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OPTIMIZING DELIVERY ROUTES AND PACKAGE ALLOCATION FOR ENHANCED LOGISTICS EFFICIENCY

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Abstract
With rapid advancements in e-commerce, increasing customer demands have put effective delivery management at the forefront of issues related to logistics and transportation companies. This study examines the Vehicle Routing Problem (VRP) and proposes a clever and metaheuristic way for effective delivery routing and distribution of items. Essentially, a means to improve scheduling, cost, resource productivity, and customer satisfaction. Research includes data on where items are delivered, where the depots are situated, what maximum loading each vehicle is capable of carrying, and obstacles to delivering services. Routing through clustering organizes the delivery points in respective modes and places where and how goods are to be delivered. Encoding uses ant colony optimization (ACO) to optimize routes through complicated problems such as vehicle constraints, time delivery, and dynamic destinations. Improvements in the algorithm performance shall also be attained by incorporating heuristics and evolution strategies. A web API was developed. During analysis, access to the most up-to-date routing information was ensured in real-time, with the application presenting the routes on interactive maps. Whereas static orders are currently managed, planned enhancements will allow for dynamic order handling, thereby enabling demand prediction via machine learning and real-time traffic information to enhance operational efficiency.

1. INTRODUCTION

Route optimization is the art of finding the best (shortest and cheapest) routes for your cars so that they can be optimized and made an optimal solution. A route optimization tool will find the best routes to ply based on the restrictions and goals of any business. The factors that will affect the routing include how many stops are required, the locations of these stop points, and time windows for delivery. But the issue is far more complicated. If you work in this field, you probably know that route planning involves identifying the best access route to the client. You may have had trouble following the right path. Damned challenges should be there if you mock them anyhow. Requests for numerous pickups and drop-offs for our parcels have almost become a given, as we want packages. Handling multiple clients increases your workload, too. The extent of multitasking will create some serious bugs and issues down the line [1]. An electrician cannot carry out a carpenter's work. Highly skilled people do the work fast and in the best possible manner. In the same way, vehicles are built for specific jobs. For example, reefers are meant for cold cargo, trucks for heavy loads, etc. Hence, it is essential to match the right vehicle to the job. Now, make sure to talk to a driver who will communicate with you and make everything easy. The service time includes the travel time and a fixed stop time per customer. Since it depends on the needs of each individual, there is no universally applicable answer to this question. You might also want to think about carrying out your plan. Determining the best route and time for a driver to deliver the goods is challenging. There may be an impending time crisis if the average time doesn't seem to be working.

Accounting is a critical function that a business will have to perform for everything else. It idealizes the report details as some of the hardest to put together. The costing of your business is properly tracked in Accounting, which, if broken down, can bring the entire organization down. Assets might have restrictions of their own [2]. These limits consist of measurements on volume, weight, and load. Exhausting resources is very easy when it comes to the limitations of one vehicle, but it becomes a very tiring process as the number changes. We frequently make last-minute changes to the delivery destination. This is undoubtedly a significant problem for your logistics business. Customers may become dissatisfied if goods are not delivered on time because it can be difficult to find an efficient route at the last minute. How, then, can one actually handle such issues? In fact, routing optimisation systems will be used to handle the persistent issues listed above. Optimising is the process of maximising or minimising a function with respect to a given set, typically referring to options that are available in a given circumstance. The function makes it possible to compare the various options and determine which one is potentially the "best." Minimal material cost, maximum profit, minimal error, optimal design, and optimal management are a few examples of very common optimisation goals. There are two main categories of optimisation. The other Heuristic Optimisation is referred to in the first Mathematical Optimisation as shown in Figure 1.

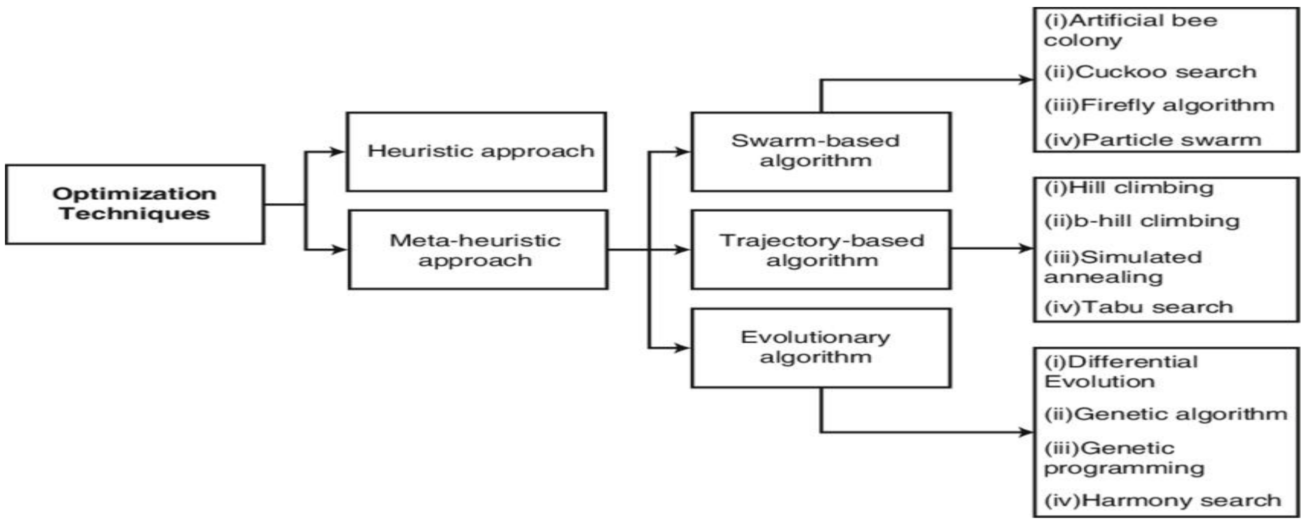

Figure 1: Optimization Techniques

A full set of documentation about accounting for all the company's finances is released when implementation is finished. It requires gathering lots of data for the most difficult financial reporting. You need accounting to make sure you are aware of how much your business is spending. Important challenges may arise at any point, which could end in business failure. So, some assets might have been managed using restricted controls. Some of the restrictions would be based on measuring meterage by volume, weight, and load. At the same time, the variety of factors in soil science can lead to the fast use up of necessary resources. Still, since the number of vehicles fluctuates, this process can be very tough and time-consuming. Most of the time, the delivery point is changed immediately after the planning stage [3]. This is truly a problem for your logistics company. Rushing to find the best route may not work when you are set to go. So, your customer, Dell might be very unhappy if they do not receive their ordered goods on time. What approaches can people use to handle all these issues? They can all be fixed using a routing optimization system. Optimization means trying to get the biggest or smallest value from a function within a certain range of options. It makes it possible to evaluate and compare the choices to find the "best" one. Many Optimization Goals Are Minimizing the Cost, getting the Highest Profit, Minimizing Errors, Creating the Best Design and Managing Resources Optimally Optimization has both internal and external aspects. Mathematical Optimization is the first form and the second is Heuristic Optimization.

Mathematical optimization means seeking the best solution by improving how the variables are set in a problem. All deep learning models depend on optimization which can be a form of supervised or unsupervised learning [4]. Optimizing a process involves choosing a method, but all these methods require you to set a starting point and a goal first. To optimize something, you should set up an objective function that will describe your goal. The function may result in either a given outcome or a certain probability. Inputs may be discrete or continuous. Restraining the size of data points keeps the data reliable within a model. An inequality constraint appears as gn (x) and an equality constraint is typically indicated by the notation hn (x). These problems do not restrict the values that the variables can have [5]. Heuristic design works by trying to find the most optimal solution by successively modifying a trial solution with a specific way of measuring quality. They work without making specific assumptions about the problem, aim to deliver the optimal solutions, search a large number of solutions and they do all this fairly quickly, but there's no guarantee that the answer is valid or free from errors. Some search optimization processes are used in heuristics, including evolutionary programming, evolution strategy, genetic algorithms, genetic programming and differential evolution. The core of every planning and scheduling task in the supply chain is to optimize something. To improve customer satisfaction and financial outcomes, the company's solution entails figuring out how to best synchronize supply and demand throughout the supply chain network. Heuristics are a popular tool used by companies to try to solve supply chain scheduling and planning issues. To put it simply, a heuristic is a problem-solving technique that employs a practical procedure (often called a "rule of thumb" or "best practice") to generate a feasible solution that is sufficient to promptly address a particular issue and short-term objectives, but is not always the best option. On the other hand, given decision variables like production, inventory, and shipment volumes, along with constraints and key performance indicators (KPIs), an optimisation model employs an intelligent, automated process to generate the best possible solution to a particular issue [6]. Supply chain optimisation aims to make your purchasing, manufacturing, storing, and shipping processes more efficient so that you can achieve maximum profitability and guarantee on-time delivery of goods. Being in charge of a logistics company makes you aware that occasionally goods must travel to a different location than anticipated. In a lot of cases, the package can be delivered somewhere other than the pickup location. How do you determine the fastest route to get to all of your destinations? How does one log into a remote system to check the state of the roads? To find the best route, you will need to use a route optimisation system. Allowing the software to determine the quickest routes will help you overcome the challenge of getting to two or more locations. Such software can also examine the business's constraints and challenges, including traffic conditions and available resources [7]. Your shipment will arrive at its destination on time if you use this system. Utilising the information provided, taking into account user preferences, and cutting down on travel time are the primary tactics frequently employed by effective route optimisation software. The three types of routing are:

Static, which is based on requirements such as quarterly or monthly plans.

Dynamic, which is based on daily developments.

Real-time dynamic routing – Developing routes based on current road and traffic conditions in real-time to help drivers on the ground.

The market for route optimization software around the world is meant to grow by 24.7% within the next four years [8]. It amounts to $5.32 billion! In some parts of the world, this market is very dominant. [9] What is it that makes people search for the best path improvement tool? Do travelers see any advantages from the best route optimization software? I'm really thrilled regarding the new product. Using route optimization software can also help you save time. Here you can read about all the different forms of yoga. Put in relatively little money, but make more profit (have a bigger return on what you invest). Use technology to design your logistics plans and raise the quality of your shipments. See all your dispatch details and order information in the central dashboard in real-time. Handle resource planning, task distribution and order assignment by using a logistics route optimization software from one dashboard. Make use of an efficiency platform to collect data analytics and other useful reports to improve how your fleet works. Field agents are able to complete orders on time using vehicle routes that are well optimized [10]. Logistics route planning software helps you plan routes by avoiding congested areas and improving how fast you get there. You can select different routes to make your vehicle move efficiently. Factor in what determines the ETA, one of which is the time it takes to generate the signals. Run your supply and delivery routes through logistics software to help uncover ways to improve and cut costs.

OTL Logistics operates in Malaysia. There are more than 250 bank branches around the globe and over 300 vehicles are used for business operations [11]. Because its fleet management system was outdated, the company had trouble running its trucks successfully. Route duplication was difficult and the company did not have reliable tracking of vehicle positions. Thanks to the route optimization system, the company's customer service and tracking improved. Besides, they enjoyed huge added benefits. The American-based home decor and furniture company Crate & Barrel was founded in 1962. The number of stores stands at over 160 and there are about 7,000 associates [12]. It also relies on about 80 delivery trucks. Most of the distribution center operations for this company are concentrated in New Jersey, San Francisco and Chicago. 300,000 is the total coverage offered by the insurance policy per year. The company, however, met with a huge problem in getting deliverables out. iane and Amit were able to do this largely through their fleet management system. I have listed their problems below. They decided to use a solution for route optimization to improve vehicle and driver job efficiency, ineffective vehicle monitoring, not collecting data properly and providing a bad customer experience. They were impressed by how special the solutions turned out [13].

Because of the "online" trend that started with Covid, the delivery industry has grown to a huge extent. Most companies are now using the internet to run their operations. Because of this, more packages needed to be delivered. Finding the most efficient route for delivering packages is now a bigger challenge and more important for delivery companies. Now, businesses of all sizes use route optimization software in the postal service, transport, logistics and other sectors. Manually planning a driving route is very difficult. With not many vehicles on 10 stops, a million different routes still become possible. Collecting a lot of routes is very difficult if you do not have the correct tools to help you. Also, the main problems with last mile delivery are delivery efficiency, margins, customer demands, how delivery agile companies can be, operating costs, number of missed deliveries and how end-customers are handled. Such issues occur daily for deliveries companies. Route management helps save fuel, time, cost, employee money, money spent on fuel and expenses for maintaining vehicles. This is why the right use of route optimization will help businesses avoid such obstacles, earn more revenue and become profitable. A good route optimization system allows delivery businesses to pay less in wages.

Saving both time and fuel by calculating the ideal possible route for every vehicle in the fleet in a very short time. As a result, we will come up with an algorithm that can cut down on the costs suffered by the company and decrease the time required to deliver a certain number of parcels. Companies like Food Panda, UberEATS, Groceries and bottled beverages have software that helps them with delivery planning. By having an optimal route such companies can help reduce the time and money needed to deliver or collect parcels which benefits delivery companies. We look to improve the planning of routes. We want to cut down on the time spent traveling. Optimization of every route and every rider will help us design an algorithm that, when planning a route, selects the best riders nearby and gives them the deliveries. A common observation is that, when people get fast food online, the delivery company usually takes longer than expected [14]. Often, the reasons include using a wrong or long route and sometimes it happens because the rider is new to the job. Many people get very bothered by these huge delays. Getting your data is the toughest step at this stage. To run tests with our algorithm, we require data that comes in real time. Receiving this data in the moment proves difficult, because no company wants to release its data because of security concerns. Our ultimate objective is to reduce the delivery time by reducing the operational expenses, such as fuel and travel time, that result from longer or less efficient routes or an inexperienced rider. Below is a list of the research's goals:

- To gather information about VRP, or Vehicle Routing Problem, which includes details about delivery and depot locations, rider/delivery vehicle capacity, and other customer-related information.
- To use various clustering techniques to separate customers or delivery locations based on similar features, such as location or delivery needs.
- To save time by developing an algorithm that, given the delivery locations and the delivery entity's (i.e., delivery van or delivery boy) capacity, would recommend the optimal route.
- To create a web API that would put the intended algorithm into practice and enable the retrieval of route data as needed.

To develop a demonstration app with maps implemented, that would visually display the routes suggested by the algorithm.

- ***Literature Review***

The purpose of route optimization is to save money, fuel and time when delivering or collecting packages. Because it has a non-deterministic polynomial time (NP-Hard) complexity, computing the shortest route takes up a lot of processing resources. Though numerous scientists have conducted research on the problem, it is still a big topic in optimization, especially for multidimensional cases. This part looks at the main methods used so far to find solutions to this problem. Most of the heuristic algorithms used for solving route optimization come under two types: Local Search and Evolutionary Search. It changes the current solution to a different solution from its 'neighborhood' each time. The approach repeats by first picking a possible solution and swapping nodes or routes as it tries to find a better solution. This repeated process tends to get stuck on local optimum solutions; hence, other creative strategies have been designed to help get a better overall result. Simulated annealing, iterated local search, large neighborhood search, variable neighborhood search and tabu search are included among these [15]. Experiments on VRPs (starting from 25 customers up to 100) that applied Local Search Heuristics are commonly found to deliver good results [3, 5, 6]. In an Evolutionary Search, all the potential answers are separated into many small solutions and the evolutionary algorithm optimizes them all at once to find the best ones. Evolutionary algorithms that work quite well for VRP are explained [16] [17]. Another [18] designed their problem solving by using the well-known evolutionary optimization scheme to start and improve solutions in the VRPTW landscape. One [19] made the genetic algorithm more efficient and solved problems involving up to 1000 customers.

Instead of looking at the voronoi diagram itself, [20] only performed research on the VRPTW by tackling it with several small problems solved using heuristics from Mothermarch. Studies discovered that the Voronoi diagram was vital in leading how the search took place. Yet, it only involves how a solution forms from breakup of the original substances. Even more improvements are possible, because the direction [21] took only solved the voronoi diagram with help from a large search algorithm. It was seen that the Voronoi diagram controls the search process smoothly. But the decomposition was only considered within the process of preparing the solution. Even more ways of improving can be discovered. To support some real-world applications, a few efficient VRP techniques have been combined with GIS-based SDSS. Similar to GIS software like ArcGIS and TransCAD, spatial data management, processing, and visualisation tools are used to gather customer orders, georeference related data, initiate the solving process, and display routes for VROs. In order to address VRO for an American retailer, [22] initially presented the use of a tabu search heuristics approach in a GIS environment in addition to local search. In order to deal with VROs in public utilities, [23] integrated a customised routing module that enhanced the quality of the commercial solutions like SAP/R3 and ArcGIS.

The efficacy of evolutionary optimisation and GIS software was confirmed through experiments conducted on a real-world case in Bogotá, Colombia, involving 323–601 clients. To address a trash collection task in Coimbra, [24] created a web-based, user-friendly SDSSs embedded with VRO. A cloud GIS-based spatial decision support framework with variable neighbourhood search heuristics for dynamic vehicle routing was presented [25] using historical traffic data. All of this demonstrates how prevalent VRO is in practical transportation applications. To accommodate the constantly growing number of clients in the various transport sectors, they also suggested that the current spatial intelligence should be enhanced. Vehicle capacity for the traditional VRP variant is constrained. With routes beginning and ending at the depot, the VRP seeks to identify the best routes that visit every customer simultaneously while taking into account each vehicle's capacity. Reducing the total distance is the traditional optimisation task. Take a look at the work of [26] for the complete model. To determine the mathematically proven optimal, some methods based on mathematical formulations will thoroughly search for the values of the variables. However, the best routes are difficult to find, and the problem was shown to be NP-hard [27]. Large-Scale VRP (LSVRP) is the term typically used to describe situations involving more than 200 customers [28]. Because of this larger size, the amount of search effort must be carefully considered. Consequently, a heuristic approach that finds good solutions more quickly rather than optimal ones is required. Simple moves that can be quickly and repeatedly searched are typically the foundation of heuristics. These fall into two categories: intra-route and inter-route, and are referred to as neighbourhoods, perturbation heuristics, and local search. The traditional 2-Opt [29] and Cross Exchange [30] are two examples of such moves.

Local Search (LS) is the most effective and efficient method for solving the VRP [31]. The primary method of evaluating the quality of LS heuristics is to move between basic and more complex neighbourhoods. Initially, the LS experiments with minor concepts that can be applied to different scenarios while still addressing challenging issues [32]. To use LS and enhance the current set of solutions, [33] and [34] collaborated with Genetic Algorithm and Set Partitioning. Furthermore, as their scale increases, as demonstrated in [35], they become inefficient enough to complete the task in a matter of minutes; instead, it takes them several hours. This can be explained by applying LS to the scales; it is too expensive to go through each neighborhood's solutions due to the large number of neighbouring solutions. Some LS-based methods address this by reducing the number of solutions examined through heuristic pruning. Using specific pruning techniques, a case completed just last month [36] was able to handle up to 30,000 customers and complete all changes quickly. According to [37], several approaches employ limitations on the search space by either classifying the clients or by putting thresholds in place. Setting up a small search area is difficult, though, as it might prevent the search from yielding the best results. Hyper-heuristics reduce the effort required to select an effective heuristic by utilising less domain knowledge. In certain instances, HHs have been successful in automating heuristic sequencing, planning, parameter control, and learning techniques [38]. You should consider the elements, techniques, and parameters that this algorithm will employ when learning heuristics.

NEC techniques, like Genetic Algorithm (GA) and Genetic Programming (GP), are a common method for creating HHs. Searching for optimal heuristic sequencing is one of the search problems for which GA has been used, as demonstrated in [39] for the bin-packing problem. Instead of enhancing the solution, as in [40] for the Dynamic Job-Shop Scheduling, GP is more often used to develop a heuristic rule that constructs a solution [41]. However, there hasn't been much research done on HHs for large-scale issues (with an emphasis on the VRP). One example [42] shows how to apply HH to an LSVRP with Time Windows, where the solution is fed into the HH after the large problem size has been resolved. The approach solves the problem and search space using a column generation technique. The goal of the deterministic Guided Local Search (GLS) algorithm is to steer clear of the local optimum that LS algorithms inevitably run. GLS offers a feature set that can be chosen to penalise the existing solution and steer it clear of the danger. Instead of altering the solution itself, this is accomplished by employing various objective functions to direct the solution [43]. In [44], the authors present Knowledge-Guided Local Search (KGLS), which applies Guided Local Search (GLS) with a recently introduced operator and penalisation functions. Later, in [45], this was scaled up. The Local Search algorithm is applied sequentially by the KGLS. These stages eliminate the undesirable aspects in an effort to uncover fresh ideas that might result in an improved final product. The same authors' study [46], which examined similarities among various VRP solutions based on a number of metrics, served as the basis for these penalisation functions. The routes' width was one of the most useful metrics.

Optimisation problems are important in both the scientific and industrial domains. Real-world examples of optimisation problems include timetable scheduling, nursing time distribution scheduling, railway scheduling, capacity planning, travelling salesman problems, vehicle routing problems, group-shop scheduling problems, portfolio optimisation, and more. Numerous optimisation strategies have been developed as a result. Ant colony optimisation is one of them. Ant colony optimisation is a probabilistic approach to choosing the best courses of action. In computer science and research, the ant colony optimisation technique is employed to address a range of computational problems. Ant colony optimisation (ACO) was introduced by Marco Dorigo in the 1990s as part of his doctoral thesis. Ants are studied to determine the path they take to return to their colony and find food. It was initially used to solve the well-known travelling salesman conundrum. It is then used to resolve a riety of challenging optimisation issues. Ants reside in communities known as colonies. They construct colonies that contain a wide variety of individuals. Ants' behaviour is determined by their need to find food. Ants searching for objects within their colonies. An ant travels around in search of food. It releases a substance known as a pheromone onto the ground below as it travels. Ants communicate with one another along pheromone-marked trails. When they find food, ants take as much of it as they can fit. Depending on the kind and quantity of food discovered, it sprays a pheromone onto the tracks. Ants are able to detect pheromones. Other ants will therefore pick up the scent and move in that direction. When more ants use a path, more pheromone is left behind, which draws more ants to use it.

3. *Methodology*

Creating a design and specification is important for any project implementation. We will explain every part of our project clearly using a diagram built from our research as shown in Figure 2. We will describe our algorithm using a flow chart to highlight the sequence of steps during optimization of route. To create the flow chart diagram is to determine the direction of the solution algorithm and arrange the system process for all steps of execution.

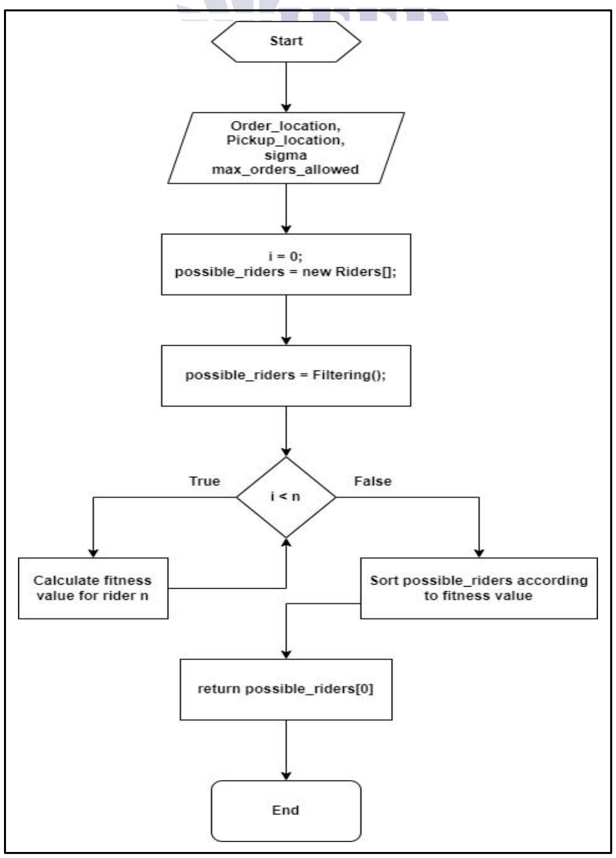

Figure 2: Flow diagram: Main Algorithm

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Following is a general flow of steps of the Filtering process, which is a part of the main algorithm as shown in Figure 3:

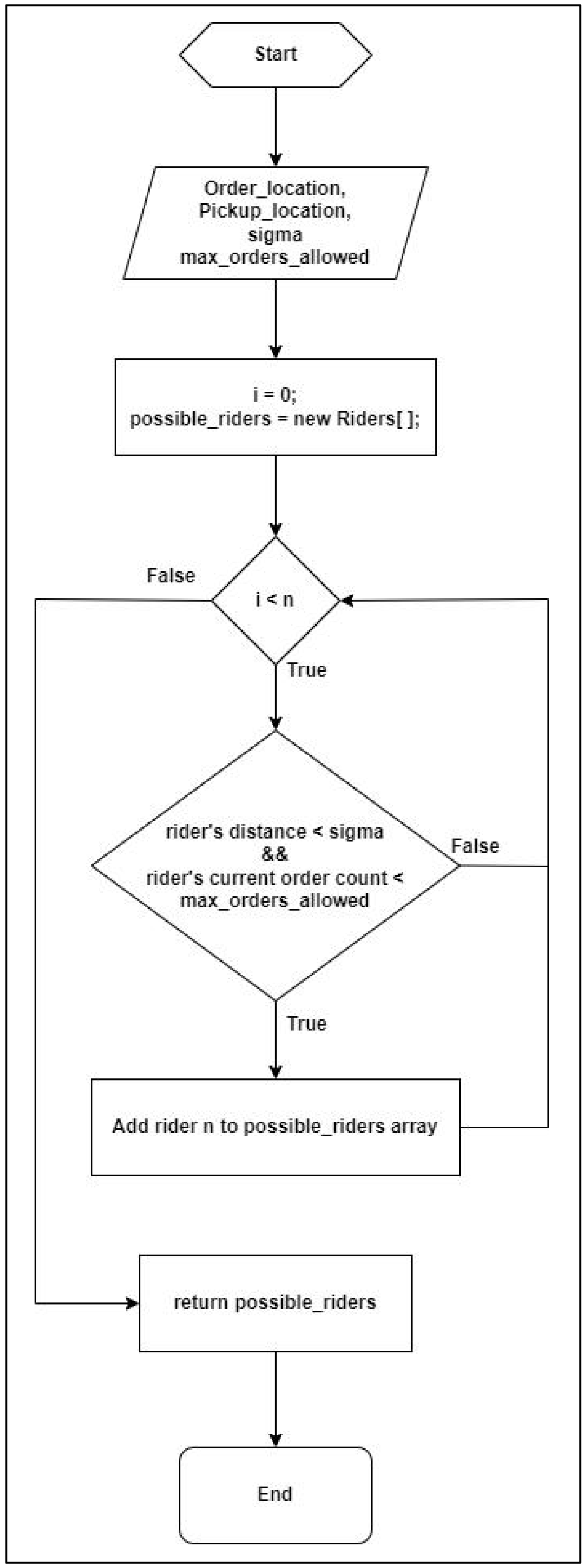


Figure 3: Flow diagram: Filtering process

This is research based project so we don't have any practical implementation except our research. The above flow chart of algorithm is drawn according to our research on optimization of route. We will discuss this algorithm in detail in next chapter.

3.1. *Algorithm*

Initially, it looks at the order details, delivery location, restaurant location, a radius called sigma (σ) and the max orders a rider can deliver at once. The system provides the rider assigned to the order and an optimized way to deliver it. The first task is to pick out riders from the area surrounding the restaurant (determined by sigma) who still have space to handle one more order. It particular, the algorithm checks how far each rider is from the restaurant and it only selects those riders whose distance is in range and whose current order count is below the maximum. All the riders that go through the filtering process are put into the possible riders list. To decide if each rider is appropriate for a delivery task, a fitness function is created using aspects such as where they are and the place the ordered item is to be delivered. Fitness scores are used to rank the riders and the most matchable rider is chosen to handle the request. As a result, this way guarantees the best and most efficient distribution of loads, lowering the amount of time needed and considering how bridges are used and where vehicles are located. Each step of the algorithm is explained below:

Pseudocode: Rider Selection and Route Optimization

Algorithm: Assign_Rider

Input: Order, Order_Location, Restaurant_Location, σ, max_orders_allowed

Output: Selected_Rider, Optimized_Route

1: possible_riders ← Filtering(Restaurant_Location, σ, max_orders_allowed)

2: for each rider in possible_riders do

3: fitness[rider] ← Fitness_Function(rider, Order_Location)

4: end for

5: sorted_riders ← Sort(possible_riders, by fitness value ascending)

6: Selected_Rider ← sorted_riders[0] ⟶Select the top-ranked rider

7: Optimized_Route ← Generate_Optimized_Route(Selected_Rider, Order_Location)

8: return Selected_Rider, Optimized_Route

- *Filtering*

In this stage, the decision-making system chooses only a certain number of riders from the large group to reach the best outcome. Riders are chosen for the above function by selecting those who live within a radius of 5 km which is what we set σ to. The population in an area might increase or decrease σ depending on whether we attract the desired number of riders. An empty array of possible_riders is set up when the system starts. We would only allow up to ten riders to be compared at any given instance to find the perfect rider. As we go through the riders, we also check if the rider is capable of taking more orders by checking if their max limit has been exceeded, as in our case, 5 orders. At this stage, we are using the same values (such as σ, max_orders and the number of riders to search for) as Uber Eats and foodpanda, but once done, we will examine the effect of changing these values. Once the rider matches the rules above, it is added to the possible_riders array. The function Filtering returns the final possible_riders array. Every part of the algorithm is given a full explanation below:

Pseudocode: Filtering Subroutine

Function: Filtering

Input: Restaurant_Location, σ, max_orders_allowed
Output: possible_riders
1: possible_riders ← ∅
2: all_riders ← Get_Riders_In_Area(Restaurant_Location)
3: for each rider in all_riders do
4: rider_distance ← Calculate_Distance(rider.location, Restaurant_Location)
5: if rider_distance ≤ σ and rider.order_count < max_orders_allowed then
6: possible_riders ← possible_riders ∪ {rider}
7: end if
8: end for
9: return possible_riders

3.1.2. *Calculation of Fitness value for each rider*

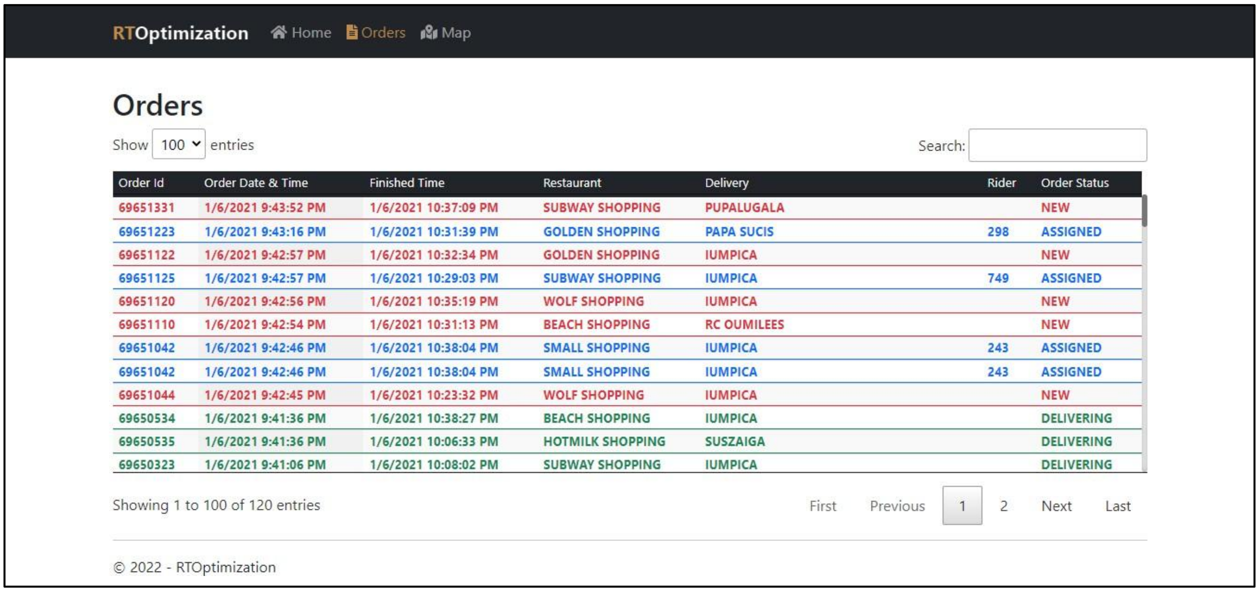
In this step, the array of riders got in step1 will be used and **for each rider**, fitness values will be calculated by calculating the total path length of the rider and then dividing it by the rider's rating.

3.1.3. *Final Rider Selection*

After getting the fitness values, the riders will be ranked according to their fitness values. After the ranking step, the top most rider will be selected and suggested as the best possible rider.

4. Results

This part covers the actual results achieved by the implemented vehicle routing and delivery package optimization system. The major features of the application such as managing orders, seeing routes and delivery tracking on a map, are clearly shown in the main screenshots. On the Main Orders Screen (Figure 4), each incoming delivery request is shown and there are details about the pickup and drop-off locations, who is assigned to the order and its current status. It lets operators keep track of and handle all the orders on the platform. Figure 5 displays the Maps Screen which offers a visual map of where the deliveries need to be made and the riders available in that territory. Using the map, it is easier to see how orders and delivery personnel are spread out, letting you track everything in real time. Figure 6 displays the Routes Screen which clearly shows the routing suggestions given by the algorithm. The graphic outlines the deliveries, organizes the chosen rider's path and indicates how this approach helps save both distance and time. It is shown that the system brings together backend optimization with a convenient frontend, making it possible to plan routes and assign riders instantly. Taking into account rider proximity and how much they can carry, together with their fitness level, makes delivery management more efficient.



Order Id	Order Date & Time	Finished Time	Restaurant	Delivery	Rider	Order Status
69651331	1/6/2021 9:43:52 PM	1/6/2021 10:37:09 PM	SUBWAY SHOPPING	PUPALUGALA		NEW
69651223	1/6/2021 9:43:16 PM	1/6/2021 10:31:39 PM	GOLDEN SHOPPING	PAPA SUCIS	298	ASSIGNED
69651122	1/6/2021 9:42:57 PM	1/6/2021 10:32:34 PM	GOLDEN SHOPPING	IUMPICA		NEW
69651125	1/6/2021 9:42:57 PM	1/6/2021 10:29:03 PM	SUBWAY SHOPPING	IUMPICA	749	ASSIGNED
69651120	1/6/2021 9:42:56 PM	1/6/2021 10:35:19 PM	WOLF SHOPPING	IUMPICA		NEW
69651110	1/6/2021 9:42:54 PM	1/6/2021 10:31:13 PM	BEACH SHOPPING	RC OUMILEES		NEW
69651042	1/6/2021 9:42:46 PM	1/6/2021 10:38:04 PM	SMALL SHOPPING	IUMPICA	243	ASSIGNED
69651042	1/6/2021 9:42:46 PM	1/6/2021 10:38:04 PM	SMALL SHOPPING	IUMPICA	243	ASSIGNED
69651044	1/6/2021 9:42:45 PM	1/6/2021 10:23:32 PM	WOLF SHOPPING	IUMPICA		NEW
69650534	1/6/2021 9:41:36 PM	1/6/2021 10:38:27 PM	BEACH SHOPPING	IUMPICA		DELIVERING
69650535	1/6/2021 9:41:36 PM	1/6/2021 10:06:33 PM	HOTMILK SHOPPING	SUSZAIGA		DELIVERING
69650323	1/6/2021 9:41:06 PM	1/6/2021 10:08:02 PM	SUBWAY SHOPPING	IUMPICA		DELIVERING

Figure 4: Main orders screen

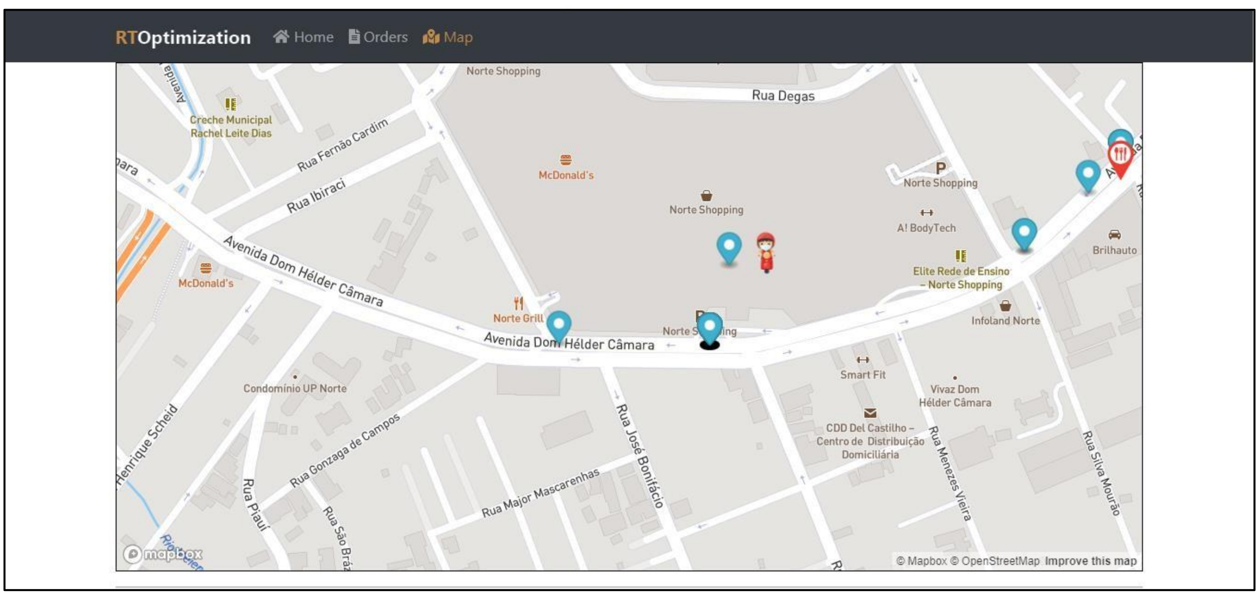


Figure 5: Maps

Screen

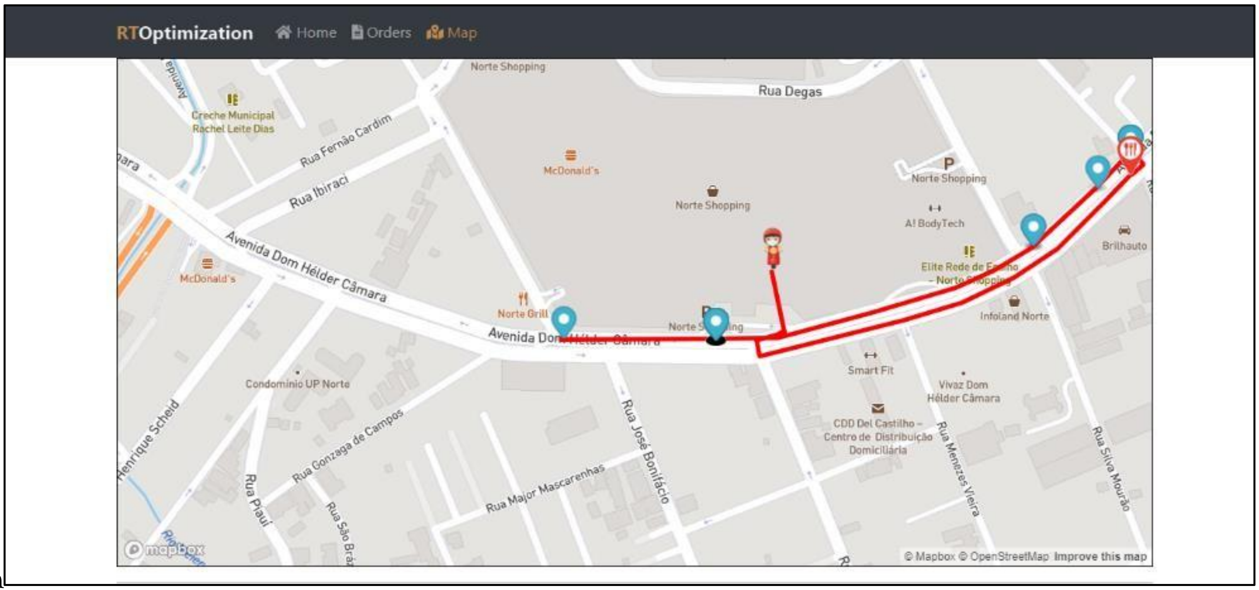


Figure 6: Routes Screen

5. Conclusion

This optimization algorithm for transportation is used in many industries because it is built with the key elements needed for transport models. So that time is better used, we created an algorithm for companies with centrally located hubs. The next improvements will focus on making the algorithm more efficient and accurate. Our problem takes only the orders available before a particular moment and lets you know which rider can do the job and what their fastest route would look like. Even if the algorithm points out the fastest route, it does not consider factors like delays, crowded roads, weather on the roads and other things that can affect actual delivery time. More investigation can be done in this field to improve the effectiveness of the solutions. A better way could be to predict how many orders will be made for each restaurant in the future by using ML prediction. So, if we predict that the orders will rush to a restaurant in the next hour, we can give the current orders to far away riders to save more riders closer to that restaurant for the next hour. An extra area for attention should be to add observations on road conditions from the current moment such as crowding, broken roads, road closures, construction areas and traffic jams. When we have real-time updates on road conditions, we can analyze how much time each route requires and this way, we can advise on the shortest roads, even when they may be a bit longer, because they are cleaner. We can conclude that an optimization algorithm plays vital role for the delivery or transport industry. An effective route optimization algorithm can not only increases efficiency of a company or an organization but can also prove to be fruitful in term of monitory benefits. The algorithm designed by us for the purpose of this project address static orders only i.e. an order is received and optimized. This approach also solves the problem to some extent. But addressing the dynamic orders could help find much better solutions. By dynamic orders we mean the orders received at the moment when the current orders are being processed i.e. when the current orders are being processed, any order received during the time of processing, should also be considered for processing. This would help suggest more optimal solutions. Another great improvement could be to predict future orders and schedule the current orders accordingly or taking into account the real- time road conditions or other such factors that may affect the overall job completion time. In the end, this is a topic with a never ending room of improvement.

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