EV charging control using coupled simulation of urban traffic and power distribution system in a real-world area

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ABSTRACT

Owing to the urgent need to mitigate climate change, efforts toward decarbonisation have intensified in recent years, globally. On the same lines, one of the most active areas is the electrification of the transportation sector, specifically the adoption of electric vehicles (EVs). However, the distributed energy resources (DERs), such as photovoltaic (PV) systems, present challenges to power distribution grids, including voltage instability and increased demand.

To better understand the grid impact of increasing EV usage, in this study, we incorporated a multidomain simulation in a suburban area with high PV penetration. We integrated detailed traffic simulations to more accurately project EV charging demands based on individual behaviours.

We used open distribution system simulator for power distribution analysis and multi-agent based traffic and environment simulator to simulate traffic flows and facilitate real-time data exchange regarding EV charging demands and controls within the grid. The simulation was focused on a specific suburban area in Japan. We examined the effects of evening EV charging and limited efficacy of PV generation on reverse power flows.

According to our study findings, even with 100% penetration of EVs, the distribution line capacity will still be exceeded owing to the reverse power flow from PV generation. Future research should primarily focus on methods for mitigating the impact of reverse power flows associated with PV generation on DERs. These include strategies, such as EV charging output control, adjustments to charging tariffs, modifications to the locations of charging stations, and alterations to the charging behaviours of EV users. This study was aimed at examining and evaluating these methods from both power and transportation perspectives, including infrastructure approaches, and to exploring and proposing appropriate mechanism designs for using DERs.

Keywords: multi-domain simulation; EV; PV; distribution system; traffic network

INTRODUCTION

The renewable energy sources and electrified automobiles are being promoted to achieve a carbon-neutral society. However, a large amount of renewable energy is connected to distribution systems with an unstable power output. Similarly, the increased demand for EV charging will have a significant impact on the distribution system. Therefore, numerous researchers investigated the impact of distributed energy resources (DER) on distribution systems.

In particular, the quality and reliability of electric power degrade owing to the concentration of charging demand due to the mass introduction of EVs. Thus, appropriate EV charging is currently being researched by focusing on the distribution system.

The charging price is often used to control EV charging. Ul-Haq et al. (2015) proposed an EV charging control method based on electricity prices for multiple EV adoption rate scenarios and demonstrated that their method reduced voltage instability. Furthermore, Dubey et al. (2015) demonstrated ways to maintain voltage quality while maintaining user convenience through a charging schedule control, which considers EV user decisions in addition to charging price control. Deb et al. (2018) proposed a method for properly locating charging

stations (CS) on distribution lines using a power quality indicator and demonstrated its effectiveness. Boglou et al. (2020) modelled EV charging using an agent-based model. They showed that EV charging within the grid can be optimised by introducing the distance from the CS substation into an index that determines the charging priority. Osório et al. (2018) studied the impact of EV charging in a distribution grid while considering the presence of renewable energy for a distribution grid connected to wind and PV. They showed the effect of the appropriate introduction of EVs on the distribution grid. Cao et al. (2016) investigated PV and EVs in a distribution grid. They demonstrated probable mitigation of the EV-charging impact on the distribution grid via PV generation.

To clarify the future impact of EV charging on the power network, simulating EV charging demand in detail is essential. However, few researchers have examined methods to simulate realistic traffic in detail, estimate the charging demand by considers the charging behaviour of each EV, and reflect EV charging control that can change the EV charging behaviour in real time.

However, many researchers in the field of traffic engineering considered the spread of EVs and focused on the optimal placement of CSs and Vehicle-to-Grid (V2G) operations. Wolbertus et al. (2021) used agent-based simulations to evaluate various strategies for deploying charging infrastructure in urban areas. Their results showed that a mixed strategy, combining level 2 chargers, cluster-type hubs, and fast-charging stations, best met the EV demand. Thus, their results highlighted the impact of economies of scale and charger accessibility on EV sales. Zhang et al. (2018) presented an approach that combined traffic and power networks to plan plug-in electric vehicle (PEV) CSs and solar power plants. This approach incorporated a probabilistic planning model for traffic and power flow. It also demonstrated that collocating PV power plants with PEV stations can reduce costs, promote renewable energy, and alleviate power congestion, particularly through reactive power control. However, these studies used simplified power system models that complicate the addressing of localised issues in distribution networks.

Therefore, to thoroughly examine the effects of DERs on both transportation and distribution, it is essential to conduct an analysis using a coupled simulation that utilizes equally detailed and realistic information on both the traffic network and the power network. In this study, a simulation environment was constructed using a distribution-line model based on actual distribution-line information provided by electric power companies and road networks in the same area. By developing and examining simulation models, we investigated the impact of the introduction of EVs and PVs in real-world areas on the power distribution network and evaluated and examined the use of DER.

METHOD

Coupled Simulation

In this study, a simulation model that coupled the traffic flow simulator (eMATES) and power distribution system simulator (OpenDSS) was used. The configuration of the coupled simulation is shown in Figure 1. The interactions between the two simulators occurred every 60 s. During the execution of the coupled simulation, eMATES first conducted a simulation for 60 s, after which the usage status of each CS was input to OpenDSS, which considered the EV charging demand. Subsequently, the same simulation was performed by OpenDSS and eMATES for the same time. During this process, the charging output values from each CS were returned to eMATES. These charging output values were used to control the CS charging demands, which if increased could adversely affect the distribution. A coupled simulation of electricity and traffic was conducted by repeating this series of interactions.

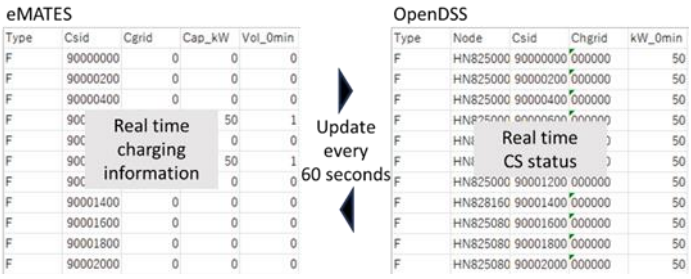


Figure 1: The configuration of the coupled simulation.

Traffic flow simulator, eMATES

Multi-agent based traffic and environment simulator (MATES) is a traffic flow simulator based on a multi-agent model. As shown in Figure 2, vehicles are referred

to as agents and act as autonomous entities that perceive their surroundings and make decisions independently. Agents interact only with nearby agents, and the accumulation of these local interactions leads to global phenomena, such as traffic congestion (Fujii et al, 2017).

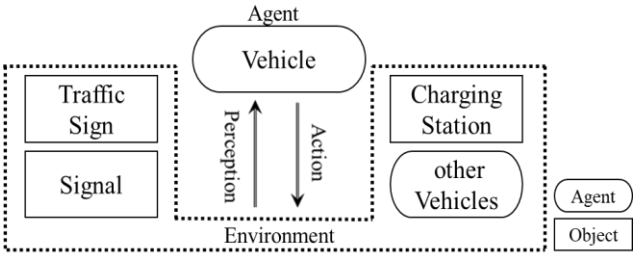


Figure 2: Overview of MATES.

eMATES is an enhanced version of MATES. It includes EV agents designed to simulate changes in the state of charge (SoC) of EVs and reproduce charging events at CS by introducing a decision-making model for CS selection and determining the charging timing. In this study, we used eMATES (Uchida et al, 2018) (Uchida et al, 2019).

In MATES, the acceleration of the vehicle agents is determined by an extended version of the generalized force model, which adjusts the acceleration of an agent based on the distance and speed differential to the vehicle ahead.

The power consumption of the EV agents was modelled based on the equations of motion. The four types of resistances involved in vehicle propulsion were calculated using Equations (1)–(4), which are the rolling, air, gradient, and acceleration resistances, respectively. If the sum of these resistance values is positive, then power is consumed to propel the vehicle. Conversely, if the sum is negative, the power is regenerated through regenerative braking. The amounts of power consumed and regenerated were calculated using Equations (5) and (6), respectively, replicating the behavior of the SoC during driving.

$$F_r = \mu_{rr} mg \cdot cos\theta, \quad (1)$$

$$F_d = \frac{1}{2} C_d \rho A v^2, \quad (2)$$

$$F_{\hbar} = mg \cdot sin\theta, \quad (3)$$

$$F_{la} = (m + M_l)a, \quad (4)$$

$$P_t = \left\{ \left(\frac{F_r + F_d + F_{\hbar} + F_{la}}{\eta} \right) \cdot v + F_{acc} \right\} \cdot \Delta t, \quad \left(F_r + F_d + F_{\hbar} + F_{la} \geq 0 \right) \quad (5)$$

$$P_{rb} = \left\{ \left(F_r + F_d + F_{\hbar} + F_{la} \right) \cdot v \cdot \eta \cdot \eta_{rb} \right\} \cdot \Delta t, \quad \left(F_r + F_d + F_{\hbar} + F_{la} < 0 \right) \quad (6)$$

m : Total vehicle mass [kg]
g : Acceleration due to gravity [m/s^2]
v : Vehicle speed [m/s]
a : Acceleration [m/s^2]
μ_{rr} : Coefficient of rolling resistance [-]
C_d : Coefficient of air resistance [-]
ρ : Air density [kg/m^3]
A : Frontal projection area of the vehicle [m^2]
M_l : Equivalent inertia mass [kg]
F_{acc} : Internal power consumption [W]
η : Drivetrain efficiency [-]
η_{rb} : Regenerative braking efficiency [-]

Power distribution system simulator, OpenDSS

Open distribution system simulator (OpenDSS) is a comprehensive power distribution system simulator developed by the Electric Power Research Institute (EPRI). It can simulate power by placing transformers and consumers in the distribution network to manage and analyze the state of the power network (Dugan et al, 2020).

OpenDSS sequentially performs tidal flow calculations; it is suitable for analyses that combine elements, such as EVs and PV. Additionally, the data format is highly versatile and scriptable and can be easily used in coupled simulations.

SIMULATION SETTINGS

Power distribution network

The distribution lines analyzed by OpenDSS were based on a distribution-line model constructed using information about the location of power poles and other data provided by Kansai Transmission and Distribution, Inc. The data pertained to an actual 6 km^2 distribution system consisting of one distribution substation and seven feeders. The area containing the distribution system under study is a suburban region in Japan with significant implementation of large-scale PV installation. Figure 3 shows the constructed distribution system model, where SS represents a substation, and F1−F7 represent feeders. The substation was equipped with an on-load tap changer (OLTC).

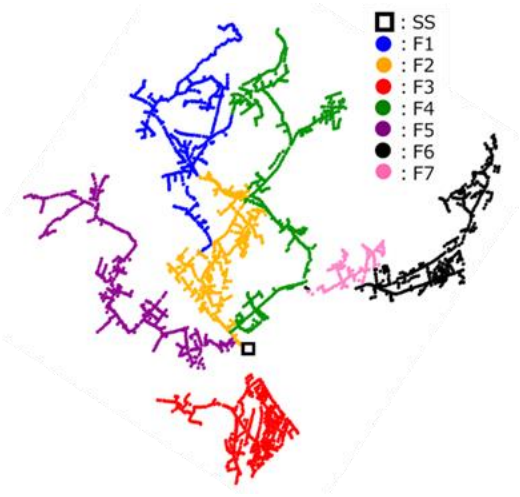


Figure 3: Power distribution system model.

Figure 6: Road network model.

The input data for the distribution network included load curves for each customer, PV generation, and EV charging demand. The grid parameters are listed in Table 1. The load curves for the electricity demand of each consumer were estimated using the actual demand data provided by Kansai Transmission and Distribution Inc., as shown in Figure 4.

The PV power generation was estimated using meteorological data based on satellite observations provided by Amaterass.org, as shown in Figure 5. The load curves and PV power generation for each customer were estimated on 1 April 2021. This is believed to be due to the significant impact of the PV reverse power flow on the distribution network. Section-wise aggregated low-voltage demand and PV were separated by a switch (eight sections per feeder) and high-voltage demand and PV were simulated for each consumer so that the sum of high-voltage demand, low-voltage demand, and PV generation matched the actual measured electricity values. The EV charging demand was estimated with maximum consideration of future EV adoption, assuming a 100% EV penetration rate, and using values output from a traffic simulation.

Traffic Network

A road-traffic model for the area, covered by the distribution-line model, was created using an Open Street Map. Figure 6 shows the constructed road-traffic network. The roads indicated by a–d in the figure are defined as major roads that connect the target area to other areas, whereas other roads are assumed to be elements that constitute living blocks with no connections to other areas. In eMATES, vehicle agents are generated at network endpoints and start their journey. Once they reached their destination, i.e., another endpoint, they are excluded from the simulations.

Therefore, traffic flow within the region was divided into four categories based on whether the origin (O) or destination (D) is either at the end of major roads or within the target area.

Table 1: Details of distribution system model.

Low Voltage Consumer (points)	7,083
High Voltage Consumer (points)	85
Total PV Capacity for Low Voltage (kW)	9,181
Total PV Capacity for High Voltage (kW)	11,636
Total Length of Distribution Lines (m)	75,241
EV Penetration Rate (%)	100

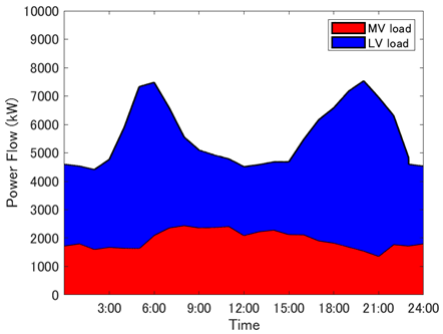


Figure 4: Electricity demand.

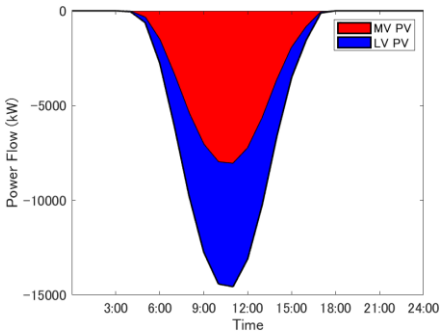
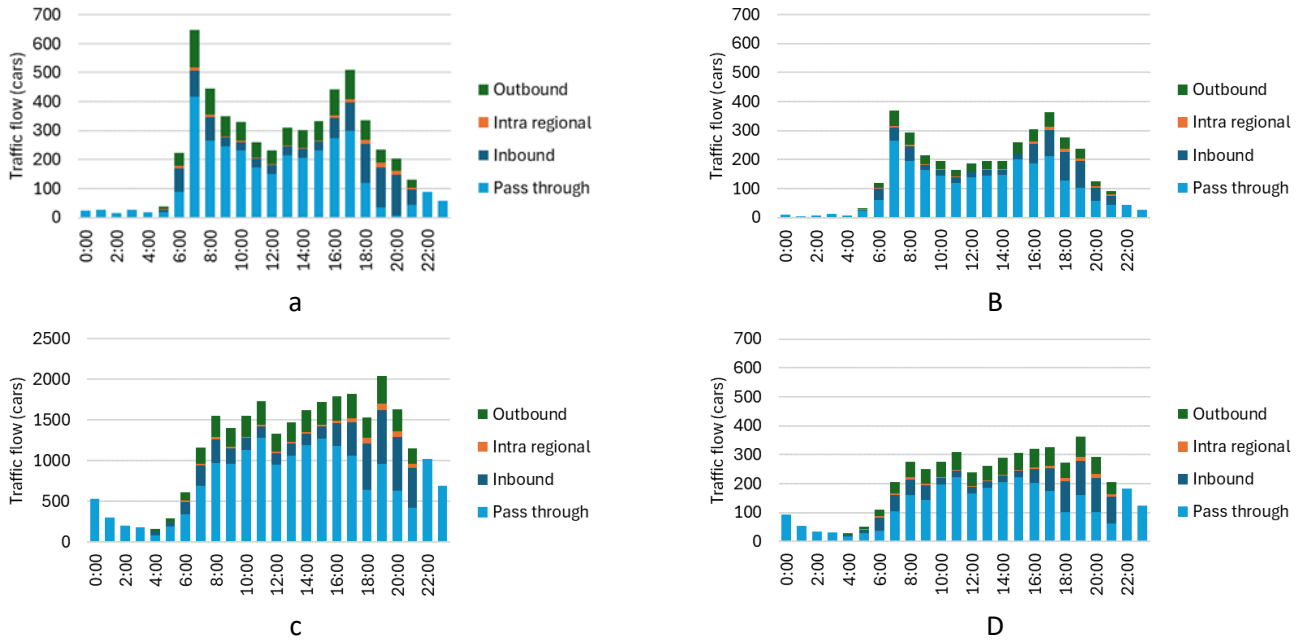


Figure 5: PV power generation.



The Figure 7: Traffic flow settings.

- Pass-through traffic: Traffic flow where OD is a major road end point.
- Outbound traffic: O is in the target area and D is one of the major road ends.
- Inbound traffic: O is a major road end, and D is within the target area.
- Intra-regional traffic: OD is within the target area.

These traffic flows were set for major roads based on traffic-volume and person-trip survey data provided by the Ministry of Land, Infrastructure, Transport, and Tourism (MLIT, 2021), as shown in figure 7.

In a scenario where the penetration rate of EVs reaches 100% and charging activities are frequent, the behaviours of EV agents can be modelled as follows: When the SoC drops below 20%, the EV agent begins to search for a CS to recharge. However, only fast charging (50 kW output) is used for passing-through traffic, normal charging (5 kW output) is used for intra-regional and inbound traffic, and no charging is performed for outbound traffic, regardless of the SoC.

EV charging output control

EV recharging was controlled in real time using OpenDSS. We used the total amount of power flow as an indicator and controlled the charging output based on the maximum allowable line loading (3638 kW). The control was set to decrease the charging output monotonically between 2910 kW (80% of the allowable value) and the allowable value (fast charging, $50-0$ kW; normal charging, $5-0$ kW).

RESULTS AND DISCUSSION

First, the results for the case without the EV charging output control are presented. Figure 8 illustrates the voltage variation for each feeder along the distribution line. The colours in the graph correspond to those of each feeder in the distribution-line model depicted in Figure 3. The solid lines represent the average voltage values at each node within the feeders, and the shaded areas indicate the ranges of maximum and minimum voltage values. We focused on the area with on-going installations of large-scale solar power plants. Significant voltage drops owing to PV generation during the daytime (6:00 – 16:00) are notable. This is attributed to the setting of a power factor (PF) of 0.95 for reactive power control. The OLTC tap control was employed to manage rapid voltage fluctuations exacerbated by increased PV generation during the daytime and a surge in EV charging demand in the evening and beyond. The feeders with a wider geographical spread, particularly at the ends of the distribution system, exhibited more significant voltage fluctuations, requiring careful attention. The target were expected in the target area,

and no increase in power demand was anticipated. Consequently, the voltage instability induced by the PV was expected to become more pronounced.

Next, the results of the voltage fluctuations with the EV charging output control are shown in Figure 9. Despite no changes in the OLTC tap control during daytime, PV generation-induced voltage dropped, and tap control was not evident in the evening or beyond. The charging output control is believed to improve the stability of the distribution system. Figure 10 shows the EV charging demand calculated using eMATES. Peaks in the EV

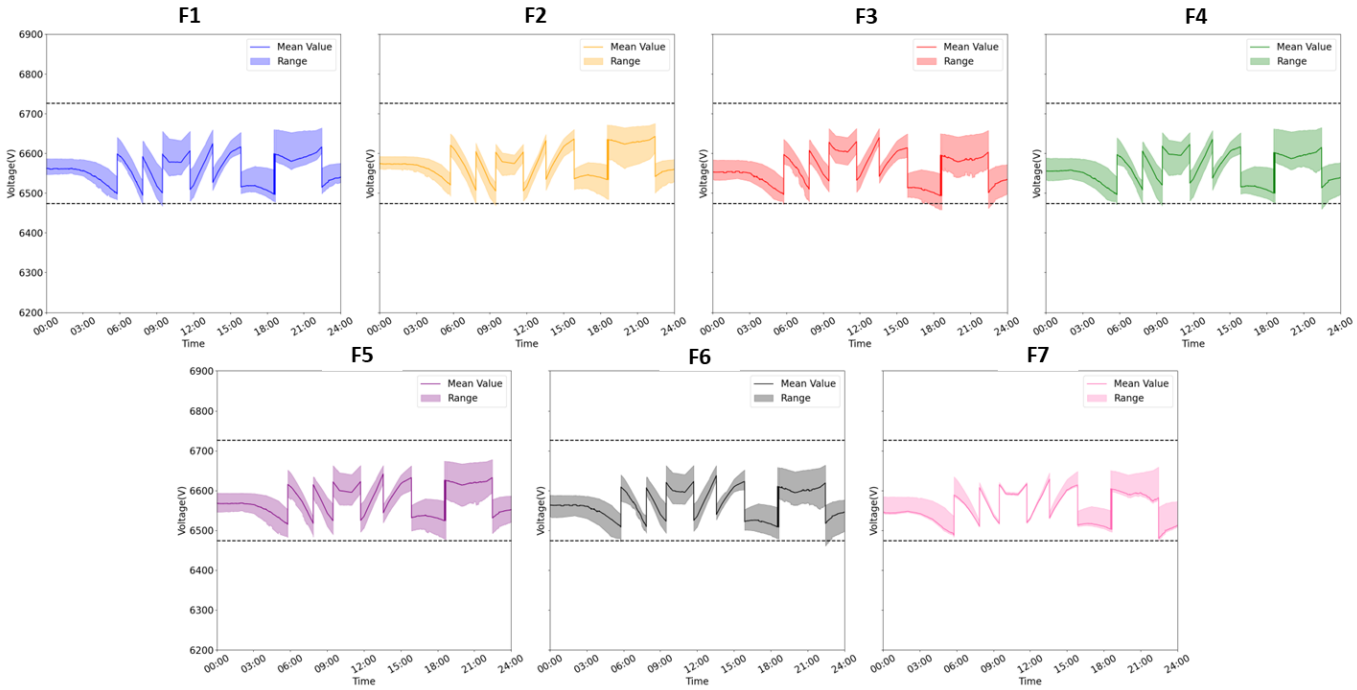


Figure 8: Voltage Fluctuations of each feeder (No control).

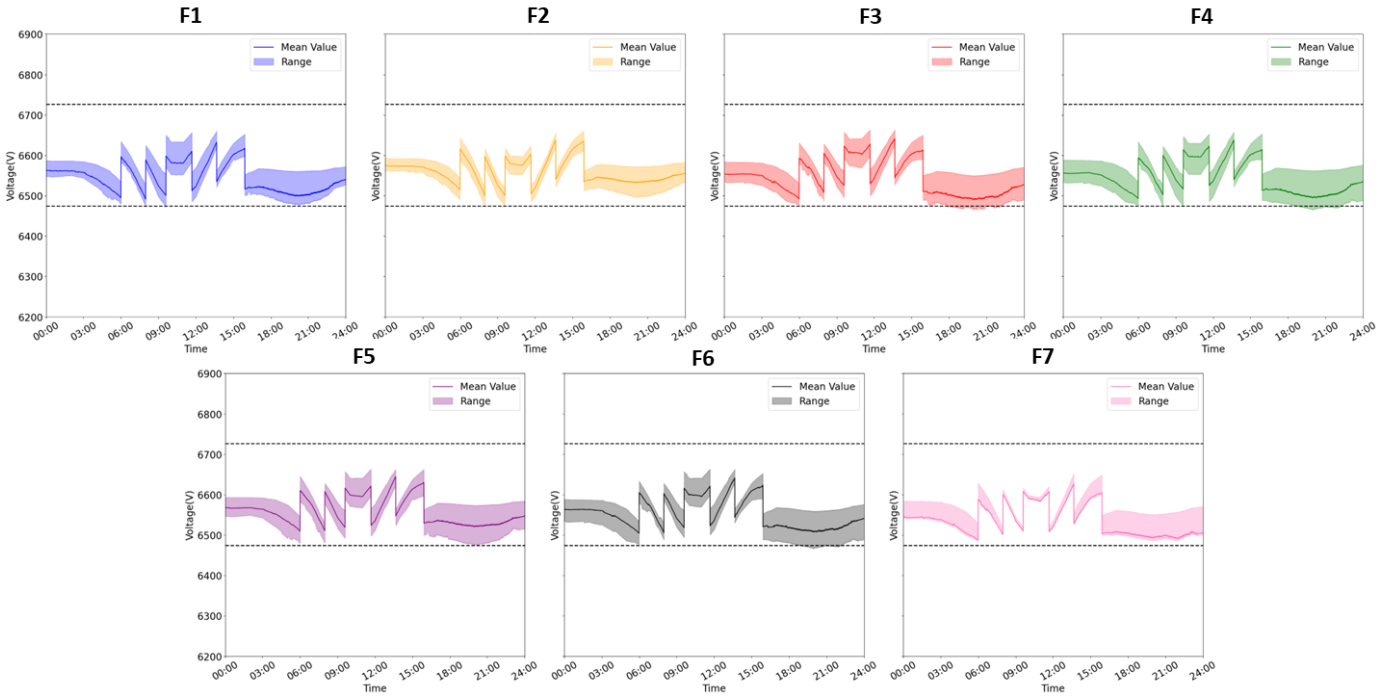


Figure 9: Voltage Fluctuations of each feeder (controlled).

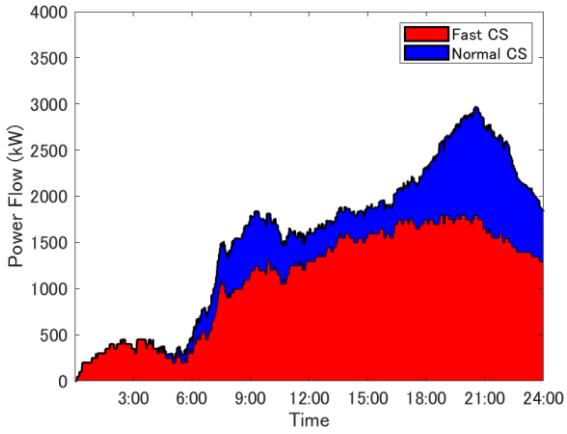


Figure 10: All EV charging demand (No control).

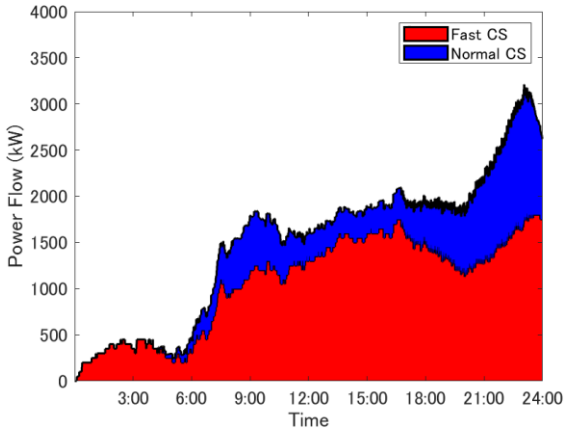


Figure 12: All EV charging demand (controlled).

charging demand coincide with increases in traffic volume in the morning and evening times, with regular charging needs primarily occurring after the evening rush hour and continuing until late at night. The additional significant EV-charging demand in the evening led to a voltage drop.

To solve this problem, output control was implemented for EV charging. The changes in the output per charger throughout the day (Figure 11) indicated that both rapid and regular charging outputs curtailed following an increase in evening demand. Consequently, the EV charging demand changed as depicted in Figure 12. This control measure effectively restrained the increase in power demand, thereby preventing tap control by the OLTC in the evenings, as previously mentioned.

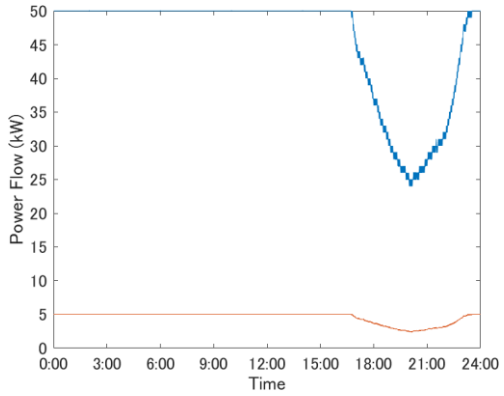


Figure 11: Changes in EV charging output.

Furthermore, an analysis of the traffic simulation revealed that the number of EVs charged at the end of the simulation was 3330 without control and 3292 with control. Considering that the simulation ran until midnight, the impact of output control on the traffic side can be inferred to be negligible. Future analyses will delve deeper into how EV charging has affected travel times and other aspects of the transportation network.

CONCLUSIONS

In this study, we developed a coupled simulation model by integrating highly detailed power and transportation simulators in real-time to elucidate the mutual interactions between electricity and transportation influenced by EV charging. Using this model, we constructed a simulation environment that targeted an actual area. The simulation accurately replicated real-world conditions based on actual vehicle traffic volumes and electricity demand settings. The electricity demand was derived from the measured values of distribution lines, considering the massive integration of DERs, such as PV and EVs, into the distribution network. The target area was a suburban region with stable weather conditions that facilitated extensive deployment of large-capacity PV systems. By analysing a coupled simulation of electricity and transportation and anticipating the future proliferation of EVs in such a context, the following insights were gained:

- The voltage instability phenomena associated with the spread of DERs, as indicated in previous studies, also occurred in simulations that closely mimicked actual areas.
- Phenomena, such as voltage drops due to PV generation, EV charging demands, and straining of distribution line capacities, occur almost independently, and the effect of improving distribution line reliability by using daytime PV generation to offset the EV charging demand was found to be limited.

- Although the output control of EV charging improved the stability of parts of the distribution network, further studies including changes in user behaviours, such as shifting charging times, are necessary for the effective utilisation of DERs.

FUTURE WORK

One of the key features of the coupled power and transportation simulation model used in this study is its high scalability, which allows for the modification of EV agent behaviours and consideration of future technological implementations. For example, in addition to charging output control, altering electricity prices to encourage more charging activities at daytime destinations, such as workplaces, can influence EV agent behaviour. Furthermore, considering future technologies, it enables considerations, such as increasing the capacity of chargers, optimal placement of CSs, and incorporation of wireless power transfer (WPT) systems for EV charging. Thus, it facilitates more flexible utilisation of DERs. To effectively utilise DERs, including PV and EVs, while maintaining the stability of the distribution lines, control methods from the supply side, such as output control, have limitations. Therefore, considerations that include user decision-making are necessary. The coupled power and transportation simulation model developed in this study, which reflects real-time interactions, is considered a highly effective method as a digital twin model for detailed examination and implementation of DERs in the future.

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