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Locational Analysis of In-motion Wireless Power Transfer System for Long-distance Trips by Electric Vehicles: Optimal Locations and Economic Rationality in Japanese Expressway Network

Yudai Honma[1] · **Daisuke Hasegawa**[2] · **Katsuhiro Hata**[1] · **Takashi Oguchi**[1]

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Abstract

The popularization of electric vehicles (EVs) is limited by their driving range and long charging times. To address this, in-motion wireless power transfer systems (WPTSs) are currently attracting attention as a new power supply system. In-motion WPTSs have coils embedded under the road to transfer power from the WPTSs to EVs while driving. However, the main drawback of WPTSs is their large investment, especially in supporting the long-distance trips of EVs on expressways. Therefore, this study proposes a new mixed-integer programming model (MIP) to determine the optimal location of WPTSs for maximized total feasible flow demand. By focusing on long-distance trips on expressways, we propose the first flow-capturing model for WPTS locations that can (i) solve for the distance of WPTS installed as continuous variables, and (ii) solve problems based on real-scale data using a general MIP solver. Our method is extended to a discussion of WPTS installations on expressways in Japan. We observe that WPTS has strong potential as an EV power supply system in terms of coverage and economic rationality. In particular, WPTS has economic rationality not only in busy networks but also in sparsely populated networks that connect urban and rural areas. Thus, this study clarifies the important insights of WPTSs in improving their effectivity to narrow down the demand and ensure the flexibility in the locations of WPTS.

Keywords Electric vehicle · Charging infrastructure · In-motion wireless power transfer · Mixed integer programing · Intelligent transportation system

✉ Yudai Honma
yudai@iis.u-tokyo.ac.jp

[1] Institute of Industrial Science, The University of Tokyo, Komaba 4-6-1, Meguro-ku, Tokyo 153-8505, Japan

[2] Center for Real Estate Innovation, The University of Tokyo, Hongo 7-3-1, Bunkyo-ku, Tokyo 113-0033, Japan

1 Introduction

Automobiles are the most common means of ground transportation. However, for the past 100 years, automobiles have been powered by fossil fuels, which poses negative environmental impacts. In recent years, there has been an increasing demand for low-carbon alternative-fuel vehicles, and several countries have pledged to ban the sale of new fossil-fuel-powered vehicles by 2040 (Vaughn 2018). Therefore, the use of electric vehicles (EVs) is expected to become widespread.

To popularize the use of EVs, their convenience needs to be improved, specifically by developing appropriate charging infrastructures. Therefore, several studies have discussed the appropriate locations of EV charging stations (Coffman et al. 2017; Fúnez Guerra et al. 2016; Demir et al. 2014; Rahman et al. 2016). There are several variations in facility location models, such as the popular classical p-median problem, which determines the location of p facilities to minimize the total travel distance (ReVelle and Swain 2010). In the context of transportation, Hodgson's (1990) flow capturing location model (FCLM) has garnered widespread attention. FCLM proposes optimal p facility locations to maximize the flow volume on the path of the facility. Several developmental studies have also been conducted (Berman et al. 1995). For the optimal location of EV charging stations, the flow refueling location model (FRLM) by Kuby and Lim (2005) is regarded as a milestone study. In the FRLM, the driving range constraints of EVs are considered, and the model is extended with the assumption of multiple instances of charging. Numerous mixed-integer programming (MIP) models have been developed to address more realistic situations and to overcome the associated computational challenges (Yıldız et al. 2016), such as considering the deviation of paths (Kim and Kuby 2012), introducing tank-level tracking (Wang and Lin 2009), multi-level covering (Capar et al. 2013), and heuristics (Lim and Kuby 2010).

The capacity of EV charging stations is a critical issue (Upchurch et al. 2009). In the early stages of EV diffusion, the capacity constraints of the stations can be ignored. However, as EV penetration progresses, the number of EVs that can be handled by stations is expected to pose a significant issue (Bruglieri et al. 2019). From this perspective, studies on the location of EV stations considering capacity constraints have also been conducted. This problem is rooted in another deficiency of EVs, which is their long charging times (Honma and Toriumi 2014). As presented by the queuing theory, unless the issue of charging time is resolved, the number of required stations will increase considerably with the spread of EVs (Honma and Toriumi 2017).

In-motion wireless power transfer systems (WPTSs) have garnered attention as a new power supply system that can solve the problems of EVs (Lukic and Pantic 2013; Miller et al. 2015). Under in-motion WPTSs, EVs receive power while being driven through coils embedded under the road, as shown in Fig. 1 (Hata et al. 2019). This allows EVs to charge their batteries without waiting at a charging station, thereby achieving an unlimited driving range. Thus, WPTSs have the potential to simultaneously solve the limitations of the driving range and long charging time of EVs.

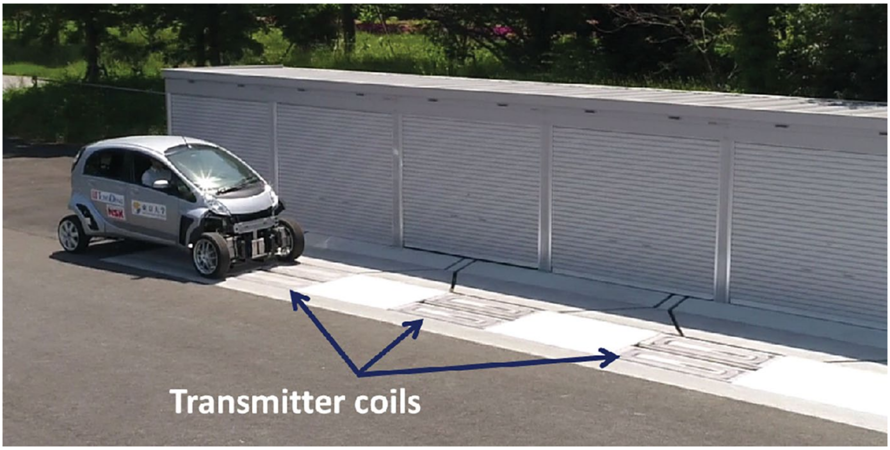


Fig. 1 In-motion wireless charging system for electric vehicles from Hata et al. (2019)

Though there are limited optimal location models for in-motion WPTS, compared to those for EV charging stations, the number of WPTS researches focusing on locational analysis and economic rationalities is steadily increasing over the last decade. Jang (2018) provided a comprehensive review of WPTSs related to infrastructure planning, costs, and benefit analysis. One of the theoretical mainstreams of location models for WPTS is analysis of equilibrium flows considering traffic congestions (Riemann et al. 2015; Chen et al. 2016; Manshadi et al. 2018; Liu et al. 2021). In their models, multiple routes are considered, and system optimizations are discussed. For example, Riemann et al. (2015) formulate a flow-capturing location model with stochastic user equilibrium. Chen et al. (2016) develop a user equilibrium model considering the relationship between speed, charge amount, and travel time. Manshadi et al. (2018) consider the interdependence between the electricity network and the transportation network whereas Liu et al. (2021) incorporate electricity prices.

In addition to the user equilibrium technique, efforts are being made to deepen the mathematical model from various perspectives. Ko et al. (2015) propose the optimal economic design using Genetic Algorithms. Chen et al. (2017) theoretically discuss the deployment balance between EV stations and WPTS. Liu and Song (2017) and Alwesabi et al. (2022) construct their models from the viewpoint of robust optimization. It should be noted, however, that the above studies have focused on mathematical developments, and thus the applied transportation networks are rather primitive.

There are several previous studies from the viewpoint of application to the real world. The research group of Y.J. Jang has conducted a series of studies that focuses on the real EV bus system with WPTS in Korea (Ko and Jang 2013; Jang et al. 2015, 2016; Hwang et al. 2018). Based on tests with actual equipment, they develop sophisticated system architectures for EV buses with WPTS. Further, Alwesabi et al. 2021 develop the model for scheduling optimization of EV buses with WPTS.

WTPS location studies using real-world networks also exist at both the metropolitan and interstate scales. From the metropolitan-scale perspective, Mubarak et al. (2021) focuses on the Chicago area network and derives the complete flow coverage solution. Yan et al. (2021) uses a mobility dataset collected in Shenzhen, China, and applied kernel density estimation to converge their data. From the interstate-scale perspective, Fuller (2016) formulates an optimization model to minimize the total cost of WPTS and applied it to the California roadway network. Similarly, Trinko et al. (2022) discuss the economic feasibility of WPTS in a high-density traffic corridor in Los Angeles, California, United States. Such economic evaluation is an essential aspect of WPTS, previously studied by He et al. (2013) and Jeong et al. (2015).

As discussed in the above studies, EV stations and WPTSs have opposing characteristics in terms of economy and convenience (Fig. 2), and the main drawback of WPTSs is their large investment. It is unneglectable especially when designed to support the long-distance trips of EVs on expressways. In particular, WPTSs must be laid for tens of kilometers because vehicles pass over them in only a few seconds; therefore, there are doubts on their economic feasibility.

This study aims to propose a new MIP model to determine the optimal locations of WPTSs to maximize the total feasible flow volume. By focusing on long-distance trips on expressways, we propose the first flow-capturing model for WPTS locations that can (i) determine the suitability for the installation of WPTSs as continuous variables instead of binary variables and (ii) solve problems based on actual data with a general MIP solver. In our formulation, we assume realistic travel based on the shortest path because the study focuses on the flow demands on the expressway. We also present a faster formulation that focuses on the shortestpath trees. In the optimization phase, the power supply pattern is determined only to confirm the feasibility of the flow demand. In addition, the probable charging behaviors of EVs are simulated using a separate algorithm. The combination of the WPTS locational optimization and algorithm representing the EV power management achieves a fast and accurate analysis. Furthermore, the proposed method is extended to a discussion of the economic rationality of the

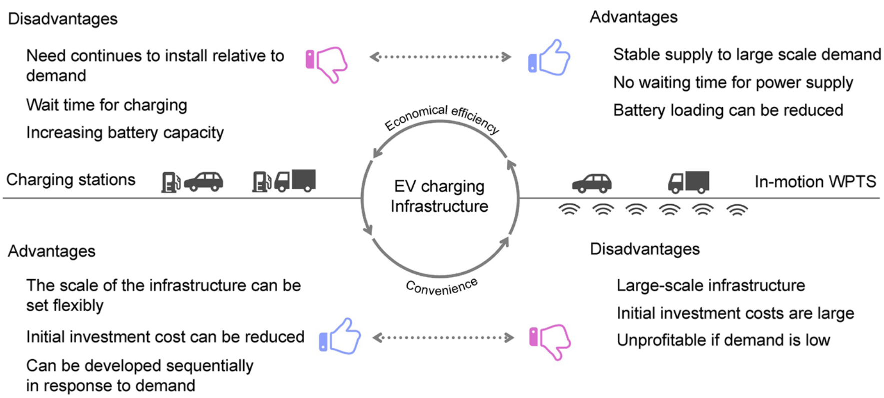


Fig. 2 Characteristics of electric vehicle charging stations and wireless power transfer systems

WPTS installations on the expressways in Japan. As the popularization of EVs is limited by their driving range and long charging times, the economic rationality of WPTS installations should be examined for long-distance travel. Particularly, the biggest concern with installing WPTSs on expressways is the high construction costs. To estimate the economic rationality under realistic assumptions, we consider the expressway network and flow demands based on the geographic information system (GIS) data. The energy consumption of the EVs is carefully prepared based on previous studies, and a sensitivity analysis is conducted.

Our study contributes to this growing literature from the theoretical/methodological, application, and policymaking aspects. First, from the theoretical and methodological viewpoints, our most important contribution is to define the decision variables for the WPTS installation as continuous variables representing the *length* of each segment. Most previous studies use binary variables to represent whether to install WPTS on a link or not (Jang 2018), echoing location models for EV charging stations that are points on the network. For analyzing long-distance road networks, however, links tend to be much longer and assuming WPTS is installed over the entire link reduces the precision and limits the flexibility of the analysis. Conversely, if longer links are more segmented to increase resolution, computational complexity explodes. In our model, the above problem is avoided by allowing the *length* of the WPTS in each link to be determined endogenously using continuous variables. Ko and Jang (2013) and a series of consecutive studies (Jang et al. 2015, 2016; Hwang et al. 2018) are the only studies to express WPTS locations as continuous variables, but their model solves for both a start point and an end point, which is rather too detailed and increased the number of variables. In representing the WPTS location, our representation is necessary and sufficient, because it is not sensitive to network resolution and does not increase the number of variables. Moreover, this strategy contributes to solving even large-size problems using a general MIP solver.

Second, an important contribution from the application aspect is that we conducted an analysis focusing on expressways with "low demand". For WPTS location analysis, research based on real networks concentrates on the analysis at the urban scale. Hence, relatively few studies have focused on long-distance motorways. As previously mentioned, Trinko et al. (2022) demonstrate that WPTS has certain economic rationality in high-density traffic corridor. Fuller (2016) also focuses on California highways, which is a mix of high-demand and low-demand networks. No previous research discussed economic rationality in low-density expressways.

Finally, a valuable contribution to policymaking is that our model provides policymakers with much-needed flexibility in planning WPTS networks. First, our analysis highlights the existence of multiple optimal solutions for the location of the WPTS. This finding allows policymakers to adjust WPTS locations while considering a variety of factors, without sacrificing optimality. Second, our model is formulated as a flow maximization problem, unlike many other previous studies that require complete coverage. This enables decision-makers to explore the relationship between the distance of the WPTS installation, demand coverage ratio, and net revenue.

In this study, we assume the operation of WPTS only, and we do not consider the combined use of WPTS and EV recharging stations for the following reasons.

First, we discuss a future scenario in which EVs comprise over 30% of all vehicles. Our previous studies (Honma and Toriumi 2014, 2017) have pointed out the insufficient quantity of charging stations to supply in a society dominated by EVs because each station has only a few slots for charging. For example, a study by Honma and Toriumi (2014) estimates the requirement of 200 slots when EVs become sufficiently widespread, assuming travel on the same expressways as in this study. As of 2021, there have been no changes in the limited slots per station in Japan (Yamada and Fukao 2021). Second, to properly evaluate the potential of WPTS, it must be analyzed under the assumption that only WPTS is deployed in our society. Our previous studies (Honma and Toriumi 2014, 2017) have indicated that it is unrealistic to cover huge EV demand only by charging stations. Therefore, we aim to evaluate the potential of WPTSs to support EVs. Should WPTS prove to be a positive contributor to EV mobility infrastructure, we can envision a future where WPTS and EV stations complement the strengths of each other. In this study, the realistic parameters ensure that the numerical results can directly be applied for policy analysis. This study demonstrates the positive potential of WPTS as an EV infrastructure, thereby depicting the difficulty of covering all demands with WPTS alone.

2 Methods

2.1 Frameworks

In this section, we assume an in-motion WPTS to be an energy-supply infrastructure for EVs and propose a new flow-capturing model to optimize WPTS locations. First, we summarize the role of EVs in completing their flow demands using WPTS. In this paper, "flow demand" is defined as the requirement to travel from an origin to a destination. Specifically, because we are focusing on expressways in this study, we define flow demand as a request to travel from one highway ramp (for example, Tokyo ramp) to a different highway ramp (for example, Osaka ramp). Because a large number of EVs is expected to share the same demand, the number of EVs making the same travel is defined as the "flow volume" for that flow demand. The unit of flow volume is the "number of EVs". Unlike previous studies on EV station locations, our study regarded flow demand as a one-way trip rather than a round trip. The tools that EVs can use for energy management are their battery capacity and WPTS charging on the way to the destination. The batteries of EVs can be full at the origin but their energy is consumed as they travel. Thus, EVs can charge when they pass through the WPTS. In this study, the flow demand is regarded as "feasible" when EVs can complete their travel from their origin to their destination without experiencing any energy shortage at any point along the route, which is facilitated by the installed WPTS. In this study, no EV charging stations are considered.

The route of the flow demand is assumed to be exogenously determined and is not affected by the location of the WPTS. In particular, we assume that all flow demands use the shortest path for the sake of simplicity. We consider this assumption to be realistic because our study focuses on long-distance trips on an expressway, and many EV drivers tend to choose the shortest route. The EVs are assumed to move at a constant speed throughout the network; thus, acceleration and deceleration are not considered. The amount of energy consumed is known for each link based on the travel speed and gradient. For a steep descent, regenerative energy can be expected, resulting in the negative power consumption of the link. Finally, this study assumed that the WPTS installation costs are proportional to their installation distance. We focus on the total installation distance as the infrastructure cost. In other words, the fixed cost of the WPTS installation is not specifically assumed in the discussion of economic rationality.

The optimization problem for each flow demand is proposed and reformulated for each origin to enhance the solution time. Subsequently, a simulation algorithm to calculate the probable energy consumption is discussed for economic rationality. All notations for the models are defined below.

Indices:

q	Index of flow demands
i, j	Index of the nodes; indicate the directed links from node i to j.
o	Index of the origins; $o(q)$ indicates the origin of flow demand q.
d	Index of the destinations; $d(q)$ indicates the destination of flow demand q.

Sets:

Q	Set of flow demands
N	Set of nodes in the entire network
E	Set of links in the entire network
O	Set of origins
D	Set of destinations
N_q	Set of nodes that flow demand q passes through
E_q	Set of links that flow demand q passes through
T_o	Set of links in the shortest path tree whose origin is o

Parameters:

s	Total length of WPTS to be installed [km]
f_q	Flow volume of flow demand q
u	Battery capacity of EV [kWh]
l_{ij}	Length of link (i,j) [km]
c_{ij}	Required electric power to pass through link (i,j) [kWh]
r_{ij}	Electric power transfer per unit distance on link (i,j) [kWh/km]
m_q	Large negative number to check the feasibility of flow demand q

Decision Variables:

x_{ij}	Length of WPTS to be installed on link (i,j) [km]
y_q	1 if the flow demand q is feasible, 0 otherwise
b_i^q	Remaining power when flow demand q reaches node i [kWh]

g_{ij}^q Electric power to be transferred for flow demand q on link (i,j) [kWh]
b_i^o Remaining power when the flow whose origin is o reaches node i [kWh]
g_{ij}^o Electric power to be transferred for the flow whose origin is o on link (i,j) [kWh]

2.2 Optimal Location Problem for In-motion WPTS

2.2.1 Flow Demand-Based Formulation

First, we formulate a flow-capturing location problem for in-motion WPTSs. A flow demand is captured when an EV with a certain battery capacity can reach its destination using its battery capacity and energy transferred via WPTS.

$$\text{Max.} \quad \sum\nolimits_{q\in Q} f_q\, y_q, \tag{1}$$

subject to:

$$b_i^q - c_{ij} + g_{ij}^q = b_j^q \qquad \forall q \in Q,\ (i,j) \in E_q \tag{2}$$

$$m_q\left(1 - y_q\right) \le b_i^q \qquad \forall q \in Q,\ i \in N_q \tag{3}$$

$$b_i^q \le u \qquad \forall q \in Q,\ i \in N_q \tag{4}$$

$$g_{ij}^q \le r_{ij}\, x_{ij} \qquad \forall q \in Q,\ (i,j) \in E_q \tag{5}$$

$$\sum\nolimits_{(i,j)\in E} x_{ij} = s \tag{6}$$

$$y_q \in \{0,1\} \qquad \forall q \in Q \tag{7}$$

$$0 \le x_{ij} \le l_{ij} \qquad \forall (i,j) \in E \tag{8}$$

$$b_i^q \ge 0 \qquad \forall q \in Q,\ i \in N_q \tag{9}$$

$$g_{ij}^q \ge 0 \qquad \forall q \in Q,\ (i,j) \in E_q \tag{10}$$

Objective function (1) maximizes the total flow that can complete the trip without a power shortage. Constraint (2) is a power-conservation equation. On each link (i,j), an EV that departs from node i with remaining power b_i^q would consume c_{ij} and recharge g_{ij}^q; thus, its energy should be equal to b_j^q when arriving at node j. Constraint (3) checks the feasibility of flow demand q, which is a key expression for our formulation. Note that the left-hand side is zero when $y_q = 1$, and a large negative number m_q when $y_q = 0$. That is, the remaining power b_i^q for flow demand q should always be positive if $y_q = 1$; meanwhile, it can be negative if $y_q = 0$. Although a uniformly large value of m_q is acceptable, it is preferable to set it individually as small as possible to improve the solution performance. For example, we can use $m_q = u - \sum_{(i,j)\in E_q} c_{ij}$. Constraint (4) aims to restrict the remaining power b_i^q under battery capacity u. Constraint (5) ensures the installation of the WPTS to transfer electric power. Constraint (6) specifies the total length of the installed WPTS; this corresponds to the budget constraints. If it is possible to install as many WPTSs as possible, all flows will be feasible. However, the budget will be insufficient if too many WPTSs are installed. Therefore, this constraint limits the total length of the WPTS that can be installed. Even if the total length of WPTSs is constant, the number of feasible flows varies greatly depending on how WPTSs are scattered over the network. We aim to determine the optimal solution to this problem. Finally, constraint (7) is for binary variables, and constraints (8) and (9) are for continuous variables. Figure 3 illustrates the variables that describe the power supply pattern of flow q to understand the equations of constraints (2)–(4), and m_q.

2.2.2 Origin-Based Formulation

Although mathematical problems (1)–(10) are straightforward, they require time to be solved because both the decision variables b_i^q and g_{ij}^q, and constraints (2) and (4) are prepared per flow demand per link. As we assume a simplified situation in which each flow demand uses the shortest path, we propose an origin-based formulation that reduces the number of variables and constraints and enables us to derive the optimal solution faster. In particular, we focus on the shortest-path tree and combined some of the decision variables and constraints per origin.

Based on Fig. 4, let us consider a situation to analyze the feasibility of flow demands A→B and A→(B)→C. Here, A→(B)→C indicates that the origin is A, the destination is C, and B is a waypoint passing through the way to C. Because we assume that every flow demand uses the shortest path, A→B and A→(B)→C share the route of A→B. Thus, the two demands have the same origin and overlapping paths. This allows us to discuss the feasibility of A→B and A→(B)→C in relation to each other. If A→B is not feasible, then A→(B)→C must also not be feasible (as shown in Fig. 4a). In contrast, if A→(B)→C is feasible, then A→B must be feasible (as shown in Fig. 4b). In other words, if there is an energy supply pattern that makes A→(B)→C feasible, then A→B is feasible with the same power supply pattern. However, the energy supply patterns analyzed using this approach are constructed for the longest paths, resulting in extra energy supplied for short distances. In fact, as shown in Fig. 4b, A→B can be reached without a power supply, but its energy supply pattern is designed to use the WPTS along the way to match A→(B)→C. Therefore, we will formulate a separate algorithm in the next section to calculate the necessary and sufficient amounts of energy supply.

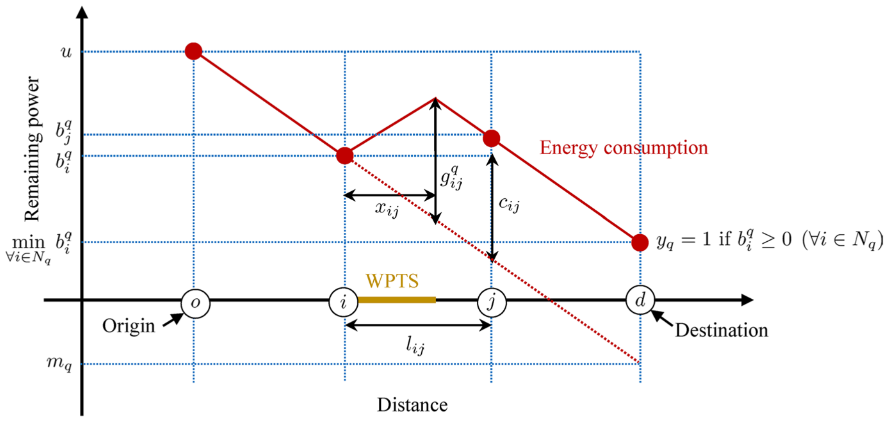


Fig. 3 Basic concepts of the variables related to energy consumption

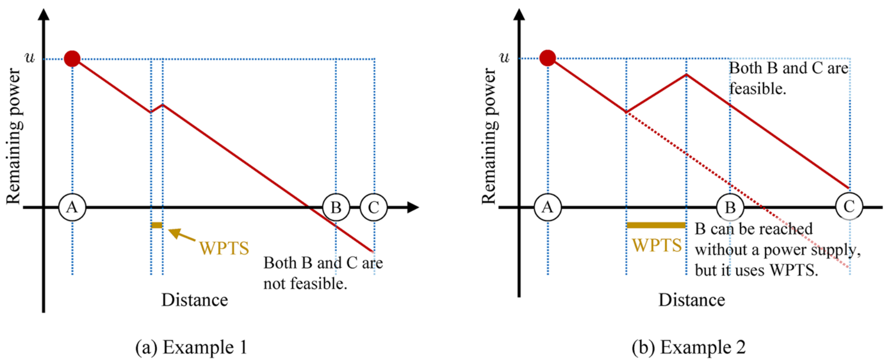


Fig. 4 Feasibility of flow demands A→B and A→(B)→C

The proposed problem, which is an origin-based formulation, is as follows:

$$\text{Max.} \quad \sum\nolimits_{q \in Q} f_q \, y_q, \tag{11}$$

subject to:

$$b_i^o - c_{ij} + g_{ij}^o = b_j^o \qquad \forall o \in O,\ (i,j) \in T_o \tag{12}$$

$$m_q\left(1 - y_q\right) \leq b_i^{o(q)} \qquad \forall q \in Q,\ i \in N_q \tag{13}$$

$$b_i^o \leq u \qquad \forall o \in O,\ i \in N \tag{14}$$

$$g_{ij}^o \leq r_{ij} x_{ij} \qquad \forall o \in O,\ (i,j) \in T_o \tag{15}$$

$$\sum_{(i,j)\in E} x_{ij} = s \tag{16}$$

$$y_q \in \{0,1\} \qquad \forall q \in Q \tag{17}$$

$$0 \le x_{ij} \le l_{ij} \qquad \forall (i,j) \in E \tag{18}$$

$$b_i^o \ge 0 \qquad \forall o \in O,\ i \in N \tag{19}$$

$$g_{ij}^o \ge 0 \qquad \forall o \in O,\ (i,j) \in T_o \tag{20}$$

Objective function (11) is similar to demand-based formulation (1); that is, it maximizes the total flow that can complete the trip without a power shortage. Constraint (12) is a power-conservation equation, in which the variables are related to the electric power per origin. We only prepare the constraints on the shortest-path tree because all flows must use the shortest tree. We check the feasibility of each flow demand, and separately calculated the necessary and sufficient amounts of power supply to summarize each origin. Constraint (13) checks the feasibility of flow demand q, which should be prepared for each demand. Constraint (14) restricts remaining power b_i^o under battery capacity u. Other constraints are the same as those of the flow demand-based formulations.

2.3 Algorithm for Recharging Behaviors of EVs

From the formulation, we calculate the actual amount of power that an EV charges via the WPTS at each demand given a certain WPTS arrangement. In the optimization problem, the amount charged using the WPTS for each q can be calculated by $\sum_{(i,j)\in E_q} g_{ij}^{o(q)}$. However, this charging amount is clearly greater than the amount needed to ensure the feasibility of the flow demand. Under a pay-as-you-go system, economically rational drivers of EVs will want to use WPTS charging as little as possible (because it is more expensive than home or work charging), and they have the control to bypass WPTS charging when desired (by driving in the non-WPTS lane); thus, we determine the required charge for a user.

The following algorithm simulates the driver's recharging behaviors and determines the recharging amount for each feasible flow demand q. Given the optimal locations $\left\{x_{ij}^*\right\}$ for WPTSs, we determine the necessary recharging amount h_q for flow demand q. A pseudocode of the algorithm is presented as follows, and this pseudocode is individually applied for all feasible flow demands q whose $y_q = 1$. Step 1 calculates a_j^q, which represents the required power at node j for demand q in the reverse direction. In step 2, we determine the necessary recharging amount h_q for flow demand q, simulating the charging and discharging of the battery in the forward order.

```
###Step1. calculate the required power a_j^q
##initialization
a_{d(q)}^q := 0;  # required power at the destination d is 0
j := d(q);  # back from the destination
##calculate for all nodes of q
while j! = o  #until reaching the origin o
      derive node i;  #let i be the node immediately before j
      a_i^q := a_j^q + c_ij;  #calculate the required power a_i^q at node i
      j := i;  #move to next upstream nodes

###Step2. calculate the necessary recharging amount h_q
##initialization
remained := u;  #remaining power at the origin is u (battery capacity)
i := o(q);  #start from the origin
h_q := 0;  #initialization of the necessary recharging amount
##scanning the route of q
while i! = d  #until reaching the destination d
      derive node j;  #let j be the node immediately after i
      if a_i^q > b_i^q
            recharge := min{a_i^q - b_i^q, r_ij x*_ij};  #recharging amount at (i,j)
            remained := remained - c_ij + recharge;  #update remained
            h_q += recharge;  #add the recharging amount to h_q
      else
            remained := b_i^q - c_ij;
      i := j;  #move to next downstream nodes
```

3 Numerical Analysis of a Japanese Expressway Network

3.1 Networks and Flow Volumes

Using the methods presented in Section 2, we apply our model to the Japanese expressway network. After identifying the optimal WPTS locations, we examine the economic rationality of the WPTS for the Japanese expressway network.

First, we summarize the network data. To analyze the Japanese expressway network, we extract each ramp and junction from OpenStreetMap and regard them as nodes of the road network. The actual distances between the nodes are calculated from the data. In addition, the elevation data of each node and average gradient of each link are calculated. The gradient data are used to calculate the energy consumption of the EVs more accurately.

Japan's expressways have a total length of approximately 9,000 km. Two representative networks are selected from these expressways, as shown in Fig. 5 and Table 1. These representative networks differ in terms of the scale of the metropolitan areas through which they pass. Specifically, the Tokyo–Osaka expressway, denoted by [N1], is the busiest network because it connects the top three metropolitan areas in Japan: Tokyo, Aichi, and Osaka. Meanwhile, the Tokyo–Aomori expressway, denoted by [N2], has Tokyo on one side and extends to the rural Aomori area. Therefore, these expressway networks have different flow-demand characteristics. Figure 6 shows the visualization of the flow demand for [N1] Tokyo–Osaka and [N2] Tokyo–Aomori.

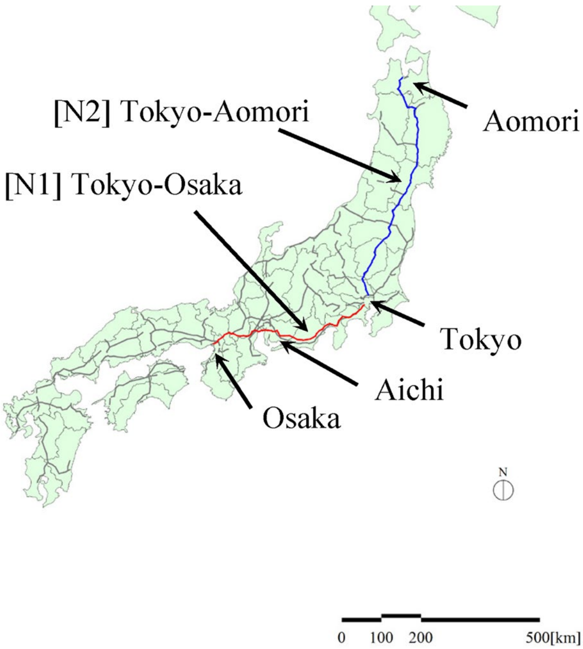


Fig. 5 Japanese expressway networks

Table 1 Summary of the Japanese Expressways analyzed in this study

Entries	[N1] Tokyo–Osaka	[N2] Tokyo–Aomori
Total distance (round-trip length) [km]	965.05	1,359.90
Total number of ramps	45	57
Total number of links	166	244
Total flow volume [$\times 10^3$ vehicles]	127,177	121,184
Total number of flow demands (between ramps)	1,397	2,547
Affected metropolitan areas	Tokyo, Aichi, Osaka	Tokyo

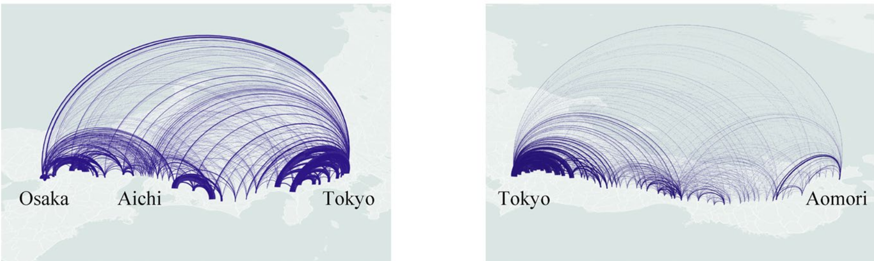
3.2 Parameter Settings

We summarize the parameter settings for the energy consumption. In this study, we use Eq. (21) to calculate the motor power [kW], based on the studies by Tanaka et al. (2008), Wu et al. (2015), and Fiori et al. (2016).

$$P(\theta) = \frac{1}{\eta} v \left(ma + mg \cos \theta f_{rl} + \frac{1}{2} \rho A_f C_D v^2 + mg \sin \theta \right) \tag{21}$$

In this study, we uniformly assume a constant speed of v =80 km/h = 22.22 m/s, which is determined based on the Japanese law concerning speed limits, and no acceleration/deceleration (a =0 m/s^2) is considered across all the networks. Therefore, Eq. (21) expresses the motor power P when road gradient is θ [°]. For θ, we assign the average gradient of each link. The parameters used in this study, based on Tanaka et al. (2008), Wu et al. (2015), Fiori et al. (2016), and The Engineering ToolBox (2008), are summarized in Table 2. In these parameters, we assumed a Nissan Leaf as the EV [P2]. In addition, we prepared patterns with a good [P1] and poor [P3] energy consumption, because the cost of electricity is highly dependent on the aerodynamic drag coefficient. [P1] assumes a car with a modern design, whereas [P3] assumes a car with a traditional design (The Engineering ToolBox 2004).

Next, we assume the transfer power of the WPTS. Although there is no global standard amount of power to be transferred by an in-motion WPTS, existing



(a) [N1] Tokyo-Osaka (b) [N2] Tokyo-Aomori

Fig. 6 Visualization of the flow demand on the chosen networks

Table 2 Parameters for calculating the motor power

Parameters	[P1] Modern	[P2] Normal	[P3] Traditional
Speed of vehicle v [m/s]	22.22		
Acceleration/deceleration of vehicle a [m/s^2]	0		
Efficiency of the electric motor η [%]	90		
Vehicle weight (including the driver) m [kg]	1640		
Gravitational acceleration g [m/s^2]	9.8066		
Rolling resistance coefficient f_{rl}	0.015		
Air mass density ρ [kg/m^3]	1.2256		
Frontal area of the vehicle A_f [m^2]	2.34		
Aerodynamic drag coefficient C_D	0.20	0.32	0.50

studies assume a power output of 20–25 kW (Hata et al. 2019). In addition, when a vehicle is stationary, a wireless power transfer, such as that of WPT4, has been proposed (SAE J2954 Standard 2020). In this study, the transfer capacity is set to 22 kW with a transfer efficiency of 85%, resulting in a power output of 18.7 kW.

For the economic rationality, we used 10^8 yen, which is approximately [one million USD], considering the overall difference in exchange rates and prices, as the unit for calculating the revenue and cost (WSJ Markets 2022). The cost of installing 1 km of a WPTS is estimated to be 2.5×10^8 yen, as per previous studies (Fuller 2016) and Japanese domestic data (Shoki 2021). Regarding the cost of WPTS, this study follows these previous studies and considers only variable costs. Although considering fixed costs is undoubtedly preferable, fixed costs are largely dependent on substation facilities, which are often shared with other pre-existing power facilities. This implies that no additional fixed costs are associated with the installation of WPTSs, or if there are, no singular price can be determined. For the economic calculation, we compare the income and expenditures per year. We derive the annual value of 0.168×10^8 yen, assuming a 3% interest rate and 20-year depreciation period based on the distance of the WPTS installation.

The revenue is assumed to follow a pay-as-you-go system based on the amount of energy supplied. Using the algorithm proposed in Section 2, the amount of electricity that EVs require to recharge their batteries can be determined. By multiplying this amount by the cost of electricity, the operator's revenue can be calculated. Here, we assume an additional price of 50 yen/kWh, which is approximately equal to that of gasoline used by fuel vehicles, and assume that the diffusion rate of EVs is 30%.

Finally, for the battery capacity, we assume [U1] 40 kWh and [U2] 30 kWh. The former assumption is equivalent to that of the current Nissan Leaf. However, when WPTS becomes a major infrastructure, a decrease in the battery capacity is expected. Therefore, [U2] 30 kWh is considered in this study for a more realistic assumption of the WPTS usage.

3.3 Computational Experiments

The above network conditions and parameter settings can be summarized into two networks ([N1] and [N2]), three power-cost patterns ([P1], [P2], and [P3]), and two battery capacities ([U1] and [U2]), achieving a total of 12 scenarios. For all these scenarios, the optimal solution is calculated by iterating the total length of WPTS to be installed, increasing it by 20 km at each iteration until the entire demand is covered. We employ flow-based and origin-based formulations and address all the above scenarios. Gurobi 9.0 is used as the general MIP solver on a PC having four 3.1 GHz cores and 64 GB RAM.

Here, let us summarize the size of both the flow-based and origin-based formulations. The flow-based formulation has a total number of variables given by $|E| + |Q| + |Q| \times |N_q| + |Q| \times |E_q|$ (corresponding to x_{ij}, y_q, b_i^q, and g_{ij}^q, respectively), and the total number of constraints is $|Q| \times |E_q| + |Q| \times |N_q| + |Q| \times |N_q| + |Q| \times |E_q| + 1 + |Q| + |E| + |Q| \times |N_q| + |Q| \times |E_q|$ (corresponding to Eqs. (2)–(10), respectively). For the [N1] network, the number of variables is 112741 and the number of constraints is 280033. Similarly, for the [N2] network, the number of variables is 279515 and the number of constraints is 695575.

In contrast, for the origin-based formulation has a total number of variables given by $|E| + |Q| + |O| \times |N| + |O| \times |T_o|$ (corresponding to x_{ij}, y_q, b_i^o, and g_{ij}^o, respectively), and the total number of constraints is $|O| \times |T_o| + |Q| \times |N_q| + |O| \times |N| + |O| \times |T_o| + 1 + |Q| + |E| + |O| \times |N| + |O| \times |T_o|$ (corresponding to Eqs. (12)–(20), respectively). For the [N1] networks, the number of variables is 16593 and the number of constraints is 40491. Similarly, for the [N2] network, the number of variables is 30721 and the number of constraints is 75107.

These calculations confirm that the origin-based formulation significantly reduces the size of the problem compared with the flow-based formulation.

4 Numerical Results

4.1 Computation Time

Table 3 presents the time taken to obtain the solution and the percentage of the exact solutions for each WPTS installation distance. For example, in scenario [N1][P1][U1], the coverage reaches 100% at 180 km; therefore, we calculate nine patterns for the total length of the WPTS: 20 km, 40 km, 180 km, and so on. Table 3 shows the minimum, average, and maximum values of such patterns in the same scenario. Because we set an upper limit of 2 h for the solution, the exact solution is not obtained in some cases if the computational load is too high. Therefore, we also summarize how many times out of all distance patterns the optimal solution with a gap of 0.00% is obtained. The objective function values are confirmed to be the same between the flow-based and origin-based models.

Table 3 Computation time to solve the problem in each scenario

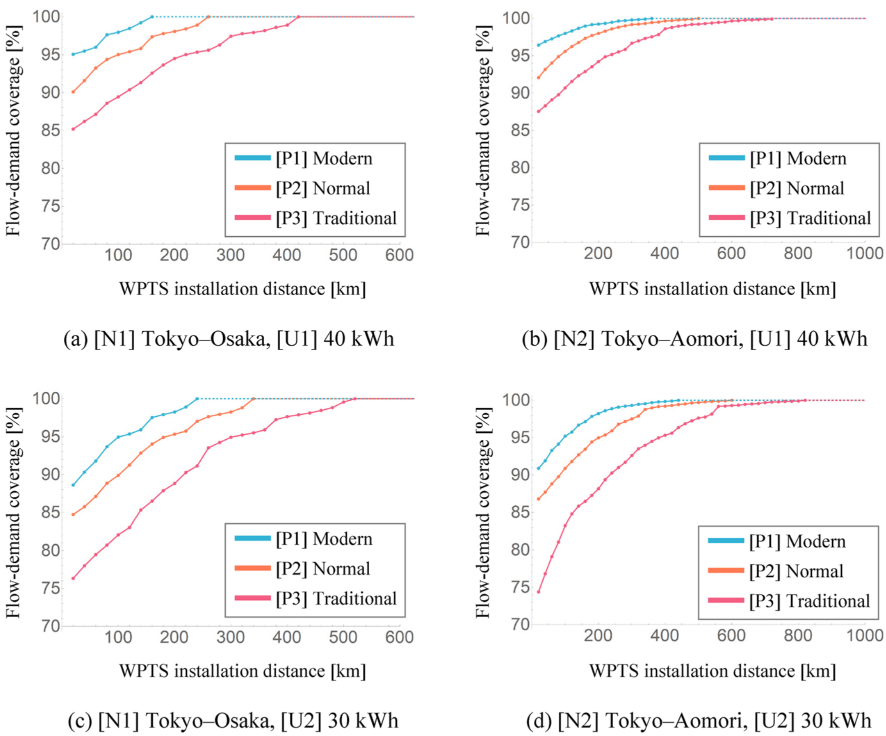
Entries	Origin-based model			Flow-based model		
	[P1] Modern	**[P2] Normal**	**[P3] Traditional**	**[P1] Modern**	**[P2] Normal**	**[P3] Traditional**
(a) [N1] Tokyo–Osaka, [U1] 40 kWh						
Min. [s]	0.17	0.45	0.59	2.14	11.58	11.32
Average [s]	1.13	3.46	7.97	3.53	14.03	33.72
Max [s]	1.79	6.15	27.7	5.55	19.92	96.91
Rate of the exact solution	100.00% (8/8)	100.00% (13/13)	100.00% (21/21)	100.00% (8/8)	100.00% (13/13)	100.00% (21/21)
(b) [N1] Tokyo–Osaka, [U2] 30 kWh						
Min. [s]	0.59	0.64	0.69	13.59	16.62	28.69
Average [s]	4.25	9.89	131.26	20.51	46.16	574.58
Max [s]	9.02	33.14	1894.1	35.63	129.68	6757.28
Rate of the exact solution	100.00% (12/12)	100.00% (17/17)	100.00% (26/26)	100.00% (12/12)	100.00% (17/17)	100.00% (26/26)
(c) [N2] Tokyo–Aomori, [U1] 40 kWh						
Min. [s]	1.30	1.65	2.56	33.37	100.90	138.42
Average [s]	17.28	64.31	706.91	115.75	316.67	1797.4
Max [s]	54.33	588.97	7200.00	300.48	815.71	7200.00
Rate of the exact solution	100.00% (18/18)	100.00% (25/25)	94.44% (34/36)	100.00% (18/18)	100.00% (25/25)	91.57% (33/36)
(d) [N1] Tokyo–Aomori, [U2] 30 kWh						
Min. [s]	1.78	2.08	2.17	161.87	147.36	151.55
Average [s]	88.13	1127.18	3349.68	527.02	2374.92	4172.69
Max [s]	515.01	7200.00	7200.00	2256.95	7200.00	7200.00
Rate of the exact solution	100.00% (22/22)	93.33% (28/30)	60.98% (25/41)	100.00% (22/22)	86.67% (26/30)	51.22% (21/41)

For [N1] Tokyo-Osaka, any [P] and [U], the exact solutions are obtained using both models. The origin-based model achieves the solution faster, consuming less than a quarter of the time for the flow-based model. In particular, for [N1][U1], any [P], the calculation is completed within 30 s, and exact solutions are obtained for all scenarios. Meanwhile, for [N2] Tokyo-Aomori, any [P] and [U], the computation time is longer for both models because of the increased number of origin–destination pairs, and the exact solution cannot be derived in some patterns. However, the exact solution is obtained for more cases with the origin-based model than with the flow-based model, which indicates the effectiveness of the former model. Because this study aims to maximize the coverage, the obtained solution guaranteed the low limit of the demand coverage and economic rationality.

4.2 Coverage of the Flow Demands

Figure 7 shows the coverage of flow demand as a function of the WPTS installation distance for all 12 scenarios. The coverage followed the order of [P1] Modern > [P2] Normal > [P3] Traditional, for any [N] and [U]. To clarify the influence of each assumption, Tables 4 and 5 summarize the results, which show different coverages at the same WPTS installation distance and different WPTS installation distances to achieve the same coverage, respectively.

Based on Table 4, the coverage ratio is approximately 5% lower for [U1] 40kWh than that for [U2] 30kWh, regardless of [N] and [P], under the same WPTS installation distance in any scenario. For example, the coverage ratio is 89.89% in scenario [N1][P2][U2] of 100 km, but the WPTS can cover 95.01% upon switching to 40 kWh, [N1][P2][U1] of 100 km. The difference in the drag coefficient has a considerable effect on the coverage, that is, the drag coefficient of [P3] Traditional is more than 10% lower than that of [P1] Modern, regardless of [N] and [U]. In scenario [N1] [P1] [U2] of 100 km, the coverage ratio is 94.94%; however, it reduces to 82.07% when [N1][P3][U2] of 100 km.



(a) [N1] Tokyo–Osaka, [U1] 40 kWh

(b) [N2] Tokyo–Aomori, [U1] 40 kWh

(c) [N1] Tokyo–Osaka, [U2] 30 kWh

(d) [N2] Tokyo–Aomori, [U2] 30 kWh

Fig. 7 Relationships between the wireless power transfer systems installation distance and coverage of flow demands

Table 4 Difference in coverage at the equal WPTS installation distance

	[U1] 40 kWh			[U2] 30 kWh		
	[P1] Modern	[P2] Normal	[P3] Traditional	[P1] Modern	[P2] Normal	[P3] Traditional
(a) [N1] Tokyo–Osaka						
0 km	93.78%	88.74%	84.42%	86.6%	81.99%	73.54%
100 km	97.96%	95.01%	89.44%	94.94%	89.89%	82.07%
200 km	100.00%	98.07%	94.5%	98.25%	95.32%	88.81%
300 km	100.00%	100.00%	97.43%	100.00%	98.25%	94.92%
400 km	100.00%	100.00%	98.9%	100.00%	100.00%	97.64%
500 km	100.00%	100.00%	100.00%	100.00%	100.00%	99.57%
600 km	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
(b) [N2] Tokyo-Aomori						
0 km	95.16%	91.19%	86.28%	89.36%	84.02%	70.61%
100 km	98.00%	95.58%	90.70%	95.20%	90.89%	83.25%
200 km	99.25%	98.00%	94.22%	98.22%	94.98%	88.16%
300 km	99.80%	99.18%	96.68%	99.31%	97.51%	92.59%
400 km	100.00%	99.67%	98.61%	99.84%	99.22%	95.32%
500 km	100.00%	100.00%	99.24%	100.00%	99.70%	97.62%
600 km	100.00%	100.00%	99.67%	100.00%	100.00%	99.29%
700 km	100.00%	100.00%	99.88%	100.00%	100.00%	99.69%
800 km	100.00%	100.00%	100.00%	100.00%	100.00%	99.90%
900 km	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Based on Table 5, the difference in battery capacity of 10 kWh is reflected in the difference in the required installation distance of 100 km or more. For example, the required WPTS distance to achieve 95% coverage is 100 km in scenario 40kWh [N1][P2][U1], but it increases to 200 km upon switching to 30kWh, [N1][P2] [U2]. Similarly, the difference in the drag coefficient has a considerable effect on the WPTS installation distance; that is, [P3] requires an installation distance that is more than 100 km worse than that of [P1], regardless of [N] and [U]. To achieve 95% coverage, the required WPTS distance is 120 km in scenario [N1][P1][U2] and 220 km in scenario [N1][P3][U2].

Finally, we examine the WPTS installation distance where 100% coverage is achieved with the combination of [P2] Normal and [U2] 30 kWh, which yields the most realistic assumption. The WPTS installation distance is 340 km for [N1][P2][U2] and 600 km for [N2][P2][U2]. This corresponds to approximately 40% of the total network extensions in both cases.

Table 5 Difference in the WPTS installation distance to achieve the same coverage

	[U1] 40 kWh			[U2] 30 kWh		
	[P1] Modern	[P2] Normal	[P3] Traditional	[P1] Modern	[P2] Normal	[P3] Traditional
(a) [N1] Tokyo–Osaka						
80%	0 km	0 km	0 km	0 km	0 km	80 km
85%	0 km	0 km	20 km	0 km	40 km	140 km
90%	0 km	20 km	120 km	40 km	120 km	220 km
95%	20 km	100 km	220 km	120 km	200 km	320 km
100%	160 km	260 km	420 km	240 km	340 km	520 km
(b) [N2] Tokyo–Aomori						
80%	0 km	0 km	0 km	0 km	0 km	80 km
85%	0 km	0 km	0 km	0 km	20 km	140 km
90%	0 km	0 km	100 km	20 km	100 km	240 km
95%	0 km	100 km	240 km	100 km	220 km	400 km
100%	360 km	500 km	720 km	440 km	600 km	820 km

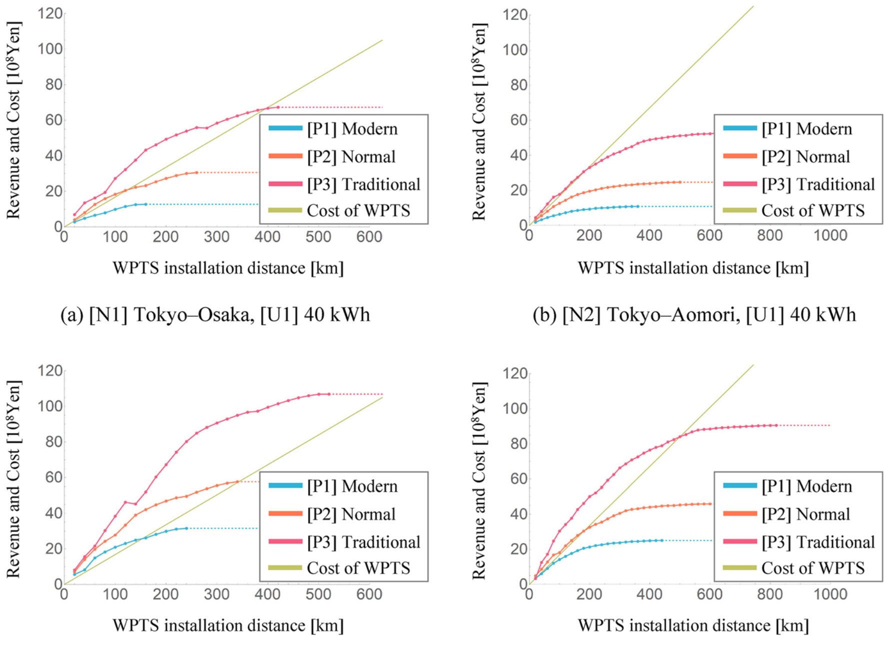
4.3 Economic Rationality

Figure 8 shows a comparison of the economic revenue and costs for all 12 scenarios with different parameter settings. The WPTS installation cost is given as a straight line because it is assumed to be constant and proportional to the installation distance, regardless of the scenario. If the revenue based on the user's charging power exceeds the projected WPTS installation cost, the project is deemed economically viable. As the revenue curve exhibits an upward convex, there is an appropriate WPTS installation distance that is economically viable in most scenarios.

Contrary to the coverage results, economic rationality is satisfied in the order of [P3] Traditional > [P2] Normal > [P1] Modern, regardless of [N] and [U]. This is because the revenue is assumed to be based on the amount of power provided to the EVs, and EVs with lower efficiency need to charge more. To demonstrate this difference clearly, Table 6 summarizes the distance ranges where the net revenue is positive for each scenario. The achieved coverage ratio at that distance is also described. For [P1] Modern, economic rationality requires [U2] for both [N1] and [N2]. For [P3] Traditional, a broad range of WPTS installation distances satisfies the economic rationality for any [D] and [U]. These results indicate that WPTS should be combined with other approaches to reduce the battery capacity of EVs.

4.4 Optimal Locations

Figure 9 shows the WPTS locations that achieved the coverages of 100% and 95% under the most realistic combination of [P2] Normal and [U2]30 kWh, for both [N1] and [N2]. Note that the flow demand here is based on the direction, and Japan is



(a) [N1] Tokyo–Osaka, [U1] 40 kWh

(b) [N2] Tokyo–Aomori, [U1] 40 kWh

(c) [N1] Tokyo–Osaka, [U2] 30kWh

(d) [N2] Tokyo–Aomori, [U2] 30 kWh

Fig. 8 Economic rationalities under various scenarios

a left-hand drive traffic area. The upstream and downstream traffic have different optimal locations. In long-distance travel, while traveling from one end of the highway to the other, the latter part of the travel will coincide with the latter part of the highway. In such cases, WPTS will be used during the latter part of the travel, when the onboard battery capacity will be insufficient. Therefore, it is optimal to install WPTSs continuously with a coverage of 100%, mainly in the latter part of the network. However, for shorter trips, the latter part of the trip will not necessarily be the latter part of the highway. Therefore, the WPTSs will need to be scattered all over the highway, not necessarily in its latter part, for a coverage of 95%. Figure 6 describes that these flows account for most of the demand. The results indicate that the optimal configuration greatly differs depending on the direction and percentage of demand to be covered.

5 Discussion

5.1 Potential of WPTS

Based on the results of the numerical experiments, coverage and economic rationality vary reasonably depending on the scenario, as shown in Tables 4 and 5. In particular, the EV performance (battery capacity and/or drag coefficient) has a significant effect, causing the WPTS installation distance to fluctuate by more than 100 km. For example, 520 km is needed for complete coverage in scenario [N1][P3][U2], whereas only 340 km is required if switched to [N1][P2][U2] and 420 km if we switched to [N1][P3][U1]. Overall, WPTS exhibits sufficient potential as an EV power-supply system. Particularly, WPTS demonstrates economic rationality not only in busy networks, such as [N1] Tokyo–Osaka, but also in relatively sparsely populated networks connecting urban and rural areas, such as [N2] Tokyo–Aomori.

The numerical results indicate that [P1] Modern and [P2] Normal do not pay off financially because the WPTS assumes that the user is charged only for the amount of recharging. However, if the system collects the basic usage fee, there is a good possibility that economic rationality can be established even for [P2] Normal. Consequently, these results indicate that the WPTS has the potential to become a major infrastructure catalyst for the large-scale diffusion of EVs.

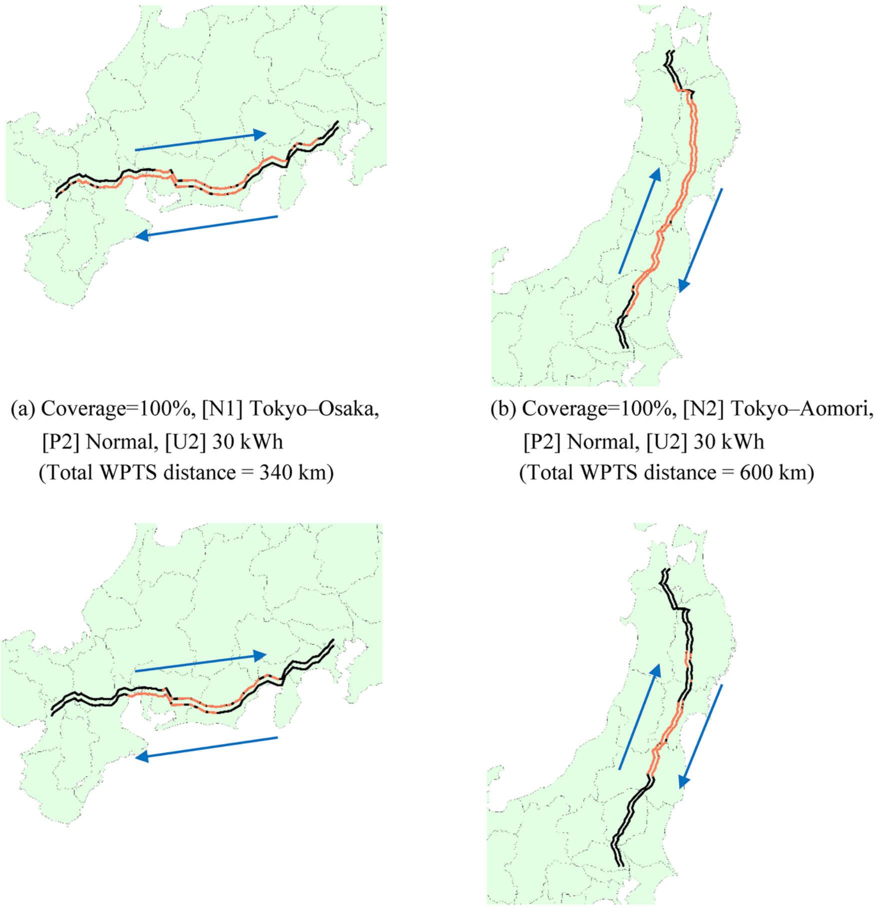
Nonetheless, the sole use of WPTSs as EV infrastructures imparts limited potential. In particular, it is more realistic to use WPTS in combination with EV recharging stations. This is clearly confirmed by the length of the new WPTS installation distance with a positive net revenue. Table 6 shows that economic rationality was not achieved with 100% coverage in most scenarios. Thus, the use of WPTS to cover 100% demand is not an economical approach. It is important to determine a good balance between the demand that should be covered by the WPTS and that by EV recharging station infrastructures. We also describe the variations of the optimal locations when the required coverage changes using our model, which is formulated as a flow-capturing location problem. These discussions highlight the importance of appropriately setting the coverage target of WPTS.

5.2 Multiple Optimal Solutions of the WPTS Locations

In this study, we formulate a mathematical model to derive the optimal locations with flexibility. Figure 10 illustrates a simplified example to demonstrate the flexibility of the WPTS locations, considering an EV with a battery capacity less than that needed to complete the trip. In this case, they can charge either in the early or

Table 6 Distance ranges and coverages with positive net revenue

	[U1] 40 kWh			[U2] 30 kWh		
	[P1] Modern	[P2] Normal	[P3] Traditional	[P1] Modern	[P2] Normal	[P3] Traditional
[N1] Tokyo–Osaka	-	20–120 km (90.08–95.39%)	20–380 km (85.18–98.60%)	20–140 km (88.61–95.91%)	20–340 km (84.72–100%)	20–520 km (76.33–100%)
[N1] Tokyo–Aomori	-	-	20–180 km (87.55–93.53%)	20–20 km (90.89–90.89%)	20–180 km (86.79–94.43%)	40–500 km (76.82–97.62%)



(a) Coverage=100%, [N1] Tokyo–Osaka, [P2] Normal, [U2] 30 kWh (Total WPTS distance = 340 km)

(b) Coverage=100%, [N2] Tokyo–Aomori, [P2] Normal, [U2] 30 kWh (Total WPTS distance = 600 km)

(c) Coverage≈95%, [N1] Tokyo–Osaka, [P2] Normal, [U2] 30 kWh (Total WPTS distance = 200 km)

(d) Coverage ≈ 95%, [N2] Tokyo–Aomori, [P2] Normal, [U2] 30 kWh (Total WPTS distance = 220 km)

Fig. 9 Optimal Locations of the wireless power transfer systems for [P2] Normal and [U2] 30 kWh

late parts of the trip. In reality, the locations of the WPTSs should be common for all feasible flows q, resulting in a limited flexibility but lenient conditions that allow more than one unique location to be determined. This characteristic is not limited to our mathematical model and is similar to earlier models of the charging station locations of alternative fuel vehicles (Kuby and Lim 2005; Struben 2006). However, unlike earlier models, such as FRLM, our mathematical model controls the locations of WPTSs using continuous variables and assumes the feasibility of demands as a one-way trip, resulting in multiple optimal solutions.

In this study, it is not possible to uniquely determine which of these possible locations is preferable because various factors need to be considered. For example,

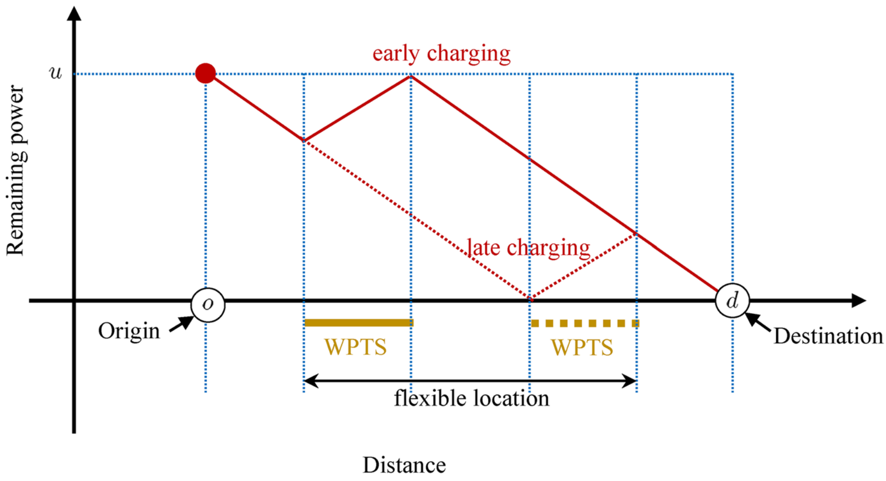


Fig. 10 Simplified example to demonstrate the flexibility of the wireless power transfer systems locations

considering two possible WPTS locations: one with more overlap in the upper and lower lines, whereas the other has less overlap, it is difficult to determine which of these configurations is preferable. In the construction phase, it may be easier to work if the WTPS on the upper and lower lines are close to each other. However, the WTPS overlapping of the upper and lower lines indicates the convergence of the power supply in spatial aspects. As the WPTS supplies a large amount of power to the vehicles, excessive convergence of power supply may overload the power network. Therefore, in terms of the power supply, it may be preferable to distribute them. In terms of the vehicle, it may be more convenient to have WPTSs near the end of their trip, rather than having them immediately after their origin. In any case, it is not easy to determine which of these scenarios is preferable.

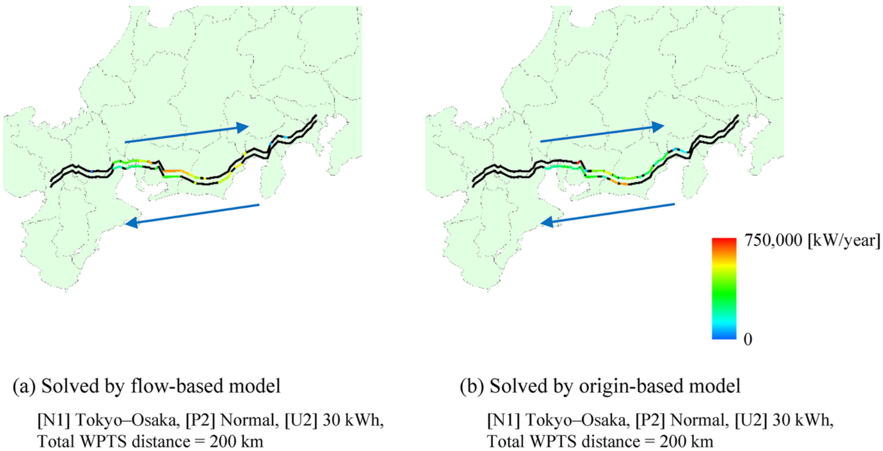


Fig. 11 Flexibility of the wireless power transfer systems locations

The flexible installation of the WPTS provides implications for its future integration with intelligent transportation systems (ITS). As an example, Fig. 11 illustrates the optimal locations of WPTS based on the flow-based and origin-based models. The models achieve different locations owing to the locational flexibility; however, we confirm that both approaches obtained equal optimal values (demand coverage), suggesting an equal set of feasible flows. The heat map, and location and mode of charging obtained based on the algorithm in Section 2.3, are visualized. The power supply has clearly different spatial distributions. This spatial distribution of the power heat map also has some flexibility. In particular, there are two flexibilities: WTPS location and recharging pattern. As the WPTSs are installed over long distances, each EV does not have to be recharged at all WPTSs along the trip. If the battery capacity and power management condition of avoiding power shortage are satisfied, they can recharge at any location with the WPTSs. As the algorithm in Section 2.3 is based on the assumption that the EV charges as early as possible, the results of the heat map are expected to be different if the EV charges as late as possible. These results demonstrate favorable characteristics for ITS systems by allowing significant control on the impact on the power system through the flexibility in the WPTS locations and power supply pattern of EVs. These discussions should be considered for the design of WPTS infrastructures to achieve an ITS society focused on EVs.

6 Conclusions

In this study, we propose a new flow-capturing location problem for charging EVs in-motion using inductive wireless power transfer systems. The model makes important theoretical and methodological contributions by formulating it using continuous decision variables to represent the length of WPTS to be built on each link. This enables the model to find lower cost solutions than are possible when WPTS must be built on an entire link or none of the link while making it possible to solve the problem using a general MIP solver. Assuming long-distance trips following their shortest paths, we convert the problem to an origin-based, maximum cover formulation, which enables faster computation than original flow-based formulation and greater flexibility than a complete coverage formulation. An algorithm to calculate the amount of energy required for each flow demand is also designed.

Using the model, we analyze the effectiveness of the WPTS in Japan's expressway network. We demonstrate that WPTS has economic rationality not only in busy networks but also in sparsely populated networks that connect urban and rural areas, which contributes to the first finding in WPTS location analyses. Given the complex tradeoffs among the distance of the WPTS installation, demand coverage ratio, and net revenue, WPTS has a positive potential as an EV infrastructure under certain scenarios. It is cost-effective to narrow down the demand to be covered, but full coverage of the entire expressway system by WPTS is not economically advisable. The analysis highlights the limitations of relying on WPTS alone for EV infrastructures, thereby providing useful insights for stimulating the mixed use of WPTS and plug-in charging stations. The results here also highlighted the flexibilities for the optimal location of WPTS and the resulting heat map of the amount of electricity supplied to EVs, which can aid decision-makers in developing an effective WPTS network design for widespread use of EVs with uneven distribution of electricity supply.

In the future, an analysis assuming the mixed use of WPTSs and EV recharging stations is essential. As shown in Fig. 2, each infrastructure has complementary characteristics; thus, it is favorable to determine the best mix strategy according to demand and network geometry. EV recharging stations are less expensive to install but cannot handle high demand; WPTSs are more expensive to install but can handle higher demand. Such integration of EV charging stations will influence the economic rationality of WPTSs. While the availability of EV stations could reduce WPTS usage by providing an alternative charging solution, they could paradoxically enhance the number of WPTS users by making long-distance EV trips more feasible. Detailed analyses based on the combined use of both WPTS and EV stations will yield a more accurate understanding of the economic rationalities for both WPTS and EV stations. In that case, more perspectives on electricity capital investment must be included, such as fixed costs due to substation facilities, which are not considered in this study.

Further, focus also should be placed on the long-term time series of gradual increases in EV penetration. Our study underscores the formulation concept, data structure, and basic properties of the optimal WPTS location, as outlined above. Note that the resulting model is static and deterministic, lacking explicit consideration of the time horizon concept. In the real world, over the depreciation period of 20 years for the WPTS, both EV penetration and demand will invariably evolve. Modifying the proposed model to account for these medium and long-term temporal aspects presents an appealing avenue for future research. In such a development, creating a spectrum of future scenarios and conducting Monte–Carlo simulations would be beneficial.

The accurate prediction of the power consumption while moving is also an important issue that should be addressed. Our model assumes no uncertainty in power consumption. This is synonymous with the assumption that the EV driver can perfectly predict power consumption and power requirements. Thus, EV drivers can opt to charge earlier, which can be achieved considering the flexibility of the locations of the WPTS. However, in practice, power consumption fluctuates depending on the acceleration/deceleration, road conditions, weather, and other factors. Moreover, it is difficult to determine when the drivers want to charge the batteries. These uncertainties in the power charging behavior should be considered as an extension of the proposed model. In terms of economic rationality, it is important to incorporate a structure with a demand that fluctuates with the price of electricity. In this study, the demand is fixed regardless of the amount of power needed to be supplied by the WPTS, whereby a higher power requirement for a smaller battery capacity and higher aerodynamic drag is found to be more profitable. However, in reality, the demand for mobility in this scenario can be reduced if more power is supplied, and its cost can be higher. As the price of electricity also varies depending on the location and time of day, it will be interesting to elaborate on these assumptions in future works.

We foresee the application of WPTS extending to freight trucks in the future, potentially providing a low-carbon solution for the logistics sector. While this study focused on passenger EVs, we acknowledge the potential for analyses that concurrently consider a variety of vehicle types, including electrically powered freight trucks. This study has the potential to serve as a foundation for more in-depth discussions on the social implementation of WPTS.

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Data Availability The data that support the findings of this study are available from the corresponding author upon request.

Code Availability Not applicable.

Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Informed Consent Obtaining informed consent was not applicable as the study did not involve any humans.

Research Involving Human Participants and/or Animals Ethical approval was not applicable as the study did not involve any humans or animals.

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