Optimal Renewable Energy Transfer via Electrical Vehicles

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***Abstract*—Using electrical vehicles (EV) in transportation systems is more cost effective and environmental friendly than using conventional vehicles. In addition, the energy storage capability and mobility of EVs provide a convenient way to transfer energy from renewable energy sources to locations that have no direct access to renewable energy. As an example, an EV can be charged by a renewable energy source and discharge energy at a charge station; other EVs passing by the charge station can get charged, and hence indirectly use the energy from the renewable energy source. In this paper, we investigate the optimal renewable energy transfer problem in a bus system. Specifically, the goal is to determine how much energy a bus should deposit or withdraw at a charge station so that the total amount of renewable energy used by the bus system is maximized. We formulate and solve the above optimization problem using linear programming. Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline scheme and provides an effective way for distributing renewable energy in bus systems.**

I. Introduction

Transportation is one of the major sources of environmental pollution that has challenged the sustainable growth of big cities all over the world [1]. Compared to conventional vehicles, electric vehicles (EVs) present many opportunities in improving energy efficiency and reducing greenhouse gas emissions, and hence have the potential to significantly reduce the environmental pollution caused by transportation. In addition, equipped with batteries and due to their built-in mobility, coordinated EVs can form a mobile and distributed energy storage system. Within the system, energy can be conveniently transported from place to place.

In our prior work [14], we propose a novel concept, *EV energy network*, for energy distribution and transmission using EVs. Specifically, an EV energy network consists of a set of EVs and EV charge stations as well as an energy transportation network. The basic idea behind an EV energy network is that EVs transfer energy from renewable energy sources (e.g., solar or wind) to users who need energy (e.g., charging stations and houses) but do not have direct access to renewable energy sources. As an example, an EV can be charged by a renewable energy source and discharge energy at a charge station. Other EVs passing by the charge station can withdraw energy from the charge station, and hence indirectly use the energy from the renewable energy source. Analogous to a data communication network, the roads work as network links where energy flows, and charge stations work as routers that store and forward energy.

In this paper, we investigate *optimal renewable energy transfer* in an EV energy network. Consider a bus transportation system in a city where all buses are hybrid EVs which can use both gas and electricity. Some buses have access to renewable energy sources on their routes, and hence can be charged directly by such sources, while the other buses can only indirectly use renewable energy through charge stations. Optimal renewable energy transfer determines how much energy an EV should deposit or withdraw at a charge station so that the total amount of renewable energy used by the bus system is maximized. We formulate and solve the above optimization problem using linear programming (LP). Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline scheme and provides an effective way to share renewable energy in a bus system, and hence can significantly reduce the environmental footprint of the bus system. Our results also demonstrate that a moderate battery size can realize most of the gains.

The rest of the paper is organized as follows. We describe the problem setting in Section II and formulate and solve the optimization problem in Section III. We then evaluate the performance of our approach through extensive simulation in Section IV. Section V briefly describes related work. Finally, we conclude the paper and describe future work in Section VI.

II. Problem Setting

Consider a bus transportation system in a city where all buses are EVs. Some bus routes have access to *renewable energy sources*, that generate electricity at a certain level (*e.g.* using solar or wind) and provide power to charge the battery of the buses running along these routes. A bus that is charged by renewable energy sources can discharge at a *charge station*, and hence transfer the renewable energy carried by its battery to the charge station, which can then charge other buses that pass by. In this way, renewable energy is transferred by a bus that has access to renewable energy sources to other buses that may not have direct access to renewable energy sources.

Fig. 1(a) shows a simple example, where the nodes represent bus stops. In particular the black node, node a, represents a renewable energy station (collocated with bus stop a), the yellow nodes, nodes b and c, represent charge stations, and

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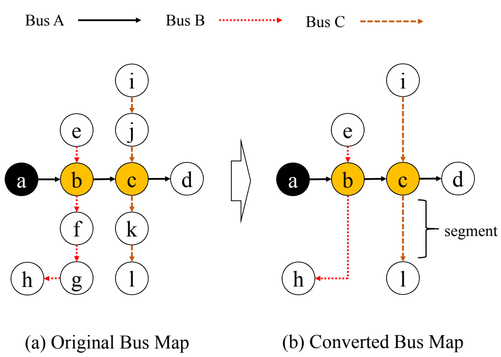

Fig. 1. A simple example to illustrate renewable energy transfer in a bus system: (a) shows the original bus map with three buses traveling on three routes, and (b) shows the converted bus map for the ease of formulation.

the white nodes are ordinary bus stops. In this example, bus A has four bus stops, $\{a, b, c, d\}$, along its route. Since there is a renewable energy station at the first bus stop, *i.e.* node a, bus A can use the renewable energy source to charge its battery before starting its trip. While bus a travels along its route, it can deposit some energy at charge stations b and c. When bus B passes charge station b, it can withdraw energy, and hence get charged by renewable energy sources indirectly. Similarly, bus A can also deposit energy at charge station c, and the energy can be picked up by bus C (when bus C arrives at bus stop c) at a later point of time.

In the example in Fig. 1(a), charge stations are placed at interchange points (bus stops) that connect two or more routes. We have studied charge station placement in [14]. Now with the locations of charge stations fixed, another important problem is how to transfer renewable energy effectively among buses. The total energy consumption (including both gas and electricity) for the periodic operation of the bus system is a constant. Our target is to maximize the electricity portion thus reduce the usage of gas. The decision variables are how much energy a bus should deposit to or withdraw from a charge station so that the total amount of renewable energy used by the bus system is maximized. As an example, suppose that in Fig. 1(a), bus A can deposit a total of 10 units of energy at charge stations b and c; bus B needs at least 7 units and bus C needs at least 3 units to finish their trip. Then the optimal solution is that bus A deposits 7 and 3 units of energy at charge stations b and c which will be picked up by bus B and C respectively. In practice, there can be a large number of buses and routes. In addition, two bus routes can share multiple charge stations and many buses may travel simultaneously along the same route (with different schedules).

III. Optimal Renewable Energy Transfer

Consider a time interval (*e.g.*, the time from the first bus starting operation to the last bus stopping operation in a day in a bus system). Let n_c denote the total number of charge stations. Let n_b denote the total number of buses running in the bus system. There can be multiple buses running along the same route but following different schedules (*e.g.*, the schedules of two buses are 30 minutes apart). These buses are treated independently. Similarly, a bus may start again after finishing a trip. For ease of formulation, the same bus that runs at different points of time is treated as different buses. We index the buses by $b = 1, \ldots, n_b$. We assume that the schedules of the buses are known beforehand. In other words, we know exactly when a bus reaches a stop. In practice, the schedule of a bus may be dynamic, *e.g.*, due to traffic jams, detours, etc. In such scenarios, with the help of modern communication and positioning technologies (e.g., GPS, cellular networks, etc.), the real-time information of the buses can be sent to a central server which can use the optimization formulation that we describe below (specifically the LP formulation) to obtain the optimal schedule and transmit to the buses and charge stations.

For any bus b, let s_b denote the total number of charge stations on its route. It is easy to see that the route of bus b can be divided into $s_b + 1$ segments by the s_b charge stations. As illustrated in Fig. 1(b), we convert each route in the original bus map in Fig. 1(a) to contain multiple segments divided by the charge stations. For instance, in the converted map, the route for bus A contains three segments, while the routes for buses B and C both contain two segments. For the route of bus b, we index the charge stations by $c = 1, \ldots, s_b$, and index the segments by $s = 0, \ldots, s_b$. If a charge station is collocated with the first/last bus stop, then we treat the first/last segment as a virtual segment of zero length.

When a bus traverses a segment, it consumes either electricity or gas. Let $d_{b,s}$ denote the absolute amount of energy required for bus b to traverse segment s, and let $g_{b,s}$ and $h_{b,s}$ denote the amount of gas and electricity that bus b consumes when traversing segment s, respectively.

Therefore the objective function of optimal renewable energy transfer can be formulated as the following minimization problem:

$$\text{minimize: } \sum_{b=1}^{n_b} \sum_{s=0}^{s_b} g_{b,s} \,. \tag{1}$$

There are multiple constraints in the optimization problem as detailed below. First, for any bus b and any segment s, the summation of the gas consumption, $g_{b,s}$, and electricity consumption, $h_{b,s}$, should be equal to the absolute energy requirement for traversing the segment. That is,

$$g_{b,s} + h_{b,s} = d_{b,s} \,. \tag{2}$$

Let G_b be the capacity of the gas tank of bus b. The gas consumption, $g_{b,s}$, should be non-negative and limited by the capacity of the gas tank. That is,

$$0 \le g_{b,s} \le G_b \,. \tag{3}$$

In addition, for any bus b, it is reasonable to assume that the size of its gas tank is sufficiently large for the bus to finish the entire route. Hence,

$$G_b \geq \sum_{s=0}^{s_b} d_{b,s} \,. \tag{4}$$

Whenever a bus arrives at a charge station, it can either charge or discharge energy. Let $x_{b,c}$ denote the amount of energy that bus b charges/discharges at charging station c. We define $x_{b,c}$ to be negative when bus b discharges (deposits energy) to charge station c, and define $x_{b,c}$ to be positive when bus b gets charged (withdraws energy) from charge station c. The decision variables in our optimization problem are

$$x_{b,c}, \forall b = 1, \ldots, n_b, \forall c = 1, \ldots, n_c, c \neq 0. \tag{5}$$

Let B_b denote the battery capacity of bus b. Let $e_{b,s}$ denote the battery status (i.e., the amount of energy stored in the battery) of bus b at the beginning of segment s. Then clearly

$$0 \leq e_{b,s} \leq B_b, \forall s = 0, \ldots, s_b \,. \tag{6}$$

After each energy exchange event, the battery status of bus b satisfies

$$e_{b,s+1} = e_{b,s} - h_{b,s} + x_{b,c_s}, \forall s = 0, \ldots, s_b - 1 \,, \tag{7}$$

where c_s is the index of the charge station at the end of segment s (or the beginning of segment $s+1$). Specifically, the above equation states that the amount of energy stored in the battery of bus b at the beginning of segment $s+1$ equals to the amount of energy at the beginning of segment s subtracted by the amount of electricity consumed when traversing segment s and the changes at charge station c_s.

Combining (6) and (7) yields a set of inequalities:

$$0 \leq e_0^b - \sum_{s=0}^{m} h_{b,s} + \sum_{s=0}^{m} x_{b,c_s} \leq B_b, \forall m = 0, \ldots, s_b \,, \tag{8}$$

where e_0^b is the initial amount of energy in the battery of bus b. We define initial energy exchange for each bus is 0, $x_{b,0} = 0$.

For any charge station c, let b_c denote the number of buses that pass c. Whenever a bus passes a charge station, there is an energy exchange event. Therefore the total number of such events for any charge station is equal to the number of buses that pass it. We order the energy exchange events according to their occurring time, and let $y_{c,j}$ be the amount of energy that is transferred in the jth event at charge station c, for $j = 1, \ldots, b_c$. Since the bus schedules are known beforehand, we know the indices of the energy exchange events beforehand. Suppose that the jth bus that passes charge station c is bus b, then $y_{c,j} = x_{b,c}$.

We assume the capacity of a charge station is sufficiently large, as charge stations usually can have much larger or more batteries installed compared to buses. Since the amount of energy withdrawn by a bus cannot exceed the amount of energy available at the charge station, for any charge station c we have

$$e_0^c - \sum_{i=1}^{j} y_{c,i} \geq 0, \forall j = 1, \ldots, b_c, \tag{9}$$

TABLE I

NOTATION USED IN PROBLEM FORMULATION.

Notation	Definition
n_b	The total number of buses
n_c	The total number of charge stations
s_b	The number of segments on the route of bus b
b_c	The number of buses that pass charge station c
e_0^b	Initial amount of energy in the battery of bus b
e_0^c	Initial amount of energy stored at charge station c
$x_{b,c}$	The amount of energy that bus b deposits (negative) or withdraws (positive) at charge station c
$d_{b,s}$	The energy requirement of traversing segment s for bus b
$g_{b,s}$	The amount of gas that bus b consumes in segment s
$h_{b,s}$	The amount of electricity that bus b consumes in segment s
$e_{b,s}$	The battery level of bus b at the beginning of segment s
$y_{c,j}$	The amount of energy of the jth energy transfer event at charge station c, $j = 1, \ldots, b_c$
G_b	Capacity of the gas tank for bus b
B_b	Capacity of the battery for bus b
R	The set of routes with renewable energy stations

$$\text{minimize:} \sum_{b=1}^{n_b} \sum_{s=0}^{s_b} g_{b,s} \tag{10}$$

subject to:

$$G_b \geq \sum_{s=0}^{s_b} d_{b,s}, b = 1, \ldots, n_b, \tag{11}$$

$$0 \leq g_{b,s} \leq G_b, s = 0, \ldots, s_b, b = 1, \ldots, n_b, \tag{12}$$

$$g_{b,s} + h_{b,s} = d_{b,s}, s = 0, \ldots, s_b, b = 1, \ldots, n_b, \tag{13}$$

$$0 \leq e_0^b - \sum_{s=0}^{m} h_{b,s} + \sum_{c=0}^{m} x_{b,c} \leq B_b, m = 0, \ldots, s_b, \tag{14}$$

$$e_0^c - \sum_{i=1}^{j} y_{c,i} \geq 0, j = 1, \ldots, b_c, c = 1, \ldots, n_c, \tag{15}$$

$$e_0^b = B_b, \forall b \in R, \, e_0^b = 0, \forall b \notin R. \tag{16}$$

Fig. 2. *Linear programming formulation for optimal renewable energy exchange*

where e_0^c is the initial amount of energy in charge station c.

Last, let R be the set of routes with renewable energy stations. For simplicity, we assume the renewable energy station on a route is at the beginning of the route. Furthermore, for any bus running on such a route, we assume it gets fully charged at the beginning of the route. For a bus that runs on a route with no renewable energy source, we assume the initial energy stored in its battery is zero. Since B_b denotes the battery capacity of bus b, we have $e_0^b = B_b, \forall b \in R$ and $e_0^b = 0, \forall b \notin R$.

In summary, the optimization problem is formulated in Fig. 2. It is a linear programming problem and can be solved using standard optimization tools (e.g., CVX [7]).

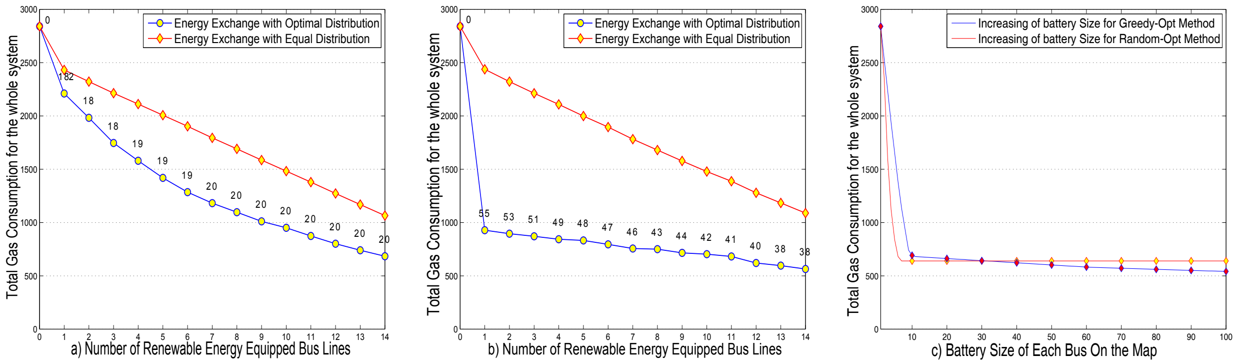

Fig. 3. Simulation Results : a) Performance comparison of the optimal and the baseline solutions by greedy placement algorithm, b) Performance comparison of the optimal and the baseline solutions by random placement algorithm, c) Impact of battery size by using optimal parameters for renewable energy lines and number of charge stations.

IV. Performance Evaluation

A. Simulation Setting

Our performance evaluation uses the data set from Manhattan city bus system [8]. This bus system contains 40 bus routes that can be separated into eight independent components (each component contains a set of bus routes where a route shares at least one bus stop with at least another route; two components are independent when they do not share any bus stop). Since the energy transfers in independent components are independent of each other, for simplicity, we only use the largest component in the rest of the paper for performance evaluation. This component contains 104 bus stops on 28 different bus routes. For simplicity, we assume on any route, traveling from one bus stop to the next bus stop requires one unit of energy. In the bus system we consider, the energy requirement of the longest route is 9 units. We assume a bus has a gas tank that can store 20 units of energy, and has a full tank of gas before starting its trip on a route. In addition, each bus is equipped with a battery that can store electrical energy. Electrical energy and gas energy will be used equivalently (i.e., traveling from one location to another requires the same amount of electrical and gas energy). Unless otherwise stated, we assume the battery of a bus can store 20 units of energy. The energy transfer loss while exchanging energy is very low (less than 10% [14]). For simplicity, we assume no energy transfer loss (the results are similar when assuming energy transfer loss of 10%). Also charging time is not considered since the technology is fast evolving and there are already commercial products that can charge very quickly [2]. A route has at most one renewable energy source. If it has a renewable energy source, for simplicity, we assume it is at the beginning of the route. A bus running on such a route is charged with a full battery of electrical energy by the renewable energy source before starting the trip.

For each route, we assume 20 buses traveling along the route. The schedule of the buses are known beforehand. Specifically, the first bus starts at time 0 and the next one leaves 30 minutes afterwards, and so on. We assume charge stations are placed at bus stops and the capacity of a charge station is sufficiently large. Charge stations should be placed so that the number of charge stations is minimized and buses on a bus route that does not have a renewable energy source can indirectly use renewable energy through charge stations. We use the two schemes, greedy and random schemes, proposed in our prior work [14] for charge station placement. Specifically, the greedy scheme picks a bus stop from the map that covers the largest number of bus lines as a charge station and adds it to a list. It then removes those bus routes (include their bus stops) from the map. It repeats the process until each bus route has at least one charge station. The random scheme differs from the greedy scheme in that it picks a bus stop randomly. More details of these two schemes can be found in [14].

We compare the performance of our proposed scheme with a baseline scheme. In the baseline scheme, a bus that is charged by a renewable energy source deposits the energy not used in its trip evenly to the charge stations along its route. In addition, when a bus that is not charged directly by a renewable energy source (*i.e.*, a bus that runs along a route without a renewable energy source) passes a charge station, it is charged as much as possible. The performance metric we use is the total gas consumption of all the buses. We randomly choose routes as the routes with renewable energy sources. The number of such routes is varied from 1 to 14. For each setting, we make 100 simulation runs (by using independent random seeds to choose the routes that have renewable energy sources) and obtain the average gas consumption along with 95% confidence interval. For each setting, we use CVX [7] tool box for MATLAB 2013 [12] to solve our optimization problem.

B. Evaluation Results

Fig. 3(a) plots the total gas consumption when charge stations are placed using the greedy scheme [14]. The results of both the optimal solution and the baseline solution are plotted in the figure. For each setting, the result is the average over 100 simulation runs (the 95% confidence intervals are tight and hence omitted from the figure). The numbers above the performance curve represent the average number of charge stations over 100 runs (rounded to the closest integer). (The optimal solution and the baseline scheme are compared under the same settings; hence we only mark the numbers of charge stations on one performance curve.) We observe that, as expected, the total amount of gas consumption decreases when increasing the number of routes that have renewable energy sources. The optimal solution leads to much more reduction than the baseline scheme. Specifically, when the number of routes with renewable energy sources is 14, the amount of gas consumption is reduced to 26% under the optimal solution (from 2840 to 740 units of energy) and is reduced to 41% under the baseline scheme. The amount of gas consumption under the optimal solution is 36.8% less than the baseline scheme. Assuming CO_2 is only generated during gas consumption in our system, the amount of CO_2 emission is also reduced to 26% under the optimal solution.

Fig. 3(b) plots the results when charge stations are placed using the random scheme [14]. We observe similar trend as that in Fig. 3(a). Since more charge stations are used when using random charge station placement, for the same energy transfer scheme (i.e., the optimal solution or baseline scheme) and the same number of routes with renewable energy sources, the total gas consumption may be even lower in Fig. 3(b) than that in Fig. 3(a).

The results presented above assume the battery size of each bus can store 20 units of energy. We next vary the battery size and investigate its impact on total gas consumption. Fig. 3(c) plots the results when using the optimal solution for energy transfer and 14 routes have renewable energy sources. Again each result is the average of 100 simulation runs (the 95% confidence intervals are tight and hence omitted) by randomly choosing routes to have renewable energy sources. The results of both charge station placement strategies are plotted in the figure. We observe a diminishing gain of battery size. Specifically, as the battery size increases from 1 to 100 units, the total gas consumption reduces dramatically at the beginning and decreases slowly afterwards. For both greedy and random charge station placement strategies, a modest battery size (in our case 10 unit) is sufficient to realize most of the performance gains.

V. Related Work

The study closest to ours is [14] that proposes the concept of EV energy network and proposes two algorithms for charge station placement. Our study solves an important problem in EV energy networks, namely how to optimally transfer renewable energy through EVs. The study in [15] develops a hypergraph based approach to reduce the sum of all route hops from renewable energy sources to charge stations, which differs in scope from our study. Several studies are on scheduling the charging of EVs [3], [4], [5], [6], [9], [10], [11]. These studies focus on when to charge an EV from the power grid, while our study focuses on renewable energy transfer by developing an optimal solution that determines how much energy an EV should charge or discharge at a charge station. Broadly, our study is related to vehicle-to-grid [13], where vehicles stores energy and transfer energy to the power grid. Our focus is however energy transfer among EVs through charge stations, which differs significantly from general vehicle-to-grid.

VI. Conclusion and Future Work

In this paper, we have studied optimal renewable energy transfer in a bus system. Specifically, we formulated and solved an optimization problem that determines how much energy a bus should deposit or withdraw at a charge station so that the total amount renewable energy used by the bus system is maximized. Simulation results using the Manhattan city bus system demonstrates that our approach provides an effective way for renewable energy to be transferred and shared in a bus system. In this study, we first determine the locations of the charge stations and then solve the optimal renewable energy transfer problem. As future work, we plan to solve these two problems jointly through an optimization framework.

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