An Adjustable Pricing Scheme for Public Charging Stations: Balancing Drivers' Range Anxiety and Operational Efficiency

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Global EV sales rose from around 2 million in 2018 to nearly 14 million in 2023. However, the proliferation of EVs might cause a shortage of public charging facilities, which has become a significant disincentive for drivers to purchase EVs. The number of public fast charging points worldwide increased from 1.2 thousand in 2018 to only 8.9 thousand in 2023, whose increasing rate is not significantly higher than that of global EV sales. The polarization of charging facilities' construction in different regions has further exacerbated the shortage of charging facilities in undeveloped regions. When the charging infrastructure expansion rate cannot catch up with the increase of EVs, it becomes essential for fast-charging operators to optimize operational strategies to meet more demand and maintain profitability.

The shortage of fast-charging infrastructure leads to an intrinsic dilemma for EV drivers. For drivers who decide to charge, crowded charging demand and limited infrastructure can cause an excessively long access time before charging, reducing their charging service experience. However, during charging, range anxiety can impel drivers to spend a long time charging their EVs to achieve a high SOC level, which can further lower the service efficiency and drive up the access time. In particular, the charging time increases superlinearly with the SOC level, since EV's charging power decreases with the current SOC due to the property of lithium-ion batteries. When drivers with a high SOC persist in charging at a slower rate and cause a longer access time for others, the dilemma between reducing access time and reducing drivers' range anxiety becomes more prominent. Therefore, it is significant to make a trade-off between satisfying drivers' target SOC and enhancing service efficiency through well-designed strategies. Considering the spatial imbalance between charging demand and charging facility supply, the time-of-day change of grid load, electricity price, and charging demand, existing studies have investigated the optimization of spatial pricing or time-of-day dynamic pricing (e.g., Zhang et al., 2018; Li et al., 2020; Lee and Choi, 2021; Babic et al., 2022). However, to the best of our knowledge, existing research predominantly examined scenarios where EVs are charged at

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fixed prices across various SOC levels. The impact of inconstant charging power on the trade-off between the reduction of range anxiety and service efficiency has not been well addressed.

To tackle such a challenge, we develop a market equilibrium model and introduce an adjustable pricing (AP) scheme in which the price per unit amount of charging (i.e., unit price) changes linearly with the SOC to affect drivers' charging decisions (i.e., whether to charge and when to stop charging) and improve social welfare, which includes drivers' utility from charging and the operator's profit. Specifically, the unit price at SOC E is set as $p_0 + mE$ in the AP scheme, where p_0 and m are the decision variables of the operator. $m > 0$ $(m < 0)$ means the operator increases (decreases) the unit price as drivers' SOC increases. The modeling framework is summarized in **Fig. 1**.

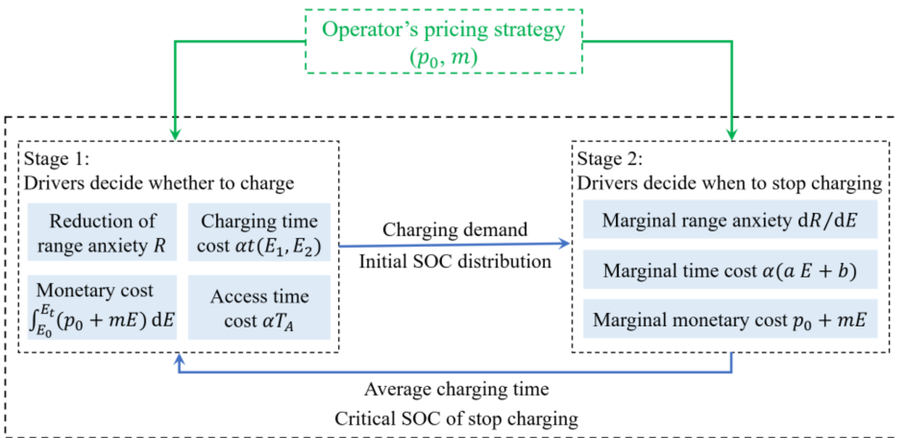

Fig. 1. Decisions of drivers and the operator in the model.

At Stage 2, drivers determine the critical SOC E_t to stop charging based on the marginal reduction of range anxiety (Valogianni et al., 2020), marginal charging time cost (with parameters calibrated by TeslaLogger (2024)), and monetary cost, as illustrated in Fig. 2.

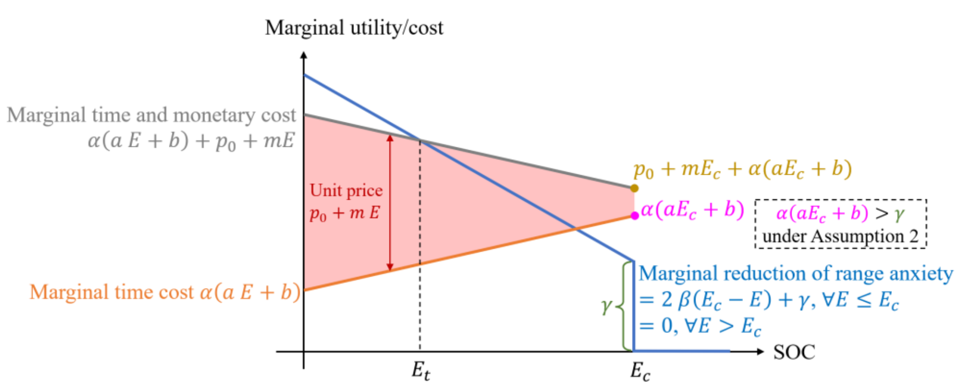

Fig. 2. Driver's marginal cost and marginal reduction of range anxiety with respect to the SOC.

At Stage 1, drivers decide whether to charge by comparing their charging utility with the access time cost. Note that drivers with a lower initial SOC are expected to obtain a higher utility, we derive that drivers with the initial SOC lower than E_{eq} decide to charge in the market equilibrium state, where E_{eq} is implicitly determined by

$$\frac{m + a\alpha + 2\beta}{2}\left(E_t - E_{eq}\right)^2 = \alpha\eta_A\left(\frac{\lambda(E_{eq})}{k/T_{avg}\left(E_{eq}, E_t\right)}\right)^n \tag{1}$$

Based on the market equilibrium characterized by E_t and E_{eq}, we derive the expression of social welfare (drivers' welfare and the operator's profit) as

$$\begin{aligned} SW(E_t, E_{eq}) &= PR + DW \\ &= \frac{\lambda(c_E + b\alpha - 2\beta E_c - \gamma)}{2}\left(E_{eq} + E_{min} - 2E_t\right) \\ &\quad + \frac{\lambda(a\alpha + 2\beta)}{6}\left({E_{eq}}^2 + E_{eq}E_{min} + {E_{min}}^2 - 3{E_t}^2\right) \end{aligned} \tag{2}$$

We further derive the theoretical properties of SW:

Lemma 1. *Monotonicity of social welfare with respect to* E_t *and* E_{eq}*:*

(a) $SW(E_t, E_{eq})$ *is a concave function of* E_t *for any given* E_{eq}*, i.e.,* $\frac{\partial^2 SW}{(\partial E_t)^2} < 0, \forall E_{eq} \in (E_{min}, E_t)$*;*

(b) When $E_t < E_t(p_0 = c_E, m = 0) = \frac{2\beta E_c + \gamma - c_E - b\alpha}{a\alpha + 2\beta}$*,* $\frac{\partial SW}{\partial E_t} > 0$*; when* $E_t > E_t(p_0 = c_E, m = 0)$*,* $\frac{\partial SW}{\partial E_t} < 0$*;*

when $E_t = E_t(p_0 = c_E, m = 0)$*,* $\frac{\partial SW}{\partial E_t} = 0$*;*

(c) When $E_{eq} + E_t < 2E_t(p_0 = c_E, m = 0)$*,* $\frac{\partial SW}{\partial E_{eq}} > 0$*; when* $E_{eq} + E_t > 2E_t(p_0 = c_E, m = 0)$*,* $\frac{\partial SW}{\partial E_{eq}} < 0$*;*

when $E_{eq} + E_t = 2E_t(p_0 = c_E, m = 0)$*,* $\frac{\partial SW}{\partial E_{eq}} = 0$.

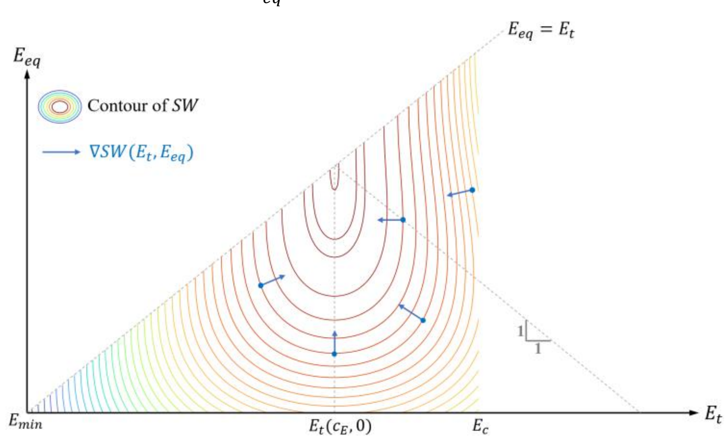

Fig. 4. Contour and gradient of social welfare: an illustration of **Lemma 1**.

Based on **Lemma 1**, we prove that:

Proposition 1. *Properties of the* SW *maximization state:*
(a) The optimal pricing strategy $\{p_0^{SW}, m^{SW}\}$ *satisfies* $p_0^{SW} + m^{SW} E_{min} = 0$. *That is, the operator should adopt a zero unit price at the minimum SOC* E_{min}.
(b) When

$$\left(\frac{c_E}{a\alpha + 2\beta} \cdot \frac{E_{eq} - E_{min}}{E_t - E_{eq}} + \frac{E_{eq} + E_t}{2}\right)\Bigg|_{p_0=m=0} > E_t(p_0 = c_E, m = 0) \tag{3}$$

we have $m^{SW} > 0$, *and the unit price* $p_0^{SW} + m^{SW} E > 0$, $\forall E > E_{min}$.

Proposition 1 implies that the welfare-oriented operator should adopt a low unit price during a low SOC, and gradually raise the unit price as SOC increases. Such a strategy attracts more drivers with a low initial SOC; meanwhile, it induces drivers to terminate charging promptly and avoids inefficient charging after the charging power is reduced. As a result, drivers' range anxiety can be alleviated effectively under a moderate total time cost.

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