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A Genetic Approach for the Optimization of Charging Stops for Fleet of Electric Vehicles

[1]Ansiya Mohammed Ali, [2]Smitha C Thomas

[1, 2] M.G University, Mount Zion College of Engineering, Pathanamthitta, India

Abstract: **Electrification of transport is the most common approach to improve transport efficiency. There are two factors mainly related to the cost of transport associated with electrical vehicles. They are the cost of acquisition and the cost of maintenance of batteries. Finding an efficient way of managing the available energy allows reducing the battery size and hence the cost associated with transport. The proposed work computes the routes for a fleet of electric vehicles by considering the battery limit of the vehicle and the concurrent use of charging stations along the route. The proposed solution minimizes the cost which is a combination of charging time, travel time and the energy consumption along the route. It is based on an evolutionary genetic algorithm with learning strategy. The proposed algorithm computes a feasible solution in a reasonable amount of time and assigns the vehicles among the charging stations to minimize the concurrency.**

Keywords: **EV, Charging Station, Battery Recharging.**

I. INTRODUCTION

Vehicular emissions are one of the most important environmental problems in cities. On an average, the second largest contributor of greenhouse gas emission in the world is due to transportation industry. In this context, to reduce emission, many countries have been promoting the usage of electric vehicles (EVs). 73% of all oil consumed in Europe is used in transport and road transport accounts for 25% of CO2 emissions of the overall transport activity.

Electric vehicles can be powered by either conventional or regenerative energy sources. EVS that are partially or fully powered by batteries will significantly dominate the road traffic of the future due to their ability to run on regenerative energy sources as well as their efficiency. The acceptance of EVs is still hindered by limited battery capacity. Thus, the important issues for EVs in the foreseeable future are the accurate prediction of remaining cruising range, energy aware routing and optimized charging stops.

For finding appropriate route EVS could use route planners which consider battery constraint. But, a battery recharge could take several minutes even with quick charging technology. In congested areas, the frequent and concurrent recharging demand would lead to high waiting time at the charging station. This adversely affects both the charging network and the vehicle travel time.

The present work addresses the problem of finding the optimal charging station sequence jointly for a fleet of electric vehicles. The main contributions of this work are the formal statement of the optimization problem that is amenable to a direct solution and the adaptation of evolutionary genetic algorithm for the solution of the problem.

II. EXISTING SYSTEM

EV users are interested in finding an energy optimal route with appropriate charging stops while not spending unnecessary time at the charging station which will allow them to extend the driving range. For EV fleets this situation is even more critical. Very few works have been proposed in literature which tries to address this problem by considering various parameters and optimization criteria.

A. Energy Optimization Criteria:

Authors in [2] address the optimal routing problem for individual EV considering the energy losses along the path. The optimization criterion is energy and the problem formulation is based on an adoption of a general shortest path algorithm, using an energy graph. A similar approach, with some enhancements has been discussed in [3] which consider the battery charging limit and discharge along the route. However, these approaches do not consider the charging stops for vehicles along the route which is essential for EVs. Another energy optimal routing is proposed in [4] where authors optimize the energy consumption along the route. This approach is limited to a single vehicle with no charging stops.

B. Time Optimization Criteria:

Apart from energy optimization, few approaches are based on time optimization. One such approach is discussed in [6] which consider the time required to charge a vehicle at the charging station. However, it assumes that a charging station is always available when a request is made which is not the case in reality. Authors in [7] also propose a time based optimization algorithm for electric vehicles, but in this approach the vehicles travel at a constant speed and hence the time of arrival at the charging station can be predicted in a deterministic way and also the charging station is available when the request is made.

C. Distance Optimization Criteria:

A distance based optimization for EV fleets is proposed in [10]. However, it is assumed that vehicles can complete the entire trip in a single charge and no charging stops are needed midway. To compute efficient routes an Electric Vehicle Routing Problem (EVRP) is first defined. The problem includes transport capacity, time and energy constraints. In a second step the charging schedule for vehicles is computed by including the state of charge, charging price and battery degradation. However, in this approach the charging and the route are treated as different problems and charging station concurrent use is not taken into consideration.

In our approach, we consider routing of EV fleets by analyzing the energy consumption along the route, charge limit or battery capacity, availability of the charging station and the time required to charge the vehicle. The solution optimizes the drive range along with best possible charging stops which will incur minimum waiting time, leading to an optimal concurrent usage of charging resources. The approach is validated with synthetic network and compared with minimum distance solution.

III. PROBLEM DEFINITION

Electric Vehicle Routing Problem (EVRP) is defined as the selection of the charging stations (CS) per each origin destination (OD) pair. This is done in such a way that it is feasible with respect to the energy available at the charging station, the concurrent use of the charging stations and the vehicle battery range. The EVRP is an important problem in the fields of transportation, logistics and distribution. It can be modelled with the graph G = (V,E).

IV. PROPOSED SYSTEM

The proposed solution consists of mainly four phases. They are listed below:

1. Map Construction
2. Route Optimization
3. Traffic Monitoring
4. Charge Monitoring

1. Map Construction:

A graph is made out of nodes and directed edges. The directed edges define a connection from one node to another node. A node also called vertex is a discrete position in a graph. Edges can be directed an undirected. Edges have an associated distance also called cost or weight of the graph. The distance between two nodes a and b is labeled as [a,b]. Mathematically, a graph can be denoted as G= {V,E}, meaning that a graph is defined by a set of vertexes (V) and a collection of edges (E). The order of a graph is the number of nodes. The size of a graph is the number of edges.

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Using the graph one can find:

- The shortest path from one specific node to another.
- Maximum possible flow though a network using maxflow- mincut theorem where each edge has a predefined maximum capacity.

This phase is mainly concerned with the optimization of shortest path of various cities. It provides accurate and shortest distance between two cities. With the help of this, a user can find shortest distance between any two cities provided he gives the source and destination. A pictorial representation showing the path is also included which the user can take print out and use as a map while travelling.

2. Route Optimization

Electric Vehicle users are interested in finding an energy optimal route with appropriate charging stops which will allow them to extend the driving range while not spending unnecessary time at the charging station. Various characteristics of EV are the following:

- the EV battery discharge
- battery charging limit
- regeneration of energy along the road
- recharging at charging stations
- energy available at charging station
- optimizing charge request per charging station
- the selection of the Charging station in the problem
- routing of the vehicle- multiple vehicles or single vehicle routing
- time windows
- Vehicle Loading Capacity

In genetic algorithms, crossover is used to generate an offspring out of two or more parents. This allows exploring new solution space based on previous experience. Normally, the possible cross over are the following (Fig. 1):

- Horizontal Crossover: routes are taken fully from parents, but each route can come from different parents.
- Route r -slicing: each route is split selecting $r-1$ points, each segment 0 - j_1,..., j_{l-1} - j_l, ..., j_{r-1} - $L-1$ is taken from one of the parents.

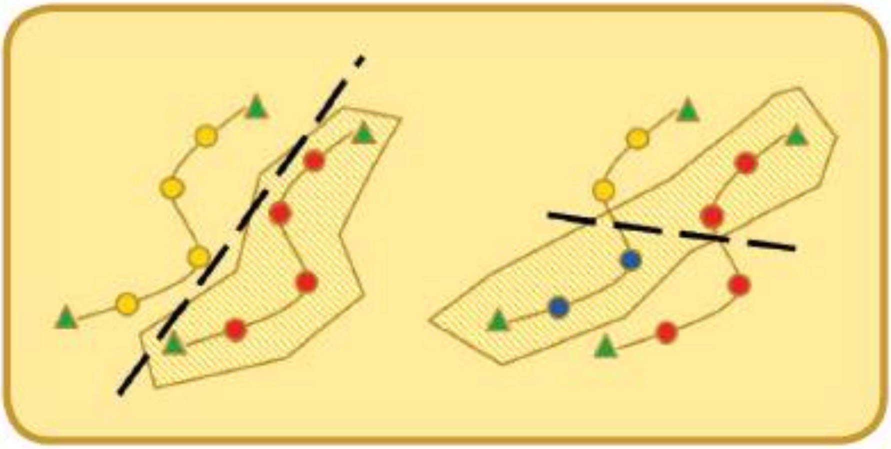

Fig. 1: Crossover Possibilities: Left is Horizontal Crossover; Right is an Example of One Point Crossover

These crossover may result in a worst solution than the one generated by each parent. For this reason an alternative approach is used.

A two point selection for each route may potentially generate non-feasible solutions. To avoid this, the following method is adopted. From the two parents the nodes are selected in such a way that which will minimize the probability of selecting the same charging station. This implies that the solution of the parents is not changed at level of the single route. This by itself is another combinatorial problem, but in this case the possible routes are from two sets, so we have 2 routes per trip. The solution of the proposed sub-problem is defined as follow (Fig. 2):

We start from one parent solution and we look if there are routes from the other parents that lower the number of concurrency at charging stations. This combinatorial problem can be defined as allocation of the two (or more) parent routes in an o optimal way.

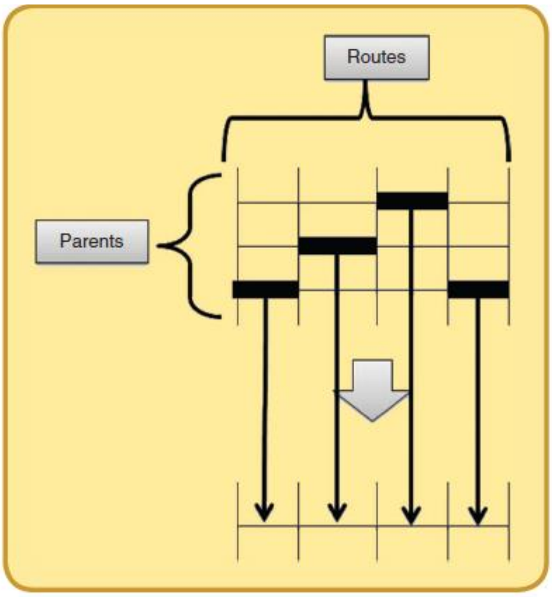

Fig. 2: Optimal Crossover

3. Traffic Monitoring:

Initially, a list of empty routes is created. While at least an EV is still available, the heuristic continues with selecting an EV k with a maximum priority. Then, it inserts iteratively the customers into an active route at the position causing minimal increase in tour cost until a violation of capacity or battery capacity of the selected EV occurs. The heuristic anticipates, when possible, any violation due to the battery capacity constraint by inserting charging stations during the tour construction.

The best charging station is selected among the compatible and available charging stations belonging to the neighborhood V (i) of the current node i, where V (i) is the set of all nodes within the circle defined by the center i and the radius α; where α is the maximum distance that could be traveled by the EV using its current state of charge. If a violation of one of the constraints occurs or the total route time exceeds T −T0, the current route is assigned to the selected vehicle, another EV with a maximum priority is selected and a new route is activated. When a customer could not be reached using any of the available EVs, it is assigned to the CV engendering the minimal cost increase in the solution cost while satisfying the capacity and the total route duration constraints, until at most the predefined number of routes (mEV +mCV) is constructed.

Genetic algorithm allows avoiding local optimal solution by sampling the solution space with different individuals and then combining the most successful individual to evolve in the solution search. In method is where anode n is not considered in the initial phase if d(source, n) or d(n, destination) $>L_k Q_k$, where L_k and Q_k are the max number of station that can be visited and the battery capacity, while source, n and destination are the nodes of the solutions, whereas d(n,m) is the energy required to go from n to m. Along with the condition mentioned before, some solutions are additionally included in the initial population.

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These are:

- Solution with no charging
- Generate all battery constrained valid shortest routes between origin and destination or the first k-shortest routes.

The actual initial generation procedure generates the set of l -shortest path route per OD pair on the connectivity graph, where all the battery capacity violating connections are removed in a pre-processing step.

4. Charge Monitoring:

To route the EV through appropriate charging stations, we modelled energy-optimal routing as a shortest path problem with constraints for battery-powered electric cars with recuperation. The energy optimal path computation considers the regenerative energy and the EV parameters. To compute an energy optimal route, the road network is considered to be a directed graph G = (V,E). Vertices $v \in$ V represent points on the map and edges $e \in$ E represent connections between these points corresponding to the road sections. Each vertex is assumed to have an elevation *z*. The length of each edge segment is considered as *l* and the speed limit on the edge is denoted by *s*. The path P, which is the desired output, is then a sequence of *k* vertices$(v_{1,} v_{2,}\ldots\ldots\ldots\ldots v_{k})$. The cost is the amount of energy consumed or gained by an EV when passing an edge in the network. The amount of energy consumed or gained and the path cost are discussed in the following subsections.

To resolve the concurrent charging requests, we apply genetic algorithm including a local search in order to speed up the convergence and recover from non-feasibility of initial population. The first aspect to define, when using a Genetic Algorithm, is the representation of solution into chromosome of individuals. The chromosome represents a full set of solutions, which, for the presented problem, is the set of routes with the associated charging station visited by the vehicles.

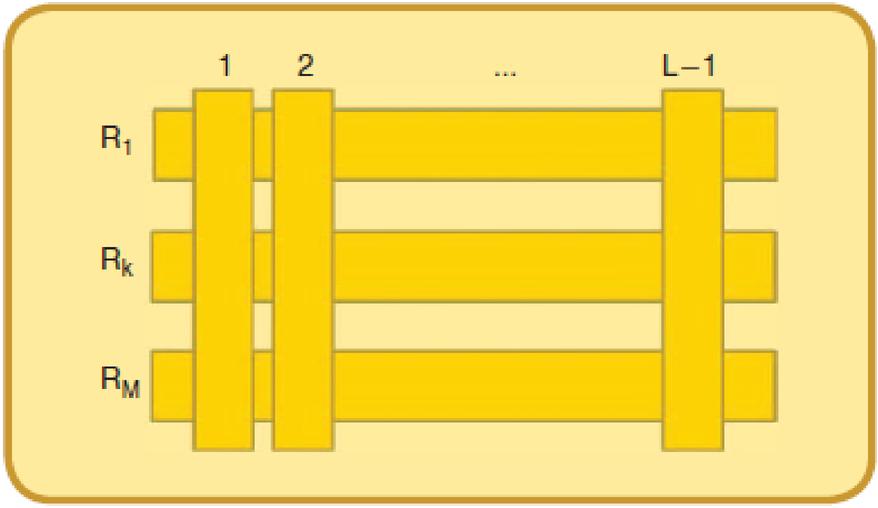

Fig. 3: Binary Representation, Rows are Routes, While Columns are Charging Stations

We represent the solution set as two dimensional binary array, where the rows represents the *k*-th route/vehicle and the columns represent the *L* charging stations. Thus an element of the chromosome $x_{kj} \in 2^{KL}$ is set to 1 if the *k*-th route stops at the *j* -th charging station.

The chosen representation (Fig. 3) is used to avoid factorial space dimension, but requires resolving the ordering of the selected charging stations for a specific route once defined the CSs that a specific vehicle will visit; we still need to define the order in which the CS will be visited. Since the non linear cost is independent of the order of visiting, the problem defined, once the charging stations are assigned to routes, can be resolved as a set of single Travel Salesman Problem (TSP) for each route. Having a limited number of charging station per route, implies that the TSP problem can also be resolved using brute force approach, since the typical maximum number of charging station per route is 2–3, leading to a maximum of 6 solutions to be evaluated.

V. CONCLUSION

The work presented addresses the problem of concurrent charging for EV fleets by computing routes that minimizing the cost constituted by travel time, charging time and the energy consumption along the route. The formulated problem is resolved by modifying the evolutionary genetic algorithm. The evaluation showed that, with the proposed procedures for EV scenario, an optimal solution can be found in a reasonable amount of time and EVs can be assigned to the charging stations with a lower conflicting situation.

In future we envision further integrating multi modality and analyzing its effects on the concurrent charging requests and validating the performance of the proposed solution.

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