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# Development of Commercial EV Traffic Simulator Targeting Last One Mile of Home Delivery

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## Executive Summary

To realize a decarbonized society, the introduction of electric vehicles (EVs) is currently being promoted in the transportation sector. Commercial vehicles account for about 40% of CO2 emissions in the transport sector, so electrification of these vehicles is especially important for decarbonization. Although the number of commercial vehicles is small, the electricity consumption when converted into EVs is large because of the long mileage; thus, the CO2 reduction potential by charging from the renewable energy such as PVs is large. It is important to utilize PV surplus electricity as much as possible. But they drive during the daytime for delivery; then, it is not easy for them to be charged directly by PV. The purpose of this paper is to develop an EV traffic simulator for commercial vehicles in order to evaluate the CO2 reduction effect by using EV delivery vehicles and charging them with PVs installed on the rooftop of the office. The last one mile of home delivery service is taken as a simulation example in this study. Through the analysis targeting medium-sized local cities of Takasaki and Maebashi in Japan, we obtained the following findings: (1) if charger output is increased, CO2 can be reduced more efficiently by combining them with energy management such as SOC control, because SOC control at early evening and night increases the amount of charge during the day; (2) by combining the increase in charger output, the SOC control, and the charging schedule management, CO2 reduction effect can be further enhanced; (3) by installing a battery swap station, about 80% of the energy consumed by the traveling can be covered by PV surplus electricity.

*Keywords: Electric Vehicles, Smart charging, Smart grid integration and grid management, Environmental impact, Energy management.*

## 1 Background: National project of commercial fleets electrification in Japan

The Japanese government has set a target to reduce national greenhouse gas (GHG) emissions by 46% by FY2030 from FY2013 levels, as part of its goal to achieve carbon neutrality by 2050. The transportation sector accounts for 17.4% of Japan's CO2 emissions, and the widespread adoption of electric vehicles (EVs) is essential to reduce these sectoral emissions. In particular, commercial vehicles account for about 40% of CO2 emissions in the transportation sector, so electrification of these vehicles is especially important for decarbonization. Although the number of commercial vehicles is small, the electricity consumption when converted into EVs is large because of the long mileage; thus, the CO2 reduction potential by energy management is large. To support this, the government has launched a nine-year national project, starting in FY2022 and running through FY2030 to build an integrated energy management system for the operation of commercial EVs and fuel cell vehicles (FCVs). This initiative, named the Smart Mobility Society Construction project, is overseen by the New Energy and Industrial Technology Development Organization (NEDO) [1]. The project encompasses three types of commercial fleets—trucks, buses, and taxis—and includes seven consortia of fleet operators and manufacturers who are participating in R&D, demonstrations, and social implementation activities. CRIEPI is involved in the project by developing simulators to support the widespread adoption of commercial EVs. These activities include traffic simulation for commercial EVs, area-wide EV charging load analysis, optimal charging infrastructure development, and impact analysis on the distribution grid.

In previous studies dealing with commercial vehicles [2], the authors made driving patterns by vehicle type—light passenger cars, normal passenger cars, light cargo vehicles, and small-size cargo vehicles—based on the road traffic census of Ministry of Land, Infrastructure, Transport and Tourism and assumed a scenario for EV spread. Under this scenario, the authors evaluated CO2 reduction effect by introducing EVs considering the power generation sector. Furthermore, the authors in [3] analyzed the survey data of origin and destination of business and logistics vehicles in Osaka Prefecture, and calculated the charging load curve, after assuming on-board battery capacity and charger output. In a previous study using vehicle probe data [4], the authors classified freight vehicles by vehicle size—large, medium, normal, light—and then analyzed the charging infrastructure based on the charge demand curves.

In order to propose an optimal charging infrastructure, a traffic simulator capable of geographical analysis is essential. A traffic simulator for private passenger cars [5]—hereafter, called simulator for passenger cars—have been developed, and optimal deployment of charging infrastructure was analyzed in [6] to [8], and the possibility of developing peak load due to quick charging was studied in [9][10]. By developing a simulator for commercial vehicles based on this simulator, it is possible to consider energy management per office basis, to evaluate the impact on the power system by charging of multiple business operators, and to propose the establishment of the optimal charging infrastructure as a whole society. In this paper, as the first step we develop an EV traffic simulator for commercial vehicles, targeting the last one mile of home delivery service, and evaluate the CO2 reduction effect by enhancement of charging infrastructure and energy management.

# 2 Development of EV traffic simulator for commercial vehicles

## 2.1 Overview of the simulator for passenger cars

A simulator for passenger cars [5], which is the base of a simulator for commercial vehicles to be developed in this paper, is outlined. In the simulator, EVs are treated as agents, and each EV travels in a road network modeled from map data [11]. The simulator classifies passenger cars into two groups: "commuter cars" that travel regularly and "non commuter cars" that travel randomly, and determines the traveling pattern stochastically based on probability distribution of trip timing and trip length given for each group. We can set parameters such as battery capacity, charger output, and charging threshold, and obtain charging load curves or the like as output. The simulator is driven by the "artisoc" (ARTIficial SOCiety), which is a multi-agent simulator for complex systems [12].

## 2.2 Overview of the simulator for commercial vehicles

Since the simulator developed in this study aims to evaluate the charging infrastructure and energy management, it is necessary to accurately estimate the charging load of EVs. The charging load can be calculated from the electricity consumption and the charging timing of EV delivery vehicles; however, there are assumed to be various patterns depending on the target business operators. Therefore, these are not uniformly set in the simulator but treated as input data. Specifically, we use the actual data of the time schedule and delivery distance to improve the estimate accuracy of the charge timing and the electricity consumption. On the other hand, the part with little effect on charging load was simplified as much as possible to reduce the calculation load. More specifically, the change in electricity consumption according to traffic jams, stop/start, and the number of packages is not considered. In addition, while the actual delivery distance is reflected as the input data, the actual delivery route is not completely reflected in the simulator.

Table 1 shows the input data of the simulator. We assumed a circle as the delivery areas of the office and that of each delivery vehicle; the input data is the center and radius of the circle. As for the input data on trips, we assumed a normal distribution as the probability distribution for a departure time, a delivery distance, a delivery time, and a loading/unloading time; the input data is the mean and standard deviation of the normal distribution. Using Fig. 1, we explain how to generate a delivery route below. We assumed a circle as the delivery area of the office and that of each delivery vehicle; the input data are the center and radius of the circle. As for the input data on trips, we assumed a normal distribution as the probability distribution for departure time, delivery distance, delivery time, and loading/unloading time; hence, the mean and standard deviation of the normal distribution are inputted. EV battery capacity and electricity consumption can be set on a delivery vehicle unit. Using Fig. 1, we explain how to generate a delivery route below.

Table 1: Input data of the simulator for commercial vehicle.

| | |
|---|---|
| Location of office | Departure time |
| Radius of delivery area of office (km) | Delivery distance (km) |
| Center of delivery area of delivery vehicle | Delivery time (min) |
| Radius of delivery area of delivery vehicle (km) | Loading and unloading time (min) |
| Number of delivery vehicles | Normal charger output (kW) |
| Capacity of EV battery (kWh) | Quick charger output (kW) |
| Electricity consumption (km/kWh) | Available time of normal charger |
| CO2 emission factor (kg-CO2/kWh) | Available time of quick charger |
| PV output curve | Available time of battery swap station |
| Load curve of office | Charging time of swap battery |
| Number of delivery services per day | SOC upper limit when charging |

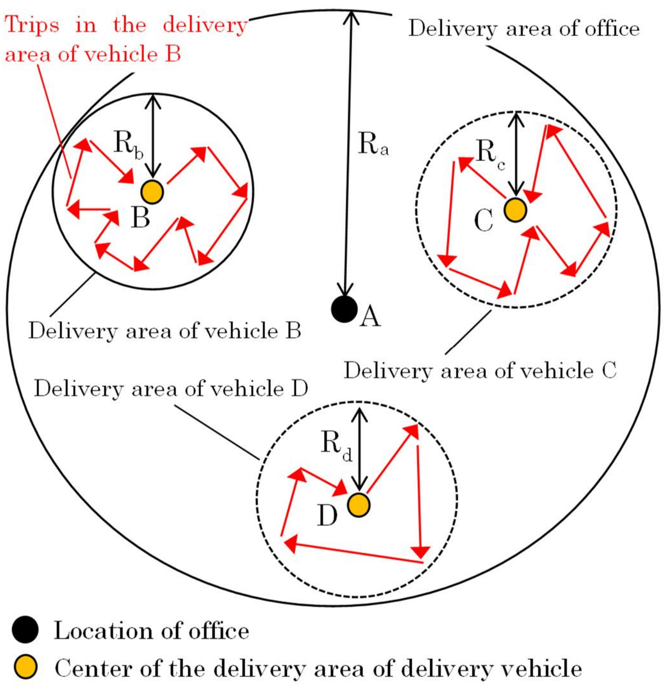


Figure 1: Generation of delivery routes of delivery vehicles.

① At the departure time, leave the office indicated by point A and move to the center of the delivery area of vehicle B indicated by point B.
② Make multiple trips within a circle of radius Rb, which is the delivery area of vehicle B, as shown by red arrow.
③ Make a trip back to the office, at the timing of fulfilling both the assigned delivery distance and delivery time.
④ Charges at the office.

⑤ Repeat ① to ④ for the number of delivery services per day.

When determining the delivery route, the density of delivery destination is also considered. Each EV travels at a speed allocated to each road and consumes or regenerates electricity according to the road gradient. Figure 2 shows the execution screen of the simulator for commercial vehicles. It models roads with a width of 3.0 m or more.

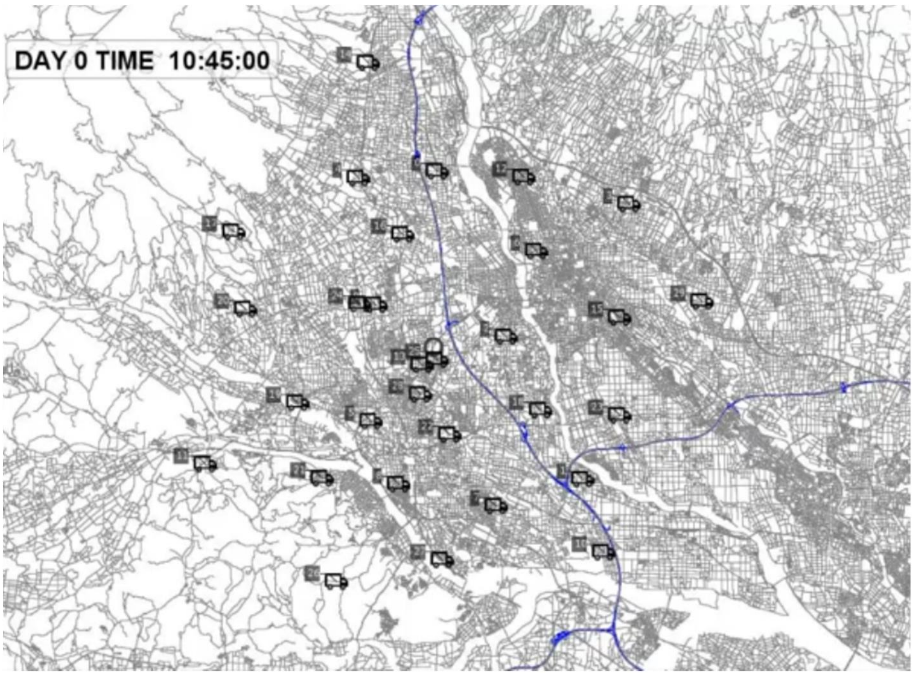


Figure 2: Execution screen of the simulator for commercial vehicles.

# 3 Simulation conditions

## 3.1 Case setting

We evaluated the CO2 reduction effect by EV delivery vehicles under the conditions shown in Table 2 and 3. The target areas are Maebashi and Takasaki cities in Gunma Prefecture, which are local cities 100 kilometers from Tokyo; Maebashi City has a population of 320,000 with an area of 241 square kilometers, and Takasaki City has a population of 370,000 with an area of 401 square kilometers. As for the delivery area for each delivery vehicle, there is no actual data at this time, so in this paper we randomly allocated it within the delivery area of the office. In all cases except the Battery swap case, we assumed that night charging starts at 23:00.

The conditions for the quick charger are as follows:
(1) One 50kW quick charger is installed in the office.
(2) The available time of QC in the QC case is 10:00 to 20:00, and that in the QC (SOC control) case and the QC (SOC control + 2group) case is 10:00 to 15:00 because these cases have a purpose to increase the amount of charge at noon the next day.
(3) When the quick charger is vacant, EVs with the lowest SOC can use it.
(4) EVs that do not use the quick charger use normal charger.

The conditions for the battery swap station are as follows:
(1) The battery swap station is available 24 hours a day.
(2) There are a total of 20 batteries, 10 of which are mounted on EVs and the remaining 10 are charged from 10:00 to 17:00 at the battery swap station.
(3) The battery swap station has 10 chargers.
(4) The mounted battery with the lowest SOC is swapped with the battery with the highest SOC stored at the station; the swapping time is 1 minute.

Table 2: Calculation conditions.

| | |
|---|---|
| Radius of the delivery area of office | 5 km |
| Number of delivery vehicles | 10 cars |
| Capacity of EV battery | 41 kWh |
| Electricity consumption | 1.92 km/kWh [13] |
| CO2 emission factor | 0.37 kg-$CO_2$/kWh [14] |

Table 3: Case setting.

| Case | PV capacity | Normal charger output | Quick charger output | SOC upper limit for the early evening and night charging | Description |
|---|---|---|---|---|---|
| EV | 0 kW | 6 kW | – | 100% | Delivery vehicles are charged only from power grid. |
| EV + PV | 150 kW | 6 kW | – | 100% | Delivery vehicles are charged from both power grid and PV surplus. |
| QC | 150 kW | 6 kW | 50 kW | 100% | Install a 50 kW quick charger. |
| QC (SOC control) | 150 kW | 6 kW | 50 kW | 60% | Install a 50 kW quick charger. Control the SOC upper limits for early evening and night charging. |
| QC (SOC control + 2 group) | 150 kW | 6 kW | 50 kW | 60% | Install a 50 kW quick charger. Control the SOC upper limits for early evening and night charging. Divide the delivery vehicles into two groups. |
| Battery swap | 150 kW | 6 kW | – | – | Install a battery swap station. |

Table 4 shows the probability distribution for the delivery pattern. As mentioned earlier, there is no actual data at this time, so we made a tentative decision by referring to [15]. The probability distribution shown in (a) is for the QC (SOC control + 2 group) case, and that shown in (b) is for the other cases. If you create a time schedule reflecting only the mean value of Table 4, it becomes shown in Table 5.

Table 4: Probability distribution for the delivery pattern.

(a) QC (SOC control + 2 group) case.

| Parameter | Group 1 | | Group 2 | |
|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation |
| Departure time | 8:00 | 10 min | 8:00 | 10 min |
| First delivery distance | 15 km | 5 km | 20 km | 5 km |
| First delivery time | 150 min | 10 min | 240 min | 10 min |
| Daytime loading and unloading time | 90 min | 5 min | 90 min | 5 min |
| Second delivery distance | 25 km | 5 km | 25 km | 5 km |
| Second delivery time | 270 min | 10 min | 270 min | 10 min |
| Early-evening loading and unloading time | 60 min | 5 min | 60 min | 5 min |
| Third delivery distance | 20 km | 5 km | 15 km | 5 km |
| Third delivery time | 210 min | 10 min | 120 min | 10 min |

(b) Cases other than the QC (SOC control + 2 group) case.

| Parameter | Mean | Standard deviation |
|---|---|---|
| Departure time | 8:00 | 10 min |
| First delivery distance | 20 km | 5 km |
| First delivery ime | 240 min | 10 min |
| Daytime loading and unloading time | 90 min | 5 min |
| Second delivery distance | 25 km | 5 km |
| Second delivery time | 270 min | 10 min |
| Early-evening loading and unloading time | 60 min | 5 min |
| Third delivery distance | 15 km | 5 km |
| Third delivery time | 120 min | 10 min |

Table 5: Power levels for charging (230 V)

(a) QC (SOC control + 2 group) case.

<table>
<tr><td>Time of day</td><td colspan="2">8:00</td><td colspan="2">9:00</td><td colspan="2">10:00</td><td colspan="2">11:00</td><td colspan="2">12:00</td><td colspan="2">13:00</td><td colspan="2">14:00</td><td colspan="2">15:00</td><td colspan="2">16:00</td><td colspan="2">17:00</td><td colspan="2">18:00</td><td colspan="2">19:00</td><td colspan="2">20:00</td></tr>
<tr><td>Group 1</td><td colspan="5">Delivery</td><td colspan="3">Office</td><td colspan="9">Delivery</td><td colspan="2">Office</td><td colspan="7">Delivery</td></tr>
<tr><td>Group 2</td><td colspan="8">Delivery</td><td colspan="3">Office</td><td colspan="9">Delivery</td><td colspan="2">Office</td><td colspan="4">Delivery</td></tr>
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(b) Cases other than the QC (SOC control + 2 group) case.

<table>
<tr><td>Time of day</td><td colspan="2">8:00</td><td colspan="2">9:00</td><td colspan="2">10:00</td><td colspan="2">11:00</td><td colspan="2">12:00</td><td colspan="2">13:00</td><td colspan="2">14:00</td><td colspan="2">15:00</td><td colspan="2">16:00</td><td colspan="2">17:00</td><td colspan="2">18:00</td><td colspan="2">19:00</td><td colspan="2">20:00</td></tr>
<tr><td>Location</td><td colspan="8">Delivery</td><td colspan="3">Office</td><td colspan="9">Delivery</td><td colspan="2">Office</td><td colspan="4">Delivery</td></tr>
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### 3.2 PV and office load data

As for the PV output, we calculated from the solar radiation data of five days from February 12th to 16th in Maebashi city [16], using (1); we assumed a panel direction of south, a panel inclination angle of 30 degrees, and a system output coefficient of 0.75[17].

$$P_{PV} = \frac{H_A}{G_S} \times \alpha \times S_{PV} \tag{1}$$

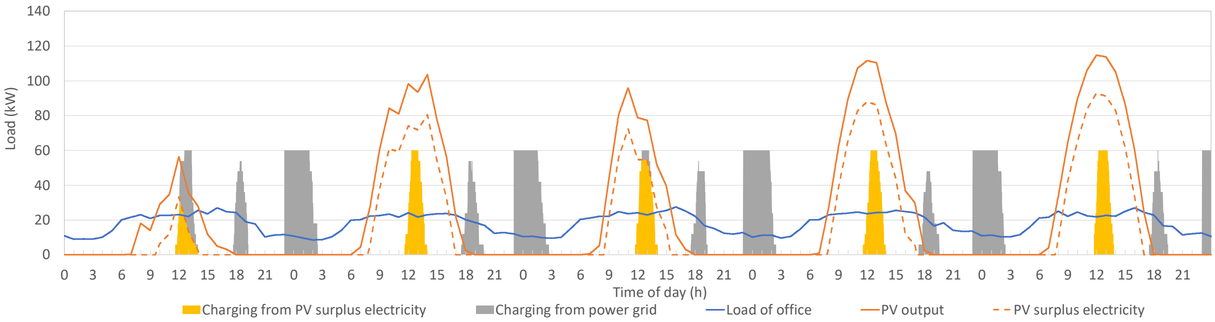
$P_{PV}$: PV output
$H_A$: Solar radiation on the inclined surface
$G_S$: Solar radiation intensity at the normal condition (= 1.0)
$\alpha$ : system output coefficient (= 0.75)
$S_{PV}$: PV panel capacity

As for the office load, we selected the office for transportation business located in the Kanto region from the open data [18] and scaled only the waveform so that the maximum annual demand was 50 kW; the period is 5 days from February 12th to 16th, which is the same time as the PV output data.

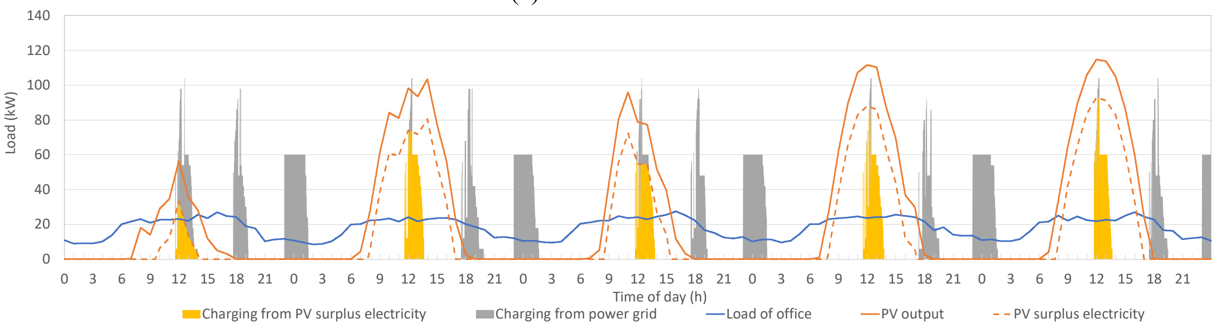
## 4 Results and discussions

### 4.1 Load curve and change in remaining battery level

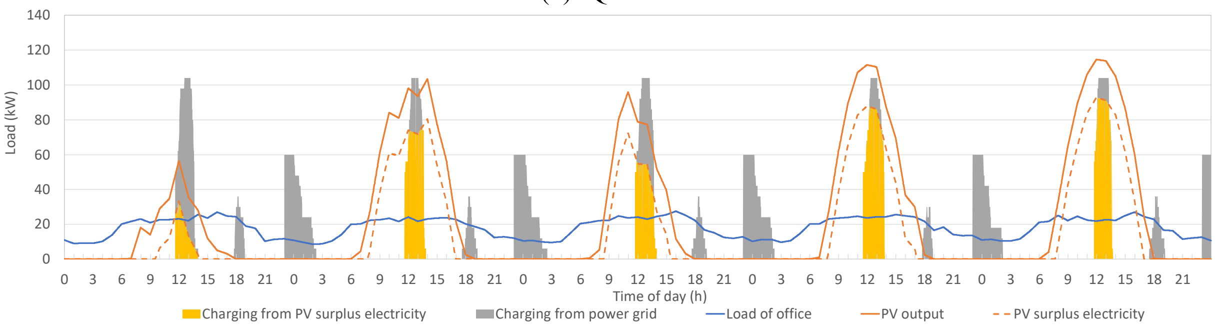
Fig. 3 shows the load curve for each case. The PV surplus electricity —orange dashed line—is obtained by subtracting the office load—blue line—from the PV output—orange line—. If the delivery vehicles are charged within the range of PV surplus electricity, it is indicated by charging from PV surplus electricity as shown by yellow area. Otherwise, it is indicated by charging from power grid as shown by gray area.



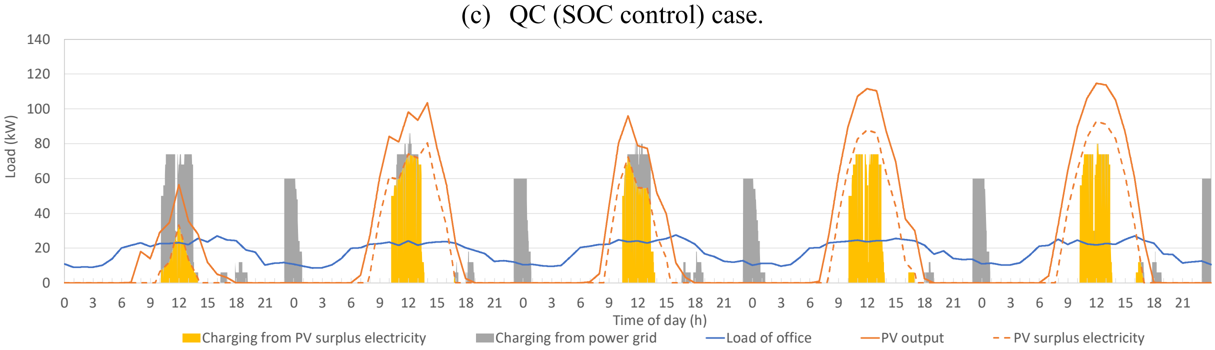

(a) EV + PV case.



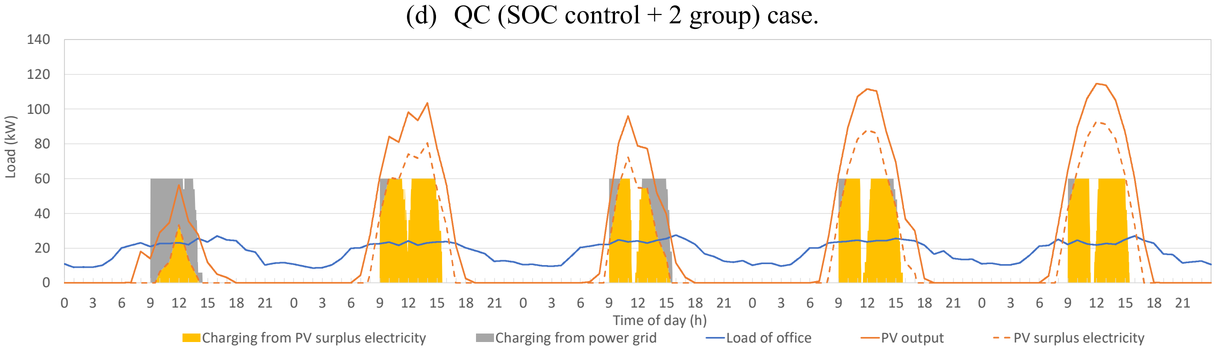

(b) QC case.




(c) QC (SOC control) case.




(d) QC (SOC control + 2 group) case.




(e) Battery swap case.

Figure 3: Load curve for each case.

Fig. 4 shows the changes in the remaining battery level of 10 vehicles in the EV+PV case. Since the changes in the remaining battery levels do not change significantly from day to day, we show the result for the fifth day as a representative. The remaining battery level is increasing by charging at 6 kW around noon, evening and night when delivery vehicles return to the office to load/unload their package. You can see from Fig. 3(a) that the delivery vehicles are charged from PV surplus electricity around noon on a sunny day and charged from power grid during the other times.

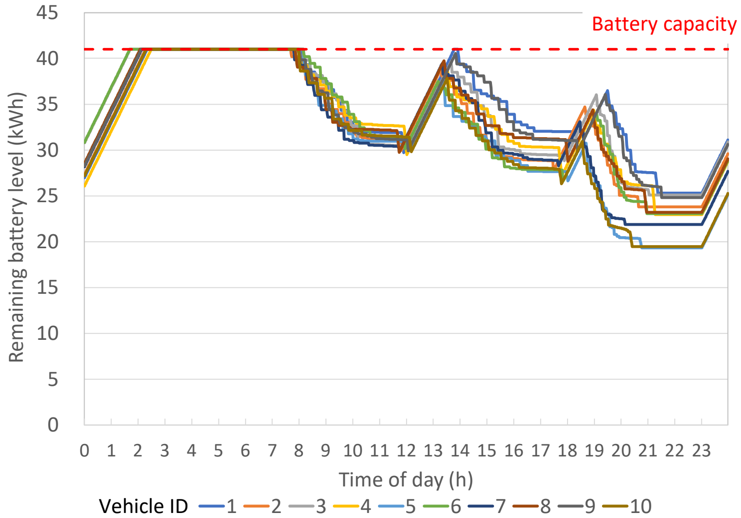



Figure 4: Changes in the remaining battery level of the EV+PV case.

Fig. 5 shows the changes in the remaining battery level of the QC case. When you look at the charging around noon and the evening, you can see that it is switched from quick charging to normal charging after reaching 80% of the battery capacity, i.e., 32.8 kWh, which is the upper limit of quick charging. In addition, since the remaining battery level at the time of arrival at the office is around 30 kWh, the quick charger is rarely used. You can see from Fig. 3(b) that the daytime charging peak is large, but the amount of charge, i.e., kWh, is not much different from that of the EV+PV case in Fig. 3(a). Therefore, if we controlled the SOC upper limit for the early evening and night charging, there would be room to increase the amount of charge around noon.

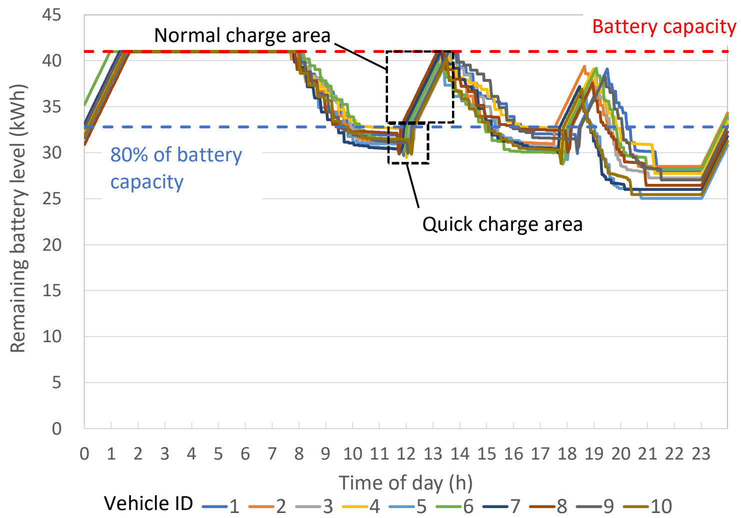



Figure 5: Changes in the remaining battery level of the QC case.

Fig. 6 shows the changes in the remaining battery level of the QC (SOC control) case. The available capacity of battery is secured through the SOC control, and the amount of charge during the day increases; as a result, the utilization ratio of quick charger has been improved. You can see from Fig. 3(c) that the daytime charging amount is increased compared to the QC case (Fig. 3(b); however, the amount of charge exceeding the PV surplus electricity is charged from the power grid. Therefore, if we dispersed the charging time during the day, there would be room for further reduction of CO2 emissions.

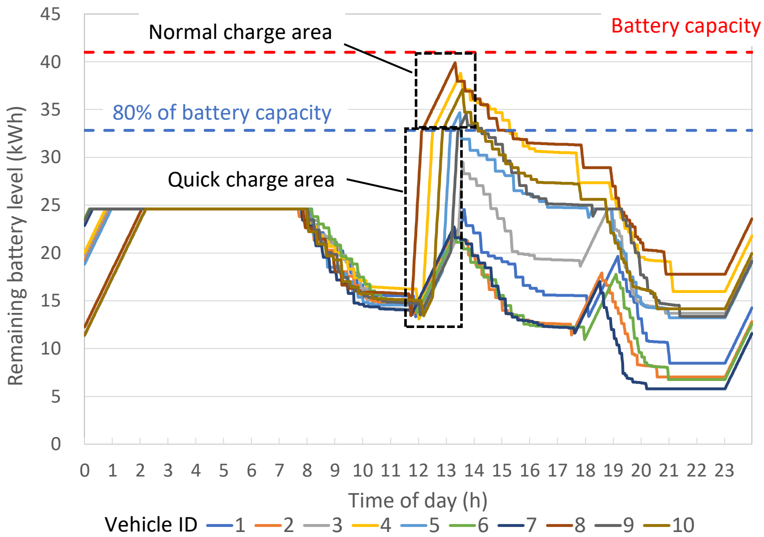



Figure 6: Changes in the remaining battery level of the QC (SOC control) case.

Fig. 7 shows the changes in the remaining battery level of the QC (SOC control + 2 group) case. You can see that by dividing the delivery vehicles into two groups, the charging time during the day is also divided into two; as a result, the utilization rate of the quick charger has been further improved. You can see from Fig. 3(d) that the charging around noon is almost covered with PV surplus electricity. Especially when comparing the QC (SOC control) case in Fig. 3(c) and the QC (SOC control + 2 group) case in Fig. 3(d) on cloudy days like the second or third day, you can find that the ratio of the charging from PV surplus electricity has increased significantly. In conclusion, by dispersing the charging time during the day, we can use PV surplus electricity more efficiently.

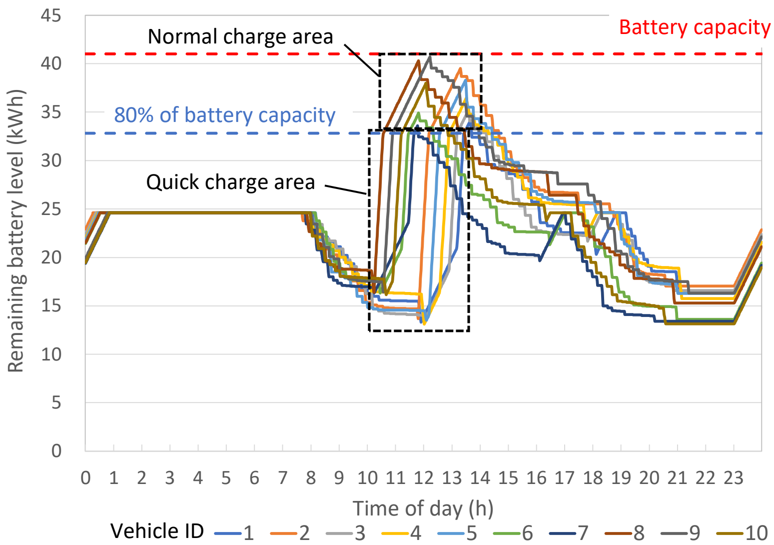
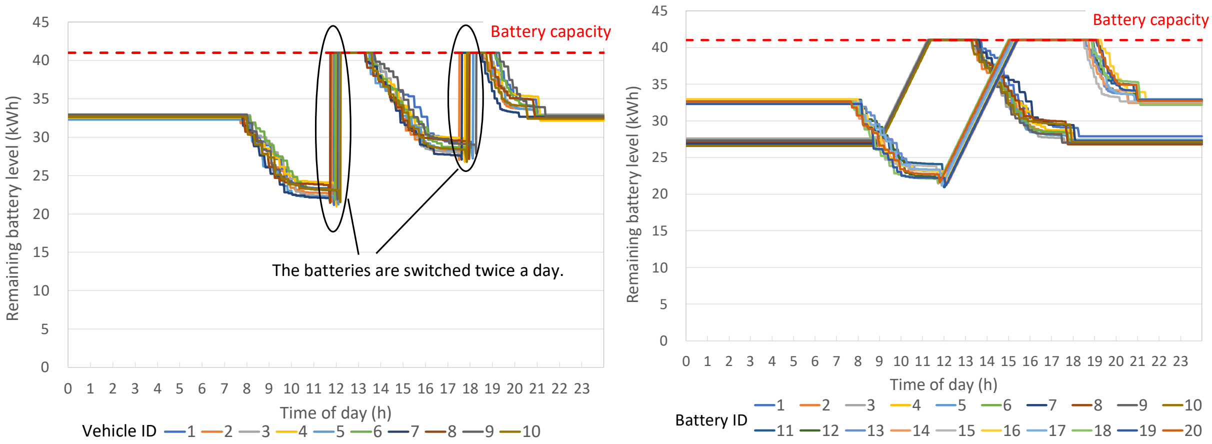



Figure 7: Changes in the remaining battery level of the QC (SOC control + 2 group) case.

Fig. 8 shows the changes in the remaining battery level of the Battery swap case. A total of 20 batteries, sum of 10 vehicle-mounted batteries and 10 station-stored batteries, are plotted in the battery unit graph. The batteries are swapped twice a day: at noon and in the early evening. The battery group swapped at noon is charged in the morning, and the battery group swapped in the early evening is charged from noon to the early evening. You can see from Fig. 3(e) that the ratio of charging with PV surplus electricity has increased significantly compared to the other cases. By matching the charging time of the station-stored batteries with the generation time of the PV surplus electricity, about 80% of the electric energy consumed by the traveling can be covered with PV surplus electricity.




(a) Delivery vehicle unit. (b) Battery unit.

Figure 8: Changes in the remaining battery level of the Battery swap case.

### 4.2 Comparison of CO2 emissions

Fig. 9 shows CO2 emissions over a simulation period of five days. The EV+PV case emits CO2 24% less than the EV cases, which is the effect by using PV surplus electricity. From now on, we will examine the CO2 reduction effect in each case when compared to the EV+PV case. The QC case emits CO2 only 5% less than the EV+PV case; hence, it is not very effective only to increase the charger output. Similarly, the QC (SOC control) case emits CO2 18% less than the EV+PV case; this result shows that it is effective to combine the upgrade of charger output with energy management such as SOC control. Furthermore, the QC (SOC control +2 grouping) case reduces CO2 emissions by 41%. We can reduce CO2 emissions more efficiently by combining the charging schedule management, the increase in charger output, and the SOC control. In addition, the Battery swap case reduces CO2 emissions by 70%, the biggest CO2 reduction effect among all cases.

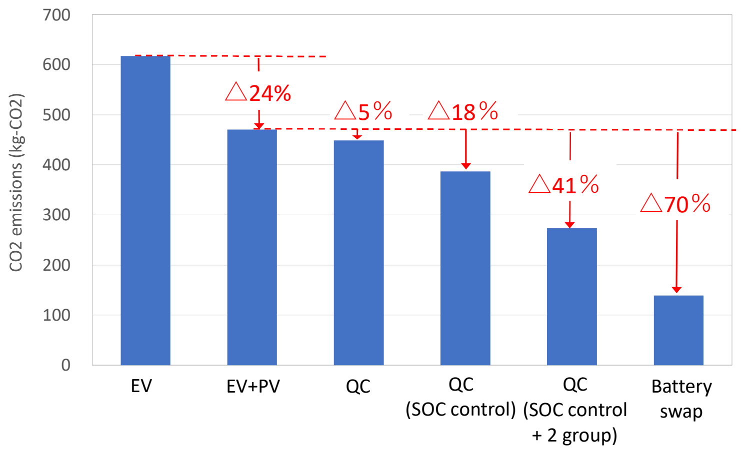



Figure 9: CO2 emissions.

## 5 Summary

We developed an EV traffic simulator for commercial vehicles, targeting the last one mile of home-delivery service, and evaluated the CO2 reduction effect by EV delivery vehicles per office basis. Through the analysis targeting Takasaki and Maebashi cities in Gunma Prefecture, we obtained the following findings.

- EV+PV case has a 24% reduction in CO2 emissions compared to the EV case, which is the effect of using PV surplus electricity. The following shows CO2 reduction effect in each case when compared to the EV+PV case.
- The QC case has only a 5% reduction compared to the EV+PV case; hence, it is not very effective only to increase charger output. Since the remaining battery level at the arrival time at the office is around 30 kWh, the quick charger is rarely used.
- The QC (SOC control) case has an 18% reduction compared to the EV+PV case; this result shows that it is effective to combine the increase in charger output with energy management such as SOC control. The

available capacity of battery is secured through the SOC control, and the amount of charge during the day increases. However, since the amount of charge exceeding the PV surplus electricity is charged from the power grid, there is room for further $CO_2$ reduction by dispersing the charging time during the day.

- The QC (SOC control + 2 group) case has a 41% reduction compared to the EV+PV case, showing that we can reduce $CO_2$ emissions more efficiently by combining the charging schedule management, the increase in charger output and the SOC control. By two groupings, the charging time is dispersed, and the amount of charge during the day is almost charged from PV surplus electricity.
- The Battery swap case has a 70% reduction compared to the EV+PV case, the biggest $CO_2$ reduction effect among all cases. By matching the charging time of the station-stored batteries with the generation time of the PV surplus electricity, about 80% of the electric energy consumed by traveling can be covered with PV surplus electricity.

It is considered as future research tasks such as studying the placement of quick chargers, reviewing the optimal battery capacity, and comparing EVs with conventional ICE.

## Acknowledgments

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