Optimal Centralized Renewable Energy Transfer Scheduling for Electrical Vehicles

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***Abstract*—Plug-in hybrid electrical vehicles (PHEVs) that can use both gas and electricity have the potential to greatly reduce air pollution from vehicles. In this paper, we consider a bus system where the buses are PHEVs, and some charging points at the bus stops are connected to a central energy storage (CES) via underground cables. The CES is charged by renewable energy sources and the buses get electricity from the CES (and thus use renewable energy) through the charging points. Since the CES has limited capacity, the energy generated by the renewable energy sources will be wasted when it exceeds the capacity of the CES. On the other hand, since each bus has a battery, the buses naturally form a distributed energy network that can help to store the energy from the CES to reduce energy waste. We formulate and solve an optimization problem that determines the amount of energy that a bus charges or discharges at the charging points to improve effective load carrying capability at the CES while maximizing the total amount of renewable energy used by the buses. Simulation results demonstrate that our approach significantly outperforms a baseline strategy. In addition, our approach uses the batteries of the buses efficiently, and hence only a small battery at the CES is sufficient to realize most of the gains.**

I. Introduction

Air pollution is a key challenge for industrial countries around the world. In the United States, transportation is one of the largest causes of air pollution [5]. Plug-in hybrid electrical vehicle (PHEV) that can use both gas and electricity is an attractive alternative technology that has the potential to significantly reduce air pollution from vehicles. In addition, with their batteries and mobility, PHEVs can form a distributed energy network where energy can be conveniently transported from place to place [11].

Our previous work [4] considers a bus transportation system in a city where all buses are PHEVs and a number of charge stations serve as energy exchange points (i.e., a bus can deposit or withdraw energy at a charge station). Some buses have access to renewable energy sources on their routes, and hence can be charged directly by such sources. A bus charged by a renewable energy source can discharge energy at a charge station; another bus passing by the charge station can withdraw energy from the charge station, and hence indirectly use the energy from the renewable energy source. We formulate an optimal energy transfer problem, which determines 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.

The above formulation assumes that each charge station is equipped with large energy storage (battery) to serve as an energy exchange point. This assumption, however, may not be feasible in practice because installing large batteries at the charge stations can be cost prohibitive [3]. This is especially true in metropolitan areas, where a large number of charge stations are needed.

In this paper, instead of using multiple energy storages that are distributed at the charge stations, we assume that there is only a *single* centralized energy storage. The infrastructure is underground, where some *charging points* have underground cables connected to the central energy storage (CES), and a central controller controls the energy exchanges between the PHEVs and the CES via the charging points. This is reasonable since many large cities already have tunnels and places for underground cables in their subterranean metro systems [10]. In addition, recent advances in Boolean Microgrids [8] allow for discrete power delivery and fully digital control mechanism that are needed in our system. We assume that renewable energy sources generate energy and store it in the CES. PHEVs can withdraw energy from the CES and hence indirectly use renewable energy sources when stopping at the charging points. The capacity of the CES is limited. Hence energy generated by the renewable energy sources can be wasted when it exceeds the capacity of the CES. On the other hand, each PHEV has a battery, and hence the PHEVs naturally form a distributed energy network that can help to store the energy from the CES to reduce energy waste. An interesting question is how to schedule charging or discharging events for the PHEVs to reduce energy waste at the CES while maximizing the total amount of renewable energy used by PHEVs. We develop an optimization based approach to solve this problem using linear programming. Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline strategy. In addition, since our approach uses the batteries of the PHEVs efficiently, only a small battery at the CES is sufficient to realize most of the gains.

The rest of this paper is organized as follows. We first present the architecture of the system in Section II. Problem formulation and solution are given in Section III. We then present simulation setting and results in Section IV. We briefly describe related work in Section V and conclude the paper in Section VI.

II. System Architecture

Consider a bus transportation system that consists of buses and bus stops. Buses are PHEVs that can use both gas and electricity. Some bus stops are charging points that have special equipment to exchange electricity with a bus when the bus stops at the charging point. The charging points do not have any electrical battery onboard. Instead, they are connected to a central energy storage (CES) using underground cables that allow energy/electricity to flow through. The CES gets energy from renewable energy sources such as solar and wind. Through the charging points, the buses can get electricity from the CES, and thus use renewable energy.

A central control system (CCS) is responsible for orchestrating electricity exchanges between buses and the CES through the charging points. Specifically, it decides how much energy a bus withdraws from or deposits into the CES at a charging point. The goal is to maximize the electricity that is used by the buses, and thus minimizing the usage of gas (since the total energy consumption, including both gas and electricity, of the bus system is a constant). The CCS arranges energy exchange using Boolean Microgrid technology [8] that allows transmitting electricity as discrete packets. Therefore, multiple charging events between buses and charging points can happen simultaneously. The buses, charging points, CES and CCS are equipped with communication devices (e.g., Wi-Fi, cellular devices), and can communicate with each other in real-time. For instance, when a bus is delayed due to traffic jams, it can send its current schedule to the CCS. Similarly, the CCS can send its decision on how much to charge or discharge at a charging point to a bus in real-time.

Fig. 1 shows the high-level architecture of the system. It depicts two layers. The upper layer shows the main components and the information flow among the various components. Specifically, information is transmitted in two directions: in one direction, the CCS sends decisions and signals to the buses, charging points, and CES; in the other direction, the buses, charging points, and CES send their current status to the CCS. For clarity, the information flow is not marked explicitly in the figure; rather it is implicitly marked by the radio waves (representing wireless communication) at the various components. The lower layer shows the underground cables and the energy flow between the CES and the charging points.

III. Optimal Centralized Energy Transfer

In this section, we present an optimization based approach that determines the optimal solution for energy transfer between the CES and the buses through the charging points. For ease of exposition, we first assume that the CCS knows the system information (bus schedules and renewable energy generation at the CES) beforehand (see Section III-A). When this is not the case, i.e., the bus schedules can change due to traffic or road conditions, or the renewable energy generation at the CES may deviate from the prediction, we describe how the CCS dynamically adjusts the decisions based on real-time information provided by the buses and CES (see Section III-B).

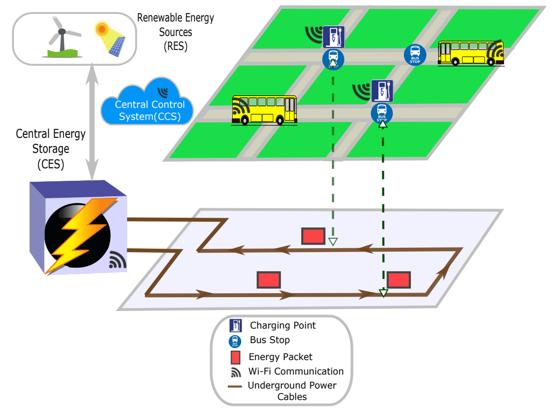

Fig. 1. High-level architecture of the system.

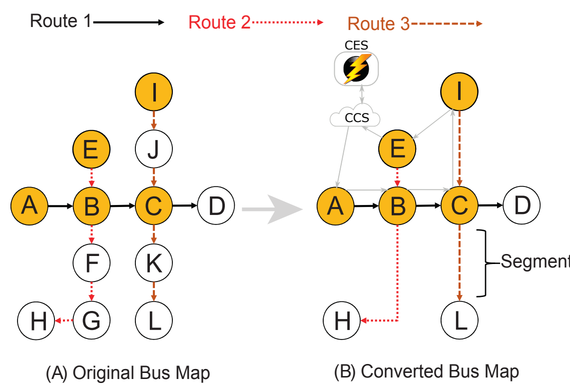

Fig. 2. A simple example: (a) shows the original bus map with three bus routes, and (b) shows the converted bus map for ease of formulation.

A. System information known beforehand

In this setting, we assume that the buses run according to their schedules, and the renewable energy generation at the CES can be accurately predicted based on historical data. In addition, the above information is known by the CCS beforehand. Therefore, the CCS solves an optimization problem that determines the optimal charging and discharging decision for each bus at the charging points. We next describe the optimization formulation.

Let n denote the total number of buses that run in the bus system during a time interval (e.g., the time from when the first bus starts operation to when the last bus stops operation in a day). There can be multiple buses running along the same route, each following a different schedule. For ease of exposition, we treat the buses independently and index the buses by $b = 1, \dots, n$.

Since our problem mainly concerns how much energy a bus needs to deposit or withdraw at a charging point, it is sufficient to focus on the charging points instead of individual bus stops. For any bus b, let s_b denote the total number of charging points on its route. It is easy to see that the route of bus b can be divided into $s_b + 1$ segments, indexed by $0, \dots, s_b$. If a charging point is collocated with the first/last bus stop, then we treat the first/last segment as a virtual segment of zero length. Fig. 2 shows an example. Fig. 2(a) shows the original bus map and Fig. 2(b) shows the converted map. In the original map, the orange nodes, A, E, I, B, and C, represent charging points;

the white nodes represent bus stops that are not charging points. Route 1 has three charging points, and Routes 2 and 3 both have two charging points. In the converted map, Route 1 has four segments, Routes 2 and 3 both have three segments, and the first segment of all three routes is a virtual segment of zero length.

When a bus travels, it consumes either electricity or gas. Let $d_{b,s}$ denote the total amount of energy required for bus b to traverse segment s. Let $g_{b,s}$ and $h_{b,s}$ denote the amount of gas and electricity that bus b consumes when traversing segment s, respectively. As discussed earlier, our goal is to maximize the total amount of electrical energy (i.e., minimize the total amount of gas) that is used by the bus system. Hence, the objective function of optimization problem can be described as

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

We next describe the constraints in the optimization problem. First, for any bus b in any segment s, the summation of the gas consumption, $g_{b,s}$, and electricity consumption, $h_{b,s}$, should be equal to the 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. 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,

$$0 \le g_{b,s} \le G_b \,, \quad \sum_{s=0}^{s_b} d_{b,s} \le G_b \,. \tag{3}$$

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

$$0 \le e_{b,s} \le B_b, \forall s = 0, \ldots, s_b. \tag{4}$$

When bus b arrives at the beginning of segment s (which is a charging point), it can either charge or discharge energy. Suppose the fraction of energy loss for an energy exchange event (charging or discharging) is λ, $0 \le \lambda < 1$. If the amount of energy that a bus obtains is x, then taking account of the energy loss, the amount of energy at the CES is reduced by $x/(1-\lambda)$. Similarly, if the amount of energy that a bus deposits is y, then taking account of the energy loss, the actual amount of energy that the CES obtains is $(1-\lambda)y$. To differentiate the charging and discharging events, we define two variables, $x_{b,s}$ and $y_{b,s}$, that denote respectively the amount of energy that bus b obtains or deposits at the beginning of segment s. As an example, if bus b gets charged by the CES by 10 units of energy, then $x_{b,s} = 10$ and $y_{b,s} = 0$; if bus b discharges 10 units of energy to the CES, then $x_{b,s} = 0$ and $y_{b,s} = 10$. Correspondingly, the amount of energy reduced at the CES is $10/(1-\lambda)$ for the former event, while the amount of energy increased at the CES is $10 \times (1-\lambda)$ for the latter event.

We next describe the constraints for $x_{b,s}$ and $y_{b,s}$. Let C denote the storage capacity of the CES. Let E_t denote the amount of energy at the CES at time t. Let $t_{b,s}$ denote the time of the energy exchange event (i.e., the time for bus b to reach the beginning of segment s). The amount of energy that bus b obtains cannot exceed its remaining battery storage and the amount of energy at the CES (taking account of the energy loss). That is,

$$0 \le x_{b,s} \le \min\big((1-\lambda)E_{t_{b,s}}, B_b - e_{b,s}\big) \tag{5}$$

Similarly, the amount of energy that bus b deposits cannot exceed the amount of energy in its battery and the remaining storage of the CES (taking account of the energy loss). That is,

$$0 \le y_{b,s} \le \min\left(\frac{C - E_{t_{b,s}}}{1-\lambda}, e_{b,s}\right) \tag{6}$$

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 the beginning of segment s. Therefore, the evolution of the battery status of bus b is

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

Combining (4) and (7), we have that for bus b and any segment $m = 0, \ldots, s_b$,

$$0 \le e_{b,0} - \sum_{s=0}^{m} h_{b,s} + \sum_{s=0}^{m} x_{b,s} - \sum_{s=0}^{m} y_{b,s} \le B_b, \tag{8}$$

where $e_{b,0}$ is the initial amount of energy in the battery of bus b, $x_{b,0} = 0$ and $y_{b,0} = 0$ (since segment 0 is the segment before the first charging point). The decision variables in our optimization problem are $x_{b,s}$ and $y_{b,s}$, $b = 1, \ldots, n, s = 1, \ldots, s_b - 1$.

We refer to an event that a bus reaches a charging point and needs to decide how much to exchange with the CES as an energy exchange event. Let the total number of energy exchange events at the CES be N. Suppose that the jth energy exchange event corresponds to the event that bus b withdraws or deposits energy at the beginning of segment s. Let u_j and v_j denote respectively the amount of energy for these two types of events (relative to the CES). Since $x_{b,s}$ and $y_{b,s}$ denote respectively the amount of energy that bus b obtains and deposits into the CES corresponding these two events, then taking account of energy loss, we have $u_j = x_{b,s}/(1-\lambda)$ and $v_j = (1-\lambda)y_{b,s}$. Since at any point of time, the amount of energy at the CES should be no more than its capacity, we need to have that for any $j = 1, \ldots, N$,

$$0 \le E_0 - \sum_{i=1}^{j} u_i + \sum_{i=1}^{j} v_i + R_j - L_j \le C, \tag{9}$$

$$0 \le L_j, \tag{10}$$

where E_0 denotes the initial energy at the CES at time 0, R_j denotes the amount of renewable energy that has been

TABLE I
NOTATION USED IN PROBLEM FORMULATION.

Notation	Definition
n	Total number of buses
s_b	Number of charging points on the route of bus b
$d_{b,s}$	Energy requirement of traversing segment s for bus b
$g_{b,s}$	Amount of gas that bus b consumes in segment s
$h_{b,s}$	Amount of electricity that bus b consumes in segment s
$x_{b,s}$	Amount of energy that bus b obtains at the beginning of segment s
$y_{b,s}$	Amount of energy that bus b deposits at the beginning of segment s
$e_{b,s}$	Battery status of bus b at the beginning of segment s
$t_{b,s}$	Time that bus b is at the beginning of segment s
λ	Fraction of energy loss during an energy exchange event
G_b	Capacity of the gas tank for bus b
B_b	Capacity of the battery for bus b
E_t	Amount of energy in the CES at time t
C	Capacity of the CES
N	Total number of energy exchange events at the CES

generated by the renewable energy sources up to the time when the jth event happens, and $L_j \geq 0$ denotes the amount of energy wasted at the CES (because of the limited storage of the CES). As mentioned earlier, R_j is known beforehand, while L_j is a decision variable.

Table I summarizes the key notation for easy references. The optimization problem is formulated in Fig. 3. Note that by definition, we should have $x_{b,s} \times y_{b,s} = 0$, and similarly $u_i \times v_i = 0$. The formulation in Fig. 3 does not contain these two constraints. This is because with energy loss during energy exchange, violating these two constraints leads to sub-optimal solutions. Therefore there is no need to include them explicitly. The formulation is a linear programming problem and can be solved using standard optimization tools (e.g., CVX [9]).

B. System information not known beforehand

In the above, we have assumed that the bus schedules and the amount of renewable energy generation are known beforehand. In practice, due to various traffic and road conditions (e.g., traffic jams, road constructions, detours, etc.), the schedule of a bus can be affected significantly, and hence affecting the timing of the relevant events and the optimal solution. Similarly, the prediction of the renewable energy generation at the CES may not be accurate. In such cases, the communication capability of the system allows real-time update to the CCS. The CCS in turn recalculates the optimal solution based on the updated information using the same approach as described earlier. Specifically, suppose that bus b detects a significant delay at time T. It then estimates the arriving time to the subsequent charging points on its route, and transmits the information through the communication infrastructure to the CCS. The CCS then solves an optimization problem as in Fig. 3 for $t \geq T$ only (the values of the various variables for $t < T$ are given as in the original optimal solution), and sends the solution to the buses. The above approach can be easily realized in practice because many cities already have early delay detection systems (e.g., New York City MTA [2]) and solving a linear programming problem is very fast on modern computers.

$$\text{minimize: } \sum_{b=1}^{n}\sum_{s=0}^{s_b} g_{b,s} \tag{11}$$

subject to:

$$0 < \sum_{s=0}^{s_b} d_{b,s} \leq G_b, b = 1, \ldots, n, \tag{12}$$

$$0 \leq g_{b,s} \leq G_b, s = 0, \ldots, s_b, b = 1, \ldots, n, \tag{13}$$

$$g_{b,s} + h_{b,s} = d_{b,s}, s = 0, \ldots, s_b, b = 1, \ldots, n, \tag{14}$$

$$0 \leq x_{b,s} \leq \min\left((1-\lambda)E_{t_{b,s}}, B_b - e_{b,s}\right), b = 1, \ldots, n, \; s = 0, \ldots, s_b \tag{15}$$

$$0 \leq y_{b,s} \leq \min\left(\frac{C - E_{t_{b,s}}}{1-\lambda}, e_{b,s}\right), \; b = 1, \ldots, n, s = 0, \ldots, s_b \tag{16}$$

$$0 \leq e_{b,0} - \sum_{s=0}^{m} h_{b,s} + \sum_{s=0}^{m} x_{b,s} - \sum_{s=0}^{m} y_{b,s} \leq B_b, \; b = 1, \ldots, n, m = 0, \ldots, s_b \tag{17}$$

$$0 \leq E_0 - \sum_{i=1}^{j} u_i + \sum_{i=1}^{j} v_i + R_j - L_j \leq C, j = 1, \ldots, N \tag{18}$$

$$0 \leq L_j, j = 1, \ldots, N \tag{19}$$

Fig. 3. Linear programming formulation for optimal renewable energy exchange

IV. PERFORMANCE EVALUATION

A. Simulation Setting

Our performance evaluation uses the data set from Manhattan city bus system [2]. This bus system contains 40 bus routes divided by 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). For simplicity, we consider only the largest component that contains 104 bus stops on 28 different bus routes. For each route, we assume 20 buses traveling along the route. The bus schedules are known beforehand; the case when the bus schedules change over time can be solved as outlined in Section III-B.

We assume that on each route, traveling from one bus stop to the next requires one unit of energy. In the bus system, the energy requirement of the longest route is 9 units. We assume a bus has a gas tank that can store 10 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. Electricity and gasoline will be consumed equivalently (i.e., traveling from one location to another requires the same amount of electrical and gas energy). We assume the battery of a bus can store 10 units of electrical energy, and the initial battery level is zero.

We assume 10% energy loss during energy exchange [11], i.e., $\lambda = 0.1$. Charging time is not considered since the technology is fast evolving and there are already commercial products that can charge very quickly [1]. A route can have multiple charging points located at the bus stops. For every route, we set the first bus stop to be a charging point. We then find the most visited bus stop (i.e., the one traversed by

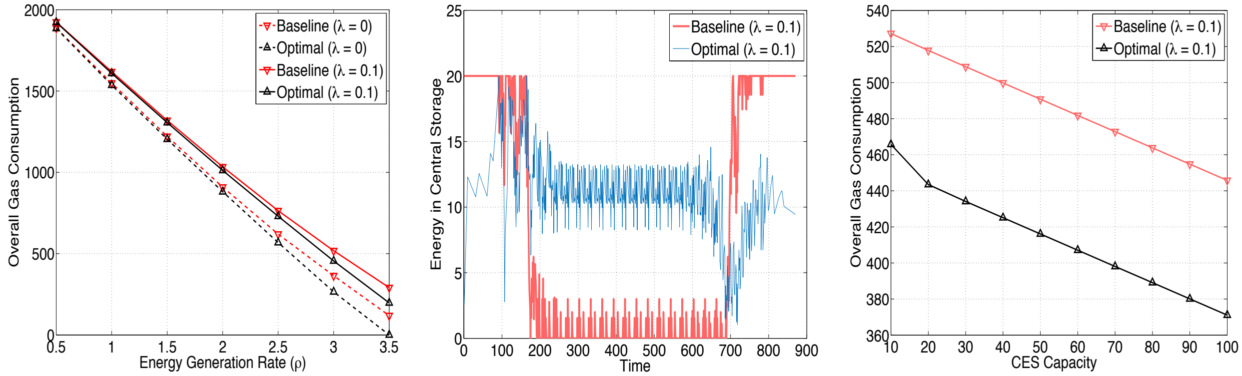

Fig. 4. Results when energy is generated throughout the simulation time. (a) The amount of gas consumption when the capacity of the CES is 20 units of energy (i.e., $C = 20$). (b) The amount of energy in the CES over time, $C = 20$, $\rho = 3$, $\lambda = 0.1$. (c) The impact of the capacity of the CES on the total gas consumption, $\rho = 3$ and $\lambda = 0.1$.

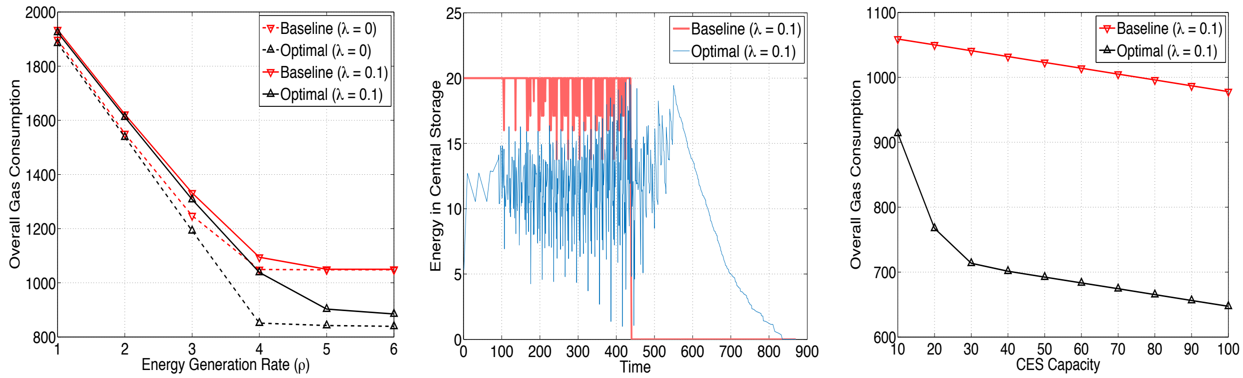

Fig. 5. Results when energy is generated only in the first half of the simulation time. (a) The amount of gas consumption when the capacity of the CES is 20 units of energy (i.e., $C = 20$). (b) The amount of energy in the CES over time, $C = 20$, $\rho = 6$, $\lambda = 0.1$. (c) The impact of the capacity of the CES on the total gas consumption, $\rho = 6$ and $\lambda = 0.1$.

most bus routes), set it as a charging point and remove the bus routes that traverses the bus stop from the map. This process is repeated until every bus route has at least one charging point.

For the CES, we assume the energy generation of the renewable energy sources is at an average rate of ρ units of energy per time unit. We consider two scenarios of energy generation. In the first scenario, energy is generated throughout the simulation time. In the second scenario, considering the intermittent energy generation of renewable energy sources, energy is only generated in the first half of the simulation time. For both cases, we assume the energy generation profile is known beforehand. When this is not the case, the problem can be solved as outlined in Section III-B. We vary the capacity of the CES from 10 to 100 and investigate its impact on the amount of gas consumption of the bus system.

The performance metric is the total gas consumption of the buses. We compare the performance of our proposed solution with a baseline scheme. The baseline scheme works in a greedy manner. Specifically, when a bus stops at a charging point, it checks the amount of energy in its battery. If the amount of energy is not sufficient for it to finish its route, it tries to get as much energy as needed from the CES.

B. *Evaluation Results*

Fig. 4 plots the simulation results for the scenario where the renewable energy sources generate energy at an average rate of ρ throughout the simulation time (from 0 to 870 time units). Fig. 4(a) plots the amount of gas consumption of the optimal and baseline schemes when the CES can store 20 units of energy, and the energy generation rate, ρ, varies from 0.5 to 3.5 units of energy per time unit. The results when the fraction of energy loss $\lambda = 0.1$ and the results for the idealized case where there is no energy loss (i.e., $\lambda = 0$) are both shown in the figure. We observe that the difference of the optimal and the baseline schemes is small when ρ is small, and becomes much more dramatic as ρ increases. For instance, when $\lambda = 0.1$, the optimal scheme consumes around 3% less gasoline than the baseline scheme for $\rho = 2$; for $\rho = 3.5$, the saving from the optimal scheme compared to the baseline scheme becomes 32%. This is because when energy is generated at a higher rate, the optimal scheme uses the generated energy more efficiently by optimally taking advantage of the batteries of the buses. Specifically, unlike the baseline scheme, a bus in the optimal scheme may take significantly more energy than it needs to finish the route to temporarily store the energy for the CES (and discharge it later to the CES) to reduce the amount of energy overflow at the CES. It may also take significantly less energy than needed (and take more energy later on) so that other buses can share the energy stored at the CES. We observe similar results under the idealized case when $\lambda = 0$. The difference between the optimal and baseline schemes is slightly less when $\lambda = 0.1$ compared to that when $\lambda = 0$. This is because when $\lambda = 0.1$, some energy is lost when a bus deposits energy back to the CES in the optimal scheme, while in the baseline scheme, a bus never deposits energy back to the CES.

Fig. 4(b) plots the energy level of the CES over the time when $\rho = 3$, $\lambda = 0.1$ and the capacity of the CES is 20. We observe that the energy level of the CES is much more stable under the optimal scheme than that under the baseline scheme. For the baseline scheme, the amount of energy of the CES quickly reaches the capacity, and then decreases to very low values (because each bus greedily takes as much energy as needed). The much more stable energy level of the CES under the optimal scheme confirms that the optimal scheme uses the distributed energy storage of the buses more efficiently. Fig. 4(c) plots the overall gas consumption of the two schemes when the capacity of the CES increases from 10 to 100, when $\rho = 3$ and $\lambda = 0.1$. As expected, the amount of gas consumption reduces for both schemes when the capacity of the CES increases.

Fig. 5 plots the simulation results when the renewable energy sources generate energy only in the first half of the simulation time (from 0 to 435 time units). Fig. 5(a) plots the amount of gas consumption of the optimal and baseline schemes when the energy generation rate, ρ, varies from 1 to 6 units of energy per time unit. We observe that in this scenario, for large ρ, the benefits of the optimal scheme in reducing gas consumption compared to the baseline scheme is even more dramatic. This is again because the baseline scheme does not use the batteries of the buses effectively, as shown in Fig. 5(b) that shows the battery level of the CES over time for $\rho = 6$ and $\lambda = 0.1$. The energy level of the CES becomes zero shortly after the renewable energy generation stops, and hence the buses that start in the second half of the simulation time cannot obtain any energy from the CES. In the optimal scheme, the battery level of the CES is non-zero even when the renewable energy generation has stopped, allowing later buses to obtain energy and reduce gas consumption. Last, Fig. 5(c) plots the amount of gas consumption when the capacity of the CES increases from 10 to 100, when $\rho = 6$ and $\lambda = 0.1$. Compared to Fig. 4(c) (where renewable energy is generated throughout the simulation), we see the optimal scheme outperforms the baseline scheme more significantly, particularly when the capacity of the CES is small. This demonstrates that optimal scheduling of energy delivery is even more important for intermittent energy generation and CES with a relatively small capacity.

V. Related Work

The study closest to ours is [4], which determines the optimal energy transfer via PHEVs assuming a number of charge stations each with its own energy storage. Our study differs from [4] in that we assume only a single centralized energy storage. In addition, we also address several practical issues including energy loss during energy exchanges, limited energy storage, and dynamic bus schedules. The study in [12] 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 PHEVs [6], [7]. These studies focus on when to charge a PHEV from the power grid, while our study focuses on renewable energy transfer by developing an optimal solution that determines how much energy a PHEV should charge or discharge at each charging point.

VI. Conclusion

In this paper, we studied how to determine the optimal energy delivery schedules for PHEVs to minimize the amount of gas consumption when there is a single centralized energy storage that stores the energy generated by renewable energy sources. We formulated an optimization problem and solved it using linear programming. Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline strategy. In addition, our approach uses the batteries of the PHEVs efficiently, and hence only a small battery at the central storage is sufficient to realize most of the gains. As future work, we plan to study vehicle to vehicle energy transfer by using only EV batteries, which can further reduce investment and operation costs.

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