JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 , Special Issue, No.-11, May (2024) pp 50-62 ISSN (Print) 0973-8975

EVOLUTIONARY APPROACH: MINIMIZING FUEL CONSUMPTION IN VRP THROUGH NATURE-INSPIRED ALGORITHM

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https://doi.org/10.26782/jmcms.spl.11/2024.05.00004

(Received: March 14, 2024; Revised: April 28, 2024; Accepted: May 15, 2024)

Abstract

Over the past few years, there has been increased awareness about the importance of protecting the environment particularly after global warming came up. The approach proposed here in this paper for reducing fuel consumption is the combination of clustering algorithms' ideas with natural optimization techniques, aimed at efficient route optimization of vehicles. It uses clustering to group customer locations together that in turn allows the development of more efficient routes. The goal of this study is to reduce fuel consumption while optimizing travel plans. This study proposed a nature-inspired algorithm-based model for minimizing fuel consumption in the vehicle routing problem. K-means clustering and the genetic algorithm have been used in this study to find the optimized route with the minimum fuel consumption. It has been observed in this study that routing plans found by the proposed approach consume fewer units of fuel than those generated using optimization techniques which optimize distance covered. This indicates that such an approach could serve as a tool for minimizing fuel consumption in different enterprises.

Keywords: Vehicle routing Problem, Fuel consumption, Genetic Algorithm, K-Means clustering

I. Introduction

The growth of Indian logistics is being propelled by technological advances and a vibrant e-commerce market. According to Shetty et al. [III], it is projected that India's logistics industry will contribute 14.4% of the country's GDP. According to industry standards, now the government of India intends to lower India's supply chain and logistics costs from 13–14% of GDP to 10% of GDP. As studied by Chandra and Jain [XIV], the growth of the social economy is increasingly dependent on logistics. The urban transport system is one of the main causes of environmental pollution and energy consumption particularly because of logistics that City Logistics Delivery seeks to address according to Russo and Comi [IV]. In India, transportation costs account for most of the total logistics costs hence the current average profit margin in the logistics sector stands at 2.5%. According to statistical figures, fuel expenses could make up about half of all operating costs in vehicles, while this ratio might increase with increasing international oil prices. Consequently, reducing fuel use is thought to be a crucial step in protecting the environment, saving energy, and lowering operating expenses for logistics companies as described in the work of Wu and Dunn, [VIII]. Reducing fuel consumption is a crucial component of vehicle routing problem (VRP)optimization due to its impact on the economy and the environment. Since VRP belongs to the NP-Hard problems class, which means the complexity of the problem increases exponentially as its size increases. According to Dantzig and Ramser,[VI] the VRP, undoubtedly, becomes a major issue in distribution, transportation, and logistics. In many industries, transport accounts for a significant part of the value added to goods. Therefore using automated transportation systems usually results in substantial savings amounting to between 5% and 20% of total cost as mentioned by Toth and Vigo, [XV].VRP also known as Vehicle Resource Planning represents the most effective routes through which a group of vehicles can access a widely spread customers' base at minimized costs or maximized productivity. The increasing need for economical and efficient delivery options stresses the importance of optimum VRP systems.

There has been more related research work that took into consideration the fuel consumption in routing from various points of view. Kara et al. [IX] proposed an approach for fuel consumption in VRP using the Cumulative VRP objective function. The Energy-Minimizing VRP and school bus routing are two further uses for the VRP that they have covered. Kuo[XVIII] also developed a simulated annealing (SA) algorithm for VRPTW with minimum total energy consumption. Suzuki, [XX] came up with an approach which minimizes fuel consumption and pollutant emissions.

This implies that advanced methods are required to decrease the fuel consumption (and carbon footprints as well) associated with transportation-related activities while simultaneously increasing route efficiency. Evolutionary procedures have gained popularity recently as effective methods for solving challenging optimization problems such as the VRP mentioned by Garcia Najera[I]. The Genetic Algorithm (GA) is one such algorithm that effectively explores solution spaces and converges on optimal or nearly optimal solutions. A viable way to meet fuel consumption reduction targets and enhance route efficiency and overall logistics performance is by incorporating GA into VRP optimization. In this research, an evolutionary strategy to minimize fuel consumption in the setting of VRP is thoroughly examined, with the main optimization framework being the Genetic Algorithm. GA can be used to generate fuel-efficient routing strategies that can dynamically alter route formations based on factors like traffic conditions, vehicle loading, and delivery precedence. Therefore, while aiming to demonstrate the efficiency of fuel consumption reduction with maximum delivery routes in the VRP domain, we must take a close look at it.

VRPTW fuel consumption has different factors like travel distance, speed, and load. Nonetheless, most researchers did not consider these important issues well when calculating the fuel consumption during the whole journey. In their travelling, drivers normally ignore the speed limits but it plays an important role when we talk about minimum fuel utilization in an effective way. We, therefore, intend to propose an inclusive methodology to measure fuel usage but using a variety of factors such as distance, speed, load and wait time, etc. The task aims to identify the best routes for decreasing the total consumption of fuel while satisfying all the customer orders. These include:

• Depot Constraints: Vehicles go from and return back to the same depot.

• Time window constraints: A vehicle must visit a client within a particular period of time window.

In the present work, a model is proposed that computes the overall fuel consumption given a vehicle routing plan by accounting for loading weight, transportation distance, and speed. In this paper, we introduced a Genetic algorithm with K means clustering proposed approach. The rest of this work is structured as follows: In Section- II we have described the problem and in section-III, a proposed model for the solution is presented. The proposed model can be used to determine the fuel consumption given a vehicle routing strategy. In Section III, a GA approach is also presented for route optimization. An analysis of the experimental results, based on standard benchmark data from an explanatory perspective, is presented in Section IV. Experimental results show how effective this way is in significantly reducing fuel consumption compared to traditional VRP solutions and thus contributing to sustainable logistics practices.

II. Problem Description

The VRP problem is about the optimal route formation of vehicles to serve a set of clients. A priori information concerning customers and depots (e.g., numbers, quantity of demand, geographical data) is known before solving the problem. Assumptions about the serving vehicles to customers are homogeneity and limited capacity. Each vehicle starts from a depot and ends up there. One customer's requirements must be satisfied on each visit of the vehicle at one time. The overall demand for all clients carried in one vehicle(truck) should not be more than its own capacity to carry.

VRP with only one restriction which is vehicle capacity constraint is known as Capacitated Vehicle Routing Problem (CVRP). The same elements that comprise CVRP, i.e., customers with specified demand locations, warehouses with known geographic positions, and a homogeneous fleet with several vehicles that have equal capacities and attributes are also found in VRPTW. What makes VRPTW different from other VRPs is that there exist specific time intervals (TE_i, TL_i) within which services may commence for every customer.

The following restrictions should be satisfied by the vehicles that must achieve the minimum possible overall fuel consumption during delivery: (1) Each vehicle starts from a depot and ends up there at the central depot; (2) every vehicle is supposed to visit one client within a prescribed time window. The vehicle can come earlier than the time the window opens up and wait for its customer until he/she becomes available. However, it should not approach if their time windows are already closed; (3) no vehicle should bear more burden than its own maximum weight limit; (4) Demand of each customer point must be fulfilled and be handled by only one truck.

III. Proposed Approach

Three processes comprise the applicable solution strategies used in our study: clustering, routing, and optimizing. The vehicle capacity restriction is taken into account while grouping the consumers. The grouped consumers are routed based on the time window limitation to provide preliminary workable solutions. GA is used to optimize the solutions, starting with these preliminary ones.

The consumers are separated into feasible clusters during the first population generation phase of GA by employing the K-means clustering method. After that, feasible optimized routes are built for every cluster with the help of GA.

Mathematical Formulation

We have considered the VRP problem in which fuel consumption along the entire route of the trip is to be minimized while serving the customers with their certain demands. To solve this problem here we have constructed a mathematical model which includes an objective function to be minimized along with a set of constraints. Given a set of clients having specified demands. All the clients will be served by one vehicle whose capacity is greater than the total cumulative demands of all the clients. In advance, we have the knowledge of the amount of fuel consumption for each kilometer (Km) without load and the extra quantity of fuel consumption for each Km with unit load. The goal is to route the vehicles so that the overall quantity of energy consumed is reduced and each client should get the service timely.

Let V = {0,1,...,n} be the collection of clients. Let V_c collection of customers without depot i.e. 0. Let q_i, i ∈ V be the demand of node i. Since node 0 refers to the distribution center, Let q_0 = 0. Let Q_i, i ∈ V refers to the load when reached node. Where total load at the Depot $Q_0 = \sum_{i \in K} q_i$. Let F_{ij} be the amount of fuel used for unit distance without load. Let TF_{ij} be the additional fuel consumption for unit distance with unit load. x_{ij} is equal to 1, if vehicle k is traveling from location i to j and x_{ij} is equal to 0, otherwise.

Assume that the vehicle's load at node i is Q_i, i ∈ V. Let $Q_0=\sum_{(i \in K)} q_i$ since the vehicles upload the items of every client at the depot. Let F_{ij} and TF_{ij} represent the fuel used for a unit of distance without a load and the extra fuel used with unit load respectively. When vehicle k is moving from point i to point j, xij equals 1, and when it is not, x_{ij} equals 0.

Then this problem can be formulated as:

$$Min \sum_{j \in V_c} \sum_{i \in V} (F_{ij} + TF_{ij} Q_j) d_{ij} x_{ij} + \sum_{i \in V} F_{ij} d_{i0} x_{i0} \quad (1)$$

$$\sum_{i \in V} x_{ij = \sum_{i \in V} x_{ij} = \sum_{i \in K} x_{ji}} \forall j \in V \quad (2)$$

$$\sum_{i \in V} x_{ij} = 1 \ \forall j \in V \quad (3)$$

$$\sum_{i,j \in U} x_{ij} \leq |U| - 1 \ \forall U \subseteq V_c \quad (4)$$

$$(Q_i - q_i - Q_j) x_{ij} = 0, \forall i \in V, \forall j \in V_c \quad (5)$$

$$t_i + T_{(i,j)}(t_i) \leq TL_j \quad (6)$$

$$w_j + S_j \leq TE_j \quad (7)$$

Equation (2) does not let any client get entered and left at different times, while (3) prevents it from being served by more than one time. Constraints (4) avoid unrelated routes with the depots. Constraints (5) make sure that when $x_{ij}=1$ then vehicular load Q_j between node i and j is equal to the difference between vehicular load Q_i arriving at node i and demand qi unloaded at node i. Equation (6) follows the constraints regarding the time window. Equation (7) confirms that waiting time and unloading time should be less than equal to the start time of the time window for the customer. As every customer point has a particular Time window $[\boldsymbol{TE_i}, \boldsymbol{TL_i}]$ during which the service to that i^th^ customer must be initiated. where TE_i and TL_irefers to the starting and ending time of service time window for i^th^ client. $T_{(i,j)}(t_i)$ refers to the travel time between point i to j.

To minimize overall fuel usage and satisfy restrictions like vehicle capacity and client demand, this mathematical model assigns routes to vehicles in an efficient manner. In the framework of the VRP, solving this model produces effective and fuel-efficient routes for the fleet of vehicles.

Model for estimating fuel consumption

In this work, a model for estimating fuel consumption in the presence of a vehicle routing strategy is proposed. We can think of a vehicle routing path as a list of each customer location. The sequence has several sub-routes too. A sub-route describes a vehicle's movement from a certain depot and via the sub-routes back to another depot. The problem with conventional VRP is trying to find routes for N customers with known demand minimizing the total distance travelled. However, it must be noted that the objective is not always concordant with environmental concerns concerning reducing fuel consumption. Furthermore, delivery expenses are more dependent on the quantity of fuel used, in an economic sense.

According to Chang and Morlok [II] the consignment and vehicle characteristics determine fuel consumption while aspects like road gradient, type of road, traffic volume, speed limit, and length affect fuel use So here we can say that, it is important to include different routes that join nodes when designing a DSD system because transportation distances are major factors of energy consumption. This study considers other roots existing between some specific pairs of nodes and proposes GA for a vehicle routing problem VRP aimed at achieving minimum fuel usage.

As per the 2008 US Department of Energy report, Schipper [X] identified several elements that affect a vehicle's fuel efficiency.

Vehicle Load: By increasing aerodynamic drag and the strain on the engine, carrying additional weight in the vehicle—such as large freight or carriers mounted on the roof—can reduce fuel efficiency.

Transportation speed: Above 60 kilometers per hour (KMH), fuel consumption often rises quickly. In addition, driving on the highway uses less fuel than driving in a city. Use of air conditioning: Air conditioning can lower a vehicle's kilometer per liter (KMPL) by as much as 20%.

Tire inflation: Maintaining the right tire pressure might increase fuel mileage.

As per this fuel efficiency-related report, factors such as loading weight, transportation speed, and distance travelled by a set of vehicles, can significantly impact the overall fuel consumption of the transportation task. Consequently, selecting a highway with a higher travel speed when routing a vehicle may result in greater overall fuel savings than selecting a route with a lower travel speed but a shorter travel distance. Kuo and Wang [XIX] also used this type of simulation problem on Vehicle routing problems. Equation (8) is used to find the fuel consumption, F_{ij}, for vehicles traveling from node i to node j without load, where (dij) is the distance between the nodes.

$$F_{ij} = \frac{d_{ij}}{KMPL_{ij}} \tag{8}$$

Moreover, a vehicle carrying an additional k Kg weight will use s (percentage) more fuel. The actual fuel used by a vehicle moving a load weighing L from customer i to customer j is described by the equation (8).

$$TF_{ij} = F_{ij} + F_{ij}.s.\frac{L}{k} \tag{9}$$

Genetic Algorithm

A genetic algorithm is an optimization technique modelled on natural selection and genetics in which a population has been developed over several generations for potential solutions. Rather than working with the parameters themselves, the Genetic Algorithm codes parameter sets. By Mittal et al.[XVI] the population size, which is a fixed size, is used by the genetic algorithm to solve problems. These chromosomes are often called binary strings which represent possible solutions. An intuitive meta-solution methodology, developed by Holland[VII] and called Genetic Algorithm, is widely used in many areas where the solution population's evolution is simulated. In this methodology, the objective of reaching an optimal solution can be studied starting with a starting population having different numbers of solutions and using different solution methods. Genetic algorithm(GA) works by imitating natural selection, in which the best people in a community are chosen to reproduce to produce the next generation. During the selection process, randomness is introduced as individual fitness is assessed probabilistically based on specified fitness functions. In addition, GA also includes mutation and crossover. In their work, Ibrahim et al.[XI] stated that mutation involves randomly varying the values of certain parameters within a child, while crossover entails randomly combining two individuals to generate one new child. According to Zainuddin, Abd Samad, and Tunggal[V], during the crossover stage of the genetic algorithm, a pair of chromosomes known as parents exchange parts of them resulting in two offspring. This phase can be used to accelerate better solutions attainment.

In their work, Kakkar et al. indicate that in this phase, one offspring is generated for each parent to avoid losing population diversity and being trapped in a local optimum point [XII]. The new generation is formed by selecting either offspring or parents with better resolutions based on their quality. The genetic algorithm stops if either the number of iterations has reached the maximum limit or no more improvements are being made to the solution or an acceptable solution has been obtained. The algorithm works by repeatedly choosing individuals based on their fitness and replacing less fitted ones with children produced via crossover and mutation. This process is for continuously improving solutions using evolutionary principles. Genetic algorithms solve optimization problems in many fields where traditional methods are either impractical or insufficient. In our research, we suggested a genetic algorithm to optimize the route of the vehicle. Fig. 1 depicts the flow chart of GA.

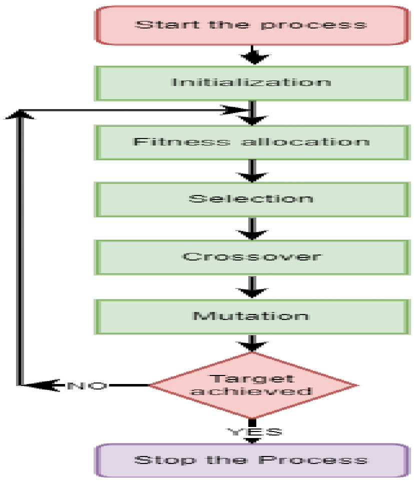

Fig.1 Flow chart of Genetic algorithm

As previously noted, natural selection serves as the inspiration for the operators used by evolutionary algorithms like the Genetic algorithm: reproduction, mutation, recombination, and selection. The genetic algorithm is very adjustable in all aspects; in this study, we concentrate on the selection process. Specifically, we test the use of the following selection techniques.

- roulette-wheel selection;
- tournament selection

In the roulette-wheel selection process, each chromosome (individuals in our population) is assigned a weight, and each weight corresponds to a section of a roulette wheel. Thus, chromosomes with greater fitness will weigh more and occupy a bigger area of the wheel where f_i represents the i^{th} individual's fitness score.
Below are the specifics of the proposed methodology:

a) **Initial solution**

In this work at the very first stage, we have used Shortest Distance Search (SD), which generated the first solution using K-means clustering based on distance data. One unsupervised machine learning technique that divides a given set of data points into clusters (K being the prescribed number) is known as K-means clustering. As presented by Kalpana and Nandhagopal [XVII], it aims to identify underlying patterns or structures in the data by grouping together similar data points. Simply put, it decreases Within- Cluster Sum of Squares (WCSS) or total squared distances between each datum point and its corresponding centroid that represents the cluster mean distance apart from its center. The centroid of a cluster is a location c_k located in P- dimensional space derived by averaging values of all variables over objects belonging to this cluster.Lastly, in an attempt to investigate a novel approach to the traditional technique, we attempt to use the K-Means clustering algorithm to lower the dimensionality of the problem and hope to enhance the genetic procedure's performance. In Fig.2 it can be seen how the clustering approach is working in our proposed method. The steps included in the K-means algorithm are described below:

K-Means Algorithm

```
choose at random the K cluster centers;
 repeat
     for every node(client) do
           calculate the distance for every cluster
           put it in the nearest cluster;
     end
 recalculate the locations of the cluster centers;
 until the end requirements are satisfied;
```

The second approach for generating initial solutions is based on the minimum fuel used search (LF). It generates the initial solution similarly, but the node that has the minimum fuel consumption is chosen to be the next node. Equation (8) can be used to determine the fuel usage between every pair of retail locations.

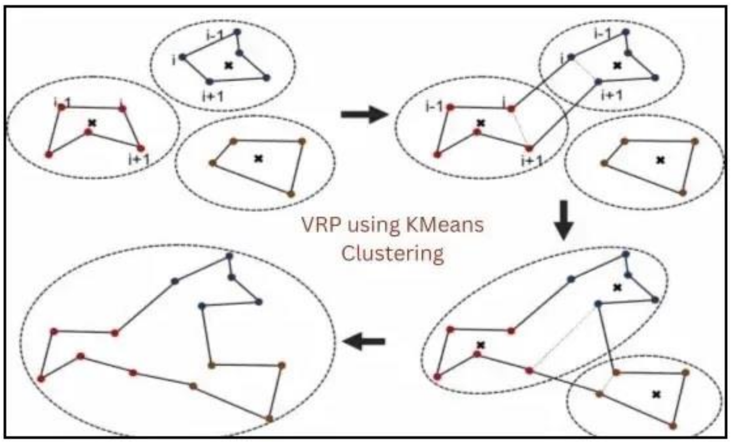

Fig .2 Inter-cluster connection process

b) ***Swapping***
When building a neighbourhood (nbd) solution for a permutation-type issue, the pairwise exchange (or swapping) approach is frequently employed. To find a neighbourhood (nbd) solution, this study exchanges two customers at random. As depicted in Fig. 2 graphically.

c) ***Final solution***
The change will be approved if the optimal option on the list outperforms the existing solution. The Genetic algorithm(GA) will go back to the original solution if a better one cannot be found. It will keep looking until the maximum number of search iterations—the halting criterion—is satisfied. One common technique used to construct a neighbourhood(nbd) solution for a permutation-type problem is the pairwise exchange (or swap) approach.

IV. Experimental Results

Some instances of Solomon's benchmark problems have been used to test our cluster-based algorithm. All the problem instances are composed of 100 customers, one depot, and homogeneous fleets. The customers' and the depots' geographical positions are given in terms of (x,y) coordinates. Their route length is obtained by Euclidean distance whose unit is in distance. It is considered that the time taken to travel 1 unit distance would be 1 unit time.

In grouping C, customers are classified into clusters. In group R, customers are distributed randomly and uniformly. Problems in classes C1 and R1 have short scheduling periods for example small interval periods at the depot window; low vehicle carrying capacity etc., whereas those belonging to classes C2 and R2 have long scheduling horizons including a wide time window for the depot, high vehicle capacities, etc.

The proposed algorithm is written in Python 3.6 computer language. A computer system operating with a processor speed of 3 GHz i5 processor technology with an 8 GB RAM capacity was used to test its implementation. Solomon's Euclidean problem with 100 customers served as a test case for this proposed VRP approach, as Solomon[XIII] proposed a standard benchmark problem for vehicle routing problems. Sets of problems r103, and r107 type have a square with the locations of its clients created consistently and randomly. One hundred customers are distributed evenly throughout a 100-order square matrix.

As we have used the K means clustering technique at the very first stage in the proposed method the Fig 3 shows that as the value of K is increasing in our method sum of square error becomes as small as possible which is a good sign to move further in the proposed approach.

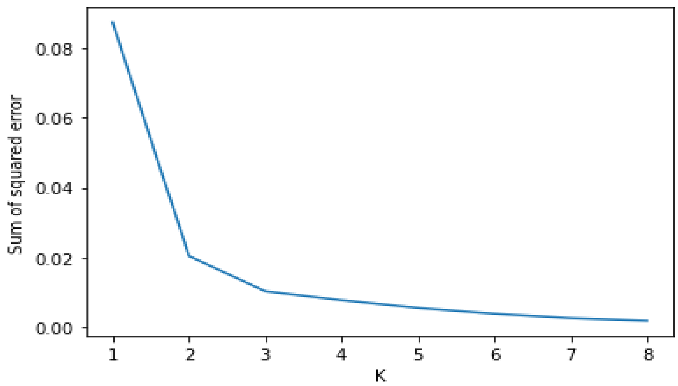

Fig. 3. Plot for the sum of square error vs K in K-Means

Table 1 displays the probability of each edge's affiliation with a certain transportation speed level in the 100-order square matrix. According to the ${}^{n}C_{r}$ combination, there would be 4950 edges in between them. Where n is equal to 100 and r is equal to 2. The depot of the experimental problem is situated in the center of a square matrix. Vehicle loading restrictions are capped at 1,400, and orders for every customer location are scattered between 100 and 200. The findings are displayed in Table -2 with maximum iterations set at 15,000.

Table 1: Experimental data sets

	The ratio of transportation speed levels		
DATA SETS	High(in %)	Medium(in %)	Low(in %)
I	40	35	25
II	20	40	20
III	40	20	40

Table 2: Minimum transportation distance (MTD) vs Minimum fuel consumption (MFC)

Instances	Data Sets	Minimum Transportation Distance (MTD)		Minimum Fuel Consumption (MFC)		TD (In %)	FC (In %)
		TD	FC	TD	FC		
r103	I	1337.03	122.40	1391.89	113.37	-3.94	7.96
	II	1329.11	130.39	1428.76	119.04	-6.97	9.53
	III	1322.02	121.99	1429.16	118.27	-7.49	3.14
	Avg.	**1329.38**	**124.92**	**1416.60**	**116.89**	**-6.13**	**6.87**
r107	I	1132.01	124.23	1146.04	123.58	-1.22	0.50
	II	1128.62	131.48	1168.89	127.61	-3.44	3.03
	III	1124.89	126.09	1179.07	121.35	-4.59	3.90
	Avg.	**1128.50**	**127.25**	**1164.66**	**124.18**	**-3.08**	**2.47**

(FC: Fuel Consumption TD: Transportation Distance Avg.: Average)

It can be observed from Table 2, that the proposed method revealed routing plans for Solomon's instance 'r103' with transportation distance (TD) that were, on average, 6.13% shorter when the least transportation distance criterion was applied. When this proposed strategy optimizes the route, it minimizes the total transportation distance (TD) and results in a 6.87% (approximately) amount of fuel savings. For the instance 'r107' with transportation lengths that were, on average, 3.08% shorter when the minimum transportation distance(MTD) approach was applied. It minimizes the total transportation distance (TD) and results in a 2.47% (average)fuel savings. This analysis exhibited that the route planning identified by the proposed technique consumes less fuel as compared to those identified through traditional optimization techniques reducing transportation distance (TD). This means that if the Depot can supply using low fuel-consuming vehicles and drivers can drive in a manner that reduces carbon emission, this is one way of continuously reducing fuel consumption.

V. Conclusion

The challenge of vehicle routing to reduce fuel consumption between nodes has been addressed in this study using K-means clustering and a genetic algorithm (GA). Nowadays, companies and different organizations instruct their drivers on how to drive in a way that reduces fuel consumption. As far as effective minimum fuel consumption is concerned, drivers should obey the speed limits which should be an important part of the routing policy of any organisation.

The purpose of this study was to discuss the approach that is useful in minimizing the fuel consumption of delivery vehicles by providing an effective vehicle route planning solution for VRPTW. According to the findings of the experiment, the policies recommended by the proposed approach consume less fuel than the traditional VRPTW solution and it is also advantageous for environmental-friendly economies. This concludes that if the distribution centers can use economic vehicles and drivers can adopt a driving style to lower carbon emissions, it will be one way of reducing fuel usage continuously.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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