THE REPRESENTATIVE CHARGING PATTERN FOR EVS BASED ON THE ACTUAL EVS CHARGING DATA FOR DISTRIBUTION SYSTEM PLANNING

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ABSTRACT

As the interests in eco-friendly energy has increased, the interests in Electric Vehicles(EVs) are increasing as well. Moreover, due to the government's economic support for EVs, penetration level of it has rapidly increased. These sharp increases, however, induce various problems in distribution system, such as voltage/frequency variations, peak demand increase, demand control, etc. To minimize these possible matters, lots of research have conducted. Nevertheless, most of it assumed extremely important factors, such as numbers and charging patterns of EVs. It inevitably results in errors in their research, and thus make it difficult to prevent the possible matters from EVs. In this paper, therefore, we use actual EVs charging data from KEPCO, and analysis and deduction of it were conducted. The simulations were carried out for three aspects (season, region, purpose).

INTRODUCTION

As interest in eco-friendly energy around the world grows, interest in electric vehicles (EVs) is increasing naturally. The government also provides a variety of subsidies to reduce the use of internal combustion engine vehicles and increase the frequency of EV use. Due to such circumstances, the EV penetration rate is expected to increase steadily. However, the unanticipated increase in demand power due to unexpected EVs charging can cause serious problems such as voltage and frequency fluctuations, peak demand power increase, and demand management in terms of grid operation and planning.
In order to identify and prepare for these problems, various studies have analyzed the effects of EV on charging demand and power system. [1] defined EVs as hybrid vehicles and pure EVs, calculated lifecycle costs for each model, and predicted demand power of EVs charging based on calculated life cycle costs based on regression analysis. However, regression analysis assumes that past trends will continue in the future. Therefore, it is difficult to reflect the explosive increase in EVs demand unlike the previous one due to changes in technological / policy environment. [2] estimated the EVs demand power using the apartment parking control system data in Seoul and the National Statistical Office (NSO), and based on this, calculated the optimal number of EV charging facilities. However, it is assumed that the number of EVs calculated by using previous pattern, and the EVs charging is to have only four charging ratios. [3] mathematically derived the EVs charging demand power characteristic equation for a special day. Also derived and analyzed the EVs demand model using the diffusion curve and traffic volume. However, EVs are simply calculated based on the penetration rate, and all EVs have the same charging pattern. In case of [4], forecast of EVs distribution was considered using weather information and actual traffic volume distribution. Based on that seasonal demand for weekday / weekend charging was analyzed. However, in order to estimate the initial state of charge (SoC) of the battery, it is arbitrarily set based on the standard distribution, also there is a limitation that the traffic volume information and the weather information utilized do not directly reflect the EVs charging pattern. [5] proposed a charging demand forecasting model for a downtown rapid charging station. To do this, the Markov-chain traffic model, which assumes that the probability of the current traffic volume will reach a certain state depends only on the traffic volume at the previous point, is used. However, since there is no information on the initial SoC, it is assumed that the SoC is between 0.2 and 0.3, and that the charging pattern of the EVs is estimated based on the driving pattern of the internal combustion engine vehicle. [6] estimated EVs travel distance and initial SoC based on the probability distribution and predicted the EVs charging demand by setting the scenario based on the time of use (ToU). However, the study assumes that EV travel distance and SoC follow the standard distribution, and has the limitation that the charging start time of each EV is arbitrarily set. [7] predicted home demand power including EVs charging demand based on stochastic programming and analyzed the effect on the system according to EVs diffusion rate in terms of maximum load increase, power loss, and voltage fluctuation. However, in this study, all EVs are charged at home, and there is a limitation that assumption is made that only one EV can be charged in each home or office at the arbitrary time.
Previous studies have introduced a variety of methods to analyze the impact of EVs on the distribution system, as described above, these attempts have paradoxically caused errors in the study results. Nevertheless, the reason why various methods are applied is due to the fundamental reason that EVs charging data does not exist. In this paper, we analyze the actual EVs charging data using actual data accumulated in "Electric Vehicle Charging Service Operation System" of KEPCO, and draw out charging pattern by region, season, and usage.

ANALYZE OF THE EVS CHARGING

As mentioned in the introduction, the biggest limitation of the existing research is that there is no real EVs charging data, so the data was generated with various assumptions. In this paper, actual EVs charging data is collected from KEPCO charging service operating system, and charging pattern for each region / season / usage is derived.

KEPCO EVs charging service management system

The "Electric Vehicle Charging Service Operation System" operated by KEPCO provides location of EVs charging station, charge status information, charge reservation service throughout the country to provide convenience to EVs users. Also information of the number of electric vehicles, the number of charging stations are provided. In particular, statistics / analysis functions can be provided so that statistical data by operator, region, time, and charge type can be confirmed. The data used in this paper are actual domestic EVs charge data collected from the system.

Figure 1 KEPCO's EVs charging service management system

Summary of EVs charging data analyse

The collected EVs charging data has the form as shown in Table 1, and provides information such as charging station jurisdiction information, charging station location information, charging type, charging start time, and charging amount.

Table 1 Example of EVs charging data

Head Quarter	Office	Charging station	Charger	Charger ID
Seoul	Gangbuk-Seongbuk	Gangbuk-Seongbuk	Slow01	47
Address	Charging type	Max capacity	Charging amount	Charging period
Seoul jung-gu	Slow	7kWh	1.04kW	0:20:00
Date	Charging start	Charging finish		
'16-01-01	13:15:00	13:35:00		

Based on collected EVs charging data, various analyses were possible, and the analytical criteria and methods are summarized as follows.

1) Analysis by application: It is possible to classify the place where the charger is installed based on the address information, and it is possible to classify the EVs application based on the installation place. For example, a charger installed in an apartment or a house can be regarded as charging data for an EVs used for home use, and a charger installed in a mart or city hall may be considered as a commercial or a public use.

2) Seasonal Analysis: Based on the date information, the seasons at the time each charge was performed can be categorized. In order to classify the seasons, it is divided into March to May as spring, June to August as summer, September to October as autumn, and November to February as winter based on EVs charging fare applied in KEPCO.

3) Analysis by region: The headquarters information can be used to classify the area where the charger is installed. The EVs charging data provided are divided into 17 regions, namely Gangwon, Gyeonggi, Northern Gyeonggi, Gyeongnam, Gyeongbuk, Gwangju, Jeonnam, Southern Seoul, Daegu, Daejeon, Chungnam, Head Office, Busan Ulsan, Seoul, Incheon, Jeonbuk, Jeju, The data of KEPCO headquarter located in Naju were analyzed by integrating with Gwangju Jeonnam and the 'Special' region such as Human Resources Development Center located in Seoul were excluded from the classification because they do not have enough representative data.

4) Analysis by time: Using the information of charge amount, charge time, start of charge, and end of charge, we analyzed when each charge started and how far it progressed. However, the charging start and charge termination information is based on the time when the charger cable is connected to and disconnected from the charger, so there may be some differences from the actual charging.

Preprocessing

The reliability of the data should be assumed in order to analyze the EVs data and derive the pattern. In this study, data is pre-processed by explaining several conditions for securing data reliability. Table 2 summarizes the conditions set in this study.

Table 2 The condition and purpose of data preprocessing

Condition	Purpose
Check missing data	Check missing data
Charging type=Max capacity	Check charging type 7/7.7kWh:slow charge 50kWh:fast charge
5min<charging period<24hour	Check abnormal data
0<charging amount<60kW	Check abnormal data
$\frac{\text{Charging amount}}{\text{charging period}} < \text{Max capacity}$	Check abnormal data

As shown in the table, pre-processing was performed to utilize the charge data without using the corresponding charge information when detecting missing and abnormal data. In case of abnormal data related to charge time and charge amount in the above pre-processing process, data is not used. If 'charge classification' and 'maximum capacity information of charger' do not match, correct the information based on 'charger' and ‘charging amount’. Through this pre-processing, only 300,549 EVs charging data among 444,048 EVs charging data were used, and it was confirmed that the data reliability was about 67.68% based on the conditions set in this study.

Configuration and statistics

Before EVs charging data analysis and pattern derivation, data structure after pre-processing was analysed. Statistics by region / year / season / charge type / use are summarized in Tables 3 ~ 8.

Table 3 Abbreviation of each regions

A	A1	Gangwon	E	E1	Daejeon-Chungnam
B	B1	Gyeonggi		E2	Chungbuk
	B2	Northern Gyeonggi	F	F1	Busan-Ulsan
C	C1	Gyeongnam	G	G1	Seoul
	C2	Gyeongbuk		G2	Southern Seoul
	C3	Daegu	H	H1	Incheon
D	D1	Gwangju-Jeonnam	I	I1	Jeju
	D2	Jeonbuk	J	J1	Head office
			K	K1	Special

Table 4 Statistics of EVs charging data by regions

A1	B1	B2	C1	C2	C3
12,857	18,174	10,318	18,008	5,576	30,761
D1	D2	E1	E2	F1	G1
22,145	5,450	18,259	11,597	13,954	16,626
G2	H1	I1	J1	K1	Sum
15,081	12,608	84,974	3,947	214	300,549

Table 5 Statistics of EVs charging data by year

2016	2017	2018	Sum
23,394	129,886	147,269	300,549

Table 6 Statistics of EVs charging data by season

Spring	Summer	Autumn	Winter	Sum
111,494	38,796	32,438	117,821	300,549

Table 7 Statistics of EVs charging data by charging type

Fast Charging	Slow Charging	Sum
225,408	75,140	300,549

Table 8 Statistics of EVs charging data by application

Public	Commercial	Residential	Sum
175,814	14,985	46,796	237,595

According to regional statistics, the data of Jeju was the largest with about 85,000 charge data, followed by Daegu with about 30,000 charge data. In the case of EVs charging data for each year, it can be confirmed that the EVs charging data in 2018 exceeded the total charging data for 2017, even though the data is up to May. In the case of seasonal charge data, spring and winter data are the largest, because the collected EVs charge data is from January 2016 to May 2018. In addition, according to the type of charge, the proportion of rapid charging significantly outperforms the slow charging, suggesting that the public or commercial purpose is higher than the purpose of residential.

Sampling

Sampling should be preceded in order to reconsider the reliability of each analysis. This is because the data according to each condition is imbalanced. For example, data of Jeju and Jeonbuk are 84,974 and 5,450, respectively. And thus direct comparison is not appropriate. In order to solve this problem, in this study, we applied a sampling method that calculates data according to each condition using R, which is a program that has a strength in big data analysis, and randomly mixes the data and takes a specific number of data.

In the case of the data specified as 'head office' in the regional data, it means the headquarters of KEPCO located in Naju. Therefore, the data was included in the data of 'Gwangju Jeonnam' region. 'Gyeongnam' and 'Gyeongbuk' are integrated as ‘Gyeongsang Privince’. Equally, set ‘Gyeonggi’ and ‘Northern Gyeonggi’ as Gyeonggi Province. Therefore, the regions are separated as Gangwon, Gyeonggi, Gyeongsang, Jeonla, Chungcheong, Busan Ulsan, Seoul, Incheon, and Jeju.

Analyze of EVs charging characteristics

After performing sampling in the manner described above, each analysis was performed using the sampled data. We analyzed EVs charging characteristics by time / region / season / usage. In addition, the 'start of charge' and 'end of charge' of the data do not mean the start and end of the actual charge but the connection and disconnection of the charge cable. Thus we assumed that the total charge is equally charged during the entire charge time.

$$P_n = P_T/(T_F - T_S)$$

P_n: EVs charging demand power at time *n*
P_T: Total charging amount
T_F: EVs charging finish time
T_S: EVs charging start time

Regional EV charging characteristics

Regional analysis was conducted using the 'headquarters' condition of collected data. 2,000 samples were sampled for each region, and correlation analysis was performed by analyzing the average amount of charge and correlation analysis of sampling data over time. Figures 2 shows the average amount of charge according to pre-mentioned method and the analysis results of regional correlation coefficients are attached in Table 9.

As can be seen in Figures 2, the regional charge patterns are similar enough that it is difficult to isolate the charge pattern for each region. As shown in Table 10, correlation coefficient of 0.7 or higher generally indicates a high degree of correlation. Therefore, the correlation coefficient of 0.7 or more can be considered that there is no specificity.

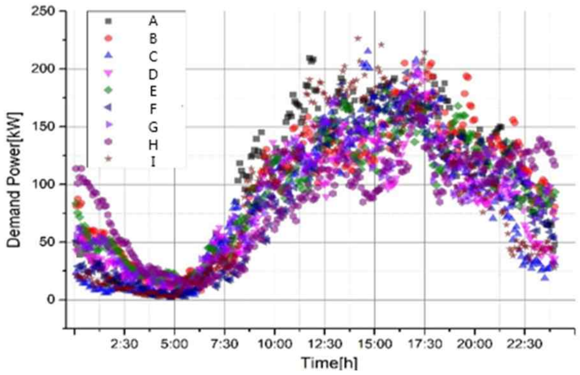

Figure 2 Hourly EVs charging demand by regions

Table 9 Correlation results of EVs charging by region

	A	B	C	D	E	F	G	H	I
A	1								
B	0.90	1							
C	0.91	0.82	1						
D	0.91	0.87	0.91	1					
E	0.90	0.91	0.86	0.88	1				
F	0.92	0.91	0.90	0.89	0.94	1			
G	0.90	0.88	0.87	0.89	0.89	0.92	1		
H	0.69	0.84	0.57	0.68	0.81	0.78	0.78	1	
I	0.92	0.81	0.93	0.91	0.86	0.90	0.86	0.60	1

Seasonal EVs charging characteristics

Seasonal charge data was analyzed using the 'date' condition of the collected data. We sampled 2,000 samples for each season and analyzed the seasonal correlations by analyzing the average amount of charge and correlation analysis of sampling data over time. Figures 3 shows the average amount of charge over time and Table 10 shows the results of the correlation analysis for each season.

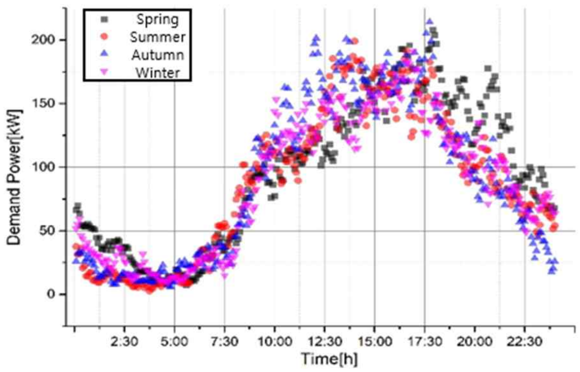

Figure 3 Hourly EVs charging demand by season

Table 10 Correlation results of EVs charging by season

Case 1	Spring	Summer	Autumn	Winter
Spring	1			
Summer	0.882	1		
Autumn	0.861	0.937	1	
Winter	0.901	0.930	0.928	1

EV charging characteristics by application

We analyzed the charge data for each application by using the 'address' condition of collected data. We sampled 2,000 samples in the same way and analyzed the correlation by analyzing the average amount of charge and correlation analysis of sampling data over time. Figures 4 shows the average charge per hour according to each method, and Table 11 shows the results of the correlation coefficient analysis for each application.

Public and commercial charging demand reaches its peak around 3 pm and charging demand is kept very low from late afternoon to the next morning. On the other hand, the demand for residential charge reaches its peak about 11 pm, and the charge demand is decreasing until 5 am. It can be interpreted that the demand for public and commercial charging occurs mostly during daytime for daily use and the demand for residential charging occurs mostly during night time. Also, through analysis, it was confirmed that the public and commercial EVs charging patterns and the residential EVs charging patterns are different. This difference means the current ToU-based charging fare impose limits on the control of public and commercial EVs charging demand.

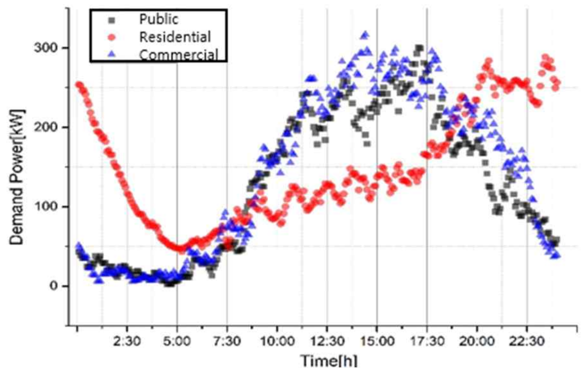

Figure 4 Hourly EVs charging demand by application

Table 11 Correlation results of EVs charging by application

Case 1	Public	Commercial	Residential
Public	1		
Commercial	0.140	1	
Residential	0.951	0.199	1

Conclusion

In this study, we analyzed the EVs charging pattern by region, season, and usage by using actual EVs charging data. In order to evaluate the reliability of the analytical results, pre-processing of erasing and correcting erroneous data was carried out. And non-restoration random sampling technique was applied according to each analysis condition. The 'start of charge' and 'end of charge' information means the time when the cable is connected to and disconnected from the charger. Therefore, it is assumed that the total charge amount is uniformly charged during the entire time.

Simulation results show that there is no specific charge pattern for each region despite the difference in the distribution of EVs and EVs charging facilities by region. In the case of the EVs charging pattern by the season, the peak demand time is somewhat delayed in the spring, but it does not have a large difference, so it is confirmed that there is no seasonal specificity. According to the analysis by application, the public or commercial EVs charging pattern that mostly requires immediate charging is concentrated on the working time, and it is confirmed that the maximum charging demand occurs especially between 12 and 17 pm. On the other hand, the residential EVs charging pattern showed the lowest demand around 5 am and peak charging demand in 8 to 11 pm. This is attributable to the lowest EVs charging fare and a sharp decrease in charging demand since 11 pm.

In addition, based on the results of the analysis conducted in this study, it can be concluded that the reevaluation of the current EVs charging fare system is necessary. Residential EVs charging demand, which accounted for 19.69% of actual total usage data, proved to be the largest demand at around 23:00 when the charging fare was lowered. However, the public and commercial EVs charging demand, which accounted for 80.31%, most of the charge demand was concentrated to daytime, and it was confirmed that the peak demand occurred especially at the maximum load time. If it is difficult to control the charging demand based on the current charging fare system due to the utilization characteristics of the public or commercial EVs, it is necessary to consider additional measures such as applying the new EVs charging control technique or controlling the peak demand using the ESS.

In this study, we analyzed EVs charging demand pattern by region, season, and usage by utilizing actual EVs charging data. In future research, we would like to derive representative model of EVs charging demand for each case (Application/Charging type). By deriving the EVs charging demand model, it would be possible to cope with the sudden increase in EVs charging load in terms of distribution operation. In terms of distribution plan, it is possible to plan considering EVs increasing trend and representative EVs charging demand model.

REFERENCES

[1] H.S.Chae, J.W.Chung, J.D.Kim, “Demand Forecast for Electric Vehicles in Korea using a Bass Diffusion Model”, Journal of Environmental Policy and Administration, No.24, Vol.1, pp.109-132, 2016.3.

[2] S.K.Jang, J.S.Huh, S.M.Cho, H.S.Shin, J.C.Kim, “The Study on Planning of EV Facilities using Prevalence Estimates of EV in the Public Housing” Journal of Korean Institute of Illuminating and Electrical Installation Engineers, No.24, Vol.10, pp.114-122, 2010.10.

[3] S.W.Hwang, J.H.Kim, “A Study on Power System Analysis Considering Special-days Load Mobility of Electric Vehicle” The Transactions of the Korean Institute of Electrical Engineers, Vol.65, No.2, pp.253-256, 2016.2.

[4] Mariz B.Arias, Sungwoo Bae, "Electric vehicle charging demand forecasting model based on big data technologies", Applied Energy, Vol.183, pp.327-339, 2016.9.

[5] Mariz B.Arias, Myungchin Kim, Sungwoo Bae, "Prediction of electric vehicle charging-power demand in realistic urban traffic networks", Applied Energy, Vol.195, pp.738-753, 2017.3.

[6] Kejun Qian, Chengke Zhou, Malcolm Allan, Yue Yuan, "Modeling of load demand due to EV battery charging in distribution systems", IEEE Transaction on Power Systems, Vol.26, No.2, pp.802-810, 2011.5.

[7] Kristien Clement-Nyns, Edwin Haesen, Johan Dresen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid", Transaction on Power Systems, Vol.25, No.1, pp.371-380, 2010.2.