Will Rice

wdr0016@auburn.edu

COMP 5660 Fall 2020 Assignment 1d

1. Description of MOEA

The design of this MOEA happens at the creation of each phenotype from a genotype, which takes place in the file src/solutionBoard.py. The three objectives are kept track of in different ways, here is how each is implemented.

Objective 1: Maximize number of cells lit up. Fitness = Number of Lit Cells / Number of White Cells. This gives a decimal value where 1.0 is the best possible fitness. It was chosen to make it a decimal to mirror the following objectives and to know when the fitness had reached its maximum.

Objective 2: Minimize number of bulbs shining on each other. Fitness = 1 / (Light Violations * 0.5 + 1). A Light Violation is counted each time one light shines on another light. This fitness formula also gives a decimal where 1.0 is the best possible fitness. It was decided to take the reciprocal of the violations because the objective is to minimize the total number of violations. The decision to add 1 was done to avoid division by zero when there are no light violations in the solution. The decision to multiply the number of light violations by 0.5 was done to make the curve more forgiving to solutions with more violations.

Objective 3: Minimize the number of black cell adjacency constraint violations. Fitness = 1 / (Black cell constraint violations * 0.5 + 1). A black cell constraint violation for the number of violations happening per black cell. For example, if a black cell with value 3 is only adjacent to 1 bulb, then the number of black cell constraint violations is increased by 2. Another example, if a black cell with value 1 is adjacent to 4 bulbs, the number of black cell constraint violations is increased by 3. The decision to make it a reciprocal with the number of violations being halved and the denominator being increased by one are all the same reasons as objective two.

In Summary:

Objective Fitness 1: Number of Lit Cells / Number of White Cells

Objective Fitness 2: 1 / (Light Violations * 0.5 + 1)

Objective Fitness 3: 1 / (Black cell constraint violations * 0.5 + 1)

The genotype operations, parent selection methods, and survival selection methods are all the same as the generic EA. In the case of the MOEA however, the fitness, or score in this code, for each genotype is determined by 1 / Level of Domination. The Level of Domination is

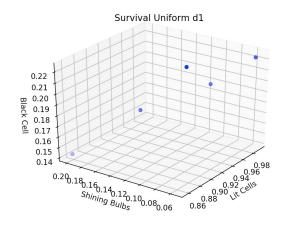
determined every time that the population is changed. The decision to take the reciprocal of the Level of Domination was done so that the more dominant levels would have higher fitness values. This is crucial for most genotype methods because most involve fitness.

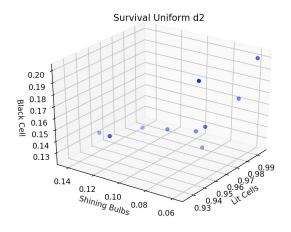
2. Determining the best configurations

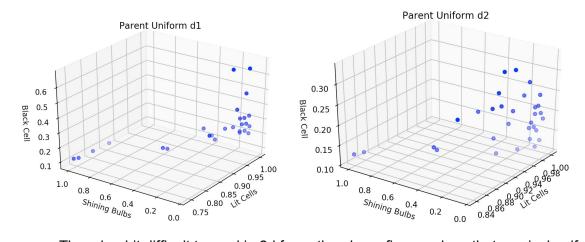
NOTE: To save time and computational intensity, all tests below were run with noChangeForNEvals set to 2000. This seemed like a good compromise to give each run a chance to still evolve, but also to avoid running the full 10,000 fitness evaluations per run. Each test is run 30 times. Configuration, log, and solution files for each test can be found in their respective subdirectories with an additional subdirectory titled "2a", or whichever letter the current experiment is on.

2a. Ruling out Uniform:

Determining the best possible configurations for this MOEA started with ruling out certain genotype methods, specifically the uniform parent selection and uniform survival selection. Both of these methods were tested still with what was assumed to be the eventual best configuration, and the results are below of the best Pareto Front found per experiment.



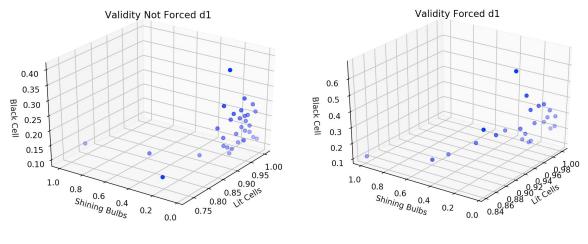


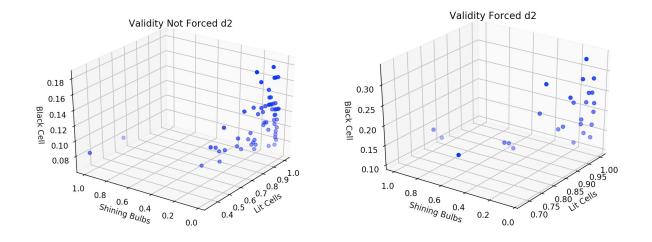


Though a bit difficult to read in 2d form, the above figures show that survival uniform and parent selection uniform do not offer very strong or diverse solutions to the problems. For survival uniform, it is shown how neither problem generates a very large variety of solutions on the Pareto front. For parent uniform, it shows how despite generating a large number of solutions, there are very few solutions that perform excellently in multiple categories. Most simply do well in number of Lit Cells, while the solutions that perform well in other categories do poorly all but one.

2b. Looking at usefulness of Validity Forced plus Uniform Random Initialization:

The next issue tested was the necessity of Validity Forced plus Uniform Random Initialization. It is already assumed that this is necessary due to experiments performed in the previous report, but tests were still run and the report is below of the best Pareto Front found.

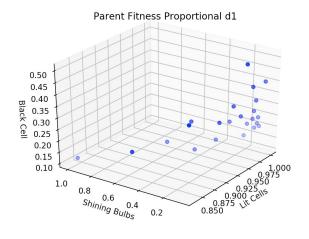


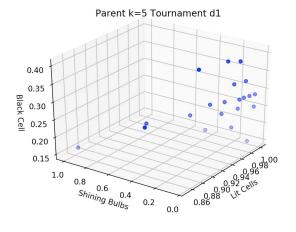


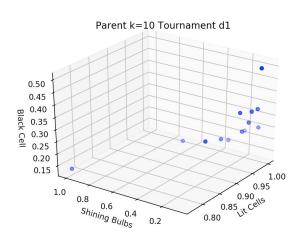
Looking at the figures above, it is clear that Validity Forced Initialization is the better of the two options. It results in both higher black cell constraint peak fitnesses and also less overall crowding in the corner of the number of lit cells.

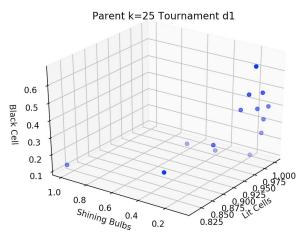
2c. Looking at different Parent Selections:

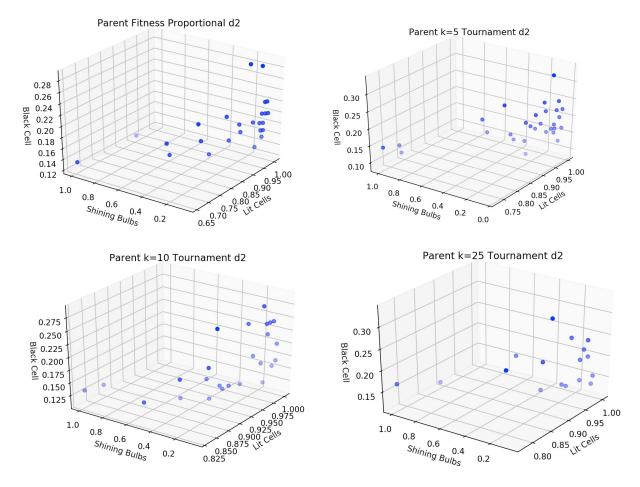
Now that uniform random parent selection has been ruled out, there are two remaining contenders: Fitness Proportional and k-Tournament. Both of these are examined below with survival truncation as the survival method, results show the best Pareto Front found by these different methods.







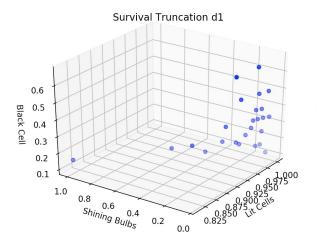


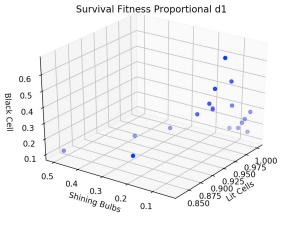


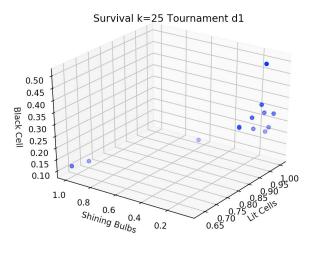
A lot can be learned by looking at these graphs. Generally though, there looks to be no clear cut winner amongst the group. It appears for d1.lup, the best could be the k=25 parent tournament, which touts the best black cell constraint value of all of the Pareto fronts. The same can be said for d2.lup, but neither have a large variety of solutions available. For both instances, The parent fitness proportional method also performs well. This will be kept in mind as experiments continue.

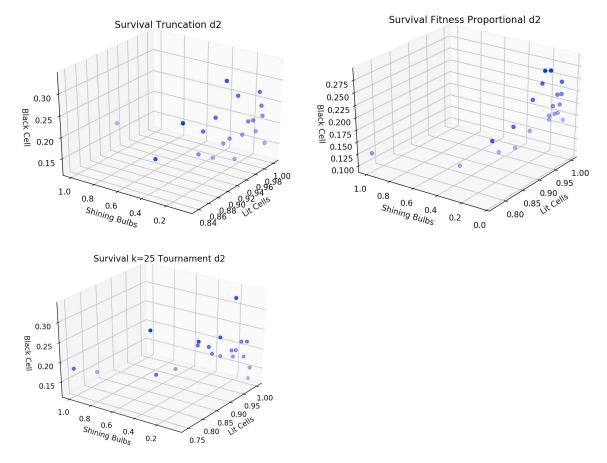
2d. Looking at different Parent Selections:

Along with parent selection methods, it is necessary to look at survival selection methods. These include: truncation, k-tournament, and fitness proportional. These are all investigated below with fitness proportional selected for the parent selection method. Results for the best Pareto Front found in any experiment are found below.





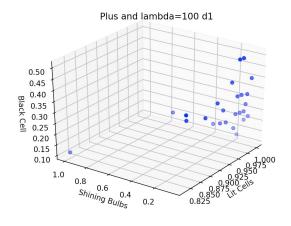


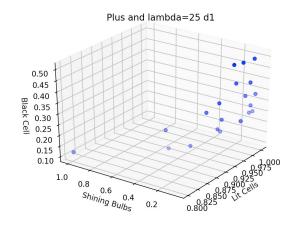


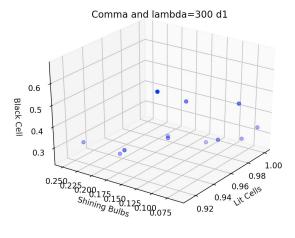
Interestingly, there again does not appear to be a far better strategy. Truncation appears to have some of the more diverse solutions in each problem set. Still, each appears to be a valid form of determining survival.

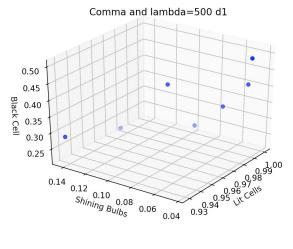
2e. Looking at Plus vs. Comma and size of lambda

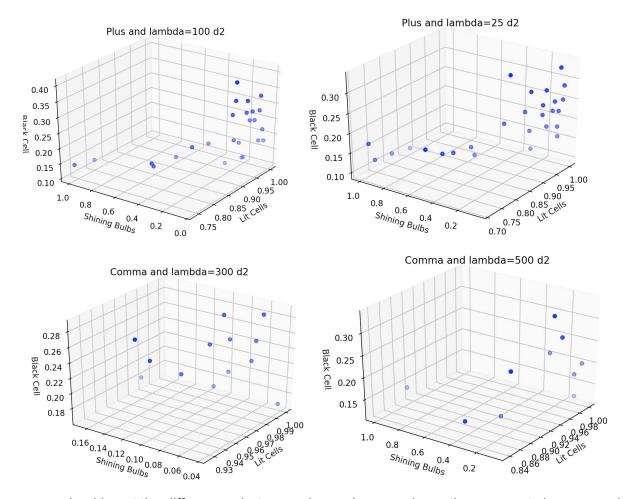
So far, the experiments have been run with Plus survival strategy and lambda set to 100, the same as mu. The below experiments focus on different combinations of Plus, Comma, and lambda sizes. Methods are run with Survival Truncation and Fitness Proportion parent selection. Below are the results showing the best Pareto Front found in each experiment.











Looking at the differences between plus and comma here, there seem to be pros and cons of each. The plus method tends to crowd in the corner with the number of lit cells while the comma method appears to be more diverse in its solutions. An apparent drawback of comma though is that it does not maximize the shining bulbs violations consistently like plus method does. This could be a random chance, but it does seem worth noting. It does not appear that lambda has a significant impact for either of the methods.

Conclusion:

Looking at all of the experiments run, the default selection was chosen to use Fitness Proportional Parent Selection, Survival Truncation, Plus Survival Strategy, and lambda=100. There were many different possible routes, but this one appeared to offer a nice set of diverse solutions that also maximized each objective in at least one solution as compared to other inferior configurations. It does tend to crowd in the number of lit cells corner for d2.lup, but there were few configurations that did not do so.