Deploying Energy Routers in an Energy Internet Based on Electric Vehicles

Ping Yi, Ting Zhu, Bo Jiang, Ruofan Jin, and Bing Wang

***Abstract*—An energy internet is a system that enables energy sharing in a distribution system such as the Internet. It has been attracting a lot attention from both academia and industry. The main purpose of this paper is to develop a model of an electric vehicle (EV) energy network to transmit, distribute, and store energy by EVs from renewable energy sources to places that need the energy. We describe the EV energy internet in detail and then formulate an optimization problem to place charging stations in an EV energy internet. We develop two solutions: one using a greedy heuristic and another based on diffusion. Simulation results using real-world data show that the greedy heuristic requires less charging stations, whereas the diffusion-based algorithm incurs less energy transmission loss.**

***Index Terms*—Electric vehicle (EV), energy internet, energy router.**

I. Introduction

THE Internet has become a critical infrastructure for people to exchange and share information. Analogous to the Internet, energy internet [1]–[3] has been proposed to allow energy to be shared similarly as information sharing on the Internet. There are some studies on energy internet, including the global energy internet [4], energy router [5], and energy packets [6]. This paper introduces a novel model for energy internet, which is called electric vehicle (EV) energy internet, that uses EVs and charging stations to transmit, distribute, and store energy from renewable energy sources to places that need the energy.

Equipped with batteries, a large number of EVs constitute a large-scale distributed energy storage system [7]. For instance, if all light vehicles in the United States become EVs, their power capacity is 24 times that of the entire electric generation system [8]. EV charging is categorized into three types: slow charging, primary charging, and fast charging. EV charger systems are categorized into off-board and on-board types with unidirectional and bidirectional power flow [9]. The energy storage of EVs can be utilized by smart grids through a vehicle-to-grid (V2G) system that allows EVs to feed energy stored in their batteries back to the grid as needed [10]–[12]. Combining V2G and the mobility of vehicles, EVs can provide a natural energy transmission method [13].

Inspired by these observations, we introduce in this paper a novel architecture for energy internet, i.e., *EV energy internet*, that uses EVs to transmit and distribute energy. Specifically, an EV energy internet is based on a transportation network that consists of EVs and EV charging stations. It transmits and distributes energy from renewable energy sources to other locations by using the EVs as carriers. An EV can be charged by a renewable energy source, be driven to a charging station, discharge energy at the charging station, from which another EV can be charged and hence indirectly benefit from the renewable energy source. Thus, energy generated by renewable energy sources is distributed to locations without power lines with the aid of the movement of the EVs. Analogous to a data communication network, an EV energy internet has *energy routers*, *energy links*, and *energy packets*.

The EV energy internet has many applications (see Section III). We describe in detail an application for an electric bus transportation system. In this application, EVs charge/discharge energy at charging stations, and hence where to place charging stations is an important problem that affects the efficiency of the EV network. Therefore, we formulate an optimization problem that minimizes both the number of charging stations and energy losses. Our main contributions are as follows.

- To the best of our knowledge, we are the first to propose the concept of EV energy internet [14]. The paper describes the concept of using EVs and charging stations as a means for better usage of renewable energy generation. This concept has great potential in improving the efficiency of renewable energy usage, facilitating the wide adoption of renewable energy sources, and reducing greenhouse gas emission.

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- Our case study provides a concrete example of EV energy internet. For this case study, formulating and solving the charge-station placement problem constitutes the first step in solving many challenges in deploying EV energy internet. We propose two heuristic algorithms to solve it. One algorithm uses a greedy heuristic, and the other is based on diffusion.
- We evaluate the performance of these two algorithms using data from two real-world bus systems. Our evaluation results demonstrate that both algorithms are efficient: The greedy heuristic requires less charging stations, whereas the heuristic based on diffusion has less energy transmission loss.

The rest of this paper is organized as follows. Section II discusses related work. Section III introduces the model of EV energy internet and some applications. Section IV formulates the charging-station placement (CSP) problem. Section V presents two heuristic solutions. Section VI presents the simulation results. Section VII discusses some potential problems, including feasibility, congestion, and other issues. Finally, Section VIII concludes this paper and describes future work.

II. Related Work

The idea of energy internet is getting more attention in both academia and industry. We discuss several concepts on energy internet and technologies related to our architecture.

A. Energy Internet

North Carolina State University presents the Future Renewable Electric Energy Delivery and Management System [15]. Germany presents e-Energy to create an energy internet [16].

Huang *et al.* presented a framework for a future electric power distribution system that is suitable for plug-and-play of distributed renewable energy and distributed energy storage devices [17]. The proposed system is an efficient electric power grid integrating highly distributed and scalable alternative generating sources and storage with existing power systems. It aims at facilitating a green and sustainable energy-based society, mitigating the growing energy crisis, and reducing the impact of carbon emissions on the environment.

Xu *et al.* presented the concept of an energy router in energy internet, which is a technological combination of power transmissions and information exchanges [5]. Energy routers interact with each other. They undertake two major tasks, namely, dynamic adjustments of energy flow and real-time communications between power devices. Corzine introduced the concept of an energy packet and a method of transferring energy packets in a power network [6]. Liang *et al.* presented a high-efficiency photovoltaic (PV) module-integrated dc/dc converter for PV energy harvest in energy internet [2]. Liang *et al.* presented a hierarchical section protection based on the solid-state transformer for energy internet [3].

In recent years, we have done some research on energy internet, including the deployment of energy routers, energy route, and energy schedule. In [14] (which is a preliminary version of this paper), we discussed the optimization problem of how to deploy energy routers in an EV energy internet. A hypergraph model is introduced to analyze the EV energy network, and an optimization problem is discussed to minimize the hops of energy route and, at the same time, transmit energy from energy sources to all charging stations [18]. In addition, we presented multiple energy transmission routes in EV energy internet from solar energy sources to places as capacity of every energy route is limited [18]. We analyzed the features of energy routes and studied the impact of traffic congestion on the EV energy internet in [19]. A bipartite graph model to analyze the EV energy internet and two different energy route algorithms were presented to find the energy routes from energy sources to charging stations under traffic jams [20]. We presented a greedy algorithm to schedule and allocate energy in EV energy internet in [21].

B. V2G Technology

As EVs have batteries that can store energy, they can be used to store energy and feed energy back to the grid as needed. This is the so-called V2G. Kempton and Tomic presented the concept of V2G in [10]. They proposed that EVs can generate or store electricity, and with appropriate connections, EVs can feed power to the grid. The advantage of V2G can benefit quick-response high-value electric services, including peak power, spinning reserves, and regulation. They presented that V2G can help renewable energy storage and backup, since the vehicle fleet has 24 times the power capacity of the entire electric generation system [8].

Xin *et al.* presented a cloud-based virtual smart grid architecture and its concept design [22]. Its architecture extends the pervasive visualization principle to the wide-area smart-grid sensory, communication, and control systems and essentially embeds the smart grid into a cloud environment. Han *et al.* developed an aggregator for V2G frequency regulation regarding the optimal control strategy [23]. They adopted a dynamic programming algorithm to compute the optimal charging control for each vehicle. Galus *et al.* presented an aggregator utilizing a model predictive control strategy that allows the inclusion of unit and grid constraints [24]. Sortomme and El-Sharkawi developed an algorithm for unidirectional regulation as regulation is the most profitable service that the EVs can perform [25]. Several smart charging algorithms are used to set the point at which the rate of charge varies while performing regulation.

Madawala and Thrimawithana presented a current-sourced bidirectional inductive power transfer system, which is particularly suitable for applications such as V2G systems [26]. Pillai and Bak-Jensen analyzed the application of V2G systems as a provider of regulation power [27], which is realized by utilizing an aggregated battery storage model in load frequency control simulations.

C. Charging and Battery Technologies

The rapid development and major accomplishments in battery technologies have resulted in significant development of EVs [28]–[30]. Hu *et al.* presented an ameliorated sample entropy-based capacity estimator for the health management of Li-ion batteries in electrified vehicles [31]. Hu and Sun [32] proposed a fuzzy-clustering-based multimodel support vector regression approach for estimating the state of charge for Li-ion batteries of EVs.

New EVs should be equipped with advanced batteries that will be able to withstand at least 10 000 rapid charges and be fully charged within less than 10 min, without any issues or performance degradation [12]. Researchers at MIT have found that one type of battery materials can achieve full battery discharge in 10–20 s [33]. Another kind of electric bus, which is called the supercapacitor bus, has run in Shanghai World Expo in China in 2010 [34]. The time to fully charge a supercapacitor bus is from 30 to 180 s [35]. Asea Brown Boveri Ltd. demonstrates a technology to power a flash charging electric bus in 15 s [36]. Compared with Li-ion batteries, the supercapacitor typically has higher power density and longer lifespan, enabling a faster response to vehicle power demand, whereas their energy density is much lower [37], [38].

Du *et al.* designed a charging-station architecture, which has a dc microgrid to interface with multiple dc–dc chargers, distributed renewable power generation and energy storage, and provides functionalities of normal and rapid charging, grid support such as V2G, current harmonic filtering, and load balancing [39]. The PV charging station for the EV was built in Santa Monica, California in 1996 [40], which can generate 3840 kWh every year. Robalino *et al.* designed a docking station for solar-charged electric and fuel cell vehicles [41].

The aforementioned works discuss the technologies in battery charging and V2G that are related to EV energy internet, as our work involves charging stations and renewable energy sources. Our proposed EV energy internet is a model for energy transportation by EVs since what we care about is that EVs transport energy to places that need it. We focus on the charging-station deployment for the EV energy internet to minimize the number of charging stations and the amount of energy loss.

III. Electric Vehicle Energy Internet

Many countries are plagued with the following dilemma. On the one hand, reducing global CO_2 emission calls for renewable energy (mainly solar and wind energy sources) and the wide adoption of EVs [42]. On the other hand, renewable energy cannot be easily connected to the power grid due to its unstable and intermittent nature, and hence a large amount of renewable energy is wasted [43]. Furthermore, although EVs have great potential in reducing CO_2 emission, they also have a huge energy demand. For instance, the United States is expected to have a million electric cars and plug-in hybrids. If every electric car needs 10 KWh per day, the total amount of energy required by all the electric cars per day will be 10 GWh. To realize the benefits of CO_2 emission reduction from EVs, the huge energy demand of EVs has to be met in large portion by renewable energy sources. The concept of EV energy internet that we propose provides a good solution to this dilemma, as will be discussed in the following section.

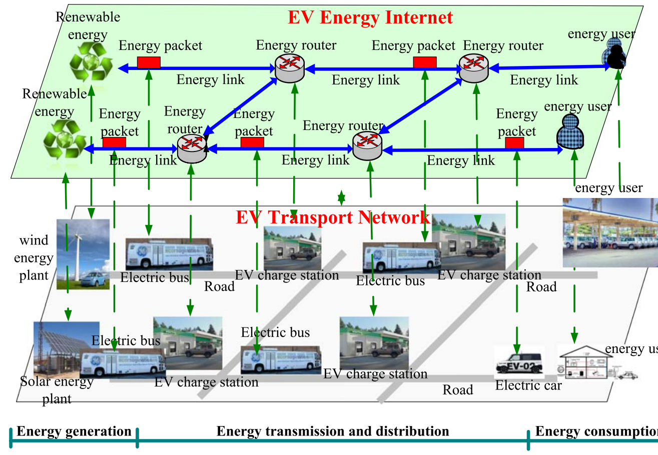

Fig. 1. Schematic of EV energy internet.

A. Concept

The basic idea of an EV energy internet is that EVs transfer energy from renewable energy sources (solar or wind) to users that need energy (e.g., charging stations and houses). Fig. 1 shows a schematic diagram of an EV energy internet. The lower layer is a physical EV transportation network. It mainly consists of three parts: energy generation, energy transportation, and energy consumption. Energy generation contains renewable energy plants. Energy transportation contains EVs and EV charging stations. Energy consumption contains users that need energy. In this EV transportation network, an EV is charged at a renewable energy source, stops at a charging station, and discharges energy to that charging station so that the energy can be picked up by another EV. Therefore, the movement of the EVs provides a natural way to transfer energy generated by renewable energy sources to other locations. Specifically, energy generated by renewable energy sources can be distributed to locations without renewable energy sources with the aid of the movement of the EVs. The upper layer in Fig. 1 is an EV energy internet that represents a logical view that corresponds to the physical EV transportation network. Energy flows inside the EV energy internet, which is analogous to that of data flow in a data communication network: The roads on which EVs move function as network links where energy flows; charging stations work as routers that store and forward energy; and energy in EVs functions as data in packets. The energy router, energy link, energy packet, energy source, and energy user (destination) form a transmission and exchange network for energy, which is called *EV energy internet*.

B. Applications of EV Energy Internet

As previously described, an EV energy internet is an energy transportation system that allows energy to be transported from its location of generation to a location where it is used to perform useful work. It provides energy transmission and distribution without the need of building power lines. It has great potential in improving the efficiency of renewable energy usage and hence in facilitating the wide adoption of renewable

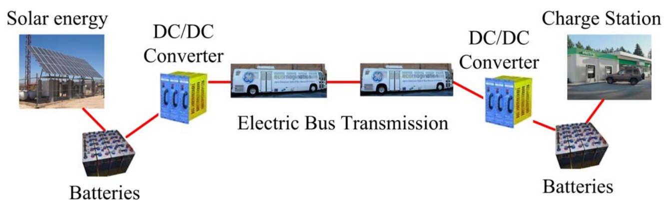

Fig. 2. Power transmission through EV energy internet.

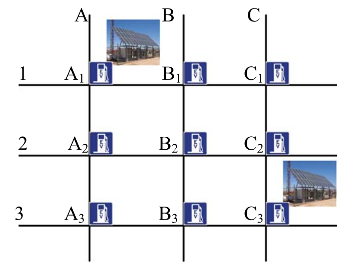

Fig. 3. Example of the CSP problem.

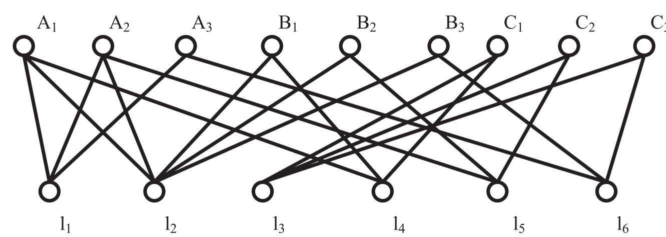

Fig. 4. Bipartite graph corresponding to the example in Fig. 3.

energy. With an EV energy internet, the unstable and intermittent energy generated by renewable energy sources (mainly solar and wind energy sources) can be used by EVs. This brings two benefits simultaneously. First, it prevents renewable energy from being wasted due to the difficulty in connecting it to the power grid [43]. Hence, it has great potential in improving the efficiency of renewable energy usage and facilitating the wide adoption of renewable energy. Second, it provides a way to serve the huge energy demand of EVs through renewable energy sources, thus reducing the potential adverse impact of EVs on the power grid [44]. The EV energy internet has many applications, including power dispatch between cities and power transportation from renewable energy sources to end users, such as EV charging stations.

We illustrate an EV energy internet using a simple application. Consider an electric bus company in a city. All buses in the company are hybrid electric buses. Suppose some buses have access to renewable energy sources (e.g., solar or wind stations), whereas the others do not. The company can place charging stations at various locations along the bus lines. The EV energy internet is responsible for transporting energy from the energy sources to charging stations in the city.

Fig. 2 shows how to transport energy through an EV energy internet. The process consists of three steps. The first step is to charge EVs using dc power. This requires a dc/dc converter. The second step is to power the transportation using EVs from solar energy stations to charging stations. The third step is to charge batteries in charging stations from EVs. Since the buses travel on fixed bus lines many times every day, they provide a "free ride" to the energy that they carry.

IV. Problem Formulation

An important problem in building an energy internet is the decision as to where to place charging stations as well as how many of them are needed. We will consider this problem for an electric bus system in which charging stations are to be placed at bus stops. The simplest solution is to place a charging station at each bus stop. However, this will incur a prohibitive cost. To reduce the investment, we should minimize the number of charging stations while satisfying the needs of all the electric buses. In the following, we formulate the CSP problem for electric bus systems.

Let $S = \{s_1, \ldots, s_n\}$ denote the set of bus stops and $L = \{l_1, \ldots, l_m\}$ the set of bus lines. For our purpose, each bus line can be identified with a subset of S, namely, the set of bus stops it stops at. Let $D = \{d_1, \ldots, d_l\}$ denote the set of renewable energy sources. For simplicity, we assume that there is a bus stop at each renewable energy site, i.e., $D \subseteq S$, so that buses can always be charged when they arrive at those bus stops. The bus system can be represented by a bipartite graph $G = \{S, L, E\}$, where $E = \{(s,l) \in S \times L | s \in l\}$, i.e., $(s,l) \in E$ if bus line l has a stop at s. Let L_s denote the set of bus lines that have a stop at s, i.e., $L_s = \{l | (s,l) \in E\}$. We will call L_s the set of bus lines *covered* by bus stop s. We say that a bus line $l \in L_d$ has *direct* access to the energy source $d \in D$ (see Table I).

Fig. 3 shows an example of an EV energy internet. There are six streets: streets A, B, C along the vertical direction and streets 1, 2, 3 along the horizontal direction. There is a bus stop at each intersection of two streets, which is denoted by A_i, B_i, or C_i, $i = 1, 2, 3$. Assume there are six bus lines: $l_1 : A_1 - A_2 - A_3$, $l_2 : B_1 - A_1 - A_2 - B_2 - B_3$, $l_3 : C_1 - C_2 - C_3$, $l_4 : A_1 - B_1 - C_1$, $l_5 : A_2 - B_2 - C_2$, and $l_6 : A_3 - B_3 - C_3$, and there are two renewable energy sources: A_1 and C_3. Fig. 4 shows the bipartite graph corresponding to the example in Fig. 3. We can see that bus lines l_1, l_2, and l_4 have direct access to renewable energy source A_1, and bus lines l_3 and l_6 have direct access to renewable energy source C_3.

Charging stations are responsible for energy storage and exchange. Buses with direct access to renewable energy sources transfer energy to charging stations, where the stored energy is used to charge other buses that do not have direct access to renewable energy sources. This way, bus lines without direct access to any renewable energy source can have *indirect* access to the renewable energy sources.

Now, the problem we face is finding the minimum number of charging stations so that all bus lines have direct or indirect access to renewable energy sources. To solve this problem, first, we need to find a minimum set of charging stations to cover all bus lines. Second, we must ensure that all the charging stations have access to the renewable energy sources, for charging stations need energy transmitted from the renewable energy sources to charge electric buses.

For any renewable energy source $d \in D$ and a charging station $c \in C$, let $P(d, c)$ denote the set of *energy transfer paths* from d to c in the bipartite graph G where all the intermediate bus stops are charging stations. Note that $\bigcup_{c\in C} L_c = L$ means all bus lines are covered by the charging stations in C. Given (S, L, D), the CSP problem can be formally defined as

$$\text{minimize} \quad |C| \tag{1}$$

$$\text{Subject to} \quad D \subseteq C \subseteq S \tag{2}$$

$$\bigcup_{c\in C} L_c = L \tag{3}$$

$$\bigcup_{d\in D} P(d, c) \neq \emptyset \quad \forall\, c \in C. \tag{4}$$

For a renewable energy source $d \in D$ and a charging station $c \in C$, let $P(d, c)$ denote the set of *energy transfer paths* from d to c in the bipartite graph G where all nodes along the path are charging stations. For convenience, let $P(d, c) = \emptyset$ if no such path exists. Then, each path in $P(d, c)$ represents a path to transfer energy from renewable energy source d to charging station c. Specifically, suppose one path is $(d, l_{[1]}, c_{[1]}, l_{[2]}, c_{[2]}, \ldots, c_{[k]}, c)$. Then, it represents that energy from renewable energy source d can be transferred through charging stations $c_{[1]}, c_{[2]}, \ldots, c_{[k]}$ and eventually to charging station c (specifically, buses running on bus line $l_{[1]}$ are charged by d and discharge at $c_{[1]}$, where the energy is picked up by buses running on $l_{[2]}$, which, in turn, discharge at $c_{[2]}$, and so on). The energy transfer path of a charging station c is defined to be the shortest path from any of the renewable energy sources to c, which represents a path to transfer energy from a renewable energy source to c with the minimum percentage of energy loss.

We next define energy loss formally. For simplicity, we consider only energy loss due to EV charge–discharge. Let β denote the efficiency of one-time energy charge and discharge for an EV. In the example in Fig. 2, suppose charging and discharging each has efficiency of 0.95. Then, $\beta = 0.95 \times 0.95 = 0.90$. Let k_c denote the number of bus lines in the energy transfer path of charging station c. Then, the percentage of energy loss for c is $1 - \beta^{k_c}$. As an example, suppose the set of charging stations $C = \{A_1, C_2, C_3\}$ in Fig. 3. For charging stations A_1 and C_3, since they are also renewable energy sources and do not require buses to transfer energy to them, their energy loss is 0. For charging station C_2, the energy transfer path from renewable source C_3 to C_2 is (C_3, l_3, C_2), with energy loss of $1 - \beta$.

It is easy to see that the problem is equivalent to the connected vertex cover problem and hence is NP-hard (the proof is found in the Appendix). A problem is NP-hard if an algorithm for solving it can be translated into one for solving any NP-problem (nondeterministic polynomial time) problem. NP-hard therefore means at least as hard as any NP-problem; although, it might, in fact, be harder [45].

V. Charging-Station Placement Algorithms

Here, we present two heuristic algorithms to solve the CSP problem. One uses a greedy heuristic. The other is based on diffusion. The two algorithms place a set of charging stations to cover all the bus lines and ensure that each charging station has at least one energy transfer path from the energy sources. Without loss of generality, we make the following two assumptions. First, we assume that the energy generated by the renewable energy sources is sufficient to support all the electric buses, i.e., the total energy consumption is less than or equal to the total amount of energy production. Second, we assume that every bus line has enough battery capacity for the energy transportation.

TABLE I
Notation Used in the CSP Problems

Name	Description
S	set of bus stops
L	set of bus lines
D	set of renewable energy stations as energy source
E	set of links between bus stops and bus lines in the bipartite graph
C	set of charging stations, $C \subseteq S$

A. Greedy Heuristic

The main idea of the greedy algorithm is as follows. Initially, we put all renewable energy sources into the set of charging stations C (i.e., $C = D$) and then remove them and all covered bus lines from the bipartite graph. The algorithm then runs in multiple rounds. In each round, we construct a bipartite graph $G' = (S', L', E')$ where L' represents the yet-to-be-covered bus lines, and S' represents the bus stops that have not been added to C (i.e., they have not been chosen to be charging stations). Each round consists of multiple steps: choose the bus stop that covers the largest number of bus lines, add it to C, and then remove it and all covered bus lines from the graph. This process repeats until all bus lines have been covered. After that, since some charging station may not have access to any of the renewable energy sources, we add more charging stations as follows. For each charging station s in C, we find the shortest path from the renewable energy sources to s and add all the bus stops along the path as charging stations. Let R be the set of charging stations thus added. Finally, output the set of charging stations $C = C \cup R$. The greedy algorithm is summarized in Algorithm 1. It is greedy in that nodes with higher degrees are added as charging stations with higher priority.

Algorithm 1: Greedy charging station placement

$C = D$;
$S' = S \setminus D$;
$L' = L \setminus \bigcup_{d\in D} L_d$;
while $L' \neq \emptyset$ **do**
  Choose bus stop $s \in S'$ that covers the largest number of bus lines in L';
  $C = C \cup \{s\}$;
  $S' = S' \setminus \{s\}$;
  $L' = L' \setminus L_s$;
Find the shortest route from s to D for $\forall s \in C$;
Let R be the set of bus stops along the shortest routes;
$C = C \cup R$;

The complexity of the aforementioned greedy heuristic is $O(mn + n^3)$, where m is the number of bus lines, and n is the number of bus stops. This is because in Algorithm 1, the running time of the loop from line 4 to line 8 is $O(mn)$. The running time of line 9 is $O(n^3)$. Therefore, the total running time is $O(mn + n^3)$.

We illustrate the greedy algorithm using the example in Fig. 4. First, we put stations A_1 and C_3 into the charging station set C since they are renewable energy sources. Then, we remove stations A_1 and C_3 from set S. We remove bus line nodes l_1, l_2, l_4 associated with A_1 and remove bus line nodes l_3, l_6 associated with C_3 from the bipartite graph. Then, we update the bipartite graph G'. Stations A_2, B_2, and C_2 have a degree of 1, and the rest of the bus stops have a degree of zero (the degree of a node in a graph is the number of edges that the node has in relation to other nodes). We arbitrarily choose C_2 (assuming breaking ties arbitrarily) and remove C_2 and the associated bus line node l_5 from the bipartite graph. At this time, all the bus lines have been covered. Then, we find the shortest route from D to C, namely, the shortest route from A_1, C_3 (renewable energy sources) to C_2 (charging station). The shortest route is $C_3 - L_3 - C_2$. In the end, the charging station set C includes A_1, C_2, C_3.

B. *Diffusion-Based Algorithm*

The main idea of the diffusion-based algorithm is as follows. First, we add all renewable energy sources as charging stations. We then consider the bus stops that are *neighbors* of the renewable energy sources, which are defined as the bus stops that are two hops away from the renewable energy sources (i.e., connected by one bus line) in the bipartite graph. For these bus stops, we add them into C (in the order of node degree, i.e., nodes that have higher degrees and hence cover more bus lines are added first) and consider their neighbors as potential charging stations. The next step considers these potential charging stations. This process continues until all bus lines have been covered by at least one charge station. We refer to this algorithm as the diffusion-based algorithm since it acts similar to water wave diffusion: Bus stops are added as charging stations based on their distance from the renewable energy sources.

The algorithm is summarized in Algorithm 2. Initially, we put all renewable energy sources into the set of charging stations C (i.e., $C = D$) and then remove them and all the bus lines that they cover from the bipartite graph. Let T be the set of stops that are neighbors of the renewable energy sources. The algorithm then runs in multiple rounds (i.e., the loop from lines 5 to 14). In each round, we construct a bipartite graph $G' = (S', L', E')$, where L' represents the yet-to-be-covered bus lines, and S' represents the bus stops associated with these lines that have not been chosen to be charging stations. In the loop from lines 5 to 14, let T' be the set of potential charging stations. First, $T' = T$ and $T = \emptyset$. Among the nodes in T', we select the node s with the largest degree (the degree refers to the degree in G') as the charging station, add it to C, and remove all the bus lines that are covered by s from the bipartite graph. We put all the neighbors of s into set T and delete all nodes whose degrees are zero from set T'. This step is repeated until all the bus lines are covered or T' is empty. When T' is empty, the algorithm returns to the step of setting $T' = T$ and $T = \emptyset$. This procedure continues until all bus lines are covered.

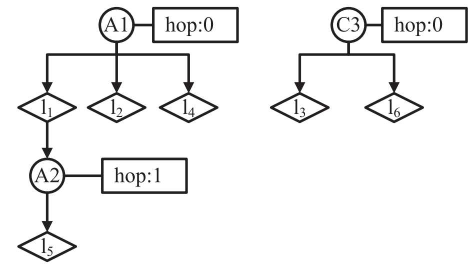

Fig. 5. Illustration of the diffusion-based algorithm.

Algorithm 2: Diffusion-based charging station placement

1 $C = D$;
2 $T = \bigcup_{d\in D} \text{neighbor}(d)$;
3 $S' = S \setminus D$;
4 $L' = L \setminus \bigcup_{d\in D} L_d$;
5 **while** $L' \neq \emptyset$ **do**
6 $\quad T' = T$;
7 $\quad T = \emptyset$;
8 $\quad$**while** $T' \neq \emptyset$ **do**
9 $\quad\quad$Select largest degree node $s \in T'$;
10 $\quad\quad C = C \cup \{s\}$;
11 $\quad\quad T = T \cup \text{neighbors}(s)$;
12 $\quad\quad S' = S' \setminus \{s\}$;
13 $\quad\quad L' = L' \setminus L_s$;
14 $\quad\quad T' = \{t \in T' : t \neq s, \deg(t) > 0\}$;

We give a brief analysis of the time complexity of the diffusion-based algorithm. Selecting the largest degree nodes (line 9) takes $O(n)$, and therefore the loop from lines 8 to 14 takes $O(n^2)$. In summary, the time complexity of the algorithm is $O(n^3)$.

We illustrate the diffusion-based algorithm by using the example in Fig. 4. The process is shown in Fig. 5. Initially, since A_1 and C_3 are renewable energy stations (their hops are 0), we put them into set C. The bus lines that node A_1 covers are l_1, l_2, l_4. The bus lines that node C_3 covers are l_3, l_6. We then remove A_1 and C_3 from set S and remove the associated lines from set L'. After that, we consider the neighbors of A_1 and C_3, i.e., $A_2, A_3, B_1, B_2, B_3, C_1, C_2$, and add them to set T'. The degree of A_2, B_2, C_2 is 1. The degree of the other A_3, B_1, B_3, C_1 is 0; hence, they are removed from set T'. Among A_2, B_2, C_2, we select A_2 (by breaking ties arbitrarily), which covers line l_5. At this time, all bus lines have been covered.

For convenience, we refer to set R in the greedy algorithm as transfer nodes (i.e., the bus stops that are selected to connect the energy source to the charging stations). Note that the diffusion-based algorithm does not require transfer nodes, as all the bus stops selected are 1, 2, ... hops away from the energy sources (i.e., connected by 1, 2, ... bus lines to the energy sources). The advantage of the greedy algorithm is that it selects the nodes of the largest degrees (i.e., the bus stops that cover the largest number of bus lines) in the bus network. The advantage of the diffusion-based algorithm is that it does not need any transfer nodes. We will evaluate the performance of these two algorithms in Section VI.

VI. Simulation and Analysis

A. Experiment Setup

Here, we evaluate the performance of the two proposed algorithms, i.e., the greedy algorithm and the diffusion-based CSP algorithms, using real-world data. In particular, the evaluation is based on two bus maps. One is the Manhattan bus map in New York City [46], which has 41 bus lines and about 400 bus stops. We select the bus stops from the two bus maps that serve two or more bus lines (since the charging station helps in the energy transfer among bus lines). After such data preprocessing, we obtain 159 bus stops in the Manhattan bus map. The bus lines in the Manhattan bus map are organized as a mesh network with high density. Most of the bus lines are for the north–south or east–west direction in Fig. 6.

The other map is the bus map of Pioneer Valley Transit Authority (PVTA) in Massachusetts. The PVTA is the largest regional transit authority in Massachusetts with 174 buses, 144 vans, 24 participating member communities, 34 bus lines, and about 200 bus stops. More detail is described in the PVTA bus map [47]. After data preprocessing, we obtain 116 bus stops in the PVTA bus map. We chose these two bus maps because they have different features. The Manhattan bus map is a typical city public transportation system. In contrast, the PVTA bus map is a typical rural public transportation system in which the bus lines are sparsely distributed as a star network.

As stated in Section IV, the main goal of our algorithms is to reduce the number of charging stations for the bus energy network as well as the energy loss during energy transportation. Therefore, we adopt two metrics to evaluate our algorithms. The first metric is the total number of charging stations, which measures the investment (cost) for the EV energy internet. The smaller the total number of charging stations is, the lower the cost for building the energy network system will be. The second metric is the average percentage of energy loss (from the renewable energy sources to the charging stations), which represents the efficiency for transferring energy in an EV energy internet. As discussed in the example shown in Fig. 2, we assume $\beta = 0.95 \times 0.95 = 0.90$.

In the simulation, the number of renewable energy sources is varied from 1 to 15. For each case, we randomly place the renewable energy sources on the bus map by using independent random seeds to obtain the results. The process is repeated 100 times to obtain averages and 95% confidence intervals. The proposed algorithms are implemented in MATLAB R2010b. We compare their performance to **random cover algorithm (RCA)**, which places charging stations randomly. Specifically, RCA arbitrarily selects a sequence of charging stations S_1 to cover all bus lines. Then, for each charging station in $s \in S_1$, it finds the shortest path from the renewable energy sources to s. All the bus stops along the shortest path compose S_2. We combine S_1 and S_2 into the cover set.

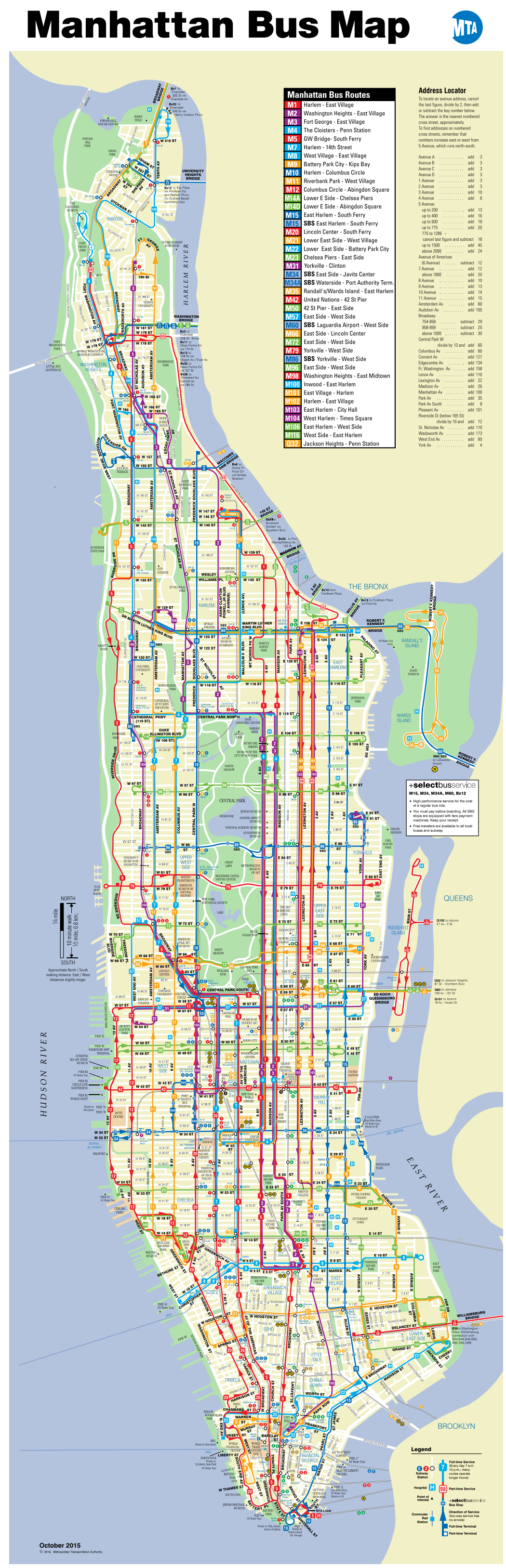

Fig. 6. Manhattan bus map [46].

B. Simulation Results

Fig. 7(a) and (b) shows the number of charging stations under three algorithms for the Manhattan bus map and the PVTA bus map, respectively. When applying the greedy and

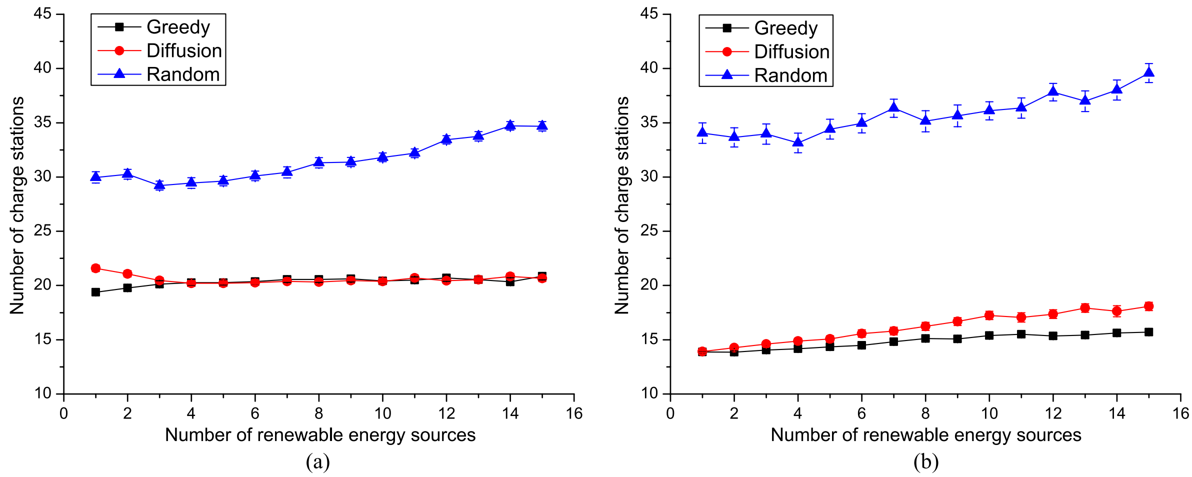

Fig. 7. Total number of charging stations under the three algorithms. (a) Manhattan bus map. (b) PVTA bus map.

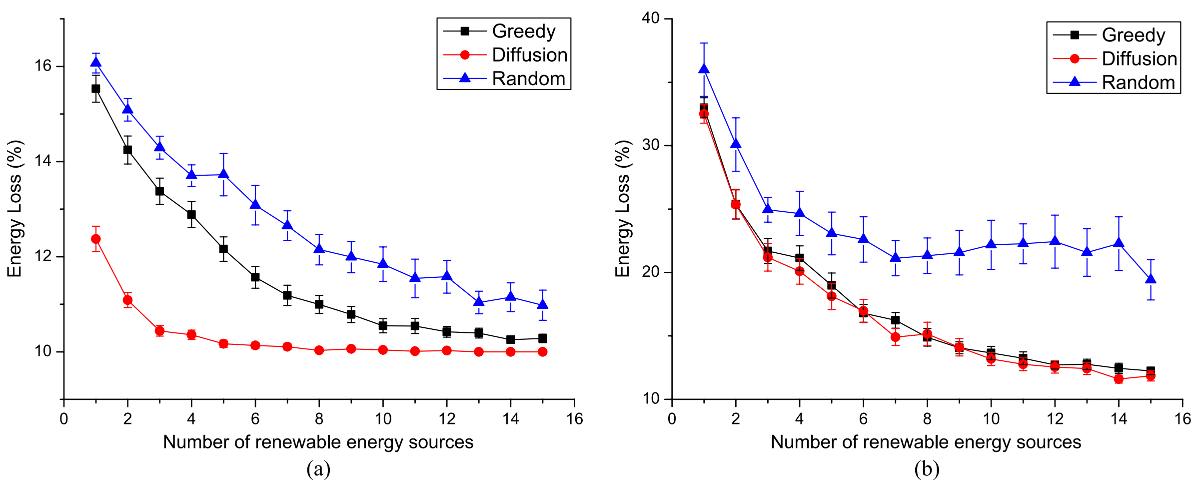

Fig. 8. Average percentage of energy loss under the three algorithms. (a) Manhattan bus map. (b) PVTA bus map.

diffusion-based algorithm, the average numbers of charging stations, when varying the number of renewable energy sources, are always significantly lower than that under the random algorithm. Specifically, for the Manhattan bus map, the number of charging stations under the greedy and diffusion-based algorithms are 31.1%–41.4% and 28.0%–40.0% lower than that under the random algorithm, respectively. For the PVTA bus map, the number of charging stations under the greedy and diffusion-based algorithm are 57.0%–60.3% and 51.5%–59.1% lower than that under the random algorithm, respectively.

In Fig. 7(a), we observe that when the number of renewable energy sources is small, the greedy algorithm achieves a slightly better performance than the diffusion-based algorithm for the Manhattan bus map because the diffusion-based algorithm selects only the bus stops of largest degree near the renewable energy sources. When the number of renewable energy sources grows, the two algorithms achieve similar performance.

In Fig. 7(b), we observe that the greedy algorithm performs better than the diffusion-based algorithm for the PVTA bus map. The reason can be explained as follows. The bus map of PVTA is similar to a star network, and some of the bus stops are located at the intersections of many bus lines such as the Springfield bus terminal. Those bus stops are of high degrees in the bipartite graph, and they cover many bus lines. The greedy algorithm can find such bus stops quickly; thus, it requires less charging stations to cover all bus lines than the diffusion-based algorithm, which first selects the bus stops near the energy sources. On the contrary, the Manhattan bus map is similar to a mesh network. Most of the streets are either from west to east or from north to south. The bus stops are densely connected, and there are no such nodes that have significantly larger degrees than other nodes. Therefore, the performance of the two algorithms is similar.

Fig. 8(a) and (b) shows the average percentages of energy loss under the three algorithms for the Manhattan and PVTA bus maps, respectively. As expected, the percentage of loss decreases when the number of renewable energy sources increases, since it is more likely to find a shorter energy transfer path when more renewable energy sources exist. For all the settings, the two proposed algorithms outperform the random algorithm. We observe that the energy loss of the diffusion-based algorithm is much less than that of the greedy algorithm in the Manhattan bus map. However, in the PVTA bus map, the energy loss of the diffusion-based algorithm is the same as that of the greedy algorithm because the PVTA bus map is a typical rural public transportation system. The bus lines are sparsely

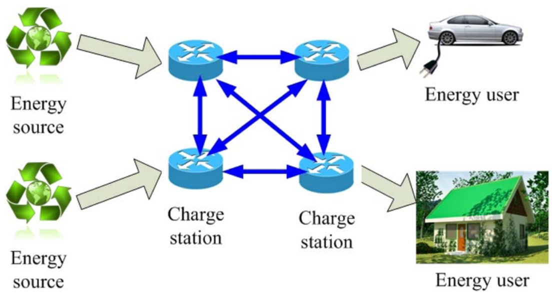

Fig. 9. Model of EV energy internet.

distributed as a star network. Most of the time, there may be only one route from one energy source to one bus stop. As a result, both algorithms use the same routes. Therefore, the energy loss in two algorithms is almost the same in the PVTA bus map.

We observe that the diffusion-based algorithm achieves a lower percentage of energy loss than the greedy algorithm in both bus maps. The reason is that the diffusion-based algorithm does not require additional transfer nodes (see Section V) so that the energy transfer paths are shorter than those in the greedy algorithm. Particularly in the mesh-network bus map in Manhattan where the bus lines are densely connected, the diffusion-based algorithm is very effective, as the percentage of energy loss quickly drops to around 10% (i.e., most of the charging stations are only one hop away from energy sources) when the number of renewable energy sources grows.

In summary, these simulation results show that the greedy algorithm requires less charging stations, whereas the diffusion-based algorithm incurs less energy transmission loss. They are both more efficient than the random algorithm: They require a fewer number of charging stations and incur less energy loss. Generally, the more charging stations are deployed, the less energy loss will be. Therefore, in practice, the tradeoff between investment (for deploying charging stations) and energy efficiency should be carefully considered in different situations (e.g., network topology, construction cost of charging stations, etc.).

VII. Discussion

Here, the EV energy internet is compared with the communication network. Some potential problems of the EV energy internet are discussed.

A. Comparison With the Communication Network

In the EV energy internet, EVs transfer energy from renewable energy (solar or wind) plants to users that need energy (e.g., charging stations and houses). Fig. 9 shows a model of EV energy internet that is similar to the communication network. In the EV energy internet, charging stations are treated as energy routers that can receive and forward energy. EVs in bus lines can transmit energy as communication links in the communication network. EVs and charging stations compose an energy transmission and distribution network called the EV energy internet.

The EV energy internet is similar to the communication network, in which charging stations are regarded as routers, in that EVs are regarded as a link, and energy is regarded as a data packet. Energy can be transmitted by EVs from one charge station to another, similar to how packets are forwarded from one router to another.

TABLE II
Contrast Between EV Energy Internet and Communication Network

Name	EV energy internet	communication network
Switching equipment	charge station	router
Transmission equipment	electric vechile	data link
Transmission object	energy	data
Transmission loss	energy loss	packet drop
Transmission delay	one hour or more	second
Transmission direction	one way	two way

However, there are some differences between the EV energy internet and the communication network. First, packets transmitted in the communication network are all different from each other. For example, a packet that is sent to node A can be received by only node A. Energy in the EV energy internet is the same in that energy users can receive and use any energy from any energy source. Moreover, a packet cannot be changed when it is forwarded in the communication network. If some bytes are changed in the packet, the packet must be dropped, and a new packet will be resent by the source node. When energy is transmitted in the EV energy internet, part of the energy will be lost because of the energy loss in the charge–discharge process.

Furthermore, the speed of packet transmissions in the communication network is extremely fast, which is comparable to the speed of light. By contrast, the speed of energy transmissions in EV energy internet is much slower. It may cost one hour or more to transmit energy from one energy source to users by EVs. In addition, packets can be bidirectionally transmitted in the communication network, whereas energy is transmitted from only sources to users. These features are summarized in Table II.

B. Feasibility

As previously mentioned, researchers at MIT have found that one type of battery materials can achieve full battery discharge in 10–20 s [33]. Supercapacitor buses that were used in the Shanghai World Expo in China in 2010 [34] can be fully charged between 30 and 180 s [35]. A TESLA car has 90-kWh battery providing 528 km of range [48]. If the distance of a round-trip travel between one's home to a company is less than 20 km, he may transmit 96% of about 86.6-kWh energy with one round-trip travel.

Winston Global Energy Holdings Limited has produced electric bus EV-2008 [49]. The total energy capacity of the battery pack in EV-2008 is more than 350 kWh. The battery pack is composed of 156 units WB-LYP700AHA [49], each of which weighs about 21 kg. The weight of the battery pack in electric bus EV-2008 is 3276 kg. The net weight of EV-2008 is 11 000 kg, including the battery pack. The cost per 100-km range is about 70 kWh. In other words, if the distance of a round-trip travel for one bus line is less than 100 km, EV-2008 may transmit about 250 kWh of energy in one round-trip travel, which means that the batteries equipped in EV-2008 are enough to transmit energy without extra batteries.

If electric bus EV-2008 needs to take an extra battery to transmit energy, how much will it cost in transmission? By a technical introduction of EV-2008, the net weight is 11 000 kg, and the weight of a battery pack is 3276 kg. The cost per 100-km range is about 70 kWh. We can get about 21 kWh in 70 kWh for battery pack transportation. Therefore, it will cost about 21 kWh per 100 km to transmit 350 kWh by an extra battery pack. It costs only 6% energy to transmit 350 kWh per 100 km. The cost for energy transmission is very little.

C. Other Issues

As in the communication network, there is congestion in the EV energy internet. For example, one energy route will be blocked when one street in the energy route is jammed with cars. Traffic jam may be the main reason of congestion in energy routes. In addition, when the batteries in a charge station are full, no more energy can be received by the charging stations, which also causes congestion in energy routers. Multipath energy routes from energy sources to users may be a solution to this problem.

The EV energy internet has some advantages. First, a lot of renewable energy (solar energy and wind energy) does not need to be transmitted by an electrical grid, if their generating energy can be transmitted by the EV energy internet. It reduces the impact from the unstable renewable power on an electrical grid. Second, the EV energy internet can transmit energy to energy users not using power lines. This will reduce some investment for power lines. Third, energy transmission by EVs is more efficient than by an electrical grid because it does not need a dc/ac inverter and an ac/dc converter. Energy transmission by an electrical grid wastes more energy in two conversion processes.

Of course, there are also some disadvantages in the EV energy internet. Energy transmission by the EV energy internet from a renewable source to a user costs more time than that by the power grid. Charging stations and users need to add energy storage units such as batteries. EVs carrying redundant power from renewable energy sources may need extra time to offload energy to a charge station and users in demand.

VIII. Conclusion

In this paper, we have proposed a model for energy internet, namely, energy transmission and distribution networks using EVs. In this model, EVs, such as electrified buses on predictable routes, may be used to improve the utilization of renewable energy sources by shuttling energy from generation sources to charging stations where other vehicles may subsequently charge. After describing its structure and features, we analyzed how to deploy energy routers in EV energy internet. We first formulated an optimization problem and then proposed two algorithms to place charging stations. We used the bus map data of Manhattan in New York city and the Pioneer Valley region in Massachusetts to test our algorithms. Simulation results show that the greedy heuristic requires less charging stations, whereas the diffusion-based algorithm incurs less energy transmission loss. Our next step of work is how to find energy transmission routes from energy sources to charging stations.

Appendix
Proof of Theorem

We prove the CSP problem is NP-hard theorem by reduction from the weak connected vertex cover (MinWCVC) problem, which is proven to be NP-hard in [50]. Recall that given a connected hypergraph $H = (V, E)$, where $E \subset 2^V$ is the set of hyperedges, the MinWCVC problem is to find a minimum-size vertex cover $C \subseteq V$ of H such that the subhypergraph induced by C is connected [50].

Now, we translate the MinWCVC problem into the language of our bus system. Let V be the set of bus stops and E the set of bus lines, and the MinWCVC problem is to find a minimum-size subset $C \subset V$, such that each bus line passes by at least one stop in S, and one can go from any stop $s \in S$ to any other stop $t \in S$ by transferring only at stops in S.

Now, we observe that the CSP problem differs from the MinWCVC problem only by the requirement that C must contain a given subset D of V, the renewable energy stations. Given any instance $H = (V, E)$ of the MinWCVC problem, we can generate in polynomial time $|V|$ instances $G_v = (V, E, D_v = \{v\})$ of the CSP problem as v ranges over V. It is straightforward to see that C is a feasible solution to H if and only if it is a feasible solution to one of the G_v's, $v \in V$. Thus, if we can solve the CSP problem, then we can solve H by taking the minimum-size solution to one of the G_v's. Since the MinWCVC problem is NP-hard, so is the CSP problem. ■

References

[1] Q. Sun, R. Han, H. Zhang, J. Zhou, and J. M. Guerrero, "A multiagent-based consensus algorithm for distributed coordinated control of distributed generators in the energy internet," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 3006–3019, Nov. 2015.

[2] Z. Liang, R. Guo, J. Li, and A. Q. Huang, "A high-efficiency PV module-integrated DC/DC converter for PV energy harvest in FREEDM systems," *IEEE Trans. Power Electron.*, vol. 26, no. 3, pp. 897–909, Mar. 2011.

[3] Z. Liang, R. Guo, J. Li, and A. Q. Huang, "A novel hierarchical section protection based on the solid state transformer for the future renewable electric energy delivery and management (FREEDM) system," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 1096–1104, Jun. 2013.

[4] Z. Y. Liu, *Global Energy Internet*. Beijing, China: China Electric Power Press, 2015.

[5] Y. Xu, J. Zhang, W. Wang, A. Juneja, and S. Bhattacharya, "Energy router: Architectures and functionalities toward energy internet," in *Proc. IEEE 2nd Int. Conf. SmartGridComm*, Brussels, Belgium, Oct. 17–20, 2011, pp. 31–36.

[6] K. A. Corzine, "Energy packets enabling the energy internet," in *Proc. Clemson Univ. PSC*, Mar. 2014, pp. 1–5.

[7] X. Hua, S. Lia, H. Peng, and F. Sun, "Charging time and loss optimization for LiNMC and LiFePO4 batteries based on equivalent circuit models," *J. Power Sources*, vol. 239, pp. 449–457, Oct. 2013.

[8] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *J. Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005.

[9] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Trans. Power Electron.*, vol. 28, no. 5, pp. 2151–2169, May 2013.

[10] W. Kempton and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, Jan. 2005.

[11] J. Tomic and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *J. Power Sources*, vol. 168, no. 2, pp. 459–468, Feb. 2007.

[12] M. Etezadi-Amoli, K. Choma, and J. Stefani, "Rapid charge electric vehicle stations," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1883–1887, Jul. 2010.

[13] M. Shahidehpour, "Electric vehicles in volatile power system operations," presented at the IEEE Power Energy Society General Meeting, San Diego, CA, USA, Jul. 2011.
[14] P. Yi, T. Zhu, B. Jiang, B. Wang, and D. Towsley, "An energy transmission and distribution network using electric vehicles," in *Proc. IEEE ICC*, Jun. 2012, pp. 3335–3339.
[15] *Freedom Systems Center*. [Online]. Available: http://www.freedm.ncsu.edu/
[16] *E-Energy*. [Online]. Available: http://www.digitaletechnologien.de/DT/Navigation/EN/Service/Abgelaufene_Programme/E-Energy/e-energy.html
[17] A. Q. Huang *et al.*, "The future renewable electric energy delivery and management (FREEDM) system: The energy internet," *Proc. IEEE*, vol. 99, pp. 133–148, Jan. 2011.
[18] P. Yi *et al.*, "Renewable energy transmission through multiple route in mobile electrical grid," in *Proc. IEEE PES ISGT*, Washington, DC, USA, Feb. 2014, pp. 1–5.
[19] G. Lin *et al.*, "Robustness analysis on electric vehicle energy distribution networks," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, Jul. 2013, pp. 1–5.
[20] P. Yi, T. Zhu, G. Lin, and Q. Zhang, "Routing renewable energy using electric vehicles in mobile electrical grid," in *Proc. 10th IEEE Int. Conf. MASS*, Hangzhou, China, Oct. 2013, pp. 19–27.
[21] P. Yi *et al.*, "Energy scheduling and allocation in electric vehicle energy distribution networks," in *Proc. IEEE PES ISGT*, Feb. 2013, pp. 1–6.
[22] Y. Xin *et al.*, "Virtual smart grid architecture and control framework," in *Proc. IEEE Int. Conf. SmartGridComm*, Brussels, Belgium, Oct. 17–20, 2011, pp. 1–6.
[23] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–71, Jan. 2010.
[24] M. D. Galus, S. Koch, and G. Andersson, "Provision of load frequency control by PHEVs, controllable loads, and a cogeneration unit," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4568–4582, Oct. 2011.
[25] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.
[26] U. K. Madawala and D. J. Thrimawithana, "A bidirectional inductive power interface for electric vehicles in V2G systems," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4789–4796, Oct. 2011.
[27] J. R. Pillai and B. Bak-Jensen, "Integration of vehicle-to-grid in the Western Danish power system," *IEEE Trans. Sustain. Energy*, vol. 1, no. 2, pp. 12–19, Jan. 2011.
[28] H. Qian, J. Zhang, J. Lai, and W. Yu, "A high-efficiency grid-tie battery energy storage system," *IEEE Trans. Power Electron.*, vol. 26, no. 3, pp. 886–896, Mar. 2011.
[29] K. Zhao, M. Pharr, J. Vlassak, and Z. Suo, "Inelastic hosts as electrodes for high-capacity lithium-ion batteries," *J. Appl. Phys.*, vol. 109, no. 1, Jan. 2011, Art. no. 016113.
[30] X. Hu, S. J. Moura, N. Murgovski, B. Egardt, and D. Cao, "Integrated optimization of battery sizing, charging, and power management in plug-in hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 3, pp. 1036–1043, 2016.
[31] X. Hu, S. E. Li, Z. Jia, and B. Egardt, "Enhanced sample entropy-based health management of li-ion battery for electrified vehicles," *Energy*, vol. 64, pp. 953–960, Jan. 2014.
[32] X. Hu and F. Sun, "Fuzzy clustering based multi-model support vector regression state of charge estimator for lithium-ion battery of electric vehicle," in *Proc. Int. Conf. IHMSC*, Aug. 2009, pp. 392–396.
[33] B. Kang and G. Ceder, "Battery materials for ultrafast charging and discharging," *Nature*, vol. 458, no. 7235, pp. 190–193, Mar. 2009.
[34] *Sunwin Exhibitions and Events*. [Online]. Available: http://www.sunwinbus.com/Global_Market/exhibitons_events_detail.html
[35] M. Chen, "Expo science and technology: Super capacitor bus," *Public Utilites*, vol. 24, no. 5, pp. 40–45, 2010.
[36] [Online]. Available: http://new.abb.com/smartcities/transport/electric-buses/flash-charging
[37] X. Hu, N. Murgovski, L. M. Johannesson, and B. Egardt, "Comparison of three electrochemical energy buffers applied to a hybrid bus powertrain with simultaneous optimal sizing and energy management," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 3, pp. 1193–1205, Jun. 2014.
[38] L. Zhang, X. Hu, Z. Wang, and D. G. Dorrell, "Experimental impedance investigation of an ultracapacitor at different conditions for electric vehicle applications," *J. Power Sources*, vol. 287, pp. 129–138, Aug. 2015.
[39] Y. Du, X. Zhou, S. Bai, S. Lukic, and A. Huang, "Review of non-isolated bi-directional DC-DC converters for plug-in hybrid electric vehicle charge station application at municipal parking decks," in *Proc. 25th IEEE APEC Conf.*, Feb. 2010, pp. 1145–1151.
[40] J. G. Ingersoll and C. A. Perkins, "The 2.1 kW photovoltaic electric vehicle charging station in the city of Santa Monica," in *Proc. IEEE Photovoltaic Spec. Conf.*, May 1996, pp. 1509–1512.
[41] D. M. Robalino, G. Kumar, L. O. Uzoechi, U. C. Chukwu, and S. Mahajan, "Design of a docking station for solar charged electric and fuel cell vehicles," in *Proc. IEEE Int. Conf. Clean Elect. Power*, Jun. 2009, pp. 655–660.
[42] S. Labatt and R. R. White, *Carbon Finance: The Financial Implications of Climate Change*. Hoboken, NJ, USA: Wiley, 2007.
[43] J. R. Agero and S. J. Steffel, "Integration challenges of photovoltaic distributed generation on power distribution systems," in *Proc. IEEE Power Energy Soc. Gen. Meet.*, Jul. 2011, pp. 1–6.
[44] P. Denholm and W. Short, "An evaluation of utility system impacts and benefits of optimally dispatched plug-in hybrid electric vehicles," Nat. Renew. Energy Lab., Denver, CO, USA, Tech. Rep. NREL/TP-620-40293, Oct. 2006.
[45] M. R. Garey and D. Johnson, *Computer and Intractability: A Guide to the Theory of NP-Completeness*. San Francisco, CA, USA: Freeman, 1979.
[46] *Manhattan Bus Map*. [Online]. Available: http://web.mta.info/nyct/maps/manbus.pdf
[47] *Pioneer Valley Transit Authority (PVTA) System Map*. [Online]. Available: http://www.pvta.com/systemMap.php
[48] *Tesla Model S*. [Online]. Available: http://www.teslamotors.com/models
[49] *Thunder Sky Winston Battery*. [Online]. Available: http://en.winston-battery.com/
[50] B. Escoffier, L. Gourves, and J. Monnot, "Complexity and approximation results for the connected vertex cover problem," in *Graph-Theoretic Concepts in Computer Science*, vol. 4769, ser. Lecture Notes in Computer Science. Berlin, Germany: Springer-Verlag, 2007, pp. 202–213.

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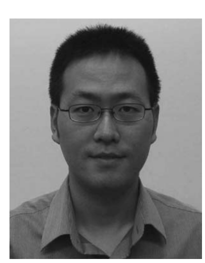

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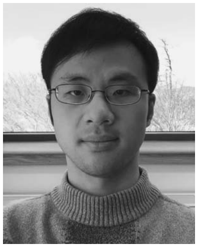

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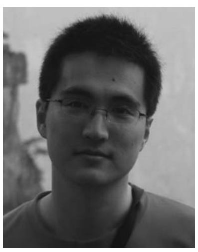

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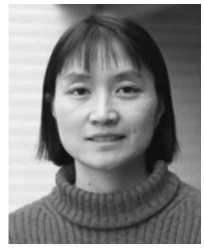

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