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Energy Transport Station Deployment in Electric Vehicles Energy Internet

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ABSTRACT Energy Internet allows energy to flow flexibly for transmission and it can transport energy to every energy user via electric vehicles (EVs). The energy that EVs use is produced from renewable energy sources like solar power. However, under bad weather conditions, the power station will stop energy generation and will need to get power transported from other places. One solution is to set up some stations, which usually store excess energy. In special times, the energy stored by these stations can be used to supply electricity to all parts of the city. In this process, the position of the station that provides power should be considered carefully for the sake of reducing energy loss during transportation. The main idea of this paper focuses on how to choose positions for the stations. We put forward the concept of energy transport station (ETS) which can store and output energy, then we propose three algorithms, namely exhausted algorithm, greedy algorithm, and segmentation algorithm, to decide where to place ETSs so that the energy loss can be minimized. The algorithms will be simulated with data of bus route maps of Manhattan and the Pioneer Valley Transit Authority (PVTA), which will show the contrast of each algorithm and find their best application scenarios.

INDEX TERMS Energy internet, electric vehicles, energy transmission.

I. INTRODUCTION

The concept of electric vehicles Energy Internet has been raised because of its advantages like saving traditional energy [1]. Electric vehicles equipped with batteries can store a lot of energy thus it can be used for energy storage [2]. The mobility of EVs makes energy in the network be transported from one place to another. The network mentioned above is what we call the EV Energy Internet which can reduce the consumption of energy transfer comparing to traditional Vehicle-to-grid [3]–[5]. As more and more traditional cars are to be replaced by electric vehicles, the energy stored in electric vehicles will become so enormous that electric vehicle-based Energy Internet will have enormous potential.

The reason we use public transport instead of dedicated electric vehicles to directly transport battery power to the charging station is because the cost of dedicated electric vehicles and drivers is also high. This cost may exceed the profit brought by the energy Internet advantage, so the use of existing public transportation lines can reduce a lot of costs, so it will bring about the problem of energy transfer.

The main advantage of EVs Energy Internet is that the energy loss of EVs Energy Internet is less than that of traditional power grids system in an ideal situation, which is proved in Section 2. EVs can be charged with renewable energy sources and travel to other places to discharge thus providing energy for other electric devices owing to its low cost of energy on the road, unfortunately the low cost can only happen under ideal circumstances. What is the ideal situation will be discussed later. However, power stations that provide renewable energy are more unreliable in power generation than traditional power plants. For example, solar power stations cannot generate electricity on cloudy days. If a place continues to rain for several days, the energy-dependent solar Energy Internet will be paralyzed. Therefore, when renewable energy has a sustainable power generation capacity, the use of electric vehicles to transfer energy to a certain place for storage, as a source of power supply for non-renewable energy stations, will effectively solve this problem. Based on this, we propose a new concept,

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namely the establishment of an energy transport station, hereinafter referred to as ETS.

ETS is used to store enough electricity when the energy supply station is able to generate electricity normally and to deliver electricity to other charge stations in the city when the energy supply station cannot work well.

At the preliminary stage of the problem, the cost of construction of ETS is considerable. We should establish a suitable number of ETS in the right places. In other words, we need to trade off the cost of building ETS and the decline of energy loss after building one more ETS. The cost of building ETS should include the cost of construction and the cost of maintenance.

Of course, the distribution algorithm of ETS is important as well. It is about how to find the best place to layout the ETS. Best place means that it can best minimize energy loss. It is the most difficult problem in this work so this paper aims to study and solve the distribution difficulty of how to deploy the energy transport.

In this paper, several algorithms are proposed and evaluated in a real urban traffic map. The average energy loss to establish 1 to 10 ETS in the city will be calculated to measure gains as the number of ETS is increased.

The main contributions of this paper are as follows.

- Some situations of energy shortage are put forward. Aiming at these situations, the solution of utilizing ETS is put forward.
- Develop several algorithms to solve the problem of best location to deploy ETS in order to minimize the total energy loss. The exhaustive algorithm can be the best algorithm, but it is very complex. Hence, we propose a greedy algorithm and a segmentation algorithm, which can both reduce complexity and obtain a good outcome. We compare them with the exhaustive algorithm and the random algorithm to prove that they perform well enough. The segmentation algorithm proves to be better than the greedy algorithm and its outcome is similar to the exhaustive algorithm.
- Test algorithms mentioned above are applied on real-world transporting data, which comes from the Manhattan bus lines and the bus map of the Pioneer Valley Transit Authority(PVTA).

The paper is organized as follows. We describe the problem of ETS in Section 2. We formulate ETS deployment problem in Section 3, and provide solutions in Section 4. Section 5 presents the evaluations and analysis. We introduce the related work in Section 6. Section 7 concludes the paper.

II. PROBLEM DESCRIPTION

EVs the have ability to store energy, as well as the mobility to transport and distribute energy from energy sources to energy users in the Energy Internet. The electric vehicle Energy Internet has three main components: energy production, energy transport and energy consumption, which is shown in Fig. 1. Energy generation consists of power plants of different energies such as renewable energy [6]. Energy consumption includes residential, energy routers and electric vehicles themselves. Energy transport consists of electric vehicles and electric car charging stations. The battery can only charge and discharge during the stop. Hence, it takes a few minutes to charge or discharge. The technology named Ultra-fast Chargers creates the conditions for the working of the EV Energy Internet [8]. We add ETS into this network, and it should be added where the energy is transported.

The significance of ETS lies in the role of power supply at the time of non-renewable energy stations, and energy stored in the ETS is transported by electric vehicles. So, the location of ETS in the city is worth exploring.

The advantages of setting up ETS at the bus stop are beyond doubt. Buses must pass through these stations every day, so the transport of energy is just a matter of convenience, and there is no need for special arrangements for transportation of energy. Therefore, we have established a model to represent the distribution of ETS bus stations in the city. To better understand this model, we first introduce some related concepts.

A. CONCEPTION OF EV ENERGY INTERNET

First of all, the reason for proposing the EV Energy Internet is that intelligent electric vehicles are suitable for the working environment of it. Because intelligent electric vehicles make it easier to run a relatively fixed route and vehicles such as buses or subways are relatively easy to implement, so they are suitable for the construction of an EV Energy Internet.

The original intention of an EV Energy Internet is to transport energy from renewable energy(solar or wind) plants to the places where users need power(e.g., charging stations and buildings). The EV transport network consists of three main parts, which are energy generation, energy transportation and energy consumption [6] [7] [1]. For instance, renewable energy plants belong to energy generation. Energy transportation is composed of EV and charging stations. The places where users need power(e.g., charging stations and buildings) are part of energy consumption.

We define some terms as follows:

Definition 1 (Energy Source): is a power station supplying electricity. As urban space is restricted, energy sources are normally located in a rural area. EVs can charge power from an energy source when passing by it.

Definition 2 (Energy Loss): happens every time the battery charges or discharges. In previous work, we know that energy loss is about 10 % in one time of charge and discharge. As energy loss is not wanted, we should try to make the times of charge and discharge as few as possible.

Definition 3 (Energy Route Metric): is a number of energy charge and discharge times in an energy path. One measure of charge and discharge is one. $A_1 - A_2$ energy route metric, energy is by A_1 EV and EV emissions from A_2. $A_1 - B_3$ energy route metric is 2, two times of charge and discharge. First, the energy is charged from A_1 to EV and then discharged from EV to A_3. Second, the energy is charged from A_3 to EV, from EV to B_3.

B. SIGNIFICANCE FOR EV ENERGY INTERNET

Transmission of electricity through the grid is one way to transmit solar energy. There are three steps to transport energy from a solar station to a planned charging station. The first step is to convert the DC generated by the solar panels into grid-connected AC power. The total lost power is about 10% of the power [35]. The second step is to transmit over the power line. It lost about 6.5% [36]. The last step in converting AC energy into DC energy results in a 15% energy loss [37]. This is charging station charging battery. The program's total energy loss of up to 28%. This simple methods can cause a lot of energy losses.

Electric vehicle Energy Internet is a new type of power transmission. The process includes three steps from the solar power station to the charging station. DC charging electric vehicles do not need to convert DC to AC, the efficiency of which process is 95% [38]. Electric cars are then used to transport electricity from the solar power station to the charging station. The battery discharges 0.03% of the total daily power [39], for the amount of electricity required to drive a vehicle cannot be attributed to the transport battery. Because the bus was supposed to be on the established track, only the additional battery power required by the increased battery load needs to be taken into account. The third step is similar to the first step. Its loss is about 5% [38]. The total energy loss for this process is about 10%.

Compared with the energy loss of power transmission, if the number of charging and discharging times is less than 3, the energy loss of the EV Energy Internet obviously decreases. Therefore, reducing the number of charging and discharging times is an important goal. In the ideal case, we can get such a small energy loss, so that the EV Energy Internet deserves to be designed.

C. CONCEPTION OF ENERGY TRANSPORT STATION

As mentioned above, the intermittence of renewable power is a headache. Although the flexible mobility of EVs can solve many problems, there are still some problems waiting to be resolved. For instance, the total power of the power station is sufficient, but weather reasons, such as a few days of rain, can lead to a small period of power shortage. To solve this problem, we put forward a new structure in the electric vehicles Energy Internet called ETS, which is used to store plenty of power and distribute it.

When the weather is suitable for power generation, there is a lot of power redundancy in power stations. Too much electricity is generated beyond the capacity of the power station, so the EVs transport large amounts of electricity into ETS. In this process, there is a lot of power redundancy, so energy loss is not so important. Thus, we assume that ETS are full of power. Meanwhile, the main problem is how to deploy ETS to minimize the energy loss. To make this problem easy, we assume ETS to be located in the bus stops and the consumption of each ETS is of the same value. So that the energy loss can be expressed as the sum of the energy loss of all users to the nearest ETS. Of course, the bus is an example of EVs. It can be replaced by the train as well.

III. PROBLEM FORMULATION

To make the problem simple, we assume that every bus station establishes a charge station and the energy used by the charge stations at each bus station is the same. EVs can exchange energy in the charge station. Then, the establishment of ETS may incur inevitable costs. In order to tradeoff the decline of energy loss and the establishment costs, the profits should be calculated accurately. In other words, it should be calculated how much energy loss will be reduced for one station built. In extreme cases, each site has an ETS. It means that each charge station can store a great deal of power. But the space is limited, so it is impossible to ensure that every station can store sufficient energy so that it can support this place for several days even dozens of days.

In our previous articles [1], we have already talked about the concept of energy route metric and have named the unit *hop*. One hop means one time of charge and discharge. We will use the number of hops to describe the rate of energy loss.

To simply illustrate the above case, Fig.2 displays the schematic diagram of bus lines. There are 2 streets, named street A and B, and two bus lines: $A1 - A2 - A3$, $B1 - A2 - B3$. Each node stands a bus station. When the start point is $A1$ and the destination is $A3$, the number of hops is one. The process is that bus1 on the A street charges at $A1$ and discharges at $A3$. However, if the start point is $A1$ and the destination is $B3$, the number of hops is two. In this case the process is that bus1 charges at $A1$ and discharges at $A2$, then bus2 on the B street will charge at $A2$ and discharge at $B3$, during which time two times of charging and discharging happens. So the number of hops is two. From this point of view, the number of hops can indicate the rate of energy loss. As mentioned above, one hop means about 10 % energy loss.

To make this problem more intuitive, we reduce the dimension of the bus line. In other words, we regard the bus line as one point so that the distance of the point is the number of the hops. In the Fig.3, there are nine points and $L = \{L_1, \cdots, L_9\}$ denote the set of bus lines. This model shows the positional relationships between the different bus lines. The connection lines between the points describe the relationship between bus lines. For example, the distance between L_1 and L_9 is two so that the number of hops is two.

In fact, we research information on each bus line and bus station. But in order to visualize the performance of the algorithms, we will simplify it as a bus line diagram. One line is chosen at one time to analyze the effect of this choice on global energy consumption. We use $C = \{C_1, \cdots, C_n\}$ to denote the set of selected lines. In the actual evaluation, we use Dijkstra's algorithm to calculate the distance between each bus station.

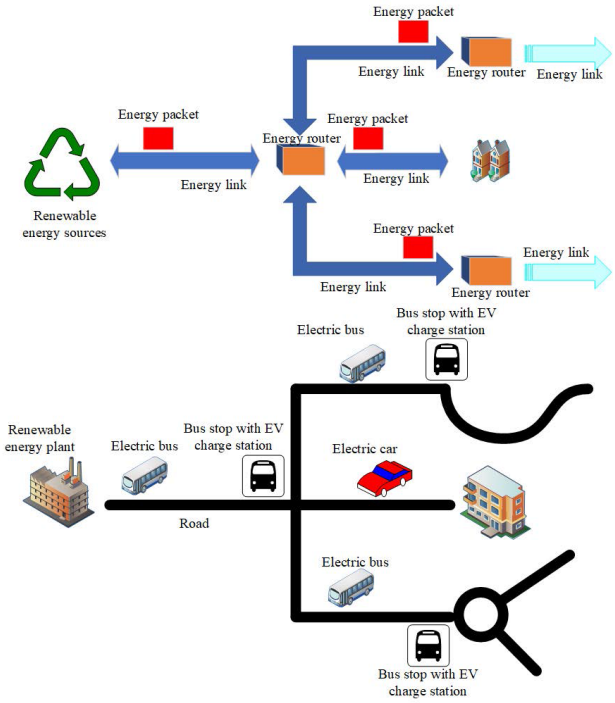

FIGURE 1. EV Energy Internet structure.

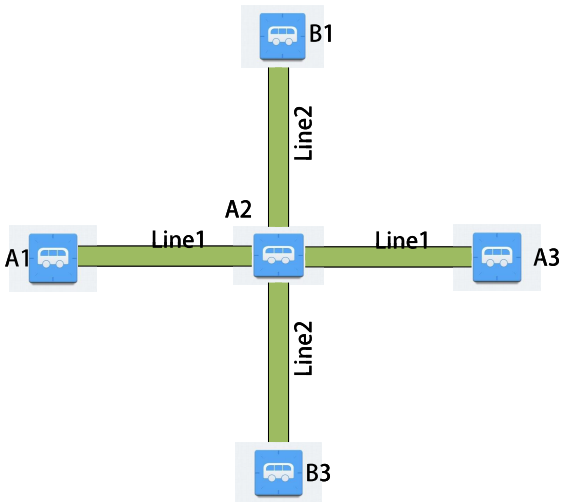

FIGURE 2. Schematic diagram of bus lines.

A. EXHAUSTIVE ALGORITHM

The problem we discuss is how to deploy ETS to get minimum energy loss. It is easy to find that the exhaustive algorithm can solve this problem with the best method. As is shown in Eq.1, best solution can be found if we test it for enough times.

$$sum_{combine} = C_n^k \tag{1}$$

The process is to find combinations of all the options, then calculate all hops from bus stations to their nearest ETS. The sum of the metric(the number of hops) is the parameter used to measure the extent of energy loss. We name the parameter EL. The calculation process is shown in Eq.2. Then the sum of the wanted ETS is m, of bus stations is n.

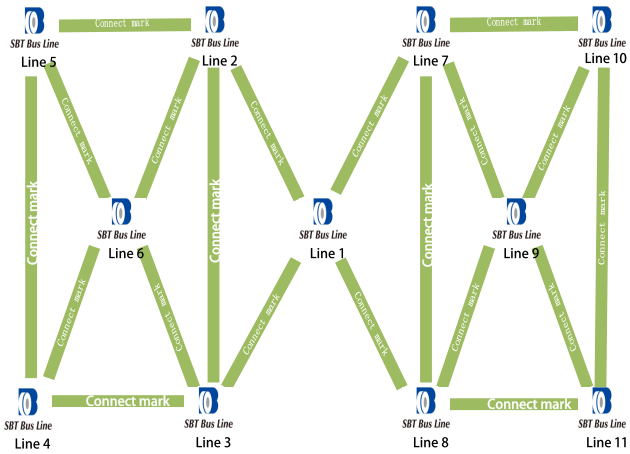

FIGURE 3. The relationship of bus lines.

$T_i = \{T_1, \cdots, T_m\}$ denote the transport stations. The metric of each bus station to T_i is $e_{ij} = \{e_{i1}, \cdots, e_{in}\}$.

$$EL = \sum_{i=1}^{n} min\{e_{1i}, \cdots, e_{ni}\} \tag{2}$$

However, the complexity of the algorithm is $O(n^n)$. Obviously, this complexity is unacceptable. Thus, this algorithm has little practical usage. However, it can be calculated when the number of ETS is small. Hence, this set of data can be used as a reference to judge whether the algorithm performs well or not. In other words, if an algorithm gets a similar energy loss rate to what the exhaustive algorithm does, then this algorithm performs well.

In a word, the practical use of exhaustive algorithm is to get the best result when the number of ETS is small and to provide a measurement for other algorithms.

B. GREEDY ALGORITHM

The greedy algorithm is another idea we use to solve the problem. The process of the greed algorithm is described in 1. This algorithm is relatively simple and effective. Of course, this algorithm has the limitations of a simple greedy algorithm. It is not likely to be the best choice. But we can use it as an example to introduce the algorithm in Fig.3 in the search process, and compare it with the other algorithms. The segmentation algorithm is to be explained in Section IV.

The complexity of the greedy algorithm we followed is $O(mn^3lg(n) + n^3)$, where m is the number of bus lines and n represents the quantity of bus stops. It is referred to in Alg 1. The process which obtains the metric of each pair of bus stations leads to complexity of $O(mn^3lg(n))$. The most important process lies here. Then we deal with the problem based on this set of data. Based on these work, the problem can be solved easily.

To explain the greedy algorithm more specifically, we assume that ETS is established on the line instead of just a station. The assumption is rigorous and the reason is illustrated as follows. With the help of Figure 3, the hop between

Algorithm 1 greedy Algorithm for ETS Placement Problem

input : Bus lines and bus stops
output: ETS cover set and total energy loss

```
Initialization: Build bipartite graph for bus lines and bus stops;
B ← bus stops;
L ← bus lines;
T ← ETS cover set;
n = 0;
Calculate the metric between each two bus station B_i and B_j, record it as D_ij;
T = ∅;
while n < ETS.Max.Number do
    n = n + 1;
    for ∀B_i ∈ B do
        E_i = 0;
        for ∀B_j ∈ B do
            ∀k ∈ T;
            E_ij = min{D_ij, D_ik};
            E_i = E_i + E_ij;
    find the min{E_i};
    ET_n = min{E_i};
    T = T ∪ B_i;
Return T, EN
```

each two bus stations is defined as energy metric. Obviously, EVs will have to charge and discharge from bus stations *line* 1 to the bus stations *line* 6 twice, thus the hop between them is 2 metrics. After establishing this simple model, it is convenient to describe the greedy algorithm. Regardless of the number of stations established on one line, the metric from one station to any station on this line shares the same metric, as long as there wont be any vehicles changing on this line.

Although in the actual evaluation we build ETS on a bus station, when we introduce the algorithm performance with the simple model mentioned before in figure 3, we assume that it is built on the bus line and we can discuss the algorithm directly based on this model. Hence, if the number of bus stations on each bus line is the same, there will be no difference calculating hops either between any of the two stations or between two lines that these two stations are on.

After obtaining the metric of each two bus stations, a set of ETS should be found and defined as T. ETS are chosen at the bus station and the best site can be settled after we add hops from all other bus stops. In figure 3, we assume the point *line* 1 to be the first ETS and the total value of metric is 16. The set T is point {*line* 1}. If we set point *line* 6 to be the second ETS, the metric of point *line* 5 decline to 1. Because the nearest ETS to point *line* 5 in the T is point *line* 6, T being {*line* 1, *line* 6} right now. The value of the total metric is 12 in this situation. Metric contribution details are: the metric of point *line* 2, *line* 3, *line* 4, *line* 5, *line* 7, *line* 8 is one and the metric of point *line* 9, *line* 10, *line* 11 is two. This process will continue until the desired number of ETS is settled.

Obviously, this greedy algorithm is not the best. The direct observation method tells that when the number of ETS is 2, the optimal result should be {*line* 6, *line* 9} while {*line* 1, *line* 6} is given by the greedy algorithm. Hence, the results of the greedy algorithm are poor when the number of ETS is even. It is urgent for us to find out a better algorithm to suit ETS in most situations.

IV. PROBLEM SOLUTION

With the prerequisite that each bus station has the ability to charge and discharge EVs, the whole network is in circulation, under which condition our algorithm is valuable. We contrast the three kinds of algorithms in detail, which are greedy algorithm, segmentation algorithm and exhaustive algorithm. Exhaustive algorithm is computed as a criterion. Considering the complexity of exhaustive algorithm is $O(n^n)$, only the first four results can be obtained. In other words, we can get results of exhaustive algorithm only when the number of ETS is smaller than 4.

The core idea to solve this problem is about the division of the graph. The failure experienced from the greedy algorithm proved that we cannot get the results one step after another. If ETS is evenly distributed in the figure, the result is likely to be satisfied. In order to make the distribution of ETS decentralized, the graph should be divided into several parts at first. Referring to the multi-centroid algorithm in Graph Theory, we find a good algorithm defined as segmentation algorithm to deal with this problem.

After building a bus-lines-relationship model and defining several concepts in section III, we can give the pseudocode of segmentation algorithm as is shown in Alg 2.

The first one to be introduced is segmentation algorithm in Alg 2. The pseudocode explains the main idea of the algorithm. After determining the metric between each two bus stations, we choose n initial ETS randomly. The second step is to build n groups for those ETS. We put all bus stations into the group of the nearest ETS. The third step is to find the centroid of the groups and to regard them as new sets of ETS. Repeat step 2 and step 3 until the collection of ETS is no longer changed. Calculate the energy loss in this set of ETS. So far we have gotten both the set of ETS and the total energy loss as the final results under the circumstance of n desired ETS. In fact, in order to simplify the complexity, we have calculated the distance between each stations in the city and stored it in a table. Based on this table, on average, the complexity of each optimization iteration is $O(n^2)$.

There are three important places in the pseudocode to pay attention to. The first one is which group to distribute when a bus station has the same shortest metric to more than one candidate ETS, in which case we define the bus stop as a *conflict node* and the several candidate ETS as *conflict point*. Each time we encounter this problem, we should firstly

Algorithm 2 Segmentation algorithm to solve ETS placement problem

input : Bus lines and bus stops.
output: ETS cover set and total energy loss

Initialization: Build relationship graph of bus lines;
$T \leftarrow set\ of\ ETS$;
$B \leftarrow bus\ stops$;
$L \leftarrow bus\ lines$;
$D \leftarrow metric\ between\ two\ bus\ stations$;
$G \leftarrow group\ of\ station\ in\ T$;
$E \leftarrow energy\ loss\ of\ the\ set\ of\ T$;
$n = 0$;
Calculate the metric between each two bus station B_i and B_j, record it as D_{ij};
while $n < ETS.Max.Number$ **do**
  $n = n + 1$;
  while *Total energy loss still decline* **do**
    $T_n = \forall\{B_1, B_2, \cdots, B_n\} \in B$;
    $\forall B_i \in B\ find\ the\ nearest\ T_{nj}$;
    $G_j = G_j \cup B_i$;
    if metric is the same, choose the group with minimal sites;
    calculate the centroid $\{T_{n1}, T_{n2}, \cdots, T_{nn}\}$ in each group;
    $\{T_{n1}, T_{n2}, \cdots, T_{nn}\}$ forms new T_n;
    calculate the new value E_n in the new T_n;
Return E,T;

record these nodes and points. Considering the segmentation algorithm is created based on the greedy algorithm, the first set of ETS is given by the greedy algorithm and each ETS is equipped with a group of bus stops. So, faced with the problem mentioned before, we will check all the bus stops on the bus lines where the conflict node lies to find out how many bus stops belong to the conflict node. As long as we find one bus stop belongs to one ETSs group, we say that degree of correlation between the node and the point increases by one. The more bus stops belong to one conflict point, the more precise the result will be that we put a conflict node into the group of this point, that is, this bus station should be put into the group with max degree of correlation. If degree of correlation happens to be the same, we will choose one ETS whose group contains less elements. Only after we have tried several evaluations, have we noticed this important problem and separating these intermediate points well results in much better consequences in our research. The second problem is to judge what is the centroid of one group. The centroid should own the lowest metric value to all other bus stops in one group. The process is similar to the greedy algorithm when only one best ETS is wanted. The third problem is how to obtain the total energy loss when the set of T_n is known. This problem can be easily solved by calculating the sum of each bus stations metric to its nearest ETS in T_n so as to represent the energy loss.

To explain more specifically, we use the figure 3 in section III to introduce the process of the segmentation algorithm. The algorithm is simulated with the bus line diagram and the evaluation will be done with the bus station diagram out of convenience and intuition because we have also proved that both diagrams share the same principle and performance equivalently in our papers discussion. In the segmentation algorithm, the first step is to get the metric between all bus lines with the direct observation method as what we did in the greedy algorithm. It can be supposed that the wanted number of ETS is 2. After obtaining the metric value of any two bus stations, we set two bus stops as ETS whose metric value is the minimum. From the analyzation above we can assume that the greedy algorithm results in two lines, *line* 1 and *line* 6. By the way we also know that whether the greedy algorithm can be further optimized is determined by our segmentation algorithm. Then the groups of *line* 1 and *line* 6 are established, which are called *group* 1 and *group* 2. The *group* 1 that belongs to *line* 1 includes {*line* 1, *line* 7, *line* 8, *line* 9, *line* 10, *line* 11}. The *group* 2 that belongs to *line* 6 includes {*line* 2, *line* 3, *line* 4, *line* 5, *line* 6}. In this case *line* 2 and *line* 3 are distributed to *group* 2, otherwise the number of elements in *group* 2 will be too less small which is against the principle mentioned in the previous paragraph. Then it is easy to find that the centroid of *group* 1 is *line* 7, *line* 8 or *line* 9. The centroid of *group* 2 is *line* 6. Whichever the centroid of *group* 1 is, the total energy loss is 6. So we regard *line* 6 and *line* 9 as ETS and repeated the steps before to build two new groups. As a result, the new groups remain unchanged which means the energy loss stays the same. Now we can judge that the process of the algorithm is over under the condition of two wanted ETS.

In general, the advantage of this algorithm is mainly reflected by its iteration. The calculation repeats until the energy consumption is reduced to minimum. It is sure that each times iteration will reduce the energy loss because the metric of a centroid of one group is destined to be smaller than that of other points. In the end the whole graph will be divided into several areas and each area will own one ETS. This is in line with our initial expectations of solving the problem.

V. EVALUATION AND ANALYSIS

In this section, we evaluate the performance of the algorithms with data from the real world to ensure the practical value of our research. The energy loss property is shown in brief to verify the validity of the algorithm.

A. EXPERIMENT SETUP

We carried out our evaluation with data from the real world and the precious data is based on two maps. One is the Manhattan bus map in New York that has 41 bus lines and about 400 bus stops [41], while another is from Pioneer Valley Transit Authority(PVTA) in Massachusetts [42]. IIn the Manhattan case, we choose two public bus stops from the two bus routes, in other words, these bus stops

are intersections(because charging stations help transport energy between bus lines). After this data pre-processing, we obtained 159 bus stops on the bus map of Manhattan [43], which proves that the bus lines in Manhattan are organized highly densely. As for the PVTA map, 34 bus lines and about 200 bus stops are recorded to make up the whole citys transportation. After the same calculation as before, we get 117 bus stops in PVTA. The reason why we choose those bus route maps is due to their different features. Compared to the dense bus lines in Manhattan, the PVTA bus lines are sparsely distributed as a star network.

Because this is a newly proposed problem recently, all the algorithms are applied comparatively foremost by us. The algorithm we mainly want to recommend is the segmentation algorithm, and the other algorithms also have their results calculated for reference.

B. EXPERIMENT RESULTS

Firstly, Fig.4 shows the evaluation performance contrast between the greedy algorithm and segmentation algorithm on the Manhattan bus map. Clearly, the segmentation algorithm is better than the greedy algorithm when the number of ETS is two and it is not hard to understand that equal energy loss occurs when the number of ETS is one. Surprisingly, in other ETS number situations the performance of the two algorithms reveals the same consequence. We analyze this phenomenon and it seems that the property of segmentation algorithm and greedy algorithm is conducted similarly in Manhattan. However, this does not mean that the performance of the segmentation algorithm is not good enough. According to the exhaustive algorithm, when the number of ETS is 2, 3, 4, the minimum energy consumption is 349, 324, 314. This is consistent with the energy consumption under the greedy algorithm and the segmentation algorithm. This means that the greedy algorithm and the separation algorithm are both close to the optimal solution in the Manhattan case. Therefore, we speculate that the greedy algorithm is more suitable for the mesh diagram. Due to the relatively strong nature of the reticular graph, the shortcomings of the greedy algorithm are greatly masked. And because the mesh diagram has more *conflict nodes*, it is not conducive to the segmentation algorithm, which results in the case that one more ETS can significantly reduce energy consumption. So, if the scale of the network is not too large, the exhaustive algorithm can also be a practical application.

In addition, since the total energy consumption reference value is less than 400 and the total number of bus stops is 159, the average energy consumption per bus station is less than 3. So, the energy consumption of the EV Energy Internet is lower than that of V2G.

Next, the simulation performance comparison between the greedy algorithm and the segmentation algorithm under PVTA circumstance is shown in Fig.5. In the PVTA network, the performance of the segmentation algorithm is obviously better than the greedy algorithm and we will focus on why the performance of segmentation algorithm in the PVTA is better.

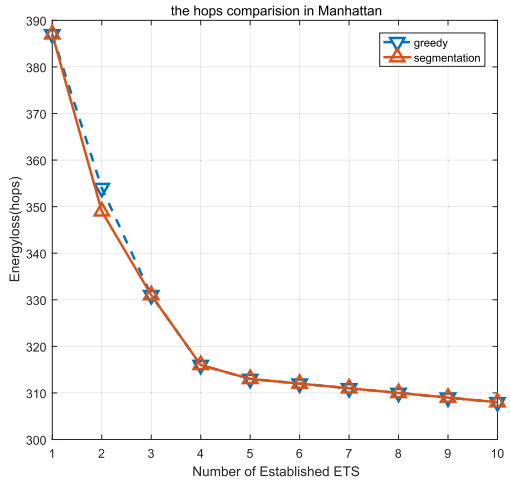

FIGURE 4. The number of total hops in Manhattan.

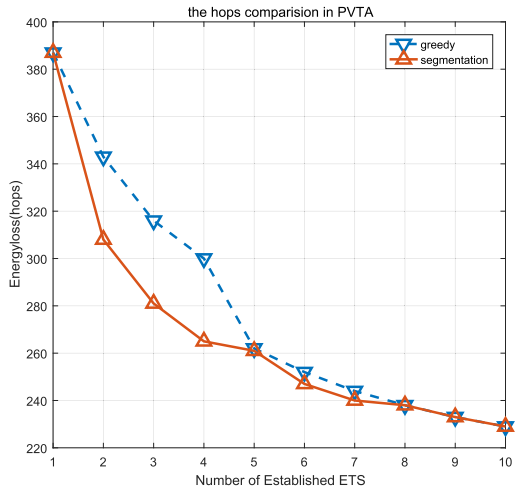

FIGURE 5. The number of total hops in PVTA.

Firstly, when the number of ETS is 1, all three algorithms will give birth to the same optimal solution, so the result is the same. When the number of ETS is larger than 1 and smaller than 8, the performance of the segmentation algorithm is better than that of the greedy algorithm and is very similar to that of the exhaustive algorithm. When the number of ETS is 2, 3, 4, the minimum energy consumption in exhaustive is 308, 281, 262, which is very close to 308, 283, 265 in the segmentation algorithm. This shows that the segmentation algorithm is quite suitable for star graphs such as the PVTA map. In the meanwhile, the greedy algorithm is much worse than the segmentation algorithm especially when the number of ETS is even. Because of the low association between stations in a star network, the use of the greedy algorithm will cause the ETS distribution on one side to be more dense than on the other side.

On the contrary, for the segmentation algorithm, regardless of the number of ETS, the map can be divided legitimately. As the bus lines are relatively sparse in a star map, which has much less *conflict point*, it is easier to segment the map, eventually leading to the segmentation algorithm in the star

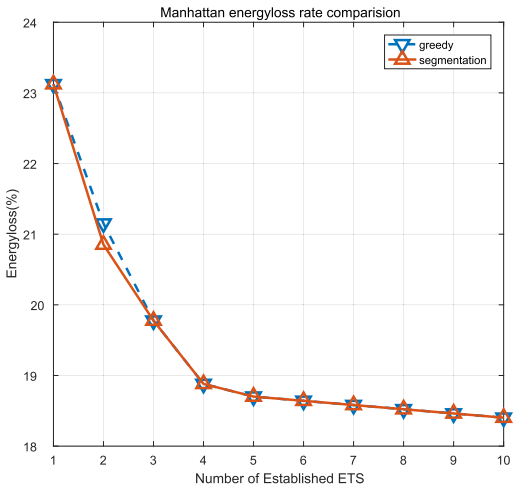

FIGURE 6. The average energy loss rate in Manhattan.

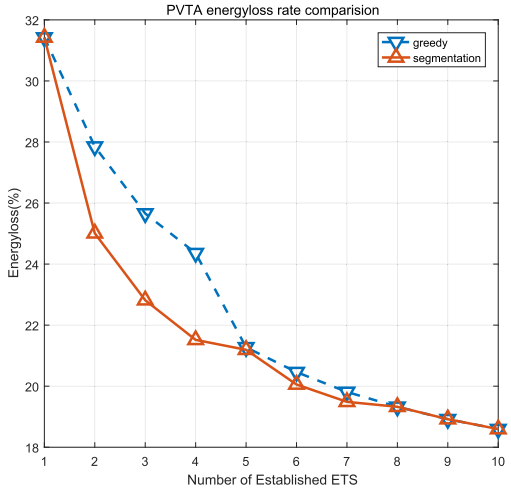

FIGURE 7. The average energy loss rate in PVTA.

map maintaining good performance. Of course, when the number of ETS is increased, the advantage of the segmentation algorithm is going to depression, this is because the total average energy consumption comes to be very low.

From the Manhattan and PVTA evaluation comparison charts we can obtain two conclusions: The first one is that the performance of the segmentation algorithm is relatively close to that of the exhaustive algorithm, which means that it has excellent performance with low complexity. The second point is that the most crucial crux, whether the segmentation algorithm can perform well, lies in the rational allocation of *conflict point*. Therefore, if we want to further improve the performance of the segmentation algorithm, we can start from the further optimization of the allocation problem of conflicting nodes. The goal is to allocate *conflict point* step by step so that each segmented area shrinks to the same size and each area has a regular shape.

As mentioned before, if the average hop per bus station to the ETS is less than 3, the energy consumption of the EV Energy Internet is definitely lower than that of the traditional V2G.

In order to show more clearly the energy consumption of different algorithms under different numbers of ETS, energy consumption is converted into a percentage form in order to make the reader have a clearer understanding of the performance of the algorithm, which is shown in Fig.6. In Manhattan, energy consumption is very low, albeit with a small difference in performance, which is lower than the 27.8 % of V2G based on the traditional power grid. In the case of our hypothesis, performance is good even if only one ETS is set up. Energy consumption is already below 20 % at 3 ETS, which means that the performance of the EV Energy Internet still maintains a significant advantage in the case that some energy sources are temporarily out of use. At ETS levels greater than 4, building an ETS is minimal for a reduction in energy consumption, which is especially true for energy percentage graphs, so that we need to consider whether it is necessary to establish so many ETS.

Therefore, we can draw a preliminary conclusion that the establishment of four ETS in Manhattan is a relatively optimal choice. In the long run, energy consumption can be reduced to 19 %, which means that on average, two transfers of energy from ETS can reach any station in Manhattan. High timeliness and energy consumption for DC power transmission is also better than the traditional high-voltage grid transmission.

In PVTA, the same percentage of energy consumption is shown in Fig.7. Among them, the biggest feature is that the energy consumption is higher than 30 % when the number of ETS is 1, which means that in this case, setting up only one ETS will result in higher energy consumption. The performance gap between segmentation algorithm and greedy algorithm is huge. At 4 ETS, the energy consumption under the segmentation algorithm is less than 22 %, but the energy consumption of the greedy algorithm is about 25 %. This shows that more optimized algorithms are more relevant in cities like PVTA.

In PVTA, our algorithm can conclude that when using multiple ETS, we can better demonstrate the energy consumption advantage of the energy Internet. We find that the choice of six ETS is a more satisfactory choice, and the energy consumption can be reduced to 20 % to a greater extent. Or considering the initial construction cost, the energy consumption of four ETS can also reach 21.5 %, which is better than the traditional power grid on average.

In general, the segmentation algorithm has a pretty good performance no matter what kind of map is used. Moreover, the complexity of the segmentation algorithm is much better than that of the exhaustive algorithm. Therefore, the low complexity and high performance of segmentation algorithms have a very strong role and prospect in establishing ETS in the larger urban traffic picture.

VI. RELATED WORK

Energy Internet also has a broader use environment, that is, private cars participate in the transportation of electricity,

but the complexity and uncertainty of private cars must be considered. The uncertainty of electric vehicles is very important and should be modeled in studies. Home arrival and departure times, driving distance, electric type, battery capacity, etc. are the main parameters of uncertainty that should be modeled properly. Several methods are presented in the literature for electric vehicles uncertainty modeling such as Monte Carlo Simulation method [10], [11], point estimate method [12], [13], fuzzy method [14], hybrid possibilistic-probabilistic method [15], Rough artificial neural network method, factor analysis method, the conditional value-at-risk method [16], stochastic copula based multi variate method [17], etc.

The rapid development and major achievements of battery technology have also provided a firm material foundation for the idea of an EV Energy Internet [18]–[21]. In previous work [22]–[31], we presented a concrete example to illustrate the usage of an EV Energy Internet, and then studied the optimization problem of how to deploy energy routers in an EV Energy Internet. We proved that the problem is NP-hard and developed a greedy heuristic solution. Evaluations using real-world data show that our method is efficient. The previous article discusses the layout issue of the charging station. The goal is to use as few charging stations as possible and to cover the entire area without considering the instability of energy supply flow at renewable energy power stations. Therefore, in this article, we establish ETS to solve the problem of energy supply instability, propose a new problem scenario and two sets of algorithms to solve it, and prove that the performance of the segmentation algorithm is superior to that of the greedy algorithm which is familiar to most of people.

Xiaosong Hu *et al*. discussed an improved sample-based entropy-based EVMI lithium-ion battery health management capability estimator [32] and proposed a fuzzy clustering-based lithium-ion battery EV state-of-charge estimation model [33]. The new electric vehicles should be equipped with advanced batteries that can withstand at least 10,000 quick-charging, fully charged in less than 10 minutes without any problems or performance degradation [5]. Researchers at the Massachusetts Institute of Technology found that a battery material can achieve full cell discharge in 10-20 seconds [34].

VII. CONCLUSION

Energy transport station in the EV Energy Internet is a new issue, for the actual use of energy Internet it is of great practical significance. And the segmentation algorithm solves the placement problem of this issue. The main work of this paper is to solve the problem of energy supply instability. A method of transferring energy from energy reserve stations is proposed, and the effectiveness of this method is simulated in practice. In this paper, we propose a comprehensive and optimal algorithm to solve practical problems. The simulation results can weigh the two dimensions of construction cost (ETS quantity) and energy consumption when the complexity of the algorithm is acceptable. This algorithm will lead to a great effect in reducing energy consumption when the EV Energy Internet is actually running in the future. Not only because the complexity of this algorithm is acceptable, but also because for the different urban traffic maps the algorithm has strong adaptability. And the soul of this algorithm is iteration. In the evaluation, the performance of the results which is near the exhaustive algorithm are also quite satisfactory.

But there are still many problems to solve, such as rapid discharge technology and the problem of robustness. In the event of urban congestion, we should consider how to ensure that electricity can be transported to the normal destination and how to deal with the energy transport between charging stations. There are a lot of practical problems looking forward to being found. I believe that in the near future, the idea of EV Energy Internet will be used because of its remarkable province electricity performance.

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