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# Multipurpose Charging Schedule Optimization Method for Electric Buses: Evaluation Using Real City Data

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**ABSTRACT** The use of electric vehicles (EVs) and photovoltaics (PV) is increasing worldwide. Transportation networks require the effective use of renewable energy (RE) for EVs, whereas power networks require local consumption of PV energy, mainly at the initiative of local governments. Although many previous studies have addressed these requirements using private EVs as mobile storages, their uncertainty and uncontrollability remain highly problematic. Therefore, our previous studies focused on electric buses because of their high controllability and certainty. These studies involved the development and evaluation of two independent minimization problems—kilowatts (KW) and kilowatt-hours (KWH) of surplus RE—as a charging schedule optimization method using mixed integer linear programming. However, the feasibility of simultaneously minimizing KW and KWH still presented technical problems. This study aims to extend and generalize the method to the simultaneous minimization of KW and KWH of the PV-derived reverse power flow (RPF). With this multiobjective optimization, the KW peak-cut of the RPF improves the hosting capacity and increases the availability of connectable RE resources, whereas the minimization of KWH promotes the local consumption of RE and decarbonization of public transportation. Two simulations using detailed data of actual bus operations and actual power flow data for a real city confirmed the feasibility of simultaneously optimizing KW and KWH and the relationship between these indicators and number of EV chargers. The optimized charging of the 17 electric buses achieved a maximum of 211.4 kW peak-cut and 1318.4 kWh RE-RPF absorption, reducing CO<sub>2</sub> emissions by 495.7 kg/day.

**INDEX TERMS** Charging control, electric bus, mixed integer linear programming, multiobjective optimization, photovoltaic, reverse power flow, sector coupling, smart city.

## I. INTRODUCTION

### A. MOTIVATION

In recent years, the electrification of transportation, such as electric vehicles (EVs), has attracted attention as a measure for smart cities to realize a decarbonized society. The sustainable development scenario [1] aims to attain a 30% market share for EVs in all modes except two-wheelers by 2030. These vehicles are powered by energy they receive in the form of electricity from a power distribution system

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through EV chargers. The EV chargers create connections between power and transportation networks, which influence each other. In such a scenario, the challenge for transportation networks is to achieve decarbonization considering the life cycle of EVs. This requires lowering the CO<sub>2</sub> emissions during EV operation, which in turn requires the effective use of renewable energy (RE) to charge these EVs [2]. Conversely, the surplus photovoltaic (PV) power resulting from the increased penetration of power networks by PV power may cause reverse power flow (RPF) at the scale of distribution substations in some areas. Surplus power in excess of the allowable current in distribution and special

high-voltage lines could cause RPF to become a constraint on new RE connections in the future. In addition, from the perspective of administrative bodies, local governments aim to localize RE production and consumption to efficiently circulate energy within their regions and revive their local economies. This has the added benefit of reducing the costs and losses associated with long-distance power transmission, from the perspective of power networks. Thus, the need exists to increase energy storage facilities to utilize RE effectively, but the investment cost is expected to be discouragingly high [3].

The purpose of our research is to effectively utilize data from both the electric power and transportation sectors to realize an optimized smart city via sector coupling rather than following the conventional approach of optimizing individual sectors. This takes cognizance of the increasing importance of data-driven sector coupling that combines multiple sectors to establish a decarbonized society [4].

## B. RELATED WORK

Several studies have been conducted on the effective use of EVs as mobile storage resources to address the aforementioned problems. For example, the coordination between EVs and the power grid was studied, and vehicle-to-grid (V2G) experiments were conducted on the hardware side [5]–[7]. The demand response potential was estimated by analyzing the charger data to evaluate the contribution potential of EVs to the grid [8]. A home energy management system that optimizes EV charging with high robustness based on the predictions of EV status was proposed for use at the household level [9]. Furthermore, considering the mobility characteristics of EVs at the city scale, the movement of EVs at the city level was simulated by generating virtual vehicles [10], [11] to evaluate their impact on power distribution systems and to plan the optimal placement of charging facilities, for quick charging by the public.

However, the above-mentioned studies focused on private EVs, which are used for different purposes. In other words, different EV owners have different lifestyles and usage patterns. Based on human intentions, the behavior of these privately owned EVs is associated with greater uncertainty and randomness than the prediction of PV power generation, which depends on natural phenomena, such as weather conditions. Hence, the prediction uncertainties and aggregate control difficulties are remaining technical challenges that need to be addressed for grid coordination using these EVs [12]. A method capable of shifting the charging timing of EVs using an auction mechanism was proposed to address the above challenges [13]. This robust system can reduce the curtailment of PV generation while guaranteeing autonomy and fairness to EV owners. However, they concluded that in cases where EV charging shifts do not occur as expected because of the aforementioned technical issues, a reduction in the effectiveness compared to the ideal case is unavoidable.

Therefore, we focused on the electrification of public fixed-route buses. They have three advantages over private

EVs in terms of the effective use of storage capacity: they are actively electrified at the request of the government, they have high certainty owing to regular operation based on timetables, and one owner can centrally control many buses. Nevertheless, compared to grid-dedicated storage batteries, buses are disadvantaged in that they may experience operational disruptions owing to power shortages and cannot be recharged while running. This motivated our study, which involved the development of a charging schedule control method that accounts for the controllability and constraints of electric buses.

However, few previous studies on electric buses consider both electric power and transportation networks simultaneously and/or are based on actual bus operation data. Previously, the operation route was optimized, a charging schedule created, and a cost curve fitted to satisfy the transportation demand of bus operators and realize low-cost charging. However, the problem was not approached from the viewpoint of the electric power network or the rate at which buses use RE [14]–[18]. In terms of data, simple models based on only round-trip buses were used, whereas other researchers used the charging history [18]. Encouragingly, recent research has begun to consider coordination with power networks. For example, a spatiotemporal arrangement plan was proposed for charging facilities that consider power network constraints and transportation network demands in the gradual diffusion of electric buses [19]. In addition, the use of electric buses for disaster recovery was considered against the background of their original research on the security of electric power networks [20], [21], [22]. This method uses surplus buses as grid storage batteries to gradually restore the transportation network, considering possible damages to both the electric power and transportation networks after a disaster. Thus, even the latest studies [19], [20], [21], did not consider optimizing the daily charging schedule of electric buses in coordination with the power network based on daily operation data.

## C. AUTHORS' PREVIOUS STUDIES

We have been researching regional energy management using electric buses to realize a smart city that promotes the effective use of RE. This led us to reproduce a spatiotemporal operation model of a daily bus using the general transit feed specification data format (GTFS) [23], which is an open data format containing data of actual bus operations. GTFS has become the de facto standard for bus operation data in recent years, and new ways of utilizing these data are being studied. Subsequently, based on the formulated bus operation model, we studied the optimization of the charging schedule using mixed integer linear programming (MILP). The energy storage capacity of the public bus fleet is constrained by the need to comply with operational requirements. The necessity is to create an optimal charging schedule that considers the times of day and amounts of power required for the transportation network and, conversely, when and how much on-board battery capacity remains available for the power

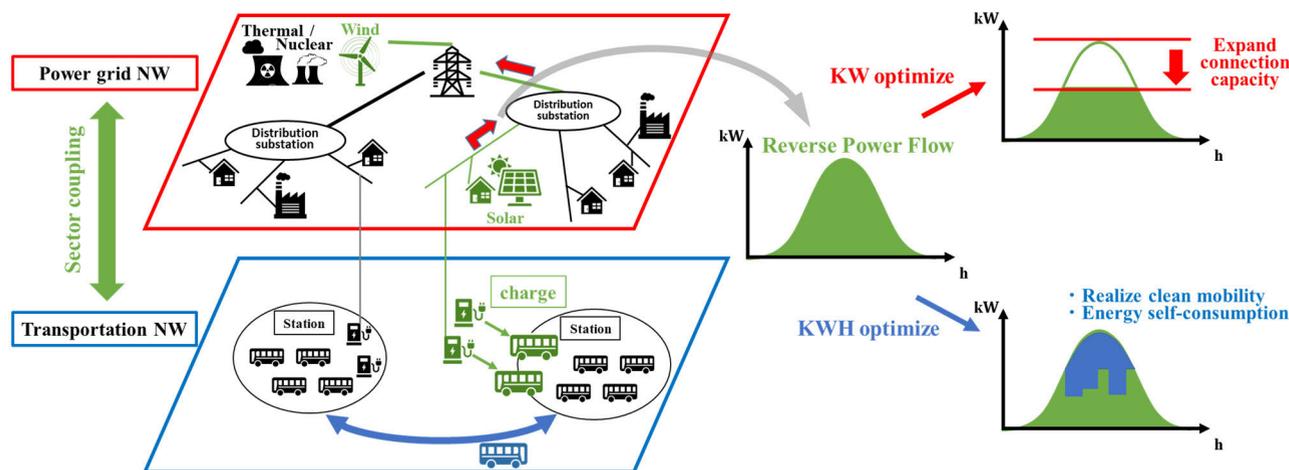


FIGURE 1. Concept of the sector coupling of the electric power and transportation networks.

network. First, in our initial study [24], bus charging was optimized to take place as much as possible during the daytime, as constrained by the operational requirements, and it showed the possibility of the PV absorption effect by electric buses. In a subsequent extension of the study [25], we mainly focused on the RPF kilowatt (hereinafter referred to as “KW” to distinguish it from the unit “kW”) peak-cut as a min-max problem on real distribution lines connected to charging stations from the perspective of the power network. In contrast, our next study [26] mainly focused on minimizing the surplus kilowatt-hours (hereinafter referred to as “KWH” to distinguish it from the unit “kWh”) when the PV is installed directly at each charging station from the bus operator’s perspective as an area minimization problem.

Although these studies demonstrated the potential of electric buses in terms of the expectation of each network, the results [25] showed that the optimization of KW does not always result in the optimization of KWH or vice versa [26]. However, as KWH is calculated using the time integration of KW, these indices are related in nature, and the improvement of one will affect the other. Accordingly, the possibility of achieving simultaneous optimization is high.

**D. CONTRIBUTIONS**

This paper summarizes the present authors’ previous papers [25], [26], [27], and generalizes the two independent charging schedule optimization problems as simultaneous optimization methods for the KW and KWH of the RPF and formulates them using MILP. In the simulation, the daily spatiotemporal behavioral patterns of 10% of the buses (17 buses) owned and operated by a single bus company in the target city were reproduced from the GTFS. Then, based on the actual RPF data of the connected distribution system in [27], we evaluate the effect of simultaneously minimizing the power (KW) and energy (KWH) of the RPF produced from RE. The contributions are twofold:

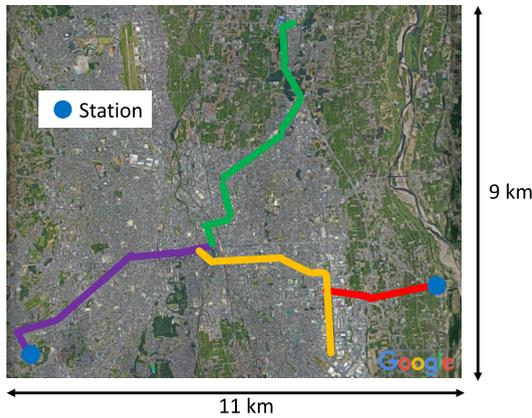
- ① To lay the foundation for an energy management system that utilizes the GTFS bus operation data. Electric buses have the advantages of high reliability and central controllability, and have been the focus of attention in recent years as moving storage batteries. By optimizing the charging schedule based on the accumulated data, it will be shown that these buses can be a very large energy storage resource.
- ② To contribute to the realization of a clean smart city that promotes the effective use of RE. In the proposed multiobjective optimization, the KW peak-cut of the RPF improves the hosting capacity by reducing congestion in the distribution system and expands the amount of RE that can be connected. In contrast, the minimization of the KWH of the RPF promotes the local production and consumption of RE and realization of clean public transportation by increasing the RE ratio of electric buses. (Fig. 1)

**E. ORGANIZATION OF THIS PAPER**

The remainder of this paper is organized as follows. Section II introduces the two charging schedule optimization case studies as a summary of our previous research [25], [26]. Section III presents our proposed method for the multiobjective optimization of electric bus charging schedules. The two simulation examples and simultaneous evaluation of optimization results are presented in Section IV. Finally, Section V summarizes the study.

**II. AUTHOR’S PREVIOUS CASE STUDIES**

In this section, the authors’ previous work [25], [26] is introduced as a prerequisite for this study. First, the actual method to analyze the bus operation data and its results, which are also used in this study, are introduced. Next, two case study scenarios for bus charging schedule optimization based on the analysis are presented.



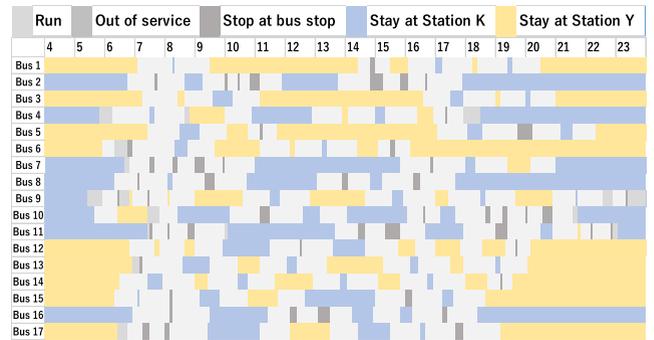
**FIGURE 2.** Example of a daily route analyzed for a single bus. Each colored line indicates one route, i.e., this bus operates on four different routes in one day.

**A. ANALYSIS OF ACTUAL BUS OPERATION DATA**

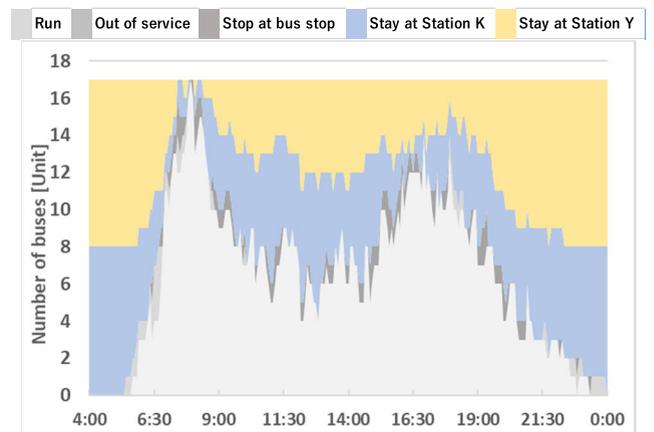
The target city for this series of studies is Utsunomiya City in Tochigi Prefecture, Japan. Data from nearly 10% of the 164 buses (17 buses) belonging to a single bus operator in the city were collected. This method uses the GTFS-compliant data and offers a standard method that can be used in other regions using the same data format.

The GTFS [23] in Japan has static (GTFS-JP) and dynamic data (GTFS-RT) [27], [28]. We use the GTFS-JP data including the bus timetables, route information, and latitude and longitude information of bus stops to estimate the journey distance of each route and to link it to the timetable. Then, using the GTFS-RT data, we obtained real-time data of bus operations on a weekday, and the spatiotemporal daily movements of each bus were simulated by connecting the individual bus information with the timetable. The daily movement of each bus thus obtained is shown in Fig. 2, which depicts an example of the route of a particular bus. As in this example, rather than involving a simple round trip, the daily movement of a bus includes multiple routes.

The available charging time and available charging capacity were calculated based on the simulated spatiotemporal movement of the buses. To determine the available charging time, stops used for long breaks and stays, such as at sales offices and garages, were assumed to be charging stations and distinguished from other stops. In this study, the two charging stations are Stations K and Y. The bus schedule was prepared such that the buses could charge during their stay at these stations. The results are shown in Fig. 3. The bus characteristics such as break timings, and the duration and location of each stay differ for each bus. This result is represented by a 0-1 binary parameter  $S_{m,j}(t)$ : “bus  $j$  can charge at station  $m$  at time section  $t$  (true = 1)” and is used as the spatiotemporal charging constraint in the optimization. In addition, Fig. 4 shows the overall trend during bus service hours. The peak time for staying at a bus station is during the daytime. In other words, it is suggested



**FIGURE 3.** Analyzed schedule of each bus operation. Each row shows the daily schedule for one bus. Light blue and light yellow indicate the available charging time at Station K and Station Y. Both run and out of service are the running states.



**FIGURE 4.** Number of buses in each state.

that there is an affinity for PV, which has its generation peak during the daytime. The next step was to analyze the energy consumption schedule of each bus to estimate its chargeable capacity. The route information in the GTFS data was used to map the stations traversed along each route and to calculate the distance traveled. On multiplying the distance traveled by the electricity usage rate, which is constant in this study, the amount of energy consumed to service each route is calculated. An energy consumption schedule for each bus is then created by dividing the energy consumption for each route by the number of travel time sections per trip. This result is represented by the parameter  $L_j(t)$ : “operating energy consumption of  $j$  at  $t$ ” and is used to calculate the state of charge (SOC) of each time section during the optimization calculation to estimate the amount of available charging capacity.

In Section II-B, two scenarios are presented as simulation cases using the analysis results of these bus operation data. In both cases, the optimal charging schedule is determined using MILP with the bus operation schedule as a constraint. The common conditions of both scenarios, such as bus specifications and charger performance, are listed in Table 1.

TABLE 1. Simulation common conditions.

Specifics of EV chargers	Output	50 kW
	Charge efficiency	98%
Specifics of electric buses	Number of buses	17 buses
	Battery capacity	79 kWh
	Electricity cost	0.94 km/kWh
SOC condition	Charge start time	4:00 a.m.
	Charge end time	1:30 a.m.
	Lower / Upper limit	10% / 90%
Evaluation period	Whole day (24 h: every 5 min from 4 a.m. to next day's 4 a.m.)	
Programming language / Solver	GAMS / CPLEX	

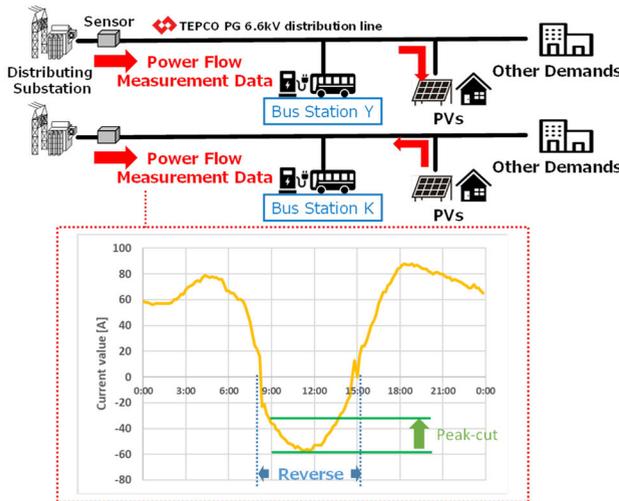


FIGURE 5. Diagram of Scenario I and power flow data.

**B. SCENARIO I: PEAK-CUT OF THE REVERSE POWER FLOW IN THE DISTRIBUTION SYSTEM [25]**

In Scenario I, from the perspective of the power network, peak-cut of the RPF was conducted to eliminate the capacity pressure on the distribution line caused by the RPF and expand the number of newly available connections for RE. The availability of new RE connections was determined by the annual maximum RPF (KW). Therefore, the peak cut of the RPF is necessary to maximize the PV capacity in the future.

**1) SETTING UP THE PROBLEM**

In this scenario, power flow data obtained from an automatic switch with built-in sensors at the root of the distribution lines were used for two 6.6 kV distribution lines connected to the two stations K and Y described in the previous section. A simulation of the RPF peak-cut was conducted for one sunny weekday in autumn. An important feature of the power flow data is that the RPF occurs only at Station K. This means that during the daytime, spatial optimization was also performed to prioritize charging at Station K. A conceptual diagram of this process is shown in Fig. 5.

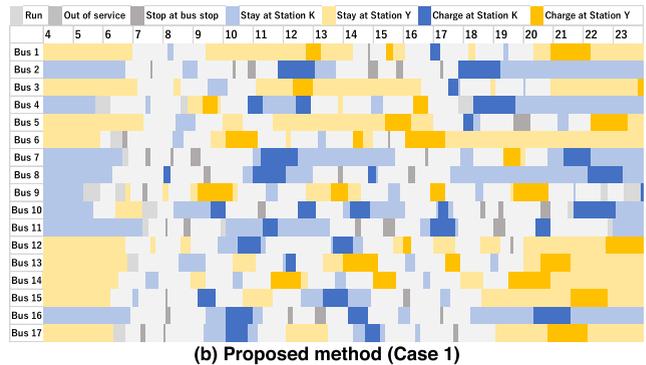
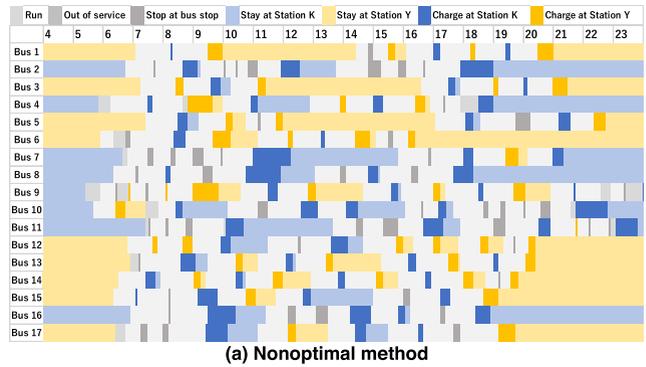


FIGURE 6. Determined charging schedule using each method. Dark blue and orange indicate charging at Station K or Station Y.

TABLE 2. Simulation cases of Scenario I.

	No. of EV charger at 2 stations	Charging management method	Initial SOC optimization
Nonoptimal	3 each	Charge on arrival	-
Case 1	3 each	Proposal	-
Case 2	4 each	Proposal	-
Case 3	4 each	Proposal	+

**2) OPTIMIZATION METHOD AND SIMULATION CASES**

A charging schedule optimization problem for electric buses using MILP was formulated as a min-max problem to minimize the maximum value of RPF to achieve the KW peak-cut of the RPF [25, eq. (1)]. Simulations were performed using the problem setup described in 1) to verify the effectiveness of this optimization method. In addition, simulations, such as a parameter survey, were conducted of the number of EV chargers installed and the initial SOC value of bus optimization to achieve a further KW peak-cut [25]. This paper presents the simulation results of four cases, including one representative case of the parameter survey. The conditions for each case are presented in Table 2. The nonoptimal case is a standard comparison case in which charging starts upon arrival and is uncontrolled. Case 1 has the same condition as the nonoptimal case, but includes the optimization method, Case 2 simulates the number of chargers optimized by the parameter survey, and Case 3 simulates the initial SOC value optimized for each bus.

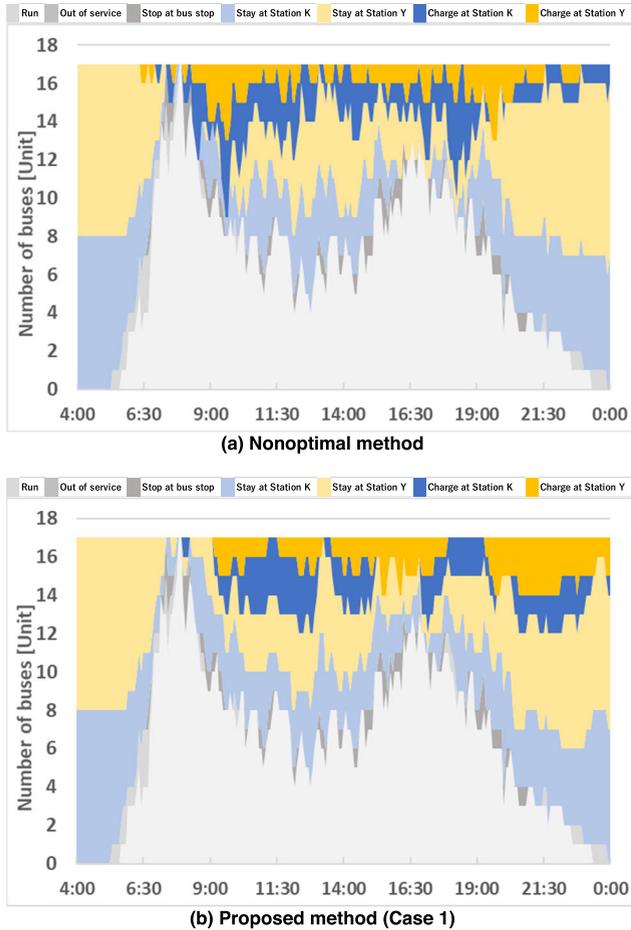


FIGURE 7. Change in number of buses in each state in each case.

### 3) SIMULATION RESULTS

First, the change resulting from the optimization is verified by comparing the nonoptimal case and Case 1, where the conditions are equal except for the charging method. Figs. 6 and 7 show the results of adding the charging behaviors to Figs. 3 and 4, respectively. In Fig. 6, the optimization of the charging schedule only selects the optimal charging timing among the available charging times and does not affect the driving schedule. In Fig. 7, the charging waveforms (dark blue and orange) are different in the two cases. In particular, the amount of charging before 9:00 and at approximately 19:00 decreases, and that between 10:00 and 14:00 increases. The changes in the RPF at Station K for each case are shown in Fig. 8. The maximum RPF value in the original case is 596.28 kW, whereas it decreased to 519.72 kW in the nonoptimal case, resulting in an improvement of 76.56 kW (12.8%) in the uncontrolled charging. Furthermore, by increasing the number of chargers in the optimization method (Case 1 to Case 2) and optimizing the initial SOC value for each bus (Case 3), the maximum value was reduced to 399.72 kW, a reduction of 196.56 kW (33.0%). In other words, the pure KW improvement from optimization was  $196.56 \text{ kW} - 76.56 \text{ kW} = 120 \text{ kW}$  ( $33.0\% - 12.8\% = 20.2 \text{ pt}$ ).

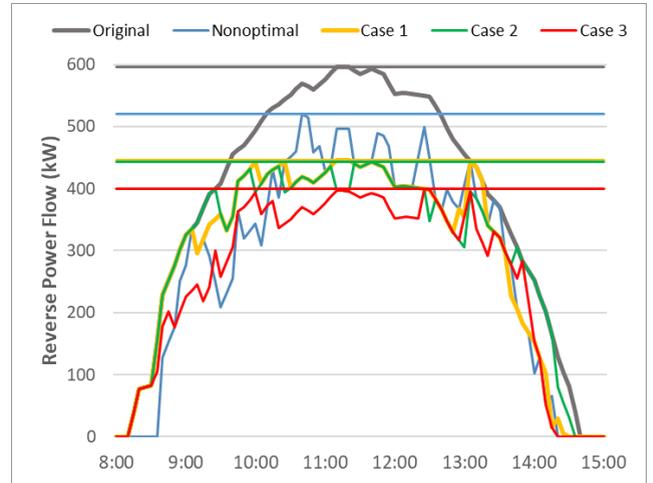


FIGURE 8. RPF waveform and maximum RPF in each case.

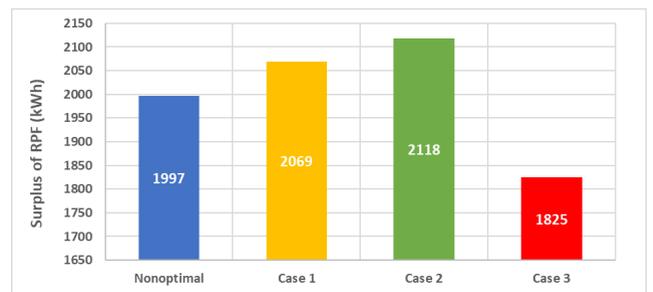


FIGURE 9. Evaluation of the surplus of RPF in each case.

In contrast, the results for KWH, which were not considered in this optimization, are shown in Fig. 9. Even though the evaluation of KW is superior to the nonoptimal evaluation in all cases, the KWH of surplus RPF is 72.5 kWh higher in Case 1 and 120.9 kWh higher in Case 2 compared to the nonoptimal case. The KW-only optimization works only on the daily RPF peak; therefore, once it is determined that the peak cannot be reduced any further, no further RPF utilization is actively pursued. Therefore, KWH cannot be optimized by optimizing KW using a min-max problem.

### C. SCENARIO II: MINIMIZING THE SURPLUS ENERGY OF PV DIRECTLY INSTALLED IN A CHARGING STATION [26]

In Scenario II, the minimization of PV surplus KWH with PV at the charging stations was studied from the bus operator's perspective of the transportation network. This is necessary to increase the RE-derived electricity use of buses and achieve clean public transportation.

#### 1) SETTING UP THE PROBLEM

In this scenario, PV is installed at two stations, K and Y, to minimize the surplus KWH and maximize self-consumption. An overview of this is shown in Fig. 10. For each charging station, a waveform is assumed by multiplying the basic waveform shown in Fig. 10 by the installed PV capacity at

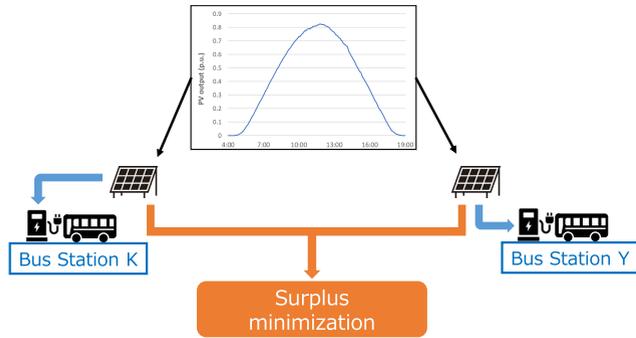


FIGURE 10. Diagram of Scenario II and basic PV waveform.

that station. As a subtheme of [26], a sensitivity analysis of the impact of the PV installed capacity on the self-consumption rate of PV and RE use rate of buses was conducted to clarify the trade-off relationship. However, because it is not related to the subject of this study, the details are omitted.

### 2) OPTIMIZATION METHOD AND SIMULATION CASES

An optimization problem using MILP was formulated as a summation minimization problem for KWH to minimize PV surplus [26, eq. (1)].

Simulations were conducted under the conditions listed in Table 1 to verify the effectiveness of this optimization method. As a specific condition of Scenario II, the installed capacity of PV is 150 kW each, and the non-optimal case, having the same conditions as the proposed case is used as a comparison case.

### 3) SIMULATION RESULTS

Fig. 11 shows the PV surplus waveforms of the non-optimal and proposed cases. The sums of the surpluses in each case are shown in Fig. 12. The energy generated by the 150 kW PV at the two charging stations is 1902 kWh. The surplus of the non-optimal and proposed case was reduced to 700 kWh and 593 kWh, respectively. In other words, the proposed KWH optimization method increased the daytime RPF absorption by 107 kWh without additional energy storage resources. Conversely, for the KW, not considered in the optimization, a sudden fluctuation occurred at approximately 11:00, as shown in Fig. 11. Thus, we conclude that the optimization of KWH using a summation minimization problem is not sufficient to optimize KW.

The results of our previous studies [25], [26] are summarized in this section. Based thereupon, Section III proposes a multiobjective optimization method to optimize KW and KWH simultaneously.

## III. A MULTIOBJECTIVE OPTIMIZATION METHOD FOR AN ELECTRIC BUS CHARGING SCHEDULE

### A. SETTINGS IN THIS METHOD

The results described in the previous section clarify that simultaneous optimization cannot be achieved by independent optimization of KW and KWH. Nonetheless, because

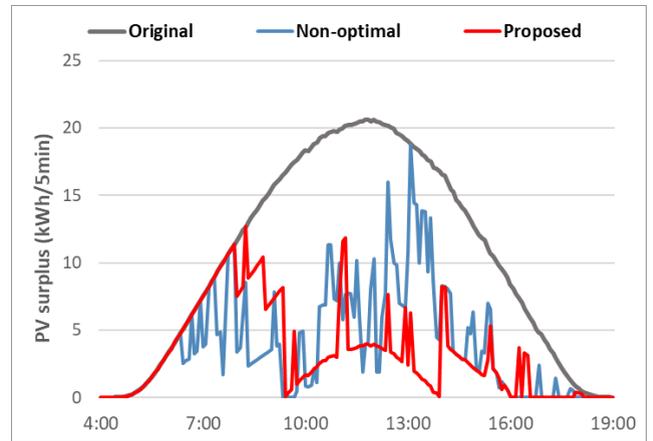


FIGURE 11. Waveform of PV surplus in each case.

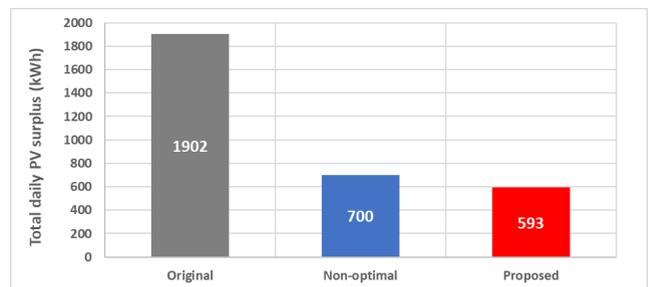


FIGURE 12. Evaluation of total daily PV surplus in each case.

the amount of KWH is the product of KW and time, these indices are related by nature and are likely to be compatible. Therefore, the objective of this study is to generalize a multiobjective optimization method for both the power and transportation networks, focusing on the PV-derived RPF. Specifically, the KW peak-cut aims to expand the connectable amount of PV and other RE sources, and KWH minimization aims to realize local production and consumption of RE and clean public transportation.

### B. NOMENCLATURE

Various symbols used in the formulation of the optimization are introduced. For details of the parameters  $S_{m,j}(t)$  and  $L_j$ , please refer to Section II-A.

#### 1) NOTATIONS

- $j$  :bus suffix number.
- $N$  :total number of buses.
- $t$  :time section suffix.
- $T$  :total number of time sections.
- $m$  :suffix number of charging station.
- $N_c$  :number of all charging stations.

#### 2) PARAMETERS

- $\alpha$  :optimization priority of KW for KWH (0~1.0).
- $RPF_m^{ori}(t)$  :original RPF at  $m$  at  $t$  [kWh].
- $P_m^{ch}$  :charging KWH per time section at  $m$  [kWh].

- $L_j(t)$  :running KWH consumption of  $j$  at  $t$  [kWh].
- $B_{\max}$  :storage capacity of the bus [kWh].
- $\eta_m$  :charging efficiency at  $m$  [-].
- $SOC_{lo}$  :lower limit of SOC [%].
- $SOC_{up}$  :upper limit of SOC [%].
- $SOC_{start}$  :initial value of SOC [%].
- $t_{start}$  :start time of charging.
- $t_{end}$  :completion time of charging.
- $S_{m,j}(t)$  : $j$  can charge at  $m$  at  $t$  (0 – 1 binary: true = 1).
- $R_j(t)$  : $j$  is running at  $t$  (0 – 1 binary: true = 1).
- $C_m^{\max}$  :number of chargers installed at  $m$ .
- $w_a$  :weight of charge frequency penalty term.
- $u$  :maximum number of charges.
- $T_{ch}$  :minimum number of sections to continue charging.
- $T_{du}$  :minimum number of sections between charges.

3) DECISION VARIABLES

- $RPF_m(t)$  :RPF generated at  $m$  at  $t$  after charging [kWh]\*<sup>1</sup>.
  - $P_m(t)$  :variable equal to  $RPF_m(t)$  or  $P_m^{used}(t)$  [kWh].
  - $C_{m,j}(t)$  : $j$  is charging at  $m$  at  $t$  (0 – 1 binary: true = 1).
  - $P_m^{other}(t)$  :charged KWH other than RPF at  $m$  at  $t$  [kWh]\*<sup>1</sup>.
  - $SOC_j(t)$  :SOC of  $j$  at  $t$  [%]\*<sup>1</sup>.
  - $\delta_j^{start}(t)$  : $j$  is starting to charge at (0 – 1 binary: true = 1).
  - $\delta_j^{end}(t)$  : $j$  is finishing to charge at (0 – 1 binary: true = 1).
- \*<sup>1</sup> These variables are always positive.

C. METHOD FORMULATION

1) OBJECTIVE FUNCTION

In (1), the first term expresses the KW peak cut of the RPF proposed in [25], and the second term indicates the minimization of the sum of KWH proposed in [26]. These priorities can be controlled by  $\alpha$ , where  $\alpha = 1.0$  optimizes only KW and  $\alpha = 0$  optimizes only KWH.  $RPF_m(t)$  is calculated using (2) and (3), the details of which are described in 2) hereafter. By minimizing this objective function, the charging timing  $C_{m,j}(t)$  that minimizes  $RPF_m(t)$  in (2) and (3) can be determined. The determination of this optimal  $C_{m,j}(t)$  is the objective of this optimization method, which determines the optimal charging schedule. The third term in (1) is a penalty term regarding the number of charges to prevent unnecessary charge splitting. Small weights are assigned to prevent them from affecting the original objective function.

$$\alpha \max (RPF_m(t)) + (1 - \alpha) \times \sum_{m=1}^{N_c} \sum_{t=1}^T RPF_m(t)$$

$$+ w_a \sum_{j=1}^N \sum_{t=1}^T (\delta_j^{start}(t) + \delta_j^{end}(t)) \rightarrow \text{minimize} \quad (1)$$

2) CALCULATING RPF

Equations (2) and (3) can be used to calculate the surplus RPF by subtracting the charging power from the original RPF at each time section for each charging station. However, a simple subtraction will result in a negative value when the charging amount exceeds  $RPF_m^{ori}(t)$ , as highlighted using a blue line  $P_m(t)$  in Fig.13. If we continue to use  $P_m(t)$  as the minimizing variable in (1), the more negative Pt is, the more it is minimized. This means that charging will act aggressively outside the RPF generation time period. Therefore, according to (3), the results of (2) are divided into two separate variables,  $P_m^{other}(t)$  for negative results and  $RPF_m(t)$  for positive results, as shown in Fig. 13. Additionally, because these variables are always positive and  $RPF_m(t)$  is minimized by (1), either  $RPF_m(t)$  or  $P_m^{used}(t)$  will always be zero. From (1), (2), and (3), the charging time  $C_{m,j}(t)$  is optimally selected to minimize the KW and KWH of  $RPF_m(t)$

$$P_m(t) = RPF_m^{ori}(t) - \sum_{m=1}^{N_c} \sum_{j=1}^N C_{m,j}(t) P_m^{ch} \quad (2)$$

$$RPF_m(t) - P_m^{other}(t) = P_m(t) \quad (3)$$

3) CALCULATING THE SOC OF A BUS

The SOC of a bus at a given time section can be calculated in three patterns: inheriting the SOC of the previous time section, subtracting power consumption, or adding the charging power, according to (4).

$$SOC_j(t)B_{\max} = SOC_j(t - 1)B_{\max} - L_j + \sum_{m=1}^{N_c} C_{m,j}(t) P_m^{ch} \eta_m \quad (4)$$

4) BUS SOC CONSTRAINTS

The SOC of the bus starts at  $SOC_{start}$  and returns to  $SOC_{start}$  at  $t_{end}$ . This allows the operation on the next day to start with the same initial value, and enables the charge of the bus in the simulation case to be unified. During the operation time, the SOC repeatedly transitions between charging and consumption within the allowable upper and lower limits.

$$SOC_{lo} \leq SOC_j(t) \leq SOC_{up} \quad (5)$$

$$SOC_j(t_{start}) = SOC_{start} \quad (6)$$

$$SOC_j(t_{end}) = SOC_{start} \quad (7)$$

5) CHARGING CONSTRAINTS

The constraints consist of the charging permission, number of chargers, and exclusion conditions, and are based on the parameters calculated from the bus operation model, that is

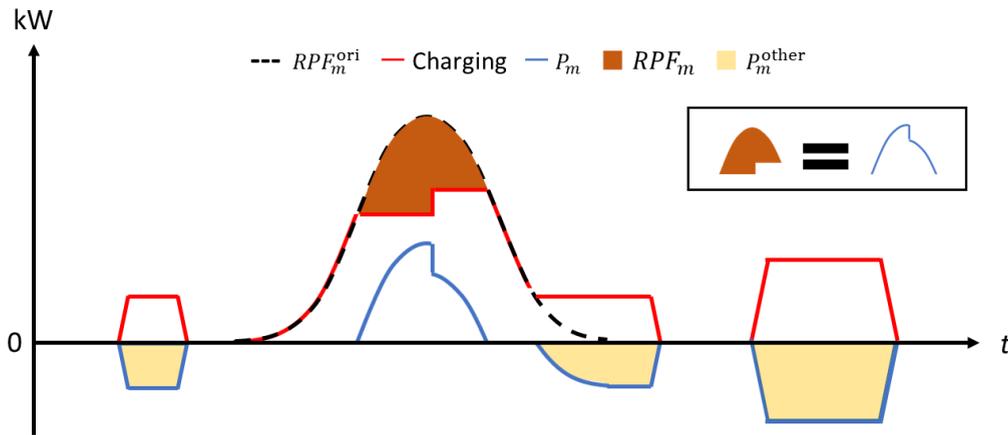


FIGURE 13. Relationships among variables related to the calculation of RPF.

$S_{m,j}(t)$  and  $R_j(t)$ .

$$C_{m,j}(t) \leq S_{m,j}(t) \quad (8)$$

$$\sum_{j=1}^N C_{m,j}(t) \leq C_m^{\max} \quad (9)$$

$$R_j(t) + \sum_{m=1}^{N_c} C_{m,j}(t) \leq 1 \quad (10)$$

#### 6) EQUATIONS FOR CHARGING START/END FLAG

When the charge state  $C_{m,j}(t)$  is different from the previous time section,  $\delta_j^{\text{start}}(t)$  or  $\delta_j^{\text{end}}(t)$  becomes true = 1.

$$\sum_{m=1}^{N_c} (C_{m,j}(t) - C_{m,j}(t-1)) = \delta_j^{\text{start}}(t) - \delta_j^{\text{end}}(t) \quad (11)$$

$$\delta_j^{\text{start}}(t) - \delta_j^{\text{end}}(t) \leq 1 \quad (12)$$

#### 7) CHARGING CONTINUATION CONSTRAINTS

The constraints consist of three equations: the maximum number of charge conditions per bus, minimum charge duration conditions per charge, and minimum interval conditions between charges:

$$\sum_{t=1}^T (\delta_j^{\text{start}}(t) + \delta_j^{\text{end}}(t)) \leq 2u \quad (13)$$

$$\sum_{\tau=t}^{t+T_{\text{ch}}-1} \sum_{m=1}^{N_c} C_{m,j}(\tau) \geq T_{\text{ch}} \delta_j^{\text{start}}(t) \quad (14)$$

$$T_{\text{du}} - \sum_{\tau=t}^{t+T_{\text{du}}-1} \sum_{m=1}^{N_c} C_{m,j}(\tau) \geq T_{\text{du}} \delta_j^{\text{end}}(t) \quad (15)$$

The MILP model comprising the above 15 equations is the optimization method proposed in this study. In the next section, examples of evaluation simulations using real city data are introduced.

TABLE 3. Conditions common to both simulations.

	$N$	17
Bus operator's situation	$N_c$	2 (Stations K, Y)
Specifics of EV chargers	Output	50 kW
	$\eta_m$	0.98
Specifics of electric buses	$B_{\text{max}}$	200 kWh
	Electricity cost	0.94 km/kWh
SOC condition	$t_{\text{start}}$	AM 4:00
	$t_{\text{end}}$	AM 3:00
	$SOC_{\text{start}}$	50 %
	$SOC_{\text{lo}} / SOC_{\text{up}}$	10% / 90%
Evaluation period	Whole day (24 h: every 5 min from 4 a.m. to next day's 4 a.m.) $\therefore t = 5\text{min}, T = 288$	
Charging continuation condition	$w_a$	0.001
	$u$	5
	$T_{\text{ch}} / T_{\text{du}}$	3 (=15 min) / 12 (=2 h)
Programming language / Solver	GAMS / CPLEX	

## IV. SIMULATIONS

This section introduces examples of simulations using real city data to evaluate the proposed multiobjective optimization method. For the transportation sector, the results of II-A are used, and for the electric power sector, a situation in which RPF occurs only at Station K, the same situation as shown in Fig. 5, is assumed. Simulation I examines the effect of changing  $\alpha$  of the objective function in (1) for the simultaneous optimization of KW and KWH. Simulation II evaluates the effect on the simultaneous optimization results when the number of installed chargers, which significantly affects the optimization of KW, is varied.

### A. DETAILED CONDITIONS OF SIMULATIONS

The conditions common to the two simulations are listed in Table 3. Two charging stations are assumed for the 17 buses, based on Section II-A. A general quick charger is assumed to be an EV charger, and the battery capacity of a bus

TABLE 4. Conditions specific to each simulation.

Simulation I	$\alpha$	From 0 to 1.0, in 0.1 increments
	$C_m^{\max}$	5 each
Simulation II	$\alpha$	0, 0.5, 1.0
	$C_m^{\max}$	4 each, 5each, 6each, 7each

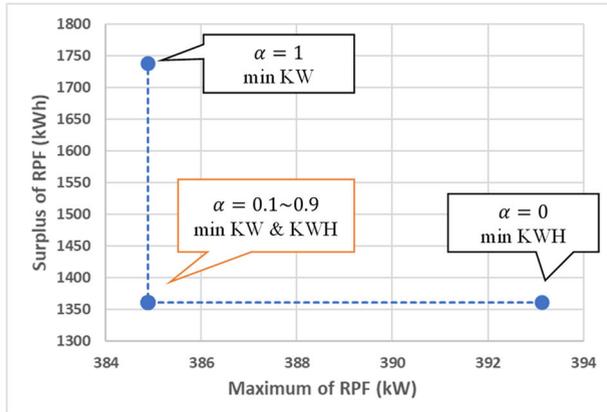


FIGURE 14. Relationship between  $\alpha$  and the simultaneous optimization of the maximum RPF and surplus of RPF.

is set to 200 kWh considering the performance of recent electric buses. The SOC conditions were set to be within the range of 10–90%, with initial and final values of 50%, to avoid battery degradation and to consider the charging characteristics. The evaluation period started at 4:00 a.m., based on the time during which the bus is in operation, and the evaluation was performed for 24 hours in 5-min increments. The calculations in 5 min increments reduced the calculation time while ensuring a certain degree of granularity in the charge waveform, and, additionally, serve as a buffer to absorb bus delays of up to 5 min. The parameters related to the continuation of charging were selected within a range that would not affect the RPF optimization results.

The conditions specific to each simulation are listed in Table 4. With regard to  $\alpha$  in Simulation I, the value is varied from 0 to 1.0, in increments of 0.1, and in Simulation II, three points are evaluated:  $\alpha = 0$ , which optimizes only KWH;  $\alpha = 0.5$ , which optimizes KWH and KW simultaneously; and  $\alpha = 1.0$ , which optimizes only KW. Simulation I assumes five chargers at each charging station. In Simulation II, the chargers range from four to seven (seven is the maximum number of buses that can stay at Station K simultaneously during the day).

**B. RESULTS AND DISCUSSION OF SIMULATION I**

The results for each value of  $\alpha$  were plotted in Fig. 14 and show that the minimum KW and KWH are simultaneously satisfied for all  $\alpha$  except for the points where only KW and KWH are minimized at  $\alpha = 1$  and 0, respectively. Hereafter,  $\alpha$  from 0.1 to 0.9 is referred to as Others. This result suggests that the properties of KW and KWH are related and that they could be simultaneously optimized relatively easily,

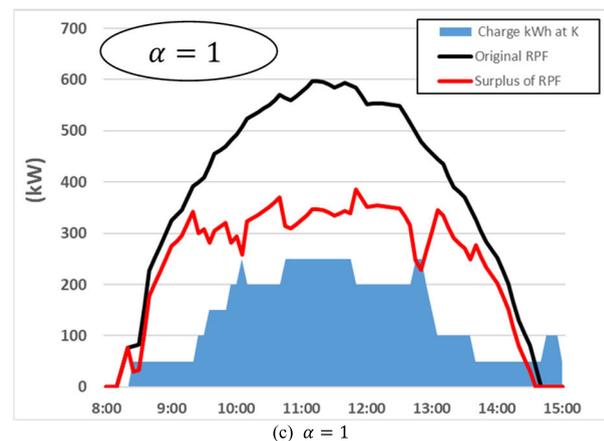
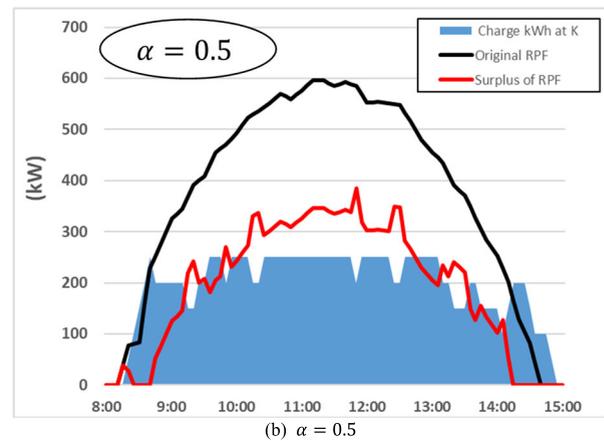
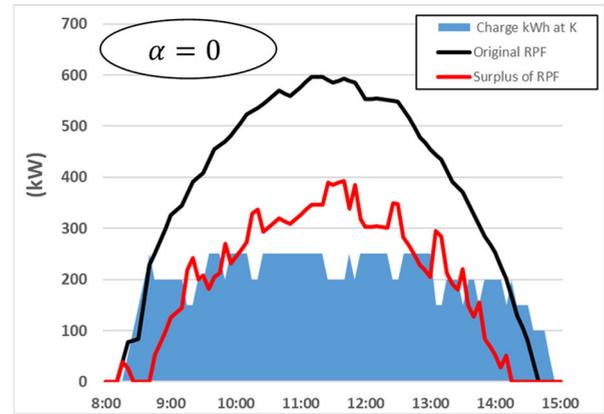


FIGURE 15. Charge waveform and RPF waveform for each  $\alpha$ .

as hypothesized at the beginning of this paper. In terms of actual figures, KWH was reduced by 920.1 kWh (34.6%) at the point where only KW was targeted for minimization ( $\alpha = 1$ ), whereas Others reduced KWH by 1297.4 kWh (48.8%) and increased the reduction by 377.4 kWh (14.2 pt) while maintaining minimum KW. In contrast, KW was  $\alpha = 0$   $\alpha = 0.5$   $\alpha = 1$  reduced by 203.1 kW (34.1%) at the point where only KWH was targeted for minimization ( $\alpha = 0$ ), whereas Others reduced KW by 211.4 kW (35.4%) while maintaining the minimum KWH, increasing the reduction by 8.2 kW (1.4 pt).

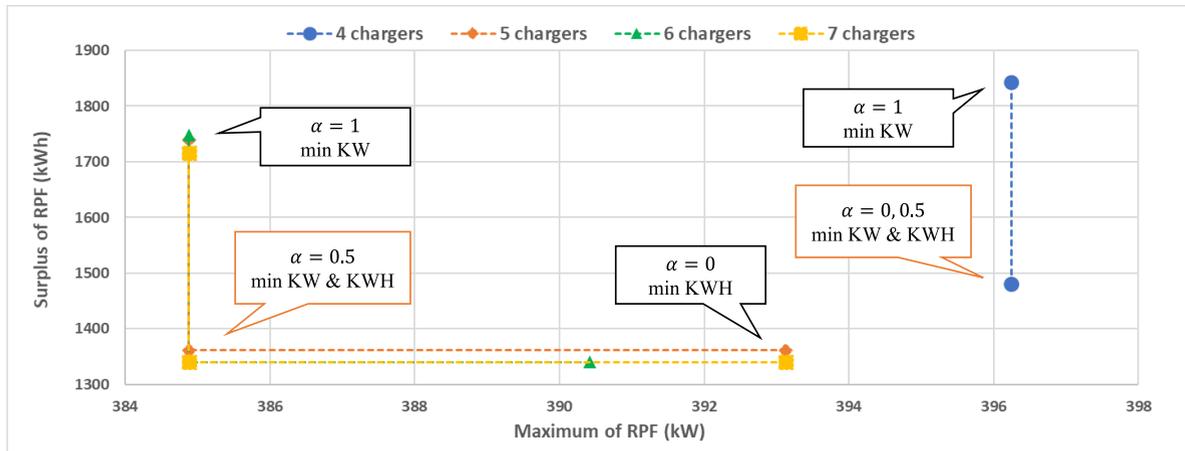


FIGURE 16. Relationship change between the maximum and surplus RPF and the number of chargers installed at each charging station.

The charging waveform of Station K and the change in surplus RPF for  $\alpha = 0, 0.5, 1.0$  are shown in Fig. 15. For KWH of the charging waveform (shown in blue in Fig. 15), for  $\alpha = 0$  and 0.5, charging is actively performed even at 9:00 and 14:00, different from  $\alpha = 1$ . The charging behavior for  $\alpha = 1$  implies that the KW-only minimization reported in our previous study [25] does not actively charge during the RPF-generation hours that do not affect the peak cut. For  $\alpha = 0.5$ , the proposed optimization method simultaneously minimizes the part of KWH that has no effect on the peak cut. Conversely, the change in the KW was small. This is because the peak-cut worsens for the time section where the peak at approximately 12:00 remains, as shown in Fig. 15(b). The maximum value of the KW peak-cut is the product of the total number of buses that can be charged (or the number of chargers installed:  $C_m^{\max}$ ) and the output of a charger in each time section:  $P_m^{\text{ch}}$ . Furthermore, for example, to reduce to 300 kW, it is necessary to continuously reduce to 300 kW during the five hours from 9:00 to 14:00 when there is an RPF of 300 kW or more. In other words, in the evaluation of KWH, the results would improve by charging for only three hours, but in the evaluation of KW, partial peaks remain, and the results are not improved. Therefore, in Simulation II, we evaluate the effect of changing the number of chargers installed, which has a significant impact on the results of KW.

### C. RESULTS AND DISCUSSION OF SIMULATION II

The results with different installed chargers  $C_m^{\max}$  are shown in Fig. 16. The first characteristic result shows that when  $C_m^{\max}$  is four, KW is reduced by 200 kW to a constant value of 396.2 kW, independent of the value of  $\alpha$ . This is because four chargers cannot efficiently utilize the energy storage capacity of the bus, and the peak-cut maximum of  $4 \times 50 \text{ kW} = 200 \text{ kW}$  was reached. With five or more chargers,  $\alpha = 0.5$  and 1 results in the same reduction of 384.9 kW, which is an additional reduction of 11.4 kW compared to four chargers. In other words, 211.4 kW is the maximum peak-cut capacity possible considering the specifications and

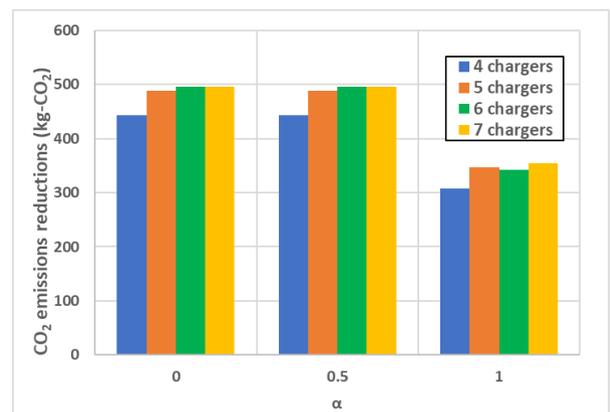


FIGURE 17. Daily CO<sub>2</sub> reduction with a different number of chargers installed at each charging station.

operating schedule of the buses, and current PV penetration status. Hence, from the viewpoint of the KW peak-cut, we conclude that it is unnecessary to use more than five chargers.

Conversely, in terms of KWH, the change from five to six chargers resulted in an additional reduction of 20.8 kWh. Because the KWH results for six and seven chargers were the same, the KWH reduction capability of the RPF to 1318.4 kWh with six chargers is considered to be the limit in this case study. However, compared to the 119.0 kWh reduction seen when the chargers were increased from four to five, the change from five to six chargers lowered the KWH by only one-sixth of that. In other words, an increase from five to six chargers should be considered, taking into account the negligible effect on the KW peak-cut and the small effect on the KWH reduction. Thus, the proposed method is expected to contribute to infrastructure planning in terms of the optimal number of charging facilities.

### D. ENVIRONMENT ASSESSMENT

The above results for KWH were evaluated in terms of the environmental impact of buses and local consumption

of RE. Fig. 17 shows the reduced CO<sub>2</sub> emissions with the PV-derived RPF for electric buses, assuming that LNG-fired power generated with 0.376 kg-CO<sub>2</sub>/kWh was originally used [29]. For  $\alpha = 0$  and 0.5, the CO<sub>2</sub> reduction increases with the number of chargers to 443, 488, and 495 kg per day. The RE utilization rate for the total bus charging capacity of 2071 kWh shows the same trend as in Fig. 17, increasing from 39.4% with four chargers and  $\alpha = 1$  to 63.7% with six chargers and  $\alpha = 0.5$ . Finally, the trend in the local consumption rate of RE (RPF) is again similar to that in Fig. 17 because the RPF waveform is fixed at 2658 kWh per day. From 30.7% with four chargers and  $\alpha = 1$ , the rate increases to 49.6% with six chargers and  $\alpha = 0.5$ .

Setting individual initial SOC values based on the operating characteristics of each bus might be effective to further reduce the RPF KWH. For example, for buses that frequently run in the morning, setting a high initial SOC could reduce the amount of charging in the morning and the power stored in the daytime could be transferred to the next day.

## V. CONCLUSION

This paper proposes a method for charging schedule optimization, developed using real data, to promote the effective use of RE, by focusing on the deterministic behavior and controllability of electric buses. Specifically, spatiotemporal bus movements were reproduced using GTFS, an open data format for actual bus operation. The charging schedule was optimized using MILP based on the calculated chargeable time and capacity. The proposed multiobjective optimization method integrates the individual methods for power (KW) and energy (KWH) optimization developed in the authors' previous studies [25], [26], respectively. The feasibility of simultaneously optimizing KW and KWH and their relationship with the number of installed EV chargers were confirmed and evaluated in two types of simulation environments focusing on the RPF of two distribution lines to which charging stations are actually connected.

The features of this method are as follows:

- ① Multiobjective optimization that simultaneously achieves three objectives: the peak KW of the RPF is reduced, the local consumption of RE in the city is increased, and the rate at which electric buses utilize RE is improved.
- ② Multiple location optimization that accounts for the spatiotemporal movements and power consumption of an actual bus.
- ③ Generic method for actual bus operation based on GTFS open data format.

The study aimed to realize a new regional energy management method for the effective use of RE by utilizing the resources of electric buses for a smart city. Apart from this, the proposed method considers the potential of electric bus resources and the interconnection of EV charging between electric power and transportation networks. The study attempted to generalize the charging schedule optimization problem to improve the RE utilization rate. At the same time,

the operational constraints of the transportation network were considered. In addition, the objective was to simultaneously reduce RPF and improve the local consumption rate of RE, the required indices of the power network, and local environment, respectively. Possible extensions of this study and future tasks are as follows:

- Optimizing the battery capacity of the buses by considering constraints such as the seating space and weight of the bus, or by individually optimizing the battery capacity of each bus by considering its operational characteristics.
- Upgrading the charging facilities and V2G by optimizing the number of installed EV chargers, evaluating the effectiveness of introducing new charging methods, such as using high voltages and charging while driving, and evaluating V2G using electric buses.
- Increasing the number of electric buses and evaluating the impact thereof by assuming a phased bus electrification scenario in the target area. An impact evaluation on 170 buses in the target area was conducted in the authors' most recent study [30]. The study concluded that a mid-to long-term bus electrification plan that considers the RE penetration is important to maximize the effects of bus electrification.
- Developing a dynamic control method by investigating real-time response methods to uncertainties in the transportation network using the real-time nature of the GTFS-RT and uncertainties in PV generation because of uncertainties in the weather forecast.
- Designing a quantitative evaluation method for moving storage batteries by evaluating a group of electric buses whose nature is essentially different from that of stationary ones. Electric buses have spatial flexibility instead of temporal constraints. If they can be charged at three locations, they may hypothetically have up to three times the actual capacity.

In the future, this research is expected to become a model case for highly sustainable smart cities based on power and transportation sector coupling.

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