Evolutionaly Computation Assignment 1&2

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I. INTRODUCTION

Vehicle Routing Problem (VRP) is a combinational optimization problem of which the objective is to find the least cost route (minimum number of vehicles and total distances) under some constraints. A typical VRP can be stated as follows: Each vehicle must depart at and return to depot. Each customer is to be serviced exactly once by only one vehicle and each vehicle has a limited capacity. The customers are placed specific coordinates. The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the VRP. Each customer has time window individually: each customer is to be serviced between ready time and duetime. If the vehicle reaches a customer before ready time, this vehicle must wait until ready time. Visiting a customer after due time is treated as a infeasible solution.

The VRPTW is NP-Complete and instances with 100 customers or more are very hard to solve optimally. I represent the VRPTW as a multi-objective problem and implement genetic algorithm (GA) solution using two types of crossover which are Uniform Order Crossove (UOX), Best Cost Route Crossover (BCRC) and three types of evaluation which are Pareto Ranking, Sum of ranks and weighted sum strategies. BCRC is one of the crossover method used in the paper [2]. The only inverse mutation and k-tournament method was used in all experiments. The two-phase algorithm which is to make feasible initial population was implemented [1]. I use a direct interpretation of the VRPTW as a multi-objective problem, in which the two objective dimensions are number of vehicles and total cost (distance).

The purpose of this paper is to consider the effects of each function part of GA and different parameters. Hence, this paper discusses four experiments as follows:

1) Compare the performance of the two crossover operators mentioned above by using various parameters and determin the most effective corossover and mutation rates reasonably.
2) Investigate the effect of population size using the best crossover and mutation rate based on the result of the experiment 1. the population size varies between 50, 100, 250, and 500.
3) Consider the effect of elitism. A certain number of chromosomes are replicated to next generations between 0, 1, 5 and 10 under the same crossover, crossover rate and mutation rate as experiment 2.
4) In experiments 1-3, only weighted sum strategy was utilized as an evaluation way. In this experiment, do a comparative study for multi-objective optimization by considering Pareto Ranking, Sum of ranks and weighted sum strategies.

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All comparison experiment's results are based on the best chromosomes of the last generation. My experimental results use the standard Solomon's VRPTW benchmark problem instances available at [3]. Solomon's data is clustered into six classes; C1, C2, R1, R2, RC1 and RC2. In this paper, these experiments were conducted with three datasets which were picked up from each class.

II. EXPERIMENTAL RESULTS AND DISCUSSIONS

In all experiments, the 18 datasets, R101, R102, R103, C101, C102, C103, RC101, RC102, RC103, R201, R202, R203, C201, C202, C203, RC201, RC202 and RC203, were used, and ran GA 10 times for each dataset. All numbers in the tables below are showed as the average number and sample standard deviation. The formula of weighted sum evaluation which was implemented in all experiments is exhibited as follow:

$$\mathrm{Fittness} = \alpha \sum_{v \in V} \mathrm{cost(v)} + \beta |\mathrm{V}| \tag{1}$$

The VRPTW is represented by a set of identical vehicles denoted by V. The objective function (1) states that total distance and the number of vehicles should be minimized. Table I presents default GA setting which were applied to these experiments.

TABLE I
DEFAULT GA SETTINGS

Population	100
Generation Span	1000
Selection	Tournament Selection
Mutation	Inversion
Tournament Size	3
Number of elites	1
α	30
β	0.1

A. Probability of Crossover and Mutation

Experiment 1) is mentioned In this subsection. This experiment was conducted to discover the more efficient crossover and mutation rates. The two crossover methods which are BCRC and UOX were implemented this GA. The crossover rates were varied betweem 0.6 and 0.9 at 0.1 intervals to determin the best crossover rates on each crossover method. After determining the best crossover rates on each crossover method, the mutation rates were varied betweem 0.1 and 0.4 at 0.1 intervals and the crossover rates were fixed the best numeric number determined above to determin the best mutation rates on each crossover method.

a) In order to discover the more efficient crossover rate, mutation rate was fixed 0.1 in this experiment. The sum of ranks was considered to determin the more efficient crossover rate. The values, the average fitnesses of 10 times run, are labeled as ranks in ascending order for each data. Each column (0.6, 0.7, 0.8 and 0.9) has a summation of the labeled ranks as a score, and the column which has the least score is chosen as the best crossover rate. By the sum of ranks method mentioned above, the best crossover rates for each crossover method are followings: UOX: 0.8, BCRC: 0.8
b) The best crossover rates for UOX and BCRC was determined 0.8. Hence, the crossover rates was fixed 0.8 and mutation rate was varied between 0.05 and 0.2 at 0.05 intervals to determin the best mutation rates for each crossover method. By the sum of ranks method mentioned above, the best mutation rates for each crossover method are followings: UOX: 0.1, BCRC: 0.05

TABLE II
CROSSOVER RATE EXPERIMENT RESULTS WITH UOX

	0.6	0.7	0.8	0.9
R101	1522.9±24.3	1513.0±37.6	1511.8±11.9	1538.1±19.9
R102	1256.3±24.0	1240.6±25.0	1243.1±30.0	1260.3±21.0
R103	1019.9±19.6	1020.2±24.2	992.5±36.2	999.9±32.4
C101	1220.1±28.0	1236.1±27.7	1225.9±37.6	1206.1±35.8
C102	1016.2±24.3	1007.3±31.5	994.2±47.7	1011.6±17.9
C103	777.2±28.3	763.2±22.9	761.0±26.9	729.6±26.8
RC101	1413.8±30.5	1421.7±24.8	1420.5±33.9	1425.0±16.8
RC102	1180.5±24.8	1175.4±36.0	1156.3±29.8	1162.4±34.5
RC103	956.9±26.5	951.8±25.3	954.2±24.1	945.8±28.2
R201	1062.8±35.4	1054.5±31.6	1070.8±19.9	1065.4±20.1
R202	852.3±22.2	848.8±21.4	872.3±15.3	857.1±24.3
R203	651.8±18.5	675.0±22.6	668.0±28.0	671.2±20.8
C201	1245.2±13.9	1228.5±24.8	1238.6±15.4	1240.5±22.0
C202	985.2±16.8	995.3±31.4	989.9±19.6	1001.8±24.3
C203	737.6±13.1	757.5±22.9	728.3±11.5	739.4±33.6
RC201	1191.3±22.7	1180.7±13.3	1177.5±25.3	1197.9±9.8
RC202	993.2±18.7	986.6±23.7	969.1±23.7	975.8±29.4
RC203	770.9±31.6	761.0±25.2	744.6±33.9	777.0±15.6

B. Effect of Population Size

Experiment 2) is mentioned In this subsection. This experiment was conducted to compare the effect difference by changing population size. The population size was varied 25, 50, 100, 250 and 500 in this experiment. Fig 1 shows the difference of each fitness average of 10 times runs of the last generation per population size. Fig 2 shows best fitnesses' average of 10 times runs of each generation for each dataset. In upper figure in Fig 1, 25 population size fitness are relatively higher than other population size fitnesses. The other populations (50, 100, 250 and 500) are relatively the same as each other particulary in the same figure in Fig 1. In lower figure in Fig 1, 250 and 500 population size fitnesses are relatively same and they converged better fitness than other population size fitnesses. Accoding to Fig 1, this program

TABLE III
CROSSOVER RATE EXPERIMENT RESULTS WITH BCRC

	0.6	0.7	0.8	0.9
R101	778.0±17.5	767.1±15.7	764.6±15.8	766.9±17.3
R102	709.1±16.9	707.9±10.7	699.5±16.0	697.0±14.4
R103	569.2±10.3	564.3±13.5	559.0±10.8	564.6±10.9
C101	465.6±28.0	464.0±26.5	443.5±9.6	453.7±19.0
C102	480.0±18.5	491.3±9.5	460.1±18.9	468.5±20.9
C103	463.9±17.5	472.1±22.3	466.3±18.5	475.8±13.3
RC101	667.2±25.2	663.5±18.2	668.0±23.0	660.8±13.2
RC102	580.8±18.2	586.0±17.9	580.6±19.3	580.7±13.0
RC103	508.0±14.5	511.4±17.1	509.0±3.9	500.8±16.5
R201	329.2±14.4	335.2±23.5	330.3±17.4	333.2±12.8
R202	305.3±11.1	310.4±16.7	314.0±20.8	300.6±12.2
R203	262.7±22.9	287.9±20.3	278.4±18.3	264.8±18.9
C201	197.0±30.0	196.9±23.2	187.2±26.9	198.0±25.7
C202	262.6±18.4	282.8±31.9	255.7±20.8	264.9±22.9
C203	293.1±23.8	289.9±33.8	285.3±13.1	288.6±27.6
RC201	359.0±14.4	359.7±30.2	355.2±15.7	352.6±18.5
RC202	341.0±27.2	339.1±21.1	343.5±33.6	338.8±28.5
RC203	276.5±19.2	284.0±17.2	282.9±23.4	303.0±18.2

TABLE IV
MUTATION RATE EXPERIMENT RESULTS WITH UOX

	0.1	0.2	0.3	0.4
R101	1529.2±23.9	1511.8±11.9	1518.7±21.9	1530.4±18.2
R102	1230.8±32.2	1243.1±30.0	1246.9±38.2	1246.4±33.1
R103	1005.2±22.7	992.5±36.2	1004.5±20.9	993.8±24.4
C101	1192.3±33.5	1225.9±37.6	1226.2±22.0	1219.6±34.0
C102	1007.0±40.5	994.2±47.7	1004.8±31.4	1013.3±28.5
C103	761.0±31.3	761.0±26.9	751.7±17.1	756.1±37.7
RC101	1416.7±32.5	1420.5±33.9	1412.8±33.9	1414.9±33.3
RC102	1178.0±32.3	1156.3±29.8	1175.2±27.7	1157.5±29.0
RC103	950.4±20.4	954.2±24.1	940.5±38.2	954.1±24.0
R201	1058.7±16.5	1070.8±19.9	1076.8±25.3	1050.8±34.3
R202	867.1±20.0	872.3±15.3	872.2±18.9	868.3±18.5
R203	670.2±18.9	668.0±28.0	667.2±23.7	666.7±17.5
C201	1234.0±38.7	1238.6±15.4	1235.6±27.6	1233.0±24.9
C202	994.2±14.5	989.9±19.6	1006.5±16.9	1000.3±14.4
C203	744.6±28.8	728.3±11.5	753.1±24.4	754.7±17.4
RC201	1196.9±34.6	1177.5±25.3	1178.3±30.5	1186.1±17.3
RC202	959.5±20.0	969.1±23.7	987.3±22.8	958.9±33.2
RC203	771.9±35.0	744.6±33.9	764.0±21.8	762.7±30.7

TABLE V
MUTATION RATE EXPERIMENT RESULTS WITH BCRC

	0.1	0.2	0.3	0.4
R101	769.5±20.7	764.6±15.8	778.8±17.7	786.6±20.1
R102	693.9±16.7	699.5±16.0	697.7±17.7	696.0±15.3
R103	568.7±4.2	559.0±10.8	567.7±10.6	559.4±12.8
C101	451.2±19.7	443.5±9.6	446.6±31.0	458.9±58.8
C102	472.0±20.9	460.1±18.9	479.4±22.4	479.7±17.8
C103	455.3±11.5	466.3±18.5	471.9±20.9	474.2±22.1
RC101	649.5±17.6	668.0±23.0	659.2±16.2	660.7±23.6
RC102	575.0±23.0	580.6±19.3	588.3±13.8	577.2±24.7
RC103	505.4±13.1	509.0±3.9	508.9±6.6	509.9±5.8
R201	327.8±16.2	330.3±17.4	340.3±8.8	334.2±15.0
R202	315.9±20.3	314.0±20.8	301.8±15.1	309.3±23.3
R203	264.7±25.6	278.4±18.3	274.6±30.2	279.4±21.3
C201	196.3±23.4	187.2±26.9	193.9±18.6	192.3±28.4
C202	255.2±11.5	255.7±20.8	262.8±20.5	258.6±21.7
C203	288.7±21.9	285.3±13.1	287.2±24.7	277.8±20.3
RC201	363.0±20.2	355.2±15.7	363.6±16.6	361.6±7.4
RC202	338.9±32.0	343.5±33.6	333.2±22.5	332.8±24.0
RC203	281.5±10.6	282.9±23.4	287.3±11.1	300.4±15.2

could discover better solution relatively with population size 250, and this can't be predicted that which population size is the best. Considered the computation time and the slightly difference between 250 and 500 population size outcoms, 250 population size is enough size to get better solution. Also, accoding to Fig 2, the fitness of last generation in 25 population size fitness converged on worse value than any other population size fitness. And the bigger population size is, the earlier they could find good solution. But if the number of generation is increased, the fitness value of 25, 50, 100 and 250 population size can be assumed that they converge almost same value as the fitness value of 500 population size. Hence, 250 population size can be expected enough population size in those default parameters in TABLE I and those datasets.

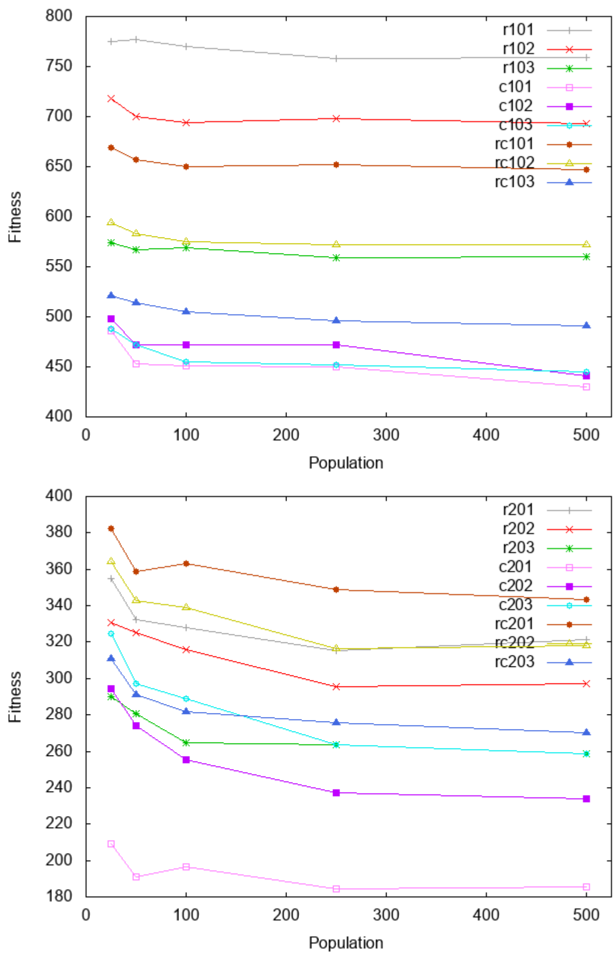

Fig. 1. Best Fitnesses of the Last Generation by Population for Each Dataset

C. Effect of Elitism

Experiment 3) is mentioned In this subsection. This experiment was conducted to compare the effect difference by changing the number of elites. The number of elites was varied 0, 1, 5 and 10 in this experiment. Fig 3 shows best fitnesses' average of 10 times runs of each generation for each dataset. According to Fig 3, the fitness with 10 elite is worse than other fitnesses with elites. This is considered that diversity in the population got lower because of the big number of elites. The fitness with 1 elite converged better solution than others in most of datasets in Fig 3. Hence, the big number of elites is not recommended because of diversity.

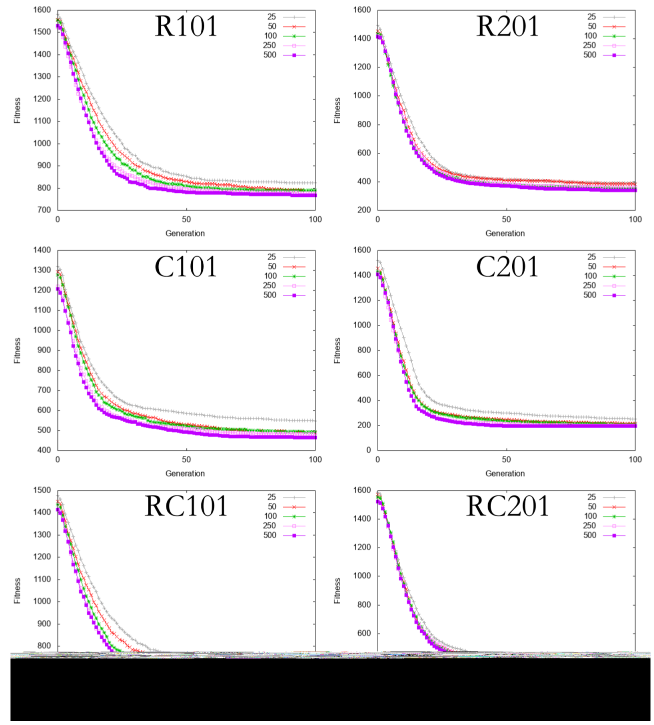

Fig. 2. Best Fitnesses of Each Generation for Each Dataset

D. Compare three types of Evaluation

Experiment 4) is mentioned In this subsection. This experiment was conducted to compare three types of elatuation strategies which are weigted sum, sum of ranks and pareto ranking strategies. Fig 4 shows minimum distances' average of 10 times runs of each generation for each dataset. Also, Fig 5 shows minimum number of vehicles' average of 10 times runs of each generation for each dataset. In Fig 4 and Fig 5, sum of ranks strategy get the worst solution out of the three strategies. In Fig 4, comparing weighted sum strategy with pareto ranking strategy, pareto ranking strategy got better solution about distance than weighted sum strategy in all datasets. On the other hand, In Fig 4, comparing both strategy same as before, both strategies got almost same solution at the last generation in dataset R101, C101, C201 and RC101. Also, weighted sum strategy got slightly better solution than pareto ranking strategy at the last generation in dataset RC201 and got much better solution than pareto ranking strategy i at the last generation in dataset R201. When focusing between 0 and 100 generation, pareto ranking strategy found better solution than weighted sum strategy in every generationson all datasets in Fig 4, but pareto ranking strategy found worse solution than weighted sum strategy in every generations on all datasets in Fig 5. These things are thought to be caused by the bigger