An Efficient Itinerary Management Scheme for Electric Vehicles using ACO

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Abstract—Electric grid has been transformed to smart grid by incorporating ICT infrastructure. This transformation of a smart grid from a conventional grid is necessary to achieve environmental targets. Smart grid technology has significantly changed the way of generation and distribution of electricity which not only helps to decrease the demand of power and cost savings, but also can comparably improve the reliability and efficiency of power system. An electric vehicle (EV), a component of smart grid is the vehicle which uses electric motors for moving the vehicle. Itinerary planning of EV is to manage the whole journey without exhausting battery capacity. The aim of the proposed model is to find the optimized route for an EV in terms of distance travelled and cost of charging from any source to destination. In this paper, an algorithm has been designed to calculate the optimized route by using Ant Colony Optimization

Keywords: Smart Grid, Electric Vehicles, Plug-in Electric Vehicle, Ant Colony Optimization, Route optimization.

(ACO) technique.

I. INTRODUCTION

Conventional grid has been transformed to a grid by included numerous technologies inside, is more efficient grid known as smart grid (SG). This transformation of a SG from a conventional grid is necessary to achieve environmental targets and to make demand response (DR) more significant. It also supports electric vehicles (EVs) as well as generation, distribution and storage efficiency [1]. In brief, it is a technology that allows a two-way communication between the distributer and its end users.

SG technology has significantly changed the way of generation and distribution of electricity which not only helps to decrease the demand of power and cost savings, but also can comparably improve the reliability and efficiency of power system [2]. Like Internet, the SG also consist of computers, controls, automation, and new technologies and devices which works together, but here these technologies works with the grid which is fully electric, to response in digital terms to our electric demand. Automated appliances, smart meters, distributed substations, smart distributors, smart power generation systems are the different components of smart grid [3]. An electric vehicle, a component of smart grid is the vehicle which uses electric motors for moving the vehicle. An electric vehicle can be powered through a battery.

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This battery can be recharged or replaced by a new battery at the charging stations in the grid.

Charging stations will get energy from the renewable sources such as windmills, solar power system, photo-voltaic cells etc.

Electric vehicles (EVs) are different from conventional vehicles in several ways. First, EV battery capacity remains low that makes the driving distance comparably limited due to which it may be required to recharge the EV several times during the journey. Secondly, in terms of energy consumption EVs are more efficient than fossil-fuel vehicles. This energy consumption is measured in the situation of continual accelerating and stopping the vehicles. Third the most important one is EVs are environment friendly. EVs uses electric energy which is produced by natural resources so they does not emit any harmful gases. Finally the last one is low operational cost of EVs over conventional vehicles make them more important [4]. Furthermore, there can be different modes to charge an EV, such as fast, slow and normal-charging. Battery swapping is also possible at some of the stations. Charging price, charging time and battery life are different for each mode [5] [6]. According to an analysis of energy trends, [5] fossil fuel which we use for transportation is a compelling source of CO2 emissions. 70-90% of total CO2 emissions are the due to the oxidation of carbon during the combustion of fuels of conventional vehicles The oxidation of carbon during combustion of fuels of conventional vehicles is responsible for 70-90% of total CO_2 emissions. For an EV which uses electric energy as the fuel, the traveling cost of a unit distance is significantly less than that of a traditional vehicles which were driven by fossil fuel. Taking an example of BYDe6 EV, its electricity consumption for distance of 100 km is only 30 kWh, which is very less when compared with fossil fuel driven vehicle [8].

The drawback of the EVs is that its driving range is relatively exceedingly low when compared with the internal combustible vehicles, therefore becoming the ultimate hurdle in its development. It is a valid point where we consider that the drivers live in the recurring threat of being unable to reach their destinations, an example being restricted movements between cities afar, using the electric vehicles.

In recent years, some policies were defined by several countries around the world. The purpose of these policies was to enhance the advancement and deployment of EVs [9]. For example, a project named as "ten cities thousand vehicles program was initiated by government of china and also gives platform to popularize the development of EV technology and its use by the customers. By the end of 2011, they installed a number of stations of charging and charging piles in china. Moreover, it was also confirmed that 905 charging stations and 2,33,000 charging piles would be installed in the near future

[10].

In [11], an intelligent energy management strategy for EVs was proposed. It takes into account various parameters such as vehicle location, current traffic conditions and road characteristics and then plan the itinerary for the trip. The design of the energy management of the batteries is one of the critical consideration in the development of EVs. It determines how the energy should be generated and distributed to the end users so that it can be used efficiently. In [12] - [15] several energy management schemes has been proposed from control and optimization prospect.

In [16], an optimization tool was developed to recognize the charge pattern of PHEVs. A simple power-train model was used to determine the fuel and energy consumption characteristics. In [17], Dantizing and Ramser *et al.* first proposed the vehicle routing problem (VRP). There can be different objectives of the VRP such as find the route with minimum distance or minimum cost or minimum driving time by the fossil-fuel vehicles. The different constraints could be loading limit of vehicle, type of vehicle or time windows limit, etc. [18]- [20]. The route optimization of EVs is comparatively the new topic for research.

In [21], a model to find the optimized route of the gasoline or diesel powered vehicles is presented. Aim of this optimization was to minimize the distance travelled by vehicle and eliminating the risk of running out of fuel considering the alternative supply of energy. The partial application of this model can be used to find the optimized for an EV.

In [23], Lin *et at.* proposed an Electric Vehicle Routing Problem. The objective of this research is to minimize the travel time, energy and number of EVs. The proposed model considered the limited battery capacity and unrestricted battery charging infrastructure at charging station. Anyhow, costs of charging was not considered in this model.

In [24], Chale-Gongora *et al.* shows the electric vehicle network and focus on the vehicle routing model. Consumption of energy and charging time were considered to assure that EV could be used beyond its limit by using the best path from a source to destination. Factors like charging cost, road tax and distance of a destination from a specific source are still not covered in recent papers.

Based on such discussions, we develop an efficient plan using the ACO algorithm that calculates the optimized route

from a specific source and reassure the driver that he will reach his destination on time. We have assumed that Internet (GPS) could be used by the driver of the vehicle to get the information like current weather condition, current traffic, distance between his current position and charging station as well as the position of charging stations. Applications like CarStations [24] or ChargeMap [25] can be used to display the positions of charging stations on a map. The roads connecting service stations through the route to the destination are an integral part of this plan. With differentiating prices and recharging speed at the different stations. Our main focus are the EVs even though we do take consider the hybrid vehicles too. The autarchy/autonomy of the EVs is fragile at many levels and factors. There a number of external and internal parameters that go into driving the EVs and evaluate its energy consumption. The algorithm presented in this paper provides the driver with a dependable plan of driving, and for this success we have to be grateful to the network analysis and autonomy calculations of the project.

A. MOTIVATION

According to an analysis of energy trends, [7] fossil fuel which we use for transportation is a compelling source of (CO_2) emissions. 70-90% of total CO_2 emissions are the due to the oxidation of carbon during the combustion of fuels of conventional vehicles. These are the reasons for which EVs could be used to improve the world policies for continuous advancement, in ecological as well as energy related sides by minimizing the emissions of CO_2 (and other harmful gases such as Nitrogen Oxide (NO₂), Hydrocarbon (HC), and Carbon Monoxide (CO)) [5]. For an Electric vehicle which uses electric energy as the fuel, the traveling cost of a unit distance is significantly less than that of a traditional vehicles which were driven by fossil fuel. The use of electric vehicles has a positive impact on both economy and ecology, particularly the climate policy and tensions on oil that EVs allow a considerable reduction in CO₂ emissions by private transport. Indeed, by using electric vehicles we can achieve energy independence because they use electricity generated from natural resources rather than relying on foreign oil. Moreover, electricity is cheaper than fossil fuel used by conventional vehicles. Natural renewable resources, such as solar energy or wind power can be used to generate electricity and therefore helps to control pollution. Moreover, EVs consumes less amount of energy than conventional vehicles and hence EVs are more efficient. Dantizing and Ramser et al. in [17] proposed vehicle routing problem that determines shortest path for fossil-fuel driven vehicles. A study has been done on fast charging mode of EV which different from normal charging mode. [13]. In [24], Chale-Gongora et al. proposed an Electric Vehicle Routing Problem. The objective of this research is to minimize the travel time, energy and number of EVs. The proposed model considered the limited capacity and unrestricted battery charging infrastructure at charging station. Anyhow, costs of charging was not considered in this model.

II. ANT COLONY BEHAVIOUR

Ants are the insects which have colonies where they live. They do not need any planning or control for a journey. All the thanks should be given to their mutual collaboration. Their potential to find the shortest route from their colony to food is the interesting fact of their complex behaviour. Some kind of ants deposit a kind of substance called pheromone/trail on path when move from anthill to food source. The ants follow the path with maximum pheromone. If there is no trail on the path then they move in random direction.

Figure 2 shows how the shortest path to the food source found by ants. Food source is marked with G and their nest A. So, after reaching at point B, ants have to decide whether to go right or left. Higher the value of pheromone on the left path, greater the chances to take left turn. The probability to turn left or right is equal for the ant which reaches first at B. The first ant which follows the path $B \rightarrow I \rightarrow D$ will reach at point D before the ant which follows the path $B \rightarrow C \rightarrow D$, because the distance of the path $B \rightarrow I \rightarrow D$ is less than the distance of the path $B \rightarrow C \rightarrow D$. Again at position D, ants have to decide whether to move right or left and similarly ant following the path $D \rightarrow F \rightarrow G$ will reach at point G before the ants which follow other path. As a result the ant returning from G will find the high level of pheromone on path $G \rightarrow F \rightarrow D \rightarrow B \rightarrow A$, because by chance half the ants selected this path to reach the G from A. So, they will prefer path $G \rightarrow F \rightarrow D \rightarrow B \rightarrow A$ to return back to A. Therefore, the path $A \rightarrow B \rightarrow D \rightarrow F \rightarrow G$ rather than $A \rightarrow B \rightarrow C \rightarrow D \rightarrow F \rightarrow G$. would be followed by most of the ants at any point of time. This is the reason, that the quantity of pheromone on the shortest route would increase quickly. So, as a result shortest path would be chosen by all the ants.

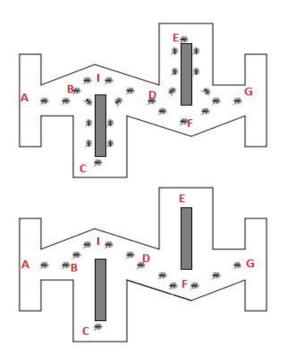


Fig. 1. Ant Colony Model

III. PROBLEM FORMULATION

Electric vehicle is the component of a smart grid. The driving range of the Electric vehicles is relatively exceedingly low when compared with the internal combustible vehicles, therefore becoming the ultimate hurdle in its development. For an electric vehicle, there are number of paths to reach a specific destination from any point. But these paths may take distance/cost which is not affordable by the driver. So, an optimized route is required in terms of distance and cost through which an electric vehicle can reach its destination without exhausting battery capacity.

A. ACO Algorithm

There are two phases in the ACO. In the first one, ants are placed at the starting node which travels to the destination node by choosing different paths. Then, in second phase, these ants move back from destination node to the source node and thereby updating the pheromone values of the paths. For better understanding there is an example of a graph. Formally a weighted directed graph, a topology is defined as G(V, E, W), where:

- V is defined as the set of nodes $v_1, v_2, v_3 \dots v_n$.
- E is defined as the set of edges which is the distance between two nodes v_i and v_i .
- W is the pheromone weight.

Every node v_i in the topology, there is a set of neighbours defined as,

$$N(v_i) = \{v_i | v_i \in V, d_{ij} > 0\}$$
 (1)

Where d_{ij} is the distance between v_i and v_j . When the ant m is at node v_i , next node $v_j \in V$ will be selected with probability P_{ij}^m . Transition probability function is used to calculate the the probability as follows:

$$P_{ij}^{m}(t) = \frac{[\omega_{ij}(t)]^{\alpha} * [\gamma_{ij}(t)]^{\beta}}{\sum_{v_{l \in N(s,i)}} [\omega_{ij}(t)]^{\alpha} * [\gamma_{ij}(t)]^{\beta}}$$
(2)

where,

• $\omega_{ij}(t)$ is the amount of pheromone deposited between nodes i and i.

- • α is a constraint to control the influence of pheromone.
- • $\gamma_{ii}(t)$ is the location function between i and j.
- • β is a constraint to control the influence of distance.

$$\gamma_{ij}(t) = \frac{1}{d_{ij}} \tag{3}$$

where,

d is the distance between i and j.

After completing a tour by every ant, pheromone is laid by each ant on the respective edges which are included in the tour explored by them. Following rules should be applied to update the amount of pheromone on each edge.

Each ants lays pheromone on the respective edges after the completion of a tour. Now m ants would follow the route with maximum pheromone for going back to the source node. Pheromone values will be updated in the following way.

$$\omega_{ij}(t) = (1 - \rho).\omega_{ij}(t) + \Delta\omega_{ij}(t)$$
 (4)

$$\Delta\omega_{ij} = \begin{cases} \frac{1}{L^m}, & \text{if m passed from } v_i \text{ to } v_j \\ 0, & \text{otherwise} \end{cases}$$
 (5

where.

 ρ is the evaporation rate. We have taken value of ρ as 0.1. L^m is the length of the tour found by m ants.

Equation (5) shows that the amount of pheromone laid by all ants is inversely proportional to the length of the trip. Therefore, the edges with large amount pheromone is the shortest tour, and vice versa. The updated pheromone value is considered by the ants to start a new round tour.

IV. PROPOSED SOLUTION

In the proposed model we have found the optimized route using Ant Colony Optimization (ACO) technique. The ants are nothing but the objects associated with the vehicles. The optimized route is the shortest path with minimum cost from the source to destination. We have considered a network, a weighted directed graph (V,E,C) in fig.1 where,

- V defines the set of nodes v₁, v₂, v₃ ... v_n which act as charging stations except source and destination nodes.
 E defines the set of edges which defines the distance to reach v_i from v_i.
- C is the cost of charging the battery which is different at various stations.

There is a source node S and destination node D. Our objective is to find the trip from S to D with minimum distance and minimum cost.

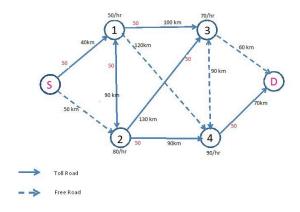


Fig. 2. Road Topology

We took various parameters to find best path from the source to destination. These parameters are as follows:

- Number of nodes $(v_1, v_2, ..., v_n)$
- Type of road (Free road/Toll road).
- Distance between two nodes.
- Driving time to reach node j from i.
- Cost of battery charging at different charging stations.
- Type of battery we have used in EVs.
- Toll price of each road.
- Probability function.

Each node v_i in the network has neighbours defined as,

$$N(v_i) = \{v_i | v_i \in V, d_i j > 0\}$$
 (6)

Where d_{ij} is the distance between v_i and v_j . when the vehicle is at node v_i , next node $v_j \in V$ will be selected with maximum probability P_{ij} which is calculated by applying transition probability formula as follows

$$P_{ij} = \frac{[\psi_i j]^{\alpha} * [\eta_i j^{\beta}]}{\sum_{v_i \in N} [\psi_i j]^{\alpha} * [\eta_i j^{\beta}]}$$
(7)

where ψ_{ij} is a cost function defined by

$$\psi_{ij} = \frac{1}{c_i j} \tag{8}$$

and, η_{ij} is the location function defined by

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{9}$$

 c_{ij} is the cost to reach vertex v_j from vertex v_i and d_{ij} is the distance from the vertex v_i to v_j . Now α is the parameter to control the influence of cost and similarly β is the parameter to control the influence of distance.

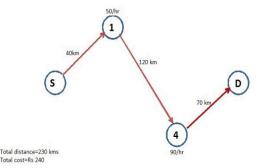
By using the equation (6), we have constructed the table given below.

Nod	Nod	Roa	Distan	Char	Batte	Toll	Tot	Pro
e	e	d	ce	ge	ry	rate	al	b
i	j	Typ	(kms)	cost	type	(IN	cost	$(P_{ij}$
		e		(per		R)	()
				hr)			INR	
)	
S	1	Toll	40	50	li-ion	50	100	0.5
								5
S	2	Toll	60	80	li-ion	0	80	0.4
								6
1	2	Toll	90	80	li-ion	50	130	0.3
								3
1	3	Toll	100	70	li-ion	50	120	0.3
								2
1	4	Fre	120	90	li-ion	0	90	0.3
		e						5
4	3	Fre	90	70	li-ion	0	70	0.3
		e						6
4	D	Toll	70	0	li-ion	50	50	0.6
								4

We have constructed the graph which shows the optimized route from source to destination by using the table. We took the source node and find the probabilities to reach each one of its neighbour. Select the path with higher probability. Now, from the selected vertex find the probabilities to all of its neighbouring vertices and choose the one with highest probability. Follow the same procedure till we reaches the destination.

V. ALGORITHM

The above algorithm gives us the optimized route from



source to destination. First of all we have initialized the variables used in the algorithm. i and j belongs to nodes of a

Fig. 3. Optimized Path

Algorithm 1 Optimization algorithm for route optimization

Initialize: i, j, S count, max, m[100][100]

Input: n, dist, cost

Output: probability $(p_i j)$

1: Function prob(m[0][0])

2: for (i=1; i<=n; i++) do

3: for $(j=1; j \le n; j++)$ do 4: if (m[i][i] = 0) then

x = compute Probability using Eq. 6

6: $node[count++] \cdot \varphi_i = i$

7: $node[count++] \cdot \varphi_j = j$

8: node[count++]· value=x

9: end if

10: end for

11: end for

12: sort(node· value)

13: return i,j 14: \forall i,j, prob (m[a][b])

graph, count keep track of the nodes, S is structure that consist of three variables(value, i index, j index,), and a matrix m[][] which shows the connectivity of the nodes. If m[i][j] is 0, it means there is no path from i to j and 1 means there is a path. Number of nodes, distance and cost are the input for the algorithm whereas probability is the output. Now line 1 defines a function 'prob' which takes base address of the matrix m as the arguments. Line 4 checks whether there is a path from node i to j and line 5 computes the probability of the path from node i to j and store it in variable x. Line 6 stores the index of i and similarly line 7 stores the index of j. We store the value of x at line 8. Line 12 sort the nodes according to value of x. Line 13 returns the value of i and j associated with x. Line 14 calls the function prob for all i and j.

VI. CONCLUSION

In this paper, we proposed an algorithm for route optimization using ACO technique. It helps EVs drivers to complete their journey in an efficient way, by reducing distance and cost to reach the destination. Moreover, the driver of EVs can decide the influence factor of distance and cost according to their situation.

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