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The Solution to the Automotive Routing Problem Using Genetic Algorithm

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Abstract

This paper aims to identify automotive routing problems using genetic algorithms. It will also find an appropriate route for the automotive industry to serve customers. Road and distance are very important for a routing problem. Genetic algorithms will reduce the distance, minimize time, and save the drivers' working hours. It will play a crucial role in preventing accidents. The automotive routing problem has wide applications in logistics and transportation and is of growing economic importance. And reducing distance and time will surely contribute to the economy. There are a variety of heuristics and approach-based solutions accessible for specific conditions and various restrictions of the automotive routing problem, but precise solutions to the problem are not possible because of the high computation time requirement. Meta-heuristic algorithms, as well as genetic algorithms, are selected to solve the introduced problem.

Keywords: Vehicle Routing Problem (VRP), Genetic algorithm, Meta heuristic algorithm, Automotive routing problem.

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1.0 Introduction

Nowadays, the world is full of planning problems. Among them, automotive routing problems help find the right way to visit a place with less travel time and save working hours.

While visiting places, we normally meet this problem. It becomes more complex when other constraints, like weather, road conditions, a festival, etc., must be considered. Time is very important in our daily lives. The automotive routing problem is a combinatorial optimization problem that has been considered by many researchers. The aim of this paper is to find an appropriate way to reduce time and save working hours.

The first idea and announcement of the automotive or vehicle routing problem came from Dantzig and Ramser (1959) [1]. We need a heuristic algorithm (LANCOST) for the automotive routing problem introduced by Wen and Eglese [2] to solve the problem.

The main objective of the automotive routing problem is to find optimized routes with less travel time from origin to destination. It is crucial to find the least-cost routes such that every delivery location is met once by just one vehicle because the vehicle's start and end points are at the same origin. The aim is to allocate a fleet of vehicles to customer destinations to deliver goods with less distance travelled. Hence, the customer waiting time is reduced, which will boost confidence in the company.

2.0 Motivation of the Research

With a higher population and unplanned urbanization, traffic problems occur, and controlling traffic flow during peak hours becomes very difficult. It creates a greater contrast between the vehicles' moving speeds and influences the clients' time window. Thus, the automotive routing problem will optimize routes, reducing time and saving countries' working hours. Unplanned routes with no proper road design will lead vehicles into dense traffic, wasting time, and customers will be forced to wait longer for no reason. So, the paper explores how:

i. To minimize travel time.
ii. To save working hours.
iii. To contribute to the country's economy.

The research aims at developing and implementing a well-organized method using a genetic algorithm to solve real-life automotive routing problems.

3.0 Objective with Specific Aims

The major objectives of this research are:

iv. To find a solution to the Automotive routing problem using genetic algorithms.
v. To implement the proposed algorithm.
vi. To determine the result and compare it with some related works.

4.0 Organization of the Research

This research has a total of five sections. In the beginning section, an "Introduction" will discuss the research ideas, goals, and primary objectives. Section two briefly discusses the illustration of the automotive routing problem with some related works. Section three describes the actual methodology to solve the introduced problem. Section four describes the implementation, and Section five contains the research conclusion.

5.0 Genetic Algorithm (GA)

The genetic algorithm is built on the population's chromosomes' genetic structure and behaviour. A viable solutionis indicated by each chromosome. The population is just a chromosomal collection. Each person in the population hasa fitness-function that describes them. As a result, a higher level of fitness is the answer. The best individuals in thepopulation are chosen to reproduce the offspring of the next generation. Because of mutation, the offspring created will have characteristics of both parents. A mutation occurs when the structure of a gene changes.

Looking out for solutions often necessitates sophisticated mathematical formulas to deliver a definitive answer [3], [4].

To solve this, a heuristic method known as the geneticalgorithm was applied to calculate the results. A genetic algorithm is a search strategy based on the natural selection mechanism and genetics [5].

The search for an optimal solution in a genetic algorithm is carried out among several optimal points based on a probabilistic function [6].

6.0 Vehicle Routing Problem (VRP)

VRP is the challenge of constructing a shipping vehicle pathwith known capacity and operating from a single depot to fulfil a collection of clients with known locations and demand for one or more certain commodities [7].

VRP belongs to the Nondeterministic Polynomial-Hard (NPH) class, which indicates that the influencing parameters are extremely complicated and the solution cannot be solved by a linear algorithm simply because it takes too long, so it must rely on a heuristic technique to discover a solution [8]. VRP, like TSP, requires each vehicle to leave a depot with a defined path, meet demand nodes along the route, and then return to the original depot [9]. After solving two routes with the shortest total distance, below is a summary of the VRP utilizing two vehicles, one depot, and twelve nodes.

Each vehicle has a maximum operating time, which is the time it can spend on the road before returning to the depot[9].

7.0 The Automotive Routing Problem

The automotive routing problem is combinational management and a method for solving the issue that queries, "What isthe best set of routes for a range of vehicles to take to deliver to a provided group of consumers?". Solving automotive route problems helps to save time and reduce traffic.

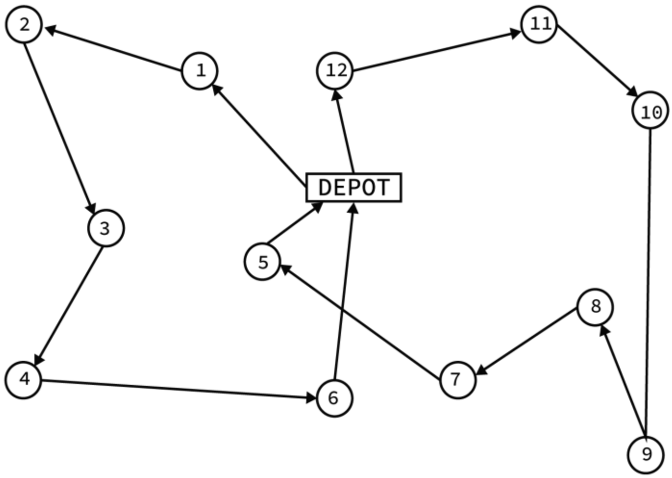


Fig. 1. Simple VRP with the number of vehicles 2.

8.0 Literature Review

8.1 Illustration of Automotive Routing Problem

Optimal route determination for a fleet of vehicles to perform a group of clients will be the main objective of automotive routing problems. The transportation starts from the central origin to reach destinations and returns to the starting point. The vehicle must be assigned the origin and destination point of its travel before its going starts. Beforethe starting of vehicles, the limitations will be satisfied, and only if done well the vehicles start travelling. The stratification of automotive routing comes with the type of restrictions such as the level of the vehicle, measurements of the route, andtime of in and out of a vehicle to a particular starting point.

The main purpose of the Automotive routing problem shall be to reduce travel time and save working hours from contributing to the economy. We need to work with large data scales in this problem, and metaheuristic algorithms can help us sort out large-scale problems efficiently.

8.2 Previous Study on Automotive Routing Problem

Automotive routing problems just not only work on travel distance, but it will work on the greenhouse effect in our environment. A new kind of problem called the multi-compartmentgreen vehicle routing problem (MCGVRP) is introduced [10]. An automotive routing problem aims to reduce customers' minimal total cost whenever it sends from the depot to the customer [11]. The Vehicle Routing problem has an extensionwith pickups and deliveries (VRPPD), where the vehicles are not only instructed to deliver goods to customers but also will pick some goods up from customer locations [12]. Solutionof the Automotive routing problem is an important step in the development of efficient solution methods that deal with thelarge range of vehicle routing problems [13].

8.3 Automotive routing problem variant

Generally, the Automotive Routing Problem is considered symmetric, where dij = dji. This means travel costs remainthe same whenever it travels from origin to destination and destination to origin.

But in real-life situations, the travel cost is seldom similarso the cost matrix will be asymmetric. This restriction needsto be considered by calculating geographic data using some sort of shortest-path algorithm.

Numerous constraints can be added to the Vehicle Routing Problem. Generally, real-life situations are constituted by theseconstraints.

Let us define a set C, which is a set of all constraints that should not be violated in the optimal solution; otherwise, that solution can not be called optimal.

8.4 Vehicle Routing Problem with Pickups and Deliveries (VRPPD)

We may consider the start point from a depot to solve the maximum vehicle routing problem. But in real life, conditions can inflict an added constraint on the Vehicle Routing Problem where goods need to be delivered from the depot to the customer's location and picked up from the customer's location to other customer's locations or brought back to the depot.

In [12], the authors described The Vehicle Routing problemas an extension with pickups and deliveries (VRPPD), where the vehicles are not only instructed to deliver goods to customers but also pick some goods up from customer locations. The presumption that goods may only be picked up after all deliveries have been completed is not made. More than that, the solution that takes heuristic routines from the Automotive Routing methodology and modifies it to trim infeasibilities so that pickups and deliveries can be combined is more suitable.

Vehicle Routing Problems with Pickups and Deliveries (VRPPD) can be classified into three main categories:

1) Delivery-first, pickup-second VRPPD
2) Concurrent pickups and deliveries VRPPD
3) Varied pickups and deliveries VRPPD

8.5 Multiple Depot Vehicle Routing Problem (MDVRP)

In multiple Vehicle Routing Problems, a depot is placed for the vehicles that could start delivery and return to the depot when the work is done. In the Multiple Depot Vehicle Routing Problem (MDVRP), multiple depots can be placed from where a vehicle could start its journey and where it could finish.

In the given diagram, there are five depots. Each colored route represents a route that is the central point of a depot.The authors defined a multi-depot extension of the Vehicle Routing Problem based on the idea of borderline customers used in [14].

In simple expression, marginal customers are those customers located approximately halfway between two depots.On the other hand, the customer a is considered a marginal customer if there is a parameter between 0.5 and 1 and b and c are the nearest and the second-nearest depots to customer a [15].

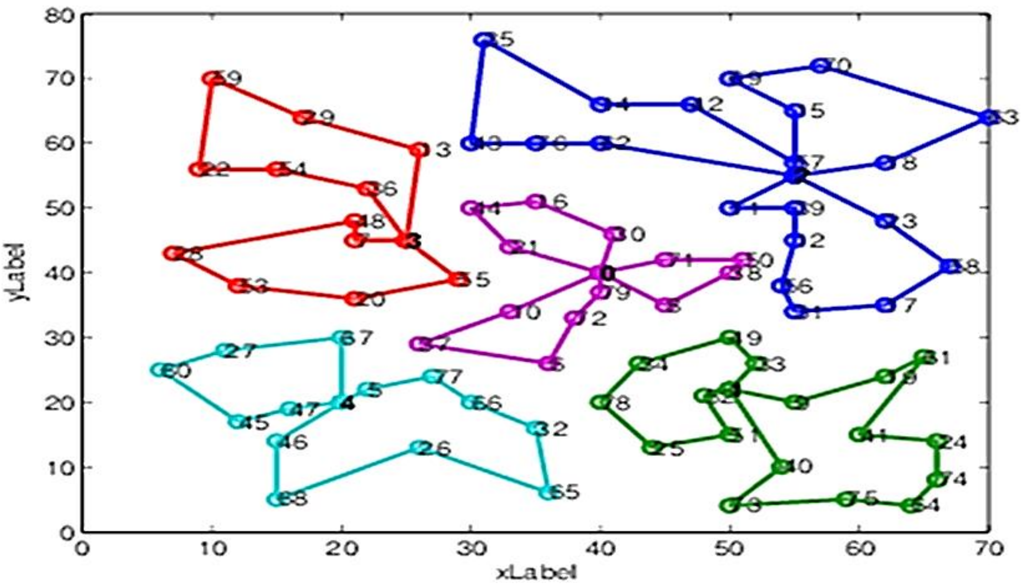


Fig. 2. Multiple Depot Vehicle Routing Problem.

8.6 Branch and Bound Cut

Branching and cutting is an optimization algorithm thatinvolves creating a tree-like structure to explore possible solutions and making cuts to eliminate suboptimal branches. It is used to solve mixed integer programming problems. On the other hand, a bound cut is a type of constraint that can be added to an optimization problem to tighten the bounds on thevariables. This can help improve the solution quality found bythe optimization algorithm. Therefore, while both techniques are used in optimization, they are not similar approaches. Branching and cutting is an algorithmic technique, while the bound cut is a type of constraint. This includes cutting edges for troubleshooting. The cut plane technique characterizes the target score as nearly as likely a plausible arrangement as possible, including direct discrepancies in the output called cuts. The cut plane method adds a linear inequality, calleda cutoff, to the problem to determine the smallest possibleset of target values. The whole program is divided into two different programs for solving. One is a simplex method, and the other is a similar linear method [16], [17]. The branching and bound process becomes a non-integer solution with linear programming as the upper bound and the integral solution as the lower bound [18], [19]. The node should be trimmed if thetop border is smaller than the bottom. An additional cutting plane must be triggered in linear programming solutions to optimize the solution.

8.7 Multi Route Based

Algorithms aim at providing an optimal solution by performing an edge sequencing of vertex transactions within or between vehicle routes. Multicourse change heuristics for the VRP considers every vehicle and works on every vehicle course gone up against a few courses at any given moment [20]. Thompson and Psaraftis suggested the technique thatdeals with the idea of cyclic exchanges that includes exchanging all the while k requests by considering the constraints across the route. Priority of the vehicles and the constraints across the route shall be prioritized, and decisions shall be made. By permitting k requests on each course, request exchanges can be performed among stages as different tocyclic changes of courses. Because of the intricacy of thecyclic exchange neighbourhood look. The 3-cycle 2 exchange manager is shown in the figure below. The multi-course heuristic for VRP looks at all vehicles and works with all vehicle directions that collide with multiple courses at any time[20]). Thompson and Psaraftis proposed a way to deal with theidea of a cyclic k-exchange, which involves the exchange of all k requests according to path constraints. Vehicle priorities androute restrictions must take precedence, and decisions mustbe made along the route. We can exchange requests between steps by allowing k requests for each rate instead of periodic rate changes. Take a look around because of the complexity of circular exchanges. The periodic exchange manager is shown in the figure below.

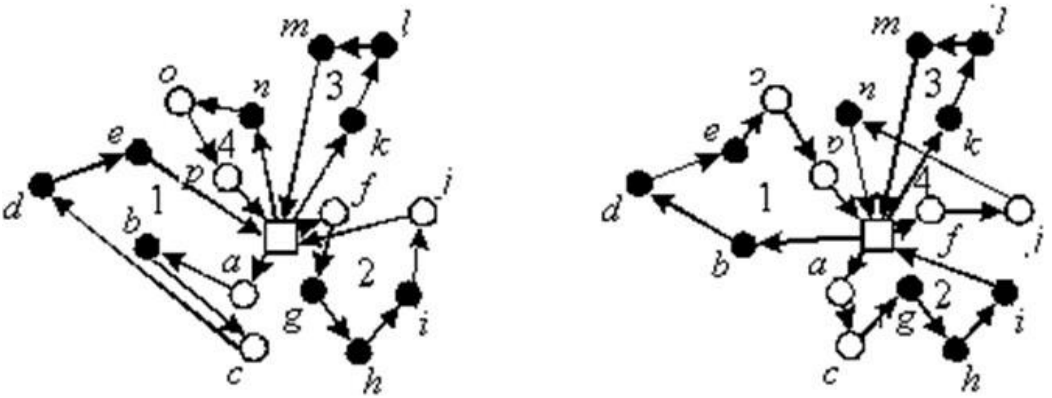


Fig. 3. Multi Route Based Vehicle Routing Problem.

The essence of the idea is the continuous movement of customers, indicated by white circles, in a circular manner within a path from figs. Clients a and c on path 1, f and j on path 2, and o and p on path 4 are sent simultaneously to paths 2, 4, and 1, respectively, and path 3 is unaffected. Similarly, a company may have many warehouses along a vehicle's route and should choose the shortest warehouse to reduce the distance. In this case, it behaves like an independent VRP because goods and services must be distributed quickly. However, if the garage and customer location are combined without considering the distance travelled, the problem must be considered for a large-scale VRP. [21] However, if customers and warehouses are mixed, MDVRP needs to be addressed. Therefore, the goal is to maximize the delivery of goods along a route while reducing distance and travel time [22]. A commonly used build heuristic for solving VRPs is:

a. Storage algorithm;
b. Saving algorithm;
c. Route-first cluster-second;
d. Cluster first path second;
e. Insertion heuristic;

8.9 Savings Algorithm

In [18], the savings algorithm was first proposed as a constructive heuristic for the Vehicle Routing Problem by Clark and Wright to be applied to the Vehicle Routing

Problemvariants in which the number of vehicles is a decision variable.In [23], the authors demonstrated that as constructive heuristics, the savings algorithm starts with the initial solution whereall nodes are visited by separate routes from the depot. Then,algorithms search and merge two routes by maximizing thedistance cost. If two routes are merged, then the route remains feasible.

8.10 Route-First Cluster-Second (RFCS)

The vehicle routing problem can be defined as designing routes for vehicles of known capacity operating from a single warehouse to serve a group of customers with specific demands that provide capacity constraints. In [24], the author described a basic Route First Cluster Two (RFCS) problem by enclosing all customers in a warehouse and forming a ”giant trip” back to the warehouse (i.e., the travelling salesperson problem). Building an optimal solution starts with an initial path through all nodes. The route starts from the garage and is divided into several routine tasks with wide vehicles. This is the opposite of the Cluster First Route Second (CFRS) method described below.

8.11 Cluster-First Route-Second (CFRS)

In [25], to define Cluster first route second (CFRS) constructive heuristics for Vehicle Routing Problem, the authors described VRP as a problem that can be solved by partitioninga set of service points or customers into a collection of routes such that each route starts and terminates at a depot.

Cluster first route second (CFRS) clusters the service pointsinto routes and then finds a good routing for each cluster suchthat path cost is optimized for each cluster. The clusters are created by solving generalized assignment problems (GAP). Intuitively, the CFRS approach should provide better-quality solutions, but the increased complexity of the necessary programming has been a barrier to practical research in the past. So, Cluster First Route Second (CFRS) builds sets of customers; then, it proceeds to find the optimal routes for each set. There are some variants of this problem, and they are described below.

8.12 The Sweep Algorithm

In [26], the Sweep algorithm was first proposed by Gillet and Miller (1974) as a variant of the cluster first route second (CFRS) constructive heuristic that can only be applied to planar vehicle routing problems. It is best known for its simplicity. This algorithm circles the warehouse by inserting new nodes into the path. At each step, the polar angle graduallyincreases. If an insert is possible, a node is inserted at the end of the root, and if no insert is found, a new root is started. Then, each path is optimized.

8.13 Taillard Algorithm

In 1993, Eric Taillard [27] defined an algorithm that is a variant of the Cluster First route second (CFRS) constructive heuristic that can only be applied to flat vehicle routing problems with added efficient features not found in Gillet and Miller [26]. This method divides the main problem into smallersubproblems, reoptimizes the path using Volgenant and Jonkeroptimization techniques, and does not apply to non-Euclidean problems as it is coordinate-based.

8.14 The Meta-Heuristic Algorithm

The meta-heuristic algorithm is an iterative search strategy for scouring the search space for superior solutions [28]. Itis a higher-level process or heuristic used to identify a good solution to an optimization issue, especially when partial or faulty information or computer capability is restricted.

The metaheuristic vehicle routing method was developed with Jsprit. The basis of this method is that it creates an initial solution with minimal constraints and discards the complete initial solution if it is not optimal compared to the reference solution. So, the original solution is solved, which strictly sets the standard mark for future search iterations. Therefore, the resulting original solution is divided into smaller parts and analyzed to find the optimal solution [29]. A solution formed early should be very effective in setting benchmarks. A very important aspect of this method is that it can solve large-scale problems by breaking down and analyzing the entire original solution generated. Best for LSVRP. The initialsolution created will depend on the constraints considered in its formation.

8.15 Simulated Annealing

The basis simulated annealing algorithm is a consequenceof a solid annealing process. The solid is first heated toa sufficiently high temperature and allowed to cool slowly.Because the particles in the solid state become disorderedwith the temperature when they are heated, then the internalenergy increases, but after the slow cooling, the particles gradually become an orderly state, in which each temperature is maintained in equilibrium so that the reference state at room temperature, the internal energy will be reduced to a minimum.By solid annealing simulation, the parameters can be optimized for better results by adjusting the core parameters withrespect to the optimum parameter. Thus energy required for annealing can be simulated with respect to temperature in thealgorithm, hence arriving at optimized solutions [30]. In summary, the simulated annealing algorithm can effectively avoidoptimizing sequential structures that tend to be minimally localand ultimately global optimal, giving the search process time-varying and finally jumping with zero probability.

9.0 SOLUTION DETAILS

9.1 Suggested Solution

In this part, we will describe the solution that will help eradicate the vehicle routing problem. Let's look at the Nondeterministic polynomial entity population as a starting point. Then, we set m = 1 as the generation number. Following that, we make Nondeterministic polynomial children and set s = 0. After that, we choose two parents through a two-tournament mating selection process. Then, using crossover and replacement mutation, we must produce two offspring. Then, we'll look at process V for local searches. If V is infeasible and we need to repair with probability Prep, we shall insert V into the infeasible subpopulation. We shall only include V in a feasible subpopulation if V is feasible. Select survivors once the subpopulation size has reached its limit. If the best option does not improve iterations for Itdiv, then spread the population. For infeasibility, adjust the penalty parameters. When both parents dominate the offspring, a split mutation is performed. Put s = s+2. If s = Np, we must choose the best Np individuals from the original population and children; otherwise, we must choose two parents using a two-tournament mating selection method. Again, we must choose the best Np individuals from the initial population and progeny. When redundant individuals are discovered, a split mutation is done. Finally, set m = m+1, and if m = NG, halt; otherwise, continue creating Np children and set m=0. Here, Np is represented as a Nondeterministic polynomial [31].

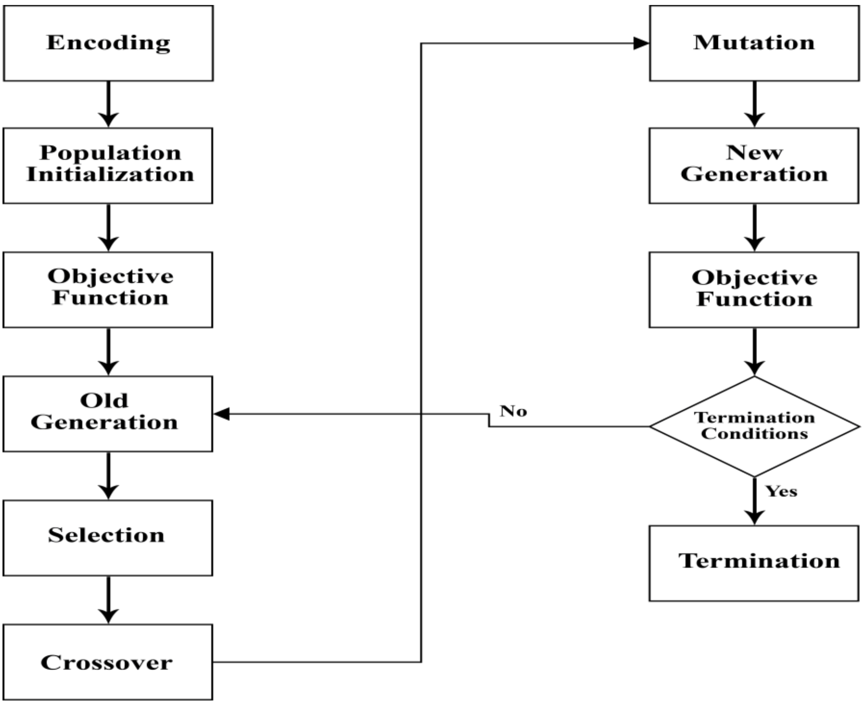
At this point, the initial population and generation number are determined. The parents are selected based on the outcomes of the two tournaments. The offspring are created by crossover. There are two types of solutions: feasible and infeasible. Combine them to create an offspring that goes through local search-based education, is repaired if impossible, and is placed in the proper subpopulation. When the population has reached its maximum size, each subpopulation is controlled separately to begin the survivor selection phase, adjust infeasibility penalties, and trigger a diversification mechanism. Split the population or choose the best individuals if the children are dominant.

9.2 Selection

In an Evolutionary Algorithm, there will be two selection steps. A selection technique is used to choose the crossover parent, and the children are created through mutation. The difference is that we enable crossover and mutation offspring to enter the population and become candidates for parents for a limited period. High-quality children can produce children almost instantly, improving productivity. Pareto levels and crowding distances are assigned to individuals.

Individuals in the population who are not controlled by others are assigned level 1, while the remainder is assigned level (l+1). The crowding distance determines whether or not two people are on the same level. If one person is superior to another, it must follow one of two rules. s and k should be on the same level, with s having more crowding, or s and k should be on thesame level, with s having more crowding distance. For the selection, we adopt a two-tournament format. In this case,two individuals are chosen at random, and the best of thetwo is chosen to be a parent. For environmental selection ($\mu = \lambda$ = NP), we employ the ($\mu + \lambda$) approach. NP offspringare produced after NP/2 times of selection, crossover, andmutation [32]. We chose the better NP individuals from the two NP individuals to restart the evolution process based on their levels and crowding distances.

Fig. 4. Genetic Algorithm Flow Diagram.



VRP Completion with Genetic Algorithm

The genetic algorithm is a search and optimization technique based on evolutionary processes and changes in living organisms' genetic structure [33].

In nature, chromosomes are a collection of genes that preserve an individual's genetic information. Genes determinean individual's qualities and characteristics, and these genes will be passed down to their offspring when they procreate.

Individuals with good genes will live longer, whereas those with bad genes will perish. Individuals with the best genesand chromosomes will live and pass on their good traits to their offspring, causing the population's average characteristic value to rise. Genetic algorithms were developed based on thisnotion to discover the best answer by crossing out existing ones. The following flow diagrams depict the processes that occur in genetic algorithms:

The genetic algorithm has multiple stages: encoding, initial population initialization, selection, crossover, and mutation. It will also perform the solution translation process after the algorithm is complete (decoding). Selection is employed to select which individuals will survive, while cross-breedingproduces new individuals to replace those that have died, preserving the population's size, and mutation allows for the unexpected formation of new individuals. After the solution search is complete, proceed to decode, which converts the coded solution into a form that individuals interpret as the solution to the difficulties encountered.

9.3 Crossovers

A genetic operator, known as the crossover, is employed in genetic algorithms to change the programming of a chromosome or chromosome from generation to generation. Crossoverrefers to the exchange of genetic characteristics between two parents. Genetic algorithms are based on reproductive andbiological crossover concepts. In neither crossing, there is a mutual exchange of genetic material between the two parents. To create a new child, they blend information from two parents. After replicating the parents to create children, each offspring selects the best path. The most efficient route is the one with the shortest average distance. Customers who arenew to the route will appear twice in the solution. The newly added routes are eliminated from the old route since theywere taken from a suitable solution. Removing clients fromthe altered routes does not impact vehicle capacity or time window constraints. As a result, it's possible that offspring will emerge. Crossover is a simple, effective, and efficient operator.We remove the worst and very short routes with only oneor two consumers to lower the number of vehicles. Allowing offspring to inherit positive traits from their parents is the bestroute exchange. By swapping the best route, some individuals in the population may have the same best route, especially at the end of evolution.

9.4 Mutation

The mutation is a genetic operator used in genetic algorithms to keep chromosome genetic variation stable over generations. In biology, genetic mutation is the same thing.It is possible to influence the occurrence of mutations. Thefirst is the most basic operator, based on client movement.The number of vehicles on the road and the total distance driven decrease as time passes. The routes improve due to this strategy, making it more difficult for consumers to find acceptable relocation areas. As a result, we plan to dismiss many clients at once to make room. Then, one by one, the clients who were removed are reintroduced. The second mutation operator is a split mutation, randomly dividing one path into two. As vehicles grow, more space is available for customer transfers. The split mutation is utilized briefly to move away from the local optimum. The split mutation is used when both parents influence the offspring and the pathways diverge at an unpredictable point.

9.5 Reparation

During the reparation procedure, the children are examined to see if they have too much or too little genetic information. Put another way, and the method determines which clients are missing from the routes and which will be served multiple times. Clients served several times are eliminated from the sequences with only one client. The position of the duplicated genes removal is picked at random. Clients who have gone missing must be re-added. The heuristic sets in at this point. Clients are not just placed in any location but in a location appropriate for them. This location is discovered by insertinga client into an existing route in a certain spot. This method is now done to all routes until the route and the place in the route where the client incurs the smallest penalty is discovered. Because this phase takes a long time, this strategy is only utilized when a specific probability is known. Otherwise, the client will be placed on a random route at a random location.

9.6 Search Space

Using exploitation to penalize the infeasible solution improves the performance of heuristics. The HGSDC search space contains infeasible solutions regarding route limitations such as duration, load, and time windows. The fleet's capacityis always significant since a solution with too many vehicles may necessitate more sophisticated cost route-reduction approaches. A "time warp" is paid to approach the edge of the time window for late arrival to a customer.

Figure 2 depicts the assumptions for a route with five stops, each with its own time frame, from bottom to top. The time dimension is represented by the horizontal axis, and the route is shown by the vertical axis. The bold line depicts a potential schedule. This schedule depicts the time spent waiting before receiving service from D2, and late arrival in D4 causes a timewarp.

Waiting times are represented by a time warp, although theyare not penalized.

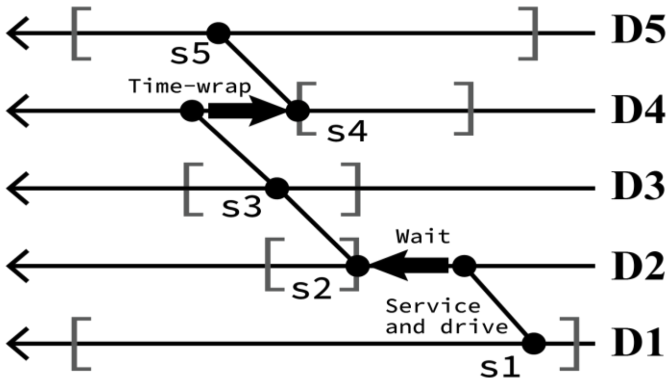


Fig. 5. Waiting times and time wraps.

10.0 Future Scope and Enhancement

It has been noted that no standards for more accurate variants of the Vehicle routing problem are obtainable. So,we can say that there is still room for more research in this area. As a result, the researchers are driven to create publicly accessible datasets and effective and efficient techniques for dealing with VRPs.

Ultimately, while static routing plans are the primary focus, technological improvements such as GPS and mobile communication may necessitate dynamic routing algorithms, which allow for modifications in routing decisions while drivers are on the move. Some scholars in this field may be motivated to continue working in these directions because of the limitations of existing research.

11.0 Conclusion

We cannot always predict what will happen on the road andchange our route in real time to suit our clients' unanticipated requirements, no matter how skilled our management and drivers are. So, to design your routes and track our driversand cars, we will need a high-tech solution. Essentially, using an advanced route optimizer is the most effective approach to resolving our VRPs and making planning and adjusting routes appearlike a walk in the park.

Genetic algorithms are a fascinating way to handle problemswhere an exact solution is impossible. We were a little upset that it took so many generations to devise a solution that was not even that good. As a result, we decided to apply some specific insertion heuristics to assist the system in approaching a good solution more quickly. The crossover approach was chosen intuitively, and we cannot know whether it is excellentor not. We created one that uses our heuristic method to insert new components as subroutes and another that performs asimple sequence-based crossover. We will discover that if weset the heuristic level too high. As a result, we modified the algorithm to strike a balance between discovering a quick solution and restricting the number of possible solutions.

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