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Improved Slow Charge Scheme for non-communication Electric Vehiclesby Predicting Charge Demand☆

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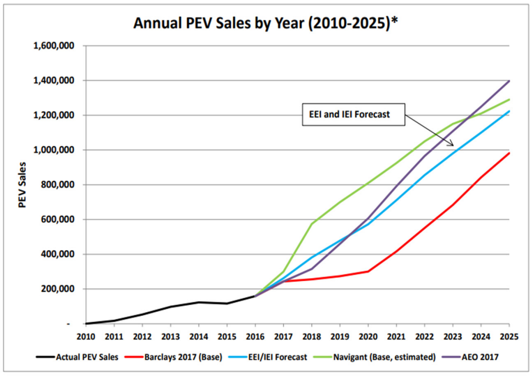
ABSTRACT

Recently, the study and development of environment-friendly energy technique have increased in worldwide due to environmental pollution and energy resources problems. In vehicle industry, the development of electric vehicle(EV) is now on progress, and also, many other governments support the study and development and make an effort for EV to become widely available. In addition, though they strive to construct the EV infra such as a charge station for EV, the techniques related to managing charge demand and peak power are not enough. The standard of EV communication has been already established as ISO/IEC 15118, however, most of implemented EVs and EV charge stations do not support any communication between each of them. In this paper, an improved slow charge scheme for non-communication EVs is proposed and designed by using predicting charge demand. The proposed scheme consists of distributed charge model and charge demand prediction. The distributed charge model is designed to manage to distribute charge power depending on available charge power and charge demand. The charge demand prediction is designed to be used in the distributed charge model. The proposed scheme is based on the collected data which were from EV slow charge station in business building during the past 1 year. The system-level simulation results show that the waiting time of EV and the charge fee of the proposed scheme are better than those of the conventional scheme.

☞ keyword : Electric vehicle, charge schedule, distributed charge, demand prediction

1. Introduction

As environmental pollution and energy resource problems have been on the rise in worldwide, the study and development of environment-friendly evergy technology have increased. In transportation industry, the research and development using electric energy instead of using fossil fuel are on progress[1-2]. Especially, electric vehicle(EV) has been considered as one of the solutions for the problems, many other governments have supported and encouraged to study and develop EV. Figure 1 and 2 show that as spreading of EV, spreading of EV charger[3-4]. As both of them are increasing, the infra and technique about EV such as an EV charge station and an efficient charge scheme are now on studying under the governments' support[5-6].



*Includes battery electric vehicles and plug-in hybrid electric vehicles

(Figure 1) The forecast of annual plug-in EV sales

An efficient EV charge scheme could be designed by using the information of EV, and the standard of EV

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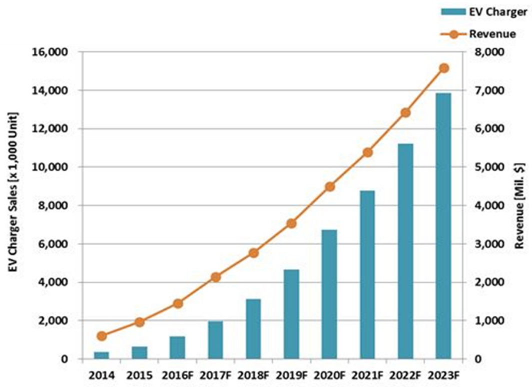


(Figure 2) Sales and revenue forecast of EV chargers

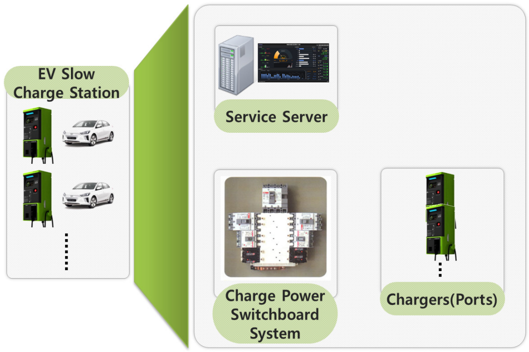
communication to get the information has been already established as ISO/IEC 15118[7]. Even that, most the constrcuted EV charge stations and already produced EVs do not invole the standard. EVs in which the standard is applied are now on manufacture, however, it is necessary to study and develop an efficient EV charge scheme considering non-communication between EVs and EV charge stations.

In this paper, an improved slowcharge scheme for non-communication between EVs and EV charge stations is proposed and designed by using predicting charge demand. In section 2, the overview of slow charge system and distributed charge power is illustrated, and the list of available datacollected by the charge system is shown. The proposed scheme is illustrated and designed in section 3, and the system-level simulation is conducted on section 4 based on the collected data from a slow charge station during the past 1 year. The simulation results in section 4 show how much more efficient the proposed scheme is than those of the conventional scheme which is uniformly distributed charge power. Finally, section 5 shows the conclusion.

2. Overview

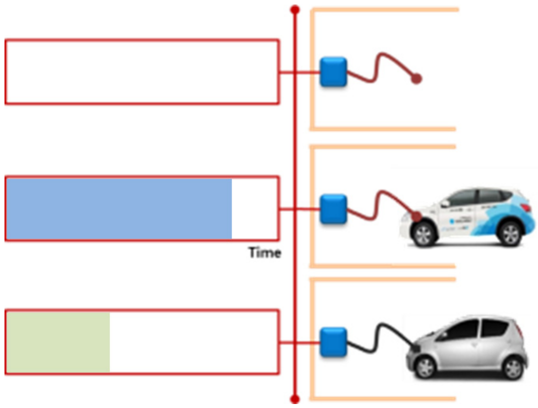
2.1 Slow Charge System

In general, EV slow charge system mainly consists of three parts which are illustrated in Figure 3. Service server is to maintain the overall system with monitoring, and to provide making a charge to clients. Charge power switchboard system is to control the charge power lines connected with chargers. In conventional system, the switchboard provides only on/off the lines, and chargers can only read the client's information by a radio frequency(RF) card.



(Figure 3) The structure of EV slow charge station

The conventional charge scheme is uniformly distributed charge power. It is illustrated in Figure 4. If the total power of the charge station is 21kW and the station has 3 chargers, each charger provides charge power as 7kW.



(Figure 4) Uniformly distributed charge scheme

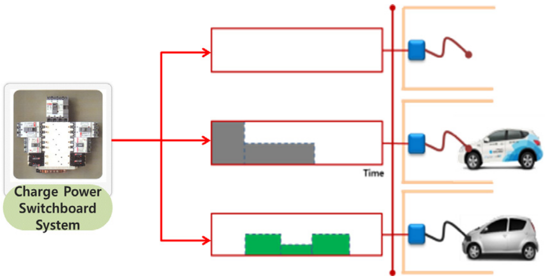
Service server usually saves client's information such as ID, and charger's information such as charge start time and end time.The server can save other data like weather if needed. Table 1 shows the item list of data that the system can collect.

(Table 1) The item list of data that slow charge system can collect

Item	Description
Date	The date of the data generated
ID	Customer's ID(EV ID)
Charge Information	Charger's information
External Information	Other information from the external

2.2 Distributed Charge Power System

Distributed charge power system consists of the same in Figure 1 except charge power switchboard system. The charge power switchboard system for distributed charge power system has internal signal processing software which conducts distributing charge power in real time. The switchboard system allocates charge power to each power line connected with each charger. It is illustrated in Figure 5.



(Figure 5) Distributed charge power system

The charge system that can distribute the charge power in variable implies that the system does't need to provide full charge power to every charger at every time. It is a very important thing for a charge station owner that the owner need not make a contract with a power supplier that the power purchase capacity must be the same to the sum of the maximum power of every charger.In addition, allocated charge power differently to each charger is able to change simultaneoulys responding to real-time demand. Therefore, the distributed charge power system will be able to provide many different ways to respond real-time charge demand such like reducing charge time or waiting time, reducing charge fee, and maintaining long-term battery life. It is very important to select what kind of charge scheme because as the charge scheme changes, how the charge scheme respondes to real-time demand will change also.

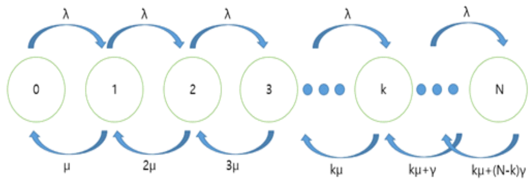
3. Proposed Scheme

3.1 Distributed Charge Power Model

Before designing distributed charge power model, it is necessary to consider that the communication between the charge station and EVs is not supported. Also, the total power of the charge station is not more than the sum of each charger's maximum charge power. For instance, if the number of chargers is 3 and the each charger's maximum charge power is 7kW, the total power of the charge station must be less than 21kW, or the distributing charge power is meaningless. In other words, it is same with uniformly distributed charge power as maximum that the charger provides.

3.1.1 Schedule Model

Schedule model is designed to distribute the charge power as scheduled time table in a day. Let arriving cars in the unit time follow a Poisson process, and the service time of charging power follow an exponential distribution. Then, the model can be desigend based on queueing theory by assuming the chargers as the queue. The concept of the schedule model is illustrated in Figure 6.



(Figure 6) The concept of the schedule model based on queueing theory

Letting N be the number of chargers as queue, the schedule model can be described as solving a problem to a solution, k^{th} charger, which is to minimize the waiting time out of k^{th} charger. That means k indicates the number of focused charge power lines. After k would be decided, the minimum charge power is allocated to the rest of chargers, $N-k$. Then, the rest of unallocated charge power is allocated to the focused line, k, as uniformly distributed no more than the maximum charge power of each charger. As illustrated in Figure 6, the state of entering the charger can be expressed in μ and γ, where μ indicates the service time of charging power, and γ indicates the allocated miminum charge power to $N-k$ chargers. As a result, the service time parameter, μ, can be expressed as follow:

$$\mu = \frac{(S-(N-k)\gamma)}{(k\times C_i)}$$

where S is the total power of the charge station, C_i is the average charge power at unit time, i. The probability, p_n, that an EV will arrive at n^{th} charger randomly can be described as a Poisson process of the average number of arrival EVs, λ. p_n can be expressed as follows:

$$p_n = \begin{cases} p_0 \dfrac{1}{n!}\left(\dfrac{\lambda}{\mu}\right)^n \\ \text{for } n = 1,2,...,k \\ \\ p_0 \dfrac{1}{k!}\left(\dfrac{\lambda}{\mu}\right)^k \prod_{t=1}^{n-k} \dfrac{\lambda}{k\mu + t\gamma} \\ \text{for } n = k+1, k+2, ..., N \\ \\ p_N \left(\dfrac{\lambda}{k\mu + (N-k)\gamma}\right)^{N-n} \\ \text{for } n = N+1, N+2, ..., \infty \end{cases},$$

$$\sum_{i=1}^{\infty} P_i = 1$$

The number of waiting EVs, L_q, out of k^{th} charger can be expressed as follows:

$$L_q = \sum_{t=1}^{\infty} t p_{k+t}$$

The expected waiting time of them, W_q, can be expressed as follows:

$$W_q = \frac{L_q}{\lambda}$$

As Little's Law, the following expression can be accepted:

$$W = \frac{L_q}{\lambda} + \frac{1}{\mu}$$

Finally, the conditions which minimize the average waiting time, W_i, in the unit time, i, can be expressed as follows:

$$\begin{aligned} &\underset{k_i}{\text{minimize}}\ W_i \\ &\text{subject to :} \\ &\quad \frac{(S-(N-k)\gamma)}{k} \le D, \\ &\quad S \le C_m, \\ &\quad \lambda = A_i, \\ &\quad \mu = \frac{(S-(N-k)\gamma)/k}{C_i} \end{aligned}$$

where D is the maximum charge power of a charger, C_m is the maximum power of the charge station, and A_i is the average number of arrival EVs in unit time, i. After solving that, k_i can be obtained in each unit time, i, and the allocated charge power to k and $N-k$, $P_{k,i}$ and $P_{N-k,i}$, can be expressed as follows:

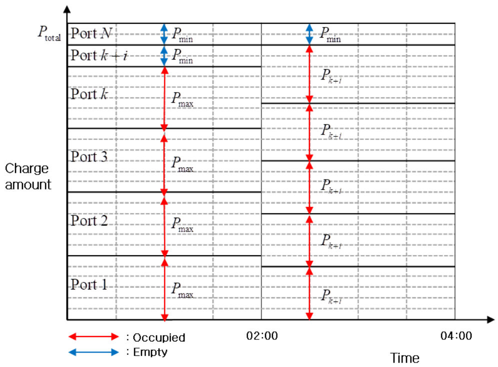
$$if\ \frac{S-(N-k)\gamma}{k} \le D, \quad \left\{ P_{k,i} = \frac{S-(N-k)\gamma}{k} \right.$$

$$if\ \frac{S-(N-k)\gamma}{k} > D, \quad \left\{ P_{k,i} = D \right.$$

$$P_{N-k,i} = \frac{S-kP_{k,i}}{N-k} = \gamma$$

3.1.2 Real-time Model

The designed schedule model has a critical restraint which the model can be calculated under perfectly predicted charge demand. If the real-time demand were different from the predicted one, the efficient of the proposed scheme will not be guaranteed.For dealing that, it can be considered to conduct rescheduling, however, there is also limitation because of no information about preexisting EVs. Consequentially, a distributed charge power model in real-time charge demand is necessary. Figure 7 shows the concept of proposed real-time model.



(Figure 7) The concept of real-time model

The real-time model is also to get a k which indicates the number of chargers that can provide the maximum charge power, P_{max}, in total N chargers. The proposed model provides full charge power till the k^{th} EV arrives. If an EV arrives after k^{th} as $(k+i)^{th}$, the rest available charge power except the sum of minium charge power of the rest of chargers, $N-(k+i)$, will be distributed uniformly by $k+i$. Eventually, if every charger is fully occupied as N, each charger divides the total charge power, P_{total}, into N. To obtain k can be expressed as follows:

$$kP_{\max} + (N-k)P_{\min} = P_{\text{total}}$$

where k is a natural number, it can be expressed as follows by using a floor function:

$$k = \left\lfloor \frac{P_{\text{total}} - (N-k)P_{\min}}{P_{\max}} \right\rfloor$$

Finally, the distribued charge power till j^{th} arrival, P_j, for j EVs and after j^{th} arrival, P_{N-j}, for $N-j$ EVs can be expressed as follows:

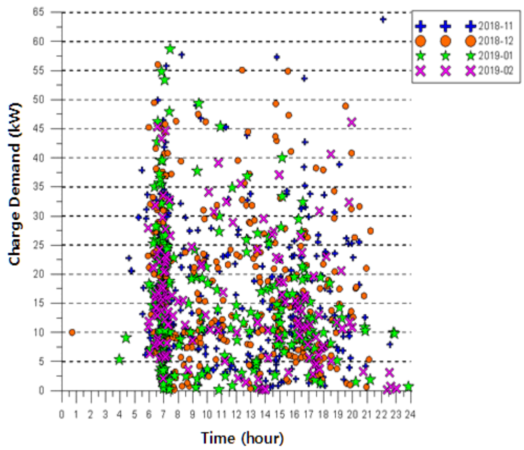
$$if\ \ j = 1, \dots, k,$$
$$\begin{cases} P_j &= P_{\max} \\ P_{N-j} &= P_{\min} \end{cases}$$

$$if\ \ j = k+1, \dots, N-1,$$
$$\begin{cases} P_j &= \dfrac{P_{\text{total}} - (N-j)P_{\min}}{j} \\ P_{N-j} &= (N-j)P_{\min} \end{cases}$$

$$if\ \ j = N,$$
$$\left\{ P_j = \frac{P_{\text{total}}}{N} \right.$$

3.1.3 Charge Demand Prediction Model

The EV charge history data at the business building which is located in Goyang-si, South Korea was collected during late 2018 to 2019. The charge patterns are illustrated in Figure 8. As the shown figure, mostly high demand forms in the commute time.



(Figure 8) EV charge data at a business building in Goyang-si, South Korea

Table 2 shows that expansion of Table 1 to save EV charge data and to predict the charge demand. The collected data is based on Table 2, however the red colored factors, StayTime and StarSoC, are not applied yet.

(Table 2) The data list of slow charge station to predict the charge demand

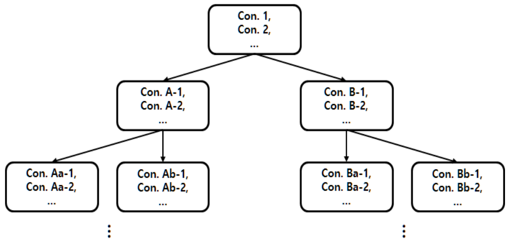
Data	Description
Date	The date of the data generated
ID	Customer's ID(EV ID)
Month	Month
Day	Day
DayofWeek	Day of the Week
Weekend	Weekend or Holiday
StartTime	Charge Start Time
EndTime	Charge End Time
StayTime	EV Stay Time
ChargeTime	Total Charged Time
StartSoC	SoC before Charge
ChargePower	Total Charged Power
DemandLevel	Charge Fee Level
Wmax	Maximum temp. of a Day
Wmin	Minimum temp. of a Day
Wcloud	Cloud amount of a Day
Wrain	Rain amount of a Day
Local	Local Characteristics

Table 3 shows the designed data list as the charge demand prediction results.

(Table 3) The data list of slow charge station to predict the charge demand

Data	Description
EVnum	The number of EVs in each unit time
EVcharge	The average charge power in each unit time
EVstay	The number of long stayed EVs in a Day

To get multiple outcomes shown in Table 3, decision tree regressor with multiple regression analysis is used[8-10]. Figure 9 shows the concept of decision tree regressor with multiple regression analysis.



(Figure 9) The concept of decision tree regressor with multiple regression analysis

As a result, the input data group, X, and the predicted output data group, Y, can be expressed as follows:

$$X = \{\text{ Month, Day, DayofWeek, Weekend, StartTime, StayTime, DemandLevel, Wmax, Wmin, Wcloud, Wrain }\}$$

$$Y = \{\text{ EVnum, EVcharge, EVstay }\}$$

$$(y_1, y_2, y_3) = (x_1, \ldots, x_{11})$$

where y_1, y_2, and y_3 indicate EVnum, EVcharge, and EVstay respectively.

3.1.4 Real-time with schedule Model

Real-time with schedule model is designed as selecting the model, C_{policy}, among the two proposed models, by comparing thereal-time occupied demand, C_{num}, with the predicted demand, y_1. In addition, it compares the predicted number of long stayed EVs with k in the selected model, and modifies the value of k as k_{adt}. C_{policy} and k_{adt} can be expressed as follows:

$$C_{policy} = \begin{cases} M_S & if\ C_{num} \le y_1 \\ M_R & else \end{cases}$$

$$k_{adt} = \min(k, N - y_3)$$

where M_S indicates the proposed schedule model, and M_R indicates the proposed real-time model. If there is y_3, it allocate the charge power of each y_3 as P_{y_3}, and if the demand level is the highest as 3, it restrains $P_{\max}$. P_{y_3} and $P_{\max}$ can be expressed as follows:

$$P_{y3} = P_{\min}$$

$$P_{\max} = \begin{cases} \dfrac{P_{total}}{N} & if\ \text{DemadLevel} = 3 \\ D & else \end{cases}$$

4. Simulation

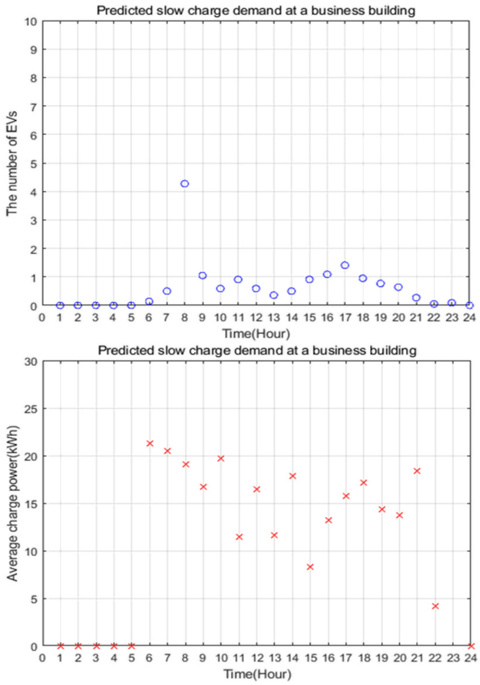
4.1 Simulation Environment

EV charge data was collected from a business building located at Goyang-si, South Korea during 2019, however, two factors in Table 3, StayTime and StartSoC,were not collected because of internal software technical issue. Therefore, some restraints must be assumed so that the system-level simulation would be conducted. In addition, though charge demand prediction uses the collected data, the simulation data for charge demand would be generated randomly by the collected data to simulate the combined two models. Table 4 shows the simulation environment.

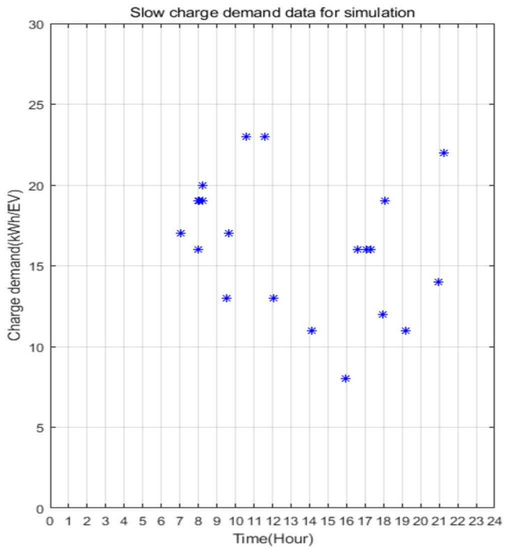
(Table 4) Simulation environment

Factor	Description
Weather	Winter
Total charge power	28kW
The number of chargers	6
The minimum and maximum charge power	1.4kW, 7kW
The unit charge power	0.1kW
The unit time	1 hour
Charge demand - the number of EV	Randomly selected data in the collected data multiplied by 1.5
Charge demand - arrival time	Randomly generated by exponential distribution only in newly generated EVs
Charge demand - charge power	Randomly generated by normal distribution with sigma as 2 only in newly generated EVs
Iteration	1000

Based on Table 4, the predicted demand and the charge demand data for simulation are illustrated as Figure 10 and 11.



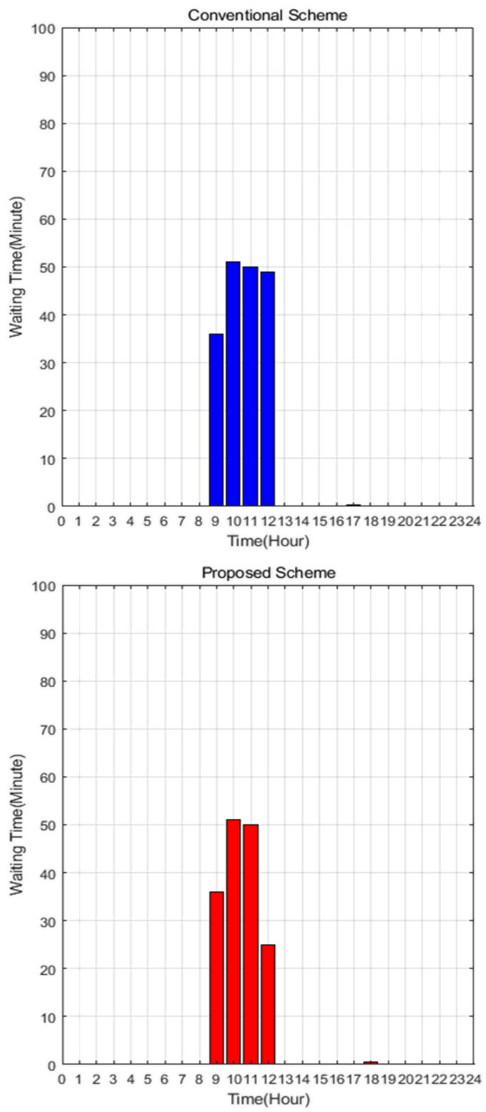
(Figure 10) Predicted charge demand at a business building



(Figure 11) Slow charge demand data for simulation

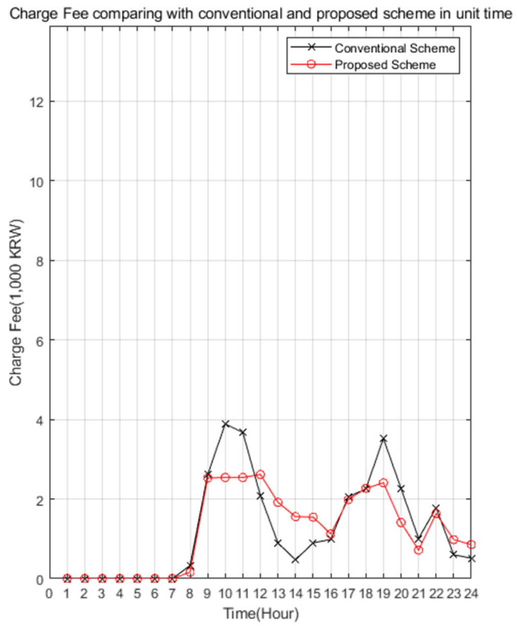
4.2 Simulation Result

Simulation results show the waiting time of EVs and the charged fee compared with the conventional scheme which distributes the charge power to all chargers uniformly. Figure 12 shows the result of waiting time.



(Figure 12) Simulation result of waiting time

The first concentration of the demand, near 9 to 11, shows almost the same waiting time both of conventional and proposed scheme, however, the proposed scheme provides more shorter waiting time near 12. The reason can be inferred by Figure 12 which shows the result of charge fee.



(Figure 13) Simulation result of charge fee

In Figure 13, the first concentration of the demand, near 9 to 11, showsthe proposed scheme provides more efficient charge fee with almost same waiting time compared with conventional scheme. After 12, it provides less efficient charge fee with much more efficient wiating time compared with the conventional one. Table 5 shows the simulatioin results comparing the conventional scheme with the proposed scheme.

(Table 5) Simulation results comparing the conventional with proposed scheme

	Conventional Scheme	Proposed Scheme
Total waiting time	186.32 mins	162.47 mins
Total charged power	254.68 kWh	264 kWh
Total charge fee	29,756 KRW	28,697 KRW
Average charge fee per 1kWh	116.83 KRW	108.7 KRW

As a result, the proposed scheme provides more efficient charge power and charge fee in a day than those of the conventional one. Both scheme are based on same charge demand, however, conventional scheme has more total waiting time than that of proposed scheme. It shows that the proposed scheme is able to deal more charge demand than that of conventional scheme. Finally, The proposed scheme reduces more 12% total waiting time than that of conventional scheme. The result causes to provide 3% efficiency in both total charged power and total charge fee than than that of the conventional one. In the perspective of charge station, the efficiency can be concluded as average charge fee per 1kWh in a day by the conditions on the decreased total waiting time and charge fee, and the increased total charge power as the fifth row of Table 5. The proposed scheme provides more 34% efficiency of average charge fee per 1kWh in a day than that of conventional scheme.

5. Conclusion

In this paper, an improved slow charge scheme for non-communication EVs is proposed and designed by using predicting charge demand. According to the simulation results, the proposed scheme provides more efficient charge power and charge fee than thoseof the conventional one. However, there are still some issues to be solved. One is to get more data to make the prediction more stable. The other is to implement the charge scheme to the system, and verify the proposed scheme. It is expected that the proposed scheme will provide more efficient distributed charge power in real system, and more, deal the demand and the peak power. In addition, it will be necessary to study and development the more efficient distributed charge scheme by using ISO/IEC 15118 in the near future.

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