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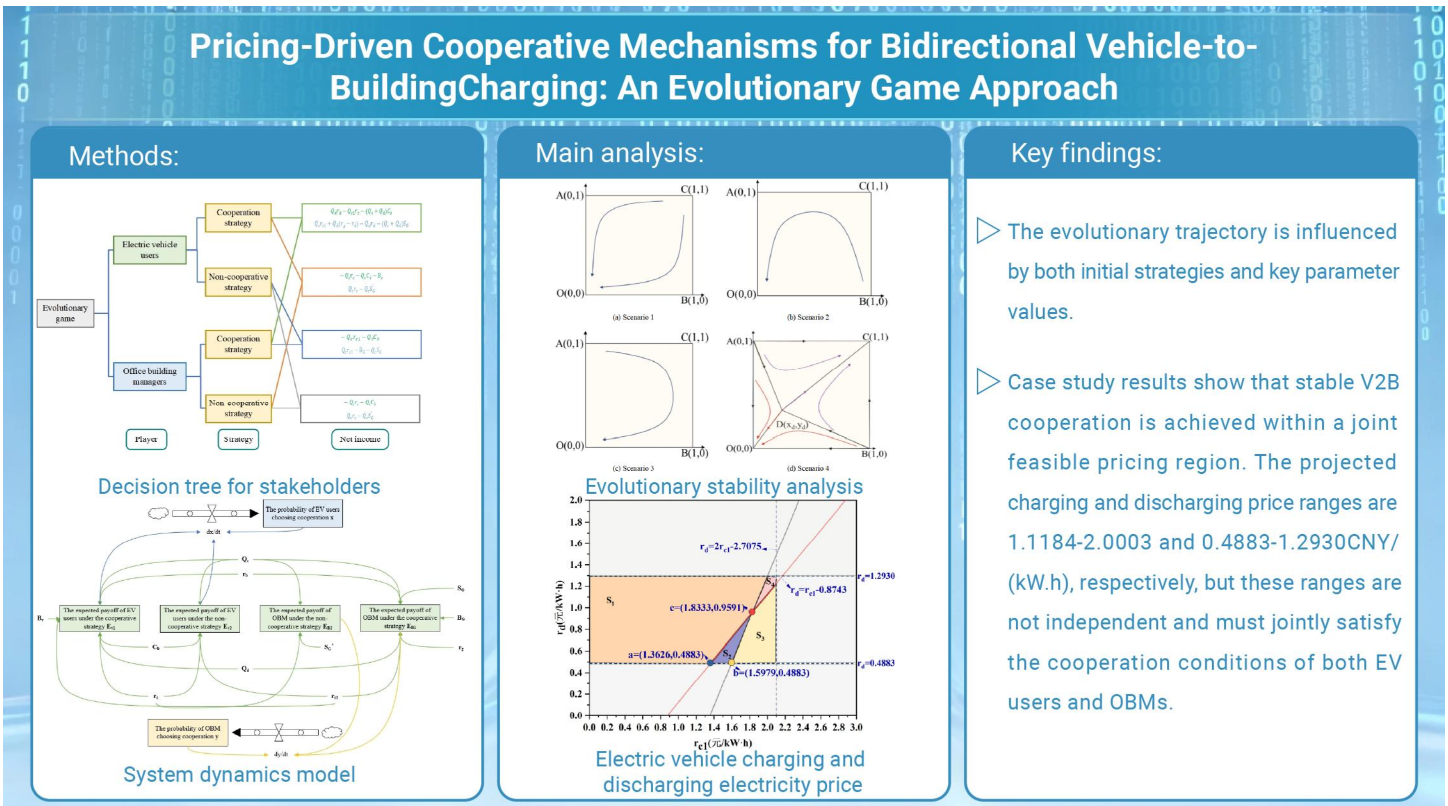
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- V2B can boost urban energy system flexibility, but prior research ignores strategic decisions of EV users and building managers under price-based coordination.
- This study integrates evolutionary game theory and system dynamics to explore pricing-driven V2B interactions and cooperative strategy evolution.
- Price incentives and discharging profits drive cooperation; larger discharge volume and lower non-cooperation losses speed up stable equilibrium.
- The case gives valid charging (1.3626–1.8333) and discharging (0.483–0.9591) price ranges (CNY/(kW·h)) for stable V2B operation.
- The results support V2B mechanism design and urban low-carbon energy management.

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With rapid growth of electric vehicles (EVs), vehicle-to-building (V2B) interactions have emerged as a promising approach to enhance flexibility and sustainability in urban energy systems. However, existing studies often overlook the strategic decision-making processes of EV users and office building managers under pricing-based coordination schemes, which may limit the stability and effectiveness of cooperative V2B operation. To address this gap, this study develops an integrated framework combining evolutionary game theory and system dynamics to investigate pricing-driven interactions between EV users and office building managers within urban energy systems. A cost-benefit model is formulated for both parties to analyse the evolution of cooperative strategies, and a case study is conducted to identify EV charging and discharging price ranges conducive to stable cooperation. The results indicate that electricity price incentives and EV discharging profitability significantly promote cooperative behaviour, while higher EV discharging volumes and lower unilateral non-cooperation losses accelerate convergence to a stable cooperative equilibrium. A case study demonstrates that stable cooperation can be achieved when EV charging and discharging prices range from 1.3626-1.8333 and 0.483-0.9591 CNY/(kW·h), respectively, in office building scenarios. These findings provide a theoretical basis for facilitating effective interactions between EVs and buildings in urban energy systems and offer practical insights for designing pricing mechanisms that support sustainable urban energy management and low-carbon transitions.

INTRODUCTION

Global electricity consumption has continued to rise alongside rapid economic growth and accelerating urban electrification. However, the widening gap between peak and off-peak demand has further aggravated supply–demand imbalances in power systems.[1] Electric vehicles(EVs), as emerging flexible energy storage devices, are capable of storing electricity during low-demand periods and discharging it to buildings during high-demand periods, thereby balancing electricity loads[2] and offering an effective means to mitigate supply–demand conflicts.

The proliferation of charging infrastructure has further strengthened the coupling between EVs and buildings,[3] and their interactions are increasingly recognized for their high flexibility potential. Unlike residential building managers who typically treat EVs as part of system-level flexibility resources, office building managers (OBMs) and EV users represent two strategic players. Issues such as battery degradation caused by frequent charging and discharging, along with the high capital cost of infrastructure, often discourage both sides from engaging in active interaction[4], thereby constraining the full utilization of their flexibility potential. Consequently, it is necessary to investigate the game-theoretic mechanism governing these interactions to strengthen incentives for active participation.

To promote bidirectional interactions between EVs and office buildings, further investigation from the perspective of stakeholders is required to explore their interactions and strategic choices, and to identify the key factors influencing strategy shifts. Evolutionary game models offer a versatile, multidisciplinary approach well suited for analyzing stakeholder behaviors.[5] Such models have been effectively applied in various domains, including solar energy utilization,[6] security inspections,[7] the development of prefabricated buildings,[8] and shared charging facilities for public transportation.[9] Nevertheless, existing literature has paid limited attention to the strategic interactions between EV users and OBMs.

To address this research gap, this study focuses on analyzing the costs and benefits arising from the interactions between electric vehicle users and an office building manager, with the aim of balancing the payoffs of both parties. An evolutionary game model is developed to represent the cost-benefit interactions between OBMs and EV users, enabling the identification of evolutionary stable strategies (ESSs) and the key factors influencing strategy evolution. In addition, a system dynamics model is constructed to examine how these factors affect the final strategy choices of both stakeholders. A case study is conducted to determine the EV charging and discharging price ranges that can satisfy the interests of both the OBM and EV users. The main contributions of this study are as follows:

(1) OBMs and EV users are explicitly defined and modelled as the two players in a game for the first time, offering a detailed understanding of their behavioral mechanisms and strategic interactions.

(2) The integration of evolutionary game theory (EGT) with system dynamics provides a novel methodological approach for analyzing the complex strategic interactions between OBMs and EV users.

(3) A case study illustrates the practical applicability of the evolutionary game model, providing actionable insights and guidance for using charging and discharging prices to steer and optimize EV-OBM interactions in real-world scenarios.

MATERIALS AND METHODS

The interaction between EV and buildings

In recent years, with the rapid expansion of electric vehicle (EV) adoption,[10]

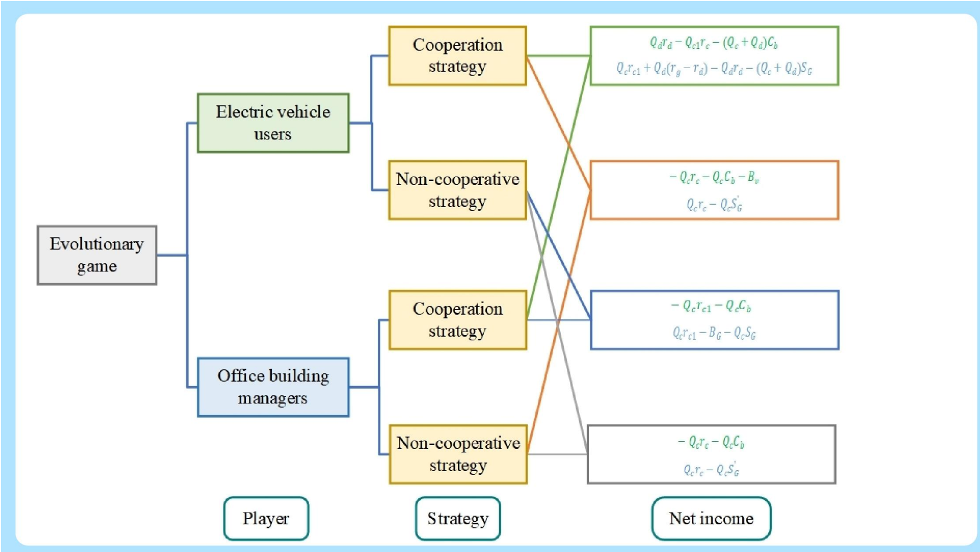

Figure 1. Decision tree for stakeholders

vehicle-to-building (V2B) technology has attracted increasing attention for its potential to enhance energy efficiency and reduce carbon emissions in both building and transportation sectors. Existing studies have demonstrated that V2B can effectively reduce grid dependency, optimize peak load management, and improve renewable energy utilization. For example, Lo et al.[11] reported significant reductions in grid electricity demand and carbon emissions through V2B strategies, while Chen et al.[12] and Jazizadeh et al.[13] highlighted its benefits in improving photovoltaic utilization and reducing operating costs.

Further research has explored optimization and operational strategies for EV-integrated building energy systems. Massat et al.[14] developed a mixed-integer linear programming model for office buildings with EVs and photovoltaic systems, focusing on energy cost and self-sufficiency, but without explicitly modeling charging–discharging interaction mechanisms. Ding et al.[15] proposed an optimal scheduling model integrating EV charging uncertainty with building systems, demonstrating enhanced flexibility and reduced costs, yet without considering strategic interactions. Liu et al.[16] treated EVs as energy storage devices in net-zero energy building frameworks, neglecting the benefit relationships between EV users and buildings. Similarly, Amin Mirjalili et al.[17] optimized EV charging costs under different solar configurations, and Ahsan et al.[18] proposed a techno-economic electricity sharing framework, but both lacked a detailed analysis of bidirectional interaction mechanisms and cost-benefit structures between EV users and building operators.

Overall, existing studies primarily focus on system optimization and operational performance, while the strategic interactions and incentive mechanisms between EV users and OBMs remain insufficiently explored. In particular, the role of pricing in shaping cooperative behavior and enabling stable bidirectional V2B interactions has not been systematically investigated.

EGT and its applications

Compared with classical game theory, EGT provides a dynamic framework for strategic decision-making by incorporating bounded rationality and emphasizing the evolution of strategies over time.[19,20] Because it captures adaptive behavior more realistically, EGT is widely regarded as an important advancement in game theory.[8] Smith et al.[21] first applied evolutionary game models to biological evolution, using them to explain conflicts and behavioral patterns driven by both individual and collective interests.

In recent years, EGT has been increasingly applied in building energy management. Gao et al.[22] proposed an evolutionary game approach to analyze residential users' participation in integrated demand response, while Wang et al.[23] developed a dynamic model to study residential energy consumption behavior. Ding et al.[24] further demonstrated that EGT-based strategies can significantly improve peak-valley load management in both residential and commercial buildings.

EGT has also shown strong potential in the EV domain. Li et al.,[25] Zhou et al.,[26] and Hu et al.[27] applied evolutionary game models to examine the effects of policy measures on EV adoption. Other studies have integrated EGT with mathematical models to address issues such as charging infrastructure diffusion,[28] charging pricing strategies,[29] and energy station allocation.[30] In addition, V2G technology enables bidirectional interactions between EVs and the grid,[31] and EGT has been used to optimize such interactions. For example, Xu et al.[32] evaluated EV aggregator responsiveness, while Chen et al.[33] and Gao et al.[34] demonstrated that EGT-based approaches can improve economic performance and reduce system costs.

In summary, although EGT has been widely applied in both building energy management and EV-related studies, its application to V2B interactions remains limited. In particular, the strategic interactions and incentive mechanisms between EV users and office building managers underpricing schemes have not been systematically investigated. To address this gap, this study employs an evolutionary game framework to explore the bidirectional interaction mechanisms between EV users and OBMs.

Problem statement

Game participants are modeled as boundedly rational agents who adapt their strategies over time to maximize individual payoffs, eventually reaching a dynamic equilibrium. In this study, an evolutionary game is developed between two key stakeholders: EV users and OBMs. Their interaction is characterized by conflicting objectives: OBMs aim to minimize the cost of acquiring discharging resources to optimize building operation, while EV users seek to maximize net benefits by balancing charging costs and battery degradation. This divergence makes stable cooperation difficult to achieve spontaneously.

In this framework, both EV users and OBMs can choose between cooperation and non-cooperation strategies. For EV users, cooperation involves charging from the building and discharging electricity back when battery capacity allows, while non-cooperation implies charging only for self-consumption. For OBMs, cooperation means both supplying electricity to EVs and accepting discharged electricity, whereas non-cooperation involves only providing charging services. Let x and y denote the probabilities that EV users and OBMs choose cooperation, respectively, with $x, y \in [0,1]$. The strategy sets are shown in Table S1, and the parameter definitions are summarized in Table S2.

Evolutionary game modeling

Payoff model. Based on the behavioral strategy analysis of EV users and OBMs in Section 3.1, four possible strategy combinations can be constructed for the game participants: (cooperation, cooperation), (cooperation, non-cooperation), (non-cooperation, cooperation), and (non-cooperation, non-cooperation), as illustrated in Figure 1.

The net payoffs of EV users and OBMs under different strategy combinations are determined by charging costs, discharging revenues, battery degradation, and infrastructure-related costs. Specifically, when both parties choose cooperation, EV users obtain revenues from electricity discharging while bearing charging and battery degradation costs. Meanwhile, OBMs benefit from charging services and peak electricity substitution, but incur discharging payments and infrastructure costs. When either party adopts a non-cooperative strategy, the corresponding side loses the benefits associated with cooperation and may additionally suffer unilateral losses. Based on the above cost-benefit structure, the net payoffs under all strategy combinations are summarized in Tables S3 & S4

Replicator dynamics equation. The replicator dynamic equation has been widely applied to describe the temporal evolution of stakeholders' strategy adoption probabilities, thereby providing an effective tool to explain and

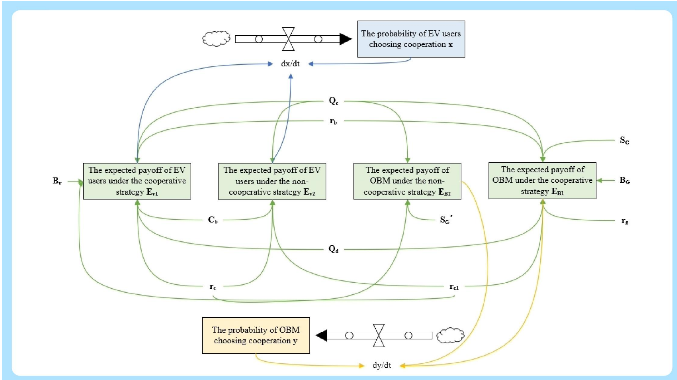

Figure 2. System dynamics model of the evolutionary game between EV users and the OBMs

predict the changing trends of group behavior. In this section, building upon the previous analysis, we calculate the expected payoffs of each stakeholder and construct the corresponding replicator dynamic equations.

For EV users, the expected payoff under the cooperative strategy can be obtained by calculating the weighted sum of the payoffs associated with all possible strategy combinations that include cooperation (Table S3), as expressed in Equation (1). Similarly, the expected payoff under the non-cooperative strategy can be derived, as shown in Equation (2). The average expected payoff of EV users is then represented as the weighted sum of the expected payoffs corresponding to all available strategies, as formulated in Equation (3).

$$E_{v1} = y[Q_d r_d - Q_c r_{c1} - (Q_c + Q_d)C_b] + (1-y)(-Q_c r_c - Q_c C_b - B_v) \tag{1}$$

$$E_{v2} = y(-Q_c r_{c1} - Q_c C_b) + (1-y)(-Q_c r_c - Q_c C_b) \tag{2}$$

$$\overline{E_v} = xE_{v1} + (1-x)E_{v2} \tag{3}$$

For the OBMs, the expected payoffs under the cooperative and non-cooperative strategies are calculated by Equations (4) & (5), respectively. The average expected payoff of the OBMs is given in Equation (6).

$$\begin{aligned} E_{B1} =& x[Q_c r_{c1} + Q_d(r_g - r_d) - Q_d r_d - (Q_c + Q_d)S_G] \\ &+ (1-x)(Q_c r_{c1} - B_G - Q_c S_G) \end{aligned} \tag{4}$$

$$E_{B2} = x(Q_c r_c - Q_c S_G') + (1-x)(Q_c r_c - Q_c S_G') \tag{5}$$

$$\overline{E_B} = yE_{B1} + (1-y)E_{B2} \tag{6}$$

According to the Malthusian equation,[35] the replicator dynamic equations of EV users and the OBMs are given in Equations (7) & (8), respectively.

$$f(x,y) = \frac{dx}{dt} = x(E_{v1} - \overline{E_v}) = x(1-x)[(r_d - C_b)yQ_d + B_v(y-1)] \tag{7}$$

$$\begin{aligned} g(x,y) = \frac{dy}{dt} = y(E_{B1} - \overline{E_B}) = y(1-y)[xQ_d(r_g - 2r_d - S_G) + \\ B_G(x-1) + Q_c(S_G' - S_G + r_c - r_{c1})] \end{aligned} \tag{8}$$

When the replicator dynamic equations of both players are equal to zero, the model reaches a stable state and the evolutionary process terminates.[37] At this point, five equilibrium points of the game system composed of EV users and the OBMs can be identified: O(0,0), A(0,1), B(1,0), C(1,1), and D(x_d,y_d). The equilibrium point D satisfies Equations (9) & (10).

$$x_d = \frac{B_G + Q_c(S_G - S_G' + r_{c1} - r_c)}{Q_d(r_g - 2r_d - S_G) + B_G} \tag{9}$$

$$y_d = \frac{B_v}{Q_d(r_d - C_b) + B_v} \tag{10}$$

System dynamics modeling

System dynamics is used to capture the dynamic evolution of the game by analyzing how parameter changes influence system outcomes. In this study, evolutionary game theory is integrated with system dynamics to model the interactions between OBMs and EV users. Based on the replicator dynamic equations in previous section, a system dynamics model is developed in Vensim. The model includes stock, flow, exogenous, and auxiliary variables, as summarized in Table S5. Specifically, the stock variables represent the probabilities of adopting cooperative and non-cooperative strategies, while the flow variables describe their rates of change. Exogenous variables are externally specified inputs, and auxiliary variables represent the expected payoffs under different strategies. The overall model structure is illustrated in Figure 2.

RESULTS AND DISCUSSION

Evolutionary stability analysis

The equilibrium points calculated from the replicator dynamic equations of EV users and the OBMs do not necessarily correspond to the ESS of the game system. Therefore, a further analysis is required to identify the ESS. A commonly adopted method for this purpose is the Jacobian matrix approach proposed by Friedman.[37]

By taking partial derivatives with respect to $f(x,y)$ and $g(x,y)$, the Jacobian matrix of the game system between EV users and the OBMs can be obtained.

$$J = \begin{bmatrix} \frac{df}{dx} & \frac{df}{dy} \\ \frac{dg}{dx} & \frac{dg}{dy} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \tag{11}$$

$$\frac{df}{dx} = a_{11} = (1-2x)[y(r_d - C_b)Q_d + B_v(y-1)] \tag{12}$$

$$\frac{df}{dy} = a_{12} = x(1-x)[(r_d - C_b)Q_d + B_v] \tag{13}$$

$$\frac{dg}{dx} = a_{21} = y(1-y)[(r_g - 2r_d - S_G)Q_d + B_G] \tag{14}$$

$$\frac{dg}{dy} = a_{22} = (1-2y)[x(r_g - 2r_d - S_G)Q_d + B_G(x-1) + Q_c(S_G' - S_G + r_{c1} - r_c)] \tag{15}$$

An equilibrium point obtained from the replicator dynamic equations can be considered a stable strategy of the system only if it satisfies both Det(J)>0 and Tr(J)<0 Therefore, by analyzing the signs of Det(J) and Tr(J) of the Jacobian matrix, the stability of the equilibrium points can be assessed to determine whether they constitute evolutionarily stable strategies. The computation of Det(J) and Tr(J) is presented in Equations (16) & (17).

$$\mathrm{Det}(J) = a_{11}a_{22} - a_{12}a_{21} \tag{16}$$

$$\mathrm{Tr}(J) = a_{11} + a_{22} \tag{17}$$

This study considers four scenarios, as summarized in Table S6. Table S7 and supplemental information present the results of the stability analysis of the equilibrium points under these scenarios. In the first three scenarios, the EV users and the OBMs find through the game that the benefits of cooperation are smaller than those of non-cooperation. Consequently, the strategy pair (non-cooperation, non-cooperation) emerges as the stable evolutionary strategy for both parties. In Scenario 4, however, the ESS of the game system composed of EV users and the OBMs are both (cooperation, cooperation) and (non-cooperation, non-cooperation). Moreover, the choice between these two ESSs depends on the initial strategy selection of cooperation by both parties at the start of the game.

The phase diagram of the co-evolutionary dynamics between EV users and the office building system under four scenarios is shown in Figure 3. Only Scenario 4 allows the strategy pair (cooperation, cooperation) to emerge as a potential evolutionary stable strategy, while in the other scenarios the system converges to non-cooperation. In Scenario 4, the final outcome depends on the initial state. If the initial state lies within the cooperative

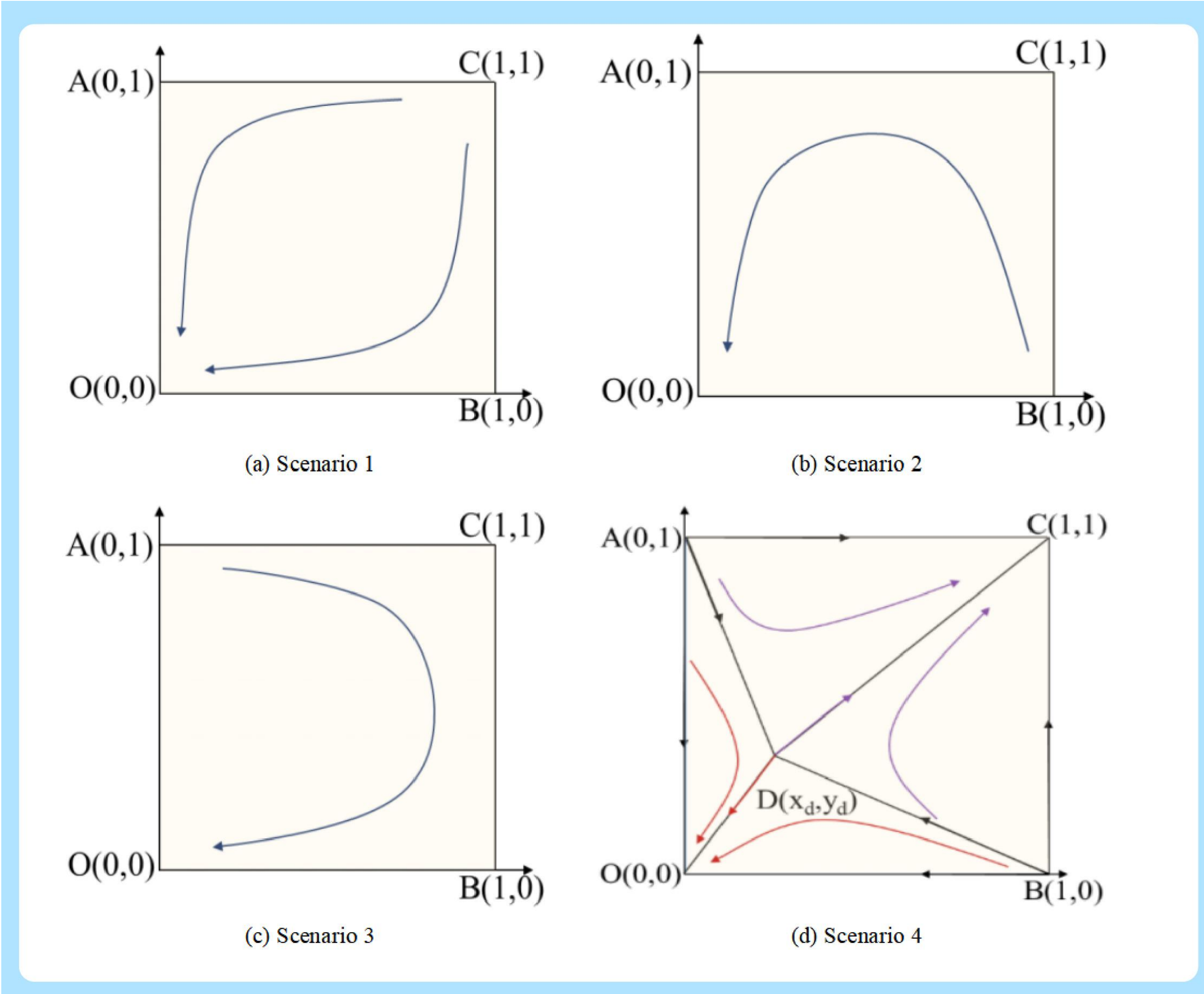

Figure 3. Schematic diagram of the synergistic evolution phase of the interactive system composed of electric vehicles and office buildings in four scenarios

region (ADBCA), the system evolves toward mutual cooperation; otherwise, it converges to non-cooperation. The likelihood of cooperation increases as the size of region ADBCA expands relative to the non-cooperative region. The size of region ADBCA is determined by system parameters, indicating that parameter changes directly influence the evolution of interaction outcomes. The analytical expression for the area of region ADBCA is provided in Equation (18).

$$\begin{aligned} S_{ADBCA} &= 1-\frac{x_d+y_d}{2} \\ &= \frac{1}{2}\left[\frac{Q_d(r_g-2r_d-S_G)-Q_c(S_G-S_G^{'}+r_c-r_{c1})}{Q_d(r_g-2r_d-S_G)+B_G}+\frac{Q_d(r_d-C_b)}{Q_d(r_d-C_b)+B_v}\right] \end{aligned} \tag{18}$$

For the sake of subsequent analysis, let $a=r_g-2r_d-S_G$, $b=S_G-S_G^{'}+r_c-r_{c1}$, $c=r_d-C_b$. Then, Equation (18) can be simplified as Equation (19). Partial derivatives with respect to a, b, c, Q_d, Q_c, B_G, B_v are calculated, and the results are summarized in Table S8. Under the assumptions of Scenario 4, $(r_g-2r_d-S_G)Q_d-Q_c(S_G\text{-}S_G^{'})>0$ and $(r_d-C_b)Q_d>0$, and considering that the cost of bidirectional charging stations is generally higher than that of unidirectional charging stations and that the charging price under cooperation is lower than that under non-cooperation(b>0), it follows that a, b, c are all greater than zero.

$$f=\frac{aQ_d-bQ_c}{bQ_d+B_G}+\frac{cQ_d}{cQ_d+B_v} \tag{18}$$

The influence of different initial strategies on the stability of equilibrium points

To further investigate whether the initial strategies of the two players influence the final stable outcomes of the game, the initial strategies were categorized as follows: EV users adopt either a high-probability cooperation strategy(x=0.99) or a low-probability cooperation strategy(x=0.01), and the OBMs adopt either a high-probability cooperation strategy(x=0.99) or a low-probability cooperation strategy(x=0.01). Consequently, the game system composed of EV users and the OBMs has four initial strategy combinations: (a) High-probability cooperation, Low-probability cooperation; (b) High-probability cooperation, High-probability cooperation; (c) Low-probability cooperation, Low-probability cooperation; and (d) Low-probability cooperation, High-probability cooperation. Simulations of these four initial strategy combinations were conducted under Scenarios 1 to 4, with the scenario-specific parameter settings summarized in Table S9.

Figure 4 presents the simulation results for Scenario 4. When the OBMs adopt a high-probability cooperation strategy, the payoff from cooperation exceeds that from non-cooperation, leading both players to gradually converge toward cooperation and resulting in a stable strategy of (coopera-

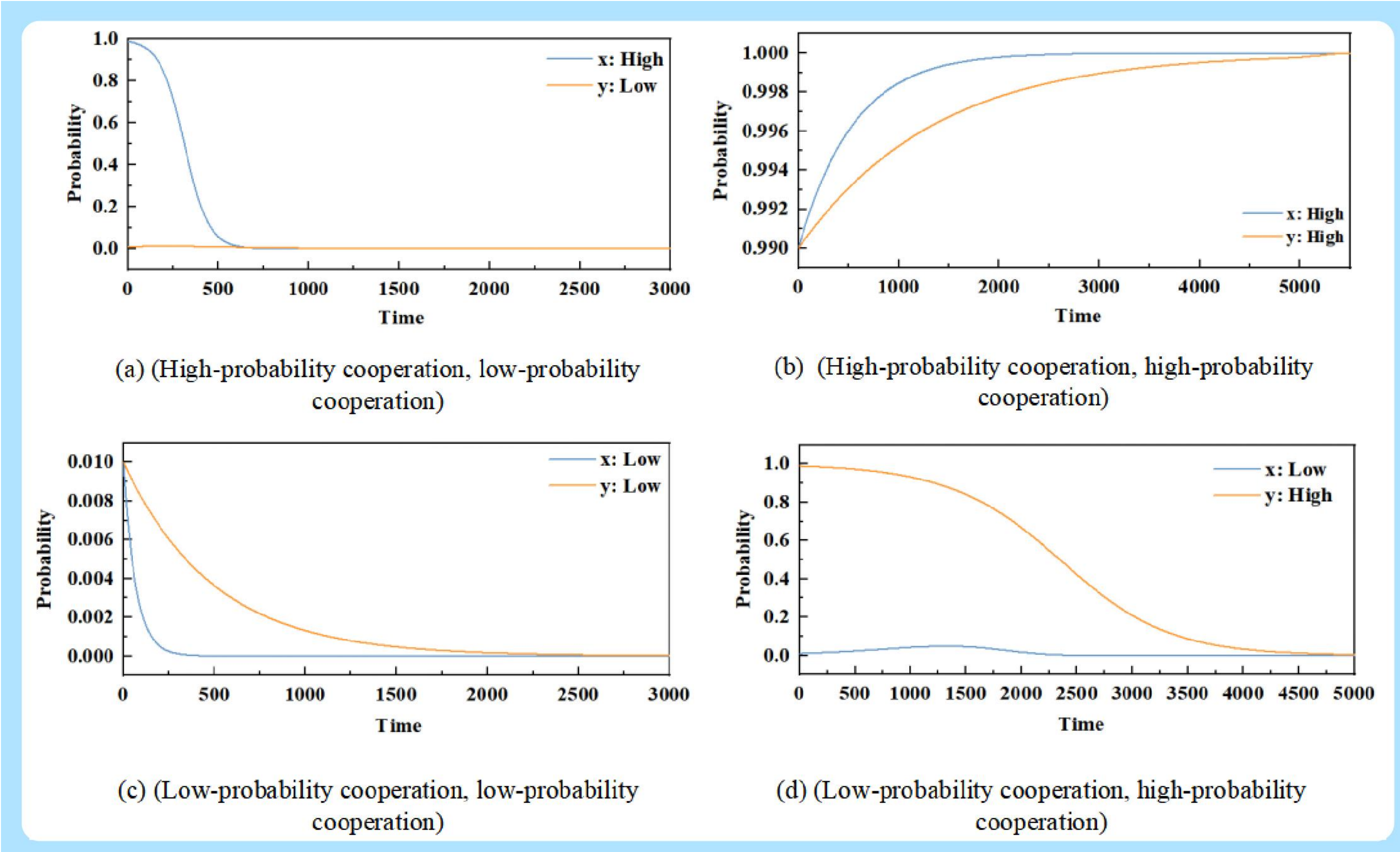

Figure 4. Simulation results of EV users and OBMs in Scenario 4 under different combinations of cooperation probabilities

tion, cooperation). In the other initial strategy combinations, non-cooperation yields higher payoffs, and the system evolves toward (non-cooperation, non-cooperation). These results are consistent with the stability analysis in Section 4.1, while results for other scenarios are provided in supplemental information.

The influence of different initial parameters on the evolutionarily stable strategy

Based on the previous analysis, Scenario 4 is the only case where the ESS corresponds to mutual cooperation between OBMs and EV users. The key parameters (a, b, c, Q_d, Q_c, B_G, and B_v) all influence the resulting ESS. Therefore, this section examines the effects of different initial parameter values on the evolution of cooperation under Scenario 4. The baseline parameter settings are given in Table S10, with initial values of x and y set to 0.5.

Figure 5A-G illustrates the impacts of key parameters on the evolution of cooperation probabilities between EV users and OBMs. As shown in Figure 5A, C & D, parameters associated with cooperative incentives, including a, c, and Q_d, significantly promote cooperation. Increasing these parameters enhances the relative payoff of cooperative strategies, thereby accelerating convergence toward a stable cooperative equilibrium. However, when these parameters are sufficiently reduced, cooperation becomes less attractive, and the system may evolve toward a non-cooperative equilibrium. In contrast, cost-related parameters such as b and Q_c, as shown in Figure 5B & E tend to weaken cooperative incentives. Moderate variations in these parameters have limited influence on the final equilibrium, while excessive increases significantly reduce the payoff of cooperation, leading both players to shift toward non-cooperation. As illustrated in Figure 5F & G, the parameters B_G and B_v, representing losses caused by unilateral non-cooperation, play a critical role in determining strategy stability. Lower loss levels promote cooperation by reducing associated risks, whereas higher losses discourage cooperation and may drive the system toward a non-cooperative equilibrium. Overall, parameters that enhance cooperative benefits or reduce associated risks facilitate convergence to stable cooperation, whereas those that increase costs or unilateral losses hinder cooperation and may result in non-cooperative outcomes.

Case study

The evolutionary game model is applied in a case study to examine its practical implementation and guide charging price design for interactions between EV users and OBMs. The peak electricity price for office buildings in Beijing is set at 1.2930 CNY/(kW·h). A 20 kW unidirectional DC charging station (8,600 CNY, 10-year lifetime) yields a unit cost of 0.0098 CNY/(kW·h) assuming 12 h daily operation, while a bidirectional station (12,000 CNY) corresponds to 0.0137 CNY/(kW·h). The EV discharging price is 0.3125 CNY/(kW·h). Field surveys of 15 nearby stations show an average non-cooperative charging price of 1.51 CNY/(kW·h), with a maximum of 2.1 CNY/(kW·h). EV charging and discharging volumes are set at 40 and 20 kW·h, respectively. These parameters support realistic simulation of evolutionary interactions and pricing effects on cooperation.

In Scenario 4, at the stable strategy point C, both EV users and the OBMs adopt the cooperative strategy. To satisfy the interests of both parties and establish a stable interactive relationship, the following conditions must be met: the payoffs obtained from participating in cooperation should exceed those from non-cooperation. For EV users, they can obtain positive payoffs only if the condition in Equation (20) is satisfied. Similarly, for the office building, positive payoffs are achieved only when the condition in Equation (21) is satisfied.

$$Q_d r_d - Q_c r_{c1} - (Q_c + Q_d)C_b > -Q_c r_c - Q_c C_b \quad (19)$$

$$Q_c r_{c1} + Q_d(r_g - r_d) - Q_d r_d - (Q_c + Q_d)S_G > Q_c r_c - Q_c S'_G \quad (20)$$

By solving Equations (20) & (21), the relationship between the EV discharge price r_d and the EV charging price r_{c1} during interaction can be obtained. Substituting the relevant data yields $2r_{c1} - 2.7075 < r_d < r_{c1} - 0.87425$, as shown in Figure 6. Here, r_{d1} and r_{d2} represent two lines that satisfy the interaction requirements of EV users and the OBMs. Specifically, r_{d3} corresponds to the peak electricity price, and r_{d4} represents the EV charging price in the

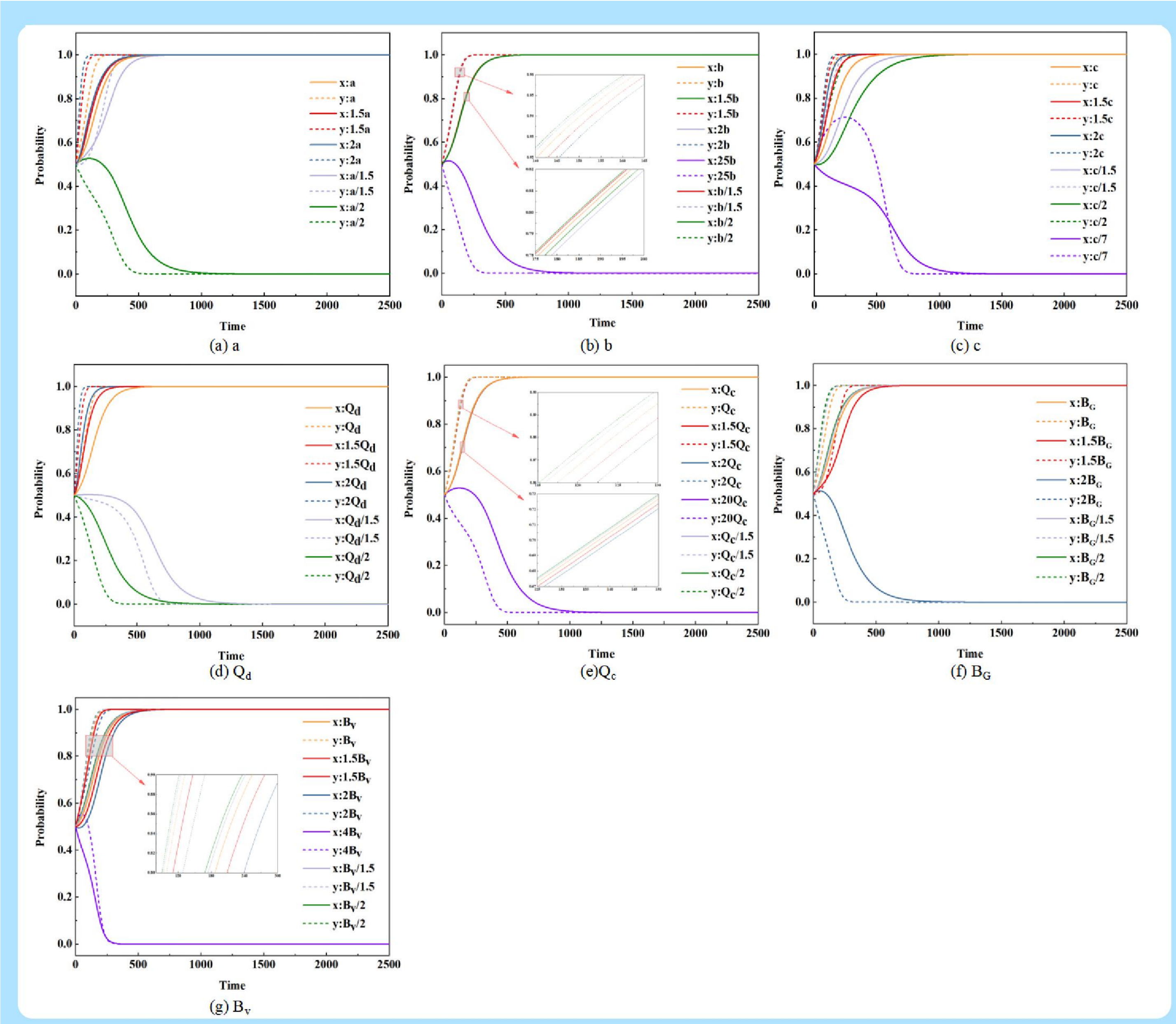

Figure 5. Impact of key parameters on cooperation probability between EV users and OBMs

residential area. In this study, the EV discharge price in the office area is set higher than the charging price in the residential area, making it more attractive for EV users to participate in the interaction.

$$\frac{Q_dC_b - Q_c(r_c - r_{c1})}{Q_d} < r_d < \frac{Q_d(r_g - S_G) - Q_c(r_c - r_{c1}) - Q_c(S_G - S_G')}{2Q_d} \tag{21}$$

In Figure 6, the region satisfying both $r_d > \frac{Q_dC_b - Q_c(r_c - r_{c1})}{Q_d}$ and $r_d < \frac{Q_d(r_g - S_G) - Q_c(r_c - r_{c1}) - Q_c(S_G - S_G')}{2Q_d}$ represents the conditions under which both EV users and the OBMs can obtain positive payoffs from interaction. In this region, both parties ultimately choose the cooperative strategy, i.e., (cooperation, cooperation). Conversely, in other regions, they will eventually adopt the non-cooperative strategy (non-cooperation, non-cooperation). Therefore, to achieve a mutually beneficial interaction, the EV charging price in the office area, r_{c1}, should lie within the range of 1.3626-1.8333 CNY/(kW·h), and the EV discharge price in the office area, r_d, should be within 0.4883-0.9591 CNY/(kW·h).

CONCLUSIONS

This study establishes an evolutionary game model between EV users and OBMs, combined with a system dynamics approach, to analyze the key factors influencing cooperation between the two parties. The results indicate that the evolutionary trajectory of the model is not only significantly affected by the initial strategies of the participants but also closely related to the values of relevant factors. The impact of these factors on the final strategy choices of both parties exhibits a nonlinear and gradual pattern. The main findings are summarized as follows:

(1) Electricity price signals play a decisive role in shaping cooperative behavior. Larger differentials between peak electricity prices, EV discharging prices, and building procurement costs significantly enhance cooperation and accelerate convergence to a stable cooperative equilibrium, especially when discharging prices exceed battery degradation costs.

(2) Infrastructure and operational cost differences have a limited impact on final strategy choices when their variation is small, indicating that pricing signals dominate behavioral outcomes.

(3) EV charging and discharging volumes significantly influence cooperation dynamics. Higher discharging volumes strengthen cooperation incentives and accelerate convergence, while lower charging demand increases cooperation willingness but has a weaker effect on convergence speed.

(4) The potential loss from unilateral non-cooperation is a key determinant

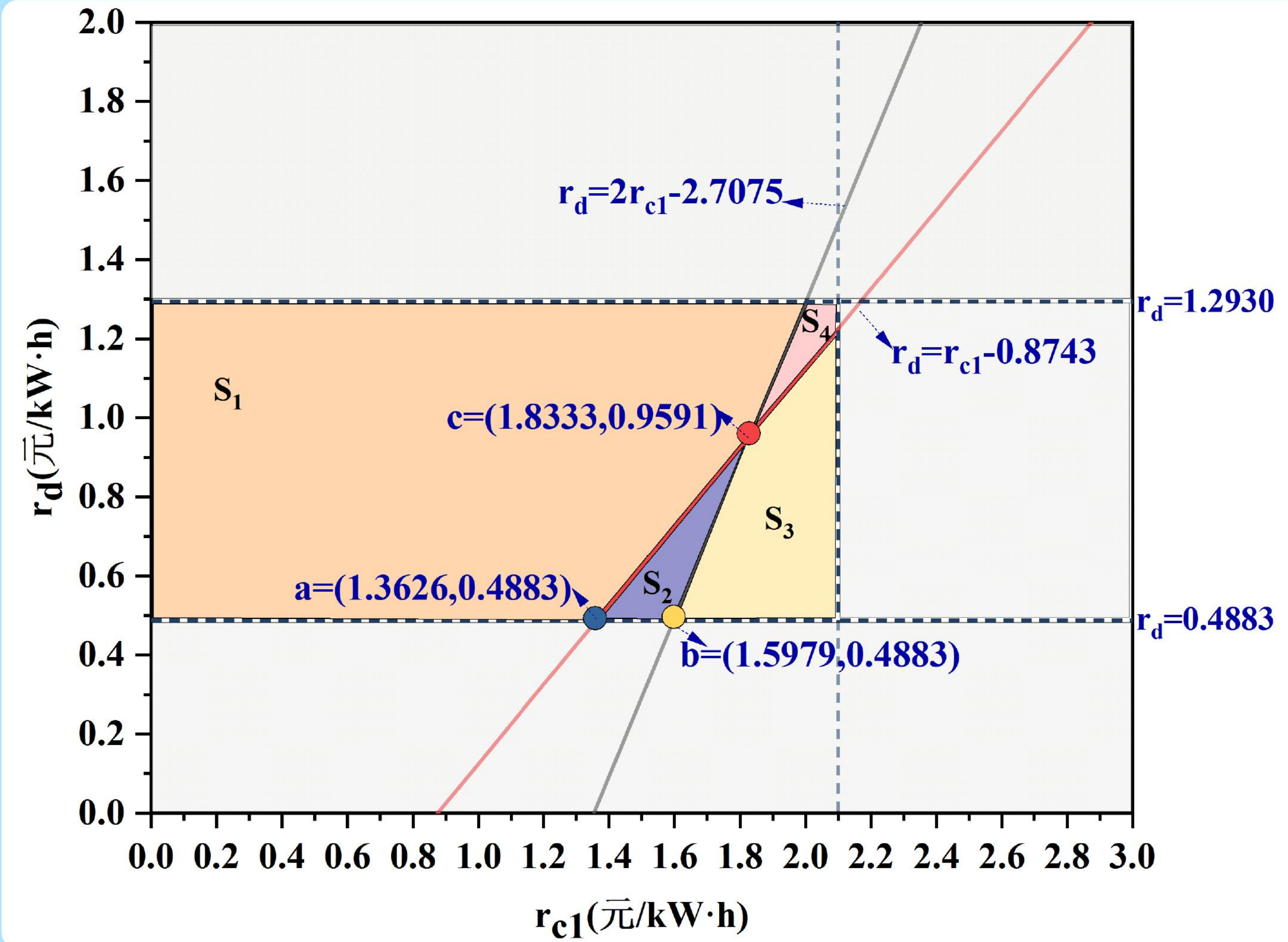

Figure 6. The relationship between EV discharging electricity price and charging electricity price in the interaction between EV users and OBMs

of strategy evolution. Lower losses for the cooperating party lead to higher expected payoffs and stronger incentives for mutual cooperation.

(5) Case study results show that, in a typical office building scenario in Beijing, stable cooperation can be achieved when EV charging prices range from 1.3626 to 1.8333 CNY/(kW·h) and the discharging price ranges from 0.4883 to 0.9591 CNY/(kW·h).

The present study has several limitations: the strategies of the OBMs are simplified to only two options: cooperation and non-cooperation. Future research should consider a wider range of strategies, such as different charging service plans (e.g., high-price fast charging versus low-price slow charging); we assume that all stakeholders are risk-neutral; future studies should incorporate heterogeneous risk preferences among different groups.; the current model lacks dynamic parameter design. Future work should account for the temporal variation of key variables, such as time-of-use electricity pricing for EV charging and discharging.

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AUTHOR CONTRIBUTIONS

All authors contributed to reviewing and editing the manuscript. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Readers may contact the corresponding authors for data upon reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/ipj.energy-use.2026.100050