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Smart EVs Charging Scheme for Load Leveling Considering ToU Price and Actual Data

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Abstract – With the current global need for eco-friendly energies, the large scale use of Electric Vehicles (EVs) is predicted. However, the need to frequently charge EVs to an electrical power system involves risks such as rapid increase of demand power. Therefore, in this paper, we propose a practical smart EV charging scheme considering a Time-of-Use (ToU) price to prevent the rapid increase of demand power and provide load leveling function. For a more practical analysis, we conduct simulations based on the actual distribution system and driving patterns in the Republic of Korea. Results show that the proposed method provides a proper load leveling function while preventing a rapid increase of demand power of the system.

Keywords:Electric vehicle, Charging load, Time-of-Use price, Smart charging, Load leveling

1. Introduction

These days sourcing and developing eco-friendly energies is a prominent research area. In addition, many regulations to protect the environment and humans from pollution have been established. The Kyoto protocol and Copenhagen climate change conferences have significantly contributed to the establishment of these regulations. With this trend, the interest in EVs has consequently increased, as they neither consume fossil fuel nor emit harmful gases [1]. However, since EVs use electricity for their power source, they need to be charged from an electrical power system. When large-scale EVs are being charged simultaneously, various severe phenomena affecting the power system could occur. In [2-10], the possible effects on the power system are described, including voltage variation, decrease of load factor, increase of power losses, increase of demand power, etc. If compensation devices are used to mitigate these negative effects, additional costs would be incurred. Thus, many studies focus on the development of an optimal EV charging scheme to minimize or mitigate any adverse effects due to charging of EVs. EVs can have a frequency regulation function for charging or discharging [2-3]. It has also been shown that EVs can be used for voltage regulation [4]. In [9-10], it was shown that the way EVs are charged can mitigate the intermittence of the renewable energy output. Some papers propose charging schemes for EVs to mitigate the possible negative effects. In [11], an optimal EV charging scheme is proposed to reduce voltage variations and power losses. This charging scheme computes an optimal charging profile of EVs by minimizing the power losses with quadratic programming. In [12], a method was proposed that can reduce the voltage variations and power losses and thus maximize the load factor. The study explored the relationship between feeder losses, load factor, and load variance. An optimal charging scheme was then developed based on this relationship. In [13], a smart EV charging profile was used to assess the impact of EVs on a specific region. However, since the smart charging profiles used were fixed, this method is only acceptable under specific conditions. An optimal EV charging scheme was proposed in [14] that can provide a valley filling function. The decentralized protocol, proposed in the paper, has an advantage when the amount of data increases due to the large scale of EVs. In [15], an EV charging scheme for valley filling was also suggested. However, it is assumed that all the EVs are connected in ideal conditions such as equal capacity and equal required time for charging, and thus is not sufficiently practical. All of the proposals summarized above have the common limitation of not considering the EV owners' driving patterns. The initial State-of-Charge (SoC) of each EV, when it is connected to the power system, is directly related to the driving distance of the EV. Therefore, consideration of the computation of the initial SoC by using a stochastic driving distance is one of the most important factors for practical analysis.

The contributions of this paper include the following.

① **We consider the EV owner's driving pattern**; As mentioned above, this is one of the most important factors for practical analysis of the possible effect of EVs on the power system.

② **We consider the EV owners' responses to the EV charging scheme**; Most papers that propose a smart charging scheme for EVs only consider the Power System Operator (PSO). That is, it is assumed that EV owners would follow any proposed control scheme, which is unrealistic. Thus, the smart EV charging scheme proposed

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in this paper is based on a ToU price based charging scheme that can reflect the response of each EV owner to the proposed charging scheme.

The remainder of this paper is organized as follows. Section II describes a computation of the EV load. In addition, Gaussian distribution based on actual traffic volume is used for the calculation of the initial SoC of each EV. Section III describes the characteristics of several EV charging schemes, including the smart EV charging scheme. Section IV shows comparisons of simulation results depending on the different types of EV charging schemes. The conclusion is then given in section V.

2. Daily Load and EVs Charging Profile

In this section, the daily load and EV charging profile are explained. To compute the daily load, we use several actual data from Seoul, Republic of Korea. The estimation of the initial SoC is an important factor in the computation of an EV's charging profile. To calculate the initial SoC, the driving pattern needs to be evaluated, whereby the starting time and duration for charging are the main variables on the EV load. The estimation of the initial SoC can be divided into three main areas as follows. ① Set the total number of EVs using actual data in Seoul, Republic of Korea, ② estimate the driving distance of each EV using the actual driving pattern, and ③ calculate the initial SoC of each EV using Gaussian distribution.

2.1 Daily load profile

To set the total number of EVs, we selected a specific region in Seoul, Republic of Korea for more practical analysis. The total length of the power system is 1.5 km and consists of two-step-type poles and a neutral line. Electric power is delivered to 13 loads in the upper portion and 11 loads in the bottom portion. The total active and reactive loads are 28.6 MW and 13.9 Mvar, respectively. In this paper, we only considered the bottom portion of the power system [16-17]. Fig. 1 shows the daily load profile in the region in which the EV load is not taken into account.

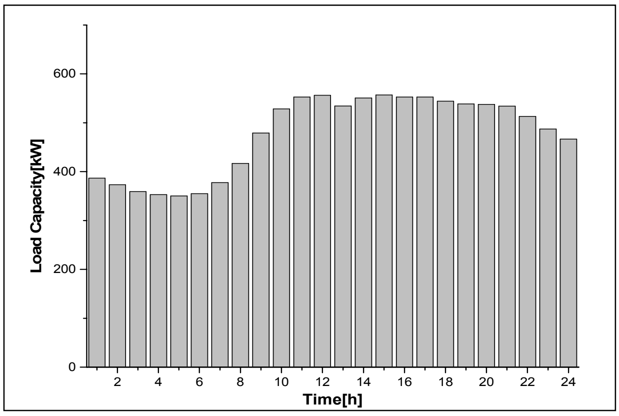

Fig. 1. Daily load profile for specific region in Seoul, Republic of Korea (summer)

2.2 Estimation of the number of EVs

An estimation of the number of EVs is required for the next procedure. According to [18], the actual number of compact vehicles in the region in 2012 was 8,961. Since the Republic of Korea government set a target that by, 10% of the total number of compact vehicles will be replaced with EVs [19], we assumed that the current total number of EVs in the region is 896. The next step is to determine the number of EVs at each time and load point. To calculate the number of EVs at each load point, we make an

Table 1. The number of EVs at each load point

Location	Load Capacity[kW]	Number of EVs	Load Ratio [%]
L1	1189	77	8.574
L2	382	25	2.754
L3	843	54	6.079
L4	1792	116	12.927
L5	565	37	4.074
L6	727	47	5.243
L7	1194	77	8.610
L8	1955	77	8.618
L9	1282	83	9.245
L10	305	20	2.199
L11	4392	284	31.674
Total	13866	896	100

Table 2. The number of vehicles and traffic volume ratio at each hour

Time	Commute	Personal	School	Business	Total	Rate [%]
0	672	437	159	710	1979	0.89
1	255	172	11	339	776	0.35
2	135	63	1	179	378	0.17
3	114	19	2	110	245	0.11
4	103	32	0	35	170	0.07
5	732	197	4	75	1009	0.45
6	2230	465	29	299	3023	1.36
7	4974	1645	224	545	7388	3.32
8	6713	5495	1041	1121	14370	6.47
9	3988	5772	1003	1780	12543	5.65
10	1696	6886	1027	2202	11811	5.32
11	1079	8624	966	2556	13225	5.95
12	1230	9764	682	3346	15022	6.76
13	1913	10100	901	3775	11689	7.51
14	1754	9360	666	3247	15027	6.76
15	2298	9652	558	3081	15589	7.02
16	3791	9845	658	3149	17443	7.85
17	4886	9031	596	3711	18224	8.20
18	5740	7469	764	4405	18378	8.27
19	3004	5361	826	4564	13755	6.19
20	1563	3981	492	3845	9881	4.45
21	1096	2688	515	2928	7227	3.25
22	886	1560	352	2134	4932	2.22
23	846	806	15	1263	2930	1.32
Total	51699	109424	11492	49398	222012	100

assumption that the large load has a large number of EVs, which is acceptable as normally a large load implies many households and thus it implies many EVs. Table 1 shows the number of EVs at each load point [16]. To determine the number of EVs at each time, we used the actual traffic volume from [20]. In [20], the actual number of vehicles at each time is given with different types of purposes such as commutation and business. With the given number of vehicles, it is possible to calculate the traffic ratio at each time. This is simply calculated in (1).

$$R_k = \frac{C_k}{C_{tot}} \tag{1}$$

where C_k refers to the number of vehicles at time k, C_{tot} refers to the total number of vehicles, and R_k refers to the traffic volume ratio at time k. Table 2 shows the number of vehicles and traffic volume ratio at each time [16].

By using data from Tables 1 and 2, it is possible to compute the number of EVs at each load and time. Also as average driving period is an hour, the number of charging EVs at time k is the number of EVs at time k-1[20]. Calculation is conducted using Eq. (2), and Fig. 2 shows the computed results of L1 and L11, which are the closest and the farthest load from the substation, respectively.

$$EV_{j.k} = R_k \times EV_{j.tot} \tag{2}$$

where $EV_{j.k}$ refers to the number of EVs at time k at j^{th} load. R_k refers to the traffic ratio at time k. $EV_{j.tot}$ refers to the total number of EVs at j^{th} load.

2.3 Computation on the initial SoC of each EV

As we set the number of EVs at each load and time, the next step involves computation of the initial SoC of each EV. Estimations of SoC for each EV are one of themost crucial factors for practical analysis of the effect of EVs on the power system. If we were to assume that all of the EVs have an equal initial SoC when they are connected to the power system, severe inaccuracy would result in the analysis. Therefore, we used the actual data of the driving pattern for the driving distance and stochastic concept. In terms of a stochastic approach, we used Gaussian distribution. For Gaussian distribution, two variables are required: average and standard deviation of driving distance. Table 3 shows these two variables [21]. In Table 3, we only consider a personal purpose vehicle because it comprises the largest portion of vehicle types. Thus, the average driving distance and standard deviation are set as 38.8 km and 21.9, respectively.

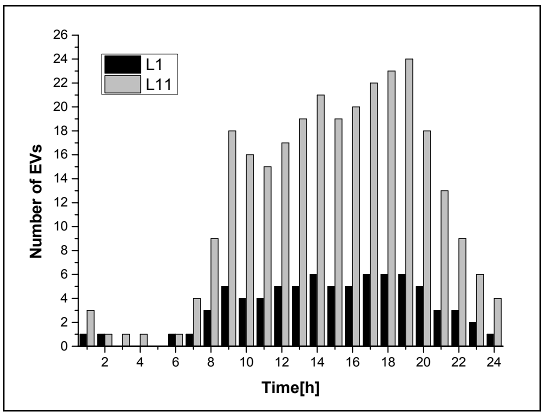

Fig. 2. The number of EVs at each hour (L1, L11)

Table 3. Average daily driving distance depending on the purpose of use

	Sample	Average (km)	Standard deviation	Range (km)
Government	28,354	31.2	21.5	199.8
Private	4,746,297	38.8	21.9	384.2
Commercial	400,416	157.5	97.8	777.0

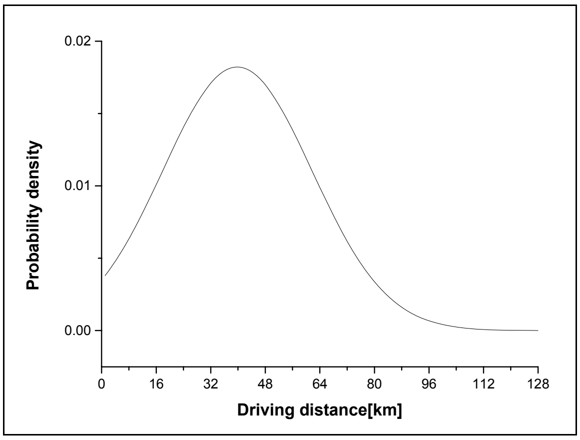

Fig. 3. Gaussian distribution for driving distance

Using above data, we can calculate the Gaussian distribution of the driving distance with (3) [22].

$$p(\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(X-\mu)^2}{2\sigma^2}} \tag{3}$$

where, μ refers to the average driving distance, σrefers to the standard deviation and X is actual driving distance. The calculation results are shown in Fig. 3. If it is assumed that SoC is linearly proportional to the driving distance, the estimation of SoC for each EV can be derived from (4) [22].

$$SoC_{ini} = (1 - \frac{\alpha X}{d_R}) \times 100\% \tag{4}$$

where, SoC_{ini} refers to the initial SoC of each EV, d_R is the maximum driving distance for one charging, αrefers to the charging cycle, and $X$is driving distance. As we assumed

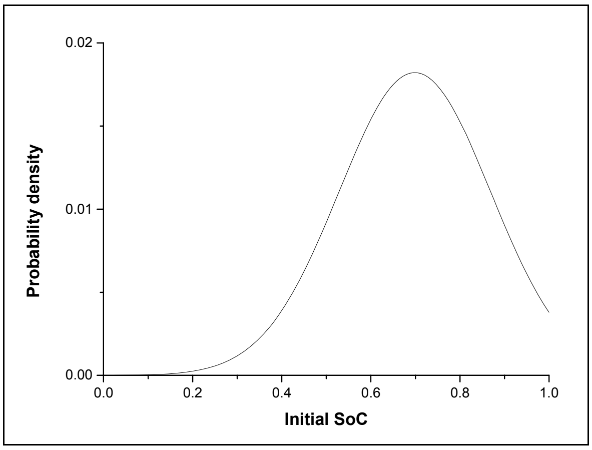

Fig. 4. Gaussian distribution for initial SoC

that SoC has a linear relationship with driving distance, it is possible to estimate the Gaussian distribution for the initial SoC using (3) and (4). The calculated results are shown in Fig. 4.

The main purpose of the estimation of the initial SoC at each EV is to consider the driving pattern of each EV owner. Depending on the driving distance, the initial SoCs will have different values and this eventually changes the EV loads. Therefore, if the concept of stochastic driving distance is not taken into account, the practical analysis of the effects of EVs cannot be accomplished.

3. EVs Charging Scheme

This section introduces the various EV charging schemes including the smart charging scheme. The characteristics of each EV charging scheme are explained in the following subsections.

3.1 Dumb charging scheme

As its name implies, the dumb charging scheme does not provide any control scheme. Thus, it is also called uncontrolled charging. In this charging scheme, the EV owners will charge their EV without considering the grid services or electricity price. The main drawback of this charging scheme is the increase of demand power during the peak load period. Typically, EV charging will be conducted when the EV owner returns home from work, which is normally during the peak load period.

3.2 Off-peak charging scheme

The off-peak charging scheme was introduced to mitigate the increase in the demand for power for EV charging during the peak load period. It limits EVs to be charged during the peak load period. However, its disadvantage is that although it can prevent the increase of demand power

Table 4. Electricity price for EV charging by KEPCO

Electrical charging price for EV (won/kWh)			
Time	Summer (7~8)	Spring/Autumn (3~6/9~10)	Winter (11~2)
Off-peak	55.80	56.90	78.20
Mid-peak	140.80	68.30	124.20
Peak	225.30	73.10	184.90

during the peak load period, it could introduce another peak load period on the power system. To be specific, if a large number of EV owners charge their vehicle as soon as the peak load period ends, another severe increase of demand power could occur at the beginning of the non-peak period.

3.3 Time-of-Use price based charging scheme

In this charging scheme, the electricity price for EV charging is set differently depending on the time. In the peak load period, the electrical charging price is set as the most expensive price. KEPCO, which is the major power utility in the Republic of Korea, has set the ToU price as shown in Table 4 [23].

According to [24], a 100% price change may produce around 20% change in demand. The following assumptions are made considering the tendency and ToU price indicated in Table 4.

1) **In peak load period**: 80% of customers who want to charge their EVs during the peak load period will shift their charging time to the off-peak load period.

2) **In mid-peak load period**: 50% of customers who want to charge their EVs during the mid-peak load period will shift their charging time to the off-peak load period.

3) **In off-peak load period**: No customers who want to charge their EVs in an off-peak load period will move their charging time to the mid-peak load or peak load period.

Using the above assumptions, we can estimate the number of charging EVs at each hour. At the same time, we can determine the number of EV drivers wanting to change their charging time. However, as the ToU price based EV charging scheme merely encourages EV owners to charge their EVs during off-peak load duration, this could lower the load leveling because there is no control for the distribution of the EVs during off-peak load duration.

3.4 Proposed smart charging scheme

The previously mentioned charging schemes such as dumb, off-peak, and ToU price based, have drawbacks in terms of the increase of demand power and load factor. The dumb charging scheme can increase the demand power during the peak load period, and during off-peak the charging scheme demand power can even severely increase when the peak load duration ends. The ToU price based charging scheme can increase the load factor as there is no control for the distribution of EVs during the off-peak period. In this paper, a smart charging scheme is therefore proposed to prevent the rapid increase of demand power and improve the load factor by controlling the charging of EVs during the off-peak period. The proposed smart charging operates based on the following steps.

1) **Measure demand power at each load**: As the proposed smart charging scheme uses demand power for controlling the use of power, the measuring demand power at each load should be conducted as the first priority.

$$P_k = V_k I_k \tag{5}$$

where P_k refers to the demand power on k load and V_k and I_k refer to the voltage and current on k load, respectively.

2) **Judge charging period**: The proposed scheme uses the ToU price based charging scheme during the peak and mid-peak load period. That is, the smart charging scheme operates only during the off-peak load period. Thus, a classification of the charging period is required.

$$\begin{cases} S_k = 1 \ (Off-peak\, load\ period) \\ S_k = 0 \ (Mid-peak\ and\ peak\, load\ period) \end{cases} \tag{6}$$

where, S_k refers to the control signal of smart charging scheme. If S_k is equal to 1, the proposed scheme operates on its own. On the other hand, when S_k is equal to 0, the proposed scheme uses the ToU price based EV charging scheme.

3) **Estimation of the state of charging EVs at each hour:** The number of charging EVs at each hour needs to be estimated in order to distribute the charging EVs during the off-peak load period. For this purpose, the matrix concept is used in this paper. To estimate the state of charging EVs, this paper assumed two conditions:

① All EVs are charged with constant current

② All the EVs would keep charging by the time SoC reaches 100 %.

Using Gaussian distribution for SoC and the two assumptions given above, the required charging time can be estimated for each EV. The estimated data are stored in the matrix.

$$\boldsymbol{A_{chage}} = \sum_{n=1}^{24} A_n \,, \boldsymbol{A_n} = \begin{bmatrix} a^n_{(1,1)} & \cdots & a^n_{(1,24)} \\ \vdots & \ddots & \vdots \\ a^n_{(r_n,1)} & \cdots & a^n_{(r_n,24)} \end{bmatrix}$$

$$\begin{cases} a^n_{(x,y)} = 1\left(n \le y \le T_{n.req\ x} + n\right) \\ a^n_{(x,y)} = 0\ \left(y \ge T_{n.req\ x} + n\ or\ y < n\right) \end{cases} \tag{7}$$

where, $\boldsymbol{A_{chage}}$ is the matrix showing charging states of all EVs in a specific region. $\boldsymbol{A_n}$ indicates charging state of all EVs which started charging at n and $a^n_{(x,y)}$ indicates the charging state of the x^{th} EV, which started charging from n, at time y. $T_{n.req\ x}$ indicates the required charging time for the x^{th} EV, which started charging from n, and n indicates the time which has the value between 1 to 24. r^n indicates the total number of vehicle which start to charge at time n. When $a^n_{(x,y)}$ has a value 1, then the x^{th} EV will be charged at time y. The total number of EVs which will charged at time n can be calculated using (8).

$$\begin{aligned} N_{EV.n} = (&A_{charge(n,1)} + A_{charge(n,2)} + \cdots \\ &+ A_{charge(n,r^n_{cum}-1)} + A_{charge(n,r^n_{cum})}) \end{aligned} \tag{8}$$

where, r^n_{cum} indicates the total cumulative number of charging EVs at time n.

4) **Estimation of required number of EVs for load leveling**: The above section explains the estimation of the total charging EVs at each hour. We can now predict the total demand power of the power system. However, the total number of charging EVs calculated in the above subsection does not include the EVs in which the charging time was changed due to the ToU price based charging scheme. Thus, the next step is the calculation of the

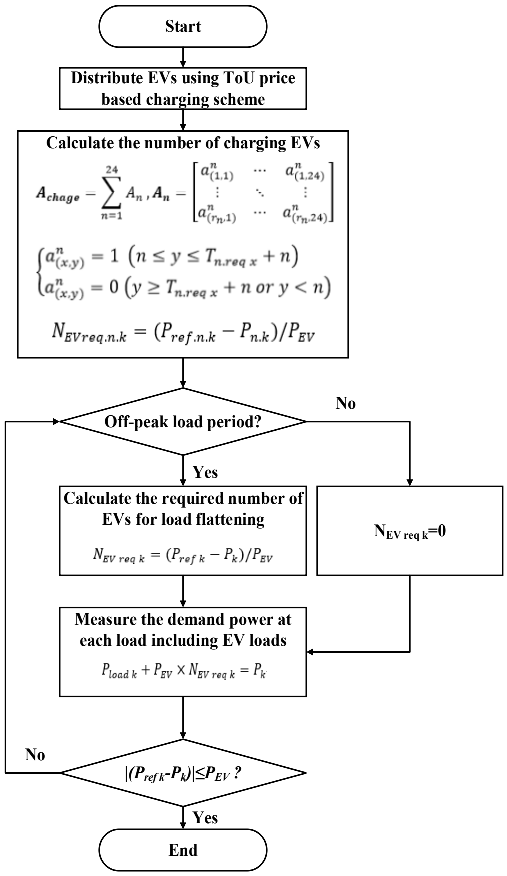

Fig. 5. Smart EV charging scheme control algorithm

required number of EVs for load leveling using the shifted EVs. The required number of EVs can easily be found using (9).

$$N_{EVreq.n.k} = (P_{ref.n.k} - P_{n.k})/P_{EV} \tag{9}$$

where $N_{EVreq.n.k}$ refers to the required number of EVs for load leveling at time n on k load. $P_{ref.n.k}$ refers to the reference demand power at time n on k load and $P_{n.k}$ refers to the system demand power at time n on k load and P_{EV} refers to the power consumption of a single EV.

5) **Feedback Loop**: The main purpose of feedback loop is to prepare unexpected change of power system. The proposed algorithm measures demand power and set the number of charging EVs. If there is any unexpected change in power system after set the number of charging EVs, however, it may not be the optimal numbers. Using feedback loop, it can adjust optimal number of charging EVs even with the unexpected changes in power system.

All the procedures mentioned above are summarized in Fig. 5.

4. Case Studies

As mentioned previously, for practical analysis, we performed case studies on the actual distribution system of KEPCO with actual traffic volume data. Additionally, as the Republic of Korea has different load patterns and traffic patterns, we focus on the data in summer that has frequent variations in the demand power and a considerable gap between minimum demand power and peak demand power in order to analyze the worst case.

4.1 Test distribution system

Fig. 6 shows a single line diagram of the distribution system. As explained in section II, we chose the bottom portion of the distribution system (shown in Fig. 6), which is a specific region in Seoul, Republic of Korea.

The main reason for considering only the bottom part of the distribution system is to increase the accuracy of the analysis. The upper portion of the system has an interconnection area that causes uncertainties and complexities in the analysis [17]. To be more specific, if there is no interconnection area, we can only consider one specific area and can use the data of that area. However, if there is an interconnection area, we can adopt neither the data of one specific area nor the combined data of several areas. In that case, we need to consider various conditions such as traffic flow and density of population. In this paper, we therefore exclude the possibilities of complexities and uncertainties by focusing only on the bottom portion of the system.

4.2 Electric vehicles

An EV consists of several components such as an electrical motor, a battery, an on-board charger, etc. However, since in most EVs the ignition is turned off during charging, we only consider the battery and the charger. Also, as most on-board chargers are designed to have a 2 to 5 kW rating considering the power contract is for family use, we assumed that the charger has a 3.3kWh charging rate [25]. The battery itself is set to have a 16.5kWh capacity [25]. That is, an EV with a 0 SoC would take 5 hours to completely charge when connected to the power system.

4.3 Dumb EV charging scheme

As the dumb EV charging scheme does not provide any control scheme, most EVs are concentrated on a peak load period. Fig. 7 shows a comparison of the demand power on the system in a dumb EV charging scheme and base case

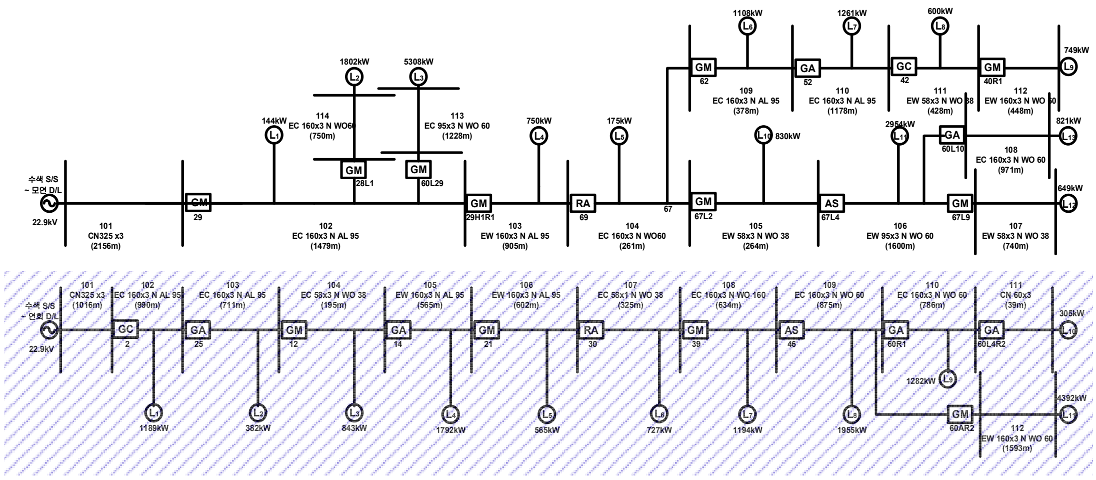

Fig. 6. Single line diagram of used distribution system

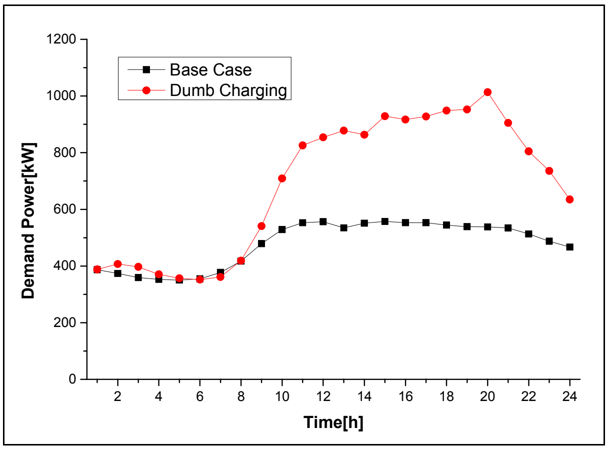

Fig. 7. The demand power of the system (Base case vs. dumb charging scheme)

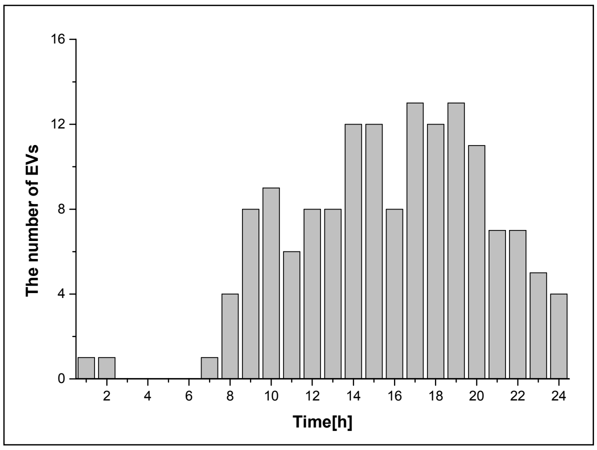

Fig. 8. The number of charging EVs at each hour (Dumb charging, L1)

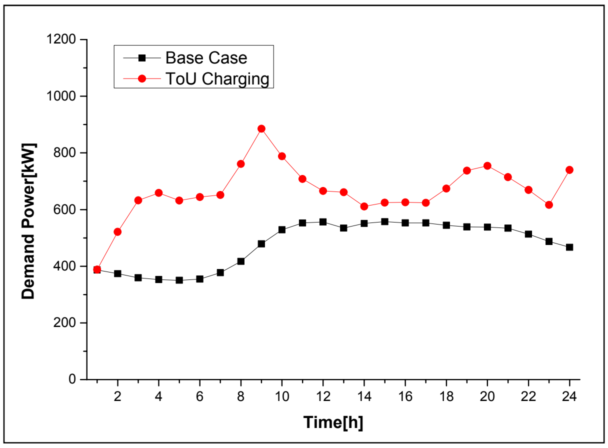

Fig. 9. The demand power of the system (Base case vs. ToU charging scheme)

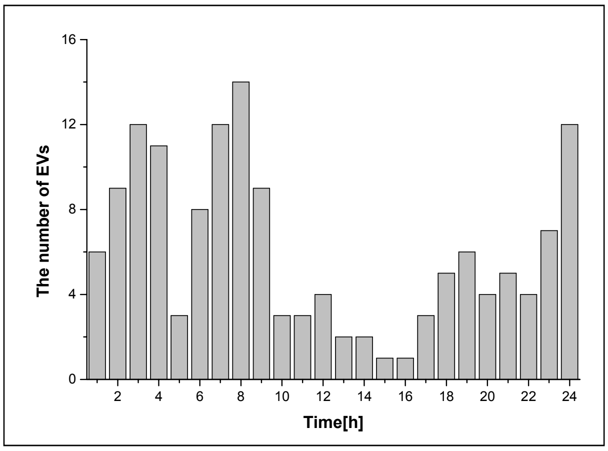

Fig. 10. The number of charging EVs at each hour (ToU price based charging, L1)

without EVs. Also, Fig. 8 shows the number of EVs at each hour under a dumb charging scheme. As shown in Fig. 7, the peak demand power for dumb charging reaches 1,013 kW, which is 1.82 times larger than that of the base case. Moreover, it is shown that the load factor would decrease with the dumb EV charging scheme. The load factor is derived from the ratio of the average demand power to peak demand power. For the base case, the load factor is 85.71%. However, when the dumb EV charging scheme is adopted, the load factor decreases to 67.80%. As a low load factor indicates the need for additional power sources and could cause severe voltage variation, the dumb charging scheme should not be used and an additional solution is required to use the charging scheme.

4.4 ToU price based EV charging scheme

When the ToU price based EV charging scheme is used, it could limit the increased power demand during the peak load period. However, as explained above, the ToU price based EV charging scheme only encourages EV owners to charge their EV during the off-peak load period. In other words, there is no additional control scheme, once the charging of the EVs commences during off-peak time. Due to this characteristic, although peak demand power is relatively lower than that of the dumb charging scheme, fluctuation still occurs in the demand power of the system as shown in Fig. 9. Also, in contrast to the dumb charging scheme, most charging EVs are concentrated in the off-peak period in the ToU price based EV charging scheme as shown in Fig. 10.

In the case of the ToU charging scheme, the peak demand power and load factor are 885.2 kW and 75.25%, respectively. Even after the ToU charging scheme is adopted, the load factor is still considerably lower than that of the base case.

4.5 Smart charging scheme

The main difference between the ToU price based EV

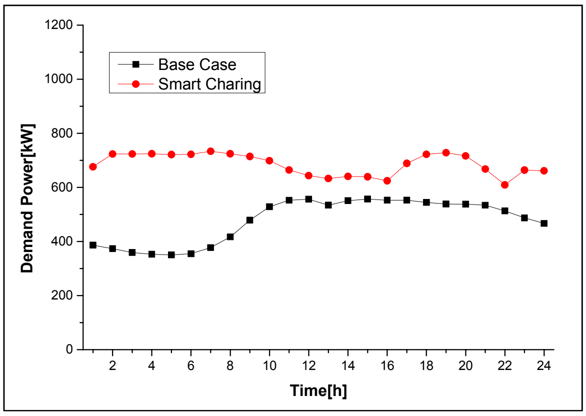

Fig. 11. The demand power of the system (Base case vs. smart charging scheme)

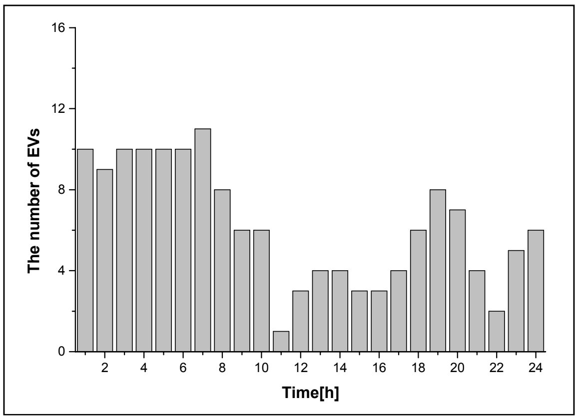

Fig. 12. The number of charging EVs at each hour (Smart charging, L1)

charging scheme and the smart EV charging scheme is the distribution of EVs during the off-peak period. The smart charging scheme determines the number of charging EVs during the off-peak load period, considering the demand power of the system. The demand power of the system and the number of charging EVs at each hour when the smart charging scheme is adopted are shown in Fig. 11 and Fig. 12, respectively.

When the smart EV charging scheme is adopted, the peak demand power of the system reaches 733.77 kW, which is 208.65 kW larger than that of the base case. In this case, the load factor increases to 93.5%. Also, the average demand power reaches 686.05 kW, which implies that the system operator can increase the portion of the base power in the system. In terms of economical and system operational aspects, an increase of the portion of the base power could bring considerable benefits. Thus, even though the proposed smart charging scheme increases the demand power of the system compared to the base case, it shows excellent performance. Fig. 13 and Table 5 show simulated results depending on each type of EV charging scheme.

Table 5. Summarization of analysis results

	Base case	Dumb charging	ToU charging	Smart charging
Average demand power(kW)	477.4004	686.99	666.08	686.05
Peak demand power(kW)	556.99	1013.2	885.2	733.77
Load Factor(%)	85.71077	67.80	75.25	93.50

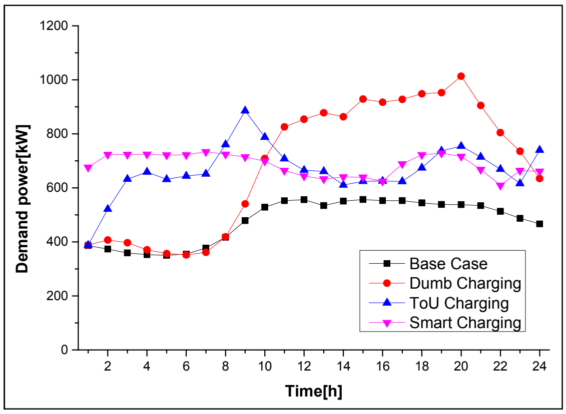

Fig. 13. The demand power of the system for each types of charging schemes

5. Conclusion

With the increased interest in EVs, the need for the analysis of EVs also increases. Without a thorough analysis of the possible effects of EVs on power system, it would be impossible to commercialize EVs. In terms of the power system, the charging of EVs could cause various adverse effects such as voltage variations, frequency variations, decrease of load factor, increase of demand power, and decrease of load factor, etc. Among these, we focused on the demand power and load factor of the system. Several types of EV charging schemes have previously been proposed. In the case of the dumb EV charging scheme, the demand power could increase during the peak load period, as there is no control scheme. Although an off-peak EV charging scheme was proposed to limit the increase in the demand power during the peak load period, the demand power still causes a problem, as it would rapidly increase as soon as the peak load period ends. The ToU price based EV charging scheme uses different charging prices, depending on the time to limit the charging of EVs in the peak load period and shift it to an off-peak load period. However, as it does not provide a charging scheme except for the ToU price, proper valley filling and load leveling cannot be accomplished. Thus, new EV charging schemes are required.

The proposed smart EV charging scheme can be divided into two main parts. First, it calculates the number of charging EVs at each hour using the ToU price based charging scheme. It then determines the distribution of EVs at each hour considering the demand power of the system using the shifted EVs due to the ToU price based charging scheme. In addition, for practical analysis, we not only consider the actual driving pattern of the EV owners and the initial SoC information, but also the use distribution system based on actual data.

Through a case study, it is shown that the proposed smart charging scheme provides excellent performance. Compared to the previous charging schemes, the proposed smart charging scheme shows an improved load factor of 93.5%, which is an even better result than that of the base case. Also, in terms of demand power, the proposed charging scheme limits the rapid increase of demand power and reduces the peak demand power to 733.77 kW, which is 279.23 kW lower than that of dumb charging and 151.43 kW lower than that of the ToU price based charging scheme, as shown in Table 5.

The low load factor means that there are considerably large gaps between the average demand power and the peak demand power. In other words, if the load factor of the system decreases due to EVs, additional power sources are required. However, if we can properly schedule the number of charging EVs, a system operator can manage the system without any additional power sources, while resulting in an even better load factor. Therefore, it is expected that the proposed smart EV charging scheme can contribute to stable power system management. Moreover, by eliminating the possible risks, it could accelerate the popularization of EVs.

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