System Architecture and Mathematical Models of Electric Transit Bus System Utilizing Wireless Power Transfer Technology

Young Jae Jang, Eun Suk Suh, and Jong Woo Kim

***Abstract*—We introduce a new type of electric transit bus (ETB) system that uses the innovative wireless power transfer technology developed by the Korea Advanced Institute of Technology (KAIST), which is called on-line electric vehicle (OLEV). In the ETB system, the wireless-charging infrastructure installed under the road charges the fleet of electric buses that are operative over that road. The technology is innovative in that the battery in the bus is charged while it is moving over the charging infrastructure. Unlike conventional electric vehicles, the OLEV-based ETB system is a road–vehicle integrated system. Since charging occurs while the vehicle is operational, the performance of the operation depends on the system integration of the vehicle and the road in which the charging infrastructure is embedded. In this paper, we qualitatively analyze the benefits of the OLEV-based ETB system from the energy logistics perspective. We then present two analytical economic design optimization models. The first model is for an ETB system operating in a "closed environment" with no traffic and no heavy vehicle interactions. The OLEV-based shuttle bus currently operating on the KAIST campus constitutes such a case. The second model is the "open environment model" and considers an ETB system operating in normal traffic conditions. We also present the result of numerical case studies for the optimization models. The goal of this paper is to present an innovative ETB system and a logical design framework for commercializing and deploying that system.**

***Index Terms*—Electric vehicle, on-line electric vehicle (OLEV), system architecture, systems optimization, wireless power transfer.**

I. Introduction

A. ETB Systems and Current Issues

MAJOR automakers and researchers have introduced several ideas for new electric-power-based vehicles and transportation systems during the past few years in response to rising demand for greener transportation solutions. The idea of adopting electric-powered vehicles for mass transportation systems is also gaining momentum. Electric transit bus (ETB) systems are one example. Many municipal governments around the world are trying to adopt such systems for public transportation. For example, Incheon International Airport in South Korea initiated a Green Cargo Hub project in 2009 and has been developing environmentally friendly logistics systems for ground operations using battery electric buses [1]. During the Beijing Olympics in 2008, the city employed 50 supercapacitor lithium-ion electric buses around the city to ferry visitors to the Games [2].

However, applying the conventional system architecture of such electric vehicles as battery electric buses—using an electric motor as a power source with an in-vehicle battery pack equipped—to ETB systems has a number of serious technical and economic drawbacks. High battery costs, long recharging time, and limited availability of charging stations are among the well-known problems of current battery electric vehicles. In additional to the existing problems of conventional electric vehicles, additional limitations and issues arise when these vehicles are used for transit bus systems. For instance, the battery pack with which current small passenger electric vehicles are equipped costs more than \$10 000, which is about one third the total cost of the vehicle [3]. Considering that a mass transit bus needs a much larger battery pack than a small passenger vehicle, the initial investment needed to deploy electric buses for a mass transit system is significant.

Moreover, a larger battery requires more *recharging downtime*, which refers to the nonoperational period of the electric vehicle during battery charging [4]. It takes at least 30 min to fully charge the battery installed in a small passenger vehicle with a level-3 charger—the fastest commercially available charging unit [4]–[6]. As an ETB is likely to require a larger battery pack, the recharging downtime with current charging solutions would be several hours. If the ETB system requires around-the-clock service, then more buses may be needed to compensate for the lengthy downtime. The last and most serious problem in applying current electric solutions to mass transportation is the limited driving range between charges. Current battery limitations prevent all-electric transit buses from operating all day after an overnight charge [7].

B. KAIST WPT Electric Vehicle—OLEV

To overcome the aforementioned issues, the Korea Advanced Institute of Science and Technology (KAIST) has developed an innovative new transportation system, which is called the on-line electric vehicle $(OLEV^{TM})$ system in which the wireless power infrastructure installed under the road charges the fleet

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Y. J. Jang and J. W. Kim are with the Korea Advanced Institute of Science and Technology (KAIST), Daejeon 305-701, Korea (e-mail: yjang@kaist.ac.kr).

E. S. Suh is with Seoul National University, Seoul 151-742, Korea.

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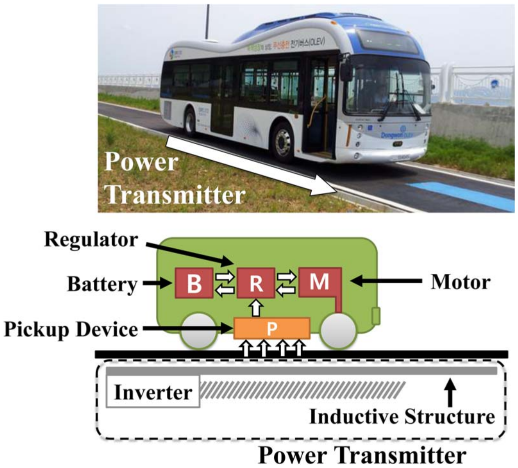

Fig. 1. Configuration of the basic structure of the OLEV system.

of electric buses operating on that road. The technology is innovative in that the battery in the bus is charged while the bus moves over the charging infrastructure. In other words, the solution developed by KAIST enables power transfer from the grid to the vehicle while the vehicle is in motion. This concept has been referred to as *dynamic charging*, *move-and-charge*, or *roadway-powered electric vehicles* [8].

As shown in Fig. 1, the OLEV system comprises vehicle units and power transmitter units. Note that although the name OLEV indicates a vehicle unit alone, it actually refers to a system comprising a vehicle or fleet of vehicles combined with the charging infrastructure a set of power transmitters, buried in the road. The vehicle in the OLEV system has a pickup device that collects electric energy from the power transmitters. When the vehicle operates in the vicinity of a power transmitter, the transmitter sends electricity remotely to the pickup device. Since charging takes place while the vehicle is in motion, the system eliminates the major problem of conventional electric vehicles. That is, there is no need to discontinue bus operation to charge the battery. Recognized as one of the "Best 50 Innovations of the Year" by *TIME Magazine* in 2010 and as one of the "Top 10 emerging technology for 2013" in *World Economic Forum*, OLEV is now being considered for next-generation green transportation in several metropolitan areas of Korea [9]–[11].

Although KAIST was the first to develop and commercialize a wireless-power electric vehicle, such as the KAIST shuttle shown in Fig. 1, several other wireless-power electric vehicles have been developed or deployed by some institutions and automotive companies around the world. For example, Utah State University (USU) recently developed a wireless-power bus system, and the technology is being commercialized by Wireless Advanced Vehicle Electrification (WAVE), a startup that was spun out of USU [12]. Wireless-power-based public transportation systems have also been tested in Torino, Italy and Utrecht, The Netherlands [13]. A number of automakers, including Nissan and Mercedes, have been working to develop commercial versions for years [14].

C. Why Adopt an Integrated System Approach?

This paper deals with an ETB system based on the OLEV technology. However, unlike conventional electric vehicles, OLEV is a road–vehicle integrated system. Since charging occurs while the vehicle is operational, performance of the operation depends on the system integration of the vehicle and the road in which charging infrastructure is embedded. Note that this perspective differs from conventional vehicle design. The refueling logistics are not the major design or engineering concern in the development of conventional electric vehicles. Designers and engineers simply assume that there will be refueling stations (gas or charging stations) at given intervals. However, when designing an OLEV-based ETB system, the charging frequency and charging allocations are directly related to the battery size of the vehicle and operational velocity projections. Therefore, the design parameters for the vehicle and the road (in this case, the allocation of the charging infrastructure) need to be analyzed at the system design stage.

D. Structure of the Paper

In this paper, we first qualitatively analyze the system architecture of the OLEV-based ETB from the energy logistics perspective. Consider that the innovation of the OLEV-based transportation system is driven by the new electric vehicle architecture, that is, the integration of road and vehicle. We discuss the high-level system architecture of the OLEV-based transportation system in comparison with other types of electric vehicles and illustrate the benefits of the OLEV-based in logical fashion. We then introduce its economic design. The performance and investment cost of the OLEV-based transportation system depend on the size of the battery and allocation of the power transmitters, and we therefore identify them as key design parameters. We present the economic design model determining these key design parameters with mathematical optimization models. We consider two economic design optimization models. The first is for an OLEV-based system operating in a "closed environment" with no traffic and no heavy vehicle interactions. The KAIST OLEV shuttle bus and OLEV trolleys in Seoul Grand Park are examples of an OLEV-based transportation system operating in a closed environment. The second model is the "open environment" model in which the OLEV-based system operates in normal traffic conditions.

Economic design issues are critical to the commercialization of OLEV-based electric vehicles. As previously noted, there are several OLEV-based systems in commercial operation, including the KAIST shuttle. However, because they are the very first commercial versions, their design parameters were selected to guarantee operational reliability rather than economic issues. After operating as a commercial system for about a year, the OLEV has been proven reliable, and the design focus is now on economic issues. At the time of writing, the South Korean city of Gumi is planning to adopt an OLEV-based ETB system [7], which will be the first commercial version of operating on city streets. Hence, the economic design has become a key issue in the successful deployment of the system.

To the best of our knowledge, the logical architectural analysis of the OLEV-based system presented here constitutes the first such work in the form of a journal article. Our presentation of economic design methods for open and closed environments is also the first. Although we deal specifically with the OLEV-based system developed by KAIST in this paper, the system architecture analysis and key design methods presented herein can be applied to the other wireless-charging vehicles previously mentioned.

The remainder of this paper is organized as follows. In Section II, we introduce the background to the research, including previous work and the basic concept of a wireless-charging electric vehicle. Section III then illustrates the OLEV system architecture with the vehicle utilization measure. The advantages of wireless-charging vehicles are qualitatively analyzed in this section. Section IV discusses the economic design method with the general mathematical optimization model, and we then present the specific mathematical optimization models for the closed and open environments in Sections V and VI, respectively. We conclude this paper and suggest directions for future research in Section VII.

II. Background

A. OLEV System

An OLEV-based ETB system is basically composed of buses and a charging infrastructure that comprises multiple power transmitters installed along the route. Fig. 1 illustrates the key components of the OLEV. The bus contains the pickup device, battery, and motor. The charging unit is the power transmitter, which consists of an inverter and an inductive structure. In the KAIST OLEV system, the power from the electric grid's 60-Hz supply is converted to a frequency of 20 kHz through the inverter, and a current of 200 A flows through the inductive structure. The magnetic flux generated by the inductive structure is transmitted when the vehicle passes by. The power is then collected by the pickup device in the vehicle and sent to generate dc power for the vehicle motor. A more detailed description of the system's power transfer mechanism and hardware configuration can be found in [15]–[18]. Each power transmitter comprises an inductive structure and an inverter. The length of the inductive structure can vary, and it determines the length of the power transmitter as shown in Fig. 1. When a shuttle is operating on the road beneath which the power transmitter is installed, the power pickup device underneath the shuttle remotely collects electricity from the transmitter and distributes power to the motor, the battery, or both, depending on the power requirement of the motor and charging level of the battery. When OLEV is running where no power transmitter unit is installed, in contrast, the motor in the shuttle uses power from the battery.

B. Previous Research

OLEV is the first successfully commercialized wireless-charging electric vehicle [19], [20], although research on other wireless-charging electric vehicles has recently appeared. Shun *et al.* [21] explained the underlying concept and mechanism of wireless power transfer systems for moving electric vehicles, using OLEV as an example. They described the electrical and practical design of the inverter, power lines, rectifier, pickup, and regulator and illustrated the experimental result of achieving 80% power transfer efficiency under a 26-cm air gap with 100 kW of power. That paper explains the key components of the OLEV system that have enabled it to achieve successful commercialization. Kim *et al.* [22] described the basic principles of magnetic field resonance applied in OLEV system design and discussed the formation of a magnetic field distribution and electromagnetic field noise suppression technique that is used in OLEV. Detailed design information on the electromagnetic issues of the technology used in OLEV can be found in [16], [19], [23], and [24]. Moreover, the technology that the OLEV uses to shield its electromagnetic field, which could be a threat to human health, is discussed in [25].

In this paper, we present a more rigorous approach in our modeling. The most similar research to ours is that in [18], although there are several clear differences. First, we introduce system architecture analysis and explain the benefits of wireless charging in terms of the operation of the ETB system. Second, [18] deals only with the system optimization of a closed environment, which can be applied to an OLEV-based transit system operating only in certain limited traffic conditions. In this paper, in contrast, we introduce a system optimization method that is applicable to general traffic conditions. Finally, this paper provides a system perspective on the design of an OLEV-based ETB, rather than focusing on a parameter design algorithm or hardware design issues. As a consequence, the goal, approach, and perspective of this paper are all clearly distinguishable from those of [18].

III. System Architecture of Electric Vehicle–Road Integrated System

This section introduces the system architecture of the OLEV-based ETB system. We interpret OLEV from the perspective of energy logistics combined with vehicle utilization. Public transportation is defined in this paper as a fleet of vehicles circulating on fixed routes and carrying passengers from one place to another. Passenger demands are known, and it is assumed that enough buses are operating to meet these demands. There is a predetermined daily operating time for the buses, which are in continuous service during that time.

We first define the parameters for a general ETB, which is a conventional battery electric bus. We then explain the benefits of the OLEV-based ETB by comparing its energy logistics with those of other types of electric buses.

For our system architecture analysis, we define the following.

1) **Mean Charging Time** $(\overline{T}_c)$: the average charging time of a vehicle.
2) **Mean Downtime for Energy Refueling** $(\overline{T}_d)$: the average time a vehicle is not in operation during battery recharging or energy refueling.
3) **Mean Operational Up-time** $(\overline{T}_u)$: the operational uptime of the vehicle each charge.
4) **Vehicle Utilization** (U_v): the fraction of time the electric vehicle is operational over all available time.

Fig. 2 illustrates the system architectures of various types of electric transportation systems. For simplicity, we assume that a transportation system is in service around the clock. The horizontal axis in each subfigure represents a time frame, and the white and red bars represent the operating and charging time, respectively. Fig. 2(a) shows the charging logistics of a conventional electric vehicle such as a battery plug-in-type vehicle, where the battery is recharged via a cable connection between the vehicle and the charging station. Because a cable connection is required in this case, the vehicle cannot operate

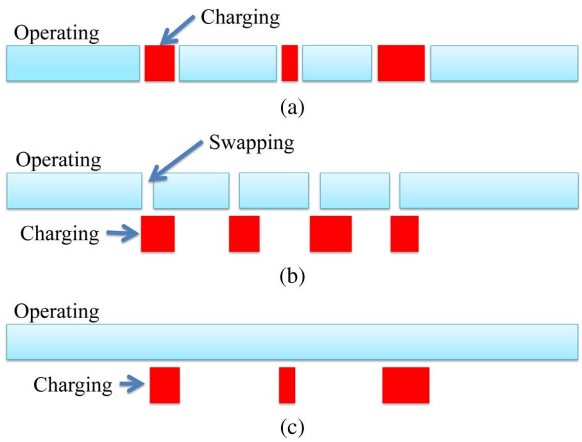

Fig. 2. System architectures of electric buses. (a) Conventional plug-in charging architecture. (b) Battery swapping architecture. (c) OLEV architecture.

while the battery is being charged. As a result, the mean downtime for energy refueling for the plug-in type architecture, i.e., $\overline{T}_d^{\text{plugin}}$, is equal to the mean charging time, i.e., $\overline{T}_c$, and the vehicle utilization is expressed as follows:

$$\overline{T}_d^{\text{plugin}} = \overline{T}_c \tag{1}$$

$$U_v^{\text{plugin}} = \frac{\overline{T}_u}{\overline{T}_u + \overline{T}_d^{\text{plugin}}} = \frac{\overline{T}_u}{\overline{T}_u + \overline{T}_c}. \tag{2}$$

Fig. 2(b) is the case of an electric vehicle with a battery swapping solution. Firms such as Better Places provide battery swapping stations that allow drivers to pull in and swap their batteries as easily as filling up with gas. With this architecture, the battery swapping time is equivalent to the downtime for energy refueling, i.e., $\overline{T}_d^{\text{swap}}$. This solution is effective only if the energy refueling time is less than the battery charging time, i.e.,

$$\overline{T}_d^{\text{swap}} < \overline{T}_c. \tag{3}$$

As a consequence, the vehicle utilization for this case is expressed as

$$U_v^{\text{swap}} = \frac{\overline{T}_u}{\overline{T}_u + \overline{T}_d^{\text{swap}}}. \tag{4}$$

If the condition in (3) is met, the following inequality can be stated:

$$U_v^{\text{swap}} > U_v^{\text{plugin}}. \tag{5}$$

The final system architecture shown in Fig. 2(c) depicts the wireless-charging solution applied in OLEV. Because the electric energy is transferred wirelessly with no physical constraint, vehicle operation is not interrupted. As long as power transmitters are appropriately installed along the vehicle route, constant operation is possible. Therefore, in theory, without considering the cost issue, the mean downtime for energy recharging is zero, and vehicle utilization is equal to 1, i.e.,

$$\overline{T}_d^{\text{olev}} = 0 \tag{6}$$

$$U_v^{\text{olev}} = \frac{\overline{T}_u}{\overline{T}_u + \overline{T}_d^{\text{olev}}} = 1. \tag{7}$$

The OLEV system effectively eliminates the recharging time problem by decoupling the physical charging event and vehicle operation. However, there is one crucial issue that we have to consider in this case—cost. Installing power transmitters in the road requires an initial investment cost—an issue we deal with in the following section.

IV. Economic Framework Formulation

A. *Optimization Issue*

As discussed in the previous section, operating performance is unaffected in the wireless-charging architecture as long as there is sufficient charging infrastructure in the vehicle path. The question then becomes how much is sufficient. Because the cost of the battery and the charging infrastructure accounts for a significant proportion of the total investment cost, evaluating these parameters economically is key to the success of commercializing an OLEV-based ETB system. We first introduce the general optimization problem (GOP) formulation for economically determining the battery size and charging infrastructure.

An optimization model is required to determine the most economical parameter design. The design parameters are the size of the battery and the allocation of the charging infrastructure along the route. The basic system requirement is that sufficient power is provided to complete the service. To better illustrate the optimization problem, we consider the two following extreme cases.

First, suppose that the battery capacity is sufficiently large that once the battery is fully charged at the base station, where buses are idle when not in service, the bus can complete the loop without recharging. In this case, the charging infrastructure is needed only at the base station. As a result, the battery cost accounts for a significant proportion of the total investment cost.

Second, suppose in contrast that the charging infrastructure is installed most part of the route, and the battery can thus be charged wherever needed. The bus requires only a small-capacity battery. As a result, the battery cost is reduced, whereas the charging infrastructure cost rises. These two extreme cases show that there is a tradeoff between the size of the battery and the allocation of the charging infrastructure. The goal of the optimization method is to determine the most economical battery size and infrastructure allocation by considering the cost factors and power requirements, simultaneously.

B. *Operational Rules and Notations*

Before we build a mathematical model, we first define the notations and operational rules for the OLEV-based ETB system. In our model, we consider a public transportation system with buses circulating on a single loop, although the model can be extended to multiple loops, which we discuss later. The buses operate with the following rules:

1) there are multiple buses operating on the route;
2) each bus is equipped with an identically sized battery;
3) there are multiple stations, and each bus stops at every station;
4) there is one base station, at which the buses are idle when they are not in service, and each service begins and ends at the base station;

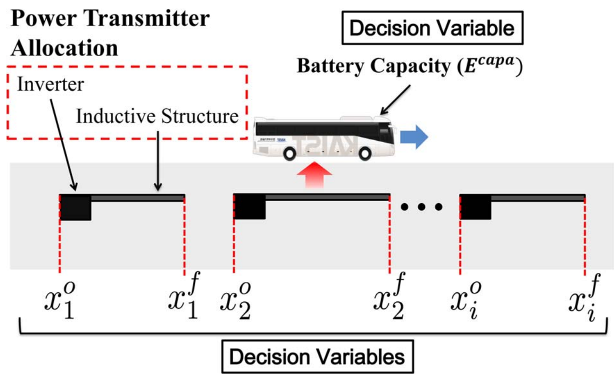

Fig. 3. OLEV system—the decision variables for system design optimization [26].

5) once a bus completes a loop (or completes a service), it remains idle at the base station for a certain amount of time that we call the *resting time*;
6) during the bus resting time at the base station, its battery is charged to its maximum level before service resumption.

These rules are not very different from the operational rules of the public transit system of any urban environment. Rule 6 stipulates that the bus stops long enough to fully recharge its battery and, thus, assumes that there is a charger at the base station. In other words, in our model, we always assume that a charger is installed at the base station. Moreover, to charge the battery in full at the base station, the charger requires sufficient power supply.

The charging infrastructure in our model specifically refers to the power transmitters, each of which comprises one inverter and one inductive structure. The length of the power transmitter, which is determined by the length of the inductive structure, may vary. Fig. 3 illustrates the design variables for system optimization. We are interested in determining the optimal allocation of the power transmitters. More specifically, we need to identify the number of power transmitters required and the length of each power transmitter.

We let the base station be the reference point, and any point on the route is described by the travel distance x from the reference point. Because the route is circular, the starting point, where $x = 0$, and the end point, where $x = L$, both indicate the base station. We consider a vehicle making one circular trip to construct the model. The vehicle begins the trip at $x = 0$ and completes it at $x = L$.

As shown in Fig. 3, the start and end points of the ith power transmitter are denoted by x_i^0 and x_i^f, respectively. These values indicate the distance measured from the base station. Suppose that N power transmitters have been allocated, then $i = 1, \ldots, N$. Note that N is one of our decision variables. The upper limit of the battery charge is denoted by E^u.

1) Decision Variables: For convenience, we define spatial set $\mathcal{X}$ as the locations of the power transmitters along the route. Then

$$\mathcal{X} = \left\{x_1^o, x_1^f, x_2^o, x_2^f, \ldots, x_N^o, x_N^f\right\}$$

where $x_i^o < x_i^f < x_{i+1}^o$. Finding the optimal values of the spatial set with an optimal battery capacity is the optimization goal. We define t as a continuous variable indicating the vehicle travel time measured from the base station. Let $v(t)$ be the velocity projection of the bus at time t. Then, the relationship between the displacement variable (x) and temporal variable (t) is described as follows:

$$x = \int_o^t v(t)\, dt. \tag{8}$$

With the relationship expressed in (8), we also define temporal set $\mathcal{T}$ as the time a vehicle is traveling over a power transmitter, i.e.,

$$\mathcal{T} = \left\{t_1^o, t_1^f, t_2^o, t_2^f, \ldots, t_N^o, t_N^f\right\}$$

where $t_i^o < t_i^f < t_{i+1}^o$.

Let us now represent (8) as function $x = F(t)$. Note that this function is monotonically increasing; therefore, there exists a unique solution for its inverse function, i.e., $t = F^{-1}(x)$. We utilize this inverse function when we set up our optimization problem.

2) Cost Function: For the optimization model, we propose a cost function that consists of the total battery cost and total cost of the power transmitters. With this cost function, the model is able to find economical design parameters by considering the tradeoff between the size of the battery and the allocation of the power transmitters. We assume that the battery cost is a function of the battery capacity, i.e., E^{capa}, which is reasonable because the battery pack widely used in commercial electric vehicles is composed of multiple battery cells. The capacity of the battery pack is determined by the number of cells therein. If the cost of each cell is known, the cost of the battery pack can be easily estimated. We denote F_b^c as the cost function of the battery. Suppose that k number of buses are operating. According to our rule, all buses operating on the route are equipped with same-sized battery. Hence, the total battery cost is $k \cdot F_b^c(E^{\text{capa}})$.

The power transmitter cost is divided into a fixed cost and a variable cost. The fixed cost is the cost incurred regardless of the length of the power transmitter. The major part of this cost is made up of the inverter cost and the labor cost to connect the power grid to the inverter. Note that each power transmitter needs one inverter. The variable cost depends on the length of the power transmitter: The longer it is, the higher the cost. The functions of the fixed and variable costs are denoted by F_f^c and F_v^c, respectively. The fixed cost refers to the cost of installing one unit of power transmitter regardless of the length of its length. The fixed cost is determined by the total number of the power transmitter, i.e., N and, therefore, is $F_f^c(N)$. On the other hand, the variable cost of each power transmitter is determined by its length of the power transmitter $x_i^f - x_i^o$. As a result, the total variable cost is the sum of the total length of the variable cost. We let L_T be the total length of the power transmitters

$$L_T = \sum_i^N x_i^f - x_i^0.$$

The total cost is thus

$$k \cdot F_b^c(E^{\text{capa}}) + F_v^c(L_T) + F_f^c(N). \tag{9}$$

3) Energy Dynamics: We denote $E(t)$ as the amount of energy in the battery at time t. The energy level should be within the lower and upper limits during travel, i.e.,

$$E^l \leq E(t) \leq E^u \tag{10}$$

where E^l and E^u are the lower and upper limits of the battery level, respectively. These values have the following relationship:

$$E^l = \alpha \cdot E^{\text{capa}} \tag{11}$$

$$E^u = \beta \cdot E^{\text{capa}} \tag{12}$$

$$0 < \alpha < \beta < 1. \tag{13}$$

The lower and upper limit parameters, i.e., α and β, are usually given by the battery provider. For convenience, we introduce variable E_0, which is

$$E_0 = E^u - E^l = (\beta - \alpha)E^{\text{capa}}.$$

Value E_0 is the actual usable capacity of the battery. Note that in our optimization problem, we are interested in the relative battery cost compared with the power transmitter cost. Therefore, it is more convenient to use the relative value in our battery cost, that is, $k \cdot F_b^c(E_0)$, rather than absolute cost $k \cdot F_b^c(E^{\text{capa}})$. Given our assumption that the upper and lower limits of the battery are proportional to values α and β regardless of the battery size, the use of relative value E_0 does not change the optimal solution. The degree of energy fluctuation depends on the energy consumption and supply rates. We define $P_d(t)$ as the energy consumption rate. This quantity depends on the velocity trajectory, road gradient, and use of peripheral devices such as the bus air conditioner. We define $P_s(t)$ as the energy supply to the battery at time t. This quantity is actually the charging rate of the battery and depends on the allocation of the power transmitters.

We assume that the state-of-charge level is linearly proportional to the charging time as long as the level of the charge is between E^u and E^l This assumption is based on the mechanism of the charging controller in the OLEV. The charging limits are set to maximize the battery life. Therefore, if the shuttle is traveling on a route with a power transmitter in place, the battery's charge level will increase. Note that although the entire spectrum of the charging state is nonlinear, the charging state within E^u and E^l, which represent the actual state range in OLEV, is almost a straight line. Therefore, the charging rate, denoted by p_s, is assumed to be constant. This linear energy charging and discharging assumption is commonly used in electric vehicle modeling [27], [28]. Then

$$P_s(t) = \begin{cases} 0, & \text{if } t \text{ when a vehicle is traveling} \\ & \text{where no power transmitter} \\ & \text{is installed or } E(t) = E^u \\ p_s, & \text{if } t \text{ when a vehicle is traveling} \\ & \text{where a power transmitter is} \\ & \text{installed and } E(t) < E^u. \end{cases} \tag{14}$$

The battery energy level in this case is described as

$$\frac{dE(t)}{dt} = -P_d(t) + P_s(t). \tag{15}$$

The GOP with the cost function in (9) is constructed as

$$\textbf{GOP}: \quad \min \quad k \cdot F_b^c(E_0) + F_v^c(L_T) + F_f^c(N)$$

subject to (8), (10), (14), and (15). Note that GOP is a conceptual model indicating that the optimal allocation is determined by the battery size, the location of the power transmitters, and the total number of power transmitters.

C. Closed and Open Environment Models

The optimization problem described in the GOP is the generalized model. Although the general model illustrates the underlying concept of the optimization well, a more detailed equation setting is required to utilize the optimization model in designing an actual OLEV-based bus system.

Here, we propose two separate optimization models—a closed environment system model and an open environment system model. For both models, the OLEV bus travels a service route with scheduled times for each stop. The major difference between the two environments is the degree of travel uncertainty. More specifically, for the closed environment system, we assume that there is no traffic congestion and no unexpected traffic delays. The environment is separated from regular vehicular traffic, and drivers follow the velocity regulations. Good examples of an OLEV system operating in a closed environment are the OLEV shuttle on the KAIST campus and the OLEV-based trolleys in Seoul Grand Park. In both systems, the drivers follow the speed regulations and travel the routes with scheduled stops. An open environment, in contrast, features traffic conditions that mirror those in a normal traffic environment on any city's streets. Compared with their counterparts in a closed environment, the drivers in an open environment system may face traffic congestion and other unexpected traffic events. From the optimization modeling perspective, the major difference between the two systems lies in the level of granularity in the energy demands on the route. Because the velocity profile is estimated and the road gradient is known in the closed environment, we can evaluate the energy requirement at each point on the service route. However, for the open environment, it may not be easy to estimate the energy requirements of the route's entire trajectory. Accordingly, we evaluate the energy consumption between a pair of bus stops instead. More detailed modeling is presented for each environment in the following sections.

V. Closed Environment Model

A. System Optimization Modeling

The major characteristic of the closed environment model is our use of the route's velocity profile and road gradient. In a closed environment system, there is limited traffic congestion and few traffic lights. We expect the vehicles in this system to closely follow the timetabled schedule and velocity regulations. As an example of a closed environment system, Fig. 4 shows the bus stops for the OLEV shuttle that operates on the KAIST campus. The schedule and velocity profiles of the shuttle system are shown in Table I and Fig. 5, respectively.

The ninth station indicated as Start & End Station in Fig. 4 is the base station, and the timetable is based on the departure time from the base station. The velocity profile and road gradient allow us to estimate the energy demand at time t, denoted by $P_d(t)$. There are various ways to evaluate energy demand, and more detailed information can be found in [18].

Fig. 4. KAIST shuttle route.

TABLE I
SERVICE SCHEDULE OF KAIST OLEV

No. of Stations	Locations	Arrival Time
Start	Base Station(Start)	00:00
1st Station	Sports Complex	01:00
2nd Station	Creative Learning Center	02:00
3rd Station	East Dormitory Hall	03:30
4th Station	Medical Center	04:40
5th Station	Main Entrance	06:40
6th Station	Central Pond	07:20
7th Station	Main Building	08:20
8th Station	Sports Complex	10:00
9th Station	Base Station(End)	11:00

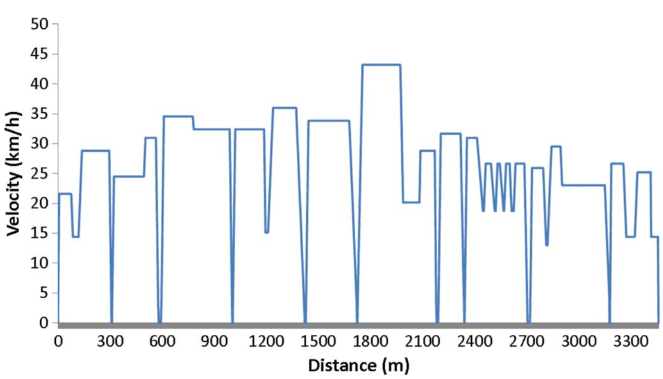

Fig. 5. Velocity profile of OLEV shuttle on KAIST campus.

We first construct the constraint equations based on the general equation setting in the GOP. In the closed environment model, the start and end points of the ith power transmitter are denoted by $x^0(i)$ and $x^f(i)$ (note that these terms are distinguished from the notations used in the GOP model x_i^0 and x_i^f). Suppose that a vehicle is about to move to the point at which the ith power transmitter is located. With our notation, this point is indicated as $x^f(i)$. The time at which the vehicle is at this point is indicated by $t^f(i)$. Again, the mapping between the displacement variable (x) and temporal variable (t) is evaluated using (8). The level of energy at $t^f(i)$ is $E(t^f(i))$. The vehicle now departs from the ith power transmitter and continuously travels along a route with no power transmitters until it reaches the next power transmitter, i.e., $i+1$, at point $x^0(i+1)$. Again, the moment at which the vehicle arrives at the next transmitter is $t^0(i+1)$. The following constraint must be satisfied:

$$E\left(t^f(i)\right) - \int_{t^f(i)}^{t^0(i+1)} P_d(t)\,dt \geq E^l. \tag{16}$$

The first term in (16) is the energy level when the vehicle leaves the ith power transmitter, and the second term indicates the amount of energy consumed while the vehicle is traveling the area with no power transmitter. Therefore, (16) represents the amount of energy in the battery when the vehicle arrives at the beginning of the $i+1$th power transmitter. The energy level needs to be greater than the lower energy limit of the battery. In other words, the power transmitter needs to be installed in such a way that the energy level is maintained at about the lower limit. We now evaluate the amount of energy at the end of the $i+1$th power transmitter, that is, the energy supply and consumption between $x^f(i)$ and $x^f(i+1)$. The level of energy in the battery at $x^f(i)$ is $E(t^f(i))$. The level of energy at $x^f(i+1)$ is thus described as

$$\min\left\{E\left(t^f(i)\right) - \int_{t^f(i)}^{t^f(i+1)} P_d(t)dt + p_s \cdot \left(t^f(i+1) - t^0(i+1)\right), E^u\right\}. \tag{17}$$

Note that the battery's energy level when the vehicle reaches the end of the $(i+1)$th power transmitter should be less than the upper limit of the battery, i.e., E^u. If the charge amount is more than the upper limit, then the energy level would be E^u at $x^f(i+1)$ owing to the power supply rule described in (14).

Next, we construct the objective function for the closed environment model. The objective function we defined in the GOP is specified as follows:

$$k \cdot c_b \cdot E_0 + c_f \cdot N + \sum_{i=1}^{N} c_v \cdot \left(x^f(i) - x^o(i)\right) \tag{18}$$

where c_b is the battery cost per unit of energy capacity (cost/kWh), c_f is the fixed cost to install a power transmitter (cost/power transmitter), and c_v is the installation cost per length of each power transmitter (cost/length). The cost of the battery is linearly proportional to the unit capacity. This linear cost approximation is widely used in industry [2]. Therefore, the term $F_b^c(E_0)$ in the objective function of GOP is translated to $c_b \cdot E_0$. Likewise, $F_f^c(N)$ in the objective function of GOP is translated to $c_f \cdot N$ in the closed environment model. That is, the fixed cost is a function of the number of power transmitters, and the fixed cost of installing one power transmitter is c_f. The variable cost in GOP $F_v^c(\mathcal{X})$ is expressed as the third term in (18). Since the variable cost of each power transmitter installation depends on its length, i.e., $x^f(i) - x^0(i)$, the total variable cost is the sum of the lengths of all the power transmitters installed.

Let T_l be the time at which the vehicle reaches the base station and L^m be the maximum length of a power transmitter. Then, the closed-environment optimization problem (COP) is then described as follows:

$$\mathbf{COP}: \min k \cdot c_b \cdot E_0 + c_f \cdot N + \sum_{i=1}^{N} c_v \cdot \left(x^f(i) - x^0(i)\right) \tag{19}$$

subject to

$$E\left(t^f(i)\right) - \int_{t^f(i)}^{t^0(i+1)} P_d(t)\,dt \geq E^l, \quad \text{for } i = 0, \ldots, N \tag{20}$$

$$E\left(t^f(i+1)\right) = \min\left\{E\left(t^f(i)\right) - \int_{t^f(i)}^{t^f(i+1)} P_d(t)dt + p_s \cdot \left(t^f(i+1) - t^0(i+1)\right), E^u\right\}, \quad \text{for } i = 0, \ldots, N-1 \tag{21}$$

$$x^*(i) = \int_{o}^{t^*(i)} v(t)\,dt, \quad \text{for } * = \{0, f\}, \text{ and } i = 1, \ldots, N \tag{22}$$

$$t^f(0) = 0, \qquad t^0(N+1) = T_l \tag{23}$$

$$E(0) = E^u, \qquad E(T_l) \geq 0 \tag{24}$$

$$x^f(i) - x^0(i) \leq L^m, \quad \text{and } x^0(i) < x^f(i), \quad \text{for } i = 1, \ldots, N \tag{25}$$

$$x^f(i) < x^0(i+1), \quad \text{for } i = 1, \ldots, N-1 \tag{26}$$

$$x^f(i) \text{ and } x^0(i) \geq 0, \quad \text{for } i = 1, \ldots, N \tag{27}$$

$$x^f(N) \leq L \tag{28}$$

$$E_0 \geq 0. \tag{29}$$

In the optimization model for the closed system, the inequality in (20) represents the minimum energy requirement constraint, and (21) is the energy level when the bus leaves the end point of each power transmitter. The boundary conditions are defined in (23) and (24), and the parameter relationships are in (25) and (26). The decision variables and their bounds are defined in (27). The COP can be solved using the metaheuristics method, and its solution algorithm is given in [18].

B. Numerical Example

We now present a numerical example with actual operational data collected from the OLEV system operating on the KAIST campus. As shown in Fig. 4, the buses travel along a 3.46-km-long circular route. There are nine stations, including the base station, and the shuttles operate according to the service schedule shown in Table I. There is a charging power transmitter at the base station, and it takes about 4 min to fully charge a battery there. Therefore, the complete service cycle is 15 min.

TABLE II
PARAMETERS FOR BASIC NUMERICAL RESULTS

Cost	Value
Unit battery cost / unit inductive cable cost	10
Unit inverter cost / unit inductive cable cost	20
k	4
p_s (kW)	100

TABLE III
RESULTS OF THE NUMERICAL CASE

Result	Value
Battery capacity	13 kWh
Number of power transmitters	4
Total inductive cable length	90 m
1st power transmitter	574 - 598
2nd power transmitter	1408 - 1433
3rd power transmitter	2177 - 2195
4th power transmitter	2700 - 2723

Fig. 5 shows the velocity requirements over the shuttle route. The points at which the velocities are close to zero are the stations, and the near-zero point at a distance of 1720 m from the base station is a crossroad with a left-turn signal. This velocity profile is based on the speed regulations, campus road conditions, and service schedule, and the drivers usually follow it. We have observed that some energy is consumed even when the velocity profile is flat, as in constant-speed areas. It is not possible for a driver to follow an exact speed profile. One way for a driver to maintain a constant speed is to accelerate and decelerate continuously around the velocity he or she is trying to maintain, which will involve some degree of energy consumption. As a result, we must also consider the additional energy consumption caused by driver. Corti [29] explained this extra energy consumption as an underestimation of the acceleration force. There are various ways to estimate such behavior-induced consumption, but the issue is beyond the scope of this paper. Our method is to use safety factors to compensate for the energy underestimation.

The system parameters used in our numerical analysis are summarized in Table II. In our numerical analysis, 3 kW of extra electrical load per hour, from such peripheral parts as the air conditioner and radio, is uniformly needed in the energy demand evaluation. This amount comes from the OLEV design specifications and is close to the electric energy consumption amount suggested in some of the academic literature, including [30].

Particle swarm optimization is used as the solution algorithm, more details of which can be found in [18]. The results obtained for this basic numerical example are summarized in Table III. Four power transmitters would need to be installed on the KAIST campus to operate shuttles with a 13-kWh battery. The start and end positions of the first power transmitter are 574 and 598 m from the base station, respectively. The second power transmitter is installed between 1408 and 1433 m of the starting and ending points, respectively. Likewise, we can see that the third and fourth power transmitters are located at 2177–2195 m and 2700–2723 m, respectively. The inductive cable lengths for the power transmitters are 24, 25, 18, and 23 m, respectively. The total length of all of the inductive cables is 90 m.

The first power transmitter is located at the second station (Creative Learning Center), and the second, third, and fourth

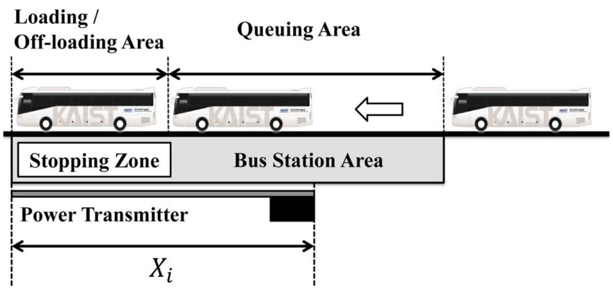

Fig. 6. Bus station.

transmitters are located at the fourth (Medical Center), fifth (Main Entrance), and seventh (Main Building) stations, respectively. The shuttle's velocity decreases as it approaches the stations and drops to zero at them. Because the energy supply amount is proportional to the time the shuttle spends at a power transmitter, it is cost efficient to install power transmitters at the shuttle stops.

VI. Open Environment Model

A. System Optimization Modeling

In an open environment, it is not easy to estimate the trajectory of the entire energy consumption over the route because of the uncertainty arising from traffic congestion and the traffic lights at intersections. As a result, a certain level of approximation is needed in the analysis. The open environment system is characterized by the two following major assumptions.

1) Power transmitters are installed only in bus station areas.
2) The energy demand between a pair of stations is known.

We assume that a vehicle stops at every station. The stations are thus good candidate locations for power transmitter installation because the amount of charge in a battery is proportional to the length of time the vehicle spends above the transmitter. In an open environment, a transit bus is more likely to spend time over the power transmitters installed in station areas than over those along the road on which it travels. However, installing power transmitters only at bus stations does not necessarily mean that we are not taking advantage of OLEV's dynamic charging ability—the battery is charging while the bus is in motion.

As shown in Fig. 6, the bus station area includes not only a loading/offloading area but also a bus queueing area. Note that in the figure, the stopping zone is the locale at which the bus makes a complete stop to load/offload passengers. When a bus approaches the station area, it slows down and moves slowly toward or waits in the station area. If a power transmitter is installed in the station area, charging can take place as the bus approaches the stopping zone or after it reaches that zone. Therefore, although the power transmitters are installed in the station areas, the dynamic charging capability of OLEV can still be effectively utilized. Hereafter, *station* refers to the *station area*.

The other assumption for the open environment is that the energy demand between stations is known. We assume that information is available at least about the aggregate energy required to move from one station to the next. This assumption of known aggregate energy demand between points is commonly found in the charging allocation problems for electric and other alternative vehicles in the literature, including [31]–[33].

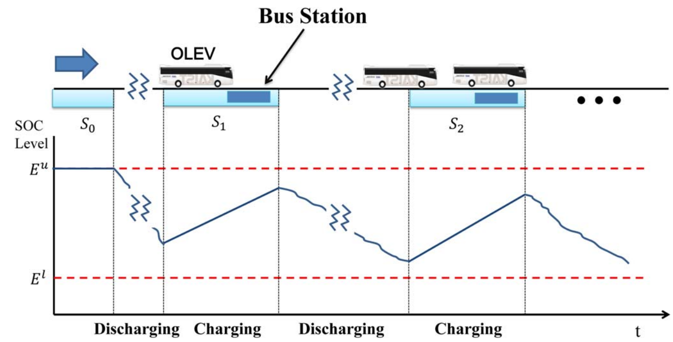

Fig. 7. Charging and depleting the battery energy.

In the open environment system, the charging infrastructure allocation problem is translated into the problem of identifying stations for installation of the power transmitters and assigning an appropriate power transmitter length of each station selected. To illustrate the problem, suppose that there is a single route with N_c candidate stations. As we assume that the base station will always have a power transmitter, the candidate stations do not include the base station.

Let S_i be the notation for a station where $i = 0, \ldots, N_c$. The station index i is sequentially arranged such that $x_i < x_{i+1}$, where x_i is the distance of the ith station from the base station. Station S_0 is the base station, which is the starting point of each trip. The bus circulates its route and comes back to the base station. For convenience, let the $N_c + 1$th station also be the base station.

We define a continuous decision variable X_i, which is the length of the power transmitter installed at station i. The minimum and maximum lengths are denoted by $X^{\min}$ and $X^{\max}$, respectively. The minimum length is the length of the bus-stopping zone, whereas the maximum length is the length of the entire station area. This maximum length is similar to L^m, the term used in the closed environment. For the continuous case, the maximum length is determined by the electric power supplied to one power transmitter (around 100 m), but for the open environment, the maximum length is determined by the station area (30–40 m). Therefore, in practical situations, $X^{\max}$ is usually less than L^m.

We denote parameter p_s as the amount of energy supplied per unit length of a power transmitter. We then approximate the amount of energy supplied at station i as $p_s \cdot X_i$. In other words, the amount of energy charged to a battery at a station is linearly proportional to the length of the power transmitter. We know that the charge amount is actually proportional to the amount of time a bus spends over the power transmitter, and it is therefore reasonable to assume that the charge amount monotonically increases with an increase in the length of the transmitter. In our model, we use a linear approximation to express this monotonically increasing trend. Then, charge rate p_s is estimated from a linear regression of the experimental results.

Fig. 7 illustrates the energy dynamics of the first three stations. Note that the vehicle operates on a circular route that begins and ends at the base station. We define E_i as the energy level of the battery just before the vehicle arrives at S_i. Let d_i be the energy demand between S_i and S_{i+1}. Note that E^u is

TABLE IV
NOTATIONS FOR OPEN ENVIRONMENT ETB SYSTEM

Notation	Description
N_c	number of candidate stations
S_i	ith station in the route
x_i	distance of station S_i measured from the base station
X_i	continuous decision variable indicating the length of the power transmitter installed at S_i
X^{min}	minimum length of power transmitter for S_i
X^{max}	maximum length of power transmitter for S_i
p_s	energy charge per unit length of power transmitter
E_i	energy level of battery just before the vehicle arrives at S_i
d_i	energy demand between S_i and S_{i+1}
y_i	binary decision variable indicating whether a power transmitter is installed at S_i

the maximum energy level of the battery and that the battery is always charged to this level at the base station. Therefore, the energy level immediately before a bus reaches the first station is $E^u - d_0$. The maximum capacity should be sufficiently large for it to travel to the first station, where it is supplied with energy in the amount of $p_s \cdot X_1$. Then, the energy level when the vehicle leaves the station should be $E_1 + p_s \cdot X_1$. This quantity should be less than the maximum capacity of the battery, i.e., E^u. At the same time, it should be large enough to allow the vehicle to travel to the next station, i.e., S_2. Hence, the following should be satisfied:

$$d_1 < E_1 + p_s \cdot X_1 < E^u.$$

As noted, the minimum and maximum lengths of the power transmitters are denoted by $X^{\min}$ and $X^{\max}$, respectively. Let y_i be a binary decision variable indicating whether a power transmitter is installed at S_i. If a power transmitter is installed at S_i, then $y_i = 1$; otherwise, $y_i = 0$. If a transmitter is installed, a cost is incurred. Similar to the closed environment model, the installation cost comprises a fixed cost and a variable cost denoted by c_f and c_v, respectively. Moreover, the unit cost of the battery is denoted by c_b.

The notations, decision variables, and parameters for the open environment system are summarized in Table IV. If we generalize the energy dynamics described above, the open-environment optimization problem (OOP) can be expressed as follows:

$$\mathbf{OOP}: \min k \cdot c_b \cdot E_0 + \sum_{i=1}^{N_c} c_v \cdot X_i + \sum_{i=1}^{N_c} c_f \cdot y_i \tag{30}$$

subject to

$$E_1 = E^u - d_0 \tag{31}$$

$$E_i = E_{i-1} + p_s \cdot X_{i-1} - d_{i-1}, \quad i = 2, \ldots, N_c + 1 \tag{32}$$

$$E_i \geq E^l, \quad i = 1, \ldots, N_c + 1 \tag{33}$$

$$E_i + p_s \cdot X_i \leq E^u, \quad i = 1, \ldots, N_c \tag{34}$$

$$y_i \cdot X^{\min} \leq X_i \leq y_i \cdot X^{\max}, \quad i = 1, \ldots, N_c \tag{35}$$

$$y_i \in \{0, 1\}, \quad i = 1, \ldots, N_c - 1 \tag{36}$$

$$X_i \in \mathbb{R}^+, \quad i = 1, \ldots, N_c - 1. \tag{37}$$

Notice that **OOP** is a mixed-integer linear program.

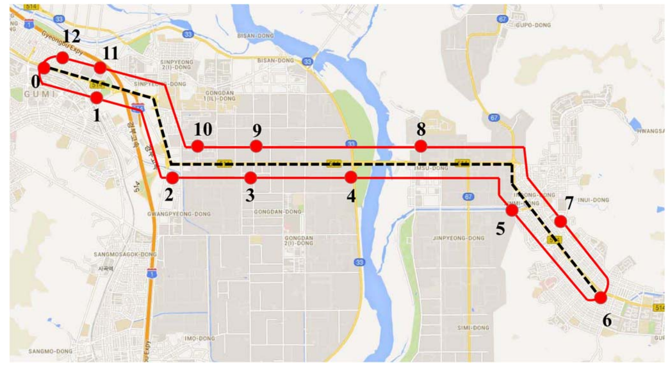

Fig. 8. Candidate OLEV-based ETB route in Gumi Metropolitan City.

TABLE V
PARAMETERS OF SAMPLE CASE

Parameters	Value
N_c [stations]	12
k [buses]	10
X^{min} [m]	10
X^{max} [m]	60
c_b [unit cost/kWh]	1
c_v [unit cost/m]	0.2
c_f [unit cost/station]	15
p_s [kWh/m]	0.1

TABLE VI
STATION(S_i) AND ENERGY DEMAND (d_i)

S_i	0	1	2	3	4	5	6
d_i [kWh]	4	5	1.67	2	3.33	4	2.33
S_i	7	8	9	10	11	12	–
d_i [kWh]	4	4.33	1.66	4	1	2.66	–

B. Numerical Analysis

We now provide numerical analysis using actual operational data collected from a route in Gumi City, where an OLEV-based ETB is being considered for service. We used CPLEX 12.5 (default settings) for the numerical example. As shown in Fig. 8, the ETBs will circulate around a 29.63-km-long route. There are 12 candidate stations and a base station. Once a bus arrives at the base station, it stays there for a while, and its battery is fully charged before it resumes service. The parameter values are listed in Table V. Note that we use the relative cost instead of the absolute cost for convenience. The fixed and variable power transmitter costs are the relative costs against the unit battery cost. For instance, $c_f = 15$ means that the absolute value of the fixed cost of the power transmitter is \$15 000 when the absolute battery cost is \$1000 per kilowatt-hour.

Table VI shows the required energy from station S_i to S_{i+1}. The optimal solution for the case of p_s that is 0.1 kWh/m is summarized in Table VII.

The results indicate that power transmitters need to be installed at stations S_1, S_2, S_5, S_7, S_8, and S_{10} and that they need to be 40, 46.67, 60, 60, 56.67, and 60 m long, respectively. Battery capacity E_0 is 7.667 kWh. However, when we reduce

TABLE VII
OPTIMIZATION RESULT

Installed station	X
S_1	40m
S_2	46.67m
S_5	60m
S_7	60m
S_8	56.67m
S_{10}	60m
E_o	7.67 kWh

the number of vehicles to four, the optimal battery capacity becomes 40 kWh, and no power transmitter installation is recommended because there is no benefit to having transmitters along the route. Instead, a bus should be equipped with a large battery to complete the route without a charge. Note that 40 kWh is sufficient energy to complete a loop. This result makes sense because power transmitters constitute the charging infrastructure, and there is a cost benefit only when there are enough buses in the ETB system.

VII. CONCLUSION

OLEV is an innovative electricity-powered transportation system that remotely picks up electricity from power transmitters buried underground. In this paper, we have interpreted the OLEV architecture from the energy logistics perspective. We constructed two mathematical models—closed and open environment models—to describe the cost tradeoff between power transmitter allocation and battery size. These mathematical models describe the dynamic behavior of the energy transferred to a battery from the power transmitters. Both models are based on a public transportation system circulating a fixed route, and we assumed that the vehicles follow predefined velocity profiles. Although the models consider simple single circular loops, the underlying concept can be extended to more complex models.

For future research, we propose the following topics. First, for the closed environment system, we assume that the vehicles always follow a predefined velocity profile. Although we confirmed that drivers do their best to follow speed regulations, there are always variations in the actual velocity of a vehicle. It would be valuable for research to investigate how randomness in speed would affect the optimal parameter design model proposed herein. The randomness in velocity results in uncertainty in energy demand. Developing a stochastic optimization or fuzzy optimization model that consider uncertainty would also be useful. In particular, the structure of OOP is similar to the discrete-lot-sizing production scheduling problem, and some studies have been conducted on production scheduling with uncertain demand including [34]–[36]. Investigating the difference between the problem structure of the OOP and the existing optimization model dealing with uncertainty might be a good starting point to extend the work. Second, for the open environment model, we assume that the amount of energy supplied in the station area is linearly proportional to the length of the station area. However, this linear approximation may not hold true for a less congested bus station. For example, suppose that a bus is approaching a station area and there are no other buses in the queue. In this case, the bus would obviously pass through the queuing area quickly. Accordingly, installing a power transmitter only in the station-stopping zone can be more beneficial than installing one that extends to the queueing area. More specifically, if we are installing a power transmitter only in the stopping zone, only a 10-m-long transmitter is required. However, if we extend it to the queueing area, we need a 20-m-long transmitter. Doubling the length of the power transmitter does not guarantee twice the power supply, which means that a nonlinear model or a piecewise linear approximation model is needed in this case. Third, another interesting research topic would be to consider more realistic cost values and perform cost-benefit analysis for an OLEV-based ETB. OLEV is a new technology, and existing OLEV systems were thus developed through custom-made manufacturing rather than mass production. Exact cost figures may not be possible. Instead, we could perform economic cost-benefit analysis with various cost scenarios. Providing a logical approach to the following question would be an example of such cost-benefit analysis: What is the maximum cost of a power transmitter that would render OLEV-based ETBs economically viable and allow them to compete with other conventional electric vehicles? We leave the answer to future research.

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Young Jae Jang received the Ph.D. degree in mechanical engineering and the double M.S. degree in mechanical engineering and operations research from Massachusetts Institute of Technology, Cambridge, MA in 2007 and 2001, respectively. He received the B.S degree in aerospace engineering from Boston University, MA, USA in 1997.

He is currently an Assistant Professor with the Industrial and Systems Engineering Department, Korea Advanced Institute of Science and Technology (KAIST), Korea, where he is also affiliated with the Cho Chun Shik Graduate School of Green Transportation. Before he joined KAIST, he was with Micron Technology, Inc., VA, USA, where, as a Project Manager, he led a global initiative to improve the efficiency of the manufacturing facilities located worldwide. While working at Micron, he was also involved in activities supporting the company's operational and strategic decision making using quantitative modeling and analysis techniques. He has been involved in the KAIST On-Line Electric Vehicle (OLEV) project, developing and commercializing the innovative wireless charging electric vehicle. The project was recognized as one of "50 Best Innovations of 2010" by TIME Magazine. His role in the project is to develop the optimal energy management system to integrate the vehicle system to the road traffic network. He has published numerous technical papers out of the OLEV technology. His recent work "The Optimal Economic Design of the Wireless Powered Transportation System" was selected as Best Paper in the 2013 International Conference on Intelligent Manufacturing and Logistics Conference. His current research includes the stochastic modeling of complex systems and optimizations in transportation and logistics systems.

Dr. Jang is the Technical Program Chair of the 2014 IEEE Vehicular Technology Workshop on Emerging Technologies on Wireless Power and the Organizing Committee Member of the Complex Systems Design and Management Asia 2014.

Eun Suk Suh received the B.S. degree in mechanical engineering from Clarkson University, Potsdam, NY, USA; the M.Eng. degree in mechanical engineering from Cornell University, Ithaca, NY, USA; and the Ph.D. degree in engineering systems from the Massachusetts Institute of Technology, Cambridge, MA, USA.

He is an Assistant Professor with the Department of Industrial Engineering, Seoul National University, Seoul, Korea. Previous to his current appointment, he was a Research Scientist with the Xerox Innovation Group, the main research organization within the Xerox Corporation, leading research activities in complex system design methodology development and implementation. He also worked as a Design Engineer working for Hyundai Motor Company's Commercial Vehicle Development Division, leading chassis suspension design and development activities for various commercial vehicles.

Jong Woo Kim received the B.S. and M.S. degrees in electronic engineering from Kyungpook National University, Daegu, Korea, in 1983 and 1992, respectively, and the Ph.D. degree in information communication from Hannam University, Daejeon, Korea, in 2005.

He is currently a Research Professor with the Wireless Power Transfer Research Center of the Korea Advanced Institute of Science and Technology, Korea. He was with the Korea Aerospace Research Institute until 2006. His current research includes wireless power transmission and electric vehicle power train systems.