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Non-cooperative Optimization of Charging Scheduling for Electric Vehicle via Stackelberg Game and Matching Theory

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Abstract: In this paper, we deal with the charging scheduling optimization problem of electric vehicle in highway via Stackelberg game and matching theory. At first, we propose an algorithm for electric vehicle allocation to charging station which aims to uniformize waiting time of each charging station. In addition, we present energy demand and price decision problem and solve it using Stackelberg game. We compare Stackelberg equilibrium point and Nash equilibrium point and confirm Stackelberg game provide bigger benefit to charging station. Finally, we show validation of proposed algorithm via numerical simulations.

Keywords: Charging scheduling, electric vehicle, matching theory, game theory.

1. INTRODUCTION

Recently, the spread of EVs(Electric Vehicles) has been actively progressed. EV can work with a distance of 120 km to 400 km with once charging, which is different from conventional gasoline and diesel cars. Therefore, it is imperative to plan a place of charging station, time and charge amount to be charged. In the United States and China, it is general for commercial organizations to set up CS (Charging Station). Electric vehicle drivers pay not only electricity fee but also additional service fee when they charge their EV. Since this service fee can be freely set by business operators, its strategy varies between operators. Therefore, businesses need to set fees so that their profits become maximum. In addition, operators need to find ways to make more effective use of their own charging station. EV concentrate on only one charging station, and if other stations are not used, businesses may lose profits. Hence, the charging station operator aims to maximize profits by controlling prices and to make all charging stations equally used.

EV determines the location of the charging station and the charge amount according to its own purpose. Distributed cooperative scheduling algorithms on highway have already been proposed Gusrialdi (2017). With this algorithm, all EVs cooperate to select their charging station. However, this assumption is unrealistic. We need to think about the situation where EV acts to maximize only its own profit. Also, some researches have not dealt with the charge of electric vehicle, and all electric vehicles must always be fully charged at the charging station. Actually, the style of charging depends on the electric vehicle, so we need to think about the framework of determining the charge amount. Thus, after choosing a charging station, the EV determines the charge amount taking into account the price and other factors.

The main contribution of this paper is the proposal of non-cooperative optimal charge scheduling algorithm using Stackelberg game Yang (2016) Tan (2017) and matching theory. First of all, we propose a matching algorithm by expressing the electric car allocation problem aiming at the charging station to equalize the utilization ratio and the electric vehicle to select the charging station by matching theory. Furthermore, we describe energy demand and energy price dicision problem using Stackelberg game and state its solution. It shows that the Stackelberg equilibrium, which is generally considered to be difficult to analyze Bayram (2015), has better results than the Nash equilibrium.

In this paper, we model the traffic flow, the dynamics of the number of vehicles in CS, EV energy consumption, EV drivers utility and CS benefit. By queuing model, we solve uniformize utilization problem and propose matching algorithm for EV optimal allocation problem. After that, we formulate Stackelberg game with EVs as followers and CS as a leader. Finally, by numerical simulation, we show a validation of the proposed algorithm.

2. PROBLEM STATEMENT

An overview of the network used in this research is shown in Fig. 1. Each CS belongs to the same business operator and exchanges information with each other. When CS scheduling interval is assumed to be T, each station presents the charging price to each vehicle at the scheduling time $k = nT(n = 1, 2, \ldots)$. This exchange is done through V2I and I2V. In addition, each EV communicates with other surrounding EVs to determine their desired charging demand while maintaining a non-cooperative attitude towards other EVs. Setting up such a network is reasonable considering that most CSs are connected to the network for paying credit cards, and car navigation systems are installed in EVs.

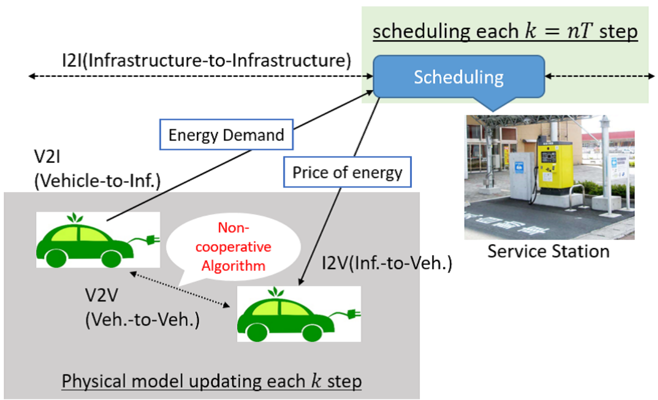

Fig. 1. Network condition

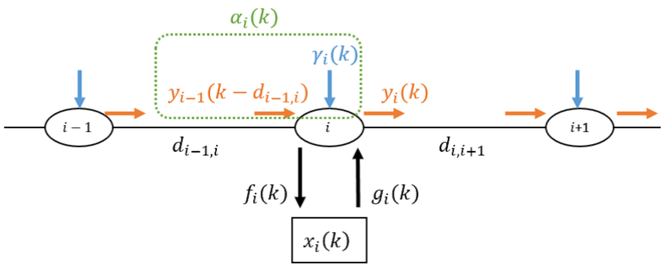

Fig. 2. Traffic flow model

2.1 EV flow

The first component of the model describes the flow of EVs on the highway. Entrances/exits or CS to each of which we associate one node of the network. Let the total number of nodes be N. We consider a chain topology in which node i is connected only with the nodes of $i-1$, $i+1$. Thus edges represente visual links between two successive entrances, exits or CS. A generic portion of the chain involving node i and its predecessor and successor is depicted in Fig. 2.

Let $\alpha(k)$ be the average EV flow arriving at a node i, which is given by

$$\alpha_i(k) = \begin{cases} \gamma_i(k), & \text{if } i = 1 \\ \gamma_i(k) + y_{i-1}(k - d_{i-1,i}), & \text{if } i \neq 1 \end{cases} \tag{1}$$

where $\gamma_i(k)$ is the exogenous flow entering the chain network at node i at time k, $y_{i-1}(k)$ is average EV flow coming from node$(i-1)$ to node i, $d_{i-1,i}$ is the time required for an EV to traverse the edge from node $i-1$ to node i. The number of EVs departing from node i, $y_i(k)$, can be written as follows.

$$y_i(k) = \alpha_i(k) + g_i(k) - f_i(k), \tag{2}$$

where $g_i(k)$ represents EV flow coming out from service station i, and $f_i(k)$ represents EV flow entering to service station i.

2.2 Queuing model

Let $x_i(k) \geq 0$ be the number of EVs existing in CS i. Then the $x_i(k)$ can be represented dynamically as the followings,

$$x_i(k+1) = x_i(k) + f_i(k) - g_i(k), \tag{3}$$

where, $f_i(k)$ is the number of vehicles flowing into the CS and is decided by EV allocation algorithm. However, even if scheduling is done, the time distribution at which the vehicle arrives can not be determined systematically. Therefore, the distribution itself of the event "vehicle arrives" follows the Poisson distribution. Also, it is not possible to schedule exactly how much EV actually stays at CS. From the above conditions, we use the $M/M/c_i$ queuing model Gusrialdi (2017) Ratliff (2016). In this problem formulation, M means the exponential distribution, where the number of chargers for CS i is c_i. The average arrival rate of costumers is λ_i and the average service rate is μ_i. Here, the following condition is assumed.

Assumption 1. The customer's average arrival rate is smaller than the average service rate. Hence, $\lambda_i < \mu_i$.

In order to obtain the number of vehicles $x_i(k)$ existing in each CS i, it is necessary to calcurate the number of outflow vehicles $g_i(k)$. From the steady solution of $M/M/c_i$, we can get

$$x_i = \frac{\rho_i^{c_i+1}}{c_i c_i!} \frac{1}{\left(1 - \dfrac{\rho_i}{c_i}\right)^2} \varphi_{i,0} + \rho_i \tag{4}$$

$$\varphi_{i,0} = \left[\sum_{n=0}^{c_i-1} \frac{\rho_i^n}{n!} + \frac{\rho_i^{c_i}}{c_i! \left(1 - \dfrac{\rho_i}{c_i}\right)} \right]^{-1} \tag{5}$$

where, $\rho_i = \lambda_i/\mu_i$. From equation (3), when steady state is achieved, $g_i = f_i = \lambda_i$. Substitute this condition into the equations (4) and (5).

$$x_i = \frac{g_i^{c_i+1}}{\mu_i^{c_i+1} c_i c_i!} \frac{1}{\left(1 - \dfrac{g_i}{\mu_i c_i}\right)^2} \varphi_{i,0} + \frac{g_i}{\mu_i} \tag{6}$$

$$\varphi_{i,0} = \left[\sum_{n=0}^{c_i-1} \frac{g_i^n}{\mu_i^n n!} + \frac{g_i^{c_i}}{\mu_i^{c_i} c_i! \left(1 - \dfrac{\rho_i}{c_i}\right)} \right]^{-1} \tag{7}$$

We could derive the relationship between $g_i(k)$ and x_i, however it is impossible to obtain $g_i(k)$ from (6) (7). If $c_i = 1$, the steady solution can be written by the following equation.

$$x_i = \frac{g_i}{\mu_i - g_i} \implies g_i = \mu_i \frac{x_i}{1 + x_i} \tag{8}$$

g_i can be apploximated by $M/M/c_i$ model as,

$$\hat{g}_i(x_i) = c_i \mu_i \frac{x_i}{1 + x_i} \tag{9}$$

2.3 EV energy model

The power consumption of the EVs is given as

$$e_{v,i+1}^- = e_{v,i}^+ - d_{i,i+1} r_v^-, \tag{10}$$

$$e_{v,i}^+ = e_{v,i}^- + \frac{E_{v,i}}{\mu_v}, \tag{11}$$

where $e_{v,i+1}^-$ is the SOC (State of Charge) when the generic EV v arrives at node $i+1$, $e_{v,i}^+$ indicates the SOC when EV v leaves the node i. $E_{v,i}$ is the amount of energy that EV v charges at node i, and μ_v is the battery capacity. Each EV bids the desired amount of charge to the CS, Since the time required to move from the node i to node $i+1$ is

$d_{i,i+1}$, r_v^- is the SOC required for unit time running. The charging strategy of each EV satisfies the following two constraints;

$$E_{v,i}^{min} \leq E_{v,i} \leq E_{v,i}^{max}, \tag{12}$$

$$e_{v,i}^- + \frac{E_{v,i}}{\mu_v} \leq 1. \tag{13}$$

Inequalities (12) are constraints that the upper and lower bounds of the amount of energy that an EV can charge at CS, and inequality (13) describes the fact that the SOC cannot exceed 100%.

2.4 Utility functions of EVs and CSs

$U_{v,i}^k$ represents the utility function of EV v, is written as follows.

$$\begin{aligned} U_v^k =& \mu_v E_{v,i}(k) - \frac{1}{2}\theta_{v,i}(k)\left(E_{v,i}(k)\right)^2 \\ &- p_{v,i}(k)E_{v,i}(k) - p_{v,i}(k)\left(E_{v,i}(k) - \bar{E}_i(k)\right), \end{aligned} \tag{14}$$

where, $\bar{E}_i(k)$ is the average energy demand of all EVs and $p_{v,i}(k)$ is a price of electricity. In addition, $\theta_{v,i}(k)$ is

$$\theta_{v,i}(k) = \frac{\dfrac{1}{\left(\mu_v - e_v^-(k)\right)}}{\sum_k \left(\dfrac{1}{\left(\mu_v - e_v^-(k)\right)}\right)}. \tag{15}$$

The equation (14) shows a satisfaction parameter indicating the measure of satisfaction of EV v obtained by charging an unit of energy with CS i. For example, if EV v has a higher need for energy demand than EV v+1 (eg, it is going to travel farther, has a larger battery, etc.) then EV v is the same to achieve satisfaction, more energy is required than EV $v+1$. Therefore, it becomes $\theta_v(k) \leq \theta_{v+1}(k)$.

The utility function of the CSs can be represented as,

$$Q_i^k = \sum_v p_{v,i}(k)E_{v,i}(k) - \frac{a}{2}\left(\sum_v E_{v,i}(k)\right)^2. \tag{16}$$

whereas the CS individually sets a price that maximizes its own profit.

2.5 Control objective

The charging station aims to gain profits by selling energy to the driver while operating the station efficiently. If the EV concentrates on a specific charging station, it causes not only congestion and equipment trouble but also a charging station that is not used is wasteful of resources. Therefore, the primary goal is to appropriately distribute EV by changing the charging price at each charging station, and the usage rate of each charging station becomes uniform. The second goal is to further maximize profits by selling energy. Meanwhile, the EV driver aims to charge the desired energy while competing with other drivers. The goal of this research is to propose a scheduling algorithm using Stackelberg game for this system. In the Stackelberg game, drivers and charging stations are treated as players, and mutual exchanges are expressed as games.

3. NON-COOPERATIVE CHARGING SCHEDULING

We consider the charge scheduling problem into two categories: "which car determines which charging station to enter" and "problem determining how much each vehicle charges at charging station". Here the following procedure is considered.

(1) The charging station determines the number of vehicles to be scheduled to the charging station in order to make the waiting time uniform (≅ uniform utilization rate)
(2) EV determines the preference for charging station by waiting time and its own SOC.
(3) The charging station determines the preference for the driver according to its own situation.
(4) Perform matching.
(5) Once the charging station and EV pair are decided, energy demand and price are determined by Stackelberg game.

3.1 EV allocation problem

In a steady state of $M/M/c_i$, the probability of n customers existing in the system, as traffic intensity $\rho_i = \frac{\lambda_i}{\mu_i}$ is as,

$$P_n = \begin{cases} P_0 \rho_i^n \dfrac{1}{n!}, & (0 \leq n \leq c_i) \\ P_0 \rho_i^n \dfrac{1}{c_i! c_i^{n-c_i}}, & (n \geq c_i) \end{cases} \tag{17}$$

$$P_0 = \left[\sum_{n=0}^{C_i - 1} \rho_i^n \frac{1}{n!} + \rho_i^{c_i} \frac{1}{c_i} \frac{1}{1 - \dfrac{\rho_i}{c_i}}\right]^{-1}. \tag{18}$$

When a customer arrives in the system, the probability that the customer will into wait queue is equal to the probability that all c_i contacts are occupied. That is,

$$E_{2,c_i}(\rho_i) = \sum_{n=c_i}^{\infty} P_n = \frac{c_i}{c_i - \rho_i} P_{c_i} \tag{19}$$

This equation is called as Erlang C formula. Using the equation, the average waiting time of this system W_i can be written by

$$W_i = E_{2,c_i} \frac{1}{\mu_i \left(c_i - \rho_i\right)}. \tag{20}$$

In order to equalize the waiting time at each station, we can control λ_i so that equation (20) is equal at each station. For getting optimal λ_i, it is obvious that $\sum_k f_i(k) = \sum \lambda_i$ when infinite intervals are considered.

Let the time horizon be H_p. At this time, the charging station solves the following problem and determines the optimum charging permitted number $f_i^*(k)$ at the k step.

$$f_i^*(k) = \arg \min_{f_i(k), i \in \mathcal{N}} \left[\max_i W_i - \min_j W_j\right] \tag{21}$$

$$\text{s.t.} \quad \lambda_i = \frac{1}{H_p} \sum_{l=0}^{Hp-1} f_i(k-l) \tag{22}$$

$$\sum_i f_i(k) = \sum_i \gamma_i(k) \tag{23}$$

We deal with how to distribute scheduled multiple EVs to each station. We consider the optimum allocation of drivers to the charging station using matching theory. Preferences are generally defined as follows.

Definition 1. On set X, preference of player i, $\succeq_i$ is a binary relation on X that satisfies the following condition.

(1) $x \succeq_i x, \forall x \in X$
(2) $[x \succeq_i y$ and $y \succeq_i z] \Rightarrow x \succeq_i z,\ \forall x, y, z \in X$
(3) $x \succeq_i y$ or $y \succeq_i x,\ \forall x, y \in X$

$x \prec_i y$ indicates that player i prefers y more than x under the preference of individual i.

Each driver consider CSs under the following conditions.

- SOC at the arrival of the charging station (lower is preferable, but it is not an option if it becomes 0 or less).
- Estimated waiting time (smaller is preferable).
- Other factor.

Let's set the current location of EV v at scheduling step as node i^0 and SOC as e^0_{v,i^0}. At this time, in determining the preference, the evaluation function of EV v to CS i can be written as follows.

$$J^i_v = \begin{cases} \omega_1 \hat{e}^-_{v,i} + \omega_2 W_i + \omega_3, & (\text{if} \quad \hat{e}^-_{v,i} > 0) \\ \omega_4, & (\text{otherwise}) \end{cases} \tag{24}$$

$$\hat{e}^-_{v,i} = e^0_{v,i^0} - \sum_{j=i^0}^{i-1} d_{j,j+1} r^-_v. \tag{25}$$

The first term of equation (24) indicates the estimated SOC when arriving at CS i, the second term relates to waiting time, and the third term is other factors. $\omega_1, \omega_2, \omega_3$ are appropriate weights. $\omega_4 \gg 0$ is a penalty to CS i which can not be reached without charging. By setting ω_v to be preference for itself of EV v, we set $0 \ll \omega_v < \omega_4$ to avoid matching with CS that can not be reached without charging.

Since EV v is the preferred CS i in descending order of the evaluation function (26), we calculate it for each i and decide the preference vector P^i_v by obtaining the index i in ascending order. Here, we set assumption 2.

Assumption 2. Each EV has an initial SOC that can reach at least the nearest CS, when it enters the highway.

Hence, all EV has one charging station that is more favorable than it at least.

Charging stations have no requirement for EVs in particular, but for EVs that can not reach the next station unless charging , charging must be permitted. The evaluation function for EV v can be written with the following equations, a next station of station i as i'.

$$J^v_i = \begin{cases} \chi_1 & \left(\text{if} \quad \hat{e}^-_{v,i'} < 0\right) \\ \chi_2 & \left(\text{if} \quad \hat{e}^-_{v,i} < 0\right) \\ \chi_3 & (\text{otherwise}) \end{cases} \tag{26}$$

where $\chi_1 \ll 0, \chi_2 \gg 0, \chi_1 < \chi_3 < \chi_2$. The condition of the first row indicates that the EV can not reach the next station without charging and the second row means the EV can not be reached to the station. For CS i, that EV v is not subject to scheduling is equivalent to not matching with that EV. We set the evaluation function value of CS i to itself as χ_i. By setting the condition of χ_i to $\chi_3 < \chi_i < \chi_2$, it is possible to exclude matching with the EV that is not subject to scheduling.

Since the smaller the evaluation function J^v_i is better for EV, so we calculate the function in order and obtain the index v to decide the CS preference vector P^v_i. Here, we set the assumptions to discuss the stability of matching.

Assumption 3. At scheduling step k, the number of EVs that $\hat{e}^-_{v,i'} < 0$ in CS i is always equal or smaller than $f^*_i(k)$.

Consider allocating charging station i for each EV using matching theory based on the determined preference. After preferences are decided, there are several algorithms to decide actual matching. In general, matching theory has a problem that the number of iterations increases exponentially as the scale of the problem gets bigger, there is a possibility that the stability of matching does not be guaranteed if the number of iterations is decreased.

3.2 Stackelberg game and its solution

At the time k, EV that toward the CS i which has c_i charger express $\mathcal{F}_i(k) := \{1, \ldots f_i(k)\}$. The CS, as EV can achieve the energy demand $E_{v,i}(k)$, reasonable price $p_i(k)$.The charging energy demand of sets of the target EV $\boldsymbol{E}(k) = [E_{1,i}(k), \ldots, E_{K(k),i}(k)]$. The CS presents the charging price so as to maximize its own profits, EV is based on the asking price. Therefore, this problem is a repetitive non-cooperative game with a hierarchical structure, CS has the decision privilege to EV. At this time, the utility function of the EV is known at the charging station and acts in anticipation of EV reaction in advance. Such a problem is formulated as one leader / multiple follower game of Stackelberg game.

From the follower model, the behavior of EV v that responds to the presented price $p_i(k)$ can be written as follows.

$$\max_{E_{v,i}(k)} U^k_{v,i} \tag{27}$$

$$\text{s.t. } E^{min}_{v,i} \le E_{v,i} \le E^{max}_{v,i} \tag{28}$$

From the charge station model, the optimization problem solving the charging station can be written below.

$$\max_{p_i(k)} Q^k_i \tag{29}$$

We deal with the Stackelberg game of one leader / multi-followers, but by considering the multi-follower as one follower returning the vector $\boldsymbol{E}_i(k)$, Analysis of the Stackelberg game as a human non-zero-sum game can be done.

Definition 2. In a two-person finite game strategy of player i is γ^i, the set of strategy is presented as Γ^i, cost funcition of each player is J^i. The set $R^2(\gamma^1) \subset \Gamma^2$ defined for each $\gamma^1 \in \Gamma^1$ by

$$R^2(\gamma^1) = \left\{\xi \in \Gamma^2 : J^2(\gamma^1, \xi) \le J^2(\gamma^1, \gamma^2), \forall \gamma^2 \in \Gamma^2\right\} \tag{30}$$

is the optimal response (rational reaction) set of player 2 to the strategy $\gamma^1 \in \Gamma^1$ of player 1.

Let consider the optimal reaction set of the EV group in this paper. The utility functions at time k, EV v were as follows.

$$\mathcal{L}_v^k = \nu_v E_{v,i}^z(k) - \frac{1}{2} b_1 \theta_v(k)(E_{v,i}^z)^2(k) - b_2 p_{v,i}(k) E_{v,i}^z(k) - b_3 E_{v,i}^z(k) \left(\frac{1}{\bar{\nu} f_i(k)} - \frac{1}{\nu_v} \right) \tag{31}$$

where,

$$\frac{\partial \mathcal{L}_v^k}{\partial E_{v,i}(k)} = 0 \tag{32}$$

then,

$$E_{v,i}^*(k) = \frac{1}{b_1 \theta_v} \left(\nu_v - b_2 p_i - b_3 \left(\frac{1}{\bar{\nu} f_i(k)} - \frac{1}{\nu_v} \right) \right) \tag{33}$$

therefore, we can get the optimal response set is

$$R_v^{ev}(p_i(k)) = \frac{1}{b_1 \theta_v} \left(\nu_v - b_2 p_i - b_3 \left(\frac{1}{\bar{\nu} f_i(k)} - \frac{1}{\nu_v} \right) \right) \tag{34}$$

In the iterative game we had dealt with before, we were able to deal with the constraints by generating the Lagrangian function by combining the upper and lower limit constraints of the energy demand amount with the utility and updating the Lagrangian function by the gradient method for each iteration. In Stackelberg games, however, we cannot deal with constraints directly, so if solutions beyond constraints are led it is necessary to constrain with lower and upper bound.

Definition 3. In a two-person finite game with player 1 as a leader, a strategy $\gamma^1 \in \Gamma^1$ is called Stakelberg equilibrium strategy for the leader, if

$$\max_{\gamma^2 \in R^2(\gamma^{1*})} J^1(\gamma^{1*}, \gamma^2) = \min_{\gamma^1 \in \Gamma^1} \max_{\gamma^2 \in R^2(\gamma^1)} J^1(\gamma^1, \gamma^2) := J^{1*} \tag{35}$$

The quantity J^{1*} is the Stackelberg cost of the leader. Regarding Stackelberg equilibrium strategy, it is well-known that every two-person finite game admits a Stackelberg strategy for the leader Basar (1999). Since Γ^1, Γ^2 are finite set and $R^2(\gamma^1) \subset \Gamma^2$ for each $\gamma^1 \in \Gamma^1$, the result readily follows from equation (35). The Stackelberg equilibrium strategy of the charging station can be written below.

$$p_i^*(k) = \arg \max_{p_i(k)} \min_{\boldsymbol{E}_i(k) \in R^{ev}(p_i(k))} Q_i^k \tag{36}$$

That is, the pricing that the charging station should take is pricing that gives maximum utility against the optimal reaction strategy that minimizes the utility of the charging station.

Here Gael-Sharpley matching algorithm is employed and X_k is the final matching set in step k, X_k' is a set of temporary matching in the algorithm. The integrted and proposed algorithm is shown as **Algorithm 1**

4. EVALUATION VIA SIMULATION

Numerical simulation was performed to confirm the effectiveness of the proposed algorithm. A simulation area was created between Japanese New Tomei Expressway Ohi Matsuda Interchange and Suruga Bay Numazu Interchange, and a simulation map was created as Fig. 3. The circle indicates the interchange, and the square indicates the service area. Black numbers between nodes mean traveling time, and red numbers show the number of charging stations in each service area. The number of vehicles inflow from outside of model is shown in Fig. 4, and the battery capacity of all vehicles and the initial SOC when inflowings are shown in Fig. 5. The simulation parameters are given in Table 1.

Algorithm 1 Charging station allocation algorithm

Require: $f_i^*(k), P_v^i, P_i^v$,and a strongly connected communication topology between EVs and CSs.
  Initialization: Set initial $X_k' = \{\}$
  for $v = 1, 2, \ldots, \sum_i \gamma_i(k)$ **do**
    EV v applies for charging to CS i with the most preference from P_v^i.
    if $|X_k'(i)| < f_i^*(k)$ **then**
      CS i accepts EV v and forms a temporary pair $X_k'(i)$.
      Update $X_k'(\underline{i})$.
    end if
    if $|X_k'(i)| = f_i^*(k)$ and $v \succ_i X_k'(\underline{i})$ **then**
      CS i resolves pair with v' such that $v' = X_k'(\underline{i})$ and accepts the application of EV v.
      Update $X_k'(\underline{i})$.
      Exclude CS i from v' preference and update $P_{v'}^i$.
      Set $v \to v'$ and restart from step 3.
    end if
    if $|X_k'(v)| = f_i^*(k)$ and $v \prec_i X_k'(\underline{i})$ **then**
      Exclude CS i from v preference and update P_v^i .
      Restart from step 3.
    end if
  end for
  $X(k) = X'(k)$

Table 1. Simulation parameter

Parameter	Symbol	setting
Number of step	K	120 [min]
Sampling time	k	1 [min]
Scheduling interval	T	15 [min]
Battery usage	r_v^-	0.05 [%/min]
average service rate	μ_i	1.1 [veh. / samp. time]
Utility function	a	0.03
weight	b_1, b_2, b_3	10,10,0.1
Preference weight	$\omega_1, \omega_2, \omega_3, \omega_4$	10,1,1,100
	χ_1, χ_2, χ_3	1,100,10
Initial Lagrangian	$\kappa(0)$	1
multipliers	$\lambda(0)$	1
Updating step size	x	0.2
	y	0.2

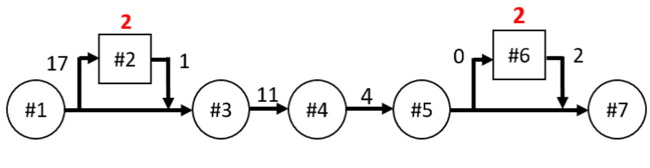

Fig. 3. Simulation map

Simulation results are shown in figures. From Fig. 6 and Fig. 7, it can be confirmed that the inflowing EVs are allocated to each charging station without leakage. Also, as a result of the allocation of EV, the time responses in Fig. 8 and Fig. 9, which indicate the estimated wait time, are almost in agreement, so the wait time equalization problem is correctly explained.

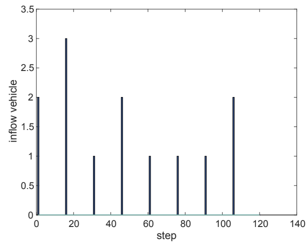

Fig. 4. Inflow

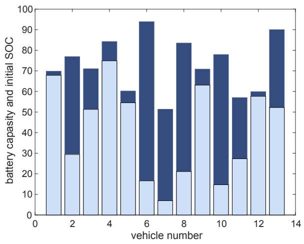

Fig. 5. Initial SOC

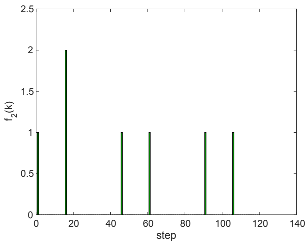

Fig. 6. Inflow to CS 2

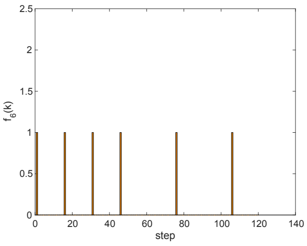

Fig. 7. Inflow to CS 6

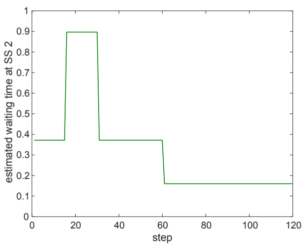

Fig. 8. Waiting time at CS 2

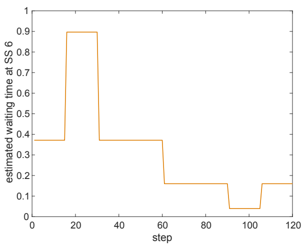

Fig. 9. Waiting time at CS 6

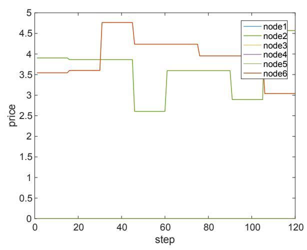

Fig. 10. Energy price

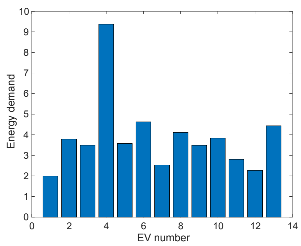

Fig. 11. Energy demand

Energy prices for each sampling time and energy demand for each EV by the Stackelberg game are shown in Fig. 10 and Fig. 11. The benefit of the charging station is given by the following equation.

$$Q_i^z = \sum_v p_i(k)E_{v,i}(k) - \frac{a}{2}\left(\sum_v E_{v,i}(k)\right)^2$$

To confirm the superiority of the Stackelberg equilibrium, the sum of the values of the above equations of charging station 2 and charging station 6 is shown in Table 2. Nash equilibrium point is also obtained by a repeating game for comparison. Based on the valuesin the table, the validity of the proposed algorithm was confirmed.

Table 2. Stackelberg game and Repeated game

Stackelberg game	Repeated game
193.6	21.8

5. CONCLUSION

In this paper, we propose non-cooperative optimal charge scheduling algorithm using Stackelberg game and matching theory. First of all, we propose a matching algorithm by expressing the electric car allocation problem aiming at the charging station to equalize the utilization ratio and the electric vehicle to select the charging station by matching theory. Furthermore, we describe energy demand and energy price decision problem using Stackelberg game and state its solution. It shows that the Stackelberg equilibrium, which is generally considered to be difficult to analyze, has better results than the Nash equilibrium.

Future works include dealing with issues that consider prices as factors of the EV allocation problem. In this case, the Stackelberg game and the matching problem are solved alternately, and it is expected that it is difficult to analyze convergence. In addition, it is necessary to propose a problem generalizing the Stackelberg game that requires a strong assumption.

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