The Diffusion Path of Distributed Photovoltaic Power Generation Technology driven by Individual Behavior

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Abstract: The widespread adoption of distributed photovoltaic (PV) power generation technologies among electricity consumers is a crucial factor in enabling the power system's low-carbon transition. While extensive research has explored consumers' willingness to adopt this technology, prior studies have primarily focused on static psychological factors. This study, however, takes a heterogeneous behavioral perspective by examining the dynamic effects of individual behavioral interactions on technology diffusion. We construct a technology diffusion model for distributed PV power generation, simulate the changes in user adoption willingness, and assess the impact of external economic interventions. Our simulation results indicate that residential environment constraints, resulting from individual behavioral differences, can influence the diffusion potential of technology. Furthermore, non-mandatory promotion methods are more effective in enhancing user adoption willingness. Interestingly, we found that free installation interventions tend to reduce the diffusion effect in later stages and should not be implemented in isolation. These insights can contribute to enhancing the diffusion of distributed PV power generation technology and furthering the development of low-carbon electricity.

Keywords: technology diffusion; distributed photovoltaic power generation; agent-based modeling; adoption willingness

1. Introduction

In the context of achieving "carbon neutrality", large-scale development of renewable energy worldwide can facilitate the clean and low-carbon transition of the energy structure, which has become an important approach to addressing climate change. With the rapid development of renewable energy in China, problems associated with grid-connected renewable energy consumption have gained wide attention, and demand-side consumption is also being constrained [1]. Distributed PV power generation technology has become one of the typical representative technologies. How to enhance large-scale consumption of distributed photovoltaic technology on the power user side is a key issue.

By the end of 2020, the proportion of the total installed capacity of renewable energy in China had reached 42.4%, but the electricity generated by renewable energy accounted for only 29.5% of the total electricity consumption in the society, which is still a considerable gap from the expected value of 2/3 by the end of the "Fourteenth Five-Year Plan". Even if new, cleaner green technologies have been developed, the adoption rate of new technologies may be slow [2-3].

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PV power generation technology as a distributed power source has a vast application prospect [4-5], which has promoted the growth of new types of distributed power users who can generate electricity for their own use, and also increased the diversified needs of power users. Compared with other renewable energy technologies, distributed PV power generation technology relies more on grassroots community construction and popularization to improve user acceptance. How to accurately grasp user needs and preferences and improve customer satisfaction has become a major challenge for the customer service center of power companies [6-7]. There are also practical impediments in the development of domestic PV power generation markets, such as high application costs, reduced subsidies, and difficulties in coordinating the interests of grid companies and user stakeholders [8]. Therefore, how to enhance the adoption willingness of power consumers toward distributed PV power generation technology in the power market is an important research direction for continuously promoting the market diffusion of renewable energy technologies [9-10], and it is also conducive to helping customer service centers formulate more precise power user service strategies.

The commonly used research methods for technology market diffusion mostly focus on macroscopic diffusion trends. The results at the individual level are accumulated to obtain macroscopic diffusion data. Scholars quantify consumers' technology preferences to depict the process of technology adoption and diffusion in the market [11-12]. Among them, discrete models are generally used to describe the impact of individual consumer preferences on technology adoption, and then to explore the key factors affecting the diffusion of technology in the market [8]. However, these studies focus on the "static" attributes and preferences of individual consumers [13], without considering the dynamic constraints in the living environment caused by the differences in subsequent energy use behaviors of consumers who have already purchased. In the early years, some scholars took into consideration the influence of internal and external dynamic factors and proposed the Bass diffusion model [3], which added the influence of external dynamic factors between consumer groups, such as information dissemination and information interference, on the diffusion law. However, most of the models used in past research are based on the premise of rational people to establish diffusion models, assuming that the accumulated behavior results of homogenous preference individuals approximate the actual market operation results, but they ignore the heterogeneity preferences of consumers in reality [14-15]. The previous technology diffusion research has certain limitations. On the one hand, due to the homogenization consideration of the rational people hypothesis, it is difficult for individual behavior differences to be depicted in previous diffusion models [16]; on the other hand, the behavior differences between users who have already adopted photovoltaics and potential users influence consumer technology adoption intentions and further determine the future technology diffusion path. Most of the previous studies are limited to individual choice decisions. The green energy use behavior of users who have already purchased will further affect market diffusion, which is rarely a concern, and there is little research on the connection and behavior interaction between individuals. These limitations of previous research have posed challenges to the power customer service center in improving customer satisfaction.

In response to the above problems, the agent-based modeling method (Agent-based modeling, ABM) is adopted. By considering the heterogeneity factors such as the technology preference choices and energy use behavior of power users [17], simulation experiments are conducted to operate the complex system, restore the real market situation, and reflect the diffusion mechanism and path more comprehensively from the perspective of behavior.

2. Modelling of distributed PV power technology diffusion

Agent-based Modeling (ABM) is used to propose a diffusion model for distributed PV power generation technology. This study selects distributed users who have already adopted distributed PV power generation technology and potential users who have not installed it as the research subjects. This section primarily introduces the framework and process of model construction, as depicted in Fig. 1.

The diffusion model mainly consists of three parts. Firstly, considering the heterogeneous factors such as the psychological preferences and energy use behavior of power users, we conduct a user decision survey to construct a dynamic decision model for multiple agents. Secondly, an attitude communication network in the power users' living environment is built. Lastly, we design rules for information dissemination and willingness updates.

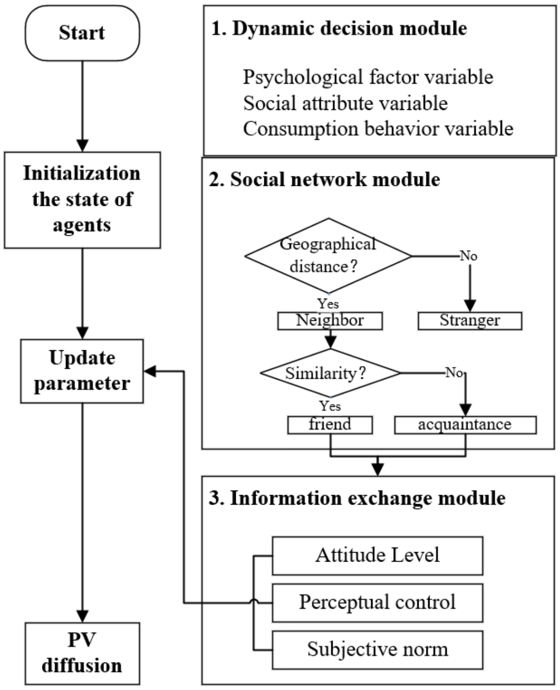


Fig. 1. Framework and process of the distributed PV power generation technology diffusion model

2.1 Description of the Data

To better characterize the technology diffusion model and meet the needs for parameter initialization, a questionnaire survey and data collection work were conducted in the early stage of the simulation. This provides data support for this study. The specific data are divided into two parts.

First, adoption willingness data. This part of the data is obtained from the questionnaire statistics, collected from July to December 2019 from urban and some rural users in Tianjin, using cluster sampling to ensure the representativeness of the sample. A Likert scale of five points is used for design, which includes users' psychological variables, social demographic attribute values, and other parameter values. A total of 1128 questionnaires were collected online and on-site, with 984 valid questionnaires after preprocessing, and an effective recovery rate of 87.2%. 219 households have installed PV power generation systems (adopted users), and 765 households have not installed photovoltaic power generation systems (potential users). By importing the questionnaire survey data into the model, we provide data support for the willingness preferences and decisions of the agents.

Second, energy use behavior data. The green energy use behavior data, which describes the use behavior after the adoption of household photovoltaics, is composed of monthly electricity data and PV power generation data from 3,620 households from January 2014 to May 2019. As the behavior data only targets users who have adopted, to match the number of subjects in the willingness part, this study randomly samples without replacement the earliest electricity use behavior data from 219 households that have adopted photovoltaics as the initial behavior variable value. This provides data support for updating the energy use behavior after the agent has been adopted.

2.2 Modeling the Decision of Agents

Social psychology believes that individual behavior will be influenced by the psychological variables of the behavior subject. Current domestic and foreign research mostly explores the influencing factors of consumer adoption from a social-psychological perspective. Early scholars based on the Theory of Planned Behavior (TPB) and the Value-Belief-Norm (VBN) theory considered factors such as self-identity, environmental awareness, and normative attitudes to study green adoption intentions [18-19].

According to the Theory of Planned Behavior (TPB), the attitude level, personal subjective norms, and perceived control of the actor determine his behavioral intention, and the intention also affects the final green adoption behavior [15][20]. This study focuses on the fact that distributed users are different from traditional consumers. For example, the psychological factors after adoption will be affected by the differences in energy use behavior among users, which may further affect the adoption willingness of potential power users. Therefore, based on the important influencing factors of previous studies, this study adds consideration of energy use behavior characteristic factors and constructs a comprehensive dynamic decision model framework. This decision framework not only includes social attributes, environmental policy factors, psychological behavior factors, etc. in the early stage of consumer behavior decision-making, but also focuses on variables such as the attitude level (AT), subjective norm (SN), and perceived behavior control (PBC) of the individual.

Firstly, based on the early questionnaire survey data on consumers' social attributes, and psychological, behavioral, and attitudinal variables, and according to the integrated model of intention theory, the influence mechanism of consumers' adoption willingness for distributed PV power generation technology is designed. Through empirical analysis, a regression model is obtained to express the willingness level, as shown in formula (1).

$$IN_{i,t} = \beta_0 + \beta_1 CONTROL + \beta_2 AT_{i,t} + \beta_3 SN_{i,t} + \beta_4 PN_{i,t} + \beta_5 PBC_{i,t} + \beta_6 POL_{i,t} + \varepsilon \quad (1)$$

in which:

$\mathrm{IN}_{i,t}$—agents' willingness level to adopt distributed PV power generation technology.

$\beta_i (i = 1,2, \ldots ,6)$—the standard coefficient between the willingness value to adopt distributed PV power generation technology and each influencing variable, obtained by empirical regression.

CONTROL —control variables, mainly composed of social statistical variables in the questionnaire, including age, gender, annual income, education level, family population size, etc.

AT—attitude.

SN—subjective norm.

PN—personal norm.

PBC—perceived behavioral control.

POL—policy factors.

ε—the error term.

Secondly, the characteristic values of electricity use behavior are calculated using household monthly electricity data and PV power generation data. As the PV power generation system is ready for use after installation, electricity generated during the day through solar radiation first meets the electricity usage of residential households, with the surplus power transferred to the local grid. At night, all household power supplies come from the power grid companies. The proportion of user-generated electricity to total PV power generation is a green behavior characteristic($GB_{i,t}$), as shown in formula (2). This behavior characteristic data will further influence power users' adoption willingness for distributed PV power generation technology.

$$GB_{i,t} = GeneratedUsed / TotalGenerated \quad (2)$$

in which:

$GB_{i,t}$—green behavior characteristic.

$GeneratedUsed$—the electricity generated by the user through PV and its own use.

$TotalGenerated$—the total amount of electricity generated by the user through PV.

Thirdly, the adoption willingness influencing parameters and electricity use behavior characteristic parameters of all consumers are imported, and the initial adoption willingness and related attitudes and behavior characteristics of each agent are clarified. This completes the initialization, thereby successfully constructing the dynamic decision module of the user.

2.3 Modeling the Social Network

The first module completes the import of the initial status of all consumers. The second module mainly simulates and builds the social communication and relationship network among individuals. This study mainly refers to the "small world" network structure proposed by previous scholars. The "small world" network is widely used in social network research because the probability of all individuals establishing connections in this network structure is fixed and random, so it can more realistically reflect the relationship between people in society.

As the adoption agent of PV power generation systems is generally power household users, based on the small world network, this study assumes that the social network of power household users is a small world network. Considering that in the same living environment, the differences in energy use behavior among different users may bring about a certain environmental constraint, which may affect the user's adoption willingness. Therefore, in this study, we focus on the influence of the living environment on the diffusion of PV power generation technology, set the physical living range of the agent, use the straight-line distance between two agents to represent the physical proximity of living, the agents within the range are set as community members, all of whom may randomly establish connections, becoming friends or neighbors, those outside the physical range are disconnected, becoming strangers, and information exchange and behavior influence mainly occur among friends and neighboring groups.

According to the degree of similarity of social attributes, it is distinguished whether it is a "friend". The similarity of social attributes between agents uses the concept of the Blau space multi-dimensional coordinate system, and the various variables of social attributes are used as each dimension for construction, as shown in formula (3). The social network construction module lays the physical foundation for the subsequent exchange and diffusion between agents.

$$\Delta_{\mathrm{ij}} = \sqrt{\sum_{m \in \mathrm{X}} (S_{\mathrm{mi}} - S_{\mathrm{mj}})^2} \tag{3}$$

in which:

S_m—the currently considered demographic variable.

S_{mi}—the variable value of a certain demographic attribute of agent i.

$\Delta_{i,j}$—the similarity of social attributes between agents.

2.4 Modeling the Information Exchange Process

The willingness of user agents to adopt solar photovoltaic technology will be changed to varying degrees in the process of information dissemination and agent communication. Based on the construction of the dynamic decision and social network modules of the agent, this section designs the rules for information exchange, thereby simulating the diffusion process of information dissemination and attitude changes.

The psychological influencing factors of the user's willingness to adopt PV power generation technology are mainly attitudes, which are characterized by uncertainty and attitude overlapping ratio. Since the indicator variable in the basic data is measured by a five-point Likert scale, each agent's attitude score is 1-5 points, so when the attitude variable value is close to 3 points, it means that the user has a neutral attitude towards PV power generation technology, and the willingness to adopt is high in uncertainty; conversely, if the attitude variable value is close to the extreme values of 1 or 5, it means that the willingness to adopt is very low or high, and the uncertainty is very low at this time. Uncertainty is calculated from attitude and is specifically expressed as a segmented normal distribution function, as shown in formula (4).

$$U_{i,t}=\begin{cases}\mathrm{N}(2,0.1) & \text{if} \quad AT_{i,t}\in[2,4]\\ \mathrm{N}(1,0.2) & \text{if} \quad AT_{i,t}\in[1,2)\cup(4,5]\end{cases} \tag{4}$$

in which:

$U_{i,t}$—the uncertainty of the attitude of agent i at time t;

AT_{ij}—the attitude level value of agent i at time t.

$(AT_{ij}-U_{i,t}, AT_{ij}+U_{i,t})$—each agent's range of attitude fluctuations.

Based on the calculation of uncertainty, the next step is to determine the degree of attitude overlap between different agents and thereby change the attitude value. In communication between agent i and any other agent in its social network, there can be a situation of attitude overlap. The degree of attitude overlap is defined as the difference between the minimum value of the upper limit of the attitude fluctuation range of two agents and the maximum value of the lower limit. At this point, the calculation formula for the degree of attitude overlap is as shown in formula (5). If the degree of attitude overlap is greater than 0, it indicates that the preference consistency is high. At this time, the change in the user's attitude value at stage t can be calculated from the degree of attitude overlap, as detailed in formula (5). If the degree of attitude overlap is negative, friends can still have information exchanges and broadcasts that cause changes in the attitude of agent i, but if they are in a relationship with strangers (disconnected), the change in the attitude of agent i is zero.

$$Overlap_{ik}=\min((AT_{i,t}+U_{i,t}),(AT_{j,t}+U_{j,t}))-\max((AT_{i,t}-U_{i,t}),(AT_{j,t}-U_{j,t})) \tag{5}$$

$$\Delta AT_{ij,t}=\frac{\left|Overlap_{ij,t}\right|}{4}\times(AT_{j,t}-AT_{i,t}) \tag{5}$$

in which:

$Overlap_{i,k}$—the degree of attitude overlap between agent i and j.

$\Delta AT_{ij,t}$—the change in the user's attitude value at stage t.

Considering the constraint influence of the agent's living environment on behavior, the attitude value is updated again based on the agent's personal norm (PN) and subjective norm (SN). Since the green behavior characteristic value of the power user who has not adopted photovoltaics is 0, the green energy use behavior of users who have already adopted PV power generation technology in the surrounding area will bring about behavior differences. The difference or loss caused by the different behavior choices of two individuals is called paired pressure [21]. Define the difference in behavior that each individual perceives between the surrounding individual and itself as pressure ($press_{i,t}=|\Delta GB_{i,t}|$), when this value exceeds the environmental constraint threshold (threshold), the individual norm and subjective norm of the agent will affect the change in attitude, thereby updating the adoption attitude. The final attitude update is as shown in formula (6).

$$AT_{i,t+1} = AT_{i,t} + \frac{SN_{i,t}}{SN_{i,t} + PN_{i,t}} \times \Delta AT_{ij,t} \tag{6}$$

in which:

$AT_{i,t+1}$—the user's attitude value at the next stage of t.

Further considering the intervention impact of external conditions, based on the theory of planned behavior, the agent will control the perception of the agent based on objective factors such as the cost of technology and personal payment ability, thereby forming perceived behavioral control (PBC). The greater the perceived behavioral control, the higher the possibility that the user agent will adopt PV power generation technology. Perceived behavioral control is affected by the purchase cost of the PV power generation system (Cost) and external economic incentives (Rsub). An increase in cost will affect the initial perceived behavioral control of user agents with lower perceived behavioral control. Changes in external incentives may also change perceived behavioral control, as shown in formula (7).

$$PBC_{i,t+1} = PBC_{i,t} - \frac{1}{PBC_{i,t}} \times (Cost - R_{\text{sub}}) \tag{7}$$

in which:

$PBC_{i,t}$—the perceived behavioral control value of agent i in stage t.

$PBC_{i,t+1}$—the perceived behavioral control value of agent i at the next stage of t.

$Cost$—the purchase cost of the PV power generation system.

R_{sub}—the external economic incentives.

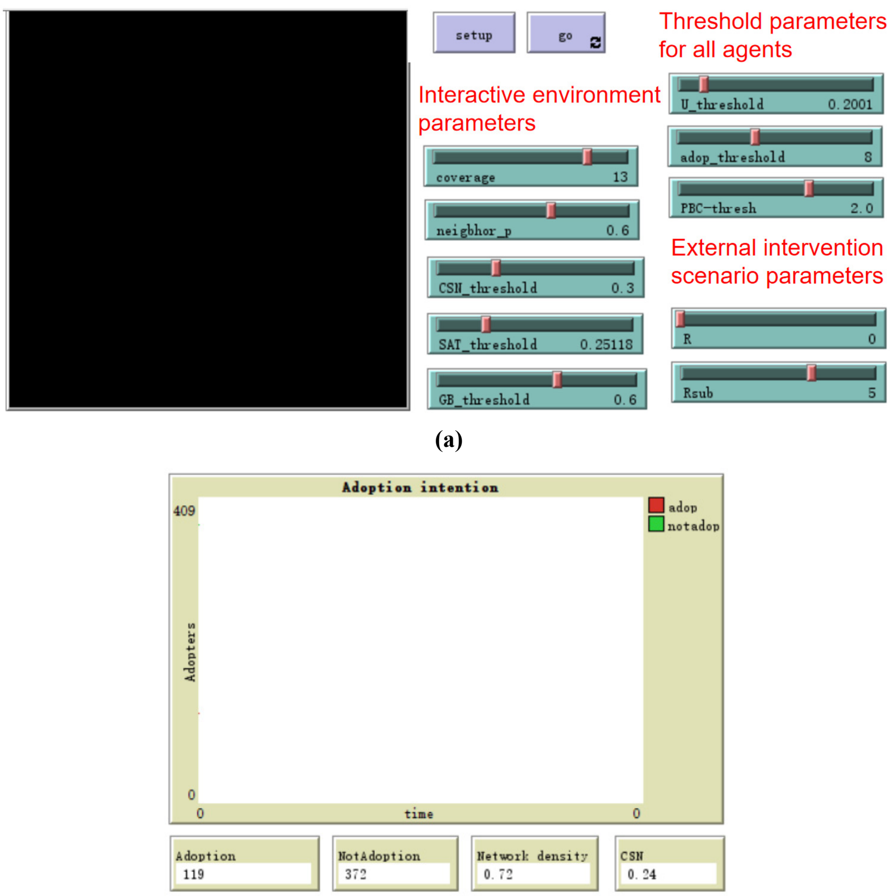
Finally, based on the updates of the above attitude values, perceived behavioral control, and personal behavior norms, the updated value of the final individual's willingness level to adopt distributed PV power generation technology (IN) is obtained. When it exceeds a certain threshold, it can be considered that the individual is willing to adopt distributed PV power generation technology.

3. Simulation Experiments and Results

3.1 Simulation

This study uses NetLogo 6.1.1 software as an interactive simulation experiment platform for social network simulation. With its excellent visualization window, it can better capture the dynamic changes of willingness in technology diffusion. By creating action buttons, view windows, and compiling codes, a simulation is conducted on the distributed PV power generation technology market diffusion model. The NetLogo interfaces of the distributed PV power generation technology diffusion model can be seen in Fig. 2. Collaboration activity sliders in the model include interactive environment parameters, external intervention scenario parameters, and threshold parameters for all agents (shown in Fig. 2 (a)). This provides a prediction for changes in the number of users willing to adopt distributed PV power generation technology in real life and evaluates the effects of adding external economic intervention measures. Simulation results are output in Fig. 2 (b).

The initial distribution and adoption status of the user agents are shown in Fig. 3. Red dots represent users willing to adopt distributed PV power generation technology, that is, the adoption intention (IN) is greater than the preset threshold, indicating a willingness to adopt; green dots represent users whose current adoption intention is not strong; the connection relationship between users is marked with a gray line, and the position of the user agent in the distribution diagram is randomly updated each time. Considering the randomness in the simulation process, to enhance the reliability of the final results, this study performs multiple simulations on the initial data and averages the calculations to ensure that the resulting data is objective and reliable.



(b)

Fig. 2. The distributed PV power generation technology diffusion model interface: (a) input and world; (b) output and plot

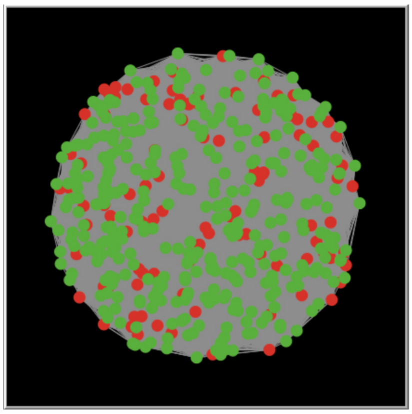


Fig. 3. Initial distribution of agents in NetLogo software

3.2 Result Analysis

This study pays attention to the fact that there are distributed users who have already installed distributed PV power generation technology in the surrounding of power users, and their energy use behavior will affect other potential users. Therefore, this study sets the difference in energy use behavior of surrounding people as the constraint force that the agent perceives from the living environment, and the dynamic changes in the constraint force of the user's living environment will affect the intention to adopt green technology.

When the environmental threshold (threshold) is low when the constraint force perceived by agent i is always greater than the threshold, the strong environmental constraint takes effect, as shown in Fig. 4 (threshold=0.1). At this time, under strong constraints, users will rush to change their adoption intention after first perceiving the pressure brought about by behavior differences, and the number of adopters quickly reaches a high point. After friend communication and consideration of payment ability, the willingness to adopt will weaken in the later period, the number of adopters shows a downward trend until stability, and the final number of willing adopters is 246, accounting for 51.04% of the number of users in the living area.

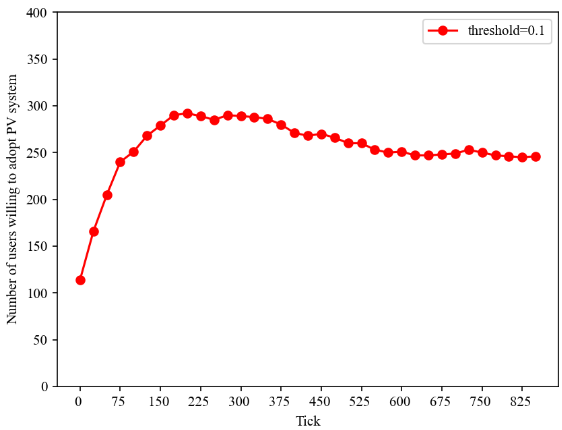


Fig. 4. Changes in the number of users willing to adopt under strong environmental constraints

When the environmental threshold (threshold) is moderate, when the effect of strong environmental constraints is greater than the weak environment, the result is as shown in the brown line in Fig. 5 (threshold=0.3); conversely, when the effect of weak environmental constraints is greater, the result is as shown in the yellow line in Fig. 5 (threshold=0.4). When strong and weak environments play a role at the same time, and when the strong environmental constraint plays a greater role (the brown line in Fig. 5), the decrease in the number of willing adopters in the later period is more obvious, and the final number of willing adopters is only 180, accounting for only 37.66% of the total number of users. At this time, due to the existence of two comparisons of strong and weak environments, it will stimulate users in the strong environment to increase the decrease in willingness due to the gap caused by the contrast between their behavior and the green behavior requirements of the environment; when the weak environment plays a greater role (the yellow line in Fig. 5), it will improve the phenomenon of a decrease in the number of willing adopters in the later period, and the final number of willing adopters is 219, which improves the final stable adoption ratio in the living environment to 44.51%, an increase of 7% compared to the former.

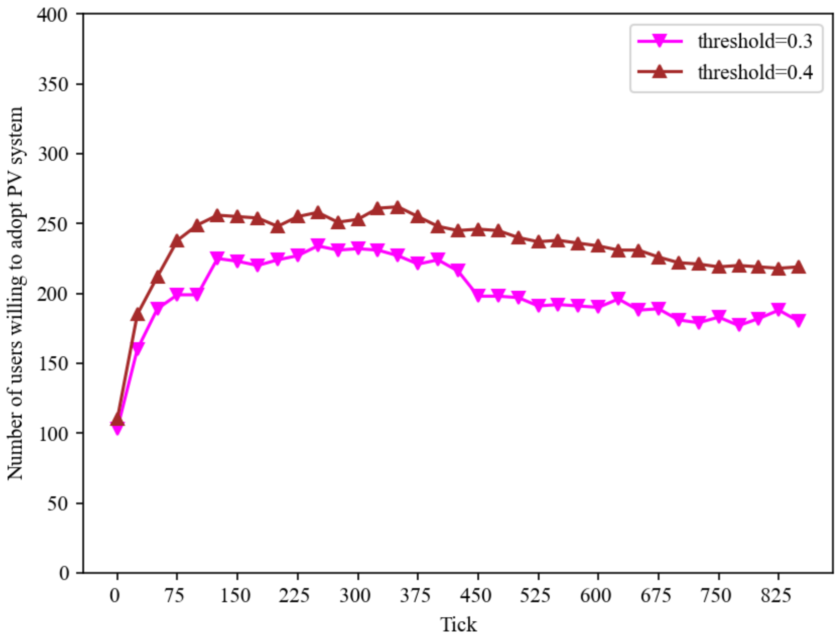


Fig. 5. Changes in the number of users willing to adopt under the joint effect of strong and weak environmental constraints

When the environmental constraint perceived by agent i is always less than the threshold, the weak environmental constraint takes effect, as shown in Fig. 6 (blue, green, and purple respectively represent threshold values of 0.7, 0.8, and 0.9). Under weak environmental constraints, the number of willing adopters will significantly increase (the numbers of willing adopters under the three thresholds successively reach 316, 366, and 378), and as the threshold increases, the final adoption ratio (respectively reaching 64.62%, 74.39%, 76.83%). This is because, under the influence of the weak environment pathway, users themselves will perceive behavioral differences and adjust through personal norms. The lack of mandatory constraints is more conducive to users increasing their adoption intention.

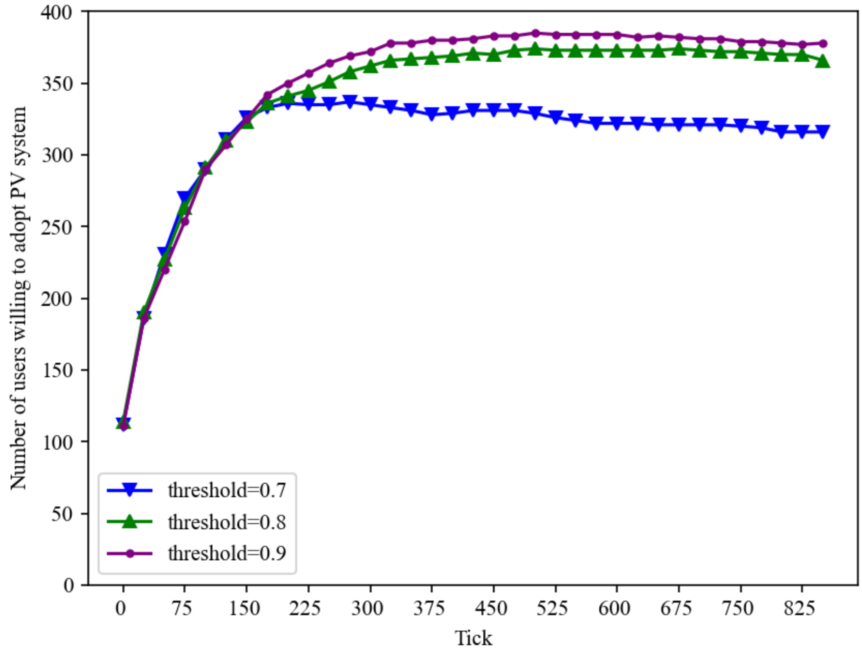


Fig. 6. Changes in the number of users willing to adopt under weak environmental constraints

In summary, strong environmental constraints only help to increase user adoption willingness in the short term; the influence of weak environmental constraints is more conducive to stably improving the adoption willingness of potential users in the long term, and ultimately increasing the overall living environment's adoption ratio for distributed PV power generation technology.

3.3 External Intervention Effect Assessment

Considering the influence of the agent's personal payment ability on the willingness to adopt distributed PV power generation technology, external economic intervention measures are added to improve the decrease in the number of willing adopters that may occur in the later period. In this part, the benchmark model selected sets the strong and weak environmental constraints to work at the same time, thereby controlling the influence of environmental constraints. The external economic incentive $(R_{sub} = 0)$ is used as the benchmark situation, as shown in the gray line in Fig. 7.- Fig. 10. At this point, the final number of willing adopters is 164, accounting for 35.04% of the final stable adoption ratio in the living environment. The external economic incentive R_{sub} is set to compare it with the technology investment cost (Cost).

When the external economic incentive $(0 < R_{sub} < Cost)$ is increased (Fig. 7), a certain cost subsidy is provided for installing the PV power generation system, and the number of willing adopters in the later period is significantly increased to 281, and the stable adoption ratio is 58.66%; When the continuous increase in external economic incentives far exceeds the cost($R_{sub} > Cost$), that is (Fig. 8), it is equivalent to an additional economic reward, at which point the incentive effect is more significant and the adoption ratio in the final environment is significantly improved, the number of adopters is 361, and the ratio is 75.84%, showing a long-term growth trend. But when the external economic incentive is just equal to the cost($R_{sub} = Cost$), that is (Fig. 9), the number of willing adopters gradually decreases, and the stable adoption ratio in the environment is also significantly reduced after stabilization. Compared with the benchmark situation, the number of adopters, 192, is not much different, and the final adoption ratio is 39.75%, which is not significantly improved. At this time, because users do not need to consider the installation cost of the PV power generation system, when the photovoltaic system is installed for free, the user's perception of behavior control will ignore the cost factor and consider more other objective conditions, and there may be technology anxiety and adoption risk for new technologies. Considering that economic incentives also exist economic penalties such as carbon tax or causing environmental pollution, it is set $R_{sub} < 0$ (Fig. 10), this time it helps to stably improve the adoption ratio to 62.19%, the number of adopters is 301, and compared with the benchmark situation, it can be found that this measure has a good incentive effect.

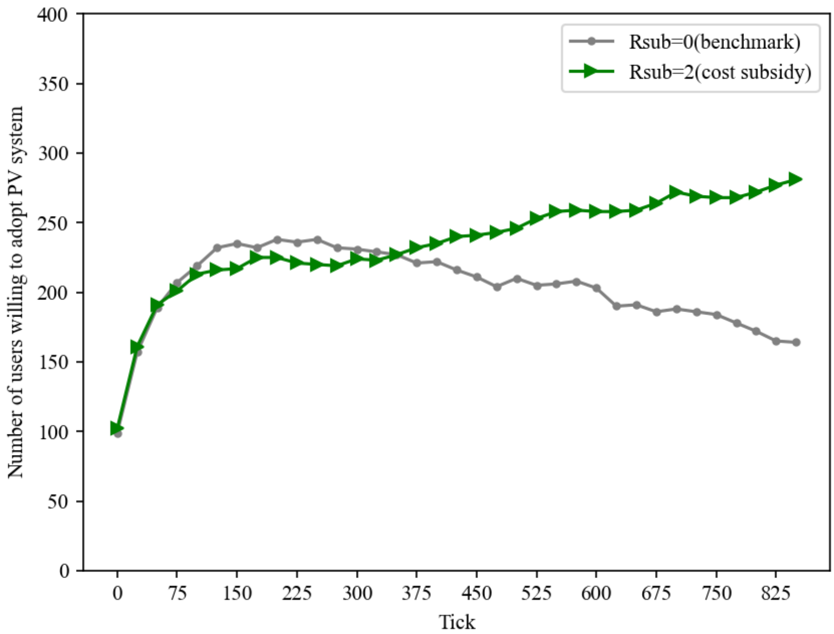


Fig. 7. The external incentive is a cost subsidy

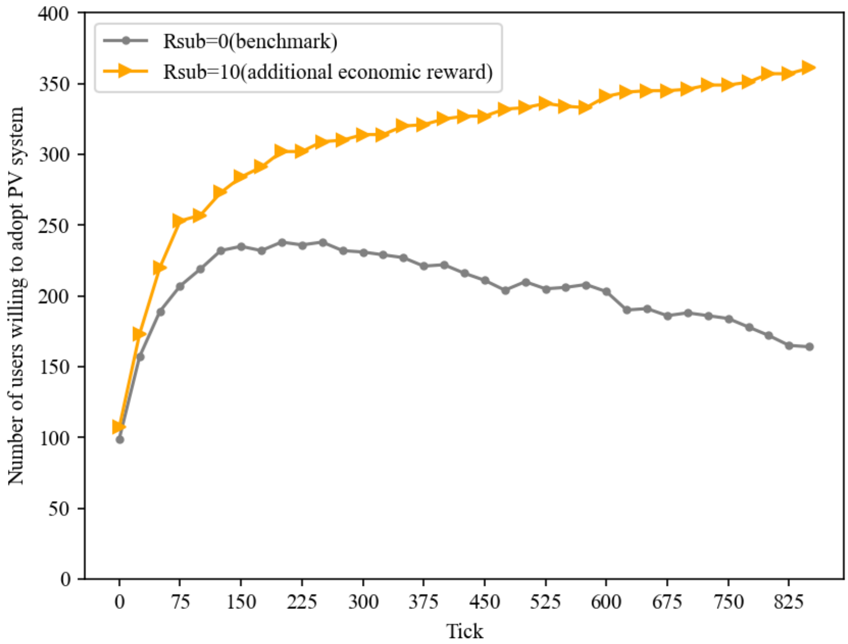


Fig. 8. The external incentive is the additional economic reward

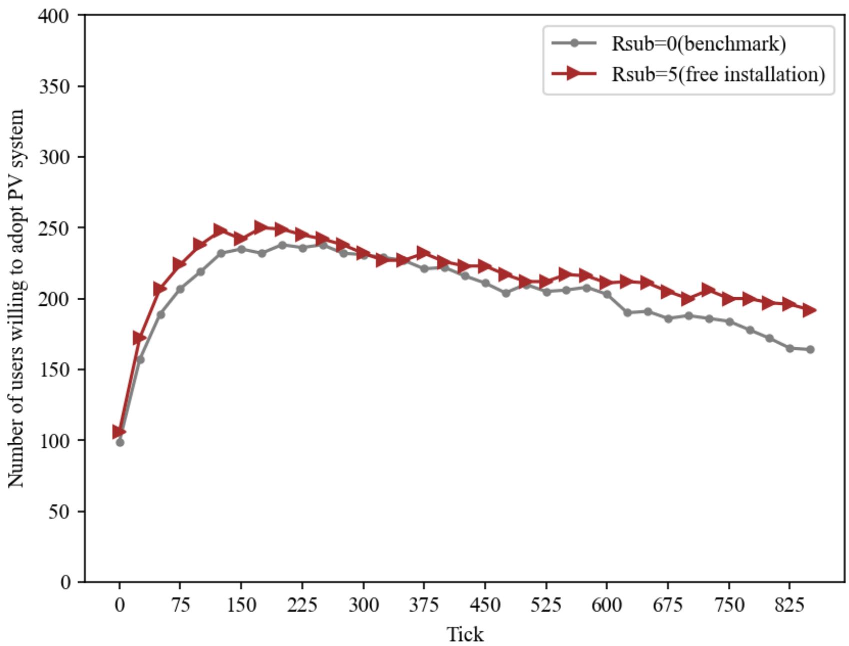


Fig. 9. The external incentive is the free installation of the distributed PV system

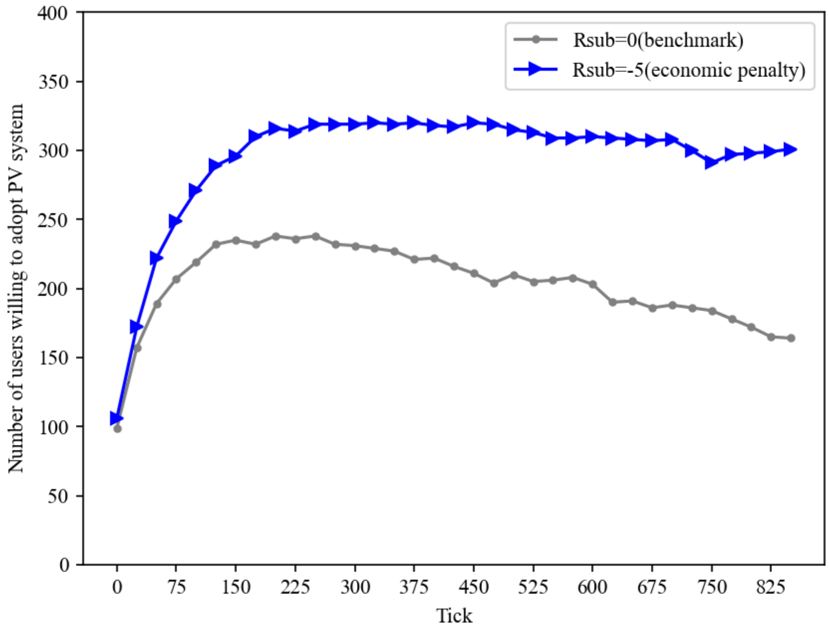


Fig. 10. The external incentive is an economic penalty

In summary, in terms of the effect of significantly improving the user ratio willing to adopt distributed photovoltaic technology, the additional economic reward effect is the best, and the cost subsidy and economic penalty effects are second; among them, economic penalties are more conducive to improving and maintaining the stability of the overall environmental greening; but free installation will reduce the adoption rate.

4. Conclusion

This study, from the perspective of individual behavior, constructs an agent-based distributed PV power generation technology diffusion model. Through simulation experiments, it simulates the dynamic changes in the willingness to adopt technology on the user side, predicts the changes in the number of users willing to adopt PV power generation technology in the demand side of the market, and evaluates the effects of adding external economic intervention measures.

Through the simulation results, this study also provides certain insights and suggestions for the energy service strategy of the power customer service center and the low-carbon development of the power system. The energy use behavior differences in the living environment of power consumers will form certain constraints and influences on whether they adopt renewable energy technologies. To improve the diffusion of green technology at the demand level, it is necessary to pay attention to the living environment of potential users. Through non-compulsory means, consumers can be incentivized, such as publicity and education, community commendation, and other side guidance for user personal norms, which can achieve a higher degree of green. In areas with good sunlight, better preferential policies can help encourage the use of household photovoltaics, which can also be "tailored to local conditions". The method of free installation will reduce the willingness to adopt in the later period, causing consumers to become more rational and consider other objective factors more. This incentive measure needs to be combined with social network relationships for marketing diffusion, relies on the word-of-mouth effect to improve user cognition and recognition of PV power generation technology, and cannot be implemented alone.

Author Contributions:

Wang X.C.: Conceptualization. He X.D.: Methodology. Sun X.Q.: Methodology, Formal analysis, Writing—original draft preparation. Qin M.C.: Formal analysis, Writing—original draft preparation. Pan R.P.: Writing—review and editing. Yang Y.Y.: Software. All authors have read and agreed to the published version of the manuscript.

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