

Capacitated, Optimal, Guided Vehicle Routing With Geo-Fencing

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Abstract: As the problem definition is mainly related to truck which is filled to its capacity in an optimal way the word capacitated is used. The main criteria of the problem is to deliver the goods ordered by multiple clients to them so that the distance covered in delivering those goods to the clients is minimal along with the vehicle or truck tracking facility using geo-fencing on a Google map in an android device hence the word optimal. Our program will display the map using Google map API's hence the word guided. The location of driver is noted using the GPS tracker of his mobile, the location of driver is constantly monitored to check if the truck is deviating from the assigned path, as we are virtually defining a boundary the word geo-fencing.

Keywords: capacitated, optimal, guided vehicle routing, geo- fencing.

1. INTRODUCTION

This is one of the most challenging combinatorial optimization tasks. Defined more than 40 years ago, this problem consists in designing the optimal set of routes for fleet of vehicles in order to serve a given set of customers. The interest in VRP is motivated by its practical relevance as well as by its considerable difficulty.

Sweep Algorithm is used in solving the Vehicle Routing Problem for public transport .The Sweep Algorithm is firstly introduced as a method to search shortest route in the Vehicle Routing Problem. In order to evaluate the result of the algorithm, current routes profile of a public transport is presented. An application is constructed based on the algorithm and tested using current routes data. The route generation is performed repeatedly using different constraints in order to obtain the optimal solution. A route is selected based on shortest time taken. Each constraint affects the route selection to gain different combination of routes. Optimal time and cost are not considered to select the best combination of routes.

Two methods in sweep algorithm were available out of which the more optimal one was implemented. The result shows that Sweep Algorithm is capable of solving vehicle routing problem for public transport under certain constraints. Geo-fence program allows an administrator to set up triggers so when a device crosses a geo-fence and enters (or exits) the boundaries defined by the administrator. A DB record is entered which the admin can check. The nearest neighbor algorithm was one of the first algorithms used to determine a solution to the problem. The salesman starts from the Godown and repeatedly visits the nearest city until all have been visited. It quickly yields a short tour, but usually not the optimal one.

Sweep algorithm, which has been implemented to choose the list of customer based on their location, has been tested and is working without any flaw. Geo-fencing, to track whether the driver is deviating from the path is working properly. Taking into account all the features map is successfully displayed on the driver's android device.

Existing system:

There are various enterprises which make use of the real time routing techniques to deliver the commodities to their clients. We can take the example of Flipkart, FedEx etc. However, the current techniques used by companies mentioned above are just concepts and techniques that just finds the shortest route using *TSP algorithms* which is explained below.

- *Nearest Neighbour or proximity search approach.*

However this system can be further optimized by making use of available Google API's and thus can be made mobile.

Proposed system:

Our system Employs the existing methodology and also optimizes the allocation of goods to clients and also finding the shortest path using the following methodologies:

- **Sweep Algorithm:** Considering the scenario in which a group of clients have to be provided with a service, this algorithm determines and categorizes these clients based on the desired conditions specified.
- **Geo Fencing:** Also known as Soft bound fencing. It gives alert to the owner if the truck driver violates by crossing borders.

2. LITERATURE SURVEY

Introduction:

The vehicle routing problem (VRP) is a combinatorial optimization and integer programming problem seeking to service a number of customers with a fleet of vehicles. Proposed by *Dantzig* and *Ramserin* 1959, VRP is an important problem in the fields of transportation, distribution, and logistics.

Description:

In the 1980s, a small group of transportation professionals recognized the impact that the Computing and communications revolutions of the Information Age could have on surface transportation. The idea of Vehicle Routing Problem originally intelligent vehicle-highway systems was born.

Vehicle Routing Problem harnesses new technology to improve the safety, efficiency, and convenience of surface transportation, both for people and for goods.

A glance at the state of transportation today—roads equipped with electronic tolling and variable message signs, passenger vehicles with navigation products and emergency notification systems, commercial vehicles equipped for non-stop weighing and cross border credentials checking, transit vehicles containing location and communications systems, infrastructure to automatically track and support the better management of traffic flow—confirms that Vehicle Routing Problem is gaining widespread acceptance within the transportation community and by the general public. At one level, Vehicle Routing Problem has been made possible by overall technological trends of the late 20th century, including ever-less-expensive and increasingly widespread computing power and communications technology. This new technology has enabled Vehicle Routing Problem products and services to become more sophisticated, v reliable and affordable over a relatively short period of time. However, an exploration of the evolution of Vehicle Routing Problem makes it clear that technology is only half the story. The success of Vehicle Routing Problem has also required careful attention to institutional and social concerns and to finding new ways of doing business. Notable among these is the focus in Vehicle Routing Problem on public-private cooperation, the linchpin of Vehicle Routing Problem since its inception. Vehicle Routing Problem associate information and communication technologies (ICT) to vehicles and their infrastructures and it improves Composite filter bank for road sign recognition the safety, reliability, efficiency and quality of transport systems. The new technologies allow performing communications between vehicles (V2V - Vehicle to Vehicle), between vehicles and static locations (V2I - Vehicle to Infrastructure).

Vehicle Routing Problem is not restricted to road transport. They include ICT for rail, water, and air transport. Modern automotive systems are the pioneer systems where the Vehicle Routing Problem concept is introduced.

Many big projects related to automotive Vehicle Routing Problem are underway around the world, some of them are, use of Short-Range communications, which provide communication between vehicle and infrastructure, use of wireless networks in Vehicle Routing Problem and Road transport and Traffic Telematics to provide system of systems network connectivity, use of facial recognition to change radio station in car, use of dynamic road information to improve driving safety and efficiency.

For years, government and industry have been raising public awareness and acceptance of Vehicle Routing Problem. Today, with more products available than ever before, Vehicle Routing Problem is becoming a common feature of surface transportation. As product development and diffusion continue, Vehicle Routing Problem applications are becoming part

of the basic fabric of transportation, not separate considerations. However, many obstacles must be overcome before the long-run viability of Vehicle Routing Problem can be assumed.

The benefits and operation of Vehicle Routing Problem products must be clear to consumers, and their costs must be justified against a wide array of competing automotive and consumer electronic products available on the market. Similarly, roadway-based Vehicle Routing Problem applications must provide clear advantages over other possible improvements to the transportation infrastructure. Reliability, ease of use, and affordability are all crucial ingredients to the future success of the industry. Some of the most difficult issues will continue to surround the allocation of scarce public and private dollars, legitimate differing viewpoints on the role and consequences of transportation, and the difficulty of effectively merging steel and Asphalt with integrated circuits and wireless communications.

The Vehicle Routing Problem (VRP) is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or several depots must be determined for a number of geographically dispersed cities or customers. The objective of the VRP is to deliver a set of customers with known demands on minimum cost vehicle routes originating and terminating at a depot. In the two figures below we can see a picture of a typical input for a VRP problem and one of its possible outputs:

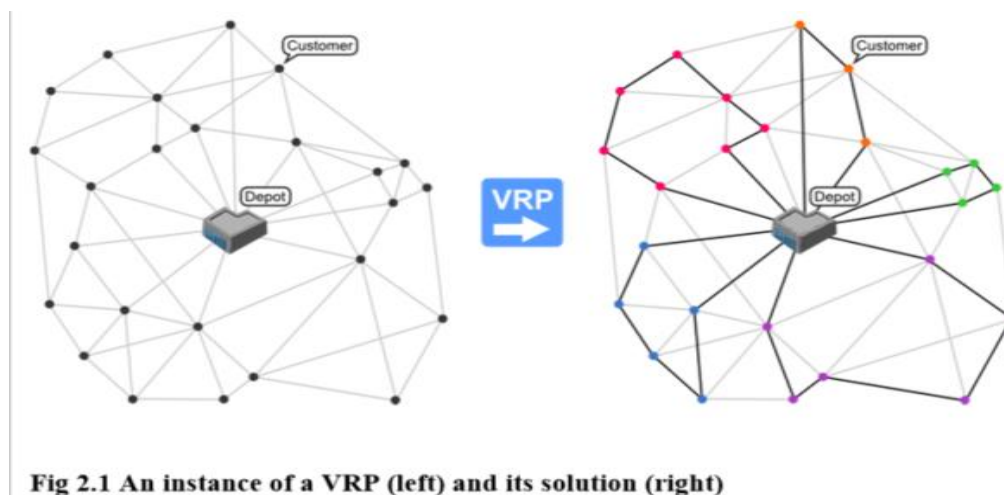


Fig 2.1 An instance of a VRP (left) and its solution (right)

Formulation:

The VRP is a combinatorial problem whose ground set is the edges of a graph $G(V, E)$. The notation used for this problem is as follows:

- $V = \{v_0, v_1, \dots, v_n\}$ is a vertex set, where: Consider a depot to be located at v_0 .
- Let $V' = V \setminus \{v_0\}$ be used as the set of n cities.
- $A = \{(v_i, v_j) \mid v_i, v_j \in V; i \neq j\}$ is an arc set.
- C is a matrix of non-negative costs or distances c_{ij} between customers v_i and v_j .
- d is a vector of the customer demands.
- R_i is the route for vehicle i .
- m is the number of vehicles (all identical). One route is assigned to each vehicle.

When $c_{ij} = c_{ji}$ for all $(v_i, v_j) \in A$ the problem is said to be symmetric and it is then common to replace A with the edge set $E = \{(v_i, v_j) \mid v_i, v_j \in V; i < j\}$.

With each vertex v_i in V' is associated a quantity q_i of some goods to be delivered by a vehicle. The VRP thus consists of determining a set of m vehicle routes of minimal total cost, starting and ending at a depot, such that every vertex in V' is visited exactly once by one vehicle.

For easy computation, it can be defined $b(V) = \lceil \sum_{v_i \in V} d_i / C \rceil$, an obvious lower bound on the number of trucks needed to service the customers in set V .

We will consider a service time δ_i (time needed to unload all goods), required by a vehicle to unload the quantity q_i at v_i . It is required that the total duration of any vehicle route (travel plus service times) may not surpass a given bound D , so, in this context the cost c_{ij} is taken to be the travel time between the cities. The VRP defined above is NP-hard.

A feasible solution is composed of:

- a partition R_1, \dots, R_m of V ;
- a permutation σ_i of $R_i \cup 0$ specifying the order of the customers on route i .

The **cost of a given route** ($R_i = \{v_0, v_1, \dots, v_{m+1}\}$), where $v_i \in V$ and $v_0 = v_{m+1} = 0$ (0 denotes the depot), is given by $C(R_i) = \sum_{m_i=0}^{m_i=i+1} c_{i,i+1} + \sum_{m_i=1}^{m_i=i} \delta_i$.

A route R_i is feasible if the vehicle stop exactly once in each customer and the total duration of the route does not exceed a prespecified bound D : $C(R_i) \leq D$.

Finally, the **cost of the problem solution** S is: $FVRP = \sum_{m_i=1}^m F(R_i)$.

3. SOLUTION METHODS

The most commonly used techniques for solving Vehicle Routing Problems are listed. Near all of them are heuristics and metaheuristics because no exact algorithm can be guaranteed to find optimal tours within reasonable computing time when the number of cities is large. This is due to the NP-Hardness of the problem.

Branch and Bound:

One of the most successful exact approaches for the CVRP is the K-tree method of Fisher that succeeded in solving a problem with 71 customers. However, there are smaller instances that have not been exactly solved yet. To treat larger instances, or to compute solutions faster, heuristic methods must be used. It uses a novel Branch and Bound procedure in which the problem is partitioned by fixing the edge incidence of selected subsets of clustered customers. The side constraints are dualized to obtain a Lagrangian relaxation that is a minimum degree-constrained K-tree problem.

The K-tree approach can be extended to accommodate realistic variations, such as asymmetric costs, time windows, and non-uniform fleets.

A branch and bound algorithm uses a divide and conquer strategy to partition the solution space into sub problems and then optimizes individually over each sub problem. Using branch and bound, we initially examine the entire solution space S . In the processing or bounding phase, we relax the problem. In so doing, we admit solutions that are not in the feasible set S . Solving this relaxation yields a lower bound on the value of an optimal solution. If the solution to this relaxation is a member of S or has cost equal to that of s^* (where $s^* \in S$), then we are done – either the new solution or s^* , respectively, is optimal.

Otherwise, we identify n subsets S_1, \dots, S_n of S , such that $\bigcup_{i=1}^n S_i = S$. Each of these subsets is called a sub problem; S_1, \dots, S_n are sometimes called the children of S . We add the children of S to the list of candidate sub problems (those which await processing). This is called branching. To continue the algorithm, we select one of the candidate sub problems and process it. There are four possible results:

- If we find a feasible solution better than s^* , then we replace s^* with the new solution and continue.
- We may also find that the sub problem has no solutions, in which case we discard (prune) it.
- Otherwise, we compare the lower bound for the sub problem to our global upper bound, given by the value of the best feasible solution encountered thus far. If it is greater than or equal to our current upper bound, then we may again prune the sub problem.
- Finally, if we cannot prune the sub problem, we are forced to branch and add the children of this sub problem to the list of active candidates. We continue in this way until the list of candidate sub problems is empty, at which point our current best solution is, in fact, optimal.

Savings Algorithm:

The *Clarke* and *Wright* savings algorithm is one of the most known heuristic for VRP. It was developed on and it applies to problems for which the number of vehicles is not fixed (it is a decision variable), and it works equally well for both

directed and undirected problems. When two routes $(0, \dots, i, 0)$ and $(0, j, \dots, 0)$ can feasibly be merged into a single route $(0, \dots, i, j, \dots, 0)$, a distance saving $s_{ij} = c_{i0} + c_{0j} - c_{ij}$ is generated. The algorithm works as follows (the first step is equal in both parallel and sequential versions):

Step 1. Savings computation

- Compute the savings $s_{ij} = c_{i0} + c_{0j} - c_{ij}$ for $i, j = 1, \dots, n$ and $i \neq j$.
- Create n vehicle routes $(0, i, 0)$ for $i = 1, \dots, n$.
- Order the savings in a non-increasing fashion.

Step 2. Best feasible merge (Parallel version)

Starting from the top of the savings list, execute the following:

Given a saving s_{ij} , determine whether there exist two routes that can feasibly be merged:

- One starting with $(0, j)$
- One ending with $(i, 0)$
- Combine these two routes by deleting $(0, j)$ and $(i, 0)$ and introducing (i, j) .

Step 3. Route Extension (Sequential version)

- Consider in turn each route $(0, i, \dots, j, 0)$.
- Determine the first saving s_{ki} or s_{jl} that can feasibly be used to merge the current route with another route ending with $(k, 0)$ or starting with $(0, l)$.
- Implement the merge and repeat this operation to the current route.
- If not feasible merge exists, consider the next route and reapply the same operations.
- Stop when not route merge is feasible.

Ants Algorithm:

After initializing the Ant System, the two basic steps construction of vehicle routes and trail update, are repeated for a number of iterations. Concerning the initial placement of the artificial ants it was found that the number of ants should be equal at each customer at the beginning of iteration. The 2-opt-heuristic (it is an exhaustive exploration of all the permutations obtainable by exchanging 2 cities) is used to shorten the vehicle routes generated by the artificial ants, considerably improves the solution quality. In addition to this straight forward local search we also introduce candidate lists for the selection of customers which are determined in the initialization phase of the algorithm. For each location d_{ij} we sort $V - \{v_i\}$ according to increasing distances d_{ij} to obtain the candidate list. The proposed AS for the CVRP can be described by the following schematic algorithm:

1. Initialize

2. For $Imax$ iterations do:

- For all ants generate a new solution using Formula 1 and the candidate lists
- Improve all vehicle routes using the two-opt-heuristic
- Update the pheromone trails using Formula 2

Construction of Vehicle Routes:

To solve the VRP, the artificial ants construct solutions by successively choosing cities to visit, until each city has been visited. Whenever the choice of another city would lead to an unfeasible solution for reasons of vehicle capacity or total route length, the depot is chosen and a new tour is started. For the selection of a (not yet visited) city, two aspects are taken into account: how good was the choice of that city, an information that is stored in the pheromone trails τ_{ij} is associated with each arc (v_i, v_j) , and how promising is the choice of that city. This latter measure of desirability, called visibility and denoted by η_{ij} , is the local heuristic function mentioned above.

With $\Omega = \{v_j \in V: v_j \text{ is feasible to be visited}\} \cup \{v_0\}$, city v_j is selected to be visited as follows:

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{k \in \Omega} [\tau_{ik}]^\alpha [\eta_{ik}]^\beta} & \text{if } v_j \in \Omega \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This probability distribution is biased by the parameters α and β that determine the relative influence of the trails and the visibility, respectively. The visibility is defined as the reciprocal of the distance, and the selection probability is then further extended by problem specific information. There, the inclusion of savings and capacity utilization both lead to better results. On the other hand, the latter is relative costly in terms of computation time (as it has to be calculated in each step of an iteration) and will therefore not be used in this paper. Thus, we introduce the parameters f and g , and use the following parametrical saving function for the visibility: $\eta_{ij} = d_{i0} + d_{0j} - g_{dij} + f|d_{i0} - d_{0j}|$.

Trail Update:

After an artificial ant has constructed a feasible solution, the pheromone trails are laid depending on the objective value of the solution. This update rule is as follows:

$$\tau_{newij} = \rho \tau_{oldij} + \sum_{\mu} \mu = 1 - \sigma - 1 \Delta \tau_{\mu ij} + \sigma \Delta \tau^*_{ij} \quad (2)$$

where ρ is the trail persistence (with $0 \leq \rho \leq 1$), thus the trail evaporation is given by $(1 - \rho)$. Only if arc (v_i, v_j) was used by the μ -th best ant, the pheromone trail is increased by a quantity $\Delta \tau_{\mu ij}$ which is then equal to $(\sigma - \mu) / L_{\mu}$, and zero otherwise (cf. second term in 2). In addition to that, all arcs belonging to the so far best solution (objective value L^*) are emphasized as if σ elitist ants had used them. Thus, each elitist ant increases the trail intensity by an amount $\Delta \tau^*_{ij}$ that is equal to $1 / L^*$ if arc (v_i, v_j) belongs to the so far best solution, and zero otherwise (cf. third term in 2).

Genetics Algorithm:

Genetic Algorithms are very likely to be the most widely known type of Metaheuristic Algorithms, today receiving remarkable attention all over the world. Genetic Algorithms are computer procedures that employ the mechanics of natural selection and natural genetics to evolve solutions to problems. The basic concepts were developed by [Holland 1975], while the practicality of using the GA to solve complex problems was demonstrated in [De Jong 1975] and [Goldberg 1989]. GA evolves a population of individuals encoded as chromosomes by creating new generations of offspring through an iterative process until some convergence criteria are met. Such criteria might, for instance, refer to a maximum number of generations, the convergence to a homogeneous population composed of similar individuals, or getting an optimal solution. The best chromosome generated is then decoded, providing the corresponding solution.

Genetic algorithms work with a population of candidate solutions instead of just a single solution, so they make a multiple way search simultaneously. Each individual represents a potential solution for the problem. In the original GAs of Holland each solution may be represented as a string of bits, where the interpretation of the meaning of the string is problem specific.

The creation of a new generation of individuals involves three major steps or phases:

- The **selection** phase consists of randomly choosing two parent individuals from the population for mating purposes. The probability of selecting a population member is generally proportional to its fitness in order to emphasize genetic quality while maintaining genetic diversity. Here, fitness refers to a measure of profit, utility or goodness to be maximized while exploring the solution space.
- The **recombination** or **reproduction** process makes use of genes of selected parents to produce offspring that will form the next generation.
- The **mutation** consists of randomly modifying some gene(s) of a single individual at a time to further explore the solution space and ensure, or preserve, genetic diversity. The occurrence of mutation is generally associated with a low probability.

A new generation is created by repeating the selection, reproduction and mutation processes until all chromosomes in the new population replace those from the old one. A proper balance between genetic quality and diversity is therefore required within the population in order to support efficient search. In the figure below we can see the pseudo code of a simple GA.

Algorithm 1 Pseudocode for a Genetic Algorithm

```

1:  $t \leftarrow 0$ ;
2: InitPopulation[ $P(t)$ ]; {Initializes the population}
3: EvalPopulation[ $P(t)$ ]; {Evaluates the population}
4: while not termination do
5:    $P'(t) \leftarrow$  Variation[ $P(t)$ ]; {Creation of new solutions}
6:   EvalPopulation[ $P'(t)$ ]; {Evaluates the new solutions}
7:    $P(t+1) \leftarrow$  ApplyGeneticOperators[ $P'(t) \cup Q$ ]; {Next generation pop.}
8:    $t \leftarrow t + 1$ ;
9: end while

```

Fig 2.2 Pseudo code of a Genetic Algorithm

For solving VRP with GAs, it is usual to represent each individual by just one chromosome, which is a chain of integers, each of them representing a customer or a vehicle. So that each vehicle identifier represents in the chromosome a separator between two different routes and a string of customer identifiers represents the sequence of deliveries that must cover a vehicle during its route. In the figure below we can see a representation of a possible solution for VRP with 10 customers and 4 vehicles. Each route begins and ends at the depot (it will be assigned the number 0). If we find in a solution two vehicle identifiers not separated by any customer identifier, we will understand that the route is empty and, therefore, it will not be necessary to use all the vehicles available.

A typical fitness function used for solving VRP with GA is $f_{eval}(x) = f_{max} - f(x)$,

Where $f(x) = \text{total distance}(x) + \lambda \text{ over capacity}(x) + \mu \text{ over time}(x)$.

Both overcapacity and overtime functions return the amount of capacity and time over the maximum allowed value. If none of the function restriction are violated, f returns the total distance traveled. In other case both capacity and time are weighted with values λ and μ . The best solutions may have values close to f_{max} , while the solutions that break any restriction will see penalized their fitness value.

4. APPLICATIONS

Numerous E-Commerce Companies have encountered Vehicle Routing problem during the transfer of goods, so this application is used in loading of goods to Ships/Trucks etc...

- **Freight Transport:** Freight transport is the physical process of transporting commodities & merchandise goods and cargo.
- **Ground:** Land or "ground" shipping can be by train or by truck. In air and sea shipments, ground transport is required to take the cargo from its place of origin to the airport or seaport and then to its destination because it is not always possible to establish a production facility near ports due to limited coastlines of countries. Ground transport is typically more affordable than air, but more expensive than sea especially in developing countries like India, where inland infrastructure is not efficient.

Shipment of cargo by trucks, directly from the shipper's place to the destination, is known as a door to door shipment and more formally as multimodal transport. Trucks and trains make deliveries to sea and air ports where cargo is moved in bulk.

- **Ship:** Much shipping is done aboard actual ships. An individual nation's fleet and the people that crew it are referred to as its merchant navy or merchant marine. Merchant shipping is like lifeblood to the world economy, carrying 90% of international trade with 102,194 commercial ships worldwide. On rivers and canals, barges are often used to carry bulk cargo.
- **Air:** Cargo is transported by air in specialized cargo aircraft and in the luggage compartments of passenger aircraft. Air freight is typically the fastest mode for long distance freight transport, but also the most expensive.
- **Intermodal:** Intermodal freight transport refers to shipments that involve more than one mode. More specifically it usually refers to the use of intermodal shipping containers that are easily transferred between ship, rail and truck.

E-Commerce:

Electronic commerce, commonly known as e-commerce, is a type of industry where buying and selling of product or service is conducted over electronic systems such as the Internet and other computer networks. Electronic commerce draws on technologies such as commerce, electronic, supply chain management, Internet marketing, online transaction processing, *electronic data interchange*(EDI), inventory management systems, and automated data collection systems. Modern electronic commerce typically uses the World Wide Web at least at one point in the transaction's life-cycle, although it may encompass a wider range of technologies such as e-mail, mobile devices social media, and telephones as well.

Electronic commerce is generally considered to be the sales aspect of e-business. It also consists of the exchange of data to facilitate the financing and payment aspects of business transactions. This is an effective and efficient way of communicating within an organization and one of the most effective and useful ways of conducting business.

Different Online Shopping Companies like Flipkart, Amazon, Home Shop 18, Myntra, Jabong, and E-Bay can rely on our application for transferring the goods to their customers in an efficient way

5. CONCLUSION

The overall objective of the proposed work and its implementation has given satisfactory results based on our output. We can simply infer from the methods and implementations we have done that E-commerce and similar industries can greatly benefit from our implementation as it can be installed in android devices and thus is independent of what kind of vehicle is used. Also most of the E-commerce companies provide home delivery system which can make use of our solution for the vehicle. Also our system takes less time as there is no computation on client side making it more efficient for the user in terms of time.

6. FUTURE ENHANCEMENTS

This implementation can be further upgraded to:

- Find out the gesture position of the client or the user.
- Whether the truck driver is sleeping or in what state the driver is at any point of time.
- Whether the truck is in halt or it is moving and at what speed.
- More optimized way of finding the shortest route.

REFERENCES

- [1] <http://www.androidhive.info/2012/05/how-to-connect-android-with-php-mysql/>
- [2] <http://www.androidhive.info/2012/01/android-json-parsing-tutorial/>
- [3] <http://developer.android.com/sdk/index.html>
- [4] <https://developers.google.com/maps/documentation/javascript/tutorial>
- [5] <https://developers.google.com/maps/documentation/android/>
- [6] <http://developer.android.com/training/index.html>
- [7] <https://developer.android.com/training/location/index.html>
- [8] <https://developers.google.com/places/training/basic-place-search>
- [9] http://link.springer.com/chapter/10.1007/978-1-4471-4628-5_11#page-1
- [10] <http://neo.lcc.uma.es/vrp/vehicle-routing-problem/>
- [11] <http://onlinepubs.trb.org/onlinepubs/millennium/00058.pdf>
- [12] <http://www.w3schools.com/googleAPI/default.asp>
- [13] <http://www.vogella.com/articles/AndroidGoogleMaps/article.html>