**Objective and Problem Definition**

Genetic Algorithms implement the theory of evolution – including the concepts of elitism, crossover, and mutation – into a computer system, to find acceptably optimal solutions to problems that can be expressed in terms of a Chromosome. The objective of this experiment was to test different implementations of a Genetic Algorithm on the Travelling Sales Person problem. Using different rates and methods of Crossover and Mutation, the experiment was run and the data was collected and analyzed. During the tests, some obvious trends appeared regarding the effectiveness of each set of parameters. The following sections outline the results, analysis, and conclusions about the effectiveness of each set of parameters.

**Summary and Parameters Used**

The experiment was done using the parameters:

* *%100 Crossover, %0 Mutation, Dynamic Mutation Off*
* *%100 Crossover, %10 Mutation, Dynamic Mutation Off*
* *%80 Crossover, %0 Mutation, Dynamic Mutation Off*
* *%80 Crossover, %10 Mutation, Dynamic Mutation Off*
* *%80 Crossover, %10 Mutation, Dynamic Mutation On*

Each of these parameters were used 5 times, for both the Uniform Order Crossover and the 2-Point Crossover. The results for these experiments are found on Table 1 & Table 2, and Figures 1 – 20. Upon observation of the results, it was concluded that with both crossover types, the best fitness resulted with the parameters: %80 crossover, 20% mutation, and dynamic mutation turned on (Figure 9, 19). The worst results came when the mutation rate was set to 0% (Figure 1, 5, 11, 15). It should be noted that the number of generations is different for each run. This is because I did not set a generation limit, rather, I had the simulation stop after 15 generations where no improvement was found for the elite fitness. So some simulations went much longer than others, especially ones with non-zero mutation.

**Results**

Referr to the Diagrams section. Figures 1-10 contain all the graphs for the Uniform Order Crossover, for each of the parameter settings, plotting the fitness over generation. Figures 11-20 contain all the graphs for the 2-Point Crossover. Tables 1 and 2 contain the overall results from all the experiments.

**Discussion**

Upon analyzing the data collected, many conclusions can be drawn. One specific conclusion is in regards to the performance increase that is added when mutation is allowed to occur. This allowed the generations to get out of local minima and increase the diversity of the population. Figure 2 shows the average fitness for each generation, with no mutation, and the trend lines always seem to be decreasing. Figure 4 shows the average fitness for each generation with mutation set to 10%, and you can clearly see the trend line display a more jagged appearance. This is because while mutation adds diversity, it doesn't always result in the mutated chromosomes being more fit than others; meaning the average fitness may decrease or increase as a result of mutation.

The jagged lines in all of the average fitness graphs that included mutation ran for many more generaitons. This means that the maximum allowed number of generations without improvement (which was set to 15 in all experiments), was enough time for the mutation to produce a more fit individual, and reset the improvement counter to zero, continuing the simulation. This is especially pronounced in Figure 10, where dynamic mutation was turned on. Dynamic Mutation was implemented to increase the mutation rate dynamically as the “number of generations without improvement” increased. This would add (1.5 x num-gen-without-mutaion) to the minimum mutation rate (set to 10% in figure 10).

In simulations without mutation, the Uniform Order Crossover yielded better results (Table 1, 2). This may be due to the way that the UOX works compared to the 2-Point Crossover. The randomness of the mask that is applied to the UOX may add more diversity to the simulation than the 2-point Crossover, which simply takes sections of the parents, and places them in the children. In simulations with mutation, the 2-point Crossover had the benfit of more direct inheritance, and was also able to make up for the lack of diversity from the crossover, with mutation (Table 2). In most simulations, the 2-Point crossover continued for more generations that the Uniform Order Crossover. This implies that the UOX method was able to get similar (and sometimes better) results in less generations than the 2-point crossover.

Not included in the results, but also worth noting, is the effect that the K-value used in the tournament selections had on the fitness. In every situation, setting the K-value to 5 resulted in the best results. Higher or lower values for K yielded worse results. The use of a different type of mutation did not make much of a difference. Originally, the program chose two cities at random and swapped them, then this was changed to select a random subset of the chromosome, and reverse it. This change in mutation type showed a very small improvement in the performance of the simulation.