Assessment 1.2: Genetic Algorithm Based Unmanned Vehicle Route Optimisation Problem in Emergency Situation

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Abstract

Natural disasters are unpredictable, and getting supplies to dangerous terrain is challenging. Unmanned Aerial Vehicles with optimum routes can be utilised to simplify delivery tasks. This study uses Genetic Algorithm to optimise the vehicle route while taking the UAVs' capacity and time window into account. Although not the first attempt to optimise Vehicle Route with time window constraints, an attempt is made to examine the effects of three distinct time window constraint on population diversity. Strict Time Window limitations, Allowance of Early Arrivals with Penalty, and Allowance of Early and Late Arrivals with Penalty are the three strategies used to adapt time window limitations. Additionally, this study intends to examine which Crossover approaches can offer a more beneficial solution to the Vehicle Routing Problem (VRP). Strict Time Window constraints and Cyclic Crossover produced better results compared to other methods.

1. Introduction

Unmanned Aerial Vehicle (UAV), expanded to non-military applications in the twenty-first century with the advancement in technologies and reduction of cost. Disaster management is one of the main applications of UAV. The catastrophe sites are frequently situated in hazardous terrain with dangerously congested traffic. Rescue workers cannot get to these places within the stipulated time. Li and Hu (2021) evaluated UAV's utilization in emergency situations in China. Supply of blood and other medical essentials to rugged environment is challenging, and UAVs can replace traditional transportation due to their adaptability and operational safety.

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In real life, the deployment of UAVs to their intended areas is much more complicated than the classic Travelling Salesman Problem, which includes many sub-problems like scheduling UAVs, maintaining capacity, and reducing the number of UAVs to cut costs (Wen et al., 2016). Real-world circumstances involve a variety of time restrictions, and it is crucial to identify the best answer possible.

The focus of the report is to optimise Vehicle Routing Problem with Time Window Constraints (VRPTW). A common route optimisation method used in city logistics is VRPTW. City logistics focuses on real-world logistical issues, where late deliveries are permitted with a cost (Qureshi et al., 2010). Using a single vehicle to carry items from a depot to clients is the focus of the classic Vehicle Routing Problem (VRP). In real life, the VRP had to take into account a number of additional issues. Capacitated VRP restricts the vehicle capacity, Time dependent VRP concentrates on the time window restrictions, and so forth (Wen et al., 2016). The primary objective of this study is to reduce the overall route distance along with the required number of UAVs while adhering to their capacity limits and time windows.

Genetic Algorithm (GA) is the metaheuristic technique applied in the study. The three time window handling strategies employed in this study are Strict Time Window Constraint (STWC), Allowance of Early Arrivals with Penalty (EWP), and Allowance of Early and Late Arrivals with Penalty (EAWP). Additionally, because crossover is a crucial part of GA, three different crossover strategies—Partially Mapped Crossover (PMX), Ordered Crossover (OX), and Cyclic Crossover (CX)—are used to examine VRPTW.

Berger and Barkaoui (2004) optimised the total distance to 1427.13 and vehicle count to 11. The study was able to surpass this with a far superior vehicle count of 7, but the total distance did not match the benchmark. The total distances attained in the comparable literature did not match the results achieved. This is due to the study's shortcomings acknowledged in the section 7.

Real world scenarios like changing customer demands, unexpected delays, and working hours are not considered in this study. Battery capacity of the UAVS which limits its flight time and range is not taken into account. Airspace regulations and weather conditions that may affect the flight path and performance of the UAVs are also not considered. The usage of dataset with 100 nodes limits the capacity to assess GA on significant and real-world problems.

The report is organised as follows. Section 2 gives a background to the general domain of VRPTW. Section 3 specifically details the problem VRPTW considered in this report. Next, section 4 discusses the optimisation methods used in this work. Section 5 discusses the experimental setup, presents the results in section 6, and discusses their implications in section 7. Finally, section 8 concludes this report and gives some future work recommendations.

2. Background: Problem Domain

A fleet of vehicles that travel exactly once to each of a group of customers that are spaced out geographically make up the VRP (Bai et al., 2015). VRPTW is an extension of VRP with the addition of visited point time windows (Yong Wang, 2014).

VRPTW is a NP-hard problem and no polynomial algorithm is available till today to solve this type of problems. Metaheuristics algorithms such as Artificial Bee Colony (Alzaqebah et al., 2016) , Simulated Annealing (Zhong & Pan, 2007), Tabu Search (Bräysy & Gendreau, 2002), Genetic Algorithm (Alba & Dorronsoro, 2006), and Ant Colony Optimization (Shi & Weise, 2013) had been proposed for solving VRPTW. Taniguchi and Heijden (2000) used GA for the evaluation of city logistics. VRPTW-Probabilistic model was calibrated using GA to solve truck scheduling and vehicle routing in the South Osaka area (Ando & Taniguchi, 2006). A hybrid GA method was employed by Chunyu and Xiaobo (2010) to optimise the multi depot VRPTW. In the absence of travel time data, GA was employed to solve multi-objective problem of VRPTW (Heng et al., 2016). The problem of Banyuwangi's tourist routes had been tackled using GA (Anggodo et al., 2017). GA provides better solutions for VRP problems compared to other meta-heuristic approaches (Tan et al., 2001; Thangiah, 1999; Thangiah et al., 1994). Based on the research, GA can optimise VRPTW and achieve the aforementioned goals.

VRPTW with Hard Time Windows was optimised as a multi-objective task (Ombuki et al., 2006). Column generation method was used to optimise VRPTW with STWC (Feillet et al., 2004). Qureshi et al. (2010) and Ibaraki et al. (2008) employed GA to optimise VRP with penalties for early and late arrivals. In contrast to other time window restrictions, VRP with STWC that permit waiting without incurring any penalties is anticipated to have a simple cost.

The main goal of the GA research field is to find the optimal set of parameters. The crossover operator is one potential variable that needs to be examined. In the comparison of crossover operators in GA for VRP, modified CX followed by PMX outperformed OX (Wibisono et al., 2021). In solving VRPTW, CX provided significantly greater fitness than other operators (Bae et al., 2007). Rachid et al. (2010) concludes the order from best to worst of crossover for CVRP as PMX, OX, and Uniform Crossover (UX). OX, followed by PMX, was shown to be the most effective operator by Karakatic and Podgorelec (2015). To tackle VRP in the logistics industry, Agardi et al. (2021) chose 2-opt, CX, PMX, and OX crossover operators in GA. The 2-opt and Partially Matched Crossover operators were efficient than other operators. A modified CX was proposed for Travelling Salesman Problem to reduce the total distance (Hussain et al., 2017).

The objectives of this study are

- minimize the total distance travelled by the UAVs without violating time window and capacity constraints.
- minimize the total number of UAVs.
- examine the impact of time window restrictions on route cost.
- analyse the impact of various crossover methods on route cost.

Based on the reviews of the literature, a GA model was implemented with various Crossover operators to optimise VRP under three different time frame restrictions.

3. Problem Instance (VRPTW with Solomon BenchMark)

Nanry and Barnes (2000), Qureshi et al. (2010), Figliozzi (2012), Wang et al. (2014), and Heng et al. (2016) used Solomon Benchmark Dataset (Solomon, 1987) to validate various optimisation techniques on VRP. Set RC101 with a combination of randomly placed and clustered customers, narrow time windows, and small vehicle capacity was used to validate the optimisation techniques. The dataset can be used to optimise 25 vehicles each with carrying capacity 200, to serve 100 customers. The link to the dataset is given in the section A.

Table 1 shows an overview of the dataset.

The objective function is adapted from the works by Qureshi (2010), Wen et al. (2016), and Ombuki et al. (2006). The complete UAV routing problem is as follows

$$Max((1/D) * (1/K)) \tag{1}$$

Table 1. Overview of Solomon Benchmark Data set (Number of vehicles : 25 , Capacity of each vehicle :200).

Customer Number	XCOORD.	YCOORD.	Demand	Ready Time	Due Date	Service Time
0	40	50	0	0	240	0
1	25	85	20	145	175	10
2	22	75	30	50	80	10

where K = Number of UAVs used and D is the total route distance.

$$D = \sum_{k \in K} \sum_{i,j \in A} (c_{ijk} + p_{ijk}) x_{ijk} \tag{2}$$

$$x_{ijk} = \begin{cases} 1, & \text{if UAV } k \text{ flies from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases}$$

p_{ijk} = penalty incurred and is equivalent to cost of a single return route from station to the node at which constraint got violated.

The constraints placed on the fitness function are as follows:

$$\sum_{k \in K} x_{ijk} = 1, \forall i \in C \tag{3}$$

$$\sum_{i \in C} d_i \sum_{j \in N} x_{ijk} \leq q, \forall k \in K \tag{4}$$

$$\sum_{j \in V} x_{0jk} = 1, \forall k \in K \tag{5}$$

$$\sum_{i \in V} x_{ihk} - \sum_{j \in V} x_{hjk} = 0, \forall h \in C, \forall k \in K \tag{6}$$

$$\sum_{i \in V} x_{i0k} = 1, \forall k \in K \tag{7}$$

$$\sum_{k=1}^{m} x_{0jk} \leq K, \forall j \tag{8}$$

$$s_{ik} + t_{ij} - s_{jk} \leq (1 - x_{ijk})M, \forall (i,j) \in A, \forall k \in K \tag{9}$$

$$a_i \leq s_{ik} \leq b_i, \forall i \in V, \forall k \in K \tag{10}$$

V = Depot Node 0 and Customer set C = {1,2,...n}

A = all feasible paths (i,j), i,j $\in V$

c_{ij} = cost (i,j) $\in A$

t_{ij} = time (i,j) $\in A$

t_{ij} = service time + travel time

Total number of vehicles = K

Demand of node i = d_i

Vehicle Capacity = q

s_{ik} = the time the UAV k starts to serve the location i.

Time Window of node i = [a_i, b_i]

Objective function Equation (1) is used to minimize the total distance travelled by UAVs and the total UAV count. Equation(2) is used to find the total route distance. The constraints considered for this problem are given below.

1. Constraint (3) states that each customer must be visited exactly once by one UAV.
2. Constraint (4) states that UAV capacity should not be exceeded.
3. Constraints (5,6,7) ensure that all UAVs start and end at central station
4. Constraint (8) ensures that the number of UAVs will not exceed K
5. Constraints (9) and (10) states that UAV must arrive at each location within the designated time window.

A multi-objective VRPTW was transformed into a single objective optimization problem. The vehicle number may be favoured in these unified score solutions. It is because the overall route is minimised in regard to the minimised vehicle count (Ombuki et al., 2006).

4. Methodology

As mentioned in section 2, GA was chosen to optimise the problem. Initially, GA was used to determine the kind of time window constraint that provides the optimum solution. The VRPTW, which offered higher fitness, was later subjected to three distinct Crossover techniques.

4.1. Chromosome Design and Initial Population

Each candidate solution consists of a collection of nodes visited and have a predetermined length of 100.

The sum of the distances between each chromosomal node will represent the overall distance travelled. A sample 11 gene chromosome from genome is given below

Chromosome = {42, 26, 100, 6, 80, 16, 81, 46, 24, 29, 91}

Each gene in the specified chromosome stands for a Customer Number. Adhering to the UAV capacity and time limit constraints, the UAV travels from the start node through each node before returning to the start node.

To produce the initial population, no particular algorithm was used. Initial population is generated by random permutation of N customer nodes.

4.2. Time Window Constraints Handling

As mentioned in section 3, three approaches chosen for handling the time window restrictions are given below.

1. **Strict Time Window Constraint**
   Each UAV must conform to the node's time frame. Any solution that fails to stick to the time window will receive a low fitness value (Ombuki et al., 2006).

2. **Allowance of Early Arrivals with Penalty**
   UAVs are permitted but subjected to penalties if they arrive early. The penalty incurred is the distance between the station and the node. If the UAVs are late, the fitness score will receive a significant low rating (Qureshi et al., 2010).

3. **Allowance of Early and Late Arrivals with Penalty**
   UAVs are allowed to arrive both early and late. If the UAV arrives outside of the node's specified time window, a penalty of distance from station to node will be charged (Ibaraki et al., 2008).

4.3. Crossover Techniques

The primary factor in determining how well a GA is implemented into VRP is Crossover (SG & Panneerselvam, 2017).

As per the study of Syswerda (1989), Ursani et al. (2011) (2011), SG and Panneerselvam (2017), and Karakatic and Podgorelec (2015), three crossover operators are selected for the research.

1. **Genetic Algorithm with Partially Mapped Crossover**
   A randomly chosen gene sequence is exchanged between two chromosomes.

2. **Genetic Algorithm with Cyclic Crossover**
   An offspring will receive a gene from one parent, but it should take the position of the other parent.

3. **Genetic Algorithm with Ordered Crossover**
   A portion of the first parent's chromosome is replicated into the offspring's. The remaining values are arranged in the offspring in the same order as they are in the second parent.

Algorithm 1 shows the logic used to handle VRPTW.

Algorithm 1 Vehicle Routing Problem With Capacity and Time Window Constraints

```
Input: Solomon Benchmark Dataset, size 101 * 7
Initialize vehicle_count = 0 , vehicle_load = 0, distance = 0.
for i = 1 to route_length do
  if vehicle_count <= 25 then
    Send a vehicle from start to node to next node
    increment the distance
    if vehicle_load >= vehicle capacity then
      vehicle_count = vehicle_count + 1
    end if
    if arrival time fails time constraints then
      distance = distance + penalty
    end if
  end if
end for
```

5. Experiments

As mentioned in section 2, this research aims to study about the effects of time window constraints handling on VRP as well as the effects of Crossover techniques on VRP.

The parameters for GA remains the same for time window constraints handling. The fitness function is modified to handle the penalty for each time window constraint as mentioned in section 4. The time window constraint with best fitness will be used for further study. The GA parameters used for three time window constraints handling and three crossover methods are given in the Table 2.

Along with the parameters in the Table 2, the parameters mentioned in Table 3 were also used for the evaluation of different crossover methods.

The dataset used is described in section 4. The fitness value of the solutions will be listed to determine the time window constraint for VRP. To find the best VRPTW solution, the fitness values, total route distance, and number of UAVs obtained using various Crossover approaches will be provided. These statistics will be sufficient to answer the questions given in section 2.

Table 2. Configuration parameters for GA to handle three time window constraints and Crossovers (Zaharie, 2009).

Parameter	Values
Type	Permutation
Iterations	30
Maximum Generations	20
Population Size	50
Crossover Rate	0.9
Mutation	0.1
Lower	1 (lowest number of node)
Upper	101 (maximum number of nodes)
Fitness	$1/D * 1/K$ D = Route distance, K = Vehicles count

Table 3. GA Configuration parameters to study the effect of different Crossovers (Ombuki et al., 2006; Qureshi et al., 2010).

Parameter	Values
Operator Probabilities	Crossover : 0.80 mutation : 0.1
Operator Probabilities	Crossover : 0.98 mutation : 0.10

6. Results

6.1. Time Constraints Handling

Table 4 shows the best fitness value obtained for each time window constraint handling method. STWC showed better fitness than other time constraint handling methods. Compared to the other two approaches, the overall distance obtained in VRP with Strict Time Window Constraints is significantly better. The minimum number of vehicles obtained as the result is 7.

6.2. Crossover Methods to Optimize VRPTW

As mentioned in section 4, different Crossover techniques were used on VRP with STWC. Hyperparameter tuning was done using the parameters listed in Table 3 in addition to those mentioned in Table 2. In comparison to other values, the crossover and mutation probability of 0.9 and 0.1, respectively, offered better fitness. Table 5 shows the best fitness, distance and number of vehicles obtained for each method. CX crossover on VRP with STWC gives the better fitness and best route compared to other methods. The best vehicle count remains the same for all methods.

The fitness scores of VRPTW with STWC using three crossover methods are plotted in the Figure 6.2, with each plot depicting the mean result from 30 runs. The error bars signify 95% confidence limit for each point.

There is overlap between the error bars for each method. The p-value returned from Welch Two Sample t-test validated that the means of each group are not statistically significantly different (Azad & Ryan, 2014).

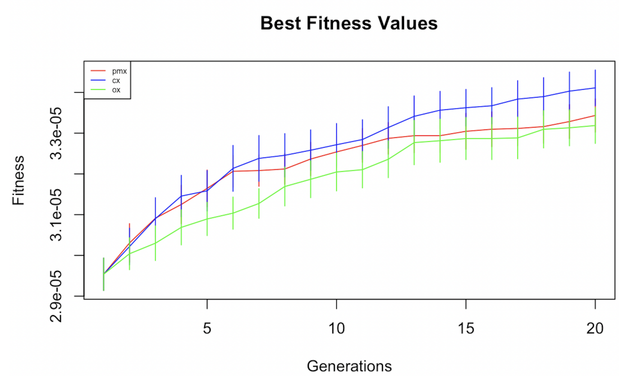

Figure 1. Best fitness of Crossover methods on VRP. CX provides better fitness.

7. Discussion

Investigating how different time window handling strategies effects VRP is one of the objectives of this study. From Table 4, it is clear that STWC gives better fitness, route distance, and vehicle count than other two methods. This is similar with the supposition presented in the section 3. Qureshi et al. (2010) mention that STWC gives the best cost because it permits waiting without any penalties. In comparison to other time constraints, STWC provided a significantly better route distance of 3906.695. Here, the solutions are shot off if they do not adhere to the severe time window restrictions. Due to the rigorous restriction on late delivery, it is not always feasible to stick to precise time

Table 4. Best Fitness, Best Distance, and Best Vehicle Count obtained for each time window constraint handling method using the parameters in Table 2.

Crossover	Best Fitness	Best Distance	Best Vehicle Count
STWC	3.656726e-05	3906.695	7
EALWP	2.913369e-05	4903.503	7
EWP	2.657606e-05	5336.113	8

Table 5. Best Fitness, Best Distance, and Best Vehicle Count obtained for three Crossovers using the parameters in Table 2.

Crossover	Best Fitness	Best Distance	Best Vehicle Count
CX	3.667696e-05	3895.011	7
PMX	3.601692e-05	3966.39	7
OX	3.656726e-05	3906.695	7

restrictions, but the simple cost of waiting without being penalised makes STWC appealing.

It is evident from Table 5 that CX provides a superior fitness score with a route distance of 3895.011. In each of the three scenarios, the optimal vehicle count stays the same. In Figure 1, as the generation grows, OX and PMX appear to have undergone premature convergence. In the early generations, PMX and CX appeared to converge, but as the generation size grew, CX outpaced PMX. In this study, CX offered greater fitness when solving VRPTW under stringent time limit restrictions. This is in contrast to the findings of Rachid et al. (2010), Agardi et al. (2021), and Karakatic and Podgorelec (2015) but comparable to those of Wibisono et al. (2021). Comparing PMX to other operators, it had the lowest fitness score, which is consistent with Ombuki et al. (2006) conclusions that PMX is unsuitable for VRP under strict time frame restrictions.

When using the Cyclic Crossover operator, the tours of the parents are split into segments, and the appropriate segments are then switched between the two parents to produce new offspring. By swapping, it is made sure that the children's tours follow their parents' schedule for delivery visits in terms of timing and order. As a result, it is more probable that the Cyclic Crossover operator's offspring will adhere to the problem's severe time window requirements.

PMX randomly selects two crossover points and then swaps the segments between these points from one parent to the other parent. This mapping may produce offspring tours that violate the strict time window constraints.

As mentioned in section 3, the vehicle number got favoured in this single optimisation problem. This is because the vehicle count is minimised first, and then the total route distance is minimised with respect to the vehicle count.

The methods used in this investigation produced total distances that were greater than those reported in the literature. Solomon dataset's RC101 set's top known result is 1352.88 (Heng et al., 2016). This is a consequence of the study's limitations. It is anticipated that applying a GA model with a population size of 1000 and generation as 250 times the number of nodes will yield better outcomes than what this study has achieved (Qureshi et al., 2010). Due to high computing expenses, generation and population growth rates were kept to a minimum. Additionally, GA was used with a population that was produced randomly. Time window restrictions weren't taken into account when constructing the original population.

8. Conclusions and Future Work

The purpose of this study was to analyse the impact of time window constraints and different crossovers on VRP. The results showed that VRP adhering to Strict Time Windows created shorter routes. But the real world application of this constraint is questionable. Allowing Early and Late arrivals gave the next better solution, which is acceptable in real world scenarios. Cyclic Crossover operator optimised the route better with high fitness score compared to other crossover operators.

To improve this research, real world datasets can be used. Research can further be improved with high generation and population sizes to analyse the impact of population sizes on VRPTW. A hybrid GA, a GA model combined with other methods, may provide better results (Berger & Barkaoui, 2004).

References

Agardi, A., Kovacs, L., and Banyai, T. An attraction map framework of a complex multi-echelon vehicle routing problem with random walk analysis. *Applied Sciences*, 11 (5), 2021. ISSN 2076-3417. doi: 10.3390/app11052100. URL `https://www.mdpi.com/2076-3417/11/5/2100`.

Alba, E. and Dorronsoro, B. Computing nine new best-so-far solutions for capacitated vrp with a cellular genetic algorithm. *Information Processing Letters*, 98(6):225–230, 2006. ISSN 0020-0190. doi: https://doi.org/10.1016/j.ipl.2006.02.006. URL https://www.sciencedirect.com/science/article/pii/S0020019006000548.

Alzaqebah, M., Abdullah, S., and Jawarneh, S. Modified artificial bee colony for the vehicle routing problems with time windows. *SpringerPlus*, 5(1298), 2016. doi: 10.1186/s40064-016-2940-8. URL https://springerplus.springeropen.com/articles/10.1186/s40064-016-2940-8.

Ando, N. and Taniguchi, E. Travel Time Reliability in Vehicle Routing and Scheduling with Time Windows. *Networks and Spatial Economics*, 6:293–311, 2006. URL https://link.springer.com/article/10.1007/s11067-006-9285-8#citeas.

Andres Figliozzi, M. The time dependent vehicle routing problem with time windows: Benchmark problems, an efficient solution algorithm, and solution characteristics. *Transportation Research Part E: Logistics and Transportation Review*, 48(3):616–636, 2012. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2011.11.006. URL https://www.sciencedirect.com/science/article/pii/S1366554511001426.

Anggodo, Y., Ariyani, A., Ardi, M., and Mahmudy, W. Optimization of multi-trip vehicle routing problem with time windows using genetic algorithm. *Journal of Environmental Engineering and Sustainable Technology*, 3(2):92–97, 2017. ISSN 2356-3117. doi: 10.21776/ub.jeest.2017.003.02.4. URL https://jeest.ub.ac.id/index.php/jeest/article/view/75.

Azad, R. M. A. and Ryan, C. A Simple Approach to Lifetime Learning in Genetic Programming based Symbolic Regression. *Evolutionary Computation*, 22(2):287–317, Summer 2014. ISSN 1063-6560. doi: doi:10.1162/EVCO_a_00111. URL http://www.mitpressjournals.org/doi/abs/10.1162/EVCO_a_00111.

Bae, S.-T., Hwang, H. S., Cho, G.-S., and Goan, M.-J. Integrated ga-vrp solver for multi-depot system. *Computers Industrial Engineering*, 53(2):233–240, 2007. ISSN 0360-8352. doi: https://doi.org/10.1016/j.cie.2007.06.014. URL https://www.sciencedirect.com/science/article/pii/S0360835207001040. Selected Papers from The 27th. International Conference on Computers Industrial Engineering - Part 2.

Bai, Y., Zhou, X., Zhang, Y., and Yang, M. Study of multi-vehicle routing problem with time window. In *12th International Symposium on Operations Research and its Applications in Engineering, Technology and Management (ISORA 2015)*, pp. 1–8, 2015. doi: 10.1049/cp.2015.0604.

Berger, J. and Barkaoui, M. A parallel hybrid genetic algorithm for the vehicle routing problem with time windows. *Computers Operations Research*, 31(12):2037–2053, 2004. ISSN 0305-0548. doi: https://doi.org/10.1016/S0305-0548(03)00163-1. URL https://www.sciencedirect.com/science/article/pii/S0305054803001631.

Bräysy, O. and Gendreau, M. Tabu Search Heuristics for the Vehicle Routing Problem with Time Windows. *ResearchGate*, 2002. doi: 10.1007/BF02579017. URL https://www.researchgate.net/profile/Olli-Braeysy-2/publication/24065418_Tabu_Search_heuristics_for_the_Vehicle_Routing_Problem_with_Time_Windows/links/00b4951a396067a0d8000000/Tabu-Search-heuristics-for-the-Vehicle-\Routing-Problem-with-Time-Windows.pdf.

Chunyu, R. and Xiaobo, W. Research on multi-vehicle and multi-depot vehicle routing problem with time windows for electronic commerce. In *2010 International Conference on Artificial Intelligence and Computational Intelligence*, volume 1, pp. 552–555, 2010. doi: 10.1109/AICI.2010.121.

Feillet, D., Dejax, P., Gendreau, M., and Gueguen, C. An Exact Algorithm for the Elementary Shortest Path Problem with Resource Constraints: Application to Some Vehicle Routing Problems. *Networks*, 44(3):216–229, 2004. URL https://onlinelibrary-wiley-com.bcu.idm.oclc.org/doi/epdf/10.1002/net.20033.

Haj-Rachid, M., andP. Chatonnay, W. R.-C., and Bloch, C. A study of performance on crossover and mutation operators for vehicle routing problem. 2010. URL https://d1wqtxts1xzle7.cloudfront.net/51161671/A_study_of_performance_on_crossover_and_20170103-12515-1oaa1e0-libre.pdf?1483440494=&response-content-disposition=inline%3B+filename%3DA_study_of_performance_on_crossover_and.pdf&Expires=1679313861&Signature=P6rXvM3pBfy9JssrQoPCzsG-30yjpHk0Dmu1wPC\VQeJE5Kdgiu4hI2I~v2cyIdOk~OLN5dsORPsiFbv\MQKlE0vJbMqxwpnE7dbsz676h~0y3SpSoWc0IGNx\9Wo-Ojol89W5mE3O6M2eVB6PRGyHo0CVB8~\Q5E6I9T--ztyPPpJyD0SQPOPmeh3FVWkeiFOVS\

gme8gNF8imVzgLJVqKZ6gDh-U-B6ZJzc7na~\I7PtJC-sB7-V2ssR0LUcFZ8uzv-XzVrCp5bAA5FD\~h1mGt5e0sbob38NE2YX3Uu3weqDG1Y~roWOu8r\gvLxJhwTFBINvv5mYXc~F0q\PIFeUdfW2ULw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA.

Heng, C. K., Nguyen, Q. C., Jiang, S., Tan, P. S., Gupta, A., Da, B., and Ong, Y. S. Application of route flexibility in data-starved vehicle routing problem with time windows. In *2016 IEEE Congress on Evolutionary Computation (CEC)*, pp. 799–805, 2016. doi: 10.1109/CEC.2016.7743873.

Hussain, A., Muhammad, Y. S., Sajid, M. N., Hussain, I., Shoukry, A. M., and Gani, S. Genetic Algorithm for Traveling Salesman Problem with Modified Cycle Crossover Operator. *Comput Intell Neurosci*, 2017. doi: doi:10.1155/2017/7430125. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5676484/#:~:text=The%20cycle%20crossover%20(CX)%20operator,1%203%206%204%207%20.

Ibaraki, T., Imahori, S., Nonobe, K., Sobue, K., Uno, T., and Yagiura, M. An iterated local search algorithm for the vehicle routing problem with convex time penalty functions. *Discrete Applied Mathematics*, 156(11):2050–2069, 2008. ISSN 0166-218X. doi: https://doi.org/10.1016/j.dam.2007.04.022. URL https://www.sciencedirect.com/science/article/pii/S0166218X07001357. In Memory of Leonid Khachiyan (1952 - 2005).

Karakatiƒç, S. and Podgorelec, V. A survey of genetic algorithms for solving multi depot vehicle routing problem. *Applied Soft Computing*, 27:519–532, 2015. ISSN 1568-4946. doi: https://doi.org/10.1016/j.asoc.2014.11.005. URL https://www.sciencedirect.com/science/article/pii/S1568494614005572.

Li, T. and Hu, H. Development of the Use of Unmanned Aerial Vehicles (UAVs) in Emergency Rescue in China. *Risk Management and Healthcare Policy*, 14:4293–4299, 2021. doi: 10.2147/RMHP.S323727. URL https://www.tandfonline.com/doi/abs/10.2147/RMHP.S323727.

Nanry, W. P. and Wesley Barnes, J. Solving the pickup and delivery problem with time windows using reactive tabu search. *Transportation Research Part B: Methodological*, 34(2):107–121, 2000. ISSN 0191-2615. doi: https://doi.org/10.1016/S0191-2615(99)00016-8. URL https://www.sciencedirect.com/science/article/pii/S0191261599000168.

Ombuki, B., J.Ross, B., and Hanshar, F. Multi-Objective Genetic Algorithms for Vehicle Routing Problem with Time Windows. *Applied Intelligence*, 24:17–30, 2006. doi: 10.1007/s10489-006-6926-z. URL https://link.springer.com/article/10.1007/s10489-006-6926-z.

Qureshi, A. G., Taniguchi, E., and Yamada, T. Exact solution for the vehicle routing problem with semi soft time windows and its application. *Procedia - Social and Behavioral Sciences*, 2(3):5931–5943, 2010. ISSN 1877-0428. doi: https://doi.org/10.1016/j.sbspro.2010.04.008. URL https://www.sciencedirect.com/science/article/pii/S187704281001061X. The Sixth International Conference on City Logistics.

SG, V. K. and Panneerselvam, D. R. A Study of Crossover Operators for Genetic Algorithms to Solve VRP and its Variants and New Sinusoidal Motion Crossover Operator. *International Journal of Computational Intelligence Research*, 13(7):1717–1733, 2017. ISSN 0973-1873. URL https://www.researchgate.net/profile/Ramasamy-Panneerselvam-2/publication/318317770_A_Study_of_Crossover_Operators_for_Genetic_Algorithms_to_Solve_VRP_and_its_Variants_and_New_Sinusoidal_Motion_Crossover_Operator/links/5963582fa6fdccc9b154ba10/A-Study-of-Crossover-Operators-for-\Genetic-Algorithms-to-Solve-VRP-and-its-\Variants-and-New-Sinusoidal-Motion-\Crossover-Operator.pdf.

Shi, W. and Weise, T. An initialized aco for the vrptw. In Yin, H., Tang, K., Gao, Y., Klawonn, F., Lee, M., Weise, T., Li, B., and Yao, X. (eds.), *Intelligent Data Engineering and Automated Learning – IDEAL 2013*, pp. 93–100, Berlin, Heidelberg, 2013. Springer Berlin Heidelberg. ISBN 978-3-642-41278-3.

Solomon, M. Algorithms for the vehicle routing and scheduling problem with time window constraints. *Operations Research*, 35:254–265, 1987. doi: http://dx.doi.org/10.1287/opre.35.2.254. URL https://pubsonline.informs.org/doi/10.1287/opre.35.2.266.

Syswerda, G. Uniform Crossover in Genetic Algorithm. 1989. URL https://www.researchgate.net/profile/Gilbert-Syswerda-3/publication/201976488_Uniform_Crossover_in_Genetic_Algorithms/links/5f84cf27299bf1b53e22ee7c/Uniform-Crossover-in-Genetic-Algorithms.pdf.

Tan, K., Lee, L., Zhu, Q., and Ou, K. Heuristic methods for vehicle routing problem with time windows. *Artificial Intelligence in Engineering*, 15(3):281–295, 2001. ISSN 0954-1810. doi: https://doi.org/10.1016/S0954-1810(01)00005-X. URL https://www.sciencedirect.com/science/article/pii/S095418100100005X.

Taniguchi, E. and Heijden, R. E. V. D. An evaluation methodology for city logistics. *Transport Reviews*, 20(1):65–90, 2000. doi: 10.1080/014416400295347. URL https://doi.org/10.1080/014416400295347.

Thangiah, S. R. A Hybrid Genetic Algorithm, Simulated Annealing and Tabu Search Heuristic for Vehicle Routing Problems with Time Windows. *CRC Press LLC*, 1999. URL http://ebrary.free.fr/Genetic%20Algorithms%20Handbook/The_Practical_Handbook_of_GA,_v3_Complex_Coding_Systems,1999/2539ch9.pdf.

Thangiah, S. R., Osman, I. H., and Sun, T. Hybrid Genetic Algorithm, Simulated Annealing and Tabu Search Methods for Vehicle Routing Problems with Time Windows. 1994. URL https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=792271ba3abbbc74134f21781348cb6079194ec2.

Ursani, Z., Essam, D., Cornforth, D., and Stocker, R. Localized genetic algorithm for vehicle routing problem with time windows. *Applied Soft Computing*, 11(8):5375–5390, 2011. ISSN 1568-4946. doi: https://doi.org/10.1016/j.asoc.2011.05.021. URL https://www.sciencedirect.com/science/article/pii/S1568494611001803.

Wen, T., Zhang, Z., and Wong, K. K. L. Multi-Objective Algorithm for Blood Supply via Unmanned Aerial Vehicles to the Wounded in an Emergency Situation. 14, 2016. doi: https://doi.org/10.1371/journal.pone.0155176. URL https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0155176.

Wibisono, E., Martin, I., and Prayogo, D. N. Comparison of crossover operators in genetic algorithm for vehicle routing problems. 2021. URL http://repository.ubaya.ac.id/40276/.

Yong Wang, Xiao-lei Ma, Y.-t. L. H.-y. Y. . Y. L. A two-stage heuristic method for vehicle routing problem with split deliveries and pickups. *Journal of Zhejiang University SCIENCE C volume*, 15:200–210, 2014. doi: 10.1631/jzus.C1300177. URL https://link.springer.com/article/10.1631/jzus.C1300177#citeas.

Zaharie, D. Influence of crossover on the behavior of differential evolution algorithms. *Applied Soft Computing*, 9(3):1126–1138, 2009. ISSN 1568-4946. doi: https://doi.org/10.1016/j.asoc.2009.02.012. URL https://www.sciencedirect.com/science/article/pii/S1568494609000325.

Zhong, Y. and Pan, X. A hybrid optimization solution to vrptw based on simulated annealing. In *2007 IEEE International Conference on Automation and Logistics*, pp. 3113–3117, 2007. doi: 10.1109/ICAL.2007.4339117.

A. Appendix

Link to the dataset is https://people.idsia.ch/~luca/macs-vrptw/problems/rc101.txt

Link to the source code files is https://github.com/meeramullamkuzhy/Modern-Optimisation