ECM3412 Nature Inspired Computation Coursework

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1 Ant Colony Optimisation Analysis

1.1 Question 1: Which combination of parameters produces the best results?

Overall the combination of m=100 and e=0.1 offered the best results overall by a large margin. From the specified parameters, m=100 and e=0.9, in addition to m=100 and e=0.5, performed the best by about the same amount.

1.2 Question 2: What do you think is the reason for your findings in Question 1?

I believe these were the optimal parameters as more paths were kept viable over increasing evaluations. The majority of good traversals for certain student flows disappeared as they were not selected by chance, causing the traversal probabilities to further decrease until they become minute and essentially unreachable. Therefore, a probabilistic small peak will be reached by the algorithm, where the ant path is locked on the initial paths used. This theory is depicted in all of the resulting line graphs, where all of the best fitnesses decreased at a decreasing rate, almost immediately hitting a local peak within 10 seconds or 500 evaluations which were the smallest intervals recorded.

The 100 ant paths enabled more paths from the approximately 2,500 possible traversals to be utilised during 5000 traversals, and more overall paths that decrease the fitness cost to be accessed. This allowed more paths' pheromones to be increased in one evaluation before evaporating all of the pheromones. The o.1 evaporation parameter decreased the rate at which good traversals that were not used by chance disappeared, resulting in a superior chance of being used in further iterations compared to higher values.

1.3 Question 3: How do each of the parameter settings influence the performance of the algorithm?

A higher m value, tends to enable the algorithm to reach a better fitness over time and over a certain number of evaluations with a higher reliability as shown clearly in all bar charts with Figure 4 e=0.1 as an anomaly. In contrast to this, a higher e value, decreases the reliability of reaching a lower fitness value as shown in the bar charts in Figures 1 and 3. Furthermore, as presented in all of the line graphs, experiments with lower e values tend to show further decreases in fitness throughout the testing time and evaluations despite all lines with higher e values generally staying constant. These observations further reinforce the conclusions conjectured in Question 2.

If an 'optimal solution' is to be reached for this problem, a massive m value must be used to allow every traversal to have a chance to be assessed. A higher e value would be beneficial in this case.

1.4 Question 4: Can you think of a local heuristic function to add?

A possible local heuristic function to be added is considering the difference between the facility distance and student flow values, due to a higher student flow being assigned to a facility with a lower distance being optimal (e.g Flow of 99 to a distance of 1 is a cost of 99 and a distance of 75 should be paired with an approximately 25 flow).

This can be done in practice by calculating the mean of all of the facility distances and student flows respectively, the difference between the flow chosen by the ant path and the mean flow is then calculated which is then multiplied by the ratio between the facility distance mean and student flow mean due to the differences in mean values. This value is then added to the facility mean distance to generate an approximate facility distance value to be traversed by the chosen flow. Subsequently, the difference between the actual paired distance to the flow can be calculated and the square of this value may be added to the current cost function as a heuristic cost.

1.5 Question 5: Can you think if any variation for this algorithm to improve your results? Explain your answer.

Differing from the specified pheromone update of 1/fitness, I believe the update would have largely benefited from a decrease in fitness by a few factors of 10. This is due to the fact that the updated probabilities from this given formula are too negligible. A new best solution according the results is approximately 1/5600000 which is an increase in 0.00000178%. A smaller value would cause better solutions to be considered more significantly.

Another variation to the specified implementation is the update conditions. Rather than only rewarding paths that decrease the fitness function, the top n fitness paths can be updated to increase or enable the possibility of leaving and reaching another better local peak. In addition, if the fitness converges, the current pheromones may be recorded and subsequently mutated by randomly adding or multiplying each pheromone by a certain value, in hopes of reaching another local peak (ACO is incredible unlikely to reach the optimal solution with a problem of this size)

1.6 Question 6: Do you think of any any other nature inspired algorithms that might have provided better results? Explain your answer.

The usage of the Ant Colony Optimisation algorithm for this problem is significantly sub optimal, since the algorithm specialises in finding the optimal solution on small and difficult problems/data sets or adapting to dynamically changing problem spaces. This problem is very large (2500 facilities) and has a constant problem space.

Genetic Programming may have yielded better results as it can handle large data sets since unlike ACO, mutation functions with the right parameters can prevent and pull out of local peaks. As less time is spent at local peaks, the algorithm would naturally reach a better fitness at a higher and more consistent rate.

2 Results and Further Experiment Descriptions

Beyond the specified experiments with five trials with the parameters m=100/e=0.50, m=100/e=0.90, m=10/e=0.90 and m=10/e=0.50, two extra experiments were added, m=100/e=0.10 and m=10/e=0.1, in order to further clarify the effects of the evaporation function. These 6 experiments, were executed under 4 underlying sets of parameters and termination conditions.

The parameters such as the initial pheromone and path selections were observed over 2 different seeds types for random numbers. Initialised and constant via trial number, and subsequently random based on the time the tests were run. The 2 termination conditions observed were 10,000 evaluations as specified and over a time period of 300 seconds, enabling a time based assessment of each parameter.

In order to generate the final charts for every set of experiments. The average values over 5 trials for every experiment were taken and subsequently plotted and displayed. The final overall scores were manually calculated by giving 6 points to the parameters with the lowest average best fitness in a set of experiments, reducing by 1 until the worst set of parameters. If two or more parameters had the same best fitness, the lowest ranking score between them is given

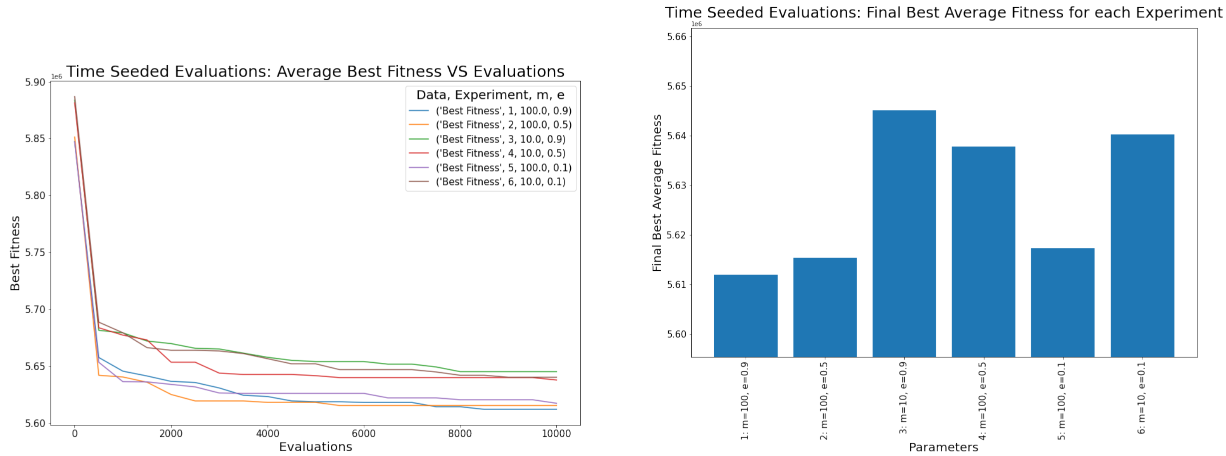

Figure 1: Time Seeded Graphs with 10,000 Evaluations Termination Condition Experiments

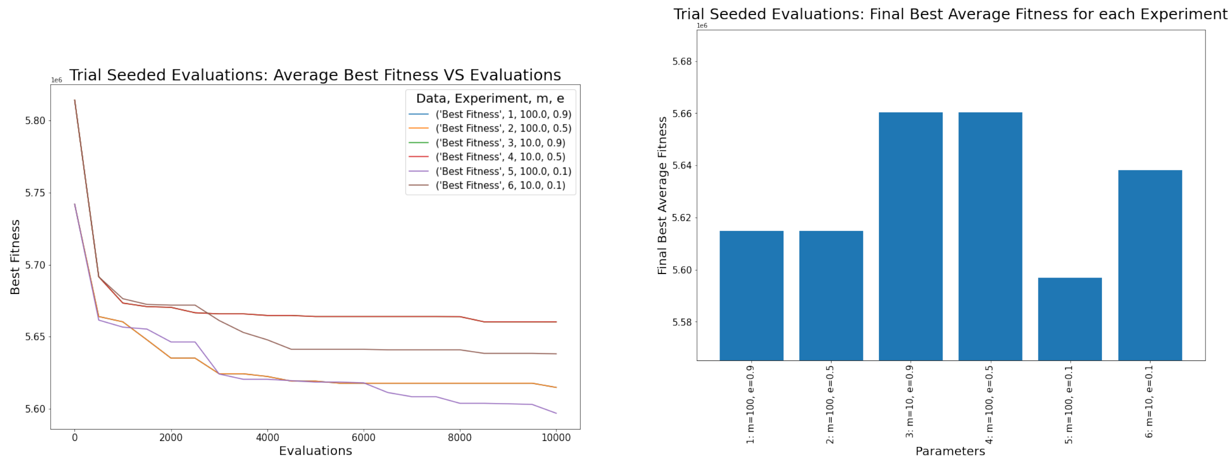

Figure 2: Trial Seeded Graphs with 10,000 Evaluations Termination Condition Experiments

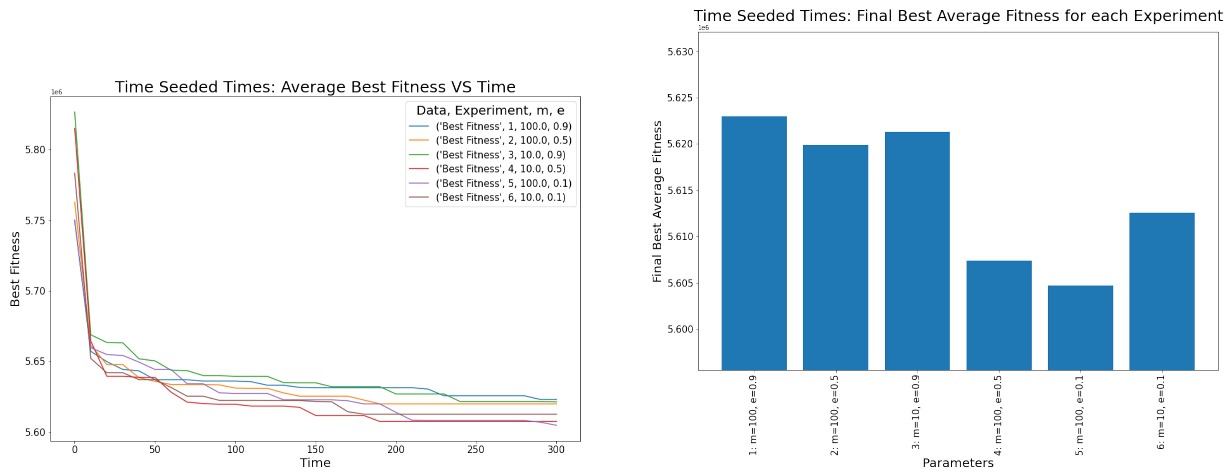

Figure 3: Time Seeded Graphs with 300 Seconds Termination Condition Experiments

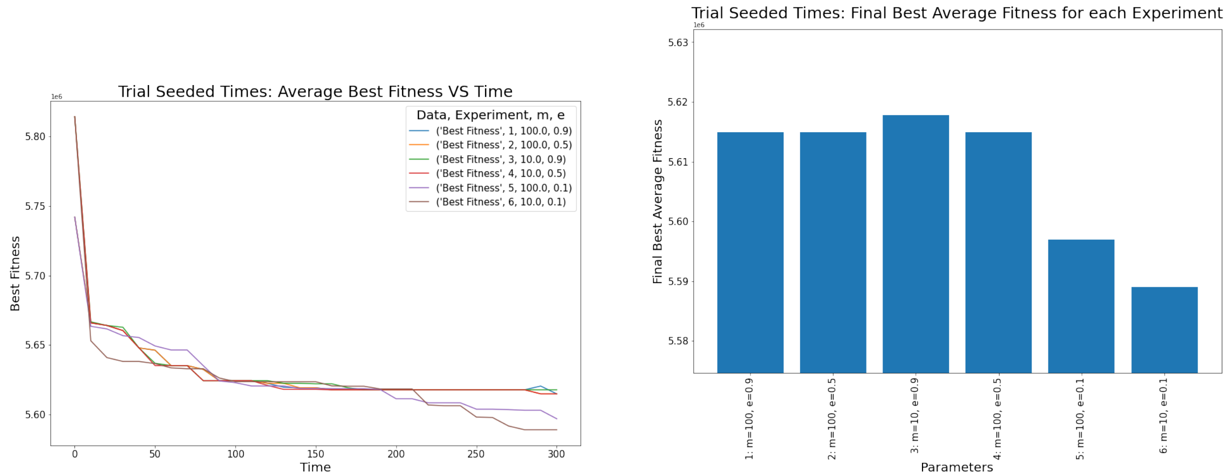

Figure 4: Trial Seeded Graphs with 300 Seconds Termination Condition Experiments

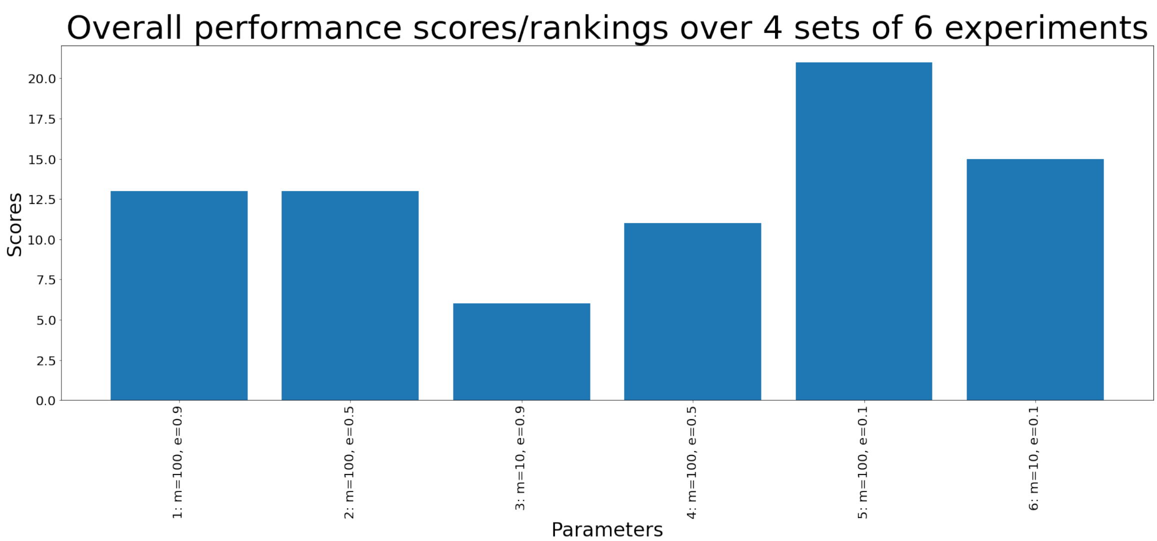

Figure 5: Overall performance scores/rankings over 4 sets of 6 experiments