IDENTIFYING THE ROBUST PATH FOR EFFECTIVE TRASH COLLECTION AND TRANSPORTATION FOR TRASH VEHICLES USING HYBRID APPROACH

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Abstract: - Waste that is both biodegradable and inert is frequently discharged, and open burning is frequent. There will be more jobs, better public health, and more tourists in India if garbage collection and transportation facilities are improved.The entire waste management process is a complicated one that involves numerous systems and sub-systems. The novelty of the research is to determine the best routes for trucks utilizing different scheduling and routing techniques. Proposed hybrid models to find the short optimal route, those are Enhanced Genetic Algorithm (EGA), Enhanced Genetic Algorithm with Adaptive variable neighborhood search method (EGAAV) and Enhanced Genetic Algorithm with Clarke & Wright's saving method (EGACW). From the proposed hybrid algorithms EGAAV outperforms well than the other two proposed algorithms. EGAAV scores a less computing time and suggests optimal routes.

Keywords: Optimal Route, Genetic Algorithm, AVNS, Evolutionary Algorithm, Vehicle Routing

1. Introduction

Municipal Solid Waste (MSW) disposal is on the rise globally as a result of population growth, industrialization, urbanization, and economic expansion. At the global level, MSW generation has a positive relationship with economic development measured in kg/capita/day. The population of cities is growing quickly as a result of both rapid industrial growth and rural-to-urban migration. Garbage production has been seen to rise yearly in direct proportion to population growth and urbanization. Due to excessive trash generation and insufficient waste collection, transport, treatment, and disposal, India confronts significant environmental difficulties. India's current waste management systems are unable to handle the volume of waste produced by an expanding urban population, which has negative effects on the environment and general welfare. Although there are many obstacles and challenges, there are also many opportunities. Effective SWM is a significant difficulty in densely populated areas. India is a varied nation with many different religious groups, cultures, and customs, making it more challenging to achieve sustainable development within a nation witnessing fast population increase and improvements in living conditions (Kumar et al., 2017). To enable far more effective value extraction and recycling, waste management must include waste segregation at the source.

Any SWM system must have waste collection, storage, and transport, but these tasks can be quite difficult in urban areas. In India, municipal corporations are in charge of collecting waste, and dumpsters are typically supplied for both biodegradable and inert waste.

The capacitated vehicle routing problem (CVRP), also known as the problem of choosing a set of vehicle routes to service a collection of clients with known geographic coordinates and known requests, shares many features with the characteristics of the open vehicle routing problem (OVRP). A route is the order of places that a vehicle must travel. The distances between the locations of the origin and between them and the destination are computed or predetermined. The vehicle leaves the origin and comes back to the origin after completing each route (Camargo et.

al., 2019). The CVRP consists of a single origin, a uniform fleet of vehicles, and a group of clients who need commodities delivered from the origin. The CVRP's goal is to create a workable system of vehicle routes that reduces the overall amount of driving and/or the overall fleet size. The route must also adhere to the requirements that each location be visited only once, that their needs be fully met, and that the vehicle capacity is not exceeded on any given route. Contrarily, under the OVRP, the businesses either do not have access to their own car or their vehicle is unfit to service their consumers. The subcontracted vehicles in this case will be rented from logistics outsourcing firms. As there is no vehicle return to the origin and no maintenance expense, the transportation cost only depends on the distance travelled from the origin to the destination. In another scenario, the vehicles could pick up things from the destination and then travel the same path back to the origin.

The most cutting-edge solutions are typically restricted to statistical, non-predictive methodologies and have a constrained perspective on reality, rendering them ineffective for handling everyday business difficulties (overflowing containers, poor quality of service, etc.). (Melakessou et al., 2020) paper gives a case study of a corporation providing a business garbage collection service that is currently being created in Luxembourg and has a lot of constraints to take into account. Investigating the utilization of various trash data sources to produce practical indications for enhancing collection procedures is the key goal. They also examine data gathered from ultrasonic sensors placed on almost 50 different containers to gauge fill levels and describe the deployment procedures, demonstrating how this strategy could be used in conjunction with anomaly detection and prediction techniques to alter the way this industry operates.

The paper organized as follows: Related works gathered and discussed in section 2, explored about the proposed models in section 3, result and analysis of the proposed model is visualized in section 4 and finally concluded in section 5.

2. Related works

The goal of the flying sidekick travelling salesman problem (FSTSP), which is a new variation of the travelling salesman issue in which trucks and drones work together to serve consumers, is to reduce the total delivery distance of vehicles at the origin after the deliveries are complete. A well-known heuristics technique that provides a better solution for the conventional vehicle routing problem is Clarke & Wright's savings algorithm. For the next iteration of the travelling salesman problem, a hybrid approach based on the savings algorithm developed by Clarke and Wright and the genetic algorithm is suggested (Özoğlu et al., 2019). The assigned truck, drone, or both are employed to service the customer in the suggested hybrid algorithm, which combines genetic algorithms with Clarke & Wright's savings algorithms sequentially. The Clarke & Wright savings algorithm improves the genetic algorithms answer, which is a well-known metaheuristic technique. According to the assignment decisions, the problem's goal is to reduce the overall delivery distance. This is the first hybrid strategy that applies genetic algorithms and Clarke & Wright's savings algorithms to the FSTSP problem. The results of the fictitious experiments performed on several occasions support the effectiveness of the strategy and provide some information about this drone delivery system.

(Gu et al., 2019) suggested improved genetic algorithm with adaptive variable neighborhood search (IGA-AVNS) is used to solve the challenging flexible job-shop scheduling problem. The enhanced genetic algorithm initially creates the initial population using a hybrid technique that combines machine assignment (MA) hybrid method selection with operation sequence (OS) random selection. Each group utilizes a better genetic operation for a global search, the best answers from each group are then kept in the elite library and for in-depth local searches, and the elite library employs an adaptive local neighborhood search. Three sets of international standard examples are used to carry out the simulation experiments. The results of the experiments demonstrate how well the IGA-AVNS algorithm works to resolve issues with flexible job-shop scheduling.

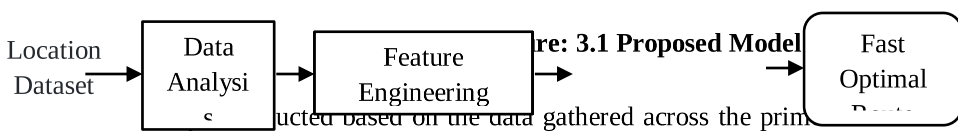
(Ochelska-Mierzejewska et al., 2021) paper explores the use of metaheuristics to the automobile routing problem, paying particular emphasis to genetic algorithms (GAs). The truck routing problem is solved using metaheuristic algorithms, with GA serving as our main implementation. GA is a member of the family of evolutionary algorithms (EAs) that employ a "survival of the fittest" principle. In order to solve the VRP and find the best solutions for complex real-world examples of the problem, this paper proposes the idea of implementing various genetic operators that have been modified for use with the VRP. Experiments are also performed to determine the best combination of genetic operators for solving the VRP. It was discovered that GA can produce good outcomes for extensive examples of the VRP. The GA must be changed or updated to offer competitive solutions for cases based on real-world situations, however they are typically less trivial than those created at random.

The core genetic algorithm for intelligent grouping systems' slow convergence and partial convergence issues are addressed by a proposed improvement to the genetic algorithm. The algorithm can quickly expand the search field by frequently rejecting similar members to ensure the group's stability and variety. As a result, (Wang, 2022) work suggests a novel approach to intelligent grouping that is based on an upgraded genetic algorithm. The new approach is more effective and simple than the old algorithm at solving the issue of early algorithm convergence. Many trials have demonstrated that the suggested algorithm extremely effectively satisfies all of the needs of physical education. The system can automatically create tests with a decent structure and a medium level of difficulty. The effectiveness of the algorithm largely determines the effectiveness of the intelligent volume grouping system. The standard algorithm has a poor success rate, and the system's limitations prevent it from being overly complicated. It also uses a lot of time and space. The success rate and convergence speed of the intelligent volume system will be greatly increased if the upgraded genetic algorithm is used. The improved genetic algorithm allows for large-scale parallel search. The algorithm can also direct the search during the search process to a search space that might hold the best solution.

In (Stenger et. al., 2013) article, we look into a routing issue that occurs during small package delivery's last mile. A variation of the Multi-Origin Vehicle Routing Problem (MDVRP), the issue is known as Multi-Origin Vehicle Routing Problem with Private Fleet and Common Carriers (MDVRPPC), where customers can either be served by the private fleet based at self-owned origins or by common carriers, or subcontractors. Based on the utilization of cyclic-exchange neighborhoods, we create a powerful variable neighborhood search algorithm that includes an adaptive mechanism to bias the random shaking step. With this method, problems like the MDVRPPC and the single-origin VRP with Private fleet and Common carriers (VRPPC) can be solved successfully, yielding high-quality solutions in a reasonable amount of time.

3. Proposed Architecture

The paper proposed a model to find the fast and optimal route for garbage vehicle. Models build to make a short travel between the max locations for collecting the waste which is highly essential.



re: 3.1 Proposed Model

ucted based on the data gathered across the prim Coimbatore city. Majorly e Sulur location (as shown in fig. 3.2) and used the longitude and latitude of the same. Nearly 500 location points gathered, sorted, and used for the research work.

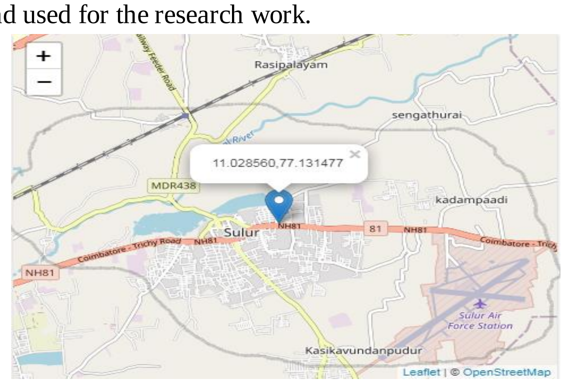


Figure: 3.2 Sulur Locations

3.2. Data Analysis

Explanatory Data analysis made on the dataset gathered to understand about it. Dataset consist of 6 columns and 450 rows (as shown in fig. 3.3). The significance of missing values can be seen in how much about our data we still don't understand. It is typically bad judgment to draw conclusions from a small number of situations.

```
o_id              o2
o_long     77.122854
o_lat      11.024376
d_id              d2
d_long     77.131397
d_lat      11.027841
Name: 1, dtype: object
```

Figure: 3.3. Dataset

```
o_id      0
o_long    0
o_lat     0
d_id      0
d_long    0
d_lat     0
dtype: int64
```

Figure: 3.4. Missing Values

Moreover, many modeling techniques fail when there are missing data, forcing the removal of the relevant rows or the necessity for some form of estimation of the values. Fortunately, there are no missing values in this dataset (as shown in fig. 3.4), which is fantastic.

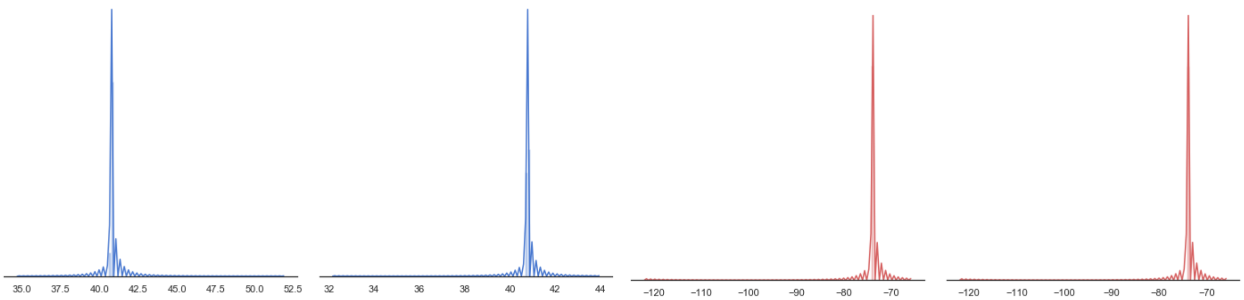


Figure: 3.5 Longitudes and Latitudes

To ensure consistency, examined the geographic or location features. Here, (as shown in fig. 3.5) red represents origin and destination Longitudes & blue represents origin and destination latitudes). It is evident from the plot above that pick and drop latitude are located between 40 and 41, and longitude are between -74 and -73. Because of some extreme coordinates, the map has been compressed, and we can now see a spike. Remove these outliers and pay closer attention to the distribution after doing so.

3.3. Feature Engineering

To improve the performance of the model, add some new features to the dataset. From evident of previous models, have to provide numeric properties only as input to the proposed models. It is now time to begin preparing the data for input into the model, but it is crucial to use the variables first to do some feature engineering process. Here are a few of suggestions for new variables, along with their justifications:

- The difference in latitude between the origin and destination locations will provide information on the distance travelled, which may be predictive.
- Variation in longitude between the origin and destination locations for the same cause
- Haversine distance between the coordinates for origin and destination to measure the actual distance travelled.

From the above discussion Distance feature is more important and has to be included as new features as shown in 3.6. Few set of features created based on distance factors. For identifying the distance 3 different forms applied, Euclidean distance, Haversine Distance and fastest route by road used.

```
o_id                  0
o_long                0
o_lat                 0
d_id                  0
d_long                0
d_lat                 0
dist_sq               0
dist_sqrt             0
haversine_distance    0
direction             0
routes                0
geometry              0
osrm_dur              0
osrm_dist             0
dtype: int64
```

Figure: 3.6 Updated dataset with new features

3.3.1. Euclidean Distance

Despite the fact that we are aware that cars cannot fly, let's calculate the Euclidean distance between the origin and destination locations to obtain a general idea of how far apart they are. The calculation of the separation between two locations on a plane is done using the Euclidean distance formula as in equ 1. In other words, the length of the line segment between two points is what is meant by defining the Euclidean distance between two locations in Euclidean space. A popular measurement of distance is the Euclidean distance. It represents the shortest distance between two points and operates on the Pythagoras theorem's basic premises. The Chinese remainder theorem can be used to find integers that meet much congruence, and the Euclidean algorithm can be used to build continuing fractions and find precise rational approximations to real numbers.

$$d(p,q) = \sqrt{\sum_{i=1}^{n} \quad (q_i - p_i)^2} \text{------- (1)}$$

where p,q is a two points, q_i , p_i is Euclidean vectors, beginning at the space's origin (initial point) and n is n-space.

3.3.2. Haversine Distance

Calculate the distance (in kilometres) between the origin and destination locations. Given two places' longitudes and latitudes, the haversine formula calculates their great-circle separation. Also, it will determine the general angle between the origin and destination locations (Kurnia et. al., 2018). The haversine function is updated to handle arrays because pd.DataFrame.apply() would be too slow. The information about the angle of the line connecting the dropoff and pickup points over the surface of the earth relative to the equator is represented by the haversine direction. Given two places' longitudes and latitudes, the haversine formula calculates their great-circle separation as in equ 2. The latitude and longitude of the two points can be used to calculate the distance between two points on the surface of a sphere using the haversine formula. A diagonal line on a triangle can be measured using the Euclidean heuristic, which is based on direct distance without any barriers. In contrast, the Haversine equation calculates the arc's length between any two latitude and longitude positions. The estimated value/least cost will find the shortest distance traveled according to a heuristic value employed by the Haversine method.

$$a = sin^2\left(\frac{\Delta\emptyset}{2}\right) + cos\ cos\emptyset_1 . cos\ cos\emptyset_2 . sin^2\left(\frac{\Delta\square}{2}\right)$$
$$c = 2.atan2\left(\sqrt{a}, \sqrt{1-a}\right) \qquad \text{----- (2)}$$
$$d = R.c$$

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km);

3.3.3. OSRM Route

In some cases, incorporating outside data is essential for enhancing the model. For each trip in our initial dataset, we will use data that was taken directly from The Open Source Routing Machine, or OSRM, in this section. OSRM is a high-performance routing engine for shortest paths in road networks that is implemented in C++. The OpenStreetMap (OSM) project's open and free road network data are combined with complex routing algorithms. In a network the size of a continent, computing the shortest path can take several seconds if there is no so-called speedup technology used. In contrast to pure route computation, which takes substantially longer, OSRM leverages an implementation of contraction hierarchies to compute and output the shortest path between any origin and destination in just a few milliseconds. The majority of the time is used to annotate the route and send the geometry through the network. OSM data files can be imported with ease because it was created with OpenStreetMap compatibility in mind (Yang, D. et al. 2022). The Karlsruhe University of Technology and earlier Geofabrik are supporting a demonstration installation. From September 2015, the screenshot image has been out of date due to the removal of attendant routing service capabilities. The 2011 Google Summer of Code class included OSRM. This will provide us with highly accurate distance estimation between the pickup and dropoff points.

3.4. Proposed Models

To find the fast and optimal route for garbage vehicle proposed a 3 hybrid methods. From the proposed models EGAAV performance outstanding and suggest the optimal route with low cost and distance for origin and destination.

3.4.1. EGA

An American academic named J.H. Holland proposed the genetic algorithm. A computational model called a genetic algorithm mimics the natural evolution of living things. It is attracting interest due to its benefits, including simplicity, robustness, global search, quick convergence, and the fact that it is not constrained by the search space (Katoch et. al., 2020). The Genetic Algorithm first encodes the problem, then calculates fitness, then chooses the mother and father by random selection, and finally generates the individuals with high fitness by crossover and mutation, which is the satisfactory solution or optimal solution of the problem, after much iteration. To create a new population from an existing one, standard selection, crossover, and mutation operators are utilised. The number of genes on each chromosome equals the number of businesses (Dolgopolov et.. al., 2019). The origin chosen for that enterprise determines each gene's potential worth. The supplies of the enterprises assigned to the same origin are consolidated in order to assess each chromosome. Following this, a vehicle routing problem is addressed for all origins that are assigned to at least two enterprises. The chromosome will be repaired to ensure that each origin already assigned to one enterprise should be assigned to at least another enterprise or it should disappear from that chromosome if a origin only appears once in the chromosome, which means the enterprise assigned to that origin will not collaborate with other enterprises (Dong et. al., 2021). The number of vehicle routing problems to be solved will be enormous since the vehicle routing problem is solved to the same extent as the number of origins for all chromosomes over all iterations of the genetic algorithm. In order to guarantee that the suggested evolutionary algorithm will run quickly, a quick heuristic for the vehicle routing problem is therefore necessary.

3.4.2. EGACW

The Clarke & Wright's Saving algorithm (CWS), first developed by Clarke and Wright in 1964, is an iterative process for creating routes by combining nodes that result in cost savings when compared to a single route for each node (Qian et. al., 2018). It is frequently employed to address the issues of vehicle routing and travelling salesmen.

The cost cij between all pairs of nodes (i,j), including the origin node, is how the Clarke & Wright's Saving algorithm (CWS) operates:

- First, when two nodes I and j are combined into a single route beginning at a origin and returning to it rather than two routes (one route for node I and another for node j), the following cost savings are calculated: Sij =c0i+cj0-cij.
- Next, order the saving values by decreasing value.
- Once all constraints (primarily the vehicle's capacity constraint) have been met, add the pair I j) to one route starting from the highest saving in the saving list. Repeat this method for the following pair until all nodes have been assigned to routes. Create a single route for all nodes that are still unable to be added to any routes.

Here, Genetic algorithm and Clarke & Wright's Saving algorithm combined and proposed as a hybrid model.

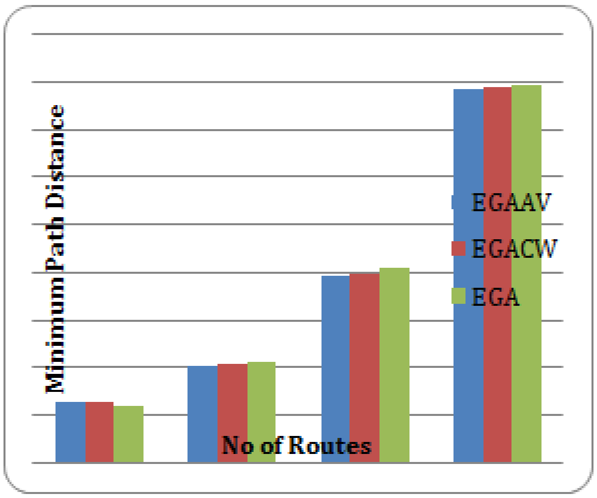
3.4.3. EGAAV

A sort of heuristic algorithm called variable neighborhood search (VNS) relies on the notion of neighborhood change to prevent becoming stuck in local optimums. Owing to its effectiveness and efficiency, it has been used in various fields and has produced great performance. In order to address the issue of supply network reconfiguration-based resilience augmentation, an improved VNS algorithm called AVNS is developed (Gu et. al., 2019). Adaptive search-based solution enhancements includes a local neighbourhood search based on community proximity, a global neighbourhood search, and an adaptive neighbourhood determination scheme in order to effectively and efficiently solve the problem.

Genetic Algorithm with AVNS a hybrid method is proposed (EGAAV). The algorithm does not conduct local search when >b. The variable neighborhood local search algorithm is added when a > b to cause it to depart from the local optimum. The pheromone matrix is reset, the search scope is expanded, and the algorithm's randomness is once more increased when the local search is employed to exit the local optimum. The local search is stopped when ‘a’ to shorten the algorithm's running duration.

4. Result and Analysis

To evaluate the performance of the proposed algorithms routes, path distance and computing time metrics are used here.



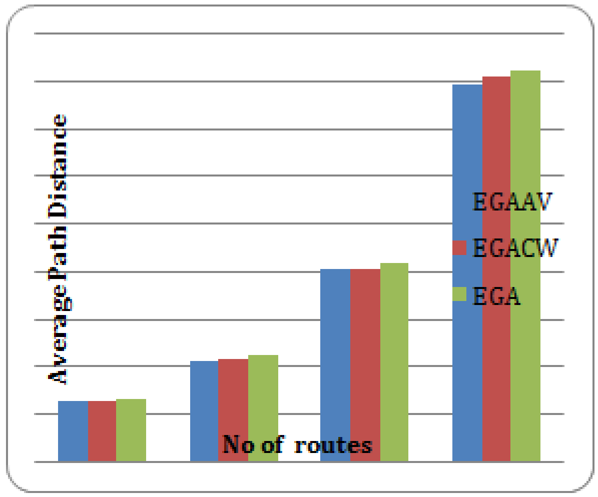
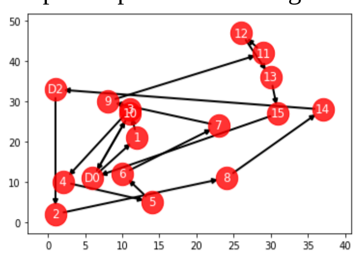
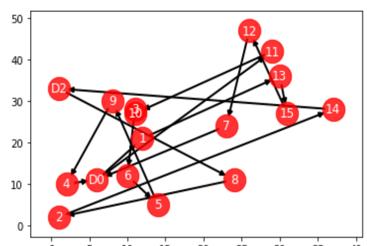


Figure: 4.1 Minimum Path Distance **Figure: 4.2 Average Path Distance**

Fig 4.1 & 4.2 displays the experiment results for proposed algorithms EGA, EGAAV and EGACW for the minimal path distance and average path distance for various routes. EGAAV outperforms well than the other two EGA and EGACW in terms of minimum path distance and average path distance across every case. At max iterations it suggests the optimal path and meeting the entire coordinate route as well.





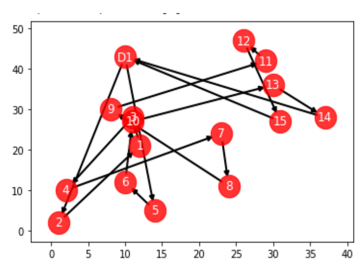
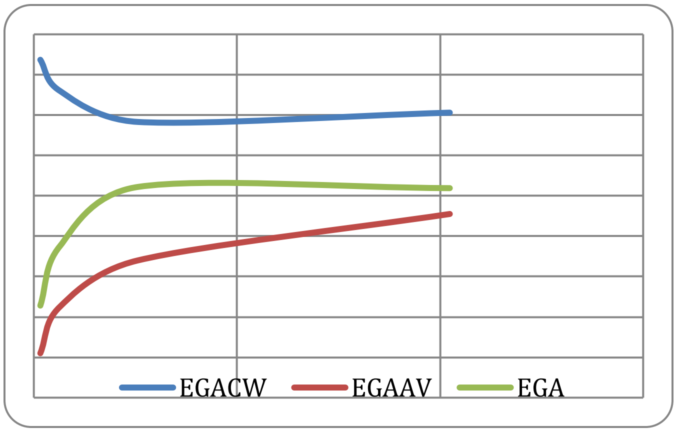


Figure: 4.3 Route of EGACW **Figure: 4.4 Route of EGAAV** **Figure: 4.5 Route of EGA**

Fig 4.3, 4.4, and 4.5 display the routes from origin to destination through the proposed algorithms, from that EGAAV suggested route having less revisit for a single coordinate than the other two proposed algorithms. Max it suggest the shortest and less revisit coordinates.



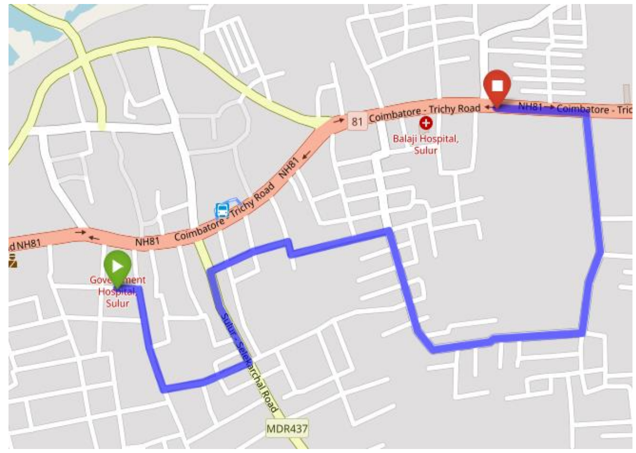


Figure: 4.6 Computing Time **Figure: 4.7 Suggested Route by EGAAV**

From fig 4.6 computing time for routes based on different coordinates EGAAV takes less time compare to other two algorithms. Based on that EGAAV route suggestion displayed using OSRM (as shown in fig. 4.7).

5. Conclusion

SWM is a significant issue in India due to population increase and, in particular, the emergence of megacities. Maximum resource extraction from trash must be linked with secure disposal of remaining garbage through the construction of engineered landfill and waste-to-energy plants to provide sustainable and economically successful waste management. In the case of waste transportation, there need a more concern in constructing the optimal path to pick up the waste. The proposed hybrid approaches for finding the optimal path is suggested, EGA, EGAAV, and EGACW. EGAAV performs well with optimal route suggestions, shortest distance and 0.022 of computing time.

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