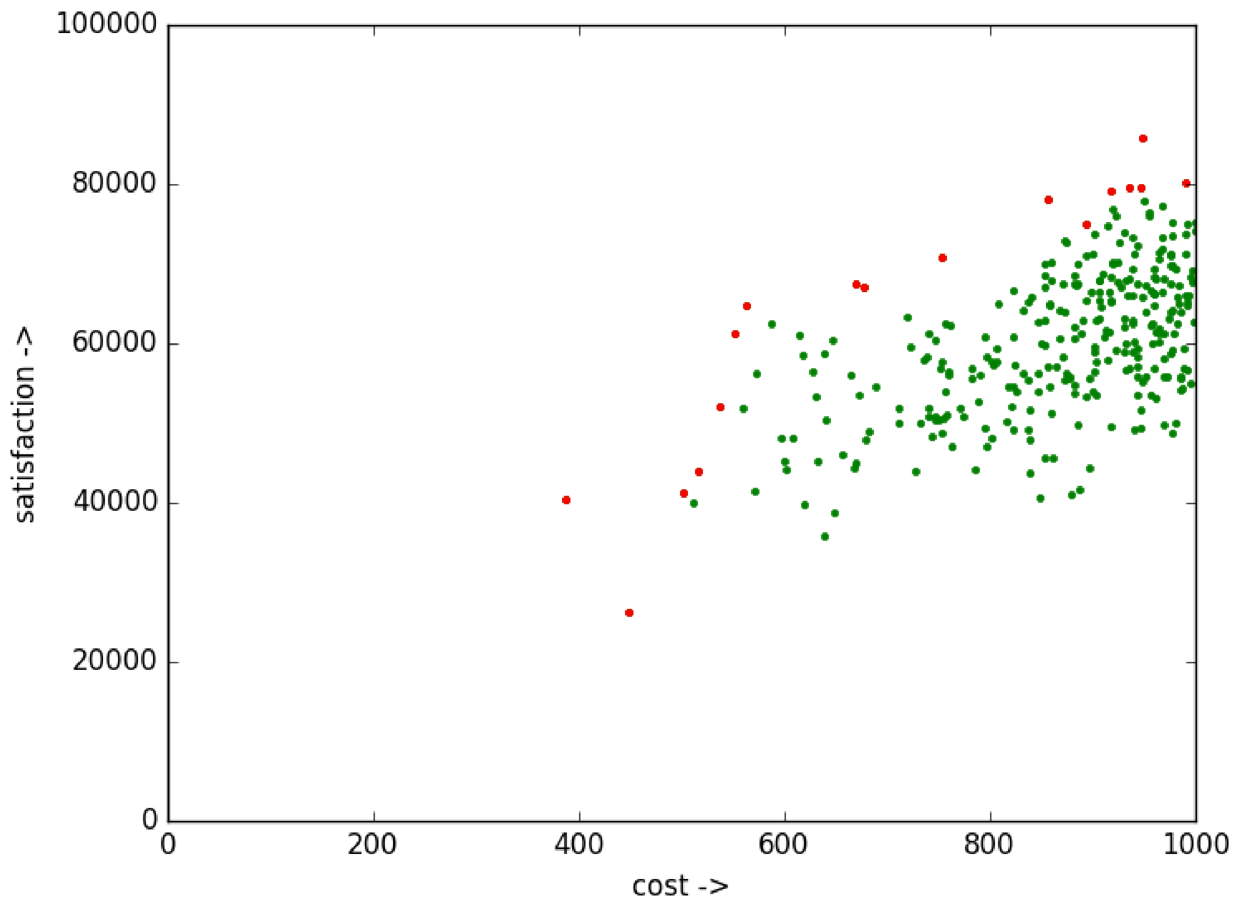


Figure 1: Initial population. Random solution. Red dots are the Pareto candidates among the initial population

6. Genetic Algorithm:

We used the standard genetic algorithm, the pseudo code for the same is as follows:

```
Generate a population
While (stopping criteria):
     Initialize a Children set.
     For (number_of_iterations):
          Mom, Dad = Pick two unique candidates from the population
          X = Crossover(Mom, Dad)
          Child = Mutate (X, mutation_rate)
          If Child satisfies the constraints:
               Add Child to the Children set.
     Union population set with the children set.
     Do Elitism to pick most FIT candidates from population.
```

The different approaches we plugged in were:

`PopulationSize: 300`

`stopping criteria`: We ran the algorithm for a fixed number of generations. (specifically 10).

`number_of_iterations:` We ran the iteration for the population size, in a hope that each candidate will be picked at least once.

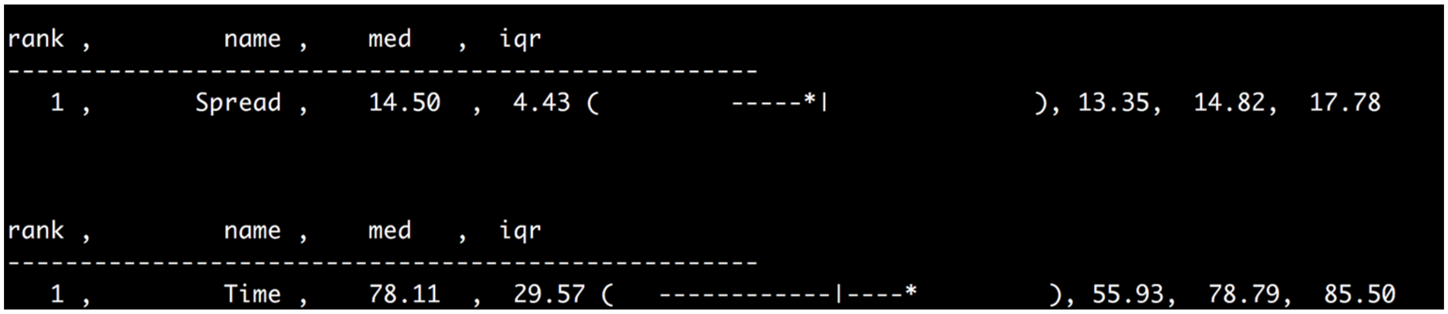
`Crossover:` We employed single point crossover, picking a character from Mom or Dad at random.

`Mutate and mutation_rate:` For each character in child, change its value if a random number is less than mutation rate.

We observed that this step was the most important step in the GA process. Variations in `mutation_rate` would generate candidates which were not valid. Initially we picked a mutation rate of 0.3 which would generate all invalid children. Picking `mutation_rate` of 0.01, generated candidates out of whom half would be valid.

`Fitness:` We determined the fitness of a candidate as the number of other candidates in the population it dominated (using CDOM). For GA, using CDOM instead didn't produce any significant improvement.

`Elitism:` Sort the candidates on the basis of decreasing Fitness and then pick the top candidates. The number of candidates we picked was the population size so that the population doesn't increase in each generation.



```
rank ,         name ,    med    ,  iqr
----------------------------------------------------
   1 ,       Spread ,    14.50   ,  4.43 (         -----*|              ), 13.35,  14.82,  17.78


rank ,         name ,    med    ,  iqr
----------------------------------------------------
   1 ,         Time ,    78.11   ,  29.57 (    ------------|----*          ), 55.93,  78.79,  85.50
```

Figure 2: Mean, Median and IQR for Spread and time over 20 runs of GA

A sample plot of objectives for the candidates after running the GA is shown in Figure 3:

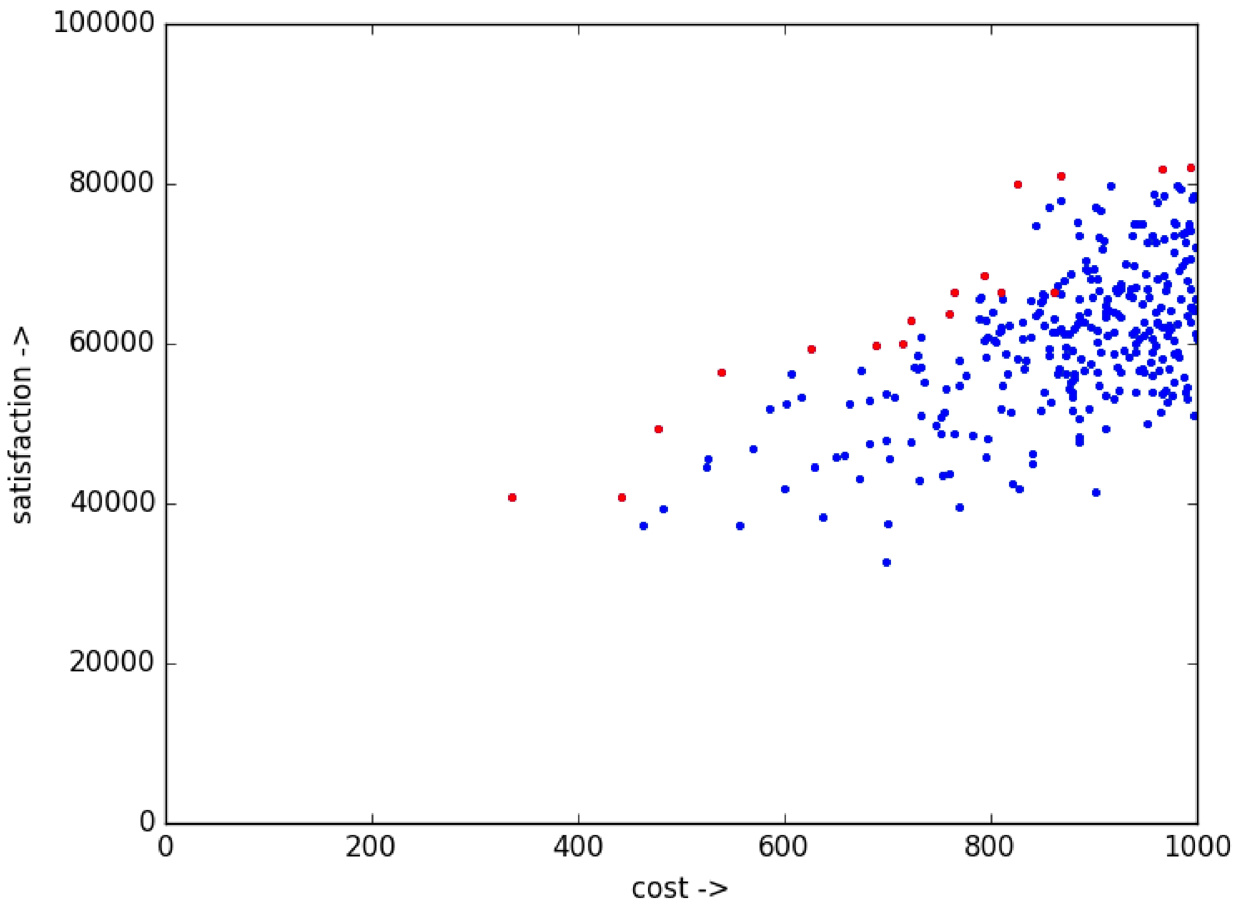


Figure 3: Population generated by GA. Blue dots represent the new candidates.

7. Differential Evolution:

We followed the Differential Evolution algorithm as introduced in [4]. Our DE scheme was DE/RAND/1 for binomial parameters. Pseudo code for the specific algorithm that we implemented is as:

```
Generate a population
While (stopping criteria):
     Pick 3 random unique candidates (A, B, C) from population.
     Generate Extrapolate Vector F.
     Generate the Child (T) by employing the DE scheme (DE/Rand/1)
     If T satisfies the constraints:
          If T dominates C and T:
               Replace C by T
```

`PopulationSize: 300`

`stopping criteria`: We ran the algorithm for a fixed number of iterations. (specifically 2000). ***NOTE***: This means that DE ran for less number of iterations than GA. (For GA it was `PopulationSize * NumberOfGenerations i.e 300 * 10.`

`Generate Extrapolate Vector`: Generate a vector of length equal to number of requirements with binomial values. The value will be 0 if a random value (between 0 and 1) is less than extrapolate amount variable. (f)

Generate the Child: In our case of binomial vectors we implemented the 'DE/rand/1' scheme as follows:

$$T = (A\ Union\ (\ F\ (\ Intersection\ (\ B\ XOR\ C\ )\ )\ )\ )$$

Pareto Dominance: We used BDOM and CDOM. The results with using CDOM were significantly better.

A sample plot of objectives for the candidates after running the DE with BDOM and CDOM is shown in figure 4 & 5 respectively.

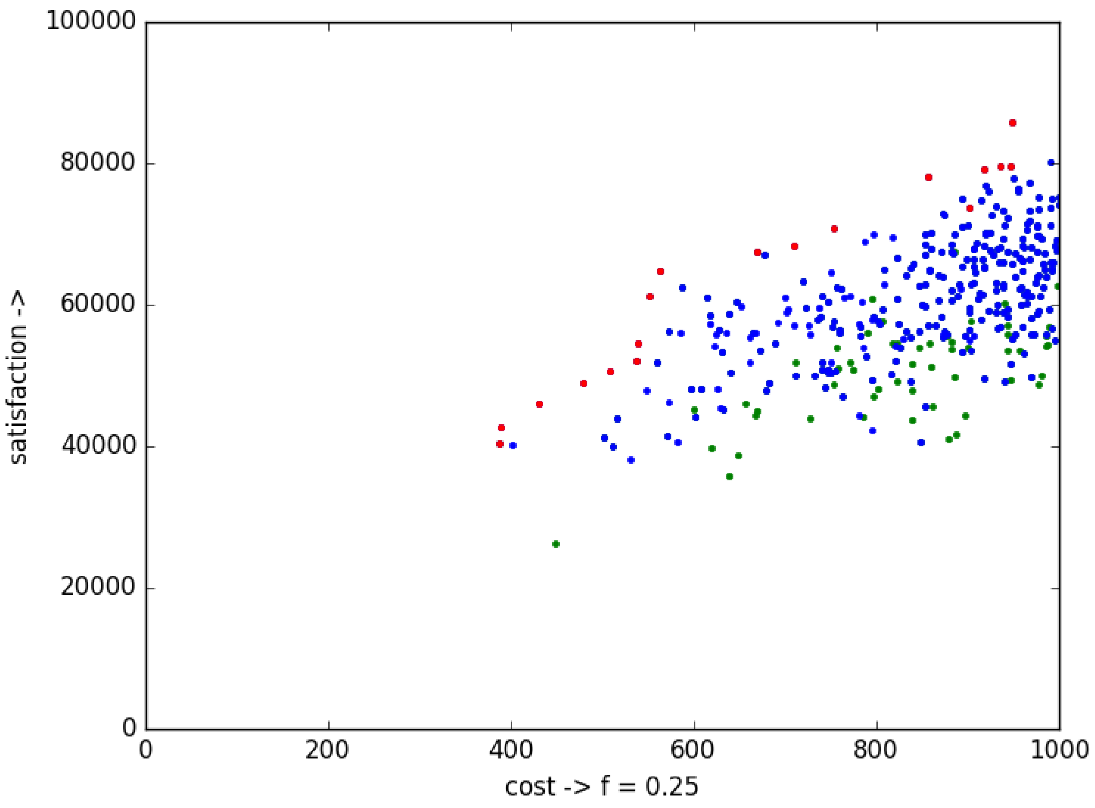


Figure 4: DE with $f = 0.25$ and using BDOM

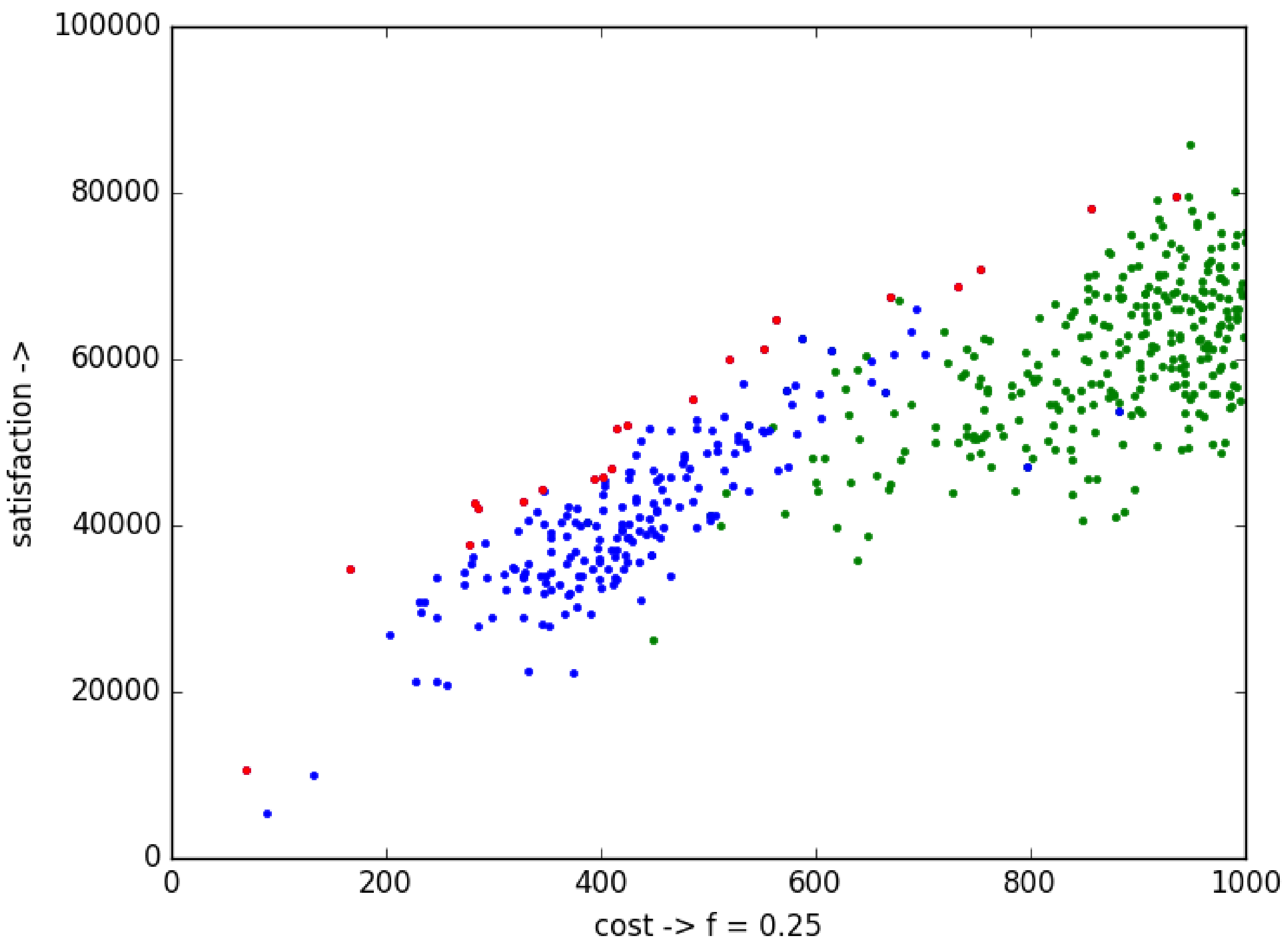
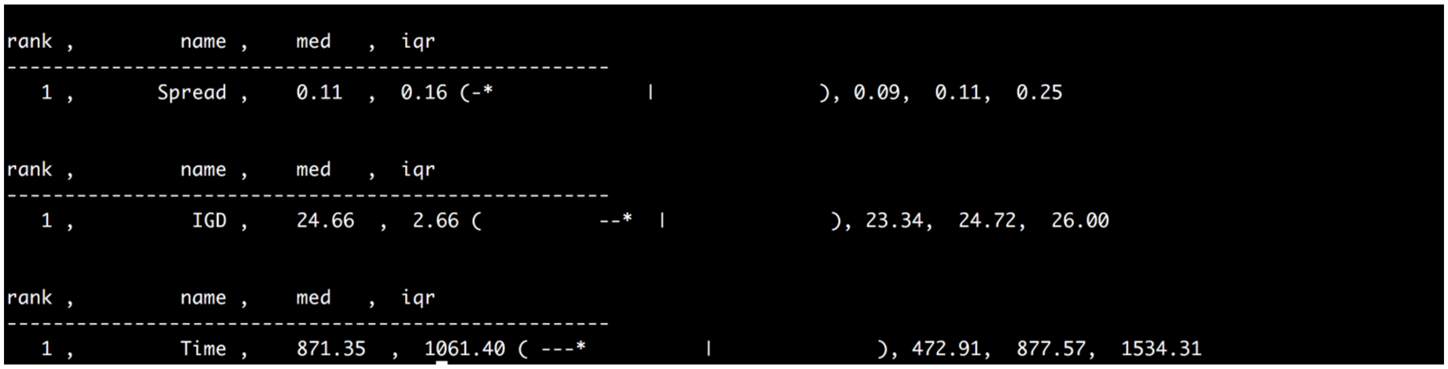


Figure 5: DE with $f = 0.25$ and using CDOM



```
rank ,         name ,    med    ,  iqr
----------------------------------------------------
   1 ,       Spread ,    0.11   ,  0.16 (-*            |            ), 0.09,  0.11,  0.25

rank ,         name ,    med    ,  iqr
----------------------------------------------------
   1 ,          IGD ,    24.66   ,  2.66 (          --*  |              ), 23.34,  24.72,  26.00

rank ,         name ,    med    ,  iqr
----------------------------------------------------
   1 ,         Time ,    871.35   ,  1061.40 ( ---*          |             ), 472.91,  877.57,  1534.31
```

Figure 6: Mean, Median and IQR for Spread, IGD and time over 20 Runs of DE with CDOM

8. Parameter tuning for Extrapolate amount (f) variable.

Decision: We observed that varying f had significant implications on performance of DE. Moreover, the same value of f wouldn't not suit for different population size and different dataset for NRP model. Hence, it seemed like a good idea to find an optimal value of f before optimizing using DE.

Objective: For a particular value of f the number of child vectors (T) generated that replaced the existing candidates. i.e. the number of 'better candidates'.

Optimizer: Since this is single objective optimization problem, we selected simulated annealing as our optimizer. (plus, SA is simple, elegant, fast and cool).

The standard SA algorithm adapted with our energy and evaluate method:

```
number_of_iterations = 500
K_MAX = 1000
best_state = generate_random_f
best_energy = current_energy = normalize( evaluate( best_state) ) )
k = 1
for number_of_iterations:
     next_f = generate_random_f
     next_energy = normalize( evaluate( best_state) ) )
     if next_energy > best_energy:
          best_energy = next_energy
     if next_energy > current_energy:
          current_energy = next_energy
     else if probability(old=current_energy, new=next_energy, k = k/K_MAX)
< random.random():
          current_enrgy = next_energy
     k += 1
```

Specifics of the methods used:

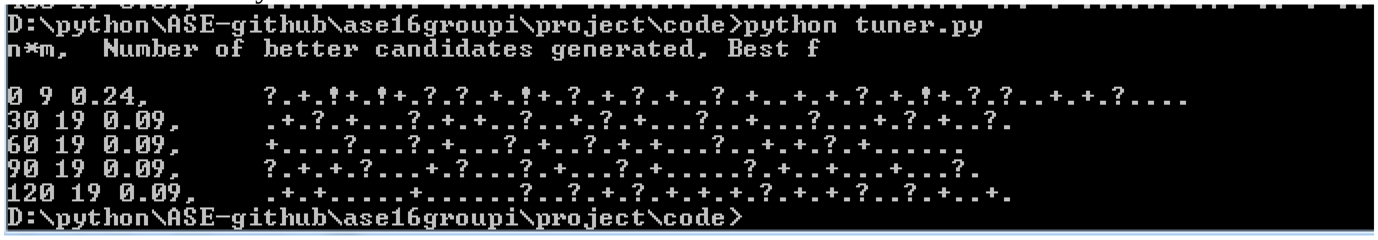
`generate_random_f`: generates a random value between 0 and 1

`evaluate`: For some f run DE and report the number of 'better candidates' generated.

`Normalize`: Normalize the value reported by evaluate between 0 and 1

`Probability(old, new, k): math.exp((new - old) / k)`

NOTE: This is a maximization problem and the way I am using it needs `probability()` to return small values initially.



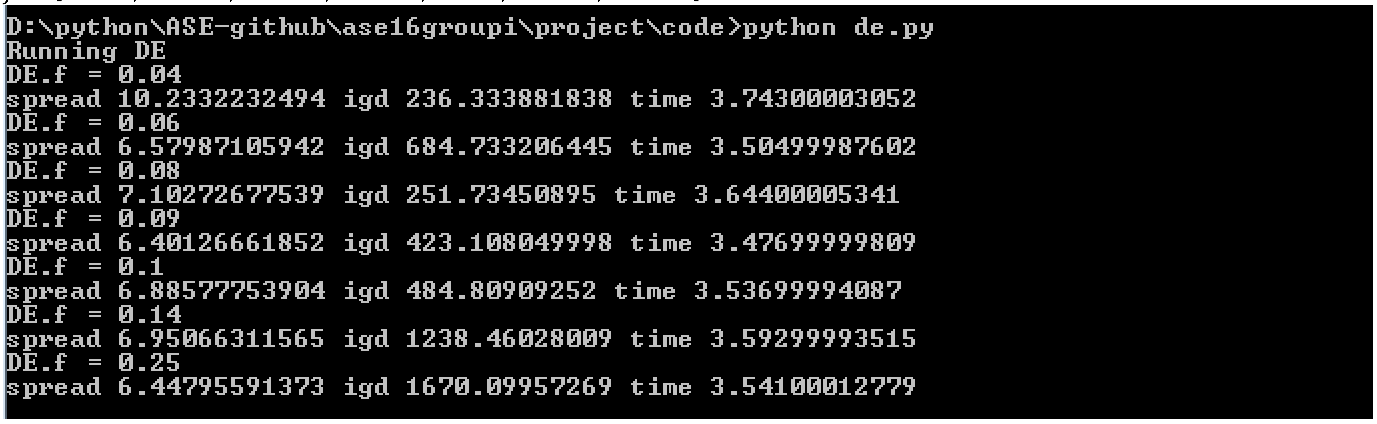
```
D:\python\ASE-github\ase16groupi\project\code>python tuner.py
n*m,  Number of better candidates generated, Best f

0 9 0.24,       ?.+.!+.!+.?.?.+.!+.?.+.?.+..?.+..+.+.?.+.!+.?.?..+.+.?....
30 19 0.09,     .+.?.+...?.+.+..?..+.?.+...?..+...?...+.?.+..?.
60 19 0.09,     +....?...?.+...?.+..?.+.+...?..+.+.?.+......
90 19 0.09,     ?.+.+.?...+.?...?.+...?.+.....?.+..+...+...?.
120 19 0.09,    .+.+.....+......?..?.+.?.+.+.+.?.+.+.?..?.+..+.
D:\python\ASE-github\ase16groupi\project\code>
```

Figure 7: Sample run of hyper-parameter tuning module.

Next we ran DE for the following values of f and the measured the spread and IGD for each f.

f =[0.04, 0.06, 0.08, 0.09, 0.1, 0.14, 0.25]



```
D:\python\ASE-github\ase16groupi\project\code>python de.py
Running DE
DE.f  = 0.04
spread 10.2332232494 igd 236.333881838 time 3.74300003052
DE.f  = 0.06
spread 6.57987105942 igd 684.733206445 time 3.50499987602
DE.f  = 0.08
spread 7.10272677539 igd 251.73450895 time 3.64400005341
DE.f  = 0.09
spread 6.40126661852 igd 423.108049998 time 3.47699999809
DE.f  = 0.1
spread 6.88577753904 igd 484.80909252 time 3.53699994087
DE.f  = 0.14
spread 6.95066311565 igd 1238.46028009 time 3.59299993515
DE.f  = 0.25
spread 6.44795591373 igd 1670.09957269 time 3.54100012779
```

Figure 8: Spread and IGD for DE with different value of f. Spread is the minimum for f = 0.09 while IGD is close to minimum.

Scope of improvement: We observed that the values of f which give the best results are closer to each other. Hence, we believe that MAX-WALK-SAT could have performed better (during the local search phase) than SA.

Furthermore, as we have tuned f for DE, we could have tuned `mutation_rate` for GA and observed the results.

9. Ant Colony Optimization:

Our implementation of Ant Colony Optimizer was based on [6]. The paper was published for a model which has single objective. We enhanced by adding cost as another objective, making it multi-objective and used C-Dom to evaluate best solution.

We divided the implementation into generating data and running the optimizer upon the generated data. The algorithms we implemented uses C-Dom to evaluate between best choices. For D.E, we have implemented both C-Dom and B-Dom to evaluate the performance. Clearly, C-Dom performance was better. There are certain constants proposed by the paper [6], for ACO.

- ALPHA = 1
- BETA = 2
- Q = 1
- P = 0.1

9.1. Assumptions

- We assume that more than one customer can be concerned with any requirement, and that all the requirements are not equally important for all the customers.
- We assume that at most 20% of dependency between requirements.

9.2 Implementation of Ant Colony Optimizer

A graph will be generated with the Release Planning problem instance information. Two types of edges will be created, representing mandatory and optional moves for an ant. Mandatory moves will be created to ensure that precedence constraints are respected. At each step, in case the random value q <= q0 (where q0 is a parameter), an ant visiting a node r_i will have the probability of moving to the node r_j is determined by [6]:

$$p_{ij}^{k} = \frac{\tau_{ij}^{\alpha} \cdot w_j^{\beta}}{\sum_{r_j \in opt\_vis_k(i)} \tau_{ij}^{\alpha} \cdot w_j^{\beta}}$$

where “tau” is the amount of pheromone in edge and ALPHA, BETA are parameters controlling the relative importance of pheromone and requirement information.

A roulette procedure, considering the heuristic information measure of a node will be employed to select the initial node of each ant. The ant will travel through the generated graph, adding requirements to the first release until no more additions are allowed, due to budget constraints. The core algorithm is [6]:

```
SINGLE RELEASE PLANNING LOOP
FOR EACH Release, $k$
    Place, using a roulette procedure, ant $k$ in a vertex $r_i \in V$,
            where $visited_i = False$ and $overall\_cost_i \leq budgetRelease_k$
    ADDS $(r_i, k)$
    WHILE $opt\_vis_k(i) \neq \emptyset$ DO
            Move ant $k$ to a vertex $r_j \in opt\_vis_k(i)$ with probability $p_{ij}^k$ or
                                        considering $max(\tau_{ij} \cdot w_j^{\beta})$.
            Update pheromone in edge $(r_i, r_j)$, with $\tau_{ij} = (1-\varphi) \cdot \tau_{ij} + \varphi \cdot \tau_0$
            ADDS $(r_j, k)$
            $i \leftarrow j$
```

9.3. Results

For given Requirements = 200, Customers = 10, Budget = 1000, we randomly generate client importance, client weight. The results are always between (977, 20780) indicating the cost, satisfaction coordinates. Below is a sample screenshot.

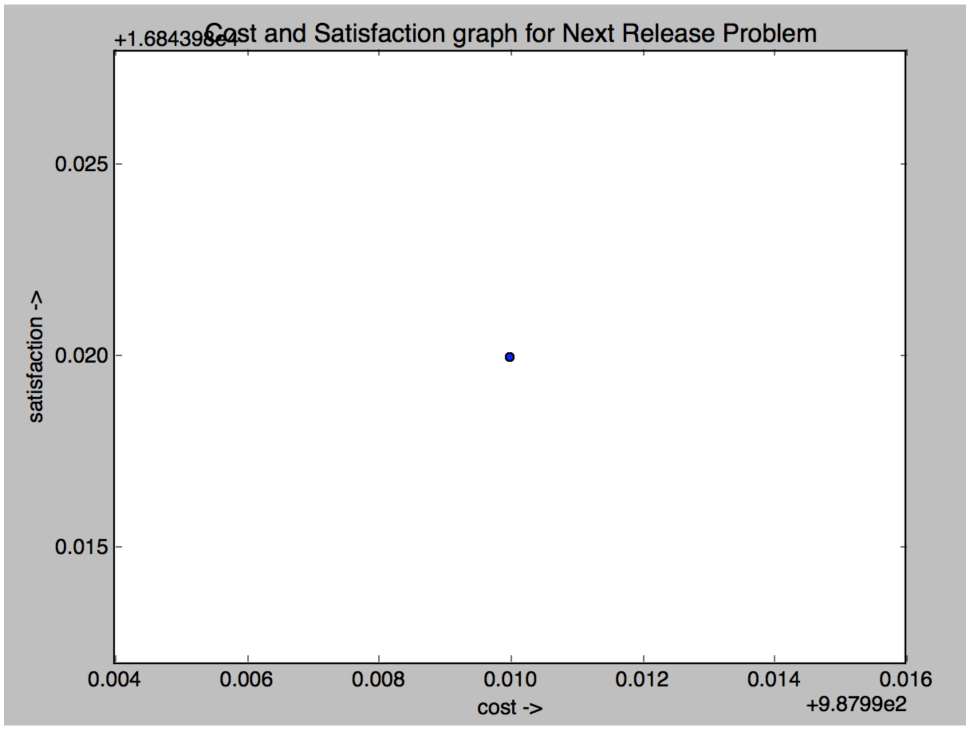


Figure 9: The cost and satisfaction have been scaled down by 100000

9.4 Conclusion

Based on our results, we can summarize Differential Evolution performs better than Ant Colony optimizer by:

- The number of results generated by D.E is very high compared to ACO.
- The best solution of ACO is usually out performed by majority of best solutions of D.E

10 Acknowledgement

We earnestly thank course instructor Dr. Tim Menzies, and teaching assistant George Mathew for giving us valuable advice in implementing the project.

11. References:

[1] J.J. Durillo et. al. “A Study of the Multi-Objective Next Release Problem.” At 1st International Symposium on Search Based Software Engineering

[2] J. Krall and T. Menzeis “GALE: Geometric Active Learning for Search-Based Software Engineering.”. IEEE Transactions on Software Engineering. VOL. 41.

[3] E. Zitzler et. al. “Indicator-based selection in multi-objective search,” in Proc. 8th Int. Conf. Parallel Problem Solving Nature, 2004, pp. 832–842.

[4] Storn, R. (1996). "On the usage of differential evolution for function optimization". Biennial Conference of the North American Fuzzy Information Processing Society (NAFIPS). pp. 519-523.

[5] *https://github.com/ai-se/softgoals/blob/master/src/utilities/de.py#L141*

[6] An Ant Colony Optimization Approach to the Software Release Planning with Dependent Requirements , Jerffeson Teixeira de Souza, Camila Loiola Brito Maia, Thiago do Nascimento Ferreira, Rafael Augusto Ferreira do Carmo, and Márcia Maria Albuquerque Brasil.