Vehicle Routing Problem Using Wisdom of Crowds with Genetic Algorithms (November 2020)

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Abstract— **This research paper provides a novel approach to solving the problem of vehicle routing, a generalization of the problem of traveling salesman, the use of genetic algorithms for wisdom of artificial. In python, the algorithm described in this paper was implemented and evaluated on multiple datasets, generating approximations superior to any single genetic algorithm in the crowd.**

Index Terms—**Genetic Algorithm, NP-Problem, Wisdom of Crowds**

I. INTRODUCTION

The vehicle routing problem (VRP) is one of the most studied problems of combinatorial optimization and deals with the optimal design of routes to be used by a vehicle fleet to serve a range of customers [1]. It first appeared in a paper published in 1959 by George Dantzig and John Ramser in which the first algorithmic methods were written and applied to supplies of fuel [2]. The background is also that of supplying goods to consumers who have placed orders for those goods located at a central depot. The VRP's aim is to minimize the cost of the total path. In 1964, using an effective greedy method called the savings algorithm, Clarke and Wright built on Dantzig and Ramser's approach [3]. VRP advance have been of interest to many areas of study, including scheduling, controls, and more, and have proved to be important for key industries such as agriculture, earth science, and transport.

The issue of VRP consists of designing low-cost distribution routes, subject to a variety of side constrains, across a collection of geographically dispersed customers [5]. This topic has a central role in the management of distribution and is faced by tens of thousands of carriers worldwide on a daily basis. Wing to the variety of constrains faced in practice, the issue occurs in many ways. The VRP has drawn the attention of a significant portion of the operational research community for over 50 years. This is partly due to the economic significance of the problem, but also to the methodological difficulties it presents. For example, for thousands and even tens of thousands of vertices, the traveling salesman problem (TSP), which is a special case of VRP, can now be solved [4]. The VRP, by comparison, is much harder to solve. In the relatively simply case, for example, where there are only power constraints, it is still difficult to solve instances with one or two hundred clients using precise algorithms. Most of the research effort in recent years shas shifted to the production of potent metaheuristics.

II. PRIOR WORK

Prior to the attempt of trying to solve vehicle routing, they were multiple project that were established to help with the solution of the vehicle routing. With the implementation of genetic algorithm and wisdom of crowds.

A. Genetic Algorithm

John Holland first introduced Genetic Algorithm (GA) in 1962, based on concepts of biology, theoretical genetics, automatic theory, and artificial adaptive systems [6]. Since 1967, when resolved by formal methods with research implementations in publication, they have been proved to be useful instruments for approximation solutions to problems subject to high time complexity. Basically, by recombining components from the parent classifiers, a genetic algorithm selects high intensity classifiers as "parents" creating "offspring." When their requirement is met, the offspring displace poor classifiers in the system and enter into competition, being enabled and evaluated [7]. Thus, a genetic algorithm mimics the genetic processes underlying evolution crudely, albeit at high speed.

While genetic algorithms behave subtly, the "central loop," the basic execution cycle, is very simple:

1. *Assessing population fitness. In compliance with fitness and selection requirements, pick pairs from the population.*
2. *Add the pairs to genetic operators, producing offspring.*
3. *With offspring, substitute the weakest classifiers*

Genetic algorithms work on string structures, such as biological structures, which using a randomized but organized exchanged of information, evolve in time according to the survival law of the fittest. Thus, a new set of strings is formed in every generation, using sections of the old set's fittest members [8]. The following are the key features of the genetic algorithm:

1. *The genetic algorithm, not the parameters themselves, works by coding the parameter set.*
2. *From a population of points, not a single location, the genetic algorithm initiates its search.*
3. *The genetic algorithm, not derivatives, uses payoff data.*
4. *Probabilistic transformation rules are used by the genetic algorithm, not deterministic ones.*

Without knowledge of the problems themselves or the search space, genetic algorithms are able to solve extremely complex problems, but these components are required in order for a genetic algorithm to function correctly[18].

1. *A genetic representation of possible solutions to the problem*
2. *A way of creating an initial population of possible solutions.*
3. *An assessment function that plays an environment role, rating solutions in terms of their health.*
4. *Genetic operators that modify children's structure*
5. *Values for different parameters used by the genetic algorithm (population size, probabilities of genetic operators being applied)*

B. Wisdom of Crowds

In the Wisdom of Crowds book by James Surowiecki, it stated that the plain but powerful reality that is at the core of this book was what Francis Galton stumbled across that day in Plymouth: "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. [9]" He goes on to describe the four conditions that characterize wise crowds:

1. *Diversity of opinion*
   i. Each person should have some private data, even if it's just an eccentric interpretation of the facts of knowledge.
2. *Decentralization*
   ii. People are able to specialize in local knowledge and to rely on it.
3. *Independence*
   iii. The beliefs of people are not dictated by the views of those around them.
4. *Aggregation*
   iv. There is a certain method to turn private decisions into a collective decision.

This WoC definition has been applied to a number of issues with positive outcomes, including the TSP. researcher at the University of Adelaide and University of California, Irvine observes these solutions. The method's suggested solution paths are generated solely on the basis of the combined city links chosen by individuals and are independent of spatial knowledge about city locations. Despite the minimal information available, the aggregation method chosen paths perform at a level that is among the best individuals on individual issues and exceeds the best individual's performance when averaged over all issues [11].

Wisdom of Artificial Crowds is implemented as a post-processing algorithm that takes as an input a series of individual solutions to create an aggregate solution that is often superior to any individual population solution. When using a multitude of genetic algorithm, this notion has been shown to successfully approximate optimal solutions to TSP [10]. Wisdom of artificial crowds is a metaheuristic algorithm inspired by the wisdom of crowd's nature-based actions [12].

III. PROPOSED APPROACH

Using the Genetic Algorithm and the wisdom of Crowds to define above to get the appropriate results for the Vehicle Routing Problems.

A. Genetic Algorithm

With a given population size, crossover process, crossover likelihood, mutation method, mutation probability, and period threshold, the algorithm is initialized. the population size denotes the number of chromosomes in the Genetic algorithm's population. The likelihood of crossover denotes the percentage of the population that will be replaced at the beginning of a generation by crossover. A crossover probability of 1 would mean that both parents would be replaced by offspring, while a crossover probability of 0 would mean that no parents would cross over to produce offspring. The probability of mutation denotes what percent of the population will undergo mutation after the crossover. A mutation probability of 1 would mean that all of the population's chromosomes are mutated, while a mutation probability of 0 would mean that none of the population's chromosomes are mutated. The threshold of the Mutation denotes how many generations the GA must create before finishing without seeing an improvement.

Fitness Function

The fitness function is a greedy execution in which the customers are split between the vehicles of the depot equally. 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 chart, and then adding the distance from the last customer back to the depot, the fitness function will be determined

There are multiple ways of implementing crossover methods to a given program.

One-point Crossover

By selecting a common crossover point in (copies of) the parent programs and then swapping the corresponding subtrees like regular crossover, one-point crossover works. If the parents were always the same size and shape, this operation could be carried out by selectin any connection as the crossover point in a single stage [13].
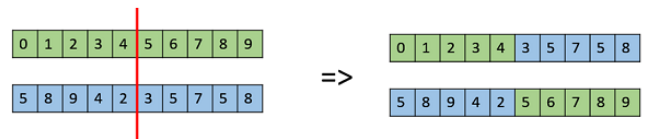
Two-point Crossover

This is a specific case of a N-point Crossover technique. With will select two crossover points, copy the binary string from the beginning of the chromosome to the first crossover point from one parent, copy the section from the first to the second crossover point from the second parent, and copy the rest from the first parent [14].
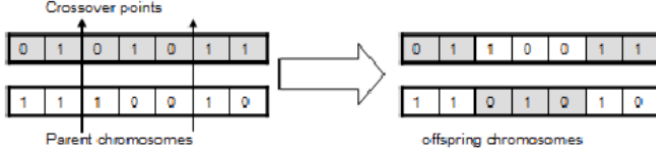
Uniform crossover

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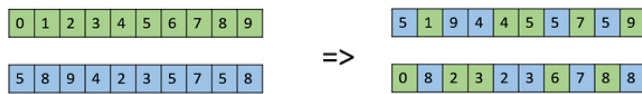
Ordered Crossover

The ordered Crossover method was the form of crossover implement for this genetic algorithm program. Ordered Crossover method implemented comes from a book by Goldberg, in which he argues using ordered crossover is useful for problem that are ordered based [16]. For this paper, a subset is randomly selected from the first parent string and then fill the remainder of the route with the genes from the second parent in the order in which they appear without duplicating any genes in the selected subset form the first parent [15].

Swap Mutation

The swap mutation was the mutation method perform for this genetic algorithm. The threshold of the mutation denotes how many generations that Genetic Algorithm must create before finishing without seeing an improvement [15].
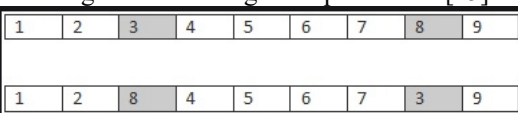
Uniform Mutation

A mutation operator that replaces the value of the gene selected with a uniform random value selected for that gene between the upper and lower bounds for that gene. This mutation operator can only be used for integer and double genes [19].

B. Wisdom of Crowds

The algorithm implemented by the Wisdom of Crowds was inspired by the implementation from Dr. Yampolskiy [10]. Running the Genetic algorithm for over 5 times to obtain sufficient day. While running it's important to retrieve the best data or solution for every run that is done with the genetic algorithm program. The selection of the chromosomes to be used in the crowd is accomplished by using predetermined weight for each GA. For example, before solution aggregation, a GA with a weight of 0.01 and a population of 100 chromosomes will provide the crowd with 1 chromosome. Next is to obtain the aggregate result of all the runs into a single solution. Using the aggregate matrix function to accomplish getting a single solution for the Wisdom of Crowds.

C. Vehicle Routing

To attempt the solution of VRP multiple steps were taken to pursue it. First the cities where partition into multiple subsets depending on the number of vehicles. Then the cost of each partition was computed. Then the partition with the minimum cost was selected. And last the cost for each subset was solve using Wisdom of Crowds from the TSP for each vehicle.

IV. EXPERIMENTAL RESULTS

A. Data

Using a software called Concorde, the data for the test were generated [17]. Concorde is an ANSI C program that produces optimal solutions to TSP graphs. The picture below shows the data generate for this test. With either predefined coordinates or random distribution, it also has the ability to create new TSP instances of any scale.

```
NAME: concorde11
TYPE: TSP
COMMENT: Generated by CCutil_writetsplib
COMMENT: Write called for by Concorde GUI
DIMENSION: 11
EDGE_WEIGHT_TYPE: EUC_2D
NODE_COORD_SECTION
1 87.951292 2.658162
2 33.466597 66.682943
3 91.778314 53.807184
4 20.526749 47.633290
5 9.006012 81.185339
6 20.032350 2.761925
7 77.181310 31.922361
8 41.059603 32.578509
9 18.692587 97.015290
10 51.658681 33.808405
11 44.563128 47.541734
```
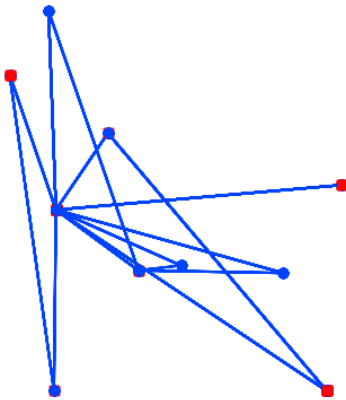
B. Results

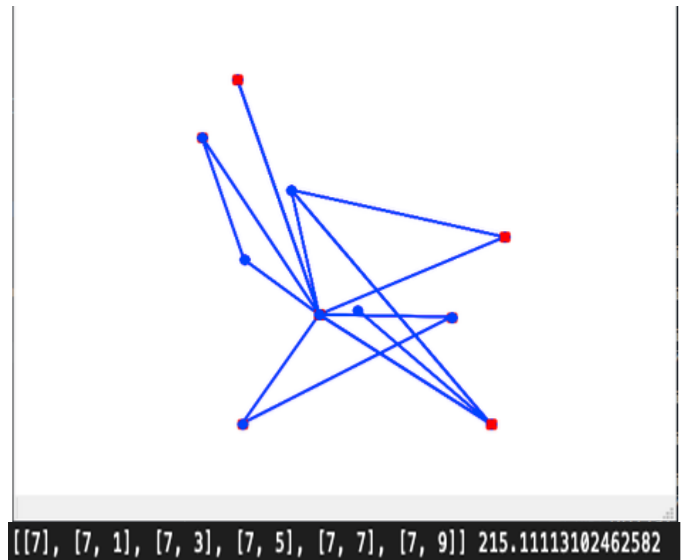*WoC Results: 3 vehicle, 1 depot, 11 Customers, with the depo being point 1 from the data*
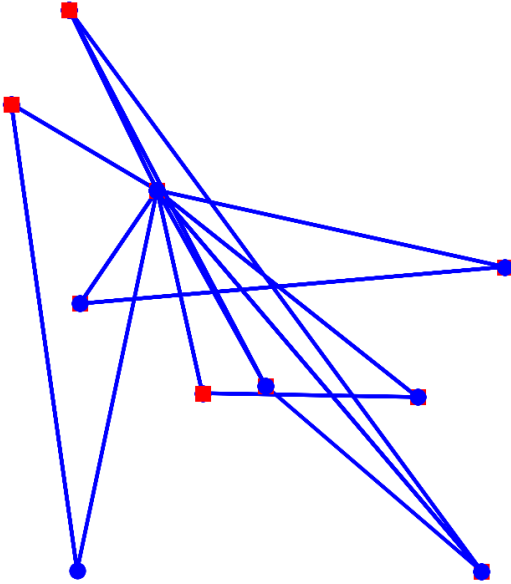
[[1, 0], [1, 2], [1, 4], [1, 6], [1, 8, 9]] 598.7453935202266

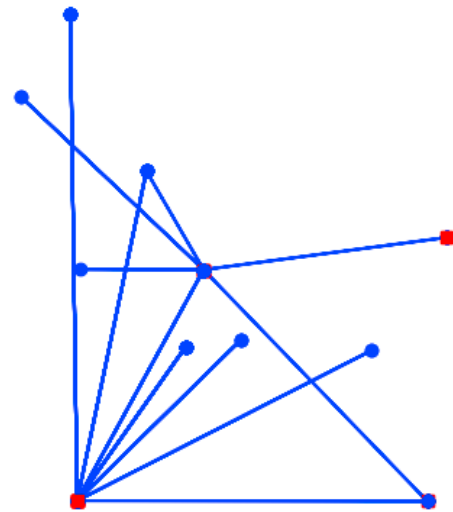*WoC Results: 3 vehicle, 1 depot, 11 Customers, with the depo being point 3 from the data*

[[3, 0], [3, 2], [3, 4], [3, 6, 8, 7], [3]] 588.628225300729

WoC Results: 3 vehicle, 1 depot, 11 Customers, with the depo being point 7 from the data

[[7], [7, 1], [7, 3], [7, 5], [7, 7], [7, 9]] 215.11113102462582

GA Results: 5 vehicle, 1 depot, 11 Customers, with the depo being point 10 from the data

[10, [10, 0], [10, 1], [10, 2], [10, 4, 3], [7, 8, 1, 10, 9, 6, 0, 5]] 660.9265683566716

V. CONCLUSIONS

The program was able to use wisdom of crowds and genetic algorithm to attempt to solve Vehicle Routing problem. The edges resulting from the program is the reason for the result show above is not a great result. Depending on the amount of vehicles the result will fluctuate tremendously. With only having one specific depot, that was the most successful output received. Bus as the number of vehicles increase the result became worst for the file. In theory, with having more vehicles the algorithm is supposed to perform better, but the program didn't accomplish that.

Compared with classical methods such as the brute force method or the regular Traveling Salesman method for approximating VRP solutions, to understand how the

algorithm presented here compares. In order to isolate the advantages and costs associated with algorithm, these algorithms need to be implemented and run on the same datasets as Vehicle Routing Problem.

In addition, as this algorithm's WoC portion can be used as a post processing technique, separate from the Genetic Algorithms mentioned in this paper, further work needs to be done on WoC computational costs alone. If it is shown to have low overhead, this approach could be used in distributed systems where it could then be processed at another point to improve their collective approximation by parallelizing less optimal approximations using Genetic Algorithms. If the computational cost could be spread out asynchronously on several devices, this could be shown to be superior over classical methods.

Our vehicle routing overview has highlighted the rapid emergence of vehicles routing as a functional tool and the interplay between principle and practice that has outcomes [20]. Transforming the vehicles routing system the problem, as a condensed operation from its original form as a simplistic operations research model to a complex model that represents the many complicated constraints that occur in practice. The very sudden surge of commercial interest in computerized routing is bound to continue to affect the market especially as the number of effective installations increases, system prices decline, and distributors become more aware of the availability and benefits of such systems. The role played by industry in shaping research directions for vehicle routing in the academic community should not be minimized.

REFERENCES

[1] B. L. Golden, S. Raghavan, and E. A. Wasil, *The vehicle routing problem: latest advances and new challenges*. New York: Springer, 2011.

[2] G. B. Dantzig and J. H. Ramser, "The Truck Dispatching Problem," *Management Science*, vol. 6, no. 1, pp. 80–91, 1959.

[3] "Vehicle routing problem," *Wikipedia*, 28-Oct-2020. [Online]. Available: https://en.wikipedia.org/wiki/Vehicle_routing_problem. [Accessed: 08-Nov-2020].

[4] G. Laporte, P. Toth, and D. Vigo, "Vehicle routing: historical perspective and recent contributions," *EURO Journal on Transportation and Logistics*, vol. 2, no. 1-2, pp. 1–4, 2013.

[5] C.-S. Liu, G. Kou, and F.-H. Huang, "Vehicle Coordinated Strategy for Vehicle Routing Problem with Fuzzy Demands," *Mathematical Problems in Engineering*, vol. 2016, pp. 1–10, 2016.

[6] J. H. Holland, "Outline for a Logical Theory of Adaptive Systems," *Journal of the ACM (JACM)*, vol. 9, no. 3, pp. 297-314, July 1962, doi: https://doi.org/10.1145/321127.321128.

[7] L. B. Booker, D. E. Goldberg, and J. H. Holland, "Classifier systems and genetic algorithms," *Artificial Intelligence*, vol. 40, no. 1-3, pp. 235-282, September 1989, doi: https://doi.org/10.1016/0004-3702(89)90050-7

[8] C. Papanicolaou and I. Papantoniou, "Optimum design of textile-reinforced concrete as integrated formwork in slabs," *Textile Fibre Composites in Civil Engineering*, pp. 245–274, 2016.

[9] J. Surowiecki, *The Wisdom of Crowds: Why the Many are Smarter Than the Few and how Collective Wisdom Shapes Business, Economies, Societies, and Nations*. Doubleday, 2004.

[10] R. V. Yampolskiy and A. EL-Barkouky, "Wisdom of artifical crowds algorithm for solving NP-hard problems," *International Journal of Bio-Inspired Computation*, vol. 3, no. 6, pp. 358-369, Jan 2011, doi: 10.1504/IJBIC.2011.043624.

[11] S. K. M. Yi, M. Steyvers, and M. D. Lee, "Wisdom of the crowds in traveling salesman problems," 2010. [Online]. Available: http://www.socsci.uci.edu/~mdlee/YiEtAl2010.pdf.

[12] L. H. Ashby and R. V. Yampolskiy, "Genetic algorithm and Wisdom of Artificial Crowds algorithm applied to Light up," presented at the 16th International Conference on Computer Games, Louisville, KY, USA, 27-30 July, 2011.

[13] R. Poli and W. B. Langdon, "Genetic Programming with One-Point Crossover," *Soft Computing in Engineering Design and Manufacturing*, pp. 180–189, 1998. doi: https://doi.org/10.1007/978-1-4471-0427-8_20

[14] "Crossover and mutation - Introduction to Genetic Algorithms - Tutorial with Interactive Java Applets", *Obitko.com*, 2020. [Online]. Available: https://www.obitko.com/tutorials/genetic-algorithms/crossover-mutation.php. [Accessed: 11- Nov- 2020].

[15] E. Stoltz, "- The Traveling Salesman: A genetic algorithm for a computationally demanding problem," *Explorations in Computing*, pp. 396–433, 2014.

[16] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, 1 ed. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 1989, p. 372.

[17] "Concorde Home", Math.uwaterloo.ca, 2020. [Online]. Available: http//www.math.uwaterloo.ca/tsp/concorde/index.html. [Accessed: 17-Nov-2020].

[18] A. Shrestha and A. Mahmood, "Improving Genetic Algorithm with Fine-Tuned Crossover and Scaled Architecture," *Journal of Mathematics*, 05-Apr-2016. [Online]. Available: https://www.hindawi.com/journals/jmath/2016/4015845/. [Accessed: 17-Nov-2020].

[19] psil123Check out this Author's contributed articles., psil123, and Check out this Author's contributed articles., "Mutation Algorithms for Real-Valued Parameters (GA)," *GeeksforGeeks*, 04-Sep-2018. [Online]. Available: https://www.geeksforgeeks.org/mutation-algorithms-for-real-valued-parameters-ga/. [Accessed: 17-Nov-2020].

[20] Golden, Bruce L., and Arjang A. Assad. "Perspectives on Vehicle Routing: Exciting New Developments." Operations Research, vol. 34, no. 5, 1986, pp. 803–810. JSTOR, www.jstor.org/stable/170738. Accessed 21 Nov. 2020.