Economic Analysis of the Dynamic Charging Electric Vehicle

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***Abstract*—A wireless charging or inductive charging electric vehicle (EV) is a type of EVs with a battery that is charged from a charging infrastructure, using a wireless power transfer technology. Wireless charging EVs are classified as *stationary* or *dynamic charging* EVs. Stationary charging EVs charge wirelessly when they are parked, and dynamic charging EVs can charge while they are in motion. The online electric vehicle developed at the Korea Advanced Institute of Science and Technology is an example of a commercially available dynamic charging transportation system. Numerous studies have reported that one of the benefits of dynamic charging is that it allows smaller and lighter batteries to be used, due to frequent charging using the charging infrastructure embedded under roads. In this paper, we quantitatively analyze the benefits of dynamic charging with an economic model of battery size and charging infrastructure allocation, using a mathematical optimization model. Particularly, we analyze by how much battery size can be reduced and what the cost saving of reducing the battery size is with the model. We also show that the dynamic charging can be beneficial to battery life.**

***Index Terms*—Dynamic charging electric vehicle, electric vehicle (EV), road charging vehicle, system optimization, wireless power transfer.**

I. Introduction

WIRELESS charging and inductive charging electric vehicles (EVs) are a new type of EVs that remotely charge their batteries using a wireless charging technology. Unlike conventional plug-in EVs, the wireless charging EVs do not require power cable connection for charging.

Wireless charging EVs are classified as either *stationary* or *dynamic* charging EVs. One of the first commercially available EVs using stationary charging was the General Motor EV1 [1], for which the primary transducer was a paddle and the secondary transducer a vehicle charger port. The topology of the charging system was introduced in [2] and [3]. Stationary charging transfers energy more efficiently than dynamic charging due to better alignment between the transducers.

Dynamic charging EVs, which are also referred to as *move-and-charge* or *road-way-charging* EVs, can charge while vehicles are in motion. The power from a primary source embedded below the pavement's surface is wirelessly transferred to a secondary pickup installed in the moving vehicle. It is known that the dynamic charging reduces the high initial cost of EVs by allowing smaller batteries [4]. Moreover, the charging infrastructure, called *power track*, is effectively used, because a large number of vehicles can use the same road segments equipped with the charging system.

Fig. 1. OLEV system in Gumi City, South Korea.

The online electric vehicle (OLEV) developed at the Korea Advanced Institute of Science and Technology (KAIST) is a commercially available dynamic charging transportation system. The first commercial version of the OLEV system was introduced in 2009 and used in a trolley system in the Seoul Grand Park. The second one was developed for shuttle buses on the KAIST campus, where it has been in operation since 2012 [5]. Gumi City, one of the biggest industrial cities in South Korea, deployed two OLEV buses on a metro bus line in 2013, shown in Fig. 1. There are plans for expansion to more bus lines in the city. Sejong City, a new Government Capital City of South Korea, plans to deploy an OLEV-based public transportation system to serve existing bus lines [6].

Numerous studies have reported that one of the benefits of dynamic charging is that it allows smaller and lighter batteries to be used, due to frequent charging using power tracks embedded under roads [2], [7]–[11]. However, none of these studies analyzed by how much battery size could be reduced and what the cost saving of reducing the battery size was. A true quantitative benefit analysis of dynamic charging has not yet been reported. It is difficult to perform a quantitative analysis of dynamic charging because the battery size is directly related to the installation of power tracks on the EV route. For instance, let us consider public transportation with dynamic charging such as metro electric buses. If power tracks are installed in many places, the buses can charge frequently with small batteries. If

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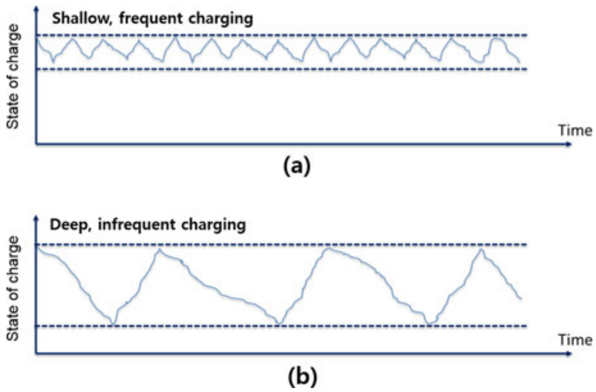

Fig. 2. (a) Shallow, frequent charging contrasted with (b) deep, infrequent charging.

not many power tracks are available, relatively larger batteries are needed for the buses. The battery size and power track allocation have to be considered together to determine the true benefit of a dynamic charging EV system.

In this paper, we analyze the benefit of the dynamic charging EV system using data collected from the OLEV buses currently operating in Gumi City, South Korea. We propose an economic design model for the dynamic charging EV system. The economic model (**EM**) offers the optimal battery size and allocation of power tracks considering the battery life while minimizing the total cost.

The battery life is specifically considered because we hypothesize that dynamic charging can improve the lifetime of an EV's battery, compared with stationary deep-cycling charging. Cost saving using dynamic charging is based on the following idea. A shallow, frequent charging [see Fig. 2(a)] for the lithium-type battery is known to be better for the battery life than a deep, infrequent charging [see Fig. 2(b)] [12]. Dynamic charging with a number of installed power tracks allows the battery to be charged on a shallow, frequent charging. In other words, installing more power tracks will improve the battery life. However, more power tracks will obviously require a greater initial investment. The goal of the optimization is to find the optimal allocation of power tracks and the optimal battery size considering this tradeoff.

We aim to answer following research questions with the proposed **EM**s.

1) By how much can dynamic charging reduce the size of an EV's battery, compared with stationary charging?
2) What is the optimum battery size and power track allocation for a given route, for a dynamic charging EV system?
3) Can dynamic charging increase the life of an EV's battery?

We summarize the related research in Section II. Then, we introduce the OLEV system's architecture and operational issues in Section III. We present an optimization issues for the dynamic charging EV system with power dynamics, energy flow, and battery life prediction models in Section IV. The economic design model for the dynamic charging EV system is developed in Section V. We implement our model with a numerical case study in Section VI, using data acquired from the OLEV bus system in Gumi City. We show that dynamic charging EV system has meaningful benefits, specifically compared to the stationary charging EV system. Sensitivity analyses presented in the section also provide insight into the dynamic charging EV system. Section VII summarizes the paper and proposes future research directions.

II. Previous Research

As already noted, wireless charging has been applied in EVs. The first such concept was presented by Bolger in 1978 and involved picking up electric energy transferred from a source embedded in a roadway. An inductive charger, consisting of a primary coil beneath the roadway, generated a magnetic field. A power pickup device in the vehicle received and converted the magnetic energy into electrical power [13]. The major issue in wireless charging for EVs is efficiency. The large air gap between the grounded primary coil and the secondary pickup coil in the EV reduces the charging efficiency. Many studies have focused on improving the charging efficiency across the air gap. Esser [7] achieved 92% charging efficiency using a 0.2-mm air gap, taking into consideration of the filters, converters, and rectifiers in an EV. Wu *et al.* [14] presented a new inductive power pick-up device with more advantages than traditional versions. Budhia *et al.* [15] also proposed a new inductive power transfer system design for improving efficiency and economics. Other studies have presented improvements in the wireless (or inductive) power transfer technology [16]–[19].

The OLEV system is one of the first commercialized dynamic charging EV systems. Many studies have presented the development of the KAIST OLEV and comprehensively described the hardware systems of the OLEV, such as [20]–[22] and [10]. They describe the wireless power transfer technology for the OLEV to accomplish higher efficiency for the dynamic charging. Although the dynamic charging technology has been improved enough to be commercialized, little research on economic system design issues for the dynamic charging EVs has been investigated.

This paper deals with the economic design of the dynamic charging EV system. We define that the *system design* is to determine the system design variables, which are the size of the battery and the allocation of power tracks. Recently, the importance of the system design for the dynamic charging EV has raised due to commercialization of the dynamic charging technology in EV applications. Ko and Jang [23] presented a nonlinear optimization model that minimizes the battery and charging infrastructure costs for the OLEV system. They first introduced the economical issues for designing the dynamic charging system. Their approach aimed to determine the battery size and the allocation of power tracks. Jang *et al.* [24] discussed a benefit of the dynamic charging from the perspective of system utilization, and proposed **EM** frameworks for the OLEV system design. Jang *et al.* [25] also dealt with the analogous problem using a mixed-integer programming. Although they have dealt with the system design issues on the OLEV system, their goals are to provide mathematical optimization algorithms with solution approaches.

Research on the wireless charging EV with the consideration of the battery life is limited. Pantic *et al.* [26] presented a heuristic approach for determining the placement of wireless charging

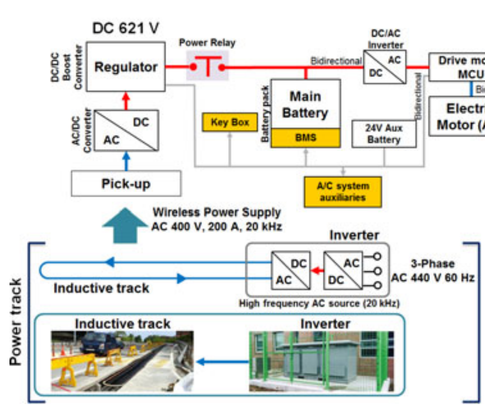

Fig. 3. Architecture of the OLEV bus system.

infrastructures on the route. Their multiobjective model relates the battery life to the peak output power. That is, it is assumed that a high-peak output power negatively affects to the battery life.

In this paper, we focus on a cost benefit analysis of the dynamic charging EV system with the consideration of the quantitative battery life. We numerically compare the benefit of dynamic charging to that of stationary charging.

III. Online Electric Vehicle

A. OLEV Architecture

Fig. 3 illustrates an architecture of the OLEV system. Each vehicle contains a pickup device, battery, regulator, and motor. A charging unit is a power track, which consists of an inverter and an inductive track. In the OLEV system, 60-Hz power supplied from the public electric grid is converted to a frequency of 20 kHz through the inverter. From the inverter, a high current flows through the coiled inductive track placed beneath the road. The high current induces a magnetic flux toward a surface of the road and the magnetic flux is transmitted to the bottom of the vehicle while the vehicle passes over. The power is then generated by converting the electromagnetic field into current at the pickup device. The remotely collected electricity is distributed to the motor, to the battery via the regulator, or both, depending on the power requirement of the motor and the battery's energy level. The more detailed system architecture can be found in [24].

B. OLEV Operations in Gumi City

The economic analysis presented in this paper is based on the operational data collected from the OLEV system in Gumi City. The OLEV system in Gumi City is the first implemented dynamic charging EV system in a public transit bus system. To verify that the OLEV system is a practicable option for an eco-friendly public transportation, Gumi City and KAIST have worked together since 2013 to install the OLEV system in an existing service line. As of Spring 2015, two OLEV buses have been in service to demonstrate the feasibility of the OLEV technology, and more buses are planned to be deployed gradually.

The upper part of Fig. 4 depicts a servicing route of the Gumi OLEV buses. There are 48 stations on the round trip and the total

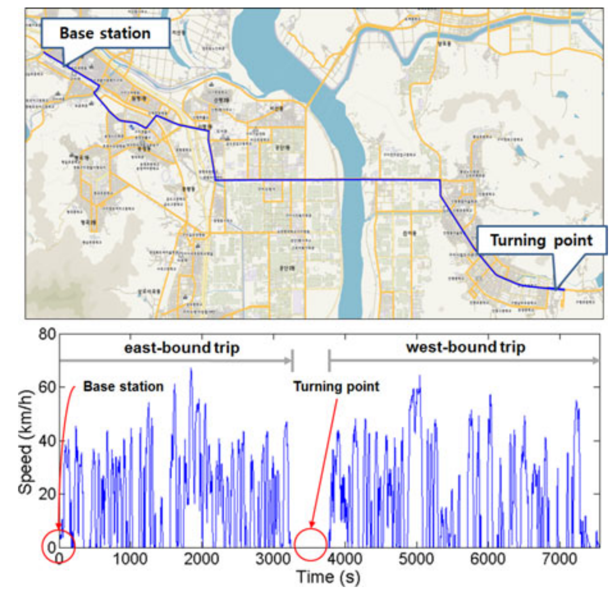

Fig. 4. Route (upper) and driving cycle (lower) of the Gumi OLEV buses.

TABLE I
Technical Specifications of the Gumi City OLEV System

Specification	Value
Inverter power capacity	100 kW
Inverter frequency	20 kHz
Power track current	200 A
Pickup power efficiency	80%
Pickup air gap	20 cm
EMF exposure level	< 10 mG
Battery size	100 kWh

trip length is 34.448 km. There are east-bound and west-bound routes. A bus leaves a base station (at the west end) and travels on the east-bound route. Once it reaches the station at the east end (a turning point), it rests for about 10 min. It then travels back to the base station on the west-bound route. The lower part of Fig. 4 shows an example of velocity profiles collected from an OLEV bus in Gumi City. It takes about 2 h, including about 10 min of resting time at the turning point. Technical characteristics of the OLEV system implemented in Gumi City are summarized in Table I.

IV. System Design Model of the Dynamic Charging EV System

In this section, we present the power dynamic and energy flow models of the dynamic charging EV to develop the economic design model of the dynamic charging EV system. The battery life prediction model adopted in this paper is also presented.

A. Optimization Issues and Model Definitions for the Dynamic Charging EVs

As a battery and power track costs account for a significant proportion of the total investment cost, economically evaluating these parameters is key to the success of commercializing

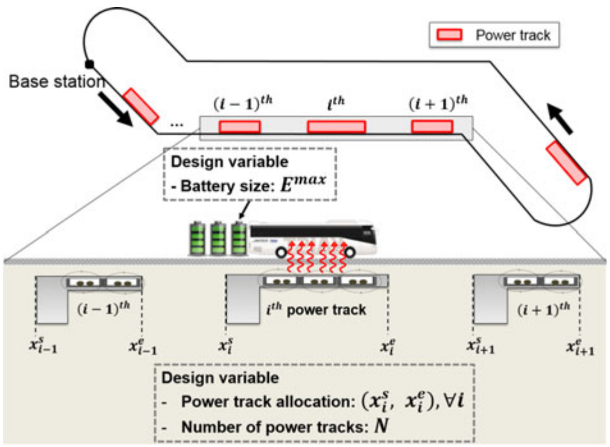

Fig. 5. Design variables in OLEV system design optimization [27].

a dynamic charging EV system. The goal of optimization is to determine the most economical battery size and power track allocation by simultaneously considering the cost factors and power requirements. We consider the design of the dynamic charging EV system, particularly as it applies to a mass transportation. More specifically, the *OLEV system model* here refers to a mass transportation system operating under the following conditions:

1) Identical buses serve passengers along a predefined route.
2) Buses follow the regulated velocity and the required driving cycle is predetermined.
3) 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.
4) Once a bus completes a service, it remains idle at the base station for a certain amount of time that we call the *resting* or *dwell time*.
5) During the base station resting time, the battery is charged fully before service resumption.

These operational rules of the model are based on the actual operation of the OLEV system in Gumi City and also based on other previous research on the OLEV system design, including [24] and [25]. The final condition stipulates that the bus must stop at the base station for enough to fully recharge its battery, and thus assumes that there is a charger at the base station. As the bus stops at the base station for a long time, there is no reason not to install a charging infrastructure [24], [25].

B. *System Design Variables and Parameters*

As aforementioned, a battery size and power track allocation are two sets of design variables. The vehicles in the system each have an identical battery size, which is denoted by $E^{\max}$. The length of each power track is determined by the length of the inductive track and can vary. Fig. 5 illustrates the design variables for optimization. We need to identify the number of power tracks required and the length of each power track. We let the base station be the reference point. Any point on the route is described by the travel distance x from the reference point. As the route is circular, the starting point where ($x = 0$), and end point where ($x = L$) both indicate the base station. We consider a vehicle making one circular trip (a service). The vehicle begins the service at $x = 0$ and completes it at $x = L$. As shown in Fig. 5, the start and end points of the ith power track are denoted by x_i^s and x_i^e, respectively. These values indicate the distance measured from the base station. Suppose that N power tracks have been allocated. Then, $i = 1, \dots, N$. Note that N is one of design variables. The optimization model aims to minimize the total cost finding the optimal design variables $E^{\max}$, and (x_i^s, x_i^e) for $i = 1, \dots, N$ by satisfying the requirement that the vehicle serves the route without any service interruption.

We define t as a continuous variable indicating the vehicle travel time measured from the base station. Let $v(t)$ be the required driving cycle of the vehicle over the route. Then, we can easily project the displacement variables onto the temporal variables. With $v(t)$, we define a function, f_{ts}, which relates the temporal and displacement variables

$$x = f_{ts}(t) = \int_0^t v(\tau) d\tau. \tag{1}$$

The displacement x, which is the distance from the reference point, is a function of the time at which the vehicle reaches that point. As it is a monotonically increasing function, there exists an inverse function. If we know a displacement value, we can evaluate the temporal value

$$t = f_{ts}^{-1}(x). \tag{2}$$

With the function in (2), we can easily calculate the times when a bus is at the start and end points of the ith power track, denoted by t_i^s and t_i^e, respectively.

We denote $E(t)$ as the amount of energy in the battery at time t. The energy level should be within a lower and upper limits during travel

$$E^{\text{low}} \leq E(t) \leq E^{\text{high}} \tag{3}$$

where E^{low} and E^{high} are the lower and upper limits of the battery level, respectively. These values have the following relationship:

$$\begin{aligned} E^{\text{high}} &= \epsilon^h \times E^{\max} \\ E^{\text{low}} &= \epsilon^l \times E^{\max} \\ 0 < \epsilon^l &< \epsilon^h < 1 \end{aligned} \tag{4}$$

where ϵ^l and ϵ^h are the lower and upper limit coefficients, respectively. This assumption is based on the mechanism of the charging controller in the OLEV. The range between E^{high} and E^{low} is set not to damage the battery and these values are set by battery providers.

The degree of energy fluctuation over time depends on the energy consumption and supply amounts. We define $P_b(t)$ as an energy consumption rate of the battery. This quantity depends on the energy usage rate of the vehicle determined by the velocity trajectory, road gradient, and use of peripheral devices such as the bus air conditioner. The analytical model for estimating the energy demand for the OLEV system and numerical validation of the model is explained in [23].

We define $P_s(t)$ as an energy supply to the battery at time t. This quantity is actually the charging rate of the battery and depends on power track allocation. We assume that $E(t)$ is linearly proportional to the charging time as long as the level of the charge is between E^{high} and E^{low}. This assumption is based on the mechanism of the charging controller in EV. If the vehicle is servicing on the route along power track in place, the battery energy level will increase. Note that although the entire spectrum of the charging rate is nonlinear, the charging rate within E^{high} and E^{low}, which represent the actual utilizing range, is almost a straight line [23]. Therefore, the charging rate, denoted by p_s, is assumed to be constant. This linear energy charging and discharging assumption is commonly used in EV modelings [28], [29]. Also, results of a numerical experiment supporting the assumption are presented in [23]. Then,

$$P_s(t) = \begin{cases} p_s, & \text{if a vehicle is on a power track} \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

The fluctuation of the battery energy level in this case is described as

$$\frac{dE(t)}{dt} = -P_b(t) + P_s(t). \quad (6)$$

Generally, the battery energy state is expressed as ratio, the state of charge (SOC), and it is represented as

$$\text{SOC}(t) = \text{SOC}(0) - \frac{1}{E^{\max}} \int_0^t \{-P_b(\tau) + P_s(\tau)\}\, \mathrm{d}\tau. \quad (7)$$

The ratio of released energy from the battery, the depth of discharge (DOD) is presented as

$$\text{DOD}(t) = 1 - \text{SOC}(t). \quad (8)$$

The trajectory DOD(t) represents the battery's discharges and is used to predict the battery degradation and the battery life.

C. Battery Life Prediction Model

The battery life prediction in EV system has been the most important research area to make decisions for commercializing EVs [30], [31]. The battery life prediction model adopted in this paper accumulates losses of battery life by discharge cycles [30], [32]. This model is called *fatigue model*, which is one of the cycle counting approaches [30], [33]. Although the fatigue model is a high-level approximation for the battery life, it is widely used due to its simplicity and succinctness [32]. Since we focus on the economic design of the dynamic charging EV system considering the battery life, the simple fatigue model is suitable for predicting the battery life with quick computations. The fatigue model assumes that every discharge affects to the battery degradation. That is, the DOD gap δ of the discharge cycle causes the battery degradation. To quantify the battery degradation caused by δ, the *cycle-to-failure* that indicates the maximum number of cycles versus a specific δ is used. Fig. 6 shows the experimental cycle-to-failure data from [34]. The curve fitted model is also plotted over the data in the figure, and the model is

$$f_n(\delta) = 10^{2.302 \cdot e^{-26.46 \cdot \delta} + 3.689 \cdot e^{-0.334 \cdot \delta}}. \quad (9)$$

The loss of life (LoL) of the battery caused by a specific δ can be estimated by the equation $1/f_n(\delta)$. The battery moves

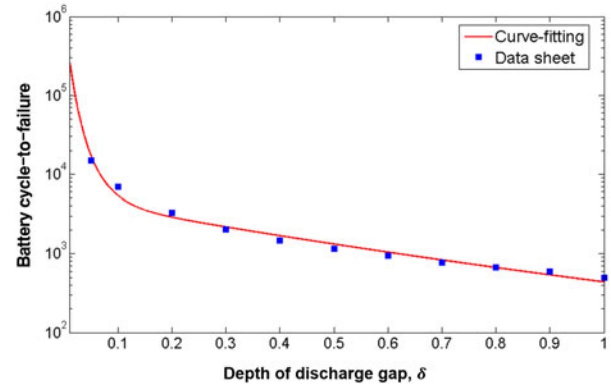

Fig. 6. Battery cycle-to-failure versus the DOD gap [34].

toward to the end of its life, the LoL approaches to 1. In the dynamic charging EV system, a number of discharges can be shown in a DOD trajectory of one service. Thus, the total losses of battery life by one service, LoL$_s$ is linearly accumulated as

$$\text{LoL}_s = \sum_{\forall j} \frac{1}{f_n(\delta_j)} \quad (10)$$

where δ_j is the DOD gap of jth discharge cycle in the DOD trajectory of vehicle's service. Therefore, the battery life can be represented by the maximum number of services with a new battery, and denoted by N_s

$$N_s = \frac{1}{\text{LoL}_s}. \quad (11)$$

If a vehicle serves N_d operations in a day, then the maximum expected lifetime of its battery T_b is represented by

$$T_b = \frac{N_s}{N_d}. \quad (12)$$

V. EM of Dynamic Charging EV

We construct the optimization model in this section. Suppose that a vehicle is about to leave the ith power track. With our notation, this point is indicated as x_i^e. The time at which the vehicle is at this point is indicated by t_i^e. The level of energy at t_i^e is $E(t_i^e)$. The vehicle now departs from the ith power track, and continuously travels along a route with no power track until it reaches the next power track, at point x_{i+1}^s. Again, the moment at which the vehicle arrives at the next power track is t_{i+1}^s. The following constraint must be satisfied:

$$E(t_i^e) - \int_{t_i^e}^{t_{i+1}^s} P_b(t)dt \geq E^{\text{low}}. \quad (13)$$

The first term in (13) is the energy level when the vehicle leaves the ith power track, and the second term indicates the amount of energy consumed while the vehicle is traveling the area with no power track. Therefore, (13) represents the amount of energy in the battery when the vehicle arrives at the beginning of the $(i+1)$th power track. The energy level needs to be greater than the lower energy limit of the battery. In other words, the power track needs to be installed in such a way that the energy level is greater than the lower limit. We now evaluate the amount of energy at the end of the $(i+1)$th power track, that is, the energy supply and consumption between x_i^e and x_{i+1}^e. The level of energy in the battery at x_i^e is $E(t_i^e)$. Thus, the level of energy at x_{i+1}^e is described as follows:

$$\min\left\{E(t_i^e) - \int_{t_i^e}^{t_{i+1}^e} P_b(t)dt + p_s \cdot \left(t_{i+1}^e - t_{i+1}^s\right), E^{\text{high}}\right\}. \tag{14}$$

Note that the battery energy level when the vehicle reaches the end of the $(i+1)$th power track should be less than the upper limit of the battery, E^{high}. If the energy amount is more than the upper limit, then the energy level would be E^{high} at x_{i+1}^e.

The objective function for the optimization model is defined as follows:

$$k \cdot c_b \cdot E^{\max} \cdot \frac{T_t}{T_b} + c_f \cdot N + c_v \cdot \sum_{i=1}^{N} \left(x_i^e - x_i^s\right) \tag{15}$$

where k is the number of vehicles, c_b is the battery cost per unit of energy capacity ($/kWh), c_f is the fixed cost to install a power track ($/each), and c_v is the installation cost per length of each power track ($/meter). The cost of the battery is linearly proportional to the unit size. This linear cost approximation is widely used in industry [35]. Therefore, the first term represents the total battery cost in the system. If the total service life of the dynamic charging EV system is T_t, the battery will be replaced in accordance with its lifetime T_b. The number of batteries required for each vehicle to cover the total service life is obtained by T_t divided by T_b. The second term and third term represent the total fixed cost and the variable cost of the power tracks, respectively.

Let T be the time at which the vehicle reaches the base station, and $L_{\text{pt}}^{\max}$ be the maximum length of a power track. Then, the **EM** economically allocating the power tracks and determining the battery size is then described as follows:

$$\textbf{EM}: \text{Minimize } k \cdot c_b \cdot E^{\max} \cdot \frac{T_t}{T_b} + c_f \cdot N + c_v \cdot \sum_{i=1}^{N} \left(x_i^e - x_i^s\right)$$

subject to

$$E(0) = E^{\text{high}} \tag{16}$$

$$E(t_i^e) - \int_{t_i^e}^{t_{i+1}^s} P_b(t)dt \geq E^{\text{low}}, \text{ for } i = 0, \ldots, N \tag{17}$$

$$E(t_{i+1}^e) = \min\left\{E(t_i^e) - \int_{t_i^e}^{t_{i+1}^e} P_b(t)dt + p_s \cdot \left(t_{i+1}^e - t_{i+1}^s\right), E^{\text{high}}\right\}, \text{ for } i = 0, \ldots, N-1 \tag{18}$$

$$E(T) \geq E^{\text{low}} \tag{19}$$

$$t_0^e = 0, t_{N+1}^s = T \tag{20}$$

TABLE II
NOTATION FOR THE EM

Notation	Description
k	Number of vehicles operating on the route
c_b	Battery cost per unit size ($/kWh)
c_f	Fixed cost of a power track ($/each)
c_v	Variable cost of a power track ($/m)
N	Number of power tracks
x_i^s	Start point of the ith power track
x_i^e	End point of the ith power track
t_i^s	Time at point x_i^s
t_i^e	Time at point x_i^e
$E^{\max}$	Battery size (kWh)
$E(t)$	Energy state at time t
E^{high}	Upper bound of the battery energy level
E^{low}	Lower bound of the battery energy level
$L_{\text{pt}}^{\max}$	Maximum length of a power track
L	Total length of the service route
T	Total trip time for a sercive
T_t	Total service life of the system
T_b	Battery lifetime
$P_d(t)$	Energy consumption rate of the battery at t
p_s	Energy supply rate

$$x_i^* = \int_0^{t_i^*} v(t)dt, \text{ for } * = \{s, e\}, \text{ and } i = 1, \ldots, N \tag{21}$$

$$x_i^s < x_i^e, \text{ for } i = 1, \ldots, N \tag{22}$$

$$x_i^e < x_{i+1}^s, \text{ for } i = 1, \ldots, N-1 \tag{23}$$

$$x_i^e - x_i^s \leq L_{pt}^{\max}, \text{ for } i = 1, \ldots, N \tag{24}$$

$$0 \leq x_i^s \leq L, \text{ for } i = 1, \ldots, N \tag{25}$$

$$0 \leq x_i^e \leq L, \text{ for } i = 1, \ldots, N \tag{26}$$

$$E^{\max} \geq 0. \tag{27}$$

In the **EM**, the constraints in (16)–(19) represent the battery energy state constraints. Specifically, the inequality in (17) represents the minimum energy requirement constraint, and (18) is the energy level when the vehicle leaves the end point of each power track. The physical allocation constraints of the power tracks are defined in (20)–(24). The design variables and their boundary conditions are defined in (25)–(27). Notations and definitions used in the **EM** are summarized in Table II.

The EM can be solved using the metaheuristics method, and its solution algorithm is given in [23].

VI. Numerical Case Study

In this section, we present a numerical case using operational data collected from the OLEV system currently operating public electric transit buses in Gumi City. The system parameters including the vehicle specification and the cost parameters are listed in Tables III and IV, respectively. These costs are close to the actual values of the OLEV system in Gumi City.

A. Basic Result

We first find a basic result of EM for the numerical case study. The result for $k = 18$, which is one of the target number

TABLE III
SYSTEM PARAMETERS OF THE OLEV SYSTEM IN GUMI CITY

Notation	Description	Value
p_s	Energy supply rate (kW)	80
ϵ^h	The SOC upper bound	0.800
ϵ^l	The SOC lower bound	0.500
$L_{\text{pt}}^{\max}$	Maximum power track length (m)	1000
L	Total route length (m)	34 448
T_t	Total service life (years)	10

TABLE IV
COST PARAMETERS

Notation	Description	Cost ($)
c_b	Battery cost per unit size	800
c_f	Fixed cost of a power track	50 000
c_v	Variable cost of a power track	500

TABLE V
RESULTS OF THE EM WHEN $k = 18$

Result	Value
Total cost	$9 375 469
Battery size	50 kWh
Battery life (service number)	1809
Number of power tracks	7
Total power track length	617 m
first power track	1970–1974
second power track	5059–5073
third power track	6503–6636
fourth power track	16 792–16 825
fifth power track	23 084–23 113
sixth power track	24 708–24 740
seventh power track	26 923–27 295
Duration on power tracks	1212 s

of buses in the route, is described in Table V. Table V shows the optimal economic decisions. Note that seven power tracks are allocated with a 50-kWh battery. Each battery enables to run 1809 services. The length of each power track is 4, 14, 133, 33, 29, 32, and 372 m, respectively. Thus, the total length of power tracks is 617 m. Although the total length of power tracks is only about 2% of the total travel distance, the total travel time on the power tracks is about 20 min, which is about 16% of the total service time. Note that in the result, the power tracks are located around bus stations including the turning point at which each bus stops for a while. Since the energy supplied from the power track is proportional to the time the bus spends on the power track, it is efficient to install the power tracks around the bus stops.

The optimal total cost of the system is $9 375 469. As we have already noted in Section V, the total cost includes both power track installation cost and the total battery cost. The power track installation costs $658 614 to install seven power tracks with 617 m long. Whenever batteries end their life after certain period, they have to be replaced by new batteries. For ten years of operation, the total battery cost is $8 716 855.

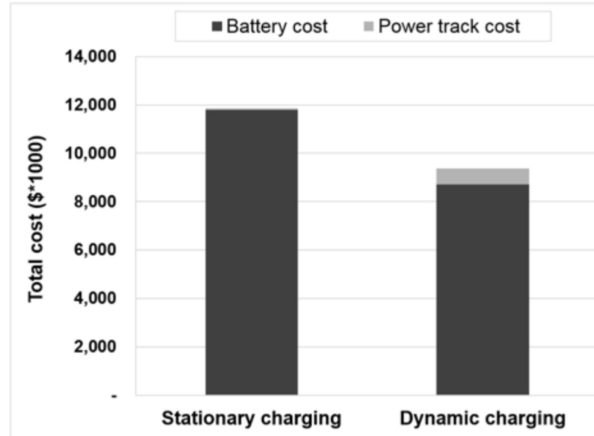

Fig. 7. Total cost comparison of a stationary and dynamic charging EV systems.

B. Comparison With Stationary Charging

Economics of the dynamic charging EV system can be clarified by comparing it with economics of the stationary charging EV system. Stationary charging is the other charging method of wireless charging EVs in which vehicles need to stop to charge the battery for a certain duration. For the Gumi City case, there is a turning point where buses stop by for 10 min in the middle of the service route. If a power track (or other charging devices) for stationary charging is installed at the turning point, the buses utilize it when the buses arrive at that point. If the stationary charging method were used for the Gumi OLEV system, each bus in the stationary charging should equip at least 100-kWh battery, which is twice larger than the optimal battery size of the dynamic charging EV.

Fig. 7 shows the total cost comparison of the stationary charging system and dynamic charging system when 18 buses are operated for ten years. The total cost of stationary charging EV system is $11 837 737, whereas the dynamic charging EV system needs $9 375 469 as we noted previously. It is expected to reduce the total cost by 20.8% when the dynamic charging system would be implemented, instead of the stationary charging system. Although the dynamic charging system requires more investments on the power tracks than the stationary charging system, more cost saving can be achieved from the smaller batteries with extended battery life.

C. Sensitivity Analyses

Fig. 8 shows the system behavior as the number of operating buses increases from 1 to 20 in increments of 1. The optimal battery size is shown in the upper part of the graph. The lower part of the graph indicates the total length of the installed power tracks. The numbers in the lower part of the graph indicate the optimal number of the power tracks. For example, if ten buses operate on the route, it is economical to use 50-kWh battery for

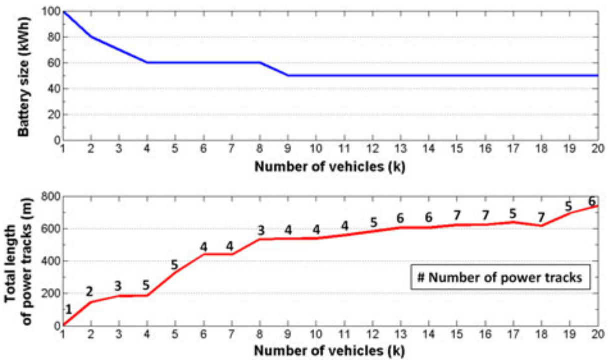

Fig. 8. Sensitivity analysis for increasing the number of buses.

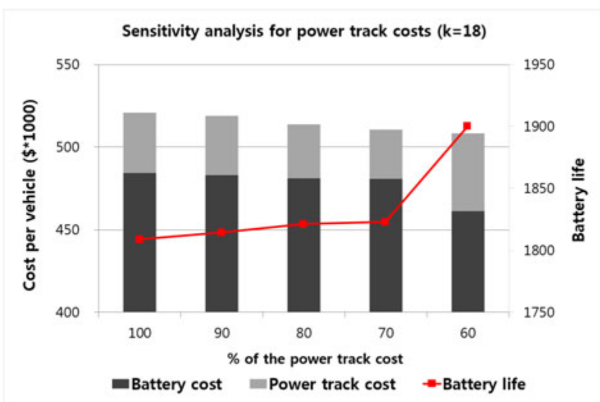

Fig. 9. Sensitivity analysis for decreasing power track cost.

each bus and to install four power tracks with a total length of around 540 m along the route.

In Fig. 8, if only one bus is in the system, it is most economical to install only one power track at the turning point, but to operate with one large battery in the bus. On the other hand, if 20 buses are in service, six power tracks with totally 740 m are needed to be installed with only 50-kWh size of the battery. Since the total battery cost becomes the dominant cost in the system as the number of buses increases, the **EM** tries to find a solution in which the buses can operate with smaller batteries. As the battery size decreases, a greater energy supply is needed. When the number of power tracks increases, the total length of the power tracks also increases. This makes sense, as the number of buses increases, which means an increasing utilities of power tracks, the cost benefit of the power tracks also increases.

Fig. 9 illustrates the cost per vehicle and battery life as the power track cost is reduced. The x-axis indicates the percent by which the power track cost is reduced from its current cost. For example, a value of 90% indicates a 10% cost reduction from the current cost (100%). The bars indicate the cost per vehicle and how that cost is broken down into the battery cost and power track cost. These costs are referenced on the left y-axis. The red line represents how the battery life responds to the cost changes.

The rationale behind reducing the power track cost is as follows. It is well known that the manufacturing cost of discrete products decreases as volume increases. According to Willcox [36], airplane production costs decrease by 10% each time when the production volume doubles. Assuming similar behavior in bus production, in view of similar production volumes, if Korea were to produce 1000-EV buses in a year, the cost of the buses would reduce by 65%. Although this scenario is somewhat optimistic and the cost of the batteries is less likely to decrease, based on recent battery costs, the cost of the power tracks is highly likely to decrease. The current power tracks are custom made and prototyping accounts for a significant portion of the total power track cost. A slight volume increase would reduce the cost. As the power tracks are manufactured in a country with low labor cost, there is a good chance that the cost can be reduced. Therefore, we analyze the case in which the power cost decreases. Note that in Fig. 9, the total cost does not decrease significantly, as we use the case with 18 buses. Eighteen batteries are needed, so the battery cost accounts for a significant part of the total cost. Notice that as the cost drops from 70% to 60% of the current cost, the battery life increases substantially. As the cost of the power track decreases, the optimal solution is to install more and longer power tracks, giving the batteries frequent charges and improving battery life. The additional cost benefits of the extended battery life such as environmental effects and battery disposal costs are not considered. If these indirect benefits are considered, the cost benefit would be greater.

VII. Conclusion and Future Research

In this paper, we introduced an **EM** for the dynamic charging EV system with the consideration of the battery life. For dynamic charging EV system, both power track allocation and battery size are the key design variables determining the system's performance. They also account for a significant portion of the total cost for dynamic charging EVs. We validated this **EM** with the real-world data collected from the OLEV system operating in Gumi City, South Korea, which is one of the first commercialized dynamic charging EV systems. Furthermore, we compared the dynamic charging EV system with the stationary charging EV system. We found that although more investments on dynamic charging infrastructure would occur at the installation stage, much more cost saving can be accomplished from the extended battery life. It implies that the dynamic charging EV system is beneficial to both the reduction of the battery size and extension of the battery life. Sensitivity analyses were also conducted to figure out the optimal designs for both increasing scale of the EVs and discounting the power track costs. We concluded that the dynamic charging system is more beneficial for large-scale EV systems and the battery costs could be significantly reducible when the power track cost drops.

Although there are some commercialized dynamic charging EVs, they are still in the very early stages of the commercialization and their system designs have been focused on proving the reliability of the systems rather than on economic values. Once these systems have been proven to be reliable by a few commercialized versions, the economic issues discussed in this paper will become critical.

For the future research, it would be more challenging to optimally design the dynamic charging EV system considering stochastic driving cycle. In this paper, it is assumed that all vehicles follow predetermined driving cycle. We did not consider the traffic and driving uncertainties that largely affect to the power and energy requirements of vehicles. The **EM** with uncertain driving behavior is a good candidate for the future research.

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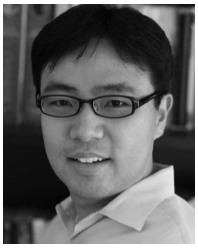

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