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Intelligent Regulation on Demand Response for Electric Vehicle Charging: A Dynamic Game Method

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ABSTRACT It has become an urgent problem to be solved that how to make electric vehicle (EV) give full play to shift the power grid peak load through the regulation of demand response (DR). Game theory is often used to provide a new solution for the optimal decision-making among multi-stakeholders. As a dynamic game, differential game can describe the dynamic changes of time-sharing electricity price (TOU price) about power grid and charging power about EV in real time. Considering the problem of "peak on top of peak" caused by a large number of electric vehicles' disordered charging, this paper makes the dispatching strategy of EVs entering the grid based on the TOU price, and establishes a dynamic differential game model for the power grid and EV decision makers. The model is solved by taking the TOU price of power grid and the charging power of EV as the strategy, and smoothing the peak valley difference of power grid and minimizes the charging cost of EV as the goal. In the end, DR for optimizing power grid load and reducing user's low cost is adopted to simulate the proposed model. The simulation results show that the peak-valley difference rate of the optimized power grid is reduced by 6.93%, and the cost of EV users is reduced by 71.52%. The simulation results verify the peak load regulation effect and the economic benefit of the differential game model on the power grid side.

INDEX TERMS EV, peak load shifting, DR, differential game, feedback nash equilibrium.

NOMENCLATURE

$r_1(t)$	Grid TOU price (grid strategy)
$r_{2_i}(t)$	EV charging power (EV strategy)
$x_i(t)$	EV battery capacity at time t
$P^T(t)$	Peak time load
$P^D(t)$	Valley time load

I. INTRODUCTION

In order to cope with climate change and global warming and reduce greenhouse gas emissions, the development of sustainable energy has become a hot issue in academia and industry. With the gradual deepening of environmental protection awareness, electric vehicles (EVs) with the advantages of no pollution, high energy efficiency, simple structure and convenient maintenance have replaced fuel cars step by step, and become an inseparable part of people's daily life [1]. In the past few years, the production and use of EVs have increased significantly, driven by the new energy vehicle subsidy policies and other related promotion policies issued by governments in various countries and regions. From January to November 2017, the sales volume of global EVs exceeded the scale of one million for the first time, reaching a number of 1.0391×10^6, with a year-on-year growth of 55%. Chinese EV market is still the largest one, accounting for more than 40% of the world's sales of EVs [2]. However, the charging load of EVs also brings unprecedented challenges to the power grid. In [3], the influence of EV charging on power grid load in Vermont under the optimal charging mode and night charging mode had been studied. And the above research shows that the Power Grid can support a number of 1×10^6 EVs charging at night, while the peak

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load charging will cause great problems in the power supply. Meyers *et al.* [4] studies the capacity of the entire U.S. power grid to charge EVs, and studies two scenarios, i.e., 24h rechargeable and 12h rechargeable. The results show that the existing power grid in the United States can withstand up to 73% of the EV load. At the same time, the large-scale disordered load resulting from EV charging will cause excessive load impact on the power grid [5], which makes the peak load rise significantly, and the phenomenon of peak adding appears [6]. All above will lead to the decrease of power quality and economic operation index [7]. Therefore, it is of great significance to make the charging operations of EVs being ordered and optimized.

Obviously, a reasonable EV charging strategy is highly critical for the EV users to guide their charging behaviors in an orderly manner [8]. Of course, the charging strategy is required to firstly meet the energy supply demand of EVs, and then disperse the charging load of EVs to non-peak hours, furthermore relieve stress on the peak supply capacity of the power grid [9]. Under the time-sharing electricity price (TOU price) strategy, most of EV users would adjust their charging habits to increase the charging ratio in the valley period, as which can play a role in cutting peak and filling valley and reducing peak-valley difference for the whole power system [10].

The demand response (DR) caused by power consumers is based on price signals or incentive mechanisms [11], in which the power consumers can change their traditional electricity consumption mode [12]. The important parts of implementing a DR project are the response behavior of power consumers to incentive measures from power companies and the changement of the load characteristic, which is caused by power consumers' adjustment of their own power consumption behavior [13]. Moreover, the way and intensity of response behavior depends on the power consumers' own response characteristics. According to the different response ways of power consumers, the DR measures can be divided into two types: price-based demand response (PBDR) and incentive-based demand response (IBDR). The price has a major influence on the power consumption behavior of consumers in the PBDR project. For this reason, combined with PBDR, the mechanism of TOU price is used to regulate the charging behavior of EV users, balance the peak valley difference [14], and achieve the role of peak load reduction, which can effectively reduce the power generation pressure of the grid and avoid a series of emergency situations due to the shortage of supply. At the same time, this mechanism can also be applied to effectively reduce the cost of EV users (including the cost of charging and the cost of battery loss), and greatly stimulate EV users to participate in the charging during non-peak hours.

In order to simulate energy trading process(the transaction process of power grid selling to EV), between electric power grid and EV users (G2V) [15], researchers have proposed several feasible solutions, among which game theory is considered as a more efficient method to solve the DR problem of EVs about the virtual energy trading process [16]. The DR mechanism is applied to the EV charging management to control the power transaction between the grid and the EV. Hu *et al.* [17] constructs a two-tier optimization model guided by electricity price, and utilizes genetic algorithm to solve the two-tier optimization model iteratively, so as to obtain the optimal dispatching plan of the upper model and the optimal charging price of the lower model. In the study of Shinde1 *et al.* [18], the researcher proposes a game model of multiple utility companies (UCs), EV users and DR users based on the actual situation. And the distributed algorithm is used to solve the game problem and maximize the benefits among the three users. Guo and Zhou [19] uses Stackelberg game to model EV discharge process, and uses KKT method to solve the utility function of Stackelberg game to obtain the optimal Stackelberg equilibrium. However, the above literature does not combine the EV user side economy and grid side benefits (peak load shifting) for discussion and analysis, but only consider the benefits of one side. On the power grid side, a large number of EVs will increase the load fluctuation and increase the load peak valley difference, which is not conducive to the stable operation of the power grid. Consequently, the power grid urgently needs to use the means of cutting peak and filling valley scientifically. For EV users, the pursuit of lower charging cost is one of their goals. Therefore, when DR is applied to the competition between power grid and EV, the power grid changes the charging behavior of EV users by adjusting the electricity price. EV users will reduce their own charging cost due to choosing to charge in the low period. At the same time, the load fluctuation of power grid is also slowed down due to the change of EV users' charging habits, and the peak valley difference is significantly reduced.

Hence, Wang [20] has considered the benefits of both EV users and the power grid, and establishes an EV charging non-cooperative game model on real-time floating price. Yu *et al.* [21] constructs an EVs charge-discharge cooperation model based on the alliance game theory. And it is verified that the peak valley difference of power grid load is significantly reduced and the plug-in hybrid electric vehicle (PHEV) users are satisfied with the lower charging cost and the higher charging state of vehicle batteries. Liu *et al.* [22] investigates the charging behavior of four kinds of EVs in Shanghai, and uses bass diffusion model to predict the inventory growth of EVs. Then, the peak valley difference is balanced and the charging cost of EV users is reduce by arranging the charging plans of EVs reasonably. In the study of Yang *et al.* [23], a robust non-cooperative Stackelberg game approach is proposed to solve the problem of energy charging scheduling between aggregator and multiple EVs under the condition of uncertain demand and the author addresses the solution by building the variational inequality theory and the Lagrange dual decomposition method (LDDM). It is proved that the robust scheduling algorithm can improve the performance with the increase of vehicle number under the condition of uncertain load demand. Wu *et al.* [24] studies how to use multiple EV batteries as distributed energy storage system to provide the auxiliary service of frequency regulation for power grid. By adopting a smart pricing policy as part of the game, the study shows that the same optimal performance can be achieved by the distributed behaviors of self-interested EVs as the centralized control system. However, the above literatures [20]–[24] did not take into account the internal loss of battery that the internal loss of battery will directly affect its service life in the process of charging and discharging, and did not consider the charging and discharging of EVs as dynamic change problem (The charging and discharging of EV and the change of power grid load will vary over time, which belongs to the dynamic change problem. Accordingly, we should study it in the way of the dynamic game theory according to the actual situation.), and also did not evaluate the economy of charging behavior in combination with the satisfaction benefits of EV users for adjusting their charging habits (The economy of charging behavior can be directly reflected by the satisfaction of EV users. The satisfaction benefit of EV users is the cost difference before and after EV users adjust charging behavior).

For this purpose, this paper regulates the EV charging behavior by the electricity price, combining the DR. As a dynamic game, the differential game can describe the dynamic changes of players in real time. On the basis of DR, in order to consider the benefits of both grid and EV users, as well as the dynamic changes of grid load and EV charging, differential game is a better way to describe the change of players over time. This paper constructs a grid EV differential game model for the purpose of achieving better choice between the two participants through mutual game. Hence, with the model's combining with the influence of the internal loss of the battery on EV, and the users' satisfaction return brought by regulating their own charging behavior, this paper studies how the model can optimize the grid load and minimize the cost of EV users (charging cost and battery loss cost) from the perspective of dynamic game model.

Main contributions of this paper are as follows:

Under the framework of DR, this paper uses differential game model to solve the problem of EV disorder charging. The advantage of this model lies in that it can effectively harmonize the relationship between the grid and EV, and can effectively help the grid reduce the peak valley difference while reducing the EV cost.

(1) Build a differential game model for G2V. DR can help to make the game decision more in-depth and more intense. The game between grid and EV can fully mobilize the enthusiasm of market DR. Considering that the load of the power grid and the charging of EV are both dynamic processes, differential game, as a dynamic game, can better describe the changes of game participants over time.

(2) Analyze the benefits of G2V under the framework of differential game. For the power grid, the effect of peak-valley difference and charging power on the power grid is considered. From the perspective of EV users, the satisfaction benefits of EV users (charging cost reduction caused by EV users' adjusting charging behavior), charging cost and battery loss cost of EV are comprehensively analyzed.

(3) Combined with the actual application, the simulation analysis is carried out to evaluate the performance of the model. Taking a city as an example for simulation analysis, the peak-valley difference for the power grid is significantly improved, and the effect of "peak load shifting" is obvious. After the optimization of the user side of the EV, the cost of the owners is greatly reduced and the economy is improved. To this end, the validity of the model is verified.

The paper is organized as follows: The first section is the introduction part, in which we analyze and discuss the negative impact of large-scale disordered charging of EVs on the power grid, and explain the current scholars' solutions and problems in this regard. Therefore, the importance of building the model is introduced. In the second section, aiming at the above problems, the differential game model of power grid to EV is constructed to explore the mutually beneficial coexistence relationship between them, so as to minimize the cost of EV users while optimizing the power grid load. In the third section, the model is solved to find the optimal strategy in the mutually beneficial coexistence relationship, so as to maximize the utility of both sides of the game; In the fourth section, the effectiveness of the optimization algorithm is verified by numerical simulation; In the fifth section, the paper is summarized and we briefly describe the following problems needed to be studied in the future.

II. THE CONSTRUCTION OF G2V DIFFERENTIAL GAME MODEL

When a large number of EVs are widely used, there will be a large number of charging loads connected to the grid. The charging loads are bound to have a certain impact which the problem of peak load growth is particularly serious on the operation of the grid. This problem is mainly reflected in aspect of randomness, mobility and aggregation about charging load of EVs. On the power grid side, if the EV charging plan is unreasonable, it is very likely that the EV will be charged in disorder during the peak load of the grid, and its charging load may coincide with the peak load of the original grid. This will lead to extreme peak load of the power grid, and further increase the peak valley difference of the power grid. Thus the above problems will threaten the economic operation and security of the power grid. Therefore, based on the reasonable DR to guide the charging behavior of EVs, the "peak staggering" measure is adopted to appropriately transfer the charging pressure in the peak period to the low period, so as to relieve the power supply pressure of the grid and avoid various system problems caused by overload. On the user side of EVs, the pursuit of the minimum charging cost is one of the goals of the owners. Owners can reasonably change their charging habits, actively participate in the regulation of DR mechanism, and reduce their charging costs by charging in the low period. For this reason, considering the benefits for power grid and EV users and the characteristics of maximizing interests of both sides in real time for differential

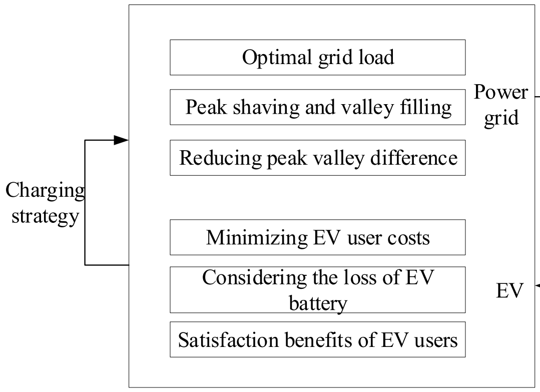

FIGURE 1. The structure of G2V differential game model.

game, we construct the G2V differential game model. In the process of EV charging, the charging power and the load of the grid vary over time. In order to describe the dynamic changes of grid load and EV charging power in real time, we need to use differential game as a dynamic game to make the charging method more suitable for the actual situation. Finally, by using the feedback Nash equilibrium to solve the game model, we can obtain the optimal strategies and benefits of both sides. The specific model structure is shown in Fig. 1.

We divide a day into 24 periods, and set the grid strategy as TOU pricing expressed in $r_1(t)$. The goal of power grid is to optimize its own load and balance the peak valley difference. The power grid feeds back the price information to the EV users. Based on the price setting for different periods, the power grid can compute its own optimal strategy to maximize its revenue under the current EV charging situation. The strategy $r_2(t) = \left\{r_{2_1}(t), r_{2_2}(t), \cdots r_{2_i}(t), \cdots, r_{2_n}(t)\right\}$of EV ($r_{2_i}(t)$represents the strategy of the i$^{\text{th}}$ EV) is the charging power corresponding to the electricity price of each time period, and the goal of the strategy is to minimize the charging cost of EV. According to the electricity price given by the grid, EV users compute the most favorable charging time period to minimize its cost. Let $x_i(t)$ represent the battery capacity of EV in period t, and $x_i(t)$ is defined as the state of the system. $\frac{dx_i(t)}{dt}$ represents the change of system state, i.e. the change rate of EV battery power. The change of system state is related to the strategies $r_1(t)$ and $r_{2_i}(t)$ of both sides and the state of the system itself. In detail, it includes: (1) The impact of grid strategy $r_1(t)$ (TOU price) on the change rate of EV battery power. When the grid load appears in peak period, the tariff is relatively high, and the charging power of EVs is relatively low. And then the change rate of EV battery power will also be affected, which is indirect. (2) The impact of EV strategy $r_{2_i}(t)$ (charging power) on the change rate of EV battery power. The EV charging power will directly affect the change rate of EV battery power, and the change rate of battery power will become faster with the increase of EV charging power, and vice versa. (3) The influence of system state $x_i(t)$ on the change rate of EV battery power. The greater the charging efficiency of EV battery is, the higher the energy conversion efficiency of EV in the charging process is, and the faster the change rate of EV battery is. To sum up, the dynamic change of the state of the system can be described by the following differential equation:

$$\frac{dx_i(t)}{dt} = \rho r_1(t) + r_{2_i}(t) + \mu x_i(t) \tag{1}$$

In (1), ρ represents the probability that EV users choose to charge in each time period in order to save charging cost, and its value range is 0 to 1. The μ represents the charging efficiency of EV batteries [25].

In the process of the game between the two sides, the power grid aims to adjust the charging habits of EV users by regulating the TOU price, so as to make their own load optimal. The factors that affect the grid load include the peak valley difference of the grid, the charging power of the EV per unit time and the total charging capacity of EV in game time.

Firstly, the influence of peak valley difference on power grid load is considered. Let $P^T(t)$ and $P^D(t)$ represent peak time load and valley time load respectively. Peak valley difference can be expressed as $P^T(t) - P^D(t)$, and then $\min[P^T(t) - P^D(t)]$is equivalent to $\min\left[\left(P^T(t) - P^D(t)\right)^2\right]$. And the load is assumed to be $Q = P^T(t) - P^D(t)$. According to the relation $Q = \alpha_1 P + \beta_1$ of load and electric price (P representing electric price) [26], it can be obtained that the minimum peak valley difference $Q = \alpha_1 r_1(t) + \beta_1$ can be equivalent to $\min\left[(\alpha_1 r_1(t) + \beta_1)^2\right]$, where α_1 and β_1 are parameters representing the relation between load and electric price.

Secondly, for the charging power is different in different periods and different electricity prices, we take the influence of unit time charging power on grid load into consider. By studying the charging power in different periods of a day, we can know the charging habits of EV users for different electricity prices on that day, which will provide reference for the adjustment of electricity prices on the next day. Therefore, parameter θ_1 is introduced here, which represents the unit cost of charging power in the game time. It is used to describe the charging situation of EV under the unit cost. $r_1(t)\, r_{2_i}(t)$ is the charging cost of EV, so the charging load(W) per unit time shall be equal to $\theta_1 r_1(t)\, r_{2_i}(t)$.

Finally, we should consider the impact of the total charging capacity of EVs on the grid load in the game time, because the overall charging capacity of EVs in the grid will directly affect the fluctuation of the grid load. At the same time, how to balance the power consumption of EV and other purposes (such as household power, industrial, commercial power, etc.) is also a problem for the grid. In this paper, $x_i(t)$ is introduced to indirectly describe the electric quantity that EVs need to purchase from the grid.

According to the above factors, the objective function of the grid is given as follows:

$$J_1 = \min\left\{\int_{t_0}^{T}\left[(\alpha_1 r_1(t) + \beta_1)^2 + \theta_1 r_1(t) r_{2_i}(t) + x_i(t)\right] \times \exp\left[-a(t - t_0)\right] dt\right\} \tag{2}$$

In (2), a represents the discount rate of grid [27], and the value range is 0 to 1.

EV users can select the optimal charging power to minimize the cost by referring to the given grid price information and combining with their own charging requirements. The cost of EV consist of three parts, i.e., the satisfaction income of EV users, the charging cost of EV and the battery loss of EV. The satisfaction income of EVs reflects the reduction of EV user's charging cost by adjusting their charging behavior.

First of all, we consider the impact of EV users' satisfaction benefits on EV costs. From the relationship between load and electricity price $Q = \alpha_1 P + \beta_1$, the electricity price $P = \left(\frac{Q-\beta_1}{\alpha_1}\right)$ can be obtained, which is equivalent to $P = \left(\frac{r_{2_i}(t)-\beta_1}{\alpha_1}\right)$, where $r_{2_i}(t)$ is the charging power. Then, charging cost can be expressed as $r_{2_i}(t)\left(\frac{r_{2_i}(t)-\beta_1}{\alpha_1}\right)$, where α_2 is the correction factor for regulating the EV user's electric behavior. So, the expression $\alpha_2 r_{2_i}(t)\left(\frac{r_{2_i}(t)-\beta_1}{\alpha_1}\right)$ is used to show that EV users reduce their charging cost by adjusting their charging behavior. Where, the value range of α_2 is [0-1]. The higher the value is, the more satisfied EV users are with regulating their charging behavior, which will greatly encourage EV users to participate in this action.

Then, the influence of EV charging cost is considered. Here, $r_1(t)\, r_{2_i}(t)$ is used to represent the charging cost of EV, which directly reflects the charging expenditure of EV users, and provides a reference for EV users to adjust their charging behavior. If the charging cost is too high to the average of a day, EV users will adjust their charging mode appropriately, try to stagger the peak charging, and even choose to charge in the low period in order to minimize the charging cost.

Last, the influence of EV battery loss on EV user cost is considered. EV will lose battery during charging, which will affect battery life. Here, $\beta_2[x_i(t) - x_0(t)]$ is used to represent the battery loss cost of EV, in which β_2 is the EV battery loss rate [28]. The parameter β_2 represents the battery loss caused by the unit charge, and is used to measure the battery attenuation degree in the charging process.

In conclusion, the objective function of EVs is as follows:

$$J_{2_i} = \min\left\{\int_{t_0}^{T}\left[-\left(\alpha_2 r_{2_i}(t)\left(\frac{r_{2_i}(t)-\beta_1}{\alpha_1}\right)\right)+r_1(t)\, r_{2_i}(t) + \beta_2[x_i(t)-x_0(t)]\right]\exp\left[-b(t-t_0)\right]dt\right\} \tag{3}$$

In (3), b is the discount rate of EV [27], and the value range is [0-1].

III. THE PROCESS OF EQUILIBRIUM SOLUTION TO THE G2V MODEL

In the light of the optimization model established in section 2, we will study the optimal strategies of grid and EV respectively in this part, so as to achieve the optimal objective function for both of them.

For power grid, the strategy set $r_1^*(t) = \phi^*(t, x_i)$ are the feedback Nash equilibrium of game models (1) and (2). If there is a continuous differentiable function $u(t, x_i) : [t_0, T] \times R^n \to R$, the following Isaac Bellman equation [27] is satisfied.

$$\begin{aligned} -u_t(t, x_i) &= \min_{r_1(t)}\Big\{\Big[(\alpha_1 r_1(t) + \beta_1)^2 + \theta_1 r_1(t)\, r_{2_i}(t) + x_i(t)\Big] \\ &\quad \times \exp[-a(t-t_0)] + u_{x_i}(t, x_i)\Big[kr_1(t) + r_{2_i}(t) + \mu x_i(t)\Big]\Big\} \end{aligned} \tag{4}$$

By taking the first partial derivative of (4) with respect to $r_1(t)$, we can get

$$\phi^*(t, x_i) = -\frac{2\alpha_1\beta_1 + \theta_1 r_{2_i}(t) + u_{x_i}(t, x_i)\, k e^{a(t-t_0)}}{2\alpha_1^2} \tag{5}$$

For EVs, strategy set $r_{2_i}^*(t) = \varphi_i^*(t, x_i)$ are the feedback Nash equilibrium of game models (1) and (3). If there is a continuous differentiable function $v^i(t, x_i) : [t_0, T] \times R^n \to R$, the following Isaacs Bellman equation is satisfied

$$\begin{aligned} -v_t^i(t, x_i) &= \min_{r_{2_i}(t)}\Big\{\Big[-\left(\alpha_2 r_{2_i}(t)\left(\frac{r_{2_i}(t)-\beta_1}{\alpha_1}\right)\right) \\ &\quad + r_1(t)\, r_{2_i}(t) + \beta_2[x_i(t) - x_0(t)]\Big] \\ &\quad \times \exp[-b(t-t_0)] + v_{x_i}^i(t, x_i)\Big[kr_1(t) + r_{2_i}(t) + \mu x_i(t)\Big]\Big\} \end{aligned} \tag{6}$$

Taking the first partial derivative of (6) with respect to $r_{2_i}(t)$, one can have

$$\varphi_i^*(t, x_i) = \frac{\alpha_1\left[v_{x_i}^i(t, x_i)\, e^{b(t-t_0)} + r_1(t)\right] + \alpha_2\beta_1}{2\alpha_2} \tag{7}$$

By substituting (5) and (7) into (4) and (6) respectively, we can obtain the following propositions:

Proposition 1: If the state equation of the system satisfies the stochastic differential equation (1) and the objective function satisfies (2) and (3), then there is a set of solutions for the partial differential equations (4) and (6), namely:

$$u(t, x_i) = \exp[-a(t-t_0)][A(t)\, x_i + B(t)] \tag{8}$$

$$v^i(t, x_i) = \exp[-b(t-t_0)][C_i(t)\, x_i + D_i(t)] \tag{9}$$

Taking the partial derivative of (8) with respect to t and x_i respectively, we get

$$\begin{aligned} u_t(t, x_i) &= \left\{-a[A(t)\, x_i + B(t)] + A'(t)\, x_i + B'(t)\right\} \\ &\quad \times \exp[-a(t-t_0)] \end{aligned} \tag{10}$$

$$u_{x_i}(t, x_i) = A(t)\exp[-a(t-t_0)] \tag{11}$$

By taking the partial derivative of (9) with respect to t and x_i respectively, we have

$$\begin{aligned} v_t^i(t, x_i) &= \left\{-b[C_i(t)\, x_i + D_i(t)] + C_i'(t)\, x_i + D_i'(t)\right\} \\ &\quad \times \exp[-b(t-t_0)] \end{aligned} \tag{12}$$

$$v_{x_i}^i(t, x_i) = C_i(t)\exp[-b(t-t_0)] \tag{13}$$

Proof: It is proved that, for power grid, the following expressions are valid in combination with (4), (5), (7) and (8)

$$\begin{aligned} &aA(t)x_i + aB(t) - A'(t)x_i - B'(t) \\ &\quad = \alpha_1^2\left(\phi^*(t,x_i)\right)^2 + \beta_1^2 + 2\alpha_1\beta_1\phi^*(t,x_i) \\ &\qquad + \theta_1\phi^*(t,x_i)\varphi_i^*(t,x_i) + x_i \\ &\qquad + A(t)\cdot\left[k\phi^*(t,x_i) + \varphi_i^*(t,x_i) + \mu x_i\right] \end{aligned} \tag{14}$$

By substituting (5), (7), (11) and (13) into (10), we can get the following equation (15), as shown at the bottom of this page.

From (15), let the coefficients of $x_i(t)$ on both sides of the equation be equal, and we can get the following equation:

$$aA(t) - A'(t) = 1 + A(t)\mu \tag{16}$$

From (16), we solve differential equation about $A(t)$ and get the following equation:

$$A(t) = \frac{e^{(a-\mu)(t-t_0)} + 1}{a-\mu} \tag{17}$$

For EVs, the following formula can be obtained by combining (6), (7) and (9)

$$\begin{aligned} &bC_i(t)x_i + bD(t) - C_i'(t)x_i - D'(t) \\ &\quad = \left\{ -\frac{\alpha_2\left[\varphi_i^*(t,x_i)\right]^2}{\alpha_1} + \frac{\alpha_2\varphi_i^*(t,x_i)\beta_1}{\alpha_1} \right. \\ &\qquad \left. + \phi^*(t,x_i)\varphi_i^*(t,x_i) + \beta_2\left[x_i(t) - x_0(t)\right] \right\} \\ &\qquad + C_i(t)\left[k\phi^*(t,x_i) + \varphi_i^*(t,x_i) + \mu x_i\right] \end{aligned} \tag{18}$$

By substituting (5), (7), (11) and (13) into (18), we can get

$$\begin{aligned} &bC_i(t)x_i + bD_i(t) - C_i'(t)x_i - D_i'(t) \\ &= -\frac{\alpha_1^2\left[C_i(t)+r_1(t)\right]^2 + \alpha_2^2\beta_1^2 + 2\alpha_1\alpha_2\beta_1\left[C_i(t)+r_1(t)\right]}{4\alpha_1\alpha_2} \\ &\quad + \beta_2\left[x_i(t) - x_0(t)\right] + C_i(t)\mu x_i \\ &\quad + \frac{C_i(t)\left[\alpha_1 C_i(t) + \alpha_1 r_1(t) + \alpha_2\beta_1\right]}{2\alpha_2} \\ &\quad - \frac{\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t) + A(t)k\right]\cdot\left[\alpha_1 C_i(t) + \alpha_1 r_1(t) + \alpha_2\beta_1\right]}{4\alpha_1^2\alpha_2} \\ &\quad + \frac{\alpha_1\beta_1 C_i(t) + \alpha_1\beta_1 r_1(t) + \alpha_2\beta_1^2}{2\alpha_1} \\ &\quad - \frac{C_i(t)k\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t) + A(t)k\right]}{2\alpha_1^2} \end{aligned} \tag{19}$$

Then, we can get

$$bC_i(t) - C_i'(t) = \beta_2 + C_i(t)\mu \tag{20}$$

Then, we solve differential equation about $C_i(t)$ and get the following equation:

$$C_i(t) = \frac{e^{(b-\mu)(t-t_0)} - \beta_2}{b-\mu} \tag{21}$$

To sum up, for the power grid, its optimal strategy is

$$r_1^*(t) = -\frac{2\alpha_1\beta_1 + \theta_1 r_{2_i}^*(t) + A(t)k}{2\alpha_1^2} \tag{22}$$

For EVs, the optimal strategy is

$$r_{2_i}^*(t) = \frac{\alpha_1 C_i(t) + \alpha_1 r_1^*(t) + \alpha_2\beta_1}{2\alpha_2} \tag{23}$$

Substituting (17) into (22) and (21) into (23), we solve equations about (22) and (23), and get the following equation:

$$\begin{aligned} r_1^*(t) = &-\frac{4\alpha_2\beta_1}{4\alpha_1\alpha_2 + \theta_1} - \frac{\theta_1 e^{(b-\mu)(t-t_0)} - \theta_1\beta_2}{(b-\mu)(4\alpha_1\alpha_2 + \theta_1)} \\ &- \frac{\theta_1\alpha_2\beta_1}{\alpha_1(4\alpha_1\alpha_2 + \theta_1)} - \frac{2\alpha_2 k e^{(a-\mu)(t-t_0)} + 2\alpha_2 k}{\alpha_1(a-\mu)(4\alpha_1\alpha_2 + \theta_1)} \end{aligned} \tag{24}$$

$$\begin{aligned} r_{2_i}^*(t) = &\frac{\alpha_1 e^{(b-\mu)(t-t_0)} - \alpha_1\beta_2}{2\alpha_2(b-\mu)} - \frac{2\alpha_1\beta_1}{4\alpha_1\alpha_2 + \theta_1} \\ &- \frac{\alpha_1\theta_1 e^{(b-\mu)(t-t_0)} - \alpha_1\theta_1\beta_2}{2\alpha_2(b-\mu)(4\alpha_1\alpha_2 + \theta_1)} - \frac{\theta_1\beta_1}{8\alpha_1\alpha_2 + 2\theta_1} \\ &- \frac{k e^{(a-\mu)(t-t_0)} + k}{(a-\mu)(4\alpha_1\alpha_2 + \theta_1)} + \frac{\beta_1}{2} \end{aligned} \tag{25}$$

According to the proof of proposition 1, the Nash equilibrium solution of differential game model (2) and (3) is derived, that is, the optimal strategy of power grid and EV. By substituting (17) and (18) into (2) and (3), the optimal cost of power grid and EV can be obtained.

$$\begin{aligned} &aA(t)x_i + aB(t) - A'(t)x_i - B'(t) \\ &= \alpha_1^2\cdot\left\{\frac{\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t)\right]^2 + A^2(t)k^2 + 2A(t)k\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t)\right]}{4\alpha_1^4}\right\} \\ &\quad - \beta_1^2 - \frac{\beta_1\theta_1 r_{2_i}(t)}{\alpha_1} - \frac{\beta_1 A(t)k}{\alpha_1} + x_i + A(t)\mu x_i \\ &\quad - \theta_1\cdot\left\{\frac{\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t) + A(t)k\right]\cdot\left[\alpha_1 C_i(t) + \alpha_1 r_1(t) + \alpha_2\beta_1\right]}{4\alpha_1^2\alpha_2}\right\} \\ &\quad - \frac{A(t)k\left[2\alpha_1\beta_1 + \theta_1 r_{2_i}(t) + A(t)k\right]}{2\alpha_1^2} + \frac{A(t)\left[\alpha_1 C_i(t) + \alpha_1 r_1(t) + \alpha_2\beta_1\right]}{2\alpha_2} \end{aligned} \tag{15}$$

TABLE 1. Related numerical simulation parameter.

Parameter	Value
α_1	-1432.83
β_1	1753.21
α_2	0-1
β_2	0.127
k	0-1
μ	0.97
a	0-1
b	0-1

IV. NUMERICAL SIMULATION

In this section, an example is given to verify the validity of the model and solution. A city with a population of millions is our research object, which has a good application environment and development prospect of EVs. It is predicted that 2% of the total population will be taken as the possession of EVs, that is, the slow charging load of 3×10^4 EVs will be analyzed. The calculation example sets the battery capacity of each EV as 40kW · h [29]. In order to prolong the battery life, the initial state of EV battery usually needs to retain a certain amount of electricity and the minimum threshold is 10% of the full battery capacity [30]. The initial time t_0 is equal to 1, and the end time of the game T is equal to 24. Other simulation parameters are set as shown in Table 1 and Table 2 respectively.

At first, we analyze the benefits of the grid side in this paper. Firstly, compared with the original, the optimized TOU price and EV charging power are analyzed and we study the peak load reduction effect of EV strategy $r_{2_i}(t)$ (EV charging power) under the regulation of grid strategy $r_1(t)$ (optimized TOU price). Secondly, we further study the influence of EV charging power adjustment on the grid side combined with the change of the total load of the grid and the trend of the grid load in each game round. Finally, compared with the original, the peak to valley ratio of EV and grid after optimization is analyzed to explore the peak regulation effect of the proposed model.

Then, we analyze the benefit of EV user side in this paper. First of all, the optimized cost of EV users is analyzed compared to the original, which directly reflects the income of EV users under the article model. Last, the cost of EV users is analyzed by combining the correction factors α_2 of EV users' charging behavior, to understand the impact of EV users' satisfaction with their charging behavior on their cost.

This paper utilizes the differential game model to optimize the charging load of EV in a city. The optimization results are shown in Fig. 2 and Fig. 3.

One can see from the purple curve (the original electricity price) in Fig. 3 that during the period of 8-15, the original EV charging load is at the peak of charging. In order to stagger the demand of EV users and other users, and avoid the phenomenon of peak adding, the power grid can adjust the

TABLE 2. The parameter of θ_1 at Time 1 to 24.

Time	Value
1	1.66
2	1.65
3	1.47
4	1.59
5	1.61
6	1.45
7	1.64
8	2.94
9	3.10
10	2.86
11	3.33
12	2.90
13	2.53
14	2.52
15	2.20
16	2.04
17	2.09
18	1.68
19	2.07
20	2.82
21	2.11
22	1.61
23	1.54
24	1.56

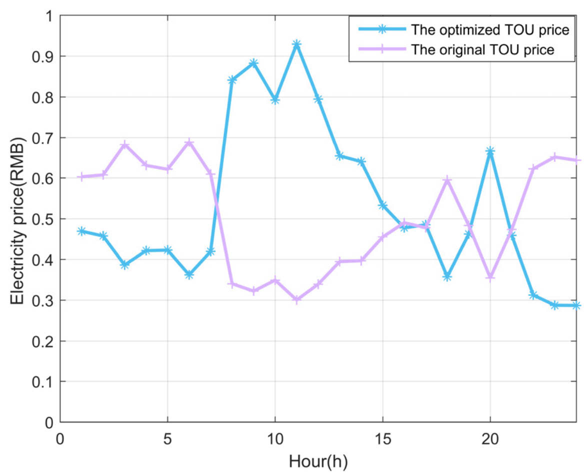

FIGURE 2. The original and optimized TOU price.

charging behavior of EVs by raising the price of electricity to achieve the purpose of "peak cutting". From 23:00 p.m. to 24:00pm and 1:00am to 7:00 a.m. the next day, the power consumption is relatively low, and the electricity price can be appropriately reduced as a charging reward to stimulate the charging behavior of EV users by power grid. By improving the enthusiasm of EV users in charging at night, the goal

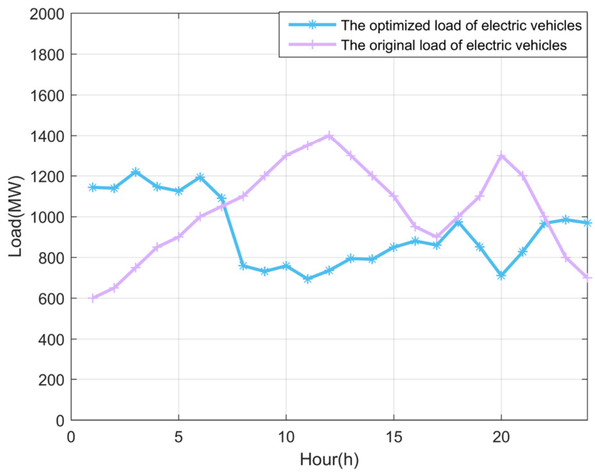

FIGURE 3. The original and optimized load of EVs.

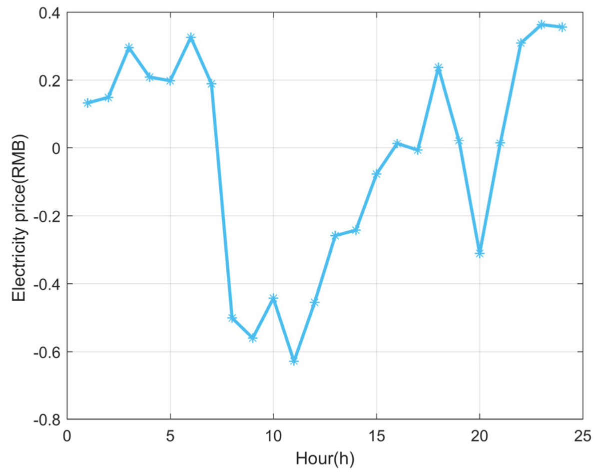

FIGURE 4. The optimized TOU price difference value comparing to the original TOU price.

of "filling the valley" is achieved. And the corresponding adjustment can be directly reflected by comparing with the curve before and after the optimization in Fig. 2. The optimized price (blue curve) of 23h to 24h and 1h to 7h is lower than the original price (purple curve), but the opposite trend appears in 8h to 15h. The effect of tariff adjustment on EV charging load can be seen in Fig. 3. After optimization, the charging load of EV at night (23h-24h and 1h-7h) shows an overall upward trend, and the average charging load in this period increases from 811MW to 1112MW, increased by 301MW. However, in the peak period of 8h to 15h, EV users reduce their own charging demand for price raising measures made by power grid. Before optimization, the peak value appears at $t = 12$h and $t = 20$h, with the peak value of 1400MW and 1300MW respectively. After optimization, it is maintained at about 700MW, which obviously leads to the effect of "peak cutting".

For the sake of making the optimized effect more clear and intuitive, and highlighting the validity of the article model, the comparison chart of TOU price difference and EV charging load difference of each game round before and after optimization is given below, as shown in Fig. 4 and Fig. 5 respectively. It can be clearly seen from Fig. 4 that the difference between the price before and after optimization is positive in the time ranging from 1:00 a.m. to 7:00 a.m., which indicates that the price after optimization is lower than that before optimization, while the difference between the loads in Fig. 5 is negative, which also indicates that the charging load of the optimized EV is higher than that before optimization. In the time range of 8:00 a.m. to 15:00 p.m., the difference between the price before and after optimization is negative, which indicates that the price after optimization is higher than the price before optimization. However, the difference between the loads in Fig. 5 is positive, which also indicates that the charging load of the optimized EV is lower than the load before optimization.

In order to explore the influence of EV charging load adjustment on the overall load of power grid and verify the

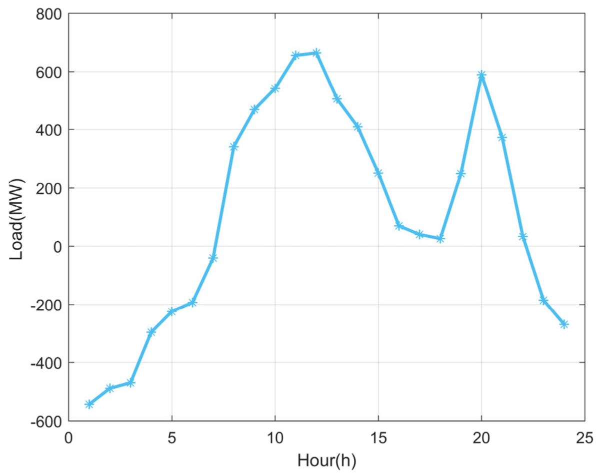

FIGURE 5. The optimized load of power grid difference value comparing to the original load of power grid.

effectiveness of the differential game model constructed in this paper on the grid side, the following will further explain the improvement of the grid load pressure under the regulation of the G2V game strategy. Fig. 6 and Fig. 7 show the changes of the total load of the grid before and after optimization and the changes of the load of the grid in each game round respectively.

It can be intuitively seen from Fig. 6 that by adjusting the charging behavior of EVs, the total load of the power grid is reduced by 2505MW. This can provide corresponding assistance for stabilizing the load fluctuation of power grid. And the benefits of "peak load shifting" of EV charging load brought by regulation and control of electricity price can also be reflected on the grid side in Fig. 7. As shown in Fig. 7, the peak value of power grid load before and after optimization appears simultaneously in 13h. Before optimization, the peak value of power grid is about 7700MW, while after optimization, the peak value decreases to about 7200MW,

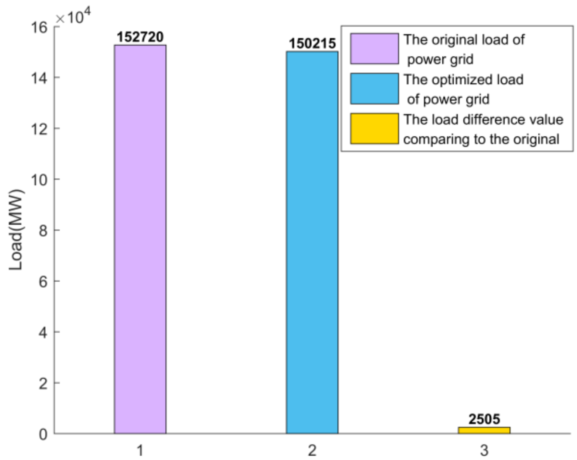

FIGURE 6. Change of total load.

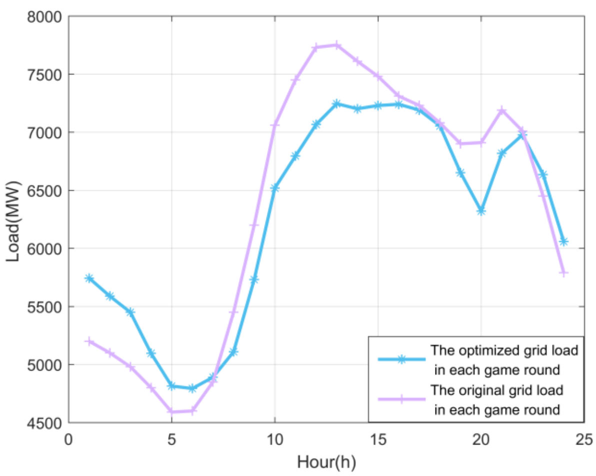

FIGURE 7. Change of grid load in each game round.

and the peak value decreases by about 500MW. At the same time, the valley value of the power grid before optimization appears in 5h, which is about 4600MW, while the valley value of the power grid after optimization appears in 6h, which is about 4800MW. The valley value of the power grid is 200MW higher than that before optimization. And in the period of 23:00-07:00, the load of the optimized power grid is always higher than the load before optimization, while in 8h-15h, the blue curve is always below the purple curve, which shows that the load of the optimized power grid is always lower than the load before optimization in this period.

To sum up, the effect of peak shaving and valley filling is obvious, which verifies the validity of the model in the power grid side.

Next, the load characteristics before and after optimization are further analyzed in combination with the peak valley difference rate of load, as shown in Fig. 8 and Fig. 9.

From Fig. 8, it can be seen that after optimization, the peak valley difference rate of EVs has been reduced by 14.1% from 57.14% to 43.04%; Similarly, the peak valley difference

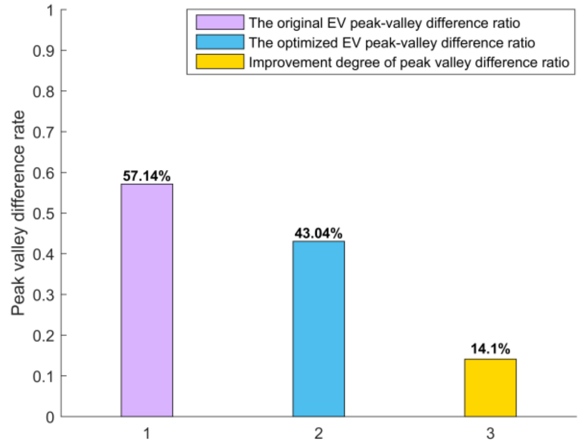

FIGURE 8. The optimized EV peak-valley difference ratio compared to the original.

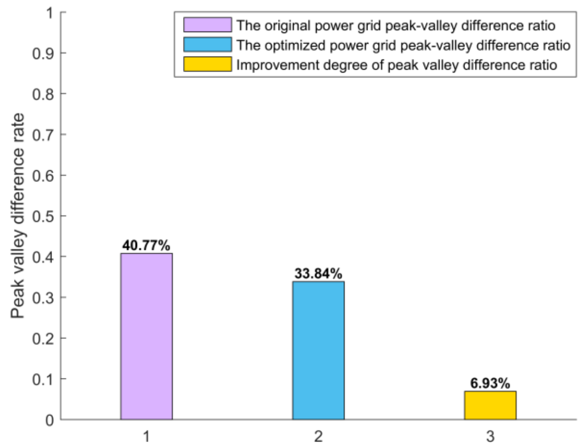

FIGURE 9. The optimized power grid peak-valley difference ratio compared to the original.

rate of power grid has also been reduced from 40.77% to 33.84% and reduced by 6.93%. The peak valley difference rate decreased significantly. On one hand, it reduces the problem of too many times of start and stop of generating units in the grid caused by too great peak valley difference, and reduces the cost of system regulation; on the other hand, reducing the peak valley difference can effectively suppress the fluctuation of grid load and ensure the safe and stable operation of the grid.

The benefits of the model for EV users can be further shown in Fig. 10, which shows the histogram of the cost and the difference between the two before and after the optimization. It can be seen clearly and intuitively from Fig. 10 that the cost expenditure of EV users will be reduced by 8524.38RMB compared with that before optimization. The measures will greatly stimulate the enthusiasm of EV users to participate in intelligent charging, and effectively respond to the DR to adjust the grid load by adjusting the electricity price.

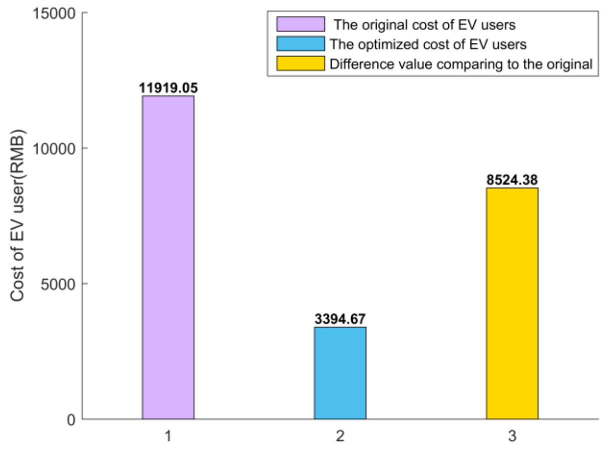

FIGURE 10. The optimized benefits of EV users compared to the original.

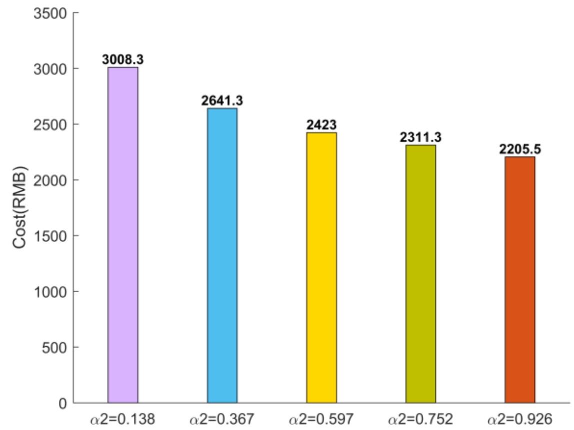

FIGURE 11. Cost for EV users in different α_2 cases.

In order to further understand the impact of EV users' satisfaction with intelligent charging behavior on their costs, this paper analyzes EV users' costs under different α_2 (the correction factor that regulates EV users' charging behavior) environments, and the results are shown in Fig. 11. As can be seen from Fig. 11, with the increase of α_2, the cost of EV users shows a decreasing trend. The cost of EV users has been reduced from 3008.3RMB to 2205.5RMB, reducing by 802.8RMB, which indicates that the higher the satisfaction of EV users to participate in adjusting self-charging behavior and the greater the satisfaction benefit is, the lower the cost is. And the rationality of the construction of the above-mentioned cost model for EV users is also verified.

V. CONCLUSION

This paper presents a differential game model of G2V to optimize the power grid loading and minimize the cost for EV users. The 24 hour electricity price of a city and the charging load of EVs are taken as the main research objects for simulation analysis. The results show that the reasonable charging of EVs can be realized by the guidance of TOU price. Ascribed to this method, the scale of improvement of peak valley rate increases significantly. The effect of peak reducing and valley filling is remarkable, which effectively eases the grid load fluctuations, and reduces the cost for the electric car owners. Finally, based on this differential game model, the power grid and the benefit of the EVs' users are well guaranteed at the same time, and both finally achieve mutually beneficial win-win situation. Based on this work, by considering the actual situation, a follow-up research of studying the impact of EV discharge phenomenon on the power grid and EV will be carried out in the next step.

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