DPOC: AN OPTIMIZATION STRATEGY OF EV EFFICIENT TRAVELLING
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Abstract
The popularity of electric vehicles (EVs) provides great help to solve the increasingly serious energy issues and environmental problems, but it also has limitation such as short driving range and long charging time. This paper proposed an optimization strategy for EVs to travel more efficiently called dynamic planned ordered charging (DPOC for short), that is, changing route dynamically to cut down time on driving and necessary charging instead of waiting or overcharge. An energy reachable graph is built firstly to protect vehicles from breaking down in the midway. Travel time, including driving time, charging time and waiting time, is taken as the optimization goal. The modeling and solution of travel time is presented. The two most important contributions of this paper are route re-plan mechanism and the proposal of charging station load and how it can be calculated. Besides, reservation for charging is also introduced to achieve the global optimization. Then the planning of efficient travel can be converted to a general graph theory problem by putting time cost onto edge weight of the graph. According to the simulation and experiment, the strategy proposed in this paper is superior to other compared strategies in many aspects.

Keywords: efficient travel strategy; charging station load; charging reservation; dynamic planned ordered charging

1. INTRODUCTION
With the growing popularity and development of EVs, problems such as short driving range, long charging time and inadequate charging infrastructure become particularly prominent. Currently, full charge driving range of EVs is about 200 km (Yang, 2011) averagely and it will decrease with battery cycles. As a result, when an EV is in a long-distance running, it needs to be recharged once or several times. However, even though in fast charging mode EVs need at least tens of minutes to be fully recharged, which is much more time-consuming than fuel vehicles. Besides, due to the inadequate charging infrastructure, unplanned charging will lead to high pressure of some particular charging stations. The above factors have greatly hindered the promotion and development of EVs. Therefore, an efficient travel strategy is of great significance. Here the efficiency involves two subjects. On one hand, each electric vehicle prefers to re-plan path if necessary to cut down time spent on driving, which is considerable in urban traffic network and necessary charging, instead of waiting in line or overcharge. On the other hand, from a global view, load balancing and resource utilization optimizing of charging network is an important issue. This paper mainly proposes a strategy for EVs to achieve efficient travel.

The remainder of this paper is organized as follows. Section 2 introduces some related works. Modeling and solution are given in section 3 and experimental result is provided in section 4 which verify the feasibility of the strategy. Finally, section 5 proposes conclusion and future work.

2. PROBLEM STATEMENT
Electric vehicle is very promising in future and efficient travel for EVs is of great significance. An efficient travel strategy not only save time and energy, but also avoid congestion and overload. Therefore, route planning or travel instructing for EVs have attracted large numbers of researchers.

Hua Qin and Wensheng Zhang (Hua, 2011) proposed a solution that takes minimizing each vehicle’s waiting time as the optimization goal. However, the applicable scenario mentioned in the paper is that vehicles travel on highway where charging piles distribute at expressway service area. That is, the method tells how to dynamically choose which station to be recharged based on fixed path between starting point and destination. As a result, it cannot help improve travel efficiency in city. Jing Li (Li, 2013) proposed a multi-objective path planning method for EVs. According to the method, time can be taken as the optimization goal. But the paper didn’t consider charging stations’ load which may lead to waiting in line and congestions in stations. Therefore the method may instruct numbers of vehicles with same starting point and destination to a same path. The path smooth at first may be congested gradually. Florian Häusler (Häußer, 2014) presented a new approach to reduce the potential for EVs’ waiting in line at the charging stations based on an analogy between the EVs/charging stations and the mobile phones/base stations. This model eliminates the central control server, but this method is more suitable for the EVs in conventional travel instead of path planning in
advancement. Ao Sun, Guibin Zhu and Tie Jang (Sun, 2012) put forward a minimum-time path time algorithm based on traffic forecasting information in vehicle dynamic navigation, and introduced the realization of dynamic path navigation strategy. This algorithm can provide real-time, high efficiency, strongly predictive planning route, but it neglects some important factors such as traffic accident and traffic congestion which may result in the failure of path navigation. Besides, it is more suitable for traditional vehicles but EVs while only taking traffic load into consideration.

This paper will mainly focus on how to work out an efficient travel plan in advance for EVs whose travelling range is random and energy is limited.

3. PROPOSED NEW MODEL AND METHOD

3.1 Modelling

This paper proposes an optimization strategy of efficient travel for EVs and mainly focuses on the electric vehicle’s time cost minimization. Time cost of EVs consists of driving time, waiting time and charging time.

3.1.1 Driving time

In city transport, driving time is mainly determined by the path distance and traffic load. In general, a vehicle does not drive at a constant velocity, its speed is affected by the road traffic running states such as road condition and traffic flow condition, and even some road has clear limits on the speed of vehicles. In the time dimension, the traffic condition of each road is changing dynamically in urban road network. Therefore, the speed of one vehicle will be changing dynamically and constantly as well. In most cases, vehicles drive slower than expected particularly in face of traffic congestion.

There are a large number of papers in the study of traffic flow prediction (Kono, 2008), and even focusing on route planning based on real-time and dynamic traffic (Faez, 2008). According to the prediction model, the traffic condition is maintained unchanged approximately over a period of time such as 5 minutes generally. In addition, average speed of every road can be regarded as a constant value. Based on these studies, the time cost of each link that some vehicle will pass through in the future can be estimated. Therefore, the following equation can be got:

\[ T_{driving} = \sum_{j,i} T_{\text{link}_i} \]  

Here, \( T_{driving} \) is driving time spent on the road, \( j \) represents index of link in a particular path which consists of several links, \( i \) is the number of time slice, \( t_i \) represents a discrete time interval in the dimension of time, \( T_{\text{link}_i} \) equals the time spent on the \( j \)th link during \( t_i \).

Taking varieties of traffic conditions into consideration, each link of the road network has its threshold of time cost which indicates that the link is under the condition of traffic congestion. When the time cost of one link exceeds the threshold, it will continue to increase even exponentially in the next period of time. In this case, \( T_{driving} \) should be recalculated immediately to update the planning route and eventually reduce the time consumption on the road. Long length allows large threshold. Therefore, the threshold of one link is defined positively correlated to the link’s length as shown in the equation below.

\[ K_{\text{link}_j} = \lambda \times L_{\text{link}_j}. \] (2)

Here, \( \lambda \) is a certain coefficient, \( L_{\text{link}_j} \) represents the \( j \)th link’s length.

When the road traffic condition is stable, and traffic flow and vehicle speed of each road section float only in a small range, \( t_i \) can be replaced by current time. Therefore, the equation can be simplified as follows which is still of a strong guiding significance.

\[ T_{driving} = \sum_{i} T_{\text{link}_i} \] (3)

3.1.2 Waiting time

Waiting time of EVs in charging stations is closely related to the charging station load, so waiting time can be estimated according to the charging station load from a macro view. That is, the heavier the load, the longer the waiting time. According to Little's law (Denning, 1978), this paper designs a quantitative model of charging station load. \( L \) represents the load of a charging station.

\[
L = \begin{cases} 
\frac{T_{\text{avg}} \times (P_{\text{total}} - P_{\text{avl}})}{P_{\text{total}}} & P_{\text{avl}} > 0 \\
\frac{T_{\text{avg}} \times (q_{\text{num}} + 1)^2}{P_{\text{total}}} & P_{\text{avl}} = 0
\end{cases}
\] (4)

Here, \( P_{\text{total}} \) is the number of charging piles, \( T_{\text{avg}} \) is the average charging time of EVs, \( q_{\text{num}} \) represents the number of queuing vehicles and \( P_{\text{avl}} \) represents the number of idle charging piles.

When there exist idle charging piles, theoretically waiting time should be zero. It is to say vehicles can be recharged immediately without queuing. However, the number of idle charging piles can only describe the real-time load instead of risk. Since even though there exist two idle piles at a time point, there may come ten vehicles to charge after one minute. As a result, although there are idle charging piles, risk should be considered when quantifying load. The risk depends on the total number of charging piles and how many have been occupied. Large total number and small occupied number lead to small risk, and vice versa.

When there are no available charging piles, new coming vehicles must wait in line to be recharged and the load is related to the number of queuing vehicles. Ideally, the load of a charging station can be represented as \( L_E \), which equals \( T_{\text{avg}} / P_{\text{total}} \times (q_{\text{num}} + 1) \). However, due to vehicles’ different
remaining electricity and unequal time requirement to be recharged, using \( L_{\text{tot}} \) to describe load may lead to conflicts easily. Because of the conflicts, one charging pile is quite thoroughly difficult to achieve full utilization and vehicles may waste a large number of time when waiting for charge, which will result in time debris for a charging pile. It is obvious that the larger the number of queuing vehicles, the greater the chance of conflicts. Square number of queuing vehicles is used to quantify the load, in this paper.

Waiting time in one charging station can be computed through the load. High load directly lead to long time waiting in line. When defining the load of charging station, actual cost, risk cost and conflict have been considered. Therefore, waiting time of a charging station is defined positively correlated to its load, as shown in the following equation where \( \hat{c} \) is a certain coefficient.

\[
T_{\text{queue}} = \hat{c} \cdot L. \tag{5}
\]

### 3.1.2 Charging time

Due to the lack of charging stations and the charging time of each EV cannot be ignored, the battery of one vehicle is not fully but necessarily charged in charging stations that merely meet the travel requirement. As a result, charging time is determined by a vehicle’s remaining electricity, required electricity and in which mode it is charged (fast filling or slow filling) (Yang, 2011). Assuming that the remaining electricity and required electricity of one vehicle are known, then charging time is only determined by charging mode. Fast or slow filling will lead to different charging time. Charging time is represented as follows.

\[
T_{\text{ch_arg ing}} = \frac{E_{\text{require}} - E_{\text{remain}}}{R_{\text{ch_arg ing}}}. \tag{6}
\]

Here, \( E_{\text{require}} \) is the electricity required to complete the trip, \( E_{\text{remain}} \) is the remaining electricity and \( R_{\text{ch_arg ing}} \) represents charging rate of the charging station piles.

\( T_{\text{total}} \) is time cost from the starting point all through to the destination and it is calculated according to the following equation.

\[
T_{\text{total}} = T_{\text{driving}} + \sum_k (T_{\text{queues}} + T_{\text{ch arg ing}}). \tag{7}
\]

Where \( T_{\text{driving}} \) equals driving time that spent on the links of a particular path, \( k \) represents index of the charging station. \( T_{\text{queues}} \) equals queuing time and \( T_{\text{ch arg ing}} \) is charging time in the \( k \)th charging station.

### 3.2 Solution

Jing Li put forward the definition of energy reachable graph and converted route planning problem into a graph theory problem. According to the initial capacity of a vehicle and charging infrastructure geographic information, energy reachable graph can be built. It consists of the starting point, the destination and multiple recharging points and it is a sub-graph of the original network. Calculating the shortest path based on energy reachable graph can protect EVs from breaking down caused by energy consumption.

In order to satisfy the premise of energy restriction, this paper firstly set up a directed sub-graph as the energy reachable graph. Then time is added to the graph as edge weight. After the above steps, making use of general path-finding algorithm (Dijkstra, 1959) can optimize traveling time.

How to introduce time to a directed graph is discussed below. First of all, the time cost of one link can be directly expressed as the graph edge weight in directed graph, while waiting time and charging time can be expressed as node weight. In general, if node weight and edge weight were independent of each other, node weight can be added to the link which pointing to the node so as to simplify the problem (West, 2001). After the simplification, the problem changes into a typical graph theory problem having only link weight without node weight. How to calculate driving time correctly and whether waiting time and charging time can be converted to edge weight of a directed graph are discussed as below.

### 3.2.1 Driving time

Driving time of EVs on the road is very considerable in EVs’ travel, particularly when the traffic is congested. When the traffic flow floats in a small range, the time cost of each link estimated is acceptable and accurate. However, as the time goes by, these estimates may be at risk of failure.

Here comes an example as shown in Fig.1 below. O is the starting point, D represents the destination, \( n \) stands for node (ordinary node or charging station node) in the graph. The edge weight in the graph tells the time cost of related link. The planning route for an electric vehicle \( V \) is link2 - \( n2 \) - link6 - \( n4 \) - link9. \( V \) is driving on link2 at this time, while unfortunately a traffic accident has taken place on link6, resulting in a sharp rise of the time cost of link6. If \( V \) travels in accordance with the previous route, then it will waste a lot of time on link6 and its driving time on the road may be greatly increased. Eventually, the total time cost will be intolerable.

![Figure 1. Calculation of driving time](image-url)
the new planned route whose total time cost is optimized and shortest in the directed graph at this moment.

Here summarizes a general method. The time cost of each link should be estimated every period defined as \( t \) and update graph edge weight in the directed graph immediately where \( t \) is not a constant value, but determined by the road traffic running states. Frequent and violent changes lead to small period, and vice versa. Since how to calculate \( t \) is not the emphases of this paper and \( t \) is also considerate as a small and constant value in other papers (Sun, 2012) according to the prediction model, such as 5 minutes.

In each estimate, if the time cost of link \( j \) meets or exceeds \( j \)'s threshold, the routes for those EVs whose path contains link \( j \) should be re-planned immediately. Therefore, the route of one electric vehicle may be re-planned several times due to the traffic condition and in the meantime, the path will be changing dynamically.

### 3.2.2 Waiting time

When a vehicle arrives at a charging station, whether it needs to wait or how long it should wait is independent of the path it has travelled through. That is, no matter from which link the vehicle came to the charging station, the load is a fixed value, which can thus be summed up to the link pointing to the station node.

According to (4), waiting time and charging station load are positively correlated, and the load is calculated with static data (such as \( P_{\text{total}} \) and \( T_{\text{ave}} \)) and dynamic data (such as \( q_{\text{in}} \) and \( P_{\text{out}} \) which change over time). Therefore, the above dynamic information should be saved for each charging station as global shared variables to support the calculation of charging station load. However, real-time data of the exactly current moment is not enough. Here is an example for why real-time data is not sufficient. According to the planning result, one vehicle \( V \) need to be recharged at a station \( S \). Referring to the calculation result, \( V \) will arrive at \( S \) at some time in the future. When calculating waiting time in \( S \), the load at the particular time in the future is necessary. In order to get enough information to predict load, for those vehicles whose path planning has been completed, a reservation record should be stored in the corresponding charging stations as globally shared variables. The record consists of several items such as the planned arriving time, charging starting time and charging finishing time. When there are new-coming vehicles requesting plan, real-time data and booking records of different charging stations should be obtained, the figure below is an example. Fig. 2 is a logic diagram of a specific charging station’s resource reservation, horizontal is timeline and ordinate represents charging piles. As the picture shows, this charging station holds five charging piles and the bar of each charging pile represents a reservation records, the yellow part is the waiting time and the green part is charging time. At this point, there is a new-coming vehicle that is expected to arrive at the charging station at \( t_0 \). First of all, according to the existing records, calculate the load and waiting time.

Then making use of A-star algorithm to find a shortest path. Once the route is chosen, an item of reservation record should be added to related charging station’s global shared variables, as shown in Fig. 3. Here, \( P_1 \) will be preferred to add the reservation record to make full use of the charging piles while \( P_5 \) is idle.

### 3.2.3 Charging time

Charging time is determined by vehicle’s remaining electricity and required electricity. How much electricity is remained depends on which path the vehicle has gone through. Similarly, how much electricity is required depends on which path the vehicle will go through. If a vehicle has two path of different length to choose, the choice will lead to different energy consumption and thus different requirement for charging time accordingly.

The following instructions are based on Fig. 4. Here, \( O \) is the starting point, \( D \) represents the destination, \( n \) stand for ordinary nodes in the directed graph, \( CS \) is charging station node. The edge weight in the graph tells the distance of link. Known that the original electricity at point \( O \) is not enough to reach \( D \), but any charging stations in the figure is reachable. The purpose is to choose a path for the vehicle from \( O \) to \( D \) to minimize its time cost.
When the vehicle chooses CS1 as the position where it can be recharged, how much electricity it needs to charge is related to its remaining electricity and required electricity. The remaining electricity equals the original electricity minus energy consumption from O to CS1. If the route is link1 - n1 - link3, the energy consumption is different from route link2 - n2 - link4. Similarly, the required electricity equals the energy consumption through the following links to the destination or next charging station. If the next route is link6 - n3 - link8, the required electricity is energy consumed on link6 and link8, while route link7 - CS2 - link9 is on link7.

Since the distance of link remains changeless and is nothing to do with dynamic traffic condition, the energy consumption can be simplified to be proportional to driving distance, namely driving energy consumption $E_{\text{drive}}$ equals $\phi \times \sum d_k$. In the equation, $\phi$ is a coefficient standing for the positive relationship, $d_k$ is the distance of the kth link.

The method of converting charging time to directed graph edge weight is to convert the charging time to a path’s energy cost. Since a vehicle’s original electricity in the starting point is given and fixed, charging time mainly depends on the energy consumption during travelling. The more electricity consumption, the less the remaining electricity, the more needed to be recharged, thus the longer the charging time, and vice versa. According to the above equation, the kth link requires energy of $\phi \times d_k$, the charging time of the particular path can be converted to

$$T_{r_{k-o}} = \frac{\phi \times d_k}{R_{ch \_avg \_ing}}.$$  \hspace{1cm} (8)

Here, $R_{ch \_avg \_ing}$ is the charging rate of the vehicle. Total time consumption of the kth link is as follows

$$T_k = T_{k_{\text{drive}}} + T_{k_{\text{chg \_ing}}},$$  \hspace{1cm} (9)

In conclusion, charging time can be transformed from node weight to edge weight by setting the time consumption $T_i$ to edge weight of the kth link in the directed graph. Below is an example telling how to calculate time weight.

Refer to Fig. 3 again. The chosen path of a vehicle is link1 - link3 - CS1 - link7 - CS2 - link9 and CS2 is the last charging station the vehicle will pass by. When calculating edge weight, driving time and charging time of all links of the path include should be summed up and minus the time compensation of the energy consumption from the original electricity. The time consumption of one particular path can be calculated using the following equation.

$$T = \sum_{j=1}^{n} (T_{j_{\text{drive}}} + T_{j_{\text{chg \_ing}}}) - \frac{(E_{\text{origin}} - E_{\text{remain}})}{R_{ch \_avg \_ing}}.$$  \hspace{1cm} (7)

4. CASE STUDIES AND DATA ANALYSIS
4.1 Simulation Environment and Data Set

TransModeler applies a variety of mathematical models of driver behavior and traffic flow theory to simulate traffic phenomena. Its models make use of detailed and varied input data about the transportation system, are capable of generating an extensive array of output statistics, and rely on a diverse set of parameters calibrated to match the models with real world observations. It has a built-in map of San Antonio.

San Antonio is a city located in the central and southern of Texas, and it covers an area of about 1205 square kilometers. The dataset of it contains 461 nodes and 618 links. Node contains the information such as Id, coordinates and edge contains the Id, starting node and end node, direction and information such as length of the link.

Firstly, 15 nodes are selected as charging stations from node set on the map. The selection is in accordance with the principle that charging stations should be distributed evenly considering the geographical position. The second step is to set random number of charging piles in each of the charging station, ranging from 5 to 25.

3.2 Simulation Method and Result

The strategy proposed in this paper is called dynamic planned ordered charging (DPOC for short) and in order to verify the effectiveness of the strategy, it was compared with shortest first charging (SFC) and planned ordered charging (POC for short), while reachable random charging (RRC) whose performance is not stable and of little significance was eliminated.

The simulation starts from randomly generating some vehicles’ data including parameters such as the starting point, destination, remaining electricity and velocity. Before the path planning for a generated vehicle, the original energy should be checked firstly. If the energy is not enough for the whole trip, the situation aligns with this paper, otherwise the traditional path planning method is applied well. When the initial energy is insufficient to meet demand, the vehicle should be recharged at least one time. There are different kinds of strategy to determine the travelling plan such as which path to go and where to charge. Three different strategies of simulation have been performed including the strategy proposed in this paper, SFC which choose charging station closest to the starting point to charge and POC which does not consider dynamic traffic condition and never changes its path once planned. This
section compares three strategies’ efficiency from multiple aspects.

Firstly, the simulation system randomly generated 200 electric vehicles satisfying the condition that they must be recharged at least one time. Secondly, time cost of each link was obtained from TransModeler every 3 minutes which had been well estimated in real-time. Thirdly, route for each vehicle was planned according to the different strategies. Fourthly, source data and planned path was put into TransModeler. Note that if time cost of one link changed substantially and eventually the threshold was met or exceeded, the third and fourth steps would be repeated base on the current state of relevant vehicles and new estimate of time cost. In the end, real-time simulation result is presented below.

4.2.1 Total Time Cost

In Fig. 5, the X-axis contains 200 discrete points representing 200 electric vehicles and Y-axis stand for total time which equals the sum of driving time, waiting time and charging time. In order to make it easy to observe, the discrete dots are sorted by total time, colored according to strategy and connected by lines. The figures below also share the same pattern. According to Fig. 4, the strategy of path planning representing by red scatter has less time cost than the other two strategies. In addition, statistical analysis is done against the sum of all vehicles’ time cost under the three different strategies, as shown in Fig. 6. According to the figure, DPOC strategy is superior to the POC and SFC strategies.

![Figure 5. Vehicle time cost statistic chart](image)

![Figure 6. Comparison between total time of three strategies](image)

4.2.2 Driving Time Cost

A specific analysis is done with the driving time. According to Fig. 6, more than half of the total time is spent on road which is called driving time. Shorter driving time leads to higher user satisfaction and better traffic condition. Fig. 7 shows the sum of driving time in three strategies. It can be seen that DPOC strategy saves significant time compared with POC and SFC which improves travel efficiency greatly.

![Figure 7. Sum of driving time](image)

4.2.3 Waiting Time Cost

The length of waiting time is one of the key evaluation criterions for user satisfaction. According to Fig. 8, the total waiting time of DPOC is less than POC and SFC, hence DPOC has a better average waiting time. Fig. 8 shows the waiting time of each vehicle. About half of the vehicles need to wait in line. For the vehicles needing to wait, the red line is significantly lower than the blue and green lines.
Besides the length of waiting time, waiting time ratio is another important criteria. It’s the percentage of waiting time in the total time. Because the total time of each vehicle is different, the comparison of waiting time ratio is more reasonable. Smaller waiting time ratio brings better user satisfaction. Fig. 9 shows the comparison between waiting time ratio of three strategies. It can be seen that DPOC’s waiting time ratio is lower than that of POC and SFC.

### 4.2.2 Distance Cost

The comparison of the total time cost shows the advantages of the proposed path planning strategy. In addition to time cost, statistical analysis also been performed for a single vehicle’s distance cost and total distance cost. Fig. 10 shows the distance cost of each vehicle and Fig. 11 shows the sum of distance cost in three strategies. DPOC changes its path dynamically to find links whose length may be longer but time cost lower base on the traffic condition. It can be seen that DPOC and POC’s distances are shorter than SFC obviously.

### 4.2.3 Charging Time Cost

In the simulation, all charging stations use the same charging rate, therefore the amount of charging electricity is in proportion to charging time. It’s more environmentally friendly to reduce charging time and save energy. On the other hand, short charging time also bring better user satisfaction. Fig. 12 shows the charging time of each vehicle and Fig. 13 represents total charging time together with average charging time using the three strategies. It can be seen from the figures that DPOC requires a little more charging time than POC because of longer distance cost analyzed before but quite less than SFC. It is reasonable that DPOC tries its best to reduce the total time at the cost of a small amount of additional energy consumption compared with POC. But DPOC saves more energy and has better user satisfaction than SFC. In this sense, DPOC has a better performance.
5. CONCLUSIONS

This paper, taking electric vehicle as the researching object, considering the actual demand of vehicle users, presents an optimization strategy to solve the problem of short running range, long charging time and inadequate charging infrastructure. Referring to the calculated travelling plan it will spend less time on driving and necessary charging instead of queuing in line. After experimental verification, no matter from a single vehicle’s aspect or a global viewpoint, DPOC strategy shows superiority and keeps a good balance between time and energy consumption.

The method proposed in this paper is based on the fixed charging stations, that is, the stations have known position. However, it is obvious that reasonable charging station distribution is critical to improving charging efficiency and optimizing travel experience. Therefore, how to distribute charging stations is a meaningful topic that can be further studied.

6. ACKNOWLEDGMENT

This work is supported by the National High-tech Research and Development Program (863) of China under Grant No. 2012AA111601, and the Fundamental Research Funds for the Central Universities.

7. REFERENCES


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