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Impact of Electric Vehicle Penetration-Based Charging Demand on Load Profile

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Abstract –This paper presents a study the change of the load profile on the power system by the charging impact of electric vehicles (EVs) in 2020. The impact of charging EVs on the load demand is determined not only by the number of EVs in usage pattern, but also by the number of EVs being charged at once. The charging load is determined on an hourly basis using the number of the EVs based on different scenarios considering battery size, model, the use of vehicles, charging at home or work, and the method of charging, which is either fast or slow. Focusing on the impact of future load profile in Korea with EVs reaching up 10 and 20 percentage, increased power demand by EVs charging is analyzed. Also, this paper analyzes the impact of a time-of-use (TOU) tariff system on the charging of EVs in Korea. The results demonstrate how the penetration of EVs increases the load profile and decreases charging demand by TOU tariff system on the future power system.

Keywords: Electric vehicles, Power demand, Charging scenario, Power system, Tariff System

1. Introduction

Electric vehicles (EVs) are an emerging alternative to combustion engines due to their low emissions and high energy efficiency. Recent technological developments in the battery industry have been had a great attention to the researchers for EVs due to pressure from the high price of gasoline, greenhouse gas emissions leading to climate change, energy security and emission reduction aims [1]. The number and variety of EV batteries connecting to an electrical distribution system are expected to increase rapidly in the future. With many EVs connected to the power system in order to charge their batteries, the charging demand can potentially increase peak demand on the utility distribution system significantly [2-4]. So far, electric power demand has been rapidly increased with fast growing economy and changes in lifestyles such as electrical air conditioning, heating and cooking. The stability and the reliability of the power system become more serious issues if EVs are introduced. Although it is expected that the EV battery can be charged during system off-peak hours without affecting peak demand, the charging behaviors of various EV users have an element of randomness. The charging demand during an on-peak period may lead to additional large and undesirable peaks [5-7]. In order to enable the utility to plan its generation and expansions of future power system, the utilities must be able to predict the EV battery charging load under various scenarios and to evaluate the ability of existing power system to accommodatethem.

Assuming the penetration level of EVs, several cases are considered to predict the overall effect of EVs on the future power system. In order to make the reasonable scenario, vehicles are classified into four types depending on model and use of vehicles. It is also important to properly set the battery size, efficiency, charging place, charging time, and charging method. Using information about the EVs, reasonable scenarios depending on the charging period are devised. By focusing on the impact of EV introduction on the load profile of the future power system in various scenarios, the estimation is carried out by allowing for considerations of actual charging characteristics of the EV batteries and the EV user charging behaviors. In addition, the impact of the time-of-use (TOU) tariff system for EV charging in Korea is analyzed. It is expected that this paper can offer the utilities an insight into the impact of TOU tariff system on power demand.

This paper is organized as follows: Section 2 determines the load profile in 2020, how the number of EVs is estimated, and specifications of the EVs. Then, Section 3 describes the process to construct the scenarios based on methodology for estimation of the charging load. Several case studies are carried out to investigate the impacts for the charging demand of the EVs. Section 4 explains the TOU for EV charging, and then the impact of the TOU is analyzed. Finally, conclusions are given in Section 5.

2. Load Profile and EV Penetration

2.1 Determination of load profile in 2020

In order to analyze the impact of EV charging on the

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power demand in 2020, it is important to know how demand will vary in the future. The load profile is determined using the peak power demand of the 5th electricity supply and demand plan in 2020 [8] and the 24 hours load pattern at the dates of peak demand in 2010 [9]. After selecting the dates of peak load for summer and winter in 2010, the load profile at peak demand in 2020 is estimated. The dates of the peak load in 2010 were August 20th in summer and December 15th in winter. Due to the different characteristics of the load profiles in summer and winter, two cases are selected. After assuming these dates of peak demand are identical in 2020, the estimation is carried out.

The power demand peak in 2020 is 99,653 MW. Based on peak demand, power demand of specific day for 24 hours is estimated. By using power demand portion to peak demand of August 20th and December 15th in 2010, load demand of the dates in 2020 is estimated. As shown in Fig. 1, the load profiles cover 24 hours for each dates corresponding to the season.

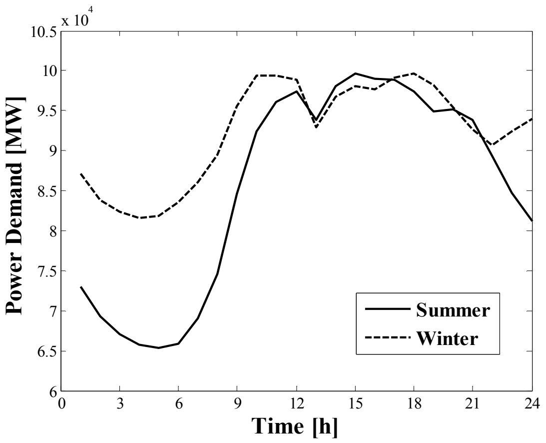

Fig. 1. Load profiles of summer and winter in 2020

2.2 Estimation of number of EVs in 2020

In this section, the number of EVs is estimated by classifying types of EVs corresponding to the model of and the use of vehicles. The car categories are divided to small, compact, midsize and full size cars, corresponding to cubic centimeter displacement. Also, the van category is divided into those holding more and less than 15 passengers. Using the annual average increase for each model of vehicle, the total number of EVs and the ratio of registered vehicles with the combustion engine in 2020 can be estimated [10]. The estimated result for the total number of vehicles with the combustion engine is 24,364,241 in Korea.

The model of EVs is expected to development except for the full size EVs for ten years from now. Assuming the percentage of each type of the vehicles with the combustion engine is applied to the EVs, the number of EV car for each model can be estimated in accordance with the rates of EV penetration as shown in Table 1. The number of the EV cars in accordance with the each model is also calculated as shown in Table 1. For the EV van, Table 2 shows the ratio of registered vans and the number of the EV van. As a result, the total numbers of EVs are expected to be 1,782,724 and 3,565,449 when the rates of EV penetration are 10 % and 20 %, respectively.

Table 1. Prospect of propagation for EV car in 2020 corresponding to model (1000 units)

Classification	Small size	Compact size	Mid size	Full size	Total
2010 car percentage [%]	10.7	21.9	50.0	17.4	100
2020EV car percentage [%]	12.9	27.0	60.4	-	100
10 % Penetration	219	450	1,022	-	1,691
20 % Penetration	438	900	2,044	-	3,382

Table 2. Prospect of propagation for EV van in 2020 corresponding to model (1000 units)

Classification	Less than 15 passengers	More than 15 passengers	Total
2020EV van percentage [%]	86.1	13.9	100
10 % Penetration	79	13	92
20 % Penetration	158	25	183

In addition to classifying by the model of vehicles, vehicles are also classified according to use. Fig. 2 represents the daily percentage of traffic to and from work for both individual and business [2]. Two peaks are observed for both individual and business vehicles. The morning peak and the evening peak of the individual vehicles are higher than the peak for business vehicles due to the commuting time. On the other hand, business vehicles run a considerable amount of time in a day due to the characteristics of business. Assuming these characteristics of the vehicles are applied to EVs, it is expected that the charging patterns will be different between individual and business EVs. The classification in accordance with the use of the vehicle determines when the EVs will be available for charging and how the EVs will be charged.

As mentioned before, vehicles can be classified according to model and use. On the basis of these classifications, this paper categorizes the EVs into four types. The Type 1 EV is an individual car with battery capacity of 30 kWh. The Type 2 EV is an individual van with a capacity of 95 kWh. The Type 3 and Type 4 EVs are a business car and van with respective capacities of 35 kWh and 87 kWh. The number of EVs depending on each type is shown in Table 3. The battery capacities are selected based on the currently developed EV depending on each type.

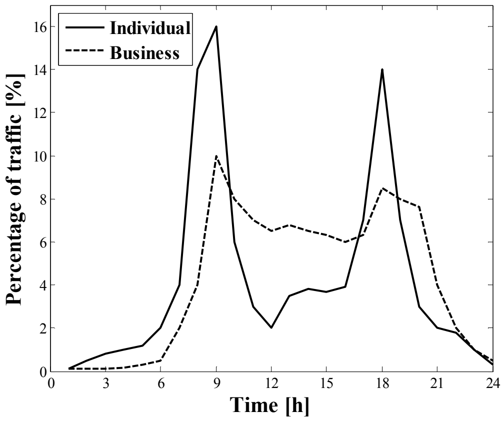

Fig. 2. Percentage of traffic [2] according to the use of vehicle

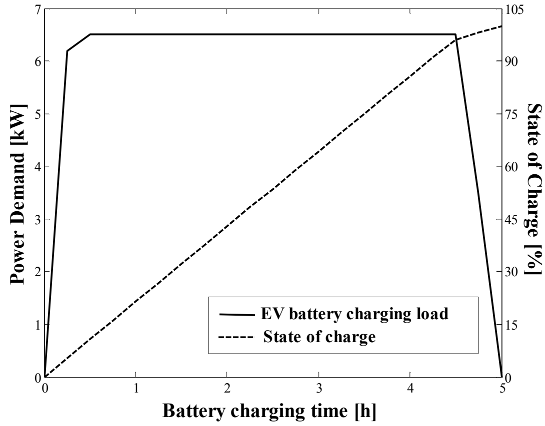

Fig. 3. Charging profile of a lithium-ion battery

Table 3. The number of vehicles for each type according to EV penetration rate(per 1000 units)

Classification		The number of vehicles 10 % Penetration	The number of vehicles 20 % Penetration	Ratio [%]
Individual	Type 1	1,632	3,264	95
	Type 2	82	165	5
Business	Type 3	59	118	87
	Type 4	9	17	13

2.3 Characteristics of EV battery

State of charge (SOC) is an index indicating the energy status of a battery. A SOC of 100 % represents a full charge, and a SOC of 0 % represents a full discharge. Because it is important to notify the user of the remaining battery life for its management, the SOC determination becomes an increasingly important issue in all applications that use a battery. In addition to the efficient use of the battery, the SOC is also related to the safety of the battery. Many systems are sensitive to deep discharge or overcharge because these states of extremely high or low SOC can lead to irreversible damage to the battery [11]. In order to keep the battery a good state and secure EVs, the battery manufacturers provide information of upper and lower limits for the state of charging the battery. The upper bound and the lower bound of an EV battery are about 95 % and 20 %, respectively. Due to the boundary, there is a difference between the rated capacity and the net amount of charging and discharging demand on a battery.

Lead-acid, lithium-ion, and nickel metal hydride (NiMH) are top three contending technologies for EV batteries. In this paper, the lithium-ion battery has been chosen to estimate the impact of the charged EV load on the load profile of power system, due to its representative position in the future battery market. Therefore, it is assumed that all EVs in the charging scenarios have a lithium-ion battery.

The power demand and the SOC corresponding to the battery charging time of the lithium-ion battery are shown in Fig. 3 [2]. These charging characteristics are different depending on the type of the battery. The unit of the battery capacity for the EVs is kWh, and the maximum capacity of the battery is determined by calculating the area under the EV battery charging load graph. The net capacity of the battery is smaller than the maximum capacity if the boundary related to the SOC is applied. For example, EVs have a battery with a maximum storage capacity of 30 kWh. This gives an available net capacity of 22.1 kWh, which is 73 % less than to the maximum capacity. The boundary can thus decrease the efficiency of the battery, but increase the stability of the battery.

2.4 Specifications of EVs

In order to construct realistic and reliable scenarios, the specifications of the EVs must be determined based on the type of EV. In fact, the power demand of an EV during charging period heavily depends on the specifications of the EV. The specifications of the EV are analyzed by separating them into several categories. The capacity of battery, charging time, the ratio of charging method which is either slow charge or fast charge for each type and the efficiency of the charger corresponding to the charging method are analyzed.

The maximum and the net capacity of batteries of each type are shown in Table 4. The maximum values are selected based on the currently developed EV depending on each type. As mentioned before, the available range within the SOC boundary is applied to the batteries of each type, and then the net capacity of each battery is determined. In addition to the net capacity of the battery, determining the method of charging is important in order to estimate the charging load profile. The charging methods are divided into fast and slow charging. In this paper, both charging methods are considered. The ratio of fast and slow charging is determined considering the daily traffic and the use characteristics as shown in Table 5. Because the typical individual EV users are mainly commuters, it is assumed that most of the charging EVs consist of the slow charging at work or home. On the other hand, the business EVs are mainly charged using the fast charging method at charging station due to travel during a considerable time in a day.

Also, the efficiency of the charger and the charging time are different depending on the method of charging. The efficiencies of fast and slow chargers are 87 % and 92 %, respectively [12]. The charging time is originally related to the capacity of the battery and the method of charging, but in this study, it is assumed that charging time is related to the method of charging and the use of the EVs as shown in Table 5. The charging time for slow charging is assumed to be 5 hours without reference to the capacity of the battery. Also, the charging time for fast charging is different corresponding to use. It is determined that the fast charging periods for individual and the business EV are 30 minutes and 1 hour, respectively. The charging times for slow and fast charging are determined considering referring currently developed the EV. In order to reasonably estimate the power demand by EV charging, the efficiency and the charging time are used to calculate the charging demand.

Table 4. Maximum and net capacities of each EV battery

Classification		Max Capacity of Battery [kWh]	Net Capacity of Battery [kWh]
Individual	Type1	30	21.9
	Type2	95	69.35
Business	Type3	35	25.55
	Type4	87	63.51

Table 5. Estimated ratio of charging methods and charging time corresponding to charging method and use

Classification		Ratio [%]	Charging time [h]
Individual	Slow	85	5
	Fast	15	0.5
Business	Slow	20	5
	Fast	80	1

3. EV Battery Charging Scenarios

The factors and assumptions contributing to the charging load of the EVs are described in Section 2. By applying them to several scenarios, the impact of charging load is analyzed in this section. Also, it is assumed that EVs can be charged either at work or at home. Two scenarios for slow charging and one scenario for fast charging are constructed, and then the combination of the three scenarios is examined. Although the usage patterns of the vehicles are identical, the cases are classified to summer and winter since the load profile is different corresponding to the season.

3.1 Methodology for estimating charging load

It is important to determine a methodology for estimating the charging load because the charging demand of the EVs depends on the characteristic of the charge. It is not realistic to assume that all EVs could be charged at the same time. In a report related to the estimation on charging demand of Korea Power Exchange (KPX), it is impossible to charge 30 % of total EVs, simultaneously [12]. In order to reflect the reality, the concept of simultaneous charging ratio is introduced. Fig. 4 represents the characteristic of the slow charging from 10:00 until 17:00. As mentioned before, the charging time of the EVs is assumed to be 5 hours. The one white box and four boxes with diagonal line pattern in Fig. 4 represent a group which is charged during that time. The white box is start point of the group charging, and 9 % is the simultaneous charging ratio.

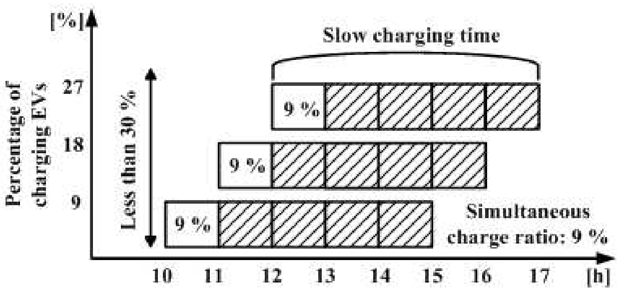

Fig. 4. Characteristics of the slow charging method

For example, at 10:00, 9 % of the number of the EVs starts charging. After 1 hour, another 9 % are charged, and then another 9 % follow in the next hour. Although three rectangles overlap, the percentage of charging the EVs is always less than 30 %. The simultaneous charging ratio is applied differently to the scenario depending on the number of charging the EVs. Namely, the ratio is increased when the charging of the EVs may converge. In addition to the charging characteristic for slow charging, the charging characteristic for fast charging must be determined. It is expected to be mainly comprised by the business EVs. Based on the characteristic of business EVs, the hourly impact of fast charging is estimated by applying a 3 % of simultaneous charging ratio.

Finally, the charging demand per hour is determined using the number of EVs and their specifications. The demand is calculated by multiplying the number of EVs of each type, the simultaneous charge ratio, the capacity of the battery, and the efficiency of the battery charger which is then divided by the charging time.

3.2 Scenarios for slow charging

The first scenario for slow charging has taken place during the afternoon. This scenario considers the commuting time for workers. Most of the individual EV users are at work from 10:00 until 17:00 in the afternoon. Because commuting times are similar for most workers, the number of EVs that will be charged during this period can probably be increased. The simultaneous charging ratio is greater than that in the other charging scenario, and is determined to 9 % for scenario 1. Although total of three EV groups can be charged, the percentage of charging EVs is lower than 30 %.

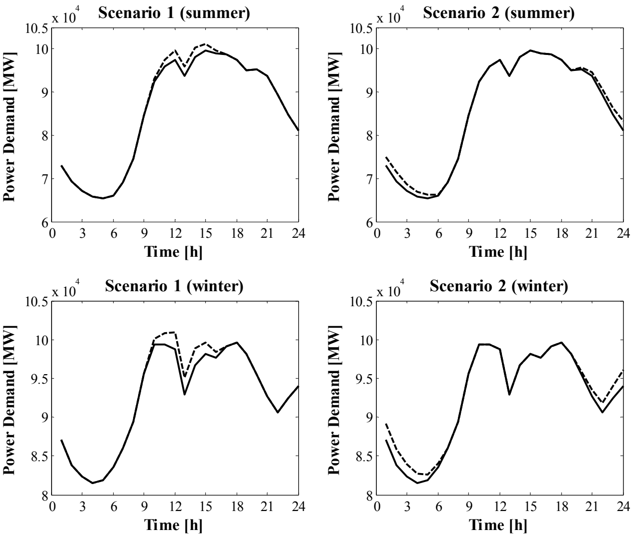

Fig. 5. Load profiles of scenario 1 and 2 for each season

The second scenario for slow charging has taken from 20:00 until 7:00. Because the period is in the middle of the night and is longer than that of scenario 1, the simultaneous charging ratio is estimated to 5 %. A total of five groups can be simultaneously charged in this scenario. In the same manner as in scenario 1, the percentage of charging EVs is less than 30 %. Also, the impact of charging demand of the EVs is analyzed according to season.

Fig. 5 shows the load profiles for slow charging in scenario 1 and scenario 2 for both summer and winter. In the left upper and lower graphs, the dashed and the solid lines represent load profiles in MW with and without the charging demand of the EVs of scenario 1, corresponding to the season, respectively. In summer, the load is considerably larger during the charging period of scenario 1. The charging of the EVs increases electric demand by 2176 MW, which is 2.2 % of the maximum value of the load when the penetration of the EVs is 10 % of total vehicles. Especially, the peak load in summer occurs from 14:00 until 15:00, and then it will most likely impact the power system if the existing system cannot accommodate them. In winter, the charging demand also affects the load profile in the first scenario because the morning peak occurs from 11:00 until 12:00. Although the amount of increased load is 1451 MW, this charging demand influences on the load profile. On the contrary to summer case, the charging demand by EVs from 14:00 until 15:00 does not affect the identical period because the power demand in winter is smaller than that in summer. The right upper graph in Fig. 5 describes the summer season of scenario 2, and the right lower graph describes the winter of scenario 2. In the same manner as the former scenario, the dashed and the solid lines represent the load profiles with and without the charging demand of the EVs of scenario 2. Although the maximum charging demand increases by 2015 MW, it does not affect the peak load due to the charging period of scenario 2.

3.3 Scenario for fast charging

Fig. 6 shows cases of fast charging corresponding to each season. In the same manner as the scenario with slow charging, the dashed and solid lines represent the load profiles with and without the charging demand of the EVs, respectively. The left and right graphs also show the cases of summer and winter, respectively. A simultaneous charging ratio of 3 % of the fast charging EVs per hour is applied. This causes hourly charging demand of 485 MW in all seasons when the penetration of the EVs is 10 %.

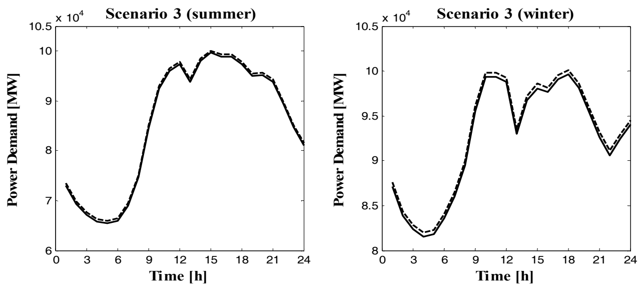

Fig. 6. Load profiles of scenario 3 for each season

3.4 Scenario for integrated charging

The combination scenario is carried out for each season to estimate the overall impact of EV charging. Also, the case for 20 % penetration of the EVs is analyzed. Fig. 7 represents the load profiles for summer with market penetrations of the EVs. As the charging profiles consist of charging demand for slow and fast charging scenarios, the charging demand as a function of the EV penetration adds to the fundamental load profile. The dotted, the dashed and the solid lines represent load profiles with 0 %, 10 % and 20 % EV penetrations, respectively. The power demand is increased by the charging demand of the EVs during the peak load. The additional power demands are 2661 MW and 5323 MW based on the EV penetration level. These charging demands are 2.6 % and 5.3 % of the peak load, respectively.

The profiles of the integrated charging scenario in winter are shown in Fig. 8. Because the usage pattern of the vehicles is identical for both seasons, the charging demand of the EVs is equivalent to the case of summer. The charging demand of EVs increases the peak load in another time period since the peak load in winter is from 10:00 until 11:00. The charging demands are 1210 MW and 2420 MW, depending on the penetration of the EVs. The values are 1.2% and 2.4% of the peak load, respectively. Furthermore, another peak load may be caused by EV charging because the load during the off-peak period is larger in winter than in summer. The time period from 12:00 until 13:00 is notoriginally a peak load time, but a new peak load is caused by the charging demands of 2661 MW and 5323 MW, depending on the penetration of EVs. The charging demand of 2661 MW is over a half of the station capacity of the steam power plant in Boryeong. Maximum electricity generation of this plant is 4800 MW. This implies that the charging demand from EVs results in enormous increase of total power demand. Therefore, it is important to have accurate estimation of the charging load resulting from large EV penetration for electric utilities.

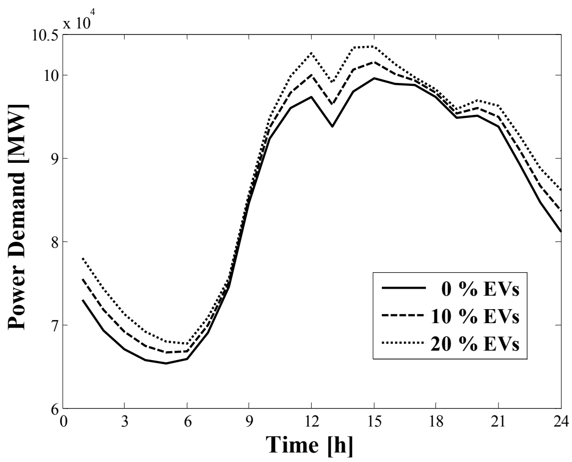

Fig. 7. Load profiles of the integrated charging scenario depending on EV penetration in summer

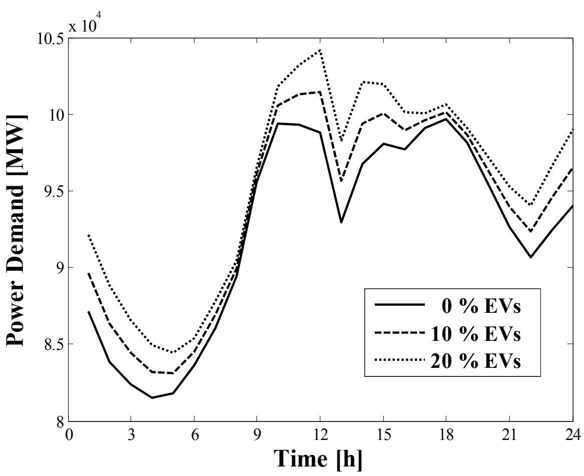

Fig. 8. Load profiles of the integrated charging scenario depending on EV penetration in winter

4. Application of Electricity Tariff System

4.1 Electricity tariff system in korea

In Korea, the tariff system for charging EVs is the TOU tariff system, which consists of different grades depending on the load profile and the season, as shown in Table 6. However, it is impossible to determine the impact of the TOU on EV charging because the tariff system has not yet been used in Korea. Therefore, the impact of the TOU is analyzed with reference to the cases of the United States.

Table 6. Classification of the TOU tariff system for EV charging depending on the period

Classification	Summer	Winter
Light load period	23:00～09:00	23:00～09:00
Medium load period	09:00~11:00 12:00~13:00 17:00~23:00	09:00~10:00 12:00~17:00 20:00~22:00
Heavy load period	11:00~12:00 13:00~17:00	10:00~12:00 17:00~20:00 22:00~23:00

Historical analysis of the TOU at Connecticut Light & Power, Pacific Gas & Electric, Wisconsin Public Service, Narragansett Electric Company, and Wisconsin Electric Power have shown significant consumption reduction of approximately 23 %, 18 %, 15 %, 7 %, and 4 %, respectively, during the peak periods [13], [14]. The reduced rates represent not the effect of TOU for EV charging but the effect of all TOU including tariff system for EV charging. In this paper, the average value of the reduced rates in cases of United States is applied to the integrated charging scenario. It is possible to reduce 13.4 % of electric charges on average. When the reduced rate is applied to the heavy load in charging scenario, the impact of the TOU is analyzed depending on the EV penetration level and the season.

4.2 Effect of TOU tariff system on load profile

As mentioned earlier, peak demand due to the application of the TOU tariff system is hourly reduced by 13.4 % of charging EVs during the heavy load period. Also, the reduction rates of 6 % and 8 % are determined considering the commuting time and the total load profile in the middle load period. The hourly reduced charging demand during the heavy load and the middle load periods are added to that of the light load period. Table 7 shows the amount by which demand is reduced in a day and the hourly addition to the light load. In the summer, the maximum of the hourly reduced charging demand is 357 MW, which is 0.3 % of the peak load. Similarly, in the winter, the value is 213 MW, which is 0.2 % of the peak load. Although the amount of the reduced charging demand is twice with the 20 % penetration level of the EVs, it is small enough to ignore, even without considering the impact of the TOU. Therefore, the result for applying the TOU is inadequate. If EV charging is rapidly introduced, it will be impossible to shift charging demand in heavy load using the present tariff system. Therefore, revision of the TOU for EV charging is absolutely indispensable to Korea.

Table 7. Reduced daily demand and shifted demand due to execution of the TOU tariff system

Classification		Daily reduction [MW]	Addition to the light load [MW]
Season	EV penetration		
Summer	10 %	2,198	219
	20 %	4,397	440
Winter	10 %	1,868	187
	20 %	3,738	374

5. Conclusions

This paper proposed a study to determine the charging load of EVs in power system. Several scenarios are constructed and analyzed depending on the season, assuming the proportion of EVs in 2020 are 10 % and 20 % of the number of total vehicles. Based on these reasonable scenarios, it is expected that a remarkable increase in power demand due to EV charging may threaten the reliability of the power supply by causing a big error of long term load forecasting. Also, the impact of the TOU tariff system for the charging of the EVs is analyzed in Korea. As a result, the good TOU rate design can shift the load at the peak time to the load at the light load period.

In order to enable utilities to plan its generation and future power system, this study help predict additional loads due to EV charging which are estimated under various scenarios. In practice, this paper could be used as the basis for adequately long term load forecasting considering the overall effect of the EVs on the power system. Finally, it contributes to decide investments required to accustom the electrical infrastructure including generation station, distribution, and transmission system with new load condition.

Acknowledgements

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