Optimization for Electric Vehicle Charging Station Placement Problems Considering Electric Vehicle Owner Distribution

Bosong Cheng[1] and Tadahiko Murata[1]

Abstract— **In recent years, there has been a growing demand for the expansion of electric vehicle charging stations (EVCS) to promote the sales of electric vehicles (EVs). Therefore, it is necessary to optimize the placement of EVCS while taking into account the charging needs of EV owners. However, many previous studies have simply estimated the distribution of EV owners based on market share, which risks creating discrepancies with the actual distribution. In this study, we simulate the actual distribution of EV owners using synthetic population data and optimize EVCS placement using the Simulated Annealing method. Furthermore, we evaluate the effectiveness of considering the actual distribution by comparing and verifying the results against those obtained under the assumption of a uniform distribution.**

I. INTRODUCTION

In response to the current situation where climate change associated with global warming is becoming increasingly severe, the "Glasgow Zero-Emission Vehicles Declaration" [1] was announced at COP26, with more than 100 countries, regions, and companies pledging to ensure that all new vehicle sales consist of zero-emission vehicles in major markets by 2035 and globally by 2040. For example, as part of the "Fit for 55" [2]) policy package proposed by the European Commission, a goal was set to reduce CO2 emissions across Europe by 15% by 2035 through the use of electric vehicles (EVs) and by ensuring that all new vehicle sales are zero-emission vehicles. Although the European Union and others have proposed some relaxations, the policy of transitioning to electric vehicles remains in place. Not only in Europe, but countries around the world are proposing various incentives, including subsidies for EV purchases. However, the expansion of public EV charging stations (hereinafter EVCS: Electric Vehicle Charging Station) is a prerequisite for promoting sales. The Japanese government has also set a goal of installing 300,000 charging points, including 30,000 public fast chargers, by 2030, and achieving 100% electric vehicles in new passenger car sales by 2035 [3].

While the expansion of EVCS is planned as described above, the question arises of how to deploy EVCS in line with the increase in EVs. A method for EVCS placement is needed that takes into account the future rise in EV penetration rates, charging convenience, and EVCS installation costs. In this study, using synthetic population data [4] that includes pseudo individual records with location information for household members, we develop an EVCS placement optimization method using the Simulated Annealing (SA) method to show the importance of considering actual distribution of EV owners in the EVCS placement problem.

*This work was supported by JST Mirai Program (JPMJMI23B1). The synthetic population data used in this study were supported by the Joint Usage/Research Center for Interdisciplinary Large-Scale Information Infrastructures (jh260056) and the High Performance Computing Infrastructure (hp240468, hp250520).

[1]Bosong Cheng and Tadahiko Murata are with the D3 Center, The University of Osaka, Osaka, Japan. tadahiko.murata.cmc@osaka-u.ac.jp

II. RELATED WORK

Ahmad et al. [5] point out that current research on EVCS deployment primarily involves calculating and optimizing costs from three perspectives: power grid operators, EVCS owners, and EV owners. Among these, the costs on the EV owner side depend most strongly on the distribution of EV owners. In many studies, the costs on the EV owner side are estimated based on travel data or data obtained from previous studies to determine the number of owners and charging demand.

For example, Huang et al. [6] and Jiang et al. [7] obtained or created regional traffic origin-destination (OD) tables from research institutions or previous studies, extracted EV owners' OD data from these tables based on EV market share, and utilized this data to estimate EV owners' charging demand.

However, since these methods simply extract EV owners' OD data based on market share, they fail to account for the diversity associated with the characteristics of EV owners. In other words, they do not consider the distribution of EV owners across different types of households. Because of the current low EV penetration rate, it is necessary to consider the actual distribution of EV owners. Conventional methods described above assume that EV owners are uniformly distributed and estimates the "number of EV owners" using OD tables and EV market share, which may differ from the actual regional distribution of EV owners.

Therefore, in this study, we create a simulated actual distribution of EV owners using synthetic population data. The synthetic population data contains pseudo individual records with location information for household members. By using synthetic population data, it is possible to simulate the distribution of EV owners while taking into account household attributes and geographical distribution. Furthermore, we optimize EVCS placement under the assumption of a uniform distribution and an actual distribution, and verify the differences between the both. This demonstrates that it is important to consider EVCS layout with considering an actual distribution characteristics of EV owners.

TABLE I

EV OWNERSHIP RATE BY THE NUMBER OF HOUSEHOLD MEMBERS

# of Members	1	2	3	4	5	6+	Total
Rate (%)	21.8	37.3	16.1	20.2	1.5	3.1	100.0

6+: 6 members or more.

TABLE II

EV OWNERSHIP RATE BY THE AGE GROUP OF HOUSEHOLD HEAD

Age Group	30-39	40-49	50-59	60-64	65+	Total
Rate (%)	4.3	10.4	27.7	31.7	25.9	100.0

65+: Age 65 or older.

III. PROPOSED METHOD

The methodology of this study consists of the following steps. First, we generate a pseudo-real distribution of EV owners using synthetic population data. Next, based on the generated distribution, we optimize the EVCS placement using the SA method. Finally, we compare and verify the results obtained when assuming a uniform distribution versus those obtained using the pseudo-real distribution.

A. Assigning EV Owner Attributes to Synthetic Populations

Synthetic population data is pseudo individual data of household members generated based on Census Data for the purpose of conducting simulation studies that target real communities. By assigning EV owner attributes to the synthetic population data, a pseudo-real distribution of EV owners can be obtained, enabling the optimization of EVCS placement that takes into account the actual distribution characteristics of EV owners. The assignment of EV owner attributes to the synthetic population is performed using the following method.

First, from the 2020 Survey on Actual CO2 Emissions from the Household Sector [8], we extract Table I, which shows the proportion of EV-owning households by household size, and Table II, which shows the proportion of EV owners by age of household head.

We use the SA method to derive a cross-tabulation table that simultaneously satisfies the two distributions described above. The SA method procedures and parameters are set as follows.

[Parameter Settings]

- Initial temperature $T_0 = 1,000$,
- Cooling rate $\alpha = 0.99$,
- Convergence temperature $T_{end} = 1 \times 10^{-6}$,
- Number of iterations at each temperature: 100

Using the above parameters, the total number of iterations becomes 206,200.

[Objective Function]

In the SA method described in this section, the following objective function E is minimized so that the generated cross-tabulation table reproduces the marginal distribution of the statistical data.

$$E = \sum_{i=1}^{6}(p_i - p_i')^2 + \sum_{j=1}^{5}(q_j - q_i')^2, \tag{1}$$

where p_i shows the EV ownership rate by the number of household members in a household ($i = 1, 2, ..., 6$) in Table I, p_i' is the EV ownership rate calculated from a cross-tabulation table by i that is generated by SA, q_i shows the EV ownership rate by the Household Head Age Classification ($j = 1, 2, ..., 5$) in Table II, and q_j' is the EV ownership rate calculated from a cross-tabulation table by j that is generated by SA. p_i' and q_j' are calculated by $p_i' = \Sigma_i x_{ij}$ and $q_j' = \Sigma_j x_{ij}$, respectively, where x_{ij} is an EV ownership rate in the cross tabulation table generated by SA.

[Generation of Initial Solution]

Generate the initial solution s_0 as follows. First, set the values of all cells in the cross-tabulation table to 0%. Repeat the operation of incrementing the value of a randomly selected cell by 0.1 until the total of all the cells reaches 100%, for a total of 1,000 iterations. Consequently, after generating an initial solution, the totals for each row and column differ from the values of the marginal distribution in Tables I and II.

[Generation of Adjacent Solutions]

Select one cell with a positive value at random. Move 0.1% value of the selected cell to one of neighboring cell (up, down, left, or right).

[Transition Decision]

For the generated neighboring solution s', calculate the change in the objective function ΔE = $E(s') - E(s)$. The acceptance probability according to the Metropolis criterion [9] is given by the following equation.

$$P = \begin{cases} 1, & \text{if } \Delta E < 0 \\ \exp(\frac{-\Delta E}{T}), & \text{if } \Delta E \geq 0 \end{cases} \tag{2}$$

Here, T denotes the current temperature. We generate a uniform random number r in [0, 1) and accept a neighboring solution if $r < P$.

[Termination Criteria]

After completing 100 iterations at each temperature, the SA method terminates and outputs the current solution as the final solution if any of the following conditions are satisfied:

• When the temperature falls below the convergence temperature ($T < T_{end}$)
• When the objective function value reaches 0 ($E = 0$)

The former indicates that the maximum number of iterations has been reached, while the latter indicates

TABLE III

AN EXAMPLE OF EV OWNERSHIP RATE BY THE NUMBER OF HOUSEHOLD MEMBERS AND THE AGE GROUP OF THE HOUSEHOLD HEAD

# of Members / Head Age	1	2	3	4	5	6+	Rate (%)
30-39	1.2	1.2	0.6	0.5	0.4	0.4	4.3
40-49	2.5	6.3	0.5	0.2	0.0	0.9	10.4
50-59	6.8	14.5	0.0	5.2	1.0	0.2	27.7
60-64	5.4	11.8	4.2	10.0	0.0	0.3	31.7
65+	5.9	3.5	10.8	4.3	0.1	1.3	25.9
Rate (%)	21.8	37.3	16.1	20.2	1.5	3.1	100.0

6+: 6 members or more.
65+: Age 65 or older.

TABLE IV

AVERAGED RESULT OF EV OWNERSHIP RATE

# of Members / Head Age	1	2	3	4	5	6+	Rate (%)
30-39	0.6	1.2	1.0	0.9	0.3	0.3	4.3
40-49	3.6	2.9	1.5	1.5	0.3	0.6	10.4
50-59	6.6	10.6	4.2	5.1	0.3	0.8	27.7
60-64	9.3	10.2	4.4	6.5	0.3	0.9	31.7
65+	1.6	12.4	4.9	6.2	0.3	0.5	25.9
Rate (%)	21.8	37.3	16.1	20.2	1.5	3.1	100.0

6+: 6 members or more.
65+: Age 65 or older.

that the cross-tabulation table has completely reproduced the marginal distribution of the statistical data. If the termination conditions are not met, the temperature is updated by $T \leftarrow \alpha T$, and the process returns to the generation of neighboring solutions. Using the proposed method, we could find the cross-tabulation table as shown in Table III.

Since the SA method is a stochastic algorithm, different results are obtained with each run. In reality, there are many different solutions that satisfy the marginal distribution, and it is not practical to consider all of them. Since this study focuses on EVCS placement optimization based on pseudo real distributions, we adopt the average of the results from 10,000 SA runs as a valid solution and use it for subsequent research. Table IV shows the final cross-tabulation table (rounded to the first decimal place). Using this cross-tabulation table of EV ownership rate by the number of household members and the age group of household head, we probabilistically select households with the specified number of household members and the specified age group of household head as owners of EV.

B. Optimization of EVCS Placement Using SA Algorithm

Using the location data of EV owners within a region, we determine the optimal EVCS placement that minimizes the distance cost to charge EVs using another SA algorithm. As in the previous section, we perform optimization using SA algorithm, however, procedures for generating initial and neighboring solutions, as well as the objective function, are different from the previous one. Note that we assume each EV owner owns only one EV. The SA algorithm procedure and parameters in this section are set as follows.

[Parameter Settings]

The parameters for the SA algorithm used in this section are set as follows.

- Initial temperature $T_0 = 10,000$,
- Cooling rate $alpha$: Varies in the following stages
– $\alpha = 0.90$, if $0.1T_0 < T$
– $\alpha = 0.92$, if $0.01T_0 < T \leq 0.1T_0$,
– $\alpha = 0.94$, if $T \leq 0.01T_0$.
- Convergence temperature $T_{end} = 0.1$,
- Number of iterations at each temperature: 5,000.

By allowing the solution to deteriorate at high temperatures, we perform a broad search; by gradually reducing the cooling rate at low temperatures, we achieve a precise local search. With the above parameters, the total number of iterations becomes 810,000.

[Objective Function]

In this optimization, we minimize the objective function F, which takes the following three factors into account:

$$F = F_1 + F_2 + F_3, \tag{3}$$

Here, each term is defined as follows:

F_1: Total distance cost for all EV owners

$$F_1 = \sum_{i=1}^{N} d_i^2, \tag{4}$$

where N is the number of EV owners, and d_i is the distance from EV owner i to the nearest EVCS. A higher cost on EV owners located farther away, we square the distance. This accounts for the fact that the convenience for EV owners decreases non-linearly as the distance to the charging station increases. This term serves as a fundamental indicator of charging convenience for all EV owners.

F_2: Maximum distance cost among EV owners

$$F_2 = w_2 \cdot d_{\max}^2, \tag{5}$$

where $d_{\max} = \max_i d_i$, which is the maximum distance to the nearest EVCS from each EV owner. This term helps prevent some owner locates in extremely inconvenient place. The weight w_2 is set as follows using the values of F_1 and $d_{\max}^2$ from the initial solution.

$$w_2 = \frac{F_1^{(0)}}{d_{\max}^{(0)2}}, \tag{6}$$

where the superscript (0) denotes the value in the initial solution. This weighting adjusts F_2 so that it has an influence comparable to that of F_1.

F_3: Deviation Cost of EVCS Installation Count

$$F_3 = w_3 \cdot \left(\frac{|n - n^{(0)}|}{n^{(0)}} \right)^2, \quad (7)$$

where, n is the number of EVCSs in the current solution, and $n(0)$ is the number of EVCSs in the initial solution. The method for setting the initial EVCS count $n(0)$ will be described later. This term prevents the number of EVCSs from deviating significantly from the initial value during the optimization process. The weight w_3 is set as follows.

$$w_3 = 2 \cdot F_1^{(0)}, \quad (8)$$

With this weighting, the deviation cost when the number of EVCS deviates by 10% from the initial value is equivalent to approximately 2% of the distance cost of the initial solution.

[Generation of Initial Solution]

In this study, assuming normal charging in urban areas, the EVCS layout for the initial solution is calculated using the following procedure.

The initial number of EVCS, $n^{(0)}$, is calculated as follows based on the European Union's Alternative Fuels Infrastructure Directive (AFID) [10] and Japanese statistical data from 2024 [11], [12].

$$n^{(0)} = \left\lceil \frac{n_c}{4} \right\rceil, n_c = \left\lceil \frac{N_{EV}}{10} \right\rceil, \quad (9)$$

where N_{EV} is the number of EV owners in the target area, n_c is the number of chargers, and $\lceil \cdot \rceil$ denotes the ceiling function (rounding up). According to this formula, the number of chargers is 1/10 of the number of EV owners, and each EVCS is equipped with four chargers. After the initial number of EVCS, $n^{(0)}$, is determined, an initial layout is generated using the K-means method. The K-means method is a technique that divides the locations of EV owners into $n^{(0)}$ clusters and places one EVCS at the center of each cluster. Using the latitude and longitude coordinates of EV owners as input data, the K-means method divides them into $n^{(0)}$ clusters and places an EVCS at the center of each cluster. The scikit-learn [13] library was used to implement the K-means method. In this study, the number of clusters $n^{(0)}$, the number of initialization trials 5,000, and the maximum number of iterations 1,000 were set as default parameters.

[Generation of Adjacent Solutions]

For the current solution, one of the following three types of operations is randomly selected to generate an adjacent solution.

Movement operation: A random rectangular area is defined within the target region, and all EVCSs within that rectangular area are moved simultaneously. Specifically, the average area for each EVCS is calculated using the current number of EVCSs, and a rectangular area with an area ranging from 1 to $\sqrt{n}$ times that value is randomly placed. For each EVCS within the region, apply a perturbation following a normal distribution proportional to the region size (standard deviation is 25% of the region width, minimum 100 m). Perform this operation twice and adopt the configuration with the smaller objective function value.

Split operation: Randomly select one of the top five EVCSs with the highest number of users, and apply the K-means method (number of clusters: 2) to the location coordinates of those users. Place new EVCSs at the centers of the two resulting clusters, and delete the original EVCSs. However, the operation is aborted if the number of users is 10 or fewer, or if the new EVCS does not satisfy the minimum distance constraint.

Deletion operation: Randomly select one of the bottom five EVCSs with the fewest users and delete it. Identify the four EVCSs closest to the deleted EVCS, and move each neighboring EVCS toward the deletion location. The amount of movement is determined based on the ratio $N_{deleted}/(N_{deleted}+N_{neighboring})$ of the number of users at the deleted EVCS to the number of users at the neighboring EVCSs.

Constraints: For the generated adjacent solution, the distance between any two EVCSs is set to be more than 50 m. If the constraint is not satisfied, the operation is not executed and the current solution is retained.

Updating the number of chargers: After executing each operation, the number of chargers at each EVCS is updated using the following equation.

$$n_c^{(i)} = \max\left(1, \left\lceil \frac{N_u^{(i)}}{10} \right\rceil \right), \quad (10)$$

where $n_c^{(i)}$ is the number of chargers at EVCS i, and $N_u^{(i)}$ is the number of EV owners who consider EVCS i to be their nearest EVCS, i.e., the number of users of EVCS i. Through this update, the appropriate number of chargers is dynamically set according to the demand at each EVCS.

[Transition Decision]

The transition decision follows the Metropolis criterion described in the previous section. For the generated neighboring solution s', the change in the objective function $\Delta F = F(s') - F(s)$ is calculated, and the acceptance decision is made by substituting E in Equation (2) with F.

[Termination Criterion]

Updates are performed according to the stepwise cooling schedule described in the parameter settings, and the algorithm terminates when the convergence temperature $T_{end} = 0.1$ is reached. As a result, approximately 160 temperature drops and a total of 810,000 search iterations are executed, yielding the final EVCS configuration.

C. Evaluation

In this study, we conduct an evaluation from the following two perspectives.

Performance Evaluation of the Optimization Method

We evaluate the optimization performance of the EVCS placement obtained using the proposed method. For the evaluation, we use the terms of the objective function without weighting and compare the following two solutions.

Solution 1 (Proposed Method): Placement optimized using the method proposed in this study,
Solution 2 (Reference): Placement of the same number of EVCS of Solution 1 using K-means.

Through comparing these solutions, we confirm the superiority of the proposed method over the K-means method (comparison of Solution 1 and Solution 2).

Evaluation of the Impact of EV Owner Distribution

We evaluate the impact on EVCS placement of the difference between the actual distribution of EV owners and the assumption of a uniform distribution where the attributes of EV owners are not considered. Specifically, we apply the EVCS placement optimized under the assumption of a uniform distribution (Solution 3) to EV owners distributed according to household attributes, and compare it with the placement optimized based on the pseudo-actual distribution (Solution 1).

The evaluation metrics used are F_1 and F_2. Through this comparison, we verify the hypothesis of this study, namely that “if the distribution of EV owners is not taken into account, a discrepancy will arise between actual charging demand and the deployment results.”

IV. EXPERIMENTS AND EVALUATION

A. Target Area and Experimental Setup

In this study, experiments will be conducted in Suita City, Osaka Prefecture, Japan. Suita City has a population of approximately 380,000 and an area of approximately 36 km², and features a diverse urban landscape that includes a large portion of Senri New Town tha was established in 1962.

We employed 2019 Passenger Car Market Trends Survey conducted by the Japan Automobile Manufacturers Association and 10 sets of Suita City’s 2015 synthetic population data. We set the EV market share to five scenarios: 0.5%, 1%, 2%, 3%, and 5%. Based on the number of EVs owned in each scenario, we generated a pseudo-real distribution—in which EV owner attributes were assigned to the synthetic population using the methodology of this study. In order to compare the effect of EV owner distribution, we also developed a uniform distribution. A total of 100 patterns (5 scenarios × 10 sets × 2 distributions) of datasets were created.

The proposed method of this study was applied to all patterns and compared according to the evaluation metrics in the previous section. Fig. 1 shows an example of EVCS placement for the pseudo-real distribution in the 0.5% EV market share in Scenario of Dataset 1. In this example, there are 653 EV owners, 23 EVCSs, and 75 chargers. The red diamonds represent EVCS, and the small dots represent EV owners with different colors to show their nearest EVCS.

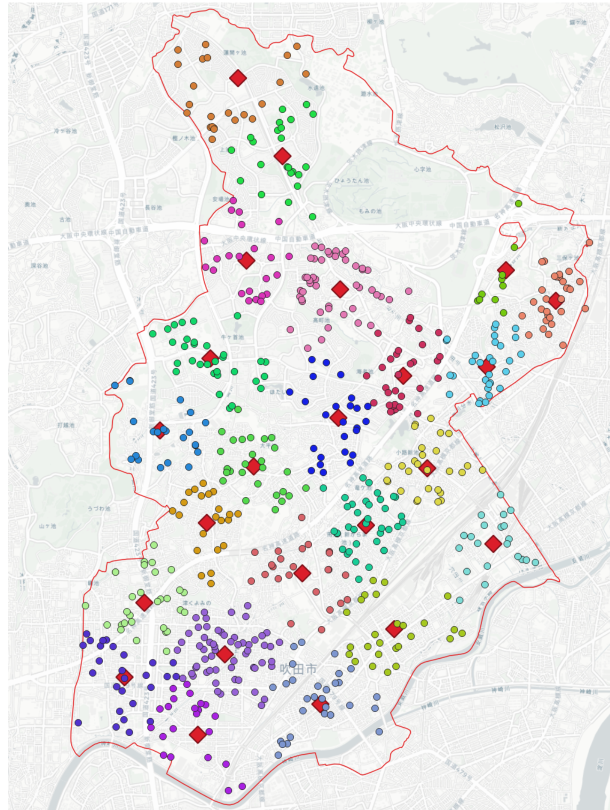

Fig. 1. Example of EVCS placement in Suita City, Osaka, Japan

B. Performance Evaluation of the Optimization Method

Fig. 2 shows the reduction rates in total distance cost and maximum distance by the proposed method (Solution 1) compared to K-means method (Solution 2). This demonstrates the degree of optimization achieved compared to the baseline K-means solution when the number of EVCSs is the same.

As shown in Fig. 2, even with the same number of EVCSs, the proposed method effectively reduces the maximum distance compared to the baseline K-means solution in all scenarios. Regarding the total distance cost, although the reduction effect is small in the scenario with an EV market share of 0.5%, the reduction rate for both costs is improved as the market share increases. Since the objective function considers both costs equally, this trend is also reasonable. Based on the above, the effectiveness of the proposed method has been verified, and a significant improvement in performance compared to the baseline K-means method has been confirmed.

C. Evaluation of the Impact of EV Owner Distribution

Fig. 3 shows a comparison of the total distance cost when Solutions 1 and 3 are applied to EV owners with a pseudo-real distribution. This allows us to evaluate the performance

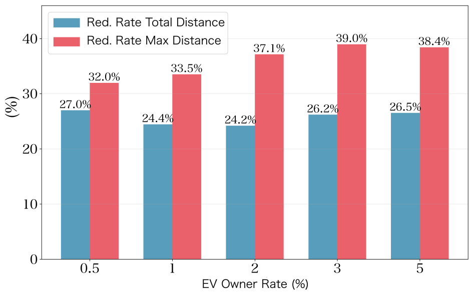

Fig. 2. The reduction rate of the proposed method (Solution 1) compared to K-means method (Solution 2).

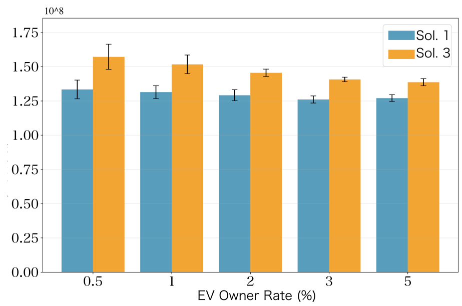

Fig. 3. The reduction rate of the proposed method (Solution 1) compared to K-means method (Solution 2).

difference between solutions based on the pseudo-real distribution and those based on a uniform distribution when EV owners follow the pseudo-real distribution.

As shown in Fig. 3, Solution 1, which is based on a pseudo-real distribution that takes into account the actual distribution characteristics of EV owners, consistently has a lower total distance cost compared to Solution 3, which is based on a uniform distribution that does not consider these characteristics. Furthermore, this difference tends to decrease as the EV market share increases. This suggests that as the number of EV owners increases, the pseudo-real distribution tends to approach a uniform distribution.

V. CONCLUSIONS

In this study, to account for the actual distribution characteristics of EV owners, we proposed a method for generating a pseudo-real distribution of EV owners using synthetic population data and the SA algorithm. Furthermore, we proposed an EVCS placement optimization method using the SA algorithm based on EV owners' location information, and evaluated the placement based on the simulated real distribution against that based on a uniform distribution. As a result, the effectiveness of the proposed method was confirmed, and the necessity of considering the actual distribution of EV owners in EVCS placement optimization was demonstrated.

Future challenges include generating EV owner distributions that take other household attributes into account and applying the method to other regions. This study is expected to provide insights for similar research where the actual distribution of individuals is important, as well as contribute to the promotion of EV adoption through the appropriate expansion of EVCS.

REFERENCES

[1] UK Government, COP26 declaration on zero emission cars and vans, `https://www.gov.uk/government/publications/cop26-declaration-zero-emission-cars-and-vans` (2021).

[2] European Council, Fit for 55, `https://www.consilium.europa.eu/en/policies/fit-for-55/` (2021).

[3] Ministry of Economy, Trade and Industry, Japan, Sector-specific Investment Strategy Report (Automobile), `https://www.cas.go.jp/jp/seisaku/gxjikkoukaigi/pdf/sankou5.pdf` (2023, in Japanese).

[4] T. Murata, T. Harada, and D. Masui, Comparing Transition Procedures in Modified Simulated-Annealing-Based Synthetic Reconstruction Method without Samples, *SICE Journal of Control, Measurement, and System Integration*, vol.10, no.6, pp.513-519 (2017).

[5] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, I. Khan, Optimal location of electric vehicle charging station and its impact on distribution network: A review, *Energy Reports*, vol.8, pp.2314-2333 (2022).

[6] Y. Huang, K. Kockelman, Electric vehicle charging station locations: Elastic demand, station congestion, and network equilibrium, *Transportation Research Part D: Transport and Environment*, vol.78, no.102179, 16 pages (2020).

[7] Q. Jiang, N. Zhang, B. Y. He, C. Lee, J. Ma, Large-scale public charging demand prediction with a scenario- and activity-based approach, *Transportation Research Part A: Policy and Practice*, vol.179, No. 103935, 27 pages (2024).

[8] Ministry of Environment, Survey on Actual CO2 Emissions from the Household Sector, `https://www.env.go.jp/earth/ondanka/ghg/kateico2tokei/r2co2.html` (2020 in Japanese).

[9] N. Metropolis, A. W. Rosenbluth, M. N. Rosenbluth, A. H. Teller, E. Teller, Equation of state calculations by fast computing machines, The Journal of Chemical Physics, vol.21, pp.1087-1092 (1953).

[10] EUR-Lex, Document 32014L0094: `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0094`

[11] Yoshinori Yorimoto, Progress in Electric Vehicle Charging Infrastructure Development / Expansion to Support EV Adoption Is Steadily Advancing, EVsmart, `https://blog.evsmart.net/electric-vehicles/electric-vehicle-charging-infrastructure-\progress-ev-adoption-support-expansion/`(2025 in Japanese).

[12] EV EneChange, Where Are Electric Vehicle (EV) Charging Stations? A Comprehensive Guide to Finding, Pricing, and Usage, `https://ev-charge-enechange.jp/articles/163/` (2025 in Japanese)

[13] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderlpas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay Scikit-learn: Machine Learning in Python, *Journal of Machine Learning Research*, vol.12, pp.2825-2830 (2011).

[14] Ministry of Economy, Trade and Industry, Japan Government, Electricity and Gas Market Surveillance Commission, 2nd Committee Meeting on Localized Electricity Demand Growth and Transmission/Distribution Networks, Document 6 (partially revised), `https://www.meti.go.jp/shingikai/mono_info_service/charging_infrastructure/pdf/007_05_00.pdf` (2025).

[15] Y. Li and A. Jenn, Impact of electric vehicle charging demand on power distribution grid congestion, Sustainability Science, vol.121, no.18, 10 pages (2024).

[16] Japan Automobile Manufacturers Association, 2019 Passenger Car Market Trends Survey (2020).