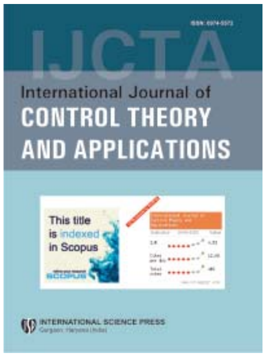

International Journal of Control Theory and Applications

ISSN : 0974–5572

Volume 10 • Number 23 • 2017

Genetic Algorithm – Optimizing for the Travelling Salesman Problem with Range based Crossover

Indra. K.R[a] and S. Lavanya[b]

[a]*Research Scholar, Dept of Mathematics, Vel's University, Chennai.*

E-mail: indrakr@yahoo.com

[b]*Asst Professor, Dept of Mathematics, Bharathi Women's College, Chennai*

E-mail: lavanyaprasad1@gmail.com

Abstract: The main operators of a GA search are selection, crossover and mutation. Genetic algorithms perform search in a population for optimized solutions or fit individuals. Fit individuals mate to produce offspring that will replace unfit individuals in the population where the chromosome (individual) must have distinct data elements such as in the travelling salesman problem, all crossovers are not suitable.We present a new crossover technique that eliminatesdata redundancyin the offspring and provides better results than the partially mapped crossover.

Keywords: *Crossover, Selection, Population, Range, Partially mapped crossover, Travelling Salesman, Optimizing, Range Based Crossover.*

1. INTRODUCTION

A travelling salesman problem (TSP) is a case where there are n cities and a salesman is required to start from one city and travel to the rest of the $n - 1$ cities and finally return to the start in such a manner as to minimize the total distance. There are$(n - 1)!$ possible ways to complete a tour. One (or more than one) tourmust have the minimum distance[3].

Many crossovers have been proposed for the Travelling Salesman Problem including PMX (partially mapped crossover), OX (ordered crossover), CX (cycle crossover), ERX (edge recombination crossover), GNX (generalized N-point crossover), TBX (tie breaker crossover), MX (moon crossover) and SCX (sequential constructive crossover)[6].

The most common crossovers used to solve TSP isthe Partially-Mapped crossover (PMX), Order crossover (OX) and Cycle crossover (CX)[4].

Crossovers may not preserve traits through generations. This document discusses proximity of data elements as a trait and how a special crossover can enhance the optimal solution by preserving this trait.

2. LITERATURE REVIEW

David Fogel claimed that the link between the parent and the offspring must be sufficiently preserved to ensure that there is a positive advancement in adaptation [2]. The argument by David Fogel was that offspring must inherit fit qualities from the parents which a crossover does not maintain as it is random. He claimed that there is an absence of a genealogical link [2]. PMX is the most frequently used crossover and was proposed by Goldberg and Lingle for the Travelling Salesman Problem [5]. It is based on a mapping exercise of individual data elements in the chromosomes.These comments have been a fundamental inspiration for the development of this experiment in which we try to see if a crossover can transfer qualities of the parents to the offspring in a certain way.

3. MATERIALS AND METHODS

3.1. TSP: Introduction

Let's consider a simple problem. We have 8 cities labelled A to H. Each city has exactly one entry and one exit. No city is visited more than once. Figure 1 shows one possible tour given by {A, B, C, D, E, F, G, H}. Figure 2 shows a second possible tour given by {A, C, B, D, E, G, F, H}.

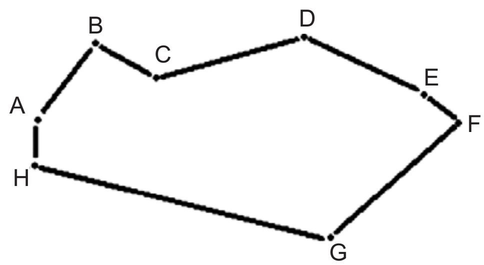

Figure 1: Short Random Tour

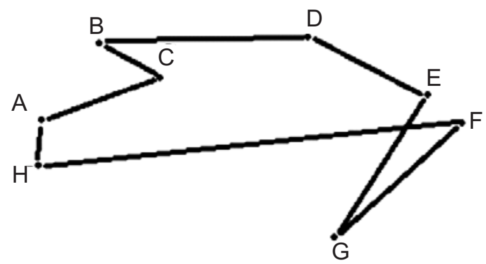

Figure 2: Long Random Tour

Similarly, a population of tours is created in which each individual has a specific order of distinct cities. Other examples of random tours are {A, C, E, H, G, B, D, F}, {A, G, F, C, B, D, E, H}, {A, B, G, F, E, D, C, H}, {A, B, G, F, E, D, C, H}, {A, H, C, B, D, E, G, F}

3.2. Fitness function

The most critical aspect of a genetic algorithm is the fitness function. A typical TSP involves defining the fitness as the total cost of travelling. For the purposes of this experiment, we use total distance travelled as a measure of fitness. If the total distance travelled is least in a route, it is considered to be the most fit.Each individual is a route and the total distance between the points is stored with the individual for sorting, selection and replacement.

3.3. Replacement

We have used steady-state replacement in which each generation replaces only two individuals. Parents and replacements are based on their fitness. The scheme is similar to Whitney's GENITOR algorithm in which parents have high fitness ranks in the population and the offspring replace the two most unfit members of the population[1].

3.4. PMX (Steps)

Partially Mapped Crossover in initiated by randomly picking two points in two parents and swapping the data between them. In order to remove redundancy and legalize the offspring, the rest of the data is changed based on the data mapping in this swapped region. In the below parents, the randomly selected segment (3rd, 4th, 5th positions) are swapped[7].

A	B	G	F	E	D	C	H

A	H	C	B	D	E	G	F

After swapping the randomly selected region, the swappeddata is mapped (C → G, B → F, D → E).

A	B	C	B	D	D	C	H
A	H	G	F	E	E	G	F

Rest of the data is changed based on this mapping to legalize the offspring.

A	F	C	B	D	E	G	H
A	H	G	F	E	D	C	B

3.5. A crossover with a genealogical link

The PMX operator based on random selection does not carry traits of parents into the offspring. Then the question is – what is a trait? A TSP individual chromosome is essentially an array with distinct data elements. The fitness of the individual is determined by the sequence of elements in the array. Data elements (cities) flocking in a region (*i.e.*, section of the individual) is a trait. If a flock of data elements can be transferred from a parent to an offspring then a genealogical link between the generations can be created. This could improve the speed of adaptations or generate better results. In order to study this transfer of traits, we have developed a new crossover operator and have run a simulation to compare its results with that of the PMX operator. This operator selects two random points in one parent and finds the shortest range of these elements in the second parent and swaps them. It then moves the redundant data from the longer offspring to the shorter offspring to legalize them. This crossover creates flocking of elements of one parent in both offspring. Since it is based on the shortest range, we simply called it "Range based crossover". The steps of this crossover are shown here below.

3.6. Range Based Crossover (RBX) Steps

1. Select the data between two random points in the first parent.
2. Select the minimum region in the second parent that has all the selected data in the first parent. Note: The length of this region will most likely be longer than the length of the selected data.
3. Swap the two strings at their current positions to create two offspring.
4. If the two offspring are of the same length, there is no redundant data and they are good.
5. If the two offspring are of different length, remove redundant data (second occurrence) from the longer offspring and append the same to the shorter offspring.

3.7. Example

Step 1: Data selected between random points 5-7 in the first parent. This has data *EDC*.

Step 2: Minimum region of *EDC* marked in the second parent. This gives string *CBDE*.

A	B	G	F	E	D	C	H

A	H	C	B	D	E	G	F

Step 3: Swapping of the strings.

A	B	G	F	C	B	D	E	H

A	H	E	D	C	G	F

Step 4: The offspring are of different lengths. Hence, move to step 5.

Step 5: Identification of redundant data in the longer offspring. Found that data B is redundant. Remove and append to other offspring.

A	B	G	F	C	**B**	D	E	H

A	H	E	D	C	G	F

Result: The data elements *EDC* in the first parent is now in the second offspring and the same flock *CDE* appears in the first offspring.

A	B	G	F	C	D	E	H

A	H	E	D	C	G	F	**B**

3.8. Experiment

Three experiments were conducted for different number of cities - 20, 50 and 100. The positions of cities were kept the same during each experiment so that the search problem was static and results from both operators could be compared. Each experiment involved running the algorithm for 3 trials of both crossover operators *i.e.*, PMX and RBX.

Keeping all parameters same, the algorithm for both crossovers were programmed and executed. The population was set to 100 individuals. Parents were randomly selected from the best 50% of the population. One mutation was performed in each legalized offspring. If the fitness of the offspring was better than 50% of the population, it replaced the most unfit individual in the population. If the average fitness of the best 20% of the population did not change in 50,000 generations, the fitness of the fittest individual was considered to be the optimized solution.

4. EXPERIMENTAL RESULTS

It was observed that RBX generated results that are 16% more fit with 20 cities, 19% more fit with 50 cities and 25% more fit with 100 cities. The table below shows the comparison of the trials.

Table 1
Results from implementing PMX

	PMX						
	Trial 1		*Trial 2*		*Trial 3*		
Cities	Generations	Fitness	Generations	Fitness	Generations	Fitness	Avg.Fitness
E-20	4201	1548	12544	1576	5234	1764	1629.3
E-50	78301	2913	52384	2816	29293	2996	2908.3
E-100	135086	5939	105040	5525	101197	5367	5610.3

Table 2
Results from implementing RBX

	RBX						
	Trial 1		*Trial 2*		*Trial 3*		
Cities	Generations	Fitness	Generations	Fitness	Generations	Fitness	Avg.Fitness
E-20	6318	1329	6929	1378	4737	1375	1360.7
E-50	25988	2395	39611	2351	75876	2310	2352
E-100	132573	3908	174028	4208	209467	4450	4188.7

The results show that RBX is more consistent (less varied)in each trial. In comparison, PMX is less consistent (more varied).

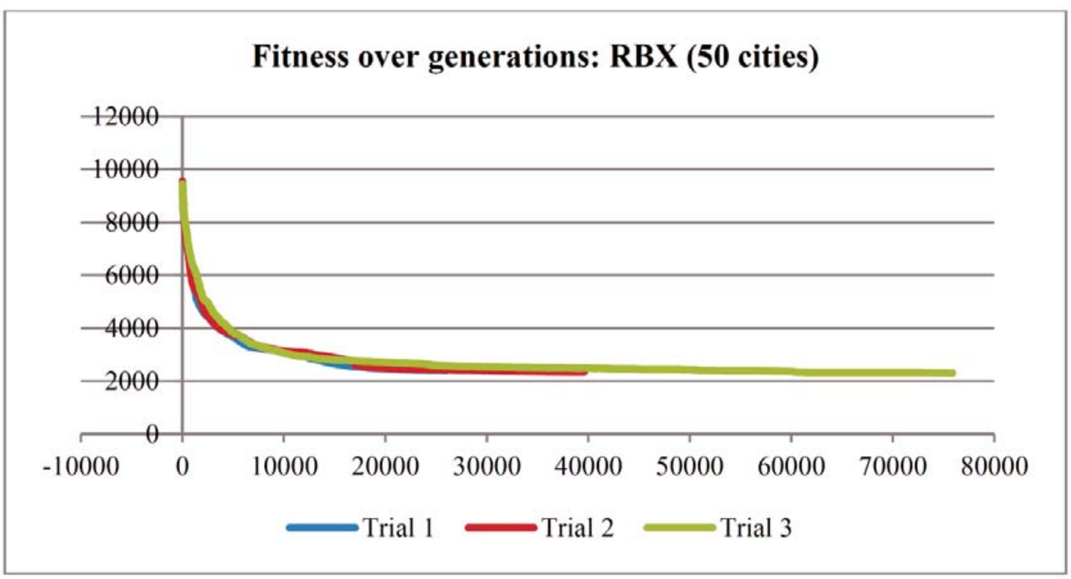

Figure 3: Performance of RBX over generations

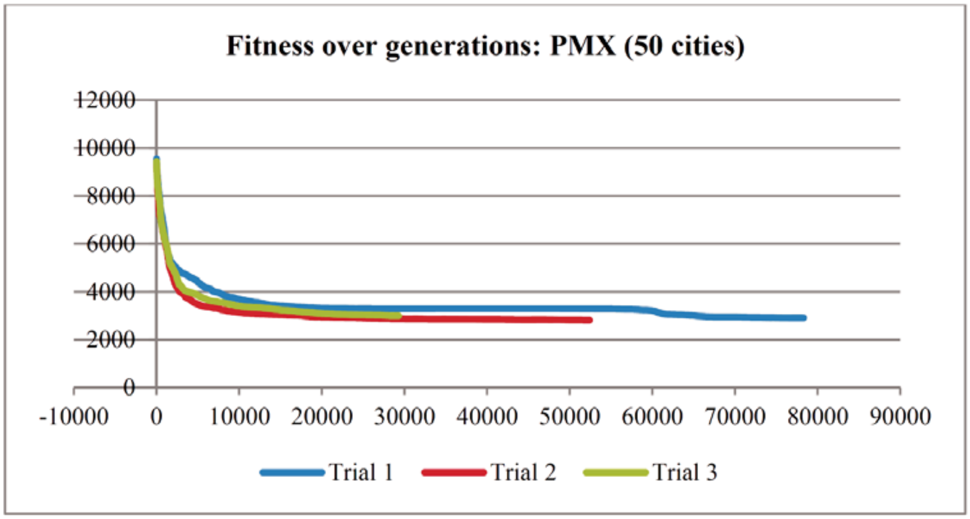

Figure 4: Performance of PMX over generations

Note: Fitness score is the total distance on the route. Lower the fitness score, better the route

As the number of cities increased, the accuracy of RBX also increased in comparison to PMX. In may be observed on the graph that in case of RBX, the curves of the three trials are very close in shape. The curves of PMX do not overlap as closely as RBX. This shows that preserving a trait, such as proximity of elements tend to provide more optimized results and better consistency. In order to achieve the most optimized results, both PMX and RBX took a varied number of generations in the trials and hence did not provide any visible observation on the time taken to achieve the results. However, a large number of simulations with different city counts may provide some insight into the time each method takes to achieve the results. It is a matter of further studies to see which trait should be preserved in order to provide better results in the shortest time.

5. CONCLUSION

RBX has shown better results and better consistency with each trial when compared to PMX. This behaviour is attributed to the fact that both the offspring always inherit one group / flock of data from a parent. A good GA algorithm should not just find the optimum result but should also do it in fewer generations. This can be done only if a crossover can carry 'good' traits from parent to offspring. The crossover algorithm (RBX) described in this paper discusses about how a trait can be transferred, but does not discuss if that is the best trait in the parent. Future scope includes defining a good trait in fit parents and transferring preferred traits by extending RBX.

REFERENCES

[1] David Beasley et. al., An Overview of Genetic Algorithms : Part 1, Fundamentals , University computing. Volume 15 (2), 58-69, 1993.

[2] David B. Fogel, Evolutionary computation: toward a new philosophy of machine intelligence, IEEE Press, Piscataway, NJ, 1995

[3] John D.C. Little et. Al.,An algorithm for the travelling salesman problem, Intelligent Automation & Soft Computing, Volume 8- Issue 3, 2002

[4] Mustafa B. AKBULUT, A. Egemen YILMAZ, A modified genetic algorithm for the generalized assignment problems,Journal Of Electrical & Electronics Engineering, Volume 9,Number 2, (951-958),: 2009

[5] NitashaSoni, Dr .Tapas Kumar, Study of Various Crossover Operators in Genetic Algorithms, International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 7235-7238

[6] Zakir H. Ahmed ,Genetic Algorithm for the Traveling Salesman Problem using Sequential Constructive Crossover Operator, International Journal of Biometrics & Bioinformatics (IJBB) Volume (3): Issue (6), 96-105, 2010