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Discrete Pricing Optimization for Dedicated Electric Vehicle Slow-Charging in a Behind-the-Meter Community

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Abstract. In a green power direct supply behind-the-meter (BTM) community, dedicated slow-charging facilities serve electric vehicle (EV) users and could purchase power from both a photovoltaic (PV) owner and the utility grid. The interaction between the charging facility operator (CFO) and EVs can be modeled as a Stackelberg game: the CFO sets charging prices to maximize net profit, while EV users adjust charging behavior to minimize charging cost. Then a discrete pricing approach is employed, where the spacing of price levels are considered and set as decision variables. To address the introduced bilinear terms by binary and continuous variables, inequality relaxations are applied. Simulation results of a sample example with four price levels illustrates the CFO's pricing strategy and the corresponding EV power optimization results, demonstrate the accuracy of the linearization method and present pricing outcomes under different price level numbers, and show that the proposed pricing model could increase the revenue of the CFO compared with a single-price scheme.

Keywords: Electric vehicle (EV), green power direct supply, behind-the-meter (BTM) community, charging facility pricing optimization, bilinear variable linearization.

1 Introduction

The charging behavior of dedicated electric vehicles (EVs) within a community is primarily associated with daily commutation [1, 2]. Typically, EV users drive to their workplaces in the morning, leave in the afternoon or evening and tend to charge their EVs during working hours [3].

For EVs connected to dedicated slow-charging facilities, their travel trajectories are relatively fixed, thus the spatial distribution of charging and discharging loads can be considered deterministic [4,5], with the charging duration relatively long. Consequently, when analyzing dedicated charging facilities, the charging and discharging power of

EVs can be regarded as a flexible load that is adjustable in both capacity and time. By employing price incentives, the charging facility operator (CFO) can guide users to adjust their charging behaviors, thereby increases CFO's own revenue [6].

The interaction between the CFO and EVs is a hot research topic. Ref. [7] focuses on CFO optimization in a rechargeable parking lot, estimating available capacity and price through a known functional relationship between pricing and EV power responses, and both day-ahead and real-time optimal decision-making strategies are addressed. The optimization results are incorporated as known quantities in the distribution system operator's model, jointly considering the uncertainty of wind and photovoltaic (PV) generation to minimize system costs and the intermittent effects caused by renewable energy curtailment. Ref. [8] considers both CFO and EV optimization perspectives under a predetermined time-of-use price. A decentralized optimization strategy for orderly charging scheduling is proposed, aiming to maximize charging station profits. By applying the well-established Lagrangian relaxation method, the traditional centralized optimization problem is decomposed into multiple EV-level subproblems. Ref. [9], while also considering both CFO and EV perspectives, builds a Stackelberg game between a park equipped with power-to-gas devices and EV users. In this framework, the park CFO determines the energy procurement strategy, while EV users adjust their energy consumption behavior according to price signals.

This paper investigates a green power direct supply behind-the-meter (BTM) community, which receives both PV generation and utility grid power and is equipped with dedicated slow-charging facilities. The combination of PV generation and EV charging can reduce dependence on the utility grid while promoting efficient utilization of green energy. A Stackelberg game model is established between the CFO and EV users. In the upper level, the CFO aims to maximize profit, while in the lower level, EV users seek to minimize their charging and discharging costs.

Unlike previous studies, the CFO's pricing strategy is designed to divide the price range into multiple nonzero levels, subject to different intervals between each level. These intervals are treated all as decision variables, resulting in a nonlinear model containing bilinear variables. To facilitate computation by commercial solvers, some inequalities are employed to relax the bilinear variables. Finally, using the Karush-Kuhn-Tucker (KKT) optimality conditions and strong duality theory, the original bi-level optimization problem is converted into a solvable single-level formulation.

The rest of this paper is organized as follows: Section 2 introduces mathematical models of the charging facility operator and EV users. Section 3 presents the modeling approach for price levels and the overall solution procedure. Section 4 demonstrates and analyzes simulation results. Section 5 concludes the paper.

2 Mathematical model

2.1 EV charging model

The CFO in a BTM community could sign a green electricity consumption agreement with a PV owner, participating in the community green power direct supply scheme that uses a dedicated self-built PV power line. By offering electricity at a lower price, the PV owner encourages the CFO to undertake and fulfill a specified share of green power consumption responsibility within a certain range. The dedicated slow-charging facility provides services for EVs adopting the slow-charging mode. The CFO guides the charging and discharging behavior of EVs at different time periods by implementing a pricing strategy with multiple price levels.

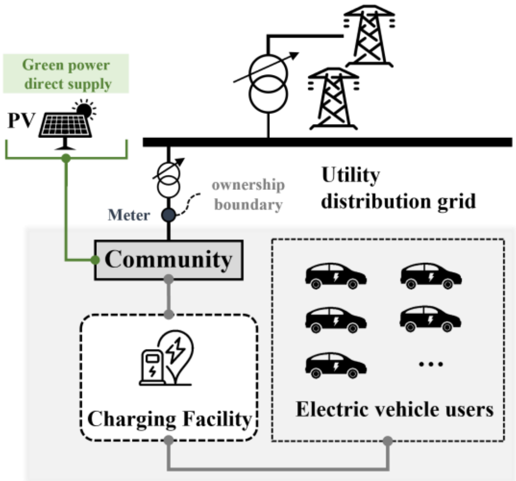

Fig. 1. Dedicated facility charging service in a BTM community green electricity direct supply scheme.

Let the decision variables of the charging facility be $P_{j,t}^{\mathrm{CF,ch}}$, $P_{j,t}^{\mathrm{CF,dis}}$, $E_{j,t}^{\mathrm{CF}}$, which respectively denote the total charging power, total discharging power, and total battery energy of the charging station at time t.

Similarly, define the decision variables of EV n as $P_{j,n,t}^{\mathrm{EV,ch}}$, $P_{j,n,t}^{\mathrm{EV,dis}}$, $\mathrm{SOC}_{n,t}^{\mathrm{EV}}$, representing the charging power, discharging power, and state of charge (SOC) of EV n at time t.

These decision variables are subject to the following constraints:

$$P_t^{\mathrm{CF,ch}} = \sum_{n=1}^{N} P_{n,t}^{\mathrm{EV,ch}} \tag{1}$$

$$P_t^{\mathrm{CF,dis}} = \sum_{n=1}^{N} P_{n,t}^{\mathrm{EV,dis}} \tag{2}$$

$$\sum_{n=1}^{N} P_{n,t}^{\mathrm{EV,ch}} \le P_{t,\max}^{\mathrm{CF,ch}} \tag{3}$$

$$\sum_{n=1}^{N} P_{n,t}^{\mathrm{EV,dis}} \le P_{t,\max}^{\mathrm{CF,dis}} \tag{4}$$

$$0 \le P_{n,t}^{\mathrm{EV,ch}} \le v_{n,t}^{\mathrm{EV}} P_n^{\mathrm{EV,ch,max}} \tag{5}$$

$$0 \le P_{n,t}^{\mathrm{EV,dis}} \le \nu_{n,t}^{\mathrm{EV}} P_n^{\mathrm{EV,dis,max}} \tag{6}$$

$$P_{n,t}^{\mathrm{EV,ch}} \cdot P_{n,l}^{\mathrm{EV,dis}} = 0 \tag{7}$$

$$\mathrm{SOC}_{\min}^{\mathrm{EV}} \le \mathrm{SOC}_{n,t}^{\mathrm{EV}} \le \mathrm{SOC}_{\max}^{\mathrm{EV}} \tag{8}$$

$$\mathrm{SOC}_{n,t_n^{\mathrm{dep}}}^{\mathrm{EV}} \ge \mathrm{SOC}_{n,\exp}^{\mathrm{EV}} \tag{9}$$

$$\begin{aligned} &\mathrm{SOC}_{n,t}^{\mathrm{EV}} = \mathrm{SOC}_{n,t-1}^{\mathrm{EV}} + \left(\eta_{\mathrm{EV,ch}} \frac{P_{n,t}^{\mathrm{EV,ch}}}{E_n^{\mathrm{EV}}} - \frac{1}{\eta_{\mathrm{EV,dis}}} \frac{P_{n,t}^{\mathrm{EV,dis}}}{E_n^{\mathrm{EV}}} \right) \Delta t \\ &\forall n \in [1,N], t \in [1,T], \mathrm{SOC}_{n,0}^{\mathrm{EV}} = C \end{aligned} \tag{10}$$

where the parameters of each EV are defined as $P_{n,t}^{\mathrm{EV,ch,max}}$, $P_{j,n}^{\mathrm{EV,dis,max}}$, $\mathrm{SOC}_{n,t}^{\mathrm{EV,min}}$, $\mathrm{SOC}_{n,t}^{\mathrm{EV,max}}$, $\mathrm{SOC}_{n,0}^{\mathrm{EV}}$, $\mathrm{SOC}_{n,t_n^{\mathrm{dep}}}^{\mathrm{EV}}$, $\nu_{n,t}^{\mathrm{EV}}$, with $\nu_{n,t}^{\mathrm{EV}} = \{0,1\}$ .These parameters respectively represent the maximum charging power, maximum discharging power, minimum SOC, maximum SOC, arrival SOC, departure minimum SOC, and connection status of EV n connected to the charging facility at time t. $\eta_{\mathrm{EV,ch}}$ and $\eta_{\mathrm{EV,dis}}$ denote the charging and discharging efficiencies of EV n, respectively.

Accordingly, the cost function of EV n can be expressed as

$$C_n^{\mathrm{EV}} = \sum_{n=1}^{N} \sum_{t=1}^{T} \left(\pi_t^{\mathrm{ch}} P_{n,t}^{\mathrm{EV,ch}} - \pi_t^{\mathrm{sell}} P_{n,t}^{\mathrm{EV,dis}} \right) \Delta t \tag{11}$$

2.2 Charging facility operation model

The charging power decision variables of the CFO are subject to the following constraints:

$$P_t^{\mathrm{CF}} = P_t^{\mathrm{buy}} + P_t^{\mathrm{RES}} + P_t^{\mathrm{sell}} \tag{12}$$

$$P_t^{\mathrm{CF}} = \sum_{n=1}^{N} \left(P_{n,t}^{\mathrm{EV,ch}} - P_{n,t}^{\mathrm{EV,dis}} \right) \tag{13}$$

$$0 \le P_t^{\mathrm{RES,min}} \le P_t^{\mathrm{RES}} \le P_t^{\mathrm{RES,max}} \tag{14}$$

$$0 \le P_t^{\mathrm{buy,min}} \le P_t^{\mathrm{buy}} \le P_t^{\mathrm{buy,max}} \tag{15}$$

$$P_t^{\mathrm{sell,min}} \le P_t^{\mathrm{sell}} \le P_t^{\mathrm{sell,max}} \le 0 \tag{16}$$

where the parameters of CFO are defined as $P_t^{\mathrm{RES,min}}$, $P_t^{\mathrm{RES,max}}$, $P_t^{\mathrm{buy,min}}$, $P_t^{\mathrm{buy,max}}$, $P_t^{\mathrm{sell,min}}$, $P_t^{\mathrm{sell,max}}$. These parameters respectively represent the minimum and maxi-

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mum power from PV, the minimum and maximum purchase power from the utility grid, the minimum and maximum sell power from the utility grid at time t.

The objective function of the CFO can be formulated as

$$C^{\mathrm{CF}} = -R^{\mathrm{EV}} + C^{\mathrm{grid}} + C^{\mathrm{RES}} \tag{17}$$

$$C^{\mathrm{grid}} = \sum_{t=1}^{T} \left(\pi_t^{\mathrm{buy}} P_t^{\mathrm{buy}} + \pi_t^{\mathrm{sell}} P_t^{\mathrm{sell}} \right) \Delta t \tag{18}$$

$$C^{\mathrm{RES}} = \sum_{t=1}^{T} \left(\pi_t^{\mathrm{RES}} P_t^{\mathrm{RES}} \right) \Delta t \tag{19}$$

$$R^{\mathrm{EV}} = \sum_{n=1}^{N} C_n^{\mathrm{EV}} \tag{20}$$

where C^{grid} denotes the cost/negative income of purchasing and selling electricity from/to the utility grid, C^{RES} represents the cost/negative income of purchasing and selling electricity from the PV owner, and R^{EV} is the revenue from providing charging services to EV users.

The electricity prices set by the utility grid and the PV owner are subject to the following constraints:

$$\pi_t^{\mathrm{buy}} > \pi_t^{\mathrm{RES}} > \pi_t^{\mathrm{sell}} \tag{21}$$

3 Pricing model of CFO considering multiple price levels

3.1 Charging service pricing constraints with different price levels

The decision variables for the CFO's charging service prices must respect the following constraints:

$$\pi_t^{\mathrm{ch}} = \sum_{i \in N^{\mathrm{ch}}} \alpha_{t,i} \pi_i^{\mathrm{ch}} \tag{22}$$

$$\sum_{i \in N^{\mathrm{ch}}} \alpha_{t,i} = 1, \alpha_{t,i} \in \{0,1\} \tag{23}$$

$$\sum_{t=1}^{T} \alpha_{t,i} \geq 1 \tag{24}$$

$$\pi_i^{\mathrm{ch}} - \pi_{i-1}^{\mathrm{ch}} \geq \Delta \pi^{\mathrm{ch}}, i \in [2, N^{\mathrm{ch}}] \tag{25}$$

$$\frac{1}{T}\sum_{t=1}^{T}\pi_t^{\mathrm{ch}} = \pi^{\mathrm{ch,fixed}} \tag{26}$$

$$\pi^{\mathrm{ch,min}} \le \pi_i^{\mathrm{ch}} \le \pi^{\mathrm{ch,max}} \tag{27}$$

where N^{ch} denotes the given number of price levels. (22) and (23) ensure that, at each time period, the charging price be corresponded to exactly one price level. (24) guarantees that each determined price level be utilized at least once. (25) enforces a discrete interval between adjacent price levels. (26) maintains the constancy of the average price.

3.2 Linearization of charging service pricing constraints

The pricing model constraint (22) contains bilinear terms, involving the product of binary and continuous decision variables, which render the model nonlinear and increase the computational complexity. So, this study adopts the inequality relaxation technique to linearize the nonlinear pricing constraint. Through this transformation, the model can be efficiently solved using commercial optimization solvers.

For (22), the following substitution can be applied:

$$\pi_t^{\mathrm{ch}} = \sum_{i\in N^{\mathrm{c}}} Y_{t,i}^{\mathrm{ch}} \tag{28}$$

$$Y_{t,i}^{\mathrm{ch}} = \alpha_{t,i}\pi_i^{\mathrm{ch}} \tag{29}$$

For the equality constraint (29), an equivalent relaxation can be achieved by introducing binary variables through inequality formulations, as follows:

$$Y_{t,i}^{\mathrm{ch}} \le \pi_i^{\mathrm{ch}} \tag{30}$$

$$Y_{t,i}^{\mathrm{ch}} \ge \pi_i^{\mathrm{ch}} - \left(1-\alpha_{t,i}\right)\pi_t^{\mathrm{ch,max}} \tag{31}$$

$$\alpha_{t,i}\pi_t^{\mathrm{ch,min}} \le Y_{t,i}^{\mathrm{ch}} \le \alpha_{t,i}\pi_t^{\mathrm{ch,max}} \tag{32}$$

In summary, the price constraints can be rewritten as (23)-(28),(30)-(32).

3.3 Stackelberg game-based pricing model between the CFO and EV users

Based on the aforementioned framework, the pricing interaction between the CFO and EV users can be formulated as a Stackelberg game. In this game structure, the CFO acts as the upper-level leader, guiding the response behavior of EV users by setting the charging service price. The EV users serve as lower-level followers, dynamically adjusting their power responses according to the received price signals.

The upper-level objective of the leader:

$$\min C^{\mathrm{CF}} = \begin{Bmatrix} -\sum_{n=1}^{N}\sum_{t=1}^{T}\left(\pi_t^{\mathrm{ch}} P_{n,t}^{\mathrm{EV,ch}} - \pi_t^{\mathrm{sell}} P_{n,t}^{\mathrm{EV,dis}}\right)\Delta t \\ +\sum_{t=1}^{T}\left(\pi_t^{\mathrm{buy}} P_t^{\mathrm{buy}} + \pi_t^{\mathrm{sell}} P_t^{\mathrm{sell}}\right)\Delta t \\ +\sum_{t=1}^{T}\left(\pi_t^{\mathrm{RES}} P_t^{\mathrm{RES}}\right)\Delta t \end{Bmatrix} \tag{33}$$

s.t. (12)-(16),(21).

The lower-level objective of the followers:

$$\min C^{\mathrm{EV}} = \sum_{n=1}^{N}\sum_{t=1}^{T}\pi_t^{\mathrm{ch}} P_{n,t}^{\mathrm{EV,ch}}\Delta t \tag{34}$$

s.t. (1)-(11),(23)-(28),(30)-(32).

For the bilevel optimization problem, a common solution approach is to employ the KKT conditions of the lower-level problem to replace it with an equivalent set of constraints in the upper-level model. Specifically, since the decision variables of the upper-level problem are treated as parameters in the lower-level problem, and the lower-level optimization itself is a continuous linear problem with convex properties, its optimal solution can be fully characterized by the KKT conditions.

The detailed steps and model will not be elaborated further. Through this transformation, the lower-level model can be equivalently converted into a series of linear constraints within the upper-level model, thereby transforming the bilevel problem into a single-level optimization problem that can be efficiently solved using standard optimization techniques[10, 11].

4 Case Study

4.1 Setting of parameters

In the simulation, a green power direct supply BTM community is considered. The CFO purchases electricity from both PV generation and the utility grid, and can also sell surplus electricity back to the grid. The EVs in the community are dedicated slow-charging vehicles. The SOC, arrival time, and departure time of each EV are assumed to follow Gaussian distributions, with specific values of which are generated using the Monte Carlo method. The detailed parameters used in the simulation are listed in Table I and Fig. 2.

Table I. Basic parameters.

Parameter setting	Value	Parameter setting	Value	Parameter setting	Value

T	24h	$\eta_{\text{EV,ch}}$	0.85	$P_n^{\text{EV,ch,max}}$	13kW
Δt	1h	$\eta_{\text{EV,dis}}$	0.85	$P_n^{\text{EV,dis,max}}$	13kW
N_{EV}	50	Cap^{EV}	32kWh	μ_{SOC}	0.5
$\text{SOC}_{\text{min}}^{\text{EV}}$	0.3	$t_{\text{arr}}^{\text{min}}$	5h	σ_{SOC}	0.1
$\text{SOC}_{\text{max}}^{\text{EV}}$	1	$t_{\text{arr}}^{\text{max}}$	11h	μ_{arr}	8.92h
$\text{SOC}_{\text{exp}}^{\text{EV}}$	1	$t_{\text{dep}}^{\text{min}}$	15h	σ_{arr}	3.24h
$\pi^{\text{Fle,fixed}}$	0.0524 $/kWh	$t_{\text{dep}}^{\text{max}}$	20h	μ_{dep}	17.47h
$\pi^{\text{EV,min}}$	0.075 $/kWh	$\pi^{\text{EV,max}}$	0.003 $/kWh	σ_{dep}	3.41h

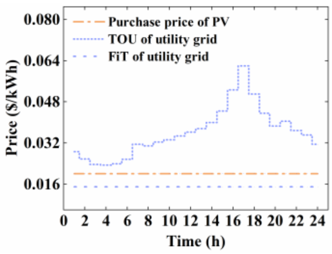

Fig. 2. Pricing parameters.

4.2 Costs of each entity under different price level numbers

First, the effectiveness of relaxing equality (29) into inequalities (30)-(32) in the optimization problem is analyzed. Five test cases are set with different numbers (from 1 to 5) of price levels, yielding five groups of optimization results. For each case, two matrices, $Y_{t,i}^{\text{ch}}$ and $Y_{t,i}^{\text{'ch}} = \alpha_{t,i}\pi_i^{\text{ch}}$, are obtained, representing the left-hand side and right-hand side of equality (29), respectively, where $t \in [1,T]$, $i \in \left[1, N^{\text{ch}}\right]$ and $N^{\text{ch}} \in \boldsymbol{N}^{\text{ch}} = \{1,2,3,4,5\}$. These two matrices are then transformed into two column vectors, $\boldsymbol{Y}^{\text{ch}}$ and $\boldsymbol{Y}^{\text{'ch}}$, of dimension $T \sum_{\substack{N^{\text{ch}} \in \\ \{1,2,3,4,5\}}} N^{\text{ch}} \times 1$.

To check whether equality (29) is respected, a linear regression is performed between the two column vectors $\boldsymbol{Y}^{\text{ch}}$ and $\boldsymbol{Y}^{\text{'ch}}$. The fitting results are shown in Table II. As presented in the table, the intercepts of the fitted linear functions are nearly zero, and the coefficients are approximately one, indicating that the relaxation is valid and the computed results are consistent with the original equality. The error metrics, mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2), further confirm this conclusion. The nearly zero MSE and RMSE values indicate negligible deviation, while an R^2 value of 1.00 demonstrates perfect fitting accuracy.

Fig. 3 provides a more intuitive illustration of the fitting results, where the boxed region shows the paired data ($\boldsymbol{Y}^{\mathrm{ch}}$, $\boldsymbol{Y}^{\prime\mathrm{ch}}$) and the corresponding linear fit. Due to overlapping data points, all points are replotted outside the solid box for clarity.

Therefore, the results in Table II. and Fig. 3 confirm that the inequality relaxation constraints (30)-(32) effectively respect the original equality constraint (29), validating the high accuracy and reliability of the inequality relaxation method.

Table II Analysis of fitting results.

Result	Intercept	Coefficient	MSE	RMSE	R^2
$Y_{t,i}^{\mathrm{ch}} = \alpha_{t,i}\pi_i^{\mathrm{ch}}$ (29)	2.60e-10	1.00	3.10e-19	5.57e-10	1.00

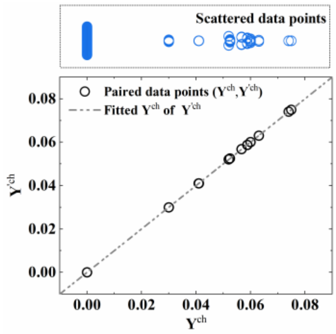

Fig. 3. Fitting results.

Next, the optimization results for different numbers of price levels are analyzed. Fig. 4 illustrates the variations in the CFO's grid purchasing cost, PV purchasing cost, charging service revenue, and total net profit under different numbers of price levels.

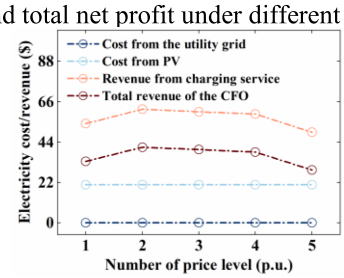

Fig. 4. Electricity purchase cost from the utility grid and PV, charging service revenue, and total net profit of the CFO under different numbers of price levels.

When the number of price levels increases from 1 to 2, both the CFO's charging service revenue and total revenue rise significantly. As the number of price levels increases from 2 to 4, these two indicators gradually decline and remain nearly stable. When the number of price levels reaches 5, both metrics decrease again. This indicates that when the number of price levels becomes excessive, they limit further improvement in revenue. During this process, the CFO's grid purchasing cost and PV purchasing cost remain almost unchanged.

4.3 Pricing Results of the CFO and Power Optimization Results of EVs under the Stackelberg Game

Fig. 5 presents the optimal pricing results of the CFO and the total charging power curve of EVs under the Stackelberg game framework. The light-yellow area indicates the maximum power available from the PV source, while the utility grid is assumed to provide an unlimited power supply.

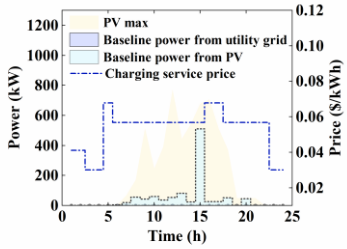

Fig. 5. Optimal pricing results and power profile of the CFO, with decomposition of power purchased from a PV owner and the utility grid.

Fig. 6(a) illustrates the time-power distribution of each EV when the number of price levels is set to four. Most EVs concentrate their charging demand in the afternoon. Since 16:00 and 17:00 correspond to high-price periods, many EVs choose to charge at 15:00 instead. The price signals thus induce a synchronized peak load pattern among EVs. Moreover, due to differences in arrival/departure times and SOC constraints, slight load staggering occurs across vehicles, resulting in an overall orderly charging distribution. Fig. 6(b) shows the variation of EV SOC over time under the same conditions, which corresponds to the power distribution pattern. Each vehicle reaches its target energy level before departure.

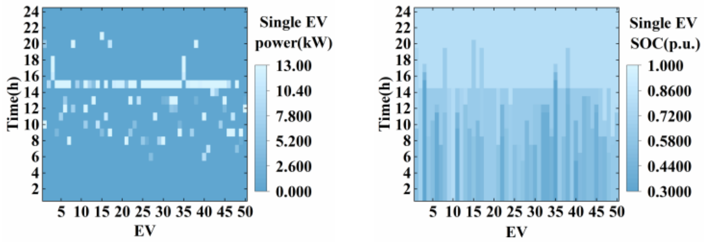

Fig. 6. (a) Charging power over time for individual EVs when the number of price levels is 4. **(b)** SOC of individual EVs over time when the number of price levels is 4.

5 Conclusion

This paper develops a discrete pricing optimization model for dedicated EV slow-charging in a BTM community. A Stackelberg game formulates the interaction between the CFO and EV users, while inequality relaxation linearizes the bilinear constraints. Simulation results demonstrate the accuracy of the proposed method and show that discrete pricing could promote orderly charging.

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