Charging and Routing of EV Cabs

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***Abstract*—The increasing demand for Electric Vehicles (EVs) necessitates the development of efficient routing and charging infrastructure. The optimal routing and scheduling of EVs' charging stations can reduce the time taken by the EVs from their initial location to the final location i.e. passenger and maximize the utilization of charging stations. The use of genetic algorithms can provide an optimal solution to this problem. This report discusses the use of genetic algorithms to optimize the routing and scheduling of EV charging stations.**

I. Introduction

The increasing popularity of Electric Vehicles (EVs) has led to a surge in demand for efficient routing and charging infrastructure. To minimize the total traveling time and maximize the utilization of charging stations, it is necessary to optimize the routing and scheduling of EVs. Optimal routing and scheduling of EV charging stations involve finding the optimal route and charging schedule for EVs based on various factors, such as the location and capacity of charging stations, the battery capacity of EVs, and the travel distance.

This problem is complex, and traditional optimization meth- ods may not be effective in finding the optimal solution. In recent years, genetic algorithms have emerged as a powerful tool for solving optimization problems. Genetic algorithms mimic the process of natural selection to generate an optimal solution by starting with a set of randomly generated solutions and then iteratively selecting, recombining, and mutating the fittest solutions until an optimal solution is found. In this report, we discuss the use of genetic algorithms to optimize the routing and scheduling of EV charging stations.

The proposed methodology involves the creation of a list of charging stations and their location, capacity, and generating a set of random routes for EVs, evaluating the fitness of each route based on the charging capacity of EVs and utilization of charging stations, selecting the fittest routes for reproduction, and applying genetic operators such as crossover and mutation to generate a new set of routes.

II. Discussion

The proposed methodology can be applied to real-world scenarios to optimize the routing and charging of EVs. By Optimizing the routing and scheduling of EV charging stations, we can reduce the total traveling time and maximize the uti- lization of charging stations, which is essential for promoting the adoption of EVs and achieving sustainable transportation. However, the effectiveness of genetic algorithms depends on the quality of the fitness function and the selection of parame- ters such as population size, mutation rate, and crossover rate. Therefore, careful tuning of these parameters is necessary to obtain an optimal solution.

The genetic algorithm was applied to solve both subprob- lems simultaneously. The population of potential solutions represented different routing and charging schedules for the EVs. Additionally, the optimized routing of the EVs i.e. which EVs are going to which charging stations according to the distance also in this concept weighting factor plays an important role, and then after charging which EVs are going to which passenger.

One of the advantages of genetic algorithms is that they can handle multiple objectives simultaneously. The fitness function for this problem is a combination of these two objectives, and genetic algorithms can optimize the solution by finding the optimal trade-off between these two objectives. The weighting factors and utilization of charging stations can be adjusted to prioritize one objective over the other.

III. Problem Statement

The problem is to optimize the time taken by each vehicle of a long distance tour booking company from its initial position to the pick-up location by finding the optimal route and charg- ing schedule for electric vehicles (EVs). This optimization involves considering various factors such as the location of the EV, charging stations, passengers, and the battery capacity of EVs, charging rate of charging stations, and the current charging value of EVs. The objective is to minimize the time taken by each vehicle while ensuring that all the vehicles are fully charged before picking up their assigned passengers.

IV. Solving the problem

A. Assumptions

While real-life optimization of the time taken by each vehicle from its initial position to the pick-up location in- volves considering numerous factors such as traffic, weather conditions, and road infrastructure, the scope of the project may limit the factors that can be included. Therefore, we will focus on identifying the most crucial factors for optimization and develop an effective strategy based on these factors. Our approach will aim to balance the optimization of the travel time with ensuring the EVs are fully charged and capable of completing the required journey while maximizing passenger comfort and safety.

- All the vehicles, charging stations, and passengers are located within the same city.
- At a time only one vehicle can be charged at a particular charging station.
- We will also assume that all the vehicles are identical and that all passenger bookings are for this type of vehicle.
- Additionally, we will consider the Euclidean distance between two points as the distance the vehicle needs to travel, while acknowledging that in reality, the roads may not always follow a straight line between the two points.
- Furthermore, we will assume that the vehicle moves at a constant speed throughout the journey, which may not always be the case in real-world scenarios.
- Finally, we will assume that the energy supply at all the charging stations is constant, and there will be no power cuts or changes in the charging time taken by the vehicle.
- While these assumptions simplify the problem, we un- derstand that real-world optimization involves a broader range of variables and factors that need to be taken into account.

B.Location of vehicle, passenger, and station

EVs	X	Y
1	0	0
2	20	28
3	26	45
4	55	71
5	78	34

Station_Loc	X	Y
1	77	45
2	42	59
3	29	25

Passenger_Loc	X	Y
1	10	8
2	39	55
3	51	43
4	62	59
5	83	72

Also, we are given data like-

- qi = [6 8 4 12 7] = current charging capacity of the vehicle.
- Ri = [6 8 10] = charging capacity of the station
- S = 30 Km/hr = average speed of the vehicle
- Q = 20 units = total capacity of each electric vehicle

C. Time Optimization

The time for each vehicle to complete the journey from its initial location to the passenger's pickup location via the charging station is given by:

$$Ti = \frac{Dij}{s} + Tqr + W + \frac{Djk}{s}$$

$$1 \leq i \leq n$$

$$1 \leq j \leq m$$

$$1 \leq k \leq n$$

where i,j and k is for vehicle, charging station and passenger respectively.

- For each vehicle we can break the whole process into 3 parts.
- T1=Taken by a vehicle to travel from their initial location to the charging station.
- T2=W+Tqr= Time spent by each vehicle in Charging Stations.
- W= Waiting time for each vehicle in their respective station.
- Tqr= Total Charging time.
- T3= Time taken by vehicle to travel from charging station to their respective passenger.

These T1 and T3 can be calculated using time functions as:

```
function f= time(x1,y1,x2,y2,speed)
f=(sqrt((x1-x2).^2+(y1-y2).^2))./speed;
```

For solving this problem we will use the inbuilt GA toolbox.

```
[x,fval,exitflag] = ga(fitnessfcn,nvars,A,b,[],[],...
    lb,ub,nonlcon,intcon,options)
```

Here for the second part of our decision variable should not be same for any other index as it represents the vehicle assigned to one of the passenger, so at a time no two vehicles will be used for one passenger. Therefore, we have to introduce one penalty term in our objective function.

For finding W ,i.e., waiting time for each vehicle in the same charging station, we have to consider all the orders and the least will be taken by the GASo, in total we will use GA two times one time for W and one time for all the 4 time stages.

IV. Decision Variables

For solving this problem, we will be using Genetic Algorithm two times

Xi : This will be of length 2n; it is a combination of two arrays of size n(equal to no. of vehicles) each.

Where;
1st half- ith vehicle is going to the jth charging station.
2nd half- ith vehicle will pick-up the kth passenger

eg: X= [3 2 3 3 1 3 1 2 5 4]

For solving the order in which the vehicles will charge (to find their waiting time in the charging station) we will again use GA.

Yi : This will be of length depending on the no. of vehicles coming to a particular station

From the previous example we can say vehicles 1,3 and 4 come to station 3 so their optimized Yi will give the order in which they will charge and the others will wait.

eg: Y=[3 1 2] - means Vehicle 4 will charge first then vehicle 1 and vehicle 4 will be charged at last.

V. Genetic Algorithm (GA)

A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution.

The basic idea behind a genetic algorithm is to create a population of potential solutions, evaluate each individual in the population based on some objective function (also called a fitness function), and then use a combination of selection, crossover, and mutation to generate new individuals that are potentially better than the previous generation. This process is repeated over multiple generations until a satisfactory solution is found or some stopping criterion is met.

The key components of a genetic algorithm are as follows:

- Solution Representation: The solution space is represented as a set of chromosomes, where each chromosome is a vector of values representing a potential solution to the problem. The chromosomes are typically encoded as binary strings or real-valued vectors.

- Fitness Function: The fitness function evaluates the quality of each chromosome in the population. It maps each chromosome to a fitness score that represents how well it solves the problem. The fitness function is typically a mathematical function that evaluates the performance of the solution.

- Selection: The selection operator chooses which chromosomes will be used to generate the next generation. Chromosomes with higher fitness scores have a higher probability of being selected. The selection operator can use different selection methods, such as roulette wheel selection or tournament selection.

- Crossover: The crossover operator combines the genetic material of two parent chromosomes to produce one or more offspring chromosomes. This is done by selecting a crossover point in the parent chromosomes and swapping the genetic material beyond that point. The result is two new chromosomes that inherit some genetic material from each parent.

- Mutation: The mutation operator randomly changes the genetic material of a chromosome. This is done to introduce new genetic material into the population and prevent the algorithm from getting stuck in local optima. The mutation operator selects a random position in the chromosome and changes the value of that position with some probability.

- Termination: The algorithm terminates when some stopping criterion is met, such as a maximum number of generations or a target fitness score.

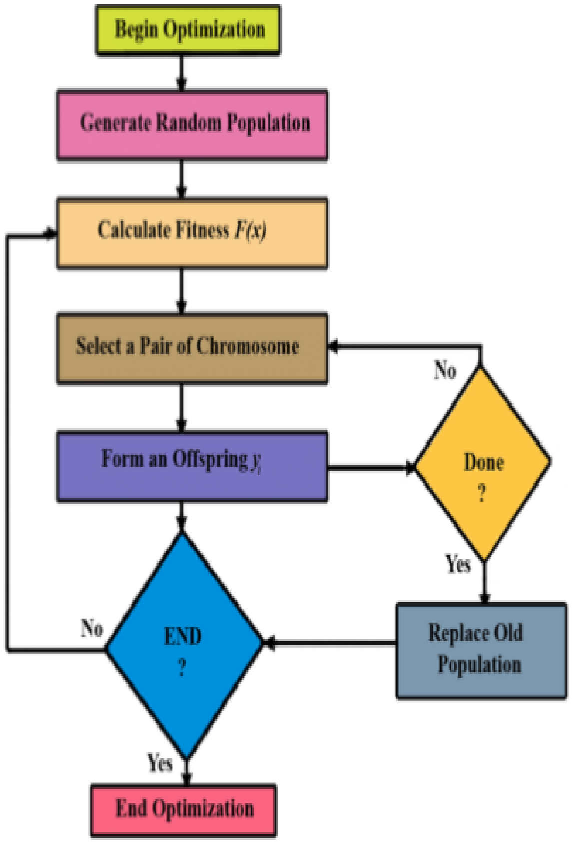

Fig. 5. Flowchart of Genetic Algorithm

Genetic algorithms have several advantages, such as being able to handle complex, nonlinear problems and finding globally optimal solutions. However, they can also be computationally expensive and require careful parameter tuning to achieve good results. Additionally, the quality of the solutions obtained by genetic algorithms depends heavily on the quality of the fitness function and the problem representation.However, the effectiveness of the algorithm depends on the quality of the fitness function and the selection of appropriate parameters such as the population size, the mutation rate, and the crossover rate.

Overall, the genetic algorithm is a powerful optimization technique that can efficiently search the solution space for optimal solutions. By mimicking the principles of natural selection and genetic inheritance, it can explore a wide range of potential solutions and converge on the best solution over time.

VI. Final Solution From Genetic Algorithm Performance

After running the MATLAB code for the project we get the results formulated as shown below:

Generations	Total Time (in hr)	Xij
1	18.9247	[3 3 3 2 1 1 4 5 2 3]
2	18.7264	[3 2 2 2 1 1 3 5 2 4]
10	18.5001	[3 3 2 1 1 1 5 2 4 3]
15	18.3264	[3 2 1 2 1 1 2 5 3 4]
20	17.267	[3 2 3 2 1 2 3 1 4 5]
50	16.2765	[3 3 2 7 7 7 6 2 4 3]
75	15.6994	[3 3 2 2 1 1 3 4 2 5]
100	15.6994	[3 3 2 2 1 1 3 4 2 5]
200	15.6994	[3 3 2 2 1 1 3 4 2 5]

As can be seen from the table above, even on increasing the generations from 75 to 100 and then to 200 the time remains the same.

- This shows that the final answer converges to 15.6994 hours and

X= [3 3 2 2 1 1 3 4 2 5]

Which means that the most optimized route for every EV becomes:

Vehicle	Station	Passenger
1 →	3 →	1
2 →	3 →	3
3 →	2 →	4
4 →	2 →	2
5 →	1 →	5

Therefore the Genetic Algorithm gives this mapping as the best route every vehicle must follow it to complete their task.

Future Improvements

- In this case we take Euclidean distance between any two points but in the future we can take more real life scenarios such as roads etc.
- In this case we take the same velocity of all vehicles but in real life scenarios this can't be possible, so in future we can take different velocities.
- In this case we have considered only one vehicle can charge at a time in the charging station but in the future we can assume multiple vehicles charging at the same time.
- The performance of other metaheuristics techniques can be evaluated to check which algorithm gives us the best results.
- We can also consider cost optimisation by considering fuel usage and battery degradation etc along with time optimisation.

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