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

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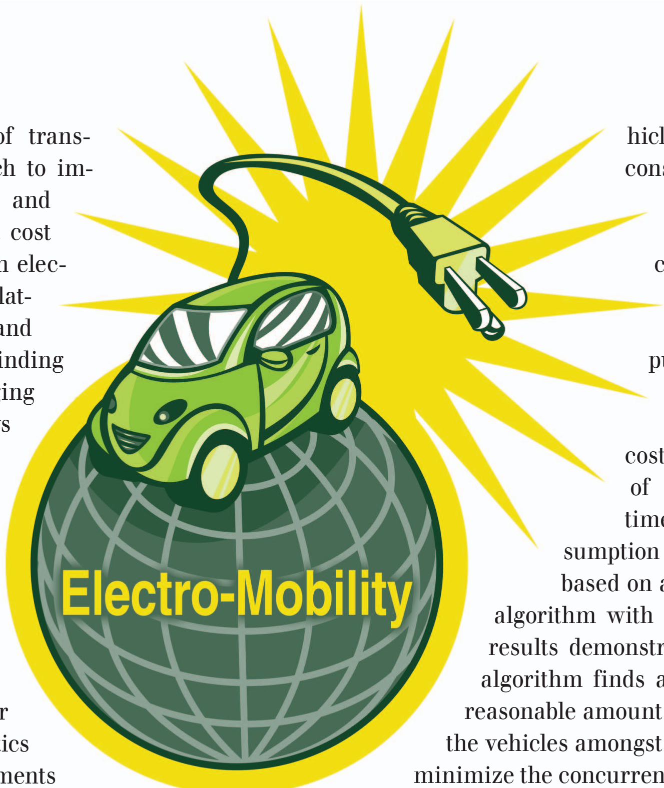

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***Abstract*—**Electrification of transport is one of the approach to improve transport efficiency and sustainability. The current cost of transport associated with electrical vehicles is mainly related to the cost of acquisition and maintenance of batteries. Finding an efficient way of managing the available energy allows reducing the size of the batteries and thus the cost associated with transport. Recently taxi services and urban delivery companies are introducing electric vehicles in their fleet. Available route planners do not consider properly the characteristics and charging stop requirements of EV fleets in decision making which results in non-optimal routing solution.

The proposed work addresses the problem of finding the routes for a fleet of electric vehicles which will not only consider the battery limit of the vehicle, but also the concurrent use of charging stations along the route. The proposed solution computes routes for the fleet of vehicles that minimizes the associated cost which is a combination of travel time, charging time and the energy consumption along the route and is based on an evolutionary genetic algorithm with learning strategy. The results demonstrate that, the proposed algorithm finds a feasible solution in a reasonable amount of time and distributes the vehicles amongst the charging station to minimize the concurrency.

The stated problem is non-polynomial and while genetic algorithm allows to efficiently explore large solution spaces, the work also presents some approximations and some strategies that allow to reduce the computational requirements and to find a solution in reasonable time.

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I. Introduction

One of the most important environmental problems in cities is caused due to vehicular emissions. On an average transportation industry is the second largest contributor of greenhouse gas emission in the world. In this context, many countries have been promoting the usage of electric vehicles (EVs) to reduce emission. United States is expected to have one million electric cars and plugin hybrids by 2015 [1]. Through various projects, The European Union (EU) as well promotes broad use of renewable and carbon-free energy sources in the transport sector, which could help the European Union's target of CO2 emission reduction.

Electric vehicles (EVs) can be powered by either conventional or regenerative energy sources and they can recover some of their kinetic and/or potential energy during deceleration phases. The recuperation or regenerative energy increases the cruising range of EVs by about 20 percent in typical urban settings [2]. However, the acceptance of EVs is still hindered by limited battery capacity, which currently allows cruising ranges of only 150 to 200 kilometers. Thus, accurate prediction of remaining cruising range, energy-aware routing and optimized charging stops are important issues for EVs in the foreseeable future.

Electrical vehicles could use route planners for finding route which considers battery constraint. But, even with quick charging technology, a battery recharge could take several minutes. In congested areas the concurrent and frequent recharging demand would lead to high waiting time at the charging area, thus affecting both charging network and vehicle travel time.

The present work address the problem of finding the optimal charging station sequence jointly for all vehicles of the fleet considering an underlying optimization problem.

The main contributions of this work are the formal statement of the optimization problem that is amenable to a direct solution, the adaptation of evolutionary genetic algorithm for the solution of the problem, the specific form of representation of the solution as binary matrix which includes the connected travel salesman problem, the initial population definition that allows to quickly recover from non feasible solutions, the crossover that includes an optimization sub-problem along with its approximation and the definition of the learning mechanism.

The rest of the paper is organized as follows, Section II analyses the existing works. Sections III and IV explain the optimization problem and the algorithm to resolve the optimization problem. Evaluations of the algorithm is presented in section V and finally section VI concludes the paper.

II. Literature Review

As discussed in section I, EV 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. This situation is even more critical for EV fleets. Very few works have been proposed in literature which try to address this problem by considering various parameters and optimization criteria.

We analyze and compare the literature based on EV characteristics which are: 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, time windows, Vehicle Loading Capacity, multiple vehicles or Single vehicle routing.

Authors in [2] address the optimal routing problem for individual EV considering the energy losses along the path. The optimization criteria is energy and the problem formulation is based on an adaption of a general shortest path algorithm, using an energy graph. A similar approach, with some enhancements has been discussed in [3] which considers 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. A significant modification using a combinatorial optimization for a fleet of electric vehicles is proposed in [5]. This approach also discusses the load on the electric fleets and the number of deliver stops which a vehicle has to do in a single trip. However, in this approach it is assumed that the fleets always recharge at the fleet center. Hence the problem of charging stops along the route never arises.

Apart from energy optimization, few approaches are based on time optimization. One such approach is discussed in [6] which considers 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. [8] proposes a multi-objective optimal path selection in electric vehicles considering the network of charging stations. In this approach, a charging station is assumed to be present at every intersection, hence it is assumed that there are plenty of resources available for charging. A similar approach based on multi-constraints optimization is discussed in [9].

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. On similar lines, in [11] authors consider

EV routing problem with battery degradation. 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.

Authors in [12] discuss the concept of energy available at the charging station along the route to schedule the charging stops. But this solution is designed for highways (straight roads) and hence no routing is implemented. Work on similar lines is discussed in [13], where a solution for simultaneous vehicle routing and charging station citing is proposed. But no routing algorithm is defined or the effects of charging demand on the route selection is addressed.

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

EV routing problem addressed in this work 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.

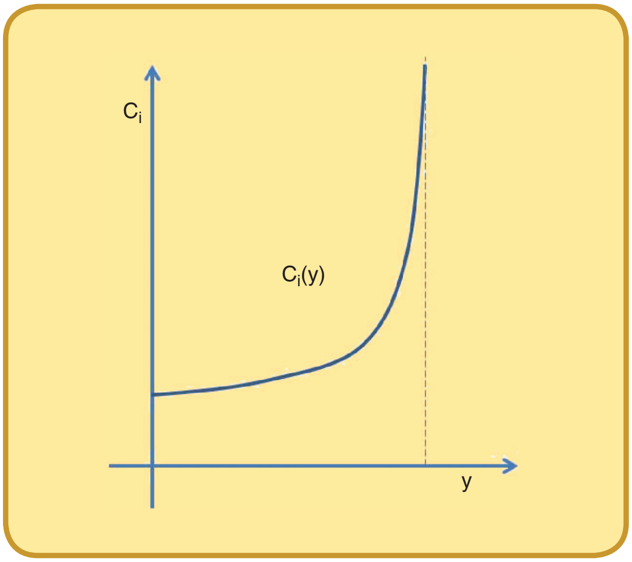

FIG 1 Example shape of the cost function.

Let K be the number of vehicles which, depending on the battery status and the destination, require charging and L be the number of charging stations.

In the model we first assume that the vehicle will be able to drive to the destination within the time horizon of the problem. Vehicles visiting the same charging station will normally arrive at different time instant. Due to concurrent charging requests, we model the cost related to waiting time at the charging station as a differentiable non-decreasing cost $c_i(y|C_i)$ proportional to number of vehicle y charging at the same charging station. A typical behavior of the cost function is shown in Fig. 1. A possible choice for the cost function is $c_i(y|C_i) = c_i^1 \times (y/C_i - y)$ or $c_i(y|C_i) = c_i^1 + c_i^2 y^{\beta}$, where c_i^1, c_i^2, β are parameters of the cost function. An additional assumption considered, is that the vehicles request the same amount of energy at the charging station they visit, thus the limit in number of vehicle or energy at the charging station are equivalent.

The cost function is composed of two terms. The first term considers the cost incurred by the vehicle along its route, which is the sum of the cost c_{ij}^0 of its links. The second term accounts for the above described waiting cost.

The underlying problem can be stated as,

$$\min_{x_{ij}^k} \sum_{k=1}^{k} \sum_{i=1,\, j=1}^{L,\, L} \left\{ \underbrace{c_{ij}^0 x_{ij}^k}_{\text{movement}} + \underbrace{c_i\left(\sum_{j',k'} x_{ij'}^{k'} \middle| C_i\right) x_{ij}^k}_{\text{charging}} \right\} \tag{1a}$$

$$\text{s.t.} \quad e_{ij} x_{ij}^k \le E_k, \tag{1b}$$

$$\sum_j x_{ij}^k = 1, \forall k, i = \text{start}(R_k), \tag{1c}$$

$$\sum_i x_{ij}^k = 1, \forall k, j = \text{end}(R_k), \tag{1d}$$

$$\sum_{j,k} x_{ij}^k \le L_k + 1, \forall k, \tag{1e}$$

$$\sum_{j,k} x_{ij}^k \le C_i, \forall i \in \text{CS}, \tag{1f}$$

$$\sum_j x_{ij}^k = \sum_j x_{ji}^k,$$

$$\forall k, i, i \ne \text{start}(R_k)$$

$$i \ne \text{end}(R_k), \tag{1g}$$

$$x_{ij}^k \in \{0,1\}, \forall k, i, j. \tag{1h}$$

Eq.(1) defines the non-linear minimization function. The variable x_{ij}^k represents if the k-th route uses the edge between the i-th and the j-th nodes. Eq.(1a) is the non-linear cost function composed by two terms. The first represents the cost involved to traverse an edge between two nodes whereas the second represents the cost associated in the concurrent usage of CS by different vehicles at the same charging station. Eq.(1b) is the energy constraint for the trip between two nodes, where e_{ij} is the energy requirement between note i and note j, whereas, eq.(1c) and eq.(1d) are used to represent starting and end points of the k-route. Eq.(1e) is a limit on the number of charging station visited by each vehicle, where within route k, at the most L_k charging stops are allowed. Eq.(1f) considers explicitly the limit on the number of vehicles that can be charged at the i-th charging station. Eq.(1g) is used to model the movement of vehicles requiring each vehicle entering into a node to exit from it, except for the starting and end node.

The proposed work looks to find an optimal route for EV with appropriate charging stops along the route.

We additionally note that the problem as stated in Eq.(1) is generally more constrained limited, but the some of the constraints can be included in the cost function, so that the problem is more cost driven. We mean with constrained limited the problem where is more critical to find a feasible solution, while on the contrary a cost driven problem has a large feasible space and the problem is to find the solutions that are closer to the optimal.

IV. Proposed Solution

The proposed work looks to find an optimal route for EV with appropriate charging stops along the route. Section IV-A presents the single electric vehicle routing problem, while in section IV-B the full genetic based solution for concurrent charging assignment is presented.

A. Efficient Energy Optimal Routing for EV

As discussed in section I, energy optimal routing for EV's will become increasingly important in the future. In this work, to route the EV through appropriate charging stations, we modeled energy-optimal routing as a shortest path problem with constraints for battery-powered electric cars with recuperation. This implementation is based on the work cited in [3]. 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 $(v_1, v_2, \ldots, v_k)$.

The cost $c(P)$ 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.

1) Potential Energy E_P

This energy results from the elevation of a vertex. When traveling along an edge *(a,b)* the energy $c_P(a,b) = E_P(z(b)) - E_P(z(a))$ has to be spent when $z(a) \leq z(b)$ or recuperated when $z(a) > z(b)$. The cost $c_P(\mathrm{a,b})$ of an edge (a,b) is given by:

$$c_P(a,b) = mg((z(b) - z(a)), \tag{2}$$

where m is the mass of the vehicle and g is the gravitational acceleration.

2) Other Energy losses E_L

Another energy loss is due the rolling, aerodynamic resistances or conventional losses, when passing an edge $e = (a,b)$. This loss increases linearly in l and monotonically in s. The cost $c_L(\mathrm{a,b})$ of an edge (a,b) is given by:

$$c_L(a,b) = \begin{cases} \eta_r . c_R(a,b) - c_P(a,b) & \text{if } c_R \leq 0 \\ \dfrac{1}{\eta_c} . c_R(a,b) - c_P(a,b) & \text{if } c_R > 0\text{'} \end{cases} \tag{3}$$

where $\eta_r \in [0,1]$ and $\eta_c \in [0,1]$ are efficiency factors and $c_R(\mathrm{a,b})$ is the auxiliary term, given by:

$$\begin{aligned} c_R(a,b) &= c_P(a,b) + f_r mgl(a,b) \\ &\quad + \frac{1}{2}\rho A c_w s(a,b)^2 l(a,b), \end{aligned} \tag{4}$$

where f_r is the coefficient of friction, ρ is the air density, A is the vehicle cross section area and c_w is the air drag coefficient. The factor η relates to the EV engine efficiency. This implies that in equation 3 more energy is drawn when EV is going uphill and energy is regenerated when EV is going downhill.

3) Path Cost

The functions $c_P(a,b)$ and $c_L(a,b)$ sum up to an edge weight and is given by

$$c^0(a,b) = c_P(a,b) + c_L(a,b). \tag{5}$$

The weighted graph $G = (V,E,c)$ can be denoted as the energy graph.

Finally, the cost incurred by an EV to travel along a path $P^k = (v_1, v_2, \ldots, v_k)$ in the network is given by:

$$c^0(P^k) = c^0(P^{k-1}) + c^0(v_{k-1}, v_k). \tag{6}$$

We apply genetic algorithms including a local search in order to speed up the convergence and recover from non-feasibility of initial population.

B. EV Charging Solution

Genetic algorithm with its extension to heuristics and meta heuristics are a common tool used to resolve non-polynomial problems [14]. An example of application of GA to vehicle routing problems can be found in [15]. Genetic algorithm allows to avoid local optimal solution by sampling the solution space with different individuals and then combining the most successful individual to evolve in the solution search. 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. In the following sub-sections we specify the different aspects that characterize the algorithm: 1) the solution representation 2) the initial population formation, 3) the crossover function, 4) the learning procedure, 5) the mutation, 6) the local search and 7) fitness computation.

1) Solution Representation

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.

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 $x_{k,j} \in 2^{KL}$ is set to 1 if the k-th route stops at the j-th charging station.

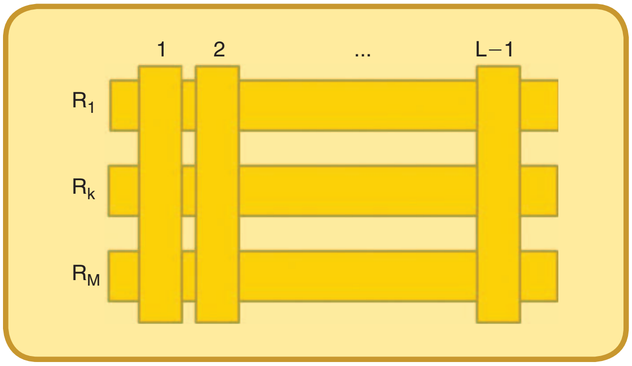

FIG 2 Binary representation, rows are routes, while columns are charging stations.

The chosen representation (Fig. 2) is used to avoid factorial space dimension, but requires to resolve 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 in eq.(1a), once the charging station 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, eq.(1e) 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.

2) Initial Population

The most common approach is to generate a feasible random solution. For concurrent charging problem it is difficult to find a random initial feasible solutions with good random properties. One approach can be to generate a solution uniformly and then transform the solution to be feasible, by removing or adding nodes. An alternative approach is to restrict solution space by avoiding the occurrence of non-feasible solution, by removing extrema points from the specific route. One additional method is where a node 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 too go from n to m.

Along with the condition mentioned before, some solutions are additionally included in the initial population. These type of solution are deterministic in nature, but due to the potential high number of elements, they can be randomly chosen in order to generate the initial population. 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.

3) Crossover

In genetic algorithms, crossover is used to generate an offspring out of two or more parents. This allows to explore new solution space based on previous experience. Normally, the possible crossover are the following (Fig. 3):

- 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.

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

We have selected a two point selection, for each route. This can potentially generate non-feasible solution. To avoid this we added a dedicated step to recover from this situation. In this approach, from the two parents the nodes are selected in a way which will minimize the probability of selecting the same charging station. This implies that the solution of the parents are 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 route per trip.

The solution of the proposed sub-problem is defined as follow: 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. (Fig. 4)

This combinatorial problem can be defined as allocation of the two (or more) parent routes in a optimal way with minimization function as:

$$\min_{y_k^p} \sum_k \sum_{ij} \left\{ c_{ij}^0 t_{ij}^k + \frac{1}{2} c_i \left(\sum_{j',k'} x_{ij'}^{k'} | C_i \right) t_{ij}^k \right\} \tag{7a}$$

$$\text{s.t.} \quad \sum_p y_k^p = 1, \tag{7b}$$

$$y_k^p \in \{0,1\}, \tag{7c}$$

$$t_{ij}^k = \sum_p y_k^p x_{ij}^{kp}, \tag{7d}$$

where eq.(7d) is only used for to simplify the formulation and x_{ij}^{kp} are the p parent solutions. This sub problem can be approximated, by looking only for a solution that improves the concurrent utilization of the charging stations. With this step the crossover improves the solution with respect to the concurrent utilization of the charging stations. The only drawback of this solution is that it increases computational requirement, whereas the use of simple randomization crossover would reduced computational requirements, but at an expense of longer convergence time. For the tested cases the maximum reduction crossover has a lower execution time with respect to two point random crossover.

Selection of the parents can be uniform random or based on their fitness. In this later case the probability of selection is given by

$$\Pr(i) \propto \frac{1}{1 + f_i - \min_j f_j} \tag{8}$$

or alternatively

$$\Pr(i) \propto \max_j f_j - f_i. \tag{9}$$

4) Strategy Learning

We consider the possibility of selecting the crossover method either at the initialization of the population, or dynamically at runtime. We measure the success rate of the available strategies and assign a corresponding probability. The probability of success is used to select the strategy which will be used for the next generation.

5) Mutation

Once an offspring is generated, it can be randomly mutated. Mutation helps in exploring new area of solution space. We used $Pr = 0.2$ of mutation for each charging station and route, which is a good compromise between randomness in the mutation and memory of parents' genome.

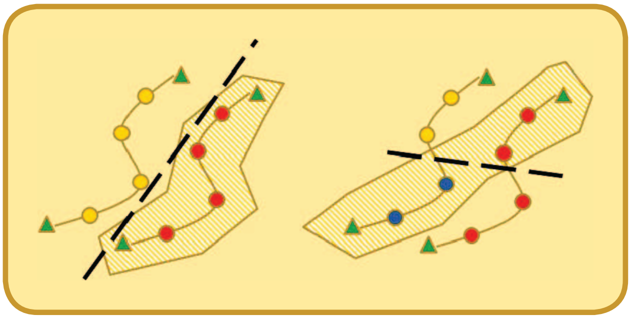

FIG 3 Crossover possibilities: left is horizontal crossover, right is an example of one point crossover.

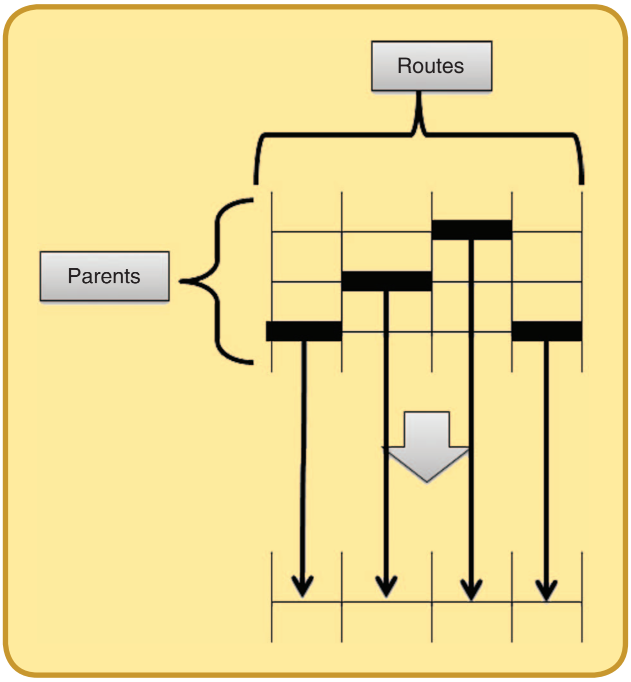

FIG 4 Optimal crossover.

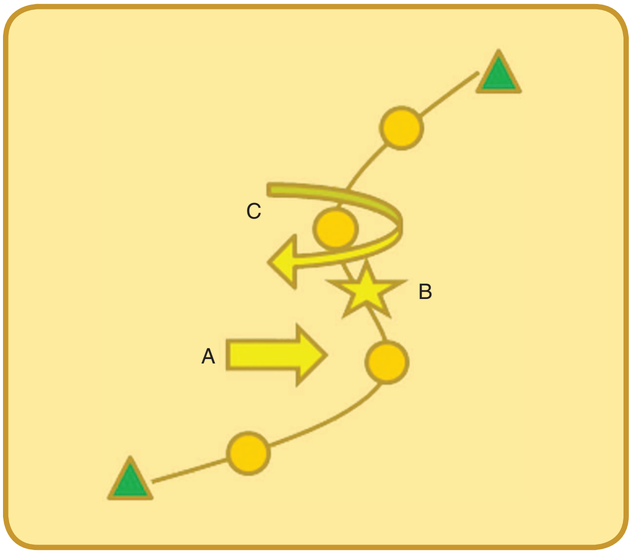

FIG 5 Mutation possibilities: (A) Remove, (B) Add, (C) Substitute.

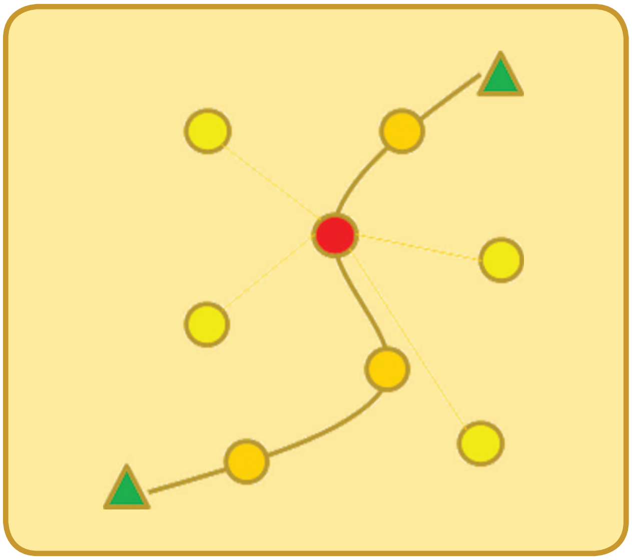

FIG 6 Restricted mutation.

Mutation can be visualized at the level of the single route. The mutation can remove a charging station, add an additional charging station to the current set or can substitute one node, with another one. Fig 5 shows graphically the possible mutation types.

Mutation may lead to non-feasible solution. Hence we define a restricted mutation, where the nodes that participate in mutation are deliberately limited. The idea is that in case of a substitution or addition for a node, only nearby nodes are considered. This allow to fine tune the solution, but may preclude more radical solution changes. The use of restricted network has a initial computational cost, but not a major impact on solutions, since mutation is used rarely. It may have a more impact when more aggressive/higher mutation probability is used.

Table 1. Simulation parameters.

Parameter	Symbol	Values
Battery capacity (in meters)	E	10000 m
Max charging station visit per route	cs max	4
Charging station loading coefficients	α, β, C_0, t_0	2, 3, 2, 100
Number of charging stations	L	$4 \times 4, 5 \times 5, 6 \times 6$
Number of routes	M	50, 75, 100, 125, 150

Restricted mutation requires to build a restricted network of charging stations in a pre-processing phase, to avoid computing it on the fly.

6) Local Search

We consider a local search, specifically we foresee the possibility to remove nodes to achieve feasibility. This has a very beneficial effect especially to improve feasibility of the initial population. Another possibility for the local search is to add nodes when possible to improve fitness.

7) Fitness

Fitness is computed according to the cost function of eq.1a. For each constraint that is violated, an additional cost is added. This additional cost for constraint violation shall be greater than the maximum cost for any feasible solution. This condition is used to reduce non-feasibility of the computed solution. It is also possible to consider different level of constraint violation, by adding a cost proportional to the difference between the actual value and the maximum allowable. The additional cost allows to accept new individual even if they violates constraints. Since the binary representation has been chosen, the fitness computation requires to solve a TSP problem. In order to avoid re-computation of the same problem over and over, a local look-up table is maintained to speed up the computation.

8) Other Considerations

From the point of view of a practical implementation, many routes can reach the final destination without stopping at any Charging Station. This fact is exploited in order to remove routes in the final solution computation since they do not interfere with other vehicle's routes. Practically this is done by excluding these route in the main steps: crossover, mutation and local search.

V. Simulation and Analysis

A. Simulation Setup

The proposed algorithm is tested on randomly generated network. The locations of the CS is first generated in an

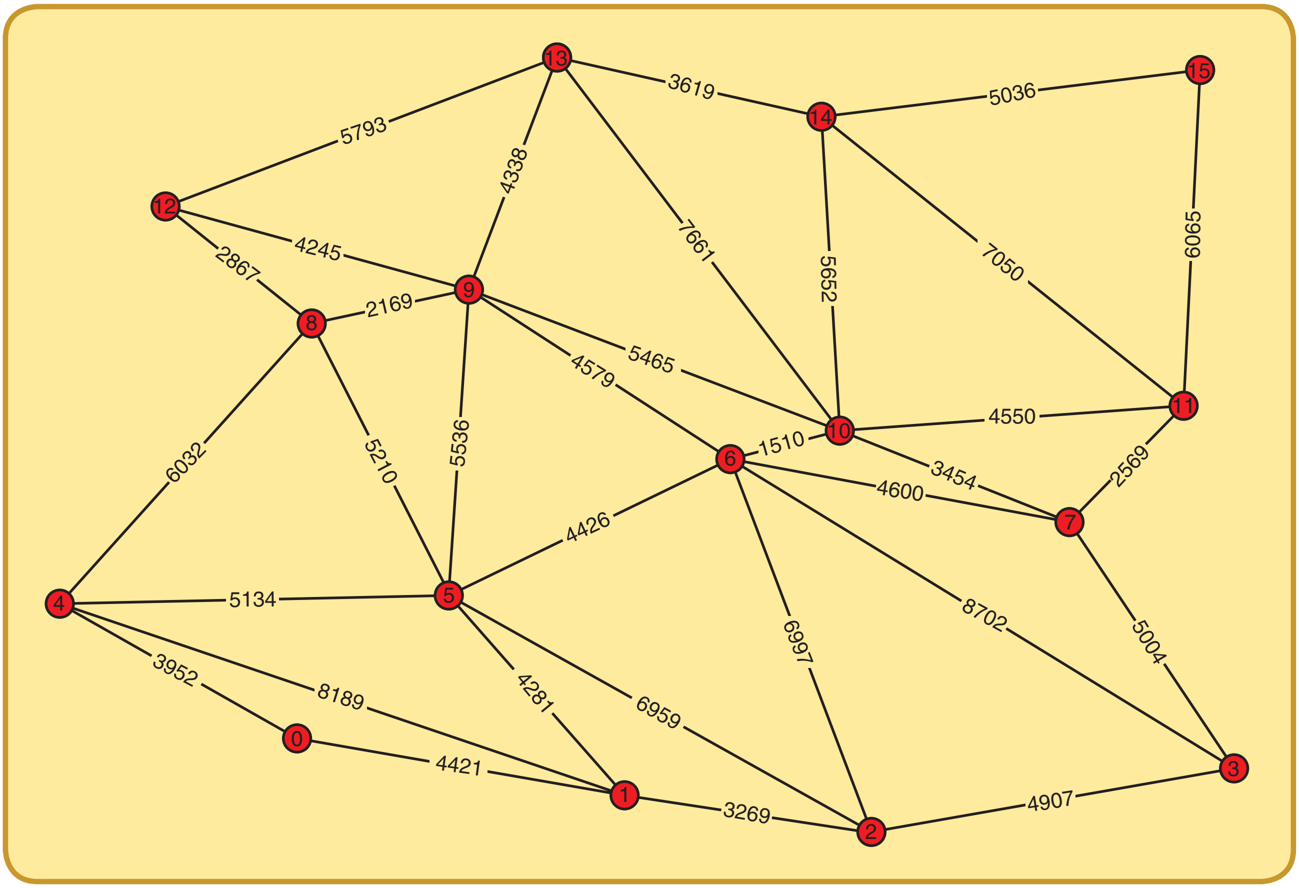

FIG 7 Simulation network in the 4×4 grid. Distance between nodes in meters is shown.

uniform square. The demand is also generated randomly on the Charging Station network. Each vehicle is not allowed to visit more then 4 charging stations along its route, while the battery capacity is define in meters and set equal for all vehicle. To simplify the simulation the battery model considered is linear. Table I summarizes the parameters of the simulation and the small test network.

In the simulation a test network is generated by randomly placing the charging station in a square grid whose edges are 4 km long. Edge cost is defined as the distance between two nodes. The network is kept constant through the simulation, while the origin and destination points are randomly selected. Vehicles have battery charge that provides 10 km autonomy. In Fig. 7 the simulation network for the 4×4 is depicted.

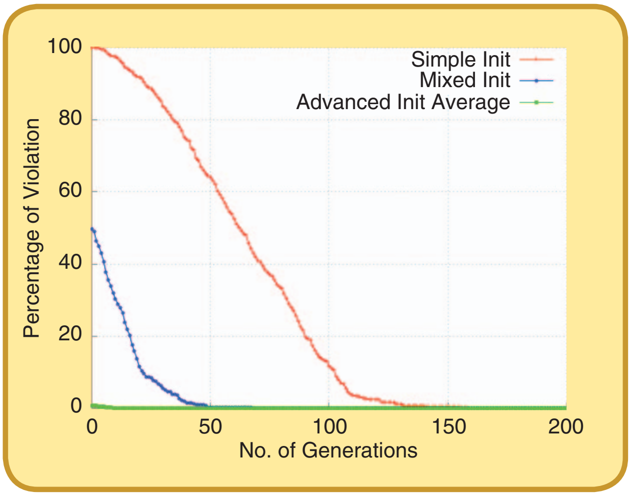

FIG 8 Number of violations based on initial population selection.

B. Comparison with Minimum Distance Solution

In the following section the proposed algorithm is compared with a reference solution. This is a minimum distance solution which considers only cost c^0, to reach the destination, including the battery constraint. This reference solution will allow to minimize the energy consumption, but at the expense of overloading some charging station and additional travel time. A few of the works based on this concept are discussed in [7], [8], [10], [12], [16]. However, in these solutions it is assumed that charging stations are always available and vehicles do not wait at the charging stations. This critical issue has been addressed in this work. The solution proposed in other works may include aspect that we do not model, so the minimum distance

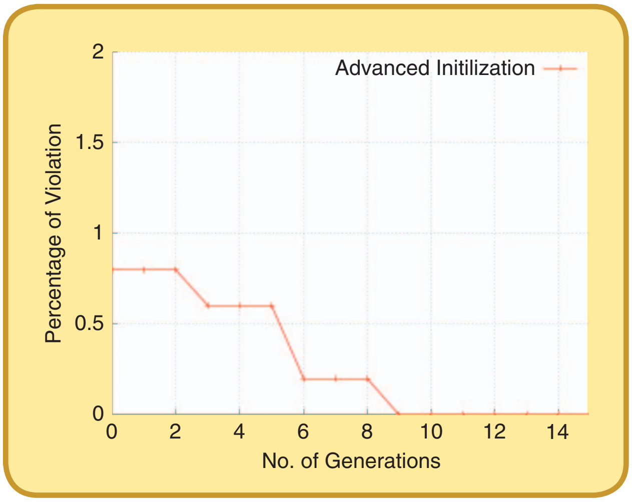

FIG 9 Number of violations based on initial population selection (expanded view).

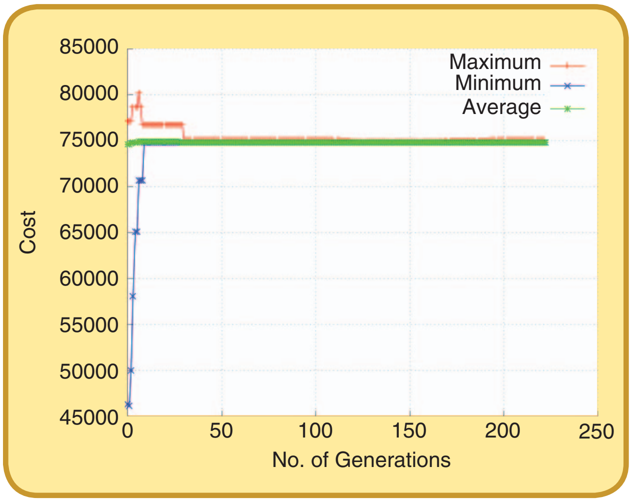

FIG 12 Fitness values over iteration of the whole population with advanced initialization.

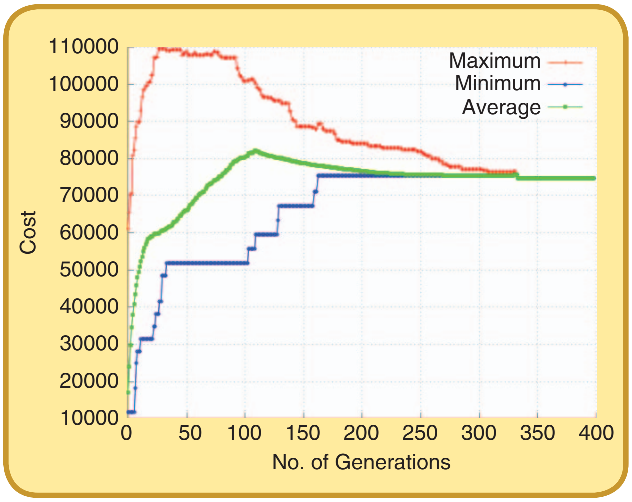

FIG 10 Fitness values over iteration of the whole population with simple initialization.

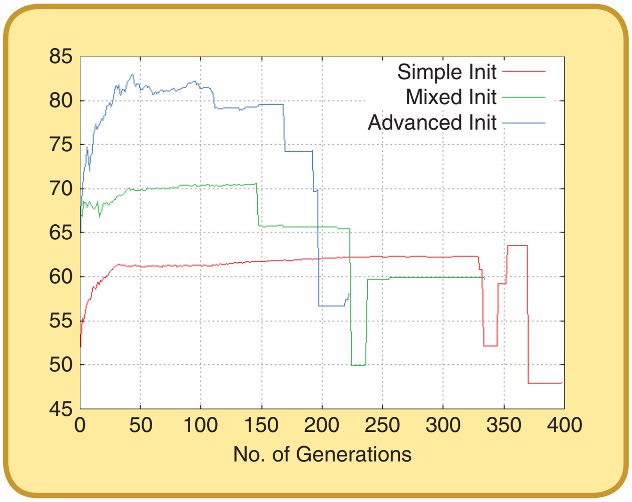

FIG 13 Learning of crossover strategy along iterations.

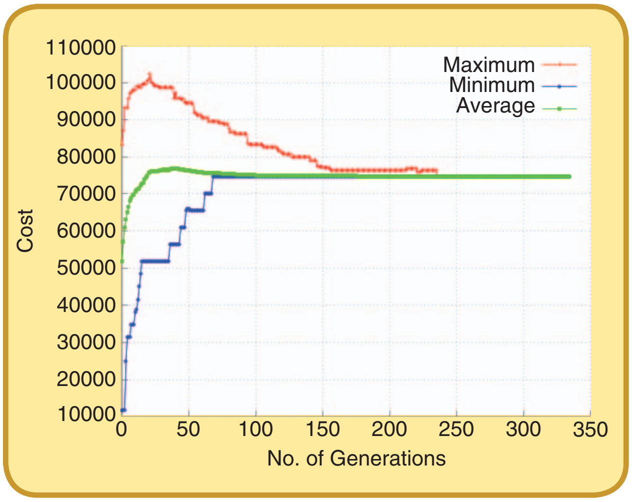

FIG 11 Fitness values over iteration of the whole population with mixed initialization.

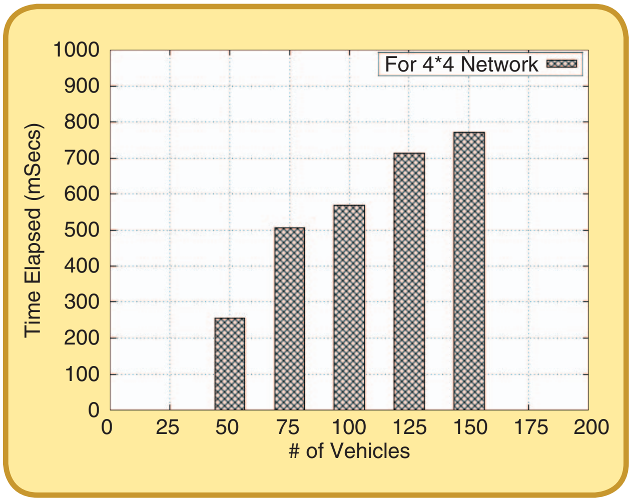

FIG 14 Average computation time per vehicle vs number of vehicles, for the 4 × 4 network size.

solution is taken as a common benchmarking solution.

C. Analysis of Results

Using the described network, we evaluate the performance of proposed solution with respect to population size of 1000. Genetic algorithms are computationally expensive and have higher convergence time [17]. A major contributor to this high costs is the selection of the initial population. Hence it is required to evaluate the percentage of initial population which violates the constraints defined in the problem Figure 8 shows the percentage of solutions which violate the conditions under normal, mixed and advanced initialization procedures. The normal procedure is the most common method where the solution is generated randomly. Advanced initialization is the method proposed in this work while mixed procedure is a combination of two.

Figure 9 shows the expanded view of the same results and it is evident here that in advanced initialization method, the violations seize by 10th generation as compared to 100th and 50th generation in the other two methods. This reduction improves the performance of the proposed genetic algorithm. More specifically, this results in a faster convergence of solutions.

This behavior is shown in Figure 10, Figure 11 and Figure 12 respectively. It is apparent that advanced initialization procedure shows better performance and convergence at a much minimal cost compared to normal initialization and mixed initialization method.

Another factor contributing to the increased convergence time is the crossover procedure. A wrong crossover will result in a non feasible solution. Due to this the algorithm has to be executed over a larger generation thereby increasing the convergence time. In the proposed work this is optimized using the learning strategy. The use of

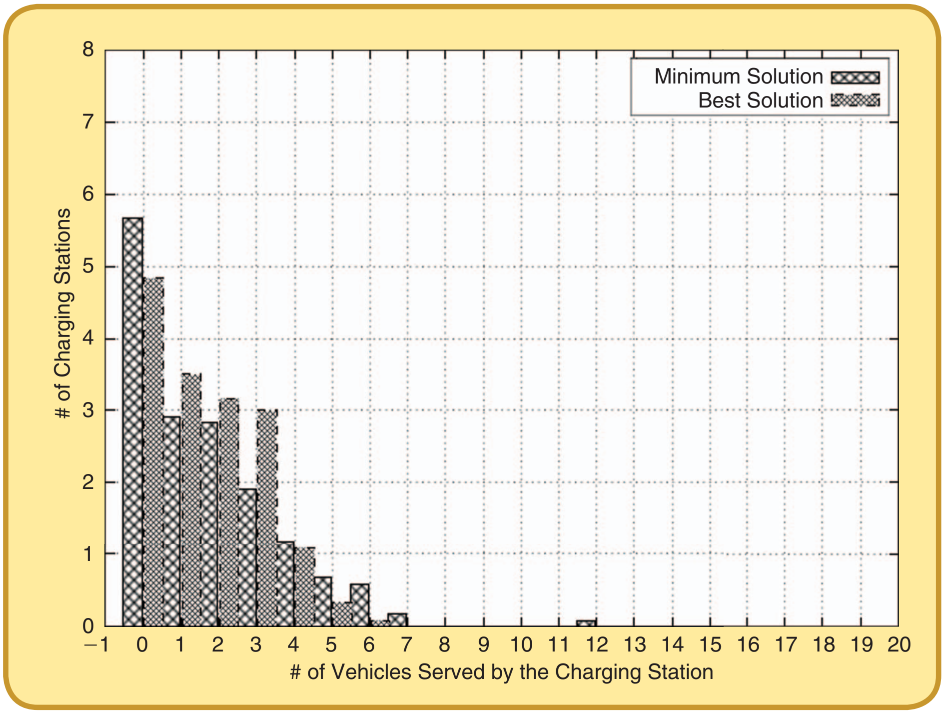

FIG 15 Number of vehicles per charging station (50 vehicles).

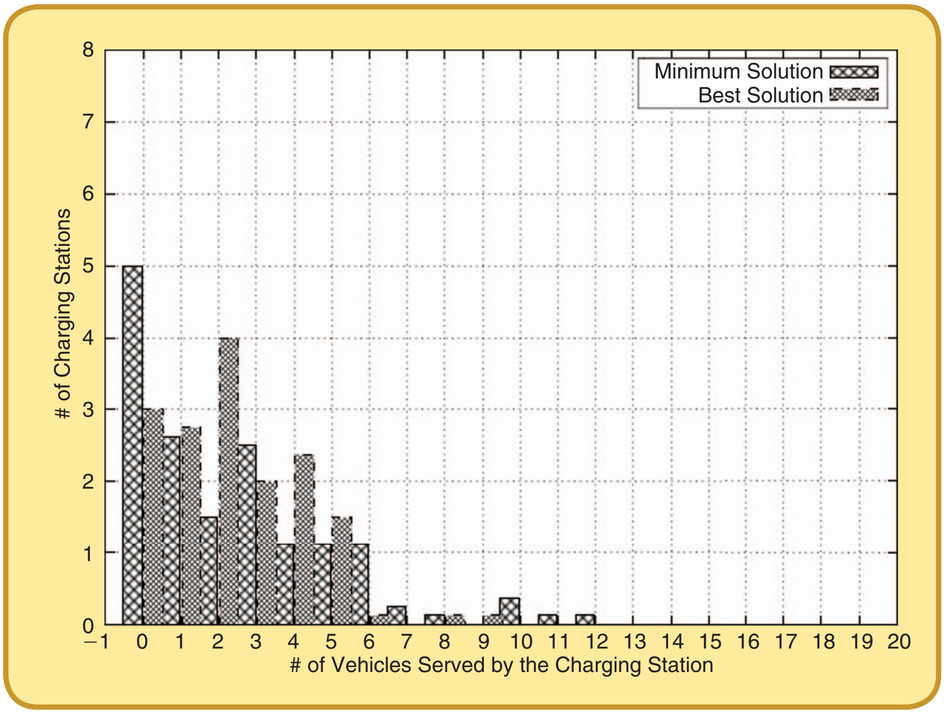

FIG 16 Number of vehicles per charging station (75 vehicles).

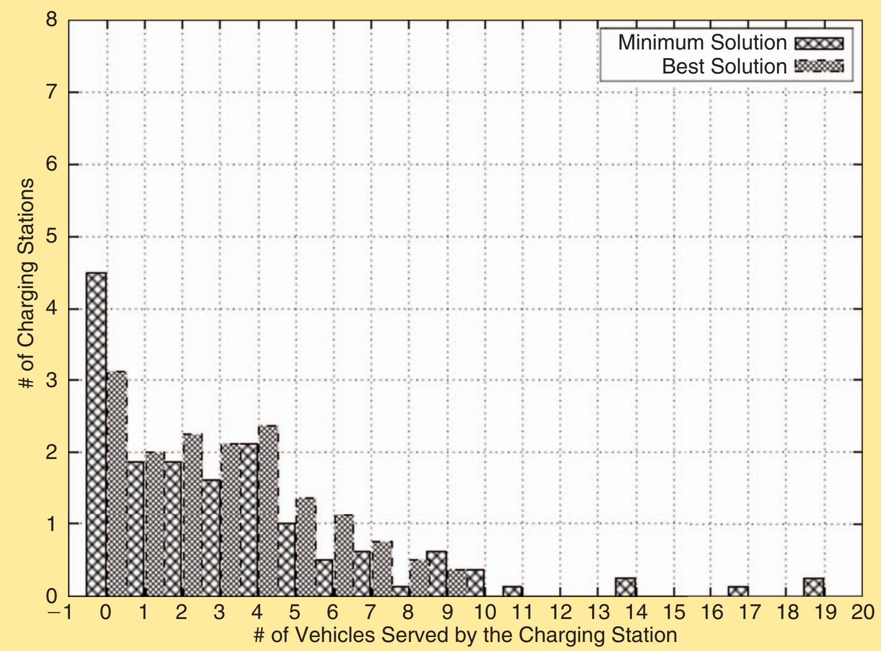

FIG 17 Number of vehicles per charging station (100 vehicles).

The additional cost is indeed mainly due to the increasing number of interaction among routes that is exponential in the number of requests.

The use of advance initialization allows to reduce the population size with a quick convergence time. Hence we use a population size of 20 and number of generation equal to 20.

We further evaluate the efficiency of the proposed method to reduce the concurrency at the charging station. Fig. 15 shows the performance of the algorithm with 50 vehicles.

It can be observed that the solution provided by the algorithm (best solution) compared to minimum distance solution, as described in Sec.V-B, is able to reduce the number of charging stations with high load. This implies that the some other charging stations will have more demand than before, but the constraints imposed ensure that there is a fair distribution of vehicles among the charging station by moving the vehicle from more congested charging station

learning strategy during the iterations is shown in Fig. 13. The non randomized crossover is more successful in the initial and middle part of the iteration process. In the last part the two strategies turn to be equally successful. This behavior is because the population is close to the optimal. Fig. 14 shows the execution time of the algorithm implementation in a standard dual core laptop with 4 Gb of RAM. The plot shows the average computational time divided by the number of concurrent vehicles. The cost is increasing with the number of vehicle, but not exponentially.

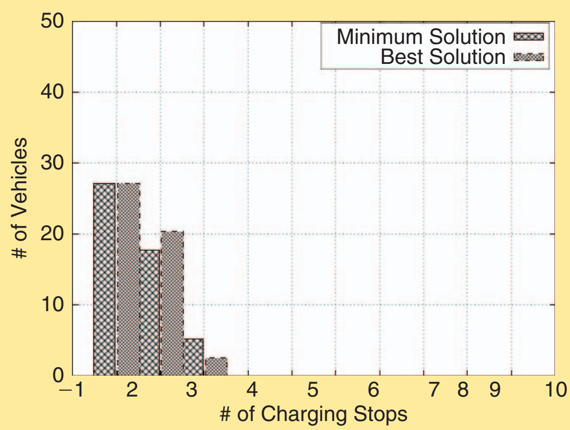

FIG 18 Number of charging station visited by vehicles with the minimum distance solution and the proposed solution (50 vehicles).

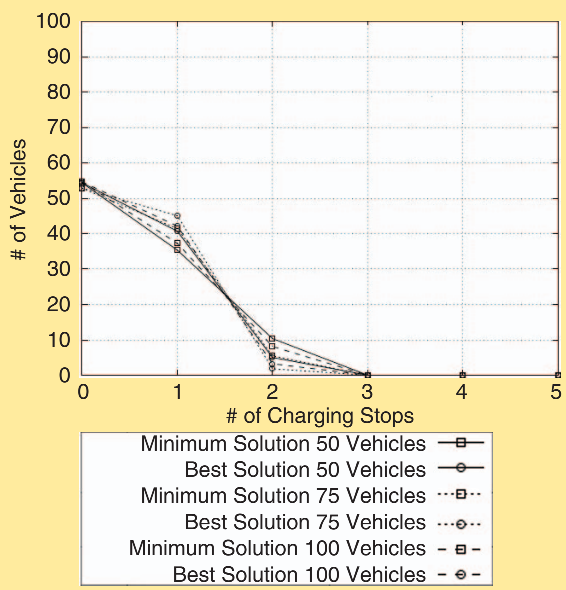

FIG 19 Number of charging station visited by vehicles with the minimum distance solution and the proposed solution (combined).

to the empty ones. This is evident by observing that the number of charging station with zero vehicles is reduced, while the higher loaded charging station shows a reduced number of vehicle. Similar behavior is observed for 75 and 100 vehicles in Fig. 16 and Fig. 17 respectively. Note as in the second case there is a no-zero probability that charging station with 19 vehicles is observed.

The proposed solution also optimizes the routes, thereby reducing the number of charging stops for the vehicles. Fig. 18 shows the number of charging stops in the network with 50 vehicles. It can be seen that as compared to the minimum distance solution the number of vehicles with maximum number of charging stops, in the Fig. 18, is reduced. Similar behavior can be observed for 75 and 100 vehicles, in Fig. 19, where is evident that vehicles move from routes with higher number of stops, to routes with lower number of stops.

VI. Conclusions

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 to further integrate multi modality and analyze its effects on the concurrent charging requests and validate the performance of the proposed solution.

The problem addressed in this work can be considered as a special case of generic Vehicle Routing Problem (VRP). A comprehensive description of VRP can be found in [18]. As a part of future work, the solution will be extended to add typical VRP requirement in the problem formulation.

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