Route Optimization using Modern Optimization Techniques

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1 Abstract:

The vehicle route optimization is a process to determine the highly cost-efficient route. It needs the inclusion of all the relevant factors like the location and the number of all required stops upon a route and time windows mainly for the deliveries. The main problem being addressed in this assessment was the vehicle route optimization with the utilization of the modern optimization methods and techniques. The vehicle route optimization is aimed towards finding the shortest route for the vehicle to reach from one destination to another or minimizing the travel distance between 2 desired locations. Ensuring reduction of the utilization of fuel and cost, minimizing time, and maximizing the overall performance are the main objectives of route optimization. According to the findings from the fitness graph, none of the mutation rates do seem to make the big difference particularly in finding the better solutions. It could mean that the algorithm has a hard time making solutions better all the time, possibly because the mutation rates are too high.

The higher rates might make things too random and mess up good solutions. So, using lower mutation rates might actually give us better solutions. Furthermore, near optimality mainly is attainable and feasible with the spreadsheet models and tools for solving the real-life problems.

2 Introduction:

The route optimization generally is regarded as a process to determine the highly cost-efficient route. It is considered to be more complex as compared to simply finding a shortest path among two points. This requires the inclusion of all the relevant factors like the location and the number of all required stops upon a route and time windows mainly for the deliveries (verizonconnect, 2024). The route optimization does continue to evolve mainly with the advancements in the technology and the rise in the use of modern optimization techniques (Guo et al., 2018). Some of the emerging technologies particularly are poised towards transforming this field with Internet of (IoT) Things with applications such as IoT sensors in vehicles are providing the real-time data about road conditions, the traffic situation and the vehicle health, which are enhancing the accuracy of route optimization (Chiang et al., 2019).

The main problem being addressed in this research is the route optimization with the utilization of the modern optimization methods and techniques. This secondary research looks at the different ways through which vehicle route optimization is done effectively with addressing of the routing challenges complexities through enhancing and substituting the traditional methods mainly with the modern optimization techniques as well as the crossroads fields like logistics, transportation, management of supply chain and the operations research for solving the routing problems (Wang et al., 2020).

3 Problem Domain:

Vehicle routing optimization is a process of organizing the routes for vehicles in a strategic method to complete various tasks and deliveries. The main purpose of Vehicle routing optimization is to minimize the cost and time of travel and optimize resource usage by identifying the best routes according to several elements such as the capacity of the vehicle, delivery locations, traffic situations, and customer requirements (Google, 2023). In this era of a rapidly evolving environment, businesses all over the world are encountering challenges in improving their vehicle management to reduce cost, minimize ecological footprint, and overall performance. This report addresses the complexities of routing challenges by enhancing or substituting traditional methods with modern optimization techniques, and crossroads fields such as logistics, transportation, supply chain management, and operations research to solve routing problems.

The core of route optimization is based on formulating strategies to manage dynamic and evolving environments where various elements such as traffic jams, different customer demands, vehicle capacities, and delivery limitations are vastly impacting routing decisions (Praveen et al., 2022). Traditional methods for vehicle routing use heuristic algorithms or manual planning Which have limited abilities to adapt to real-time changes and optimize routes efficiently. Nevertheless, using modern optimization techniques such as genetic algorithms, simulated annealing, ant swarm optimization, and machine learning-based methods are more efficient ways to solve routing problems and generate optimized routes (Ali Aghadavoudi Jolfaei et al., 2023).

Modern optimization techniques create more opportunities to solve complicated optimization objectives such as reducing travel distance, optimizing vehicle usage, managing the distribution of workload, and considering time frames and delivery preferences (Douglas, 2022). These techniques exploit advanced mathematical models and computational algorithms to navigate extensive solution spaces, identify optimal or near-optimal solutions, and manage routes according to real-time data and feedback. To summarize vehicle routing by modern optimization techniques offers vast and challenging opportunities for both practical application and research (Douglas, 2022). Businesses can obtain significant benefits, minimize costs, and strategic benefits in vehicle management and logistics operations by exploiting advanced optimization algorithms and adapting to advanced technologies.

4 Problem Specification:

Vehicle route optimization aims for the shortest route for the vehicle to reach from one destination to another and encompasses an essential but crucial element for routing optimization (Lähdeaho and Hilmola, 2024). Minimizing the travel distance between 2 desired locations, reducing the utilization of fuel and cost, minimizing time, and maximizing the overall performance are the main objectives of route optimization. The primary objective is to identify the route with the least distance between the two travel points, by using the optimized routes organization can obtain several significant benefits such as cost savings in fuel usage and vehicle maintenance alongside minimizing the ecological footprint by reducing carbon emissions (Lähdeaho and Hilmola, 2024).

The data being used in this report is taken from Kaggle, which contains the distance between some major Indian cities. The author has collected that data from Google Maps by using real-time shortest distance, during data collection, the author has rounded decimal values to discrete numbers (Kaggle, 2024). The data contains 3 columns which are origin, destination, and distance. The origin and destination represent the cities meanwhile the distance shows the distance between the origin and the destination in kilometers (Kaggle, 2024). Minimizing the total distance for a vehicle to travel is the objective function of optimizing routes.

In mathematical terms, the objective function can be shown as:

Minimize: = Pn-1 i=1 di,i+1

Where:

• di, i+1 shows the distance between Sequential points i and i+1i+1 along the route. • n shows the total number of waypoints or nodes in the route. • Identifying the shortest route for a vehicle includes the following constraints:

– The route must start from a specified origin point and end at a designated destination point. – Every point along the route must be connected to precisely one preceding point and one succeeding point, creating a connected path. – In addition to minimizing distance, constraints on travel time (e.g., adhering to delivery time windows) may be imposed to meet operational requirements.

Devising and solving the optimization problem includes balancing the objective of minimizing travel distance with the satisfaction of the specified constraints. Several optimization techniques, such as linear programming, integer programming, or heuristic algorithms, and genetic algorithms, can be utilized to find viable and optimal solutions that fulfill the objectives and constraints in identifying routes.

5 Experimental Setup:

Genetic Algorithms (GAs) have proven highly effective for tackling routing optimization problems such as the Travelling Salesman Problem (TSP) or Vehicle Routing Problem (VRP), Genetic Algorithms are inspired by the natural evolution theory of Charles Darwin, specifically the concept of natural selection (Yao, 2017). GAs mirror the natural selection and survival of the fittest where the fittest individuals are chosen for reproduction to generate offspring of the next generation. The genetic algorithm operates with various configurations, including adjustments to crossover, mutation, and population size. Within these configurations, crossover and mutation each have multiple types, which researchers have extensively explored in the context of the Travelling Salesman Problem (TSP) (Yao, 2017). The genetic algorithm was utilized in this assessment with change in mutation rate.

Modifying the mutation rate in the Genetic Algorithm setup for the TSP can significantly influence outcomes. This rate dictates how often mutations occur within the population of routes (Mallawaarachchi, 2017). A higher mutation rate increases the frequency of route alterations, introducing greater variability into the population.

6 Results:

It is advantageous when GA becomes trapped in local optimum, as it enhances likelihood of exploring new regions within the solution space. The mutation rates effect on how well GA work is studied very much. The De Jong's (1975), important study known as the "Analysis of the Behavior of a Class of Genetic Adaptive Systems," suggested that the mutation rate is really important for keeping a good mix of genes in the population. This helps prevent the algorithm from getting stuck in not-so-great solutions too early. Having a high mutation rate can be good because it keeps things varied and stops the algorithm from only focusing on one kind of solution (Katoch, Chauhan and Kumar, 2020). But if the mutation rate is too high, it might mess up the progress toward finding the best solution.

Input: Electric vehicle (EV), Charging station (CS), application traffic graph ATG(P,E).
Output: Opt-path, time and charging cost.
Initialization Initialize the *Bats* parameter (i.e., distance d_i) ;
Objective function O_f= minimum routing path;
Generate initial set of bats (distance among source, destination and charging stations);
Compute each bat fitness (b_i);
Choose the most constructive bat equivalent to the minimum fitness value ;
while *Iteration* $>$ *Max Iterations* **do**
  Generate new set of traffic graph by adjusting source, destination and charging station points;
  if ($rand > d_i$) **then**
    Select a minimum distance from Electric vehicle position to charging station (i.e., optimal routing path) ;
  end
  if ($rand < O_f$) **then**
    Select that path as objective function.
  end
  Find the optimal routing path M_* among all the bats;
  Find minimum time and cost using Eq. (1) and Eq. (2);
end
Opt-path = M_* ;

Figure 1: Fitness Function Logic

On the other hand, if the mutation rate is too low, the algorithm might find a solution quickly, but it might not be the best one overall because it didn't explore enough options. In this assessment the different mutation rates were tried, but when the higher rates were used there was not much difference in how well these worked. Looking at the fitness graph in figure-1 below, none of the mutation rates do seem to make the big difference particularly in finding the better solutions. It could mean that the algorithm has a hard time making solutions better all the time, possibly because the mutation rates are too high (V, 2024). High rates might make things too random and mess up good solutions. So, using lower mutation rates might actually give us better solutions. Figure-1 above presents GA fitness function logic, whereas figrue-2, figrue-3 and figrue-4 presents output graphs.

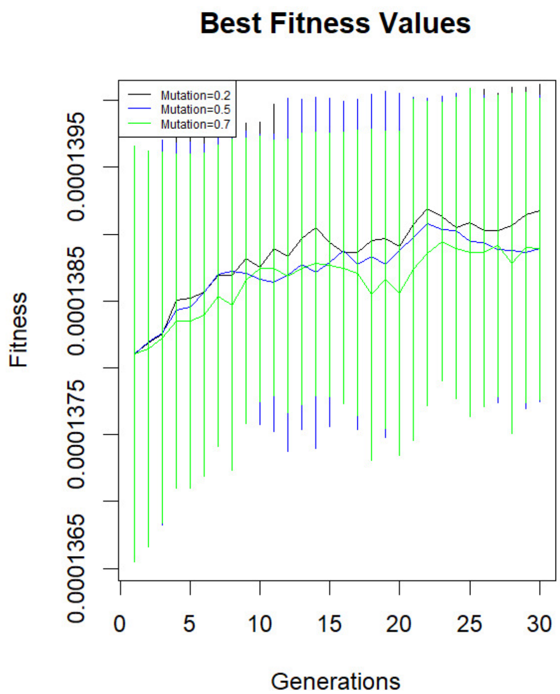

Figure 2: The Fitness Graph Seperate

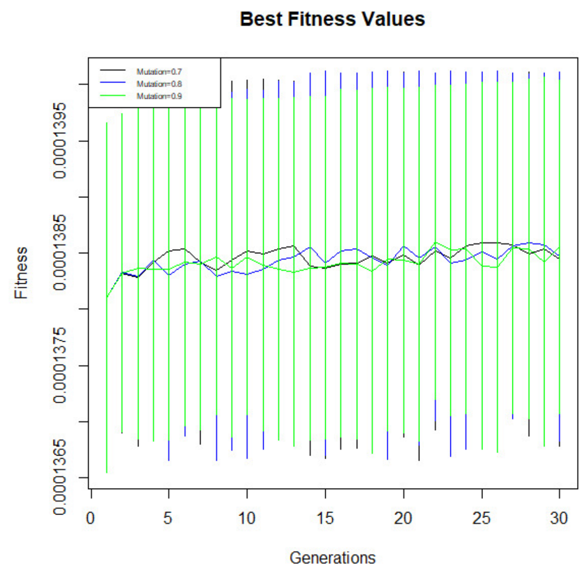

Figure 3: The Fitness Graph

7 Discussion:

The main problem being addressed in this research was the route optimization with the utilization of the modern optimization methods and techniques. This secondary research looked at the different ways through which vehicle route optimization is done effectively with addressing of the routing challenges complexities through enhancing and substituting the traditional methods mainly with the modern optimization techniques as well as the crossroads fields like logistics, transportation, management of supply chain and the operations research for solving the routing problems (Wang et al., 2020). As vehicle route optimization aims for the shortest route for the vehicle to reach from one destination to another and encompasses an essential but crucial element for routing optimization (Lähdeaho and Hilmola, 2024).

Minimizing the travel distance between 2 desired locations, reducing the utilization of fuel and cost, minimizing time, and maximizing the overall performance are the main objectives of route optimization. Therefore, the data used in this report was taken from Kaggle known as the ”Indian Cities Distance Dataset”, which contains the distance between some major Indian cities. The author has collected that data from Google Maps by using real-time shortest distance, during data collection, the author has rounded decimal values to discrete numbers (Kaggle, 2024). The data contains 3 columns which are origin, destination, and distance. According to the fitness graph, none of the mutation rates do seem to make the big difference particularly in finding the better solutions. It could mean that the algorithm has a hard time making solutions better all the time, possibly because the mutation rates are too high (V, 2024). High rates might make things too random and mess up good solutions. So, using lower mutation rates might actually give us better solutions.

The findings of the Lähdeaho and Hilmola (2024), study shows that near optimality mainly is attainable and feasible with the spreadsheet models and tools for solving the real-life problems. The decision-makers have the ability of solving the optimization vehicle routing problems with the limited access of higher-end optimization tools (Lähdeaho and Hilmola, 2024).

8 Conclusion and Future Works:

It is concluded that vehicle route optimization mainly is a process to determine the highly cost-efficient route. This requires the inclusion of all the relevant factors like the location and the number of all required stops upon a route and time windows mainly for the deliveries. The main problem that was addressed in this research was the vehicle route optimization with the utilization of the modern optimization methods and techniques. The vehicle route optimization is aimed towards finding the shortest route for the vehicle to reach from one destination to another and encompasses an essential but crucial element for routing optimization. Minimizing the travel distance between 2 desired locations, reducing the utilization of fuel and cost, minimizing time, and maximizing the overall performance are the main objectives of route optimization. According to the findings from the fitness graph, none of the mutation rates do seem to make the big difference particularly in finding the better solutions. It could mean that the algorithm has a hard time making solutions better all the time, possibly because the mutation rates are too high.

The higher rates might make things too random and mess up good solutions. So, using lower mutation rates might actually give us better solutions. Furthermore, near optimality mainly is attainable and feasible with the spreadsheet models and tools for solving the real-life problems. In future works it is important to consider how the decision-makers can solve the optimization vehicle routing problems with the limited access of higher-end optimization tools.

9 References:

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10 Apendix

https://github.com/MuhammadIrfan5/modernoptimization