Approximating solutions to the vehicle routing problem using wisdom of artificial crowds with genetic algorithms

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*Abstract*—This paper presents a novel approach to solving the vehicle routing problem, a generalization of the Traveling Salesman Problem, using Wisdom of Artificial Crowds with genetic algorithms as well as a novel approach to injecting cognitive diversity into an artificial crowd of genetic algorithms. The algorithm presented in this paper was implemented in Python and tested on several datasets producing approximations superior to any of the genetic algorithms in the crowd at the cost of post processing overhead.

*Index Terms*—Shortest path problem, Genetic algorithms, NP-hard, Routing

# INTRODUCTION

The Vehicle Routing Problem (VRP) is a generalization of the well-known Traveling Salesman Problem (TSP). VRP has been a topic of scientific publication since it was first introduced by George Dantzig and John Ramser in 1954 [1] and studied longer in its special TSP case with record of mathematicians Thomas Kirkman and W. R. Hamilton’s work as far back as the 1800s.

The context of the problem is that there is one depot with one or more vehicles that must deliver goods to one or more customers with preference to minimizing the cost of travel. This contrasts with TSP which only has one vehicle per depot. The problem is considered a non-deterministic polynomial-time hard problem due to its factorial complexity. Advancements in VRP have been of interest to many research domains including scheduling, controls, and more [2] and proven to be valuable for vital industries such as agriculture [3].

# Prior Work

## Genetic Algorithms

Genetic Algorithms (GA) were first introduced by John Holland in 1962 based on principles from biology, theoretical genetics, automata theory, and artificial adaptive systems [4]. They have been proven to be valuable tools for approximating solutions to problems subject to high time complexity when solved by formal methods with research applications in publication since 1967 [5].

Booker, et al. describes the “central loop” of genetic algorithms as the following steps:

### Determine fitness of population. Select pairs from the population according to fitness with preference to choosing pairs with more preferred fitness values.

### Apply genetic operators to the pairs, creating offspring.

### Replace weakest classifiers with offspring.

Studies to determine preferred genetic operators for TSP have been performed following this central loop method [6]. Abdoun, et al. uses a sequence of genetic operators, first applying a crossover method to produce the offspring and then applying a mutation method to a percentage of the remaining population. Their work presents eight different crossover methods found in a literature review with their performance achieved when attempting to approximate solutions for TSP using the Reverse Sequence Mutation (RSM) mutation operator.

## Wisdom of Artificial Crowds

“Wisdom of Crowds” (WOC) was first coined by James Surowiecki in 2004 where he argues, “Under the right circumstances, groups are remarkably intelligent, and are often smarter than the smartest people in them. Groups do not need to be dominated by exceptionally intelligent people in order to be smart. Even if most of the people within a group are not especially well-informed or rational, it can still reach a collectively wise decision” [7]. He continues to describe five criteria required for a crowd to be wise:

### Cognitive Diversity – individuals should not share information

### Independence – individual’s opinions are not influence by other individual’s opinions

### Decentralization – individuals can specialize

### Aggregation – there exists an aggregation method for combining individual’s opinions.

### Trust – individuals trust the group to be fair.

This concept of WOC has been applied to a variety of problems including TSP with promising results. Researchers at University of California, Irvine and the University of Adelaide observed the average performance of their aggregation method out performing even the best individual when applying WOC to the results of individuals’ attempts at producing optimal paths for TSPs [8].

“Wisdom of Artificial Crowds” (WoAC) is a metaheuristic algorithm inspired by the nature-based behavior utilized in WOC [9]. WoAC is implemented as a post processing algorithm that takes a collection of individual solutions as an input to produce an aggregate solution that is often superior than any individual solution in the population. This concept has been shown to successfully approximate optimal solutions to TSP when using a crowd of genetic algorithms [10]. Cognitive diversity was achieved with different initializations of the genetic algorithm’s population.

# Proposed Approach

## Genetic Algorithm

The genetic algorithm implemented follows the central loop described by Booker, et al. closely [5]. The algorithm is initialized with a given population size, crossover method, crossover probability, mutation method, mutation probability, and epoch threshold. The population size denotes the number of chromosomes in the GAs population. The crossover probability denotes the percentage of the population to be replaced by crossover at the start of a generation. A crossover probability of 1 would mean offspring will replace all parents while a crossover probability of 0 would mean that no parents would crossover to produce offspring. The mutation probability denotes what percent of the population after crossover will undergo mutation. A mutation probability of 1 would mean all chromosomes in the population are mutated while a mutation probability of 0 would mean none of the chromosomes in the population are mutated. Epoch threshold denotes how many generations the GA must produce without seeing an improvement before finishing.

The crossover methods implemented were inspired by Otman and Abouchabaka’s work on comparing adaptive crossover operators for GAs aimed at approximating solutions to TSP [6]. The mutation methods implemented were inspired by similar work from Abdoun, et al. where they analyzed the performance of mutation operators for similar purposes [11].

*Roulette Wheel Selection*

The selection method implemented was influenced by the work of Zhong, et al. The roulette wheel selection methods aims to reduce the likelihood all chromosomes will converge to a single local optimum solution. To accomplish this, it calculates the probability of selection for each chromosome by dividing its fitness value by the sum of all fitness values of the chromosomes in the population. This differs from a straightforward elitist selection method that selects a percentage of the best performing chromosomes.

*Uniform Crossover*

The Uniform Crossover produces a child by alternating randomly between the alleles of the two parents.

*Ordered Crossover (OX)*

The Ordered Crossover method implemented comes from a book by Goldberg, in which he argues using OX is useful for problems that are ordered based [12]. The implementation used in this paper was slightly altered to produce only one child. OX is performed by randomly partitioning two parent chromosomes into three contiguous sections.

Table . The partition of a parent

|  |  |  |
| --- | --- | --- |
| S1 | S2 | S3 |

The child inherits sections S1 and S3 from parent 1 while S2 is determined from the left-over alleles in parent 2 while retaining order.

*Partially Mapped Crossover (PMX)*

The Partially Mapped Crossover method implemented was first described in a 1985 book from Goldberg and Lingle in which the parents are partitioned randomly into three sections as shown in Table 1. Sequences S1 and S3 from parent 1 are copied into the child. S2 is determined from parent 2’s alleles by starting at S2 and skipping over any allele that is already present in the child.

*TWORS Mutation*

The TWORS Mutation method randomly swaps two alleles in a chromosome.

*Reverse Sequence Mutation (RSM)*

The Reverse Sequence Mutation method randomly partitions the chromosome into three sections as shown in Table 1. The Sequence S2 is reversed while S1 and S3 remain constant.

*Fitness Function*

The fitness function is a greedy implementation in which the customers are evenly divided between the depot’s vehicles. Table 2 below shows an example of how a series of 11 vertices with one depot and 4 vehicles would divide it’s customers while evaluating its fitness. In this example, the depot is at vertex 9, while all other vertices 1-8 and 10-11 are customers. The fitness function is then calculated by iterating over the vehicles, adding the distance between the depot and the first customer, summing the distance between each adjacent customer in the vehicles list, and then adding the distance from the last customer back to the depot.

Table 2. Vehicle Customer Allocation

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Vehicle 1 | | | Vehicle 2 | | Vehicle 3 | | Vehicle 4 | |
| 5 | 3 | 2 | 8 | 6 | 4 | 1 | 10 | 11 |

## Wisdom of Artificial Crowds

The Wisdom of Artificial Crowds algorithm implemented is similar to that used by Yampolskiy, et al. although a novel approach was used for injecting cognitive diversity. In contrast to injecting cognitive diversity through a series of initializations of the same genetic algorithm, multiple GAs with differing crossover methods and mutation methods were used. Each GA has the same population size, selection method, and epoch threshold.

Gathering the chromosomes to be used in the crowd is done by using predetermined weights for each GA. For example, a GA with a weight of 0.05 and a population of 100 chromosomes would provide 5 chromosomes to the crowd before solution aggregation. These weights were selected after developing an understanding of a GA with these methods’ performance when approximating TSP. The weights used for different crossover and mutation combinations of GA during experimentation are summarized in Table 3 below.

Table . Weights of GAs with Crossover and Mutation Method Combinations

|  |  |  |
| --- | --- | --- |
| Crossover Method | Mutation Method | Weight |
| Uniform | TWORS | 0.05 |
| Uniform | RSM | 0.05 |
| OX | TWORS | 0.4 |
| OX | RSM | 0.2 |
| PMX | TWORS | 0.05 |
| PMX | RSM | 0.05 |

# Experimental Results

## Data

## Results

# Conclusions

# Acknowledgements

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