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Community Flexible Load Dispatching Model Based on Herd Mentality

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Abstract: In the context of smart electricity consumption, demand response is an important way to solve the problem of power supply and demand balance. Users participate in grid dispatching to obtain additional benefits, which realises a win-win situation between the grid and users. However, in actual dispatching, community users' strong willingness to use energy leads to low enthusiasm of users to participate in demand response. Psychological research shows a direct connection between users' herd mentality (HM) and their decision-making behavior. An optimal dispatching strategy based on user herd mentality is proposed to give full play to the active response-ability of community flexible load to participate in power grid dispatching. Considering that herd mentality is generated by the information interaction between users, by calling on some users to share the experience of successfully participating in demand response in the community information center and using the Nash social welfare function to model herd mentality to explore the impact of the user. The analysis of an example shows that the proposed strategy gives full play to the potential of community flexible loads to participate in demand response. When users have similar electricity consumption behavior, the herd mentality can effectively improve users' enthusiasm to participate in demand response, and the user response effect meets managers' expectations.

Keywords: demand response; herd mentality; social welfare function; user psychology; flexible load

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1. Introduction

With the acceleration of urbanisation, the widespread penetration of clean energy and the increasing demand for loads have brought new challenges to the power system's balance of supply and demand [1]. The user's flexible load as a dispatchable resource to participate in demand response is considered an essential way to solve the power supply and demand balance problem. Demand response refers to the use of a series of measures to stimulate end-users to change their electricity consumption patterns for the purpose of peak load shifting, mostly in the form of incentives or dynamic pricing [2]. The implementation of demand response projects can reduce customers' electricity costs and increase grid dispatch flexibility; thus, flexible load in smart communities as a means to flexibly participate in demand response has received widespread attention. However, due to the general improvement of people's living standards and the increase of users' awareness of independent energy use, the attractiveness of economic compensation to users' participation in response is gradually weakening, and relying on economic compensation alone can no longer effectively stimulate the enthusiasm of enhancing users' participation in demand response. In order to give full play to the regulation potential of community load participation in demand response, it is necessary to further explore its influencing factors.

Uncertain electricity consumption behavior caused by users' autonomous energy consumption intention is an important factor limiting the development of community demand response [3]. Studies have shown that users' electricity consumption behavior is usually affected by family information such as age, income, education level, environmental factors, comfort preferences, conformity psychology and other psychological factors [4,5]. For this reason, most of the existing studies incorporate factors such as user education, income, and average age into the problem of uncertainty of demand response [6], or use fuzzy methods and flexible load probability distribution forms to describe the uncertainty of response behavior [7,8]. Such processes take the uncertainty of the overall characteristics of users into account, suitable for dispatching scenarios of large power grids. However, for the community-level load scheduling system, the user's actual response often does not match the planned expectations due to the strong randomness of the user's energy consumption behavior. Therefore, from the perspective of community users, some studies have used theories related to consumer psychology to describe the response behavior of users [9–11]. The peak and valley difference electricity price guides users to participate in the response behavior to maximize the active response-ability of community flexible load to participate in grid dispatching, which has practical reference significance. However, the above studies only consider the influence of external factors on users' energy use behavior but ignore the irrational phenomenon that demand response behavior is influenced by mentality, which further increases the uncertainty of community load participation in demand response.

In recent years, some scholars have observed the irrational phenomenon of user participation in demand response and found that the conventional economic influences cannot explain such behavior of users. For this reason, many scholars have turned their attention to psychology to provide a rational explanation for the phenomenon of irrational economics from the perspective of psychological research. Ref. [12] found that user attitudes have a significant impact on user participation in demand response programs, and the stronger the users' awareness of environmental pollution and energy shortage problems, the more likely they are to accept demand response programs, but further research is still needed on how to change users' attitudes; Ref. [13] states that interpersonal relationships influence user participation in demand response programs but does not examine the irrational phenomenon of user participation in demand response in terms of psychological interactions between users. Ref. [14] tries to explain the irrational phenomenon of user participation in demand response by considering the endowment effect of users and the time discounting problem; the endowment phenomenon indicates that operators need to invest more money to change the original energy consumption habits of users [15], and the endowment effect can only explain the reasons for the irrational phenomenon of users, and cannot solve the problem of the low initiative of flexible load dispatching. Ref. [16] investigated the cognitive biases and irrational behavior of users participating in demand response projects and found that users often care about the performance of others or tend to follow others' decisions when making decisions, which is known as herding psychology in psychology. The phenomenon of herding can change the decisions of other users, which makes it possible to increase the initiative of flexible load scheduling. Ref. [17] investigates the influence of user psychology on the implementation of the photovoltaic (PV) projects and confirms that herd mentality and different forms of interpersonal communication influence the willingness of residents to participate in PV projects; research shows that, based on the herd mental, users are easily influenced by others' decisions when making energy use decisions, resulting in herd behavior. Especially during peak electricity price periods, users are often praised for subsidising high electricity prices by imitating others to participate in demand response to obtain additional revenue. Ref. [18] established an electric vehicle charging model of user interaction to achieve demand In response to the purpose of shaving peaks and filling valleys, the user's information security is guaranteed by the administrator; Ref. [19] conducted research and survey on users' willingness to share, and the survey results showed that, on the premise of ensuring information security, users showed a positive attitude towards the behavior of sharing their energy use to achieve community development; Ref. [20] realises the information interaction between users with the intervention of intermediary agencies.

There is a mature theoretical basis for the study of social psychology on electricity energy saving [21], but the analysis of the impact of user psychology on demand response in existing studies is not yet clear. On the one hand, influenced by their psychological factors, the community flexible load (FL) participation in demand response has greater uncertainty, which further aggravates the operational risk of regional dispatch; on the other hand, the existing dispatching strategy fails to fully consider the influence of users' psychological factors and cannot fully play its demand response potential.

Based on existing research, this paper proposes a community flexible load demand response and its optimal scheduling strategy guided by herd mentality to solve the above problems. The main innovations of the article are as follows:

(1) A flexible load optimisation scheduling strategy based on user herd mentality is proposed. The proposed method can improve the initiative and flexibility of users in the community to participate in demand response and give full play to the potential of community flexible load to participate in demand response.

(2) This paper uses the Nash social welfare function to model the herd mentality of the uncertainty of user demand response and realises the quantitative analysis of the impact of user herd mentality on community flexible load scheduling.

2. The Herd Mentality of Community Users

Much literature has confirmed that people's decision-making behavior will be affected by information transmission. When the received information is similar, it often produces a herd mentality and changes its decision-making. However, it is still unknown whether community users will be influenced by herd mentality and change their willingness to participate in demand response. So, this paper sets up the Likert scale according to [22–24] for the two dimensions of user information influence and HM, and proposes two hypotheses for this:

Hypothesis 1 (H1). *Users are influenced by other information when making decisions.*

Hypothesis 2 (H2). *Follow-up behavior occurs when users receive similar information from neighbours.*

250 questionnaires were distributed in total, and 210 effective questionnaires after deducting incomplete answers were obtained. The number of questionnaires is 19 times different from the number of questionnaire questions, which initially meets the statistical requirements. The specific information and data of the Likert scale are given in Appendix A. The rationality of the Likert scale data can be obtained by analysing the basic information of the Likert scale (age, gender, education), and the content of the Likert scale conforms to the laws of demography [22]. According to the SPSS software statistical the Likert scale data, the Cronbach's Alpha coefficient of the reliability information of two influencing factors can be obtained, as shown in Table 1. If Cronbach's Alpha is greater than 0.6 and CITC is greater 0.5, the assumption is valid, users are easily affected by other information in the community, and when users receive similar information, they will produce follow behavior.

Table 1. Information of the Likert scale.

Constructs	Items	CITC	Cronbach's α
Herd mentality [22]	Q4	0.652	0.816
	Q5	0.682	0.808
	Q6	0.669	0.811
	Q7	0.666	0.812
	Q8	0.604	0.828
Information impact [23,24]	Q9	0.539	0.666
	Q10	0.590	0.608
	Q11	0.550	0.644

The above research shows that under the premise that the data meets the requirements of statistics and reliability, it can be concluded that users often have a herd mentality after receiving similar information, which affects their decision-making behavior. However, due to the limited data dimension, the statistical analysis method cannot further quantify the influence of the user's decision-making behavior by the herd mentality, and the field of finance can provide an effective solution. The behavioral motivations for learning and imitating people are usually classified into two types. One is based on the consideration of strategy benefits, whether the behavior subject chooses a certain strategy that can bring considerable rewards and benefits; the other is based on the psychology of conformity. That is, behavior subjects determine their strategy by observing and imitating the preferences of most people in the group [25].

Based on the quantitative method of conformity psychology in finance, this paper proposes a quantitative conformity model based on social welfare function. Currently, in finance, three typical social welfare functions represented by the Utilitarian, the Rawlsian, and the Nash types are widely recognized. Different social welfare functions have different application scenarios, and the Utilitarian social welfare functions usually emphasize overall benefit maximization. The Rawlsian social welfare function emphasizes safeguarding the social welfare of the poor. The Nash-type social welfare function places more emphasis on the fairness of the overall society, and the more similar the social welfare among the members of the society, the greater the social benefits generated, which is more compatible with the description of the scenario based on herding psychology in this study, therefore, this paper adopts the Nash-type social welfare function to quantify the utility of herding psychology generated by users. The specific modeling is as follows:

When the user's psychology tends to follow others, the psychological utility obtained by it is shown in (1) [26]:

$$U_{user} = U_1 + M \times \mathrm{Comfo}msitValue \tag{1}$$

where U_{user} is the total utility obtained by user n, U_1 represents Utility gained by user n engaged in other activities, $\mathrm{Comfo}msitValue(CV)$ represents the psychological utility obtained when herd mentality occurs, and M is the weight coefficient. The utility CV generated by HM is expressed as:

$$CV = \prod_{i=1}^{N} b_i \times d \tag{2}$$

where $\prod_{i=1}^{N} b_i$ is the Nash social welfare function. The meaning of the representation is that when the welfare values of individuals in the community are more similar, the total welfare of the community is more significant at this time [27]. b_i is the value of personal benefits. d is the action taken by the user.

When the above research is applied to the community flexible load scheduling scenario. p_i is the utility coefficient of the herd mentality by the user. d is the user's flexible load usage changed due to herd mentality. N is the number of users in the community. To verify the rationality of the Nash social welfare function, it is assumed that there are two users A and B in the community, and the total benefits obtained by the two users in the community are constant K. U_{sum} is the total welfare within the community. U_a and U_b distributions represent the user's personal welfare. The total welfare within the community is $U_{sum} = U_a \cdot U_b$. According to the assumption, the user's total welfare is a constant value K. So the total welfare within the community is $U_a \cdot (K - U_a)$. When $U_a = U_b = -\frac{K}{2}$, social welfare is the largest. Therefore, this paper adopts the Nash social welfare function to describe the user's behavior.

Next, the information community and user model are further elaborated.

3. Community Structure Guided by Herd Mentality

The information community structure is shown in Figure 1. PV, energy storage (ES), shiftable load and fixed load are comprehensively considered. To encourage herding among users, CM set up the information exchange center.

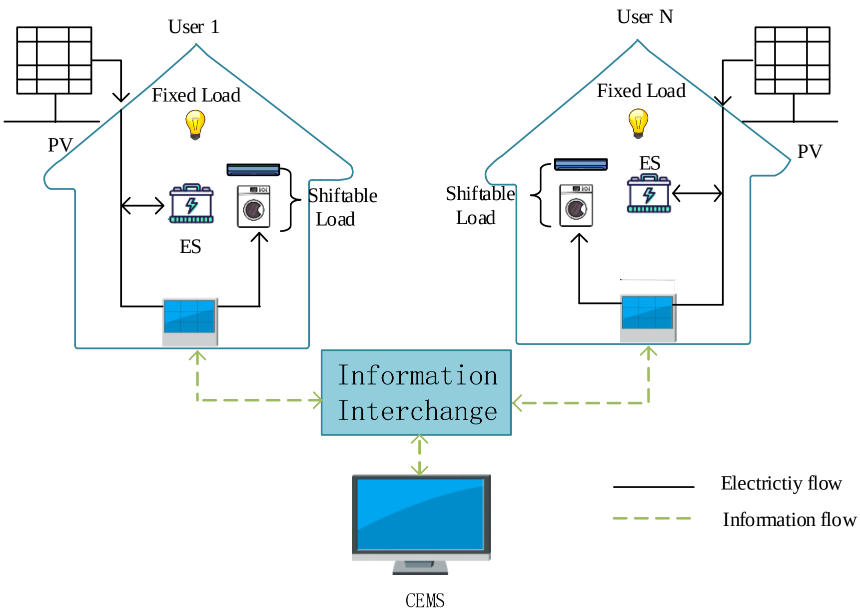

Figure 1. Structure and information exchange model of community.

Community manager (CM) releases electricity price information, guidance information and energy-saving information in the information exchange center. On the one hand, CM improve the frequency of community users entering the information exchange center. On the other hand, CM hope to potentially use the information center to affect and improve users' energy consumption habits. In addition, CM calls on some users to share some successful experiences in the information center and promote such users as community models, hoping to use their influence to improve the response behavior of other users in the community.

To improve the community benefit and reduce the uncertain behavior of users in response, the CM will publish some information in the information exchange center in Figure 1 to guide users to make energy use decisions. Residents will receive messages similar to Figure 2. This information potentially affects the electricity behavior of user through psychological factors [28]. Such messages typically contain three broad categories: the first is an inducement message from a demand response user, which is usually provided by a user who has successfully participated in demand response and received additional benefits; the second type is the guidance information issued by the community manager, such as energy coupons. For example, if a customer uses 5% less electricity in a certain period, the customer can receive an energy coupon to offset the electricity bill. The third type of information is the comparison information among users, which usually exploits the comparison psychology among users to improve their energy consumption habits. This paper attempts to increase user engagement by using the above information in order to guide the interaction between users. In addition, to ensure users' privacy, the community manager will only distribute information related to the user's authorization. The community manager will be responsible for the leakage of the rest of the information.

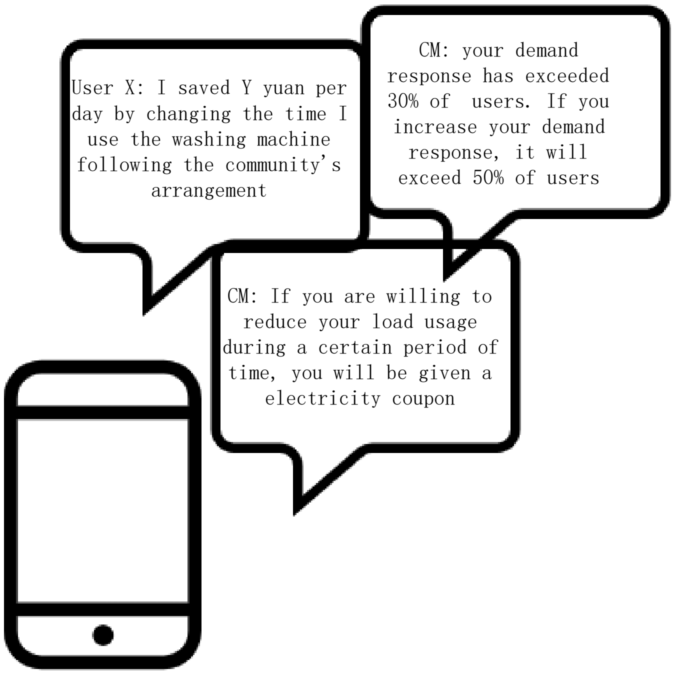

Figure 2. Community information.

4. Community Energy System Model

4.1. Community User Model

This paper considers the user's flexible load scheduling problem in the smart community, assuming that the user's actions are determined according to their maximum utility. The first step is to build the user's demand response uncertainty model. The second step is to incorporate the influence of HM into the user's model to study the effect of HM on users' electricity consumption behavior.

The utility of users is the sum of the electricity charge paid to the power grid U_g^t and the utility that the sers achieve from consuming electric power U_d^t. The maximum utility of user n in a scheduling cycle T is :

$$\max U_{user} = \sum_{t=1}^{T} (U_g^t + U_d^t) \tag{3}$$

$$U_g^t = -c_{gs}^t \cdot \max(0, P_e^t - P_v^t) \cdot \Delta t \tag{4}$$

$$U_d^t = E \cdot \log(P_e^t + 1) \tag{5}$$

where Equation (4) is the electricity purchase cost of the user at time t. In practice, the users' energy use and satisfaction are in a state of diminishing marginal returns and are therefore expressed in logarithmic form. In this paper, we use Equation (5) to represent the utility that the users get from consuming electricity at time t [29]. E represents the user's preference coefficient.

According to the principle of consumer psychology, there is a minimum perceptible difference for the user's stimulation. Within the range of this difference threshold, the user has no response or the response is minimal (dead region); beyond the range of dead region, the user will respond, which is related to the degree of stimulation (linear region); users also have a saturation value for incentives. Beyond this value, users will not respond (saturated region). Different types of users have different response curves. A piecewise linear function often represents the response process to simplify the problem. The user responsiveness of different levels will eventually be reflected in the different parameters: peak-to-valley electricity price difference p, start threshold p_f and saturated threshold p_s. λ is the level of user demand response and Maximum demand response of users λ_{max} [8].

Refs. [9–11] establishes users' response model under time-of-use price as shown in Figure 3. They assume that the degree of users' participation in demand response is related to the peak valley difference price. Users should decide whether to participate in demand response and how much they participate. Considering the above, this papers need to assume that users can choose freely the deliverable flexible load P_s^t and the non-deliverable flexible load P_z^t. Further, the electricity load model of the user is expressed as:

$$P_e^t = P_d^t + P_s^t(P_z^t) \tag{6}$$

where when a flexible load transfer occurs when the customer is affected by the tariff, the customer's flexible load is the deliverable flexible load and the electrical load is denoted as $P_d^t + P_s^t$; when the user is free to use energy according to his preference, the user's flexible load is a non-deliverable flexible load at this time, and the load is expressed as $P_d^t + P_z^t$.

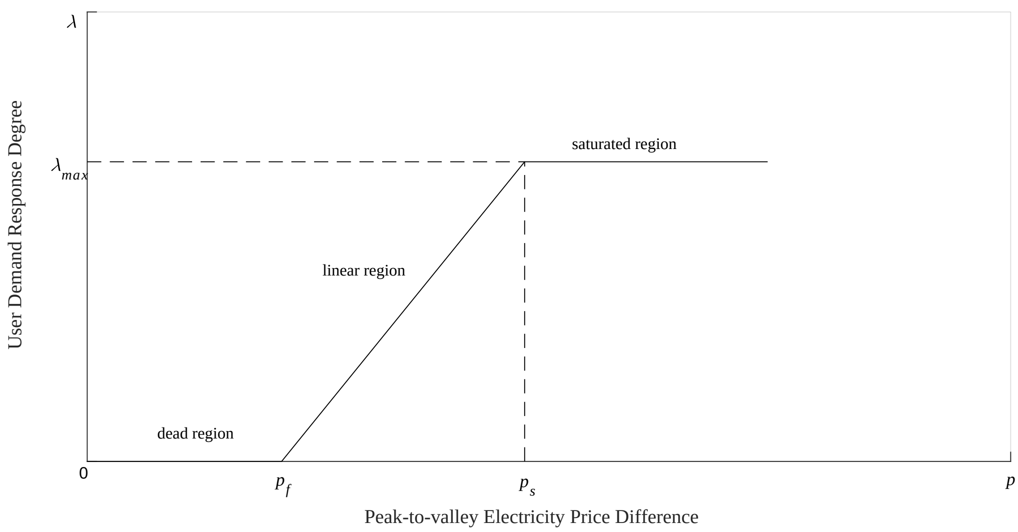

Figure 3. Demand response degree model of users.

The electricity load consists of fixed load and flexible load. The fixed load is required to maintain residents' normal life, which external factors do not affect. The flexible load is the load that the user decides to use at the period and is easily affected by the price of electricity and its attitude. When the user preference coefficient is large, the user's energy consumption arrangement is not constrained by the electricity price. FL is regulated by itself, and the community cannot use this part of the flexible load resources. The user preference coefficient is small, the user's willingness to use energy independently is not strong. The relationship between users' energy consumption preference and flexible load resources can be calculated from Equations (4) and (5), as shown in Figure 4.

According to Equations (3)–(6), the demand response model considers user wishes, the deliverable flexible load of the user demand response is P_s^t, the user refuses to respond to the non-deliverable flexible load P_z^t, and the user's response degree is determined by the user's energy preference coefficient E, as:

$$\max U_{user} = \sum_{t=1}^{T}(-c_{gs} \cdot \max(0, P_d^t + P_s^t - P_v^t) \cdot \Delta t + E \cdot \log(P_d^t + P_z^t + 1)) \quad (7)$$

where Equation (7) is a demand response model considering the willingness of users to participate. In this paper, the relationship between users' preference and deliverable flexible load is calculated based on Equation (7), as shown in Figure 4.

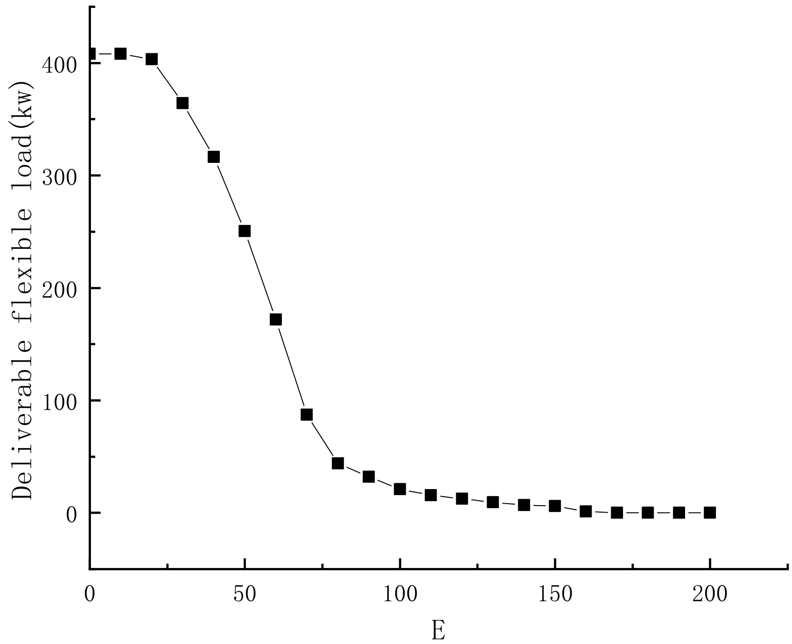

Figure 4. Curves of the preference parameter and deliverable flexible load.

According to Figure 4, the flexible load resources provided by users decrease with the increase of user energy consumption preference coefficient E. Users with $E < 20$ can provide a large amount of FL, and such users do not exist or have less default behavior (the saturated region). $20 < E < 80$ refers to some users who can provide part of the deliverable FL. Such users have certain breach of contract (the linear region). $E > 80$ users cannot provide FL (the dead region)

Deliverable flexible load and non-deliverable flexible load are the same for users. They are converted to each other under different preferences of users. They satisfy the following requirements:

$$\underline{W} \leq P_s^t + P_z^t \leq \overline{W} \quad (8)$$

where Equation (8) indicates that the user's FL has a certain margin. The user's deliverable flexible load includes shiftable load and energy storage. The details are as follows:

$$P_s^t = P_{ec}^t - P_{ed}^t + P_{sl}^t \quad (9)$$

In this paper, only shiftable load is considered, and there is no reducible load. Shiftable load need to satisfy the following constraints:

$$\underline{P_{sl}^t} \leq P_{sl}^t \leq \overline{P_{sl}^t}, t \in [\alpha, \beta] \tag{10}$$

$$P_{sl}^t = 0, t \notin [\alpha, \beta] \tag{11}$$

$$\sum_{t=1}^{T} P_{sl}^t = Q \tag{12}$$

where $[\alpha, \beta]$ indicates the electric power of optional time interval; the shiftable load of the user in $[\alpha, \beta]$ is P_{sl}^t. When shiftable load is not in this range $[\alpha, \beta]$ is 0. The number of shiftable load of users in a cycle T is constant Q; the ES generic model includes ES state, ES upper and ES lower limits, and ES capacity changes, as:

$$P_{ec}^t \cdot P_{ed}^t = 0 \tag{13}$$

$$0 \leq P_{ec}^t \leq \overline{P_{ec}^t} \tag{14}$$

$$0 \leq P_{ed}^t \leq \overline{P_{ed}^t} \tag{15}$$

$$\underline{SOC} \leq SOC \leq \overline{SOC} \tag{16}$$

$$SOC_n^t = SOC_{n-1}^t + \frac{\eta \cdot P_{ec}^t - P_{ed}^t / \eta}{S} \tag{17}$$

where Equation (13) indicates that the user's ES can only exist in a state of charging or discharging in unit time t, constraints (14) and (15) are the maximum and minimum energy storage charge and discharge limit per unit time. $\overline{P_{ec}^t}$ is ES charge maximum. $\overline{P_{ed}^t}$ is ES discharge maximum. Constraints (16) is the upper and lower limits of ES capacity change per unit time. Equation (17) is the ES capacity per unit time. S is ES capacity. η is the charge or discharge loss coefficient.

In order to limit the behavior of users' random response, CM will take punitive measures for users' non-deliverable flexible load electricity [30].

$$U_c^t = -c_{gc}^t \cdot P_z^t \cdot \Delta t \tag{18}$$

where c_{gc}^t is penalty price. To simplify the calculation, the penalty tariff here is a fixed tariff.

4.2. User Herd Mentality Model

The benefits obtained by community users due to HM are expressed by Equation (1). This paper studies the availability of FL. At the same time, to avoid excessive utility in the form of product, the utility coefficient obtained by users is expressed in the form of normalization:

$$q_n^t = \frac{(P_d^t + P_{sl}^t)}{P_d^t} \tag{19}$$

where q_n^t represents the herd utility coefficient normalized by user n at time t; from Equations (2) and (19), it can be deduced that the utility obtained by imitating others is:

$$U_h^t = M \times \prod_{i=1}^{n} q_n^t \times P_{sl}^t \tag{20}$$

when community users have similar FL decisions simultaneously, the utility coefficient q_n^t is more significant. When users receive similar information from other users, herd behavior is prone. Users are willing to provide more FL resources to the community.

To sum up, the community flexible load scheduling model considering HM is:

$$\begin{cases} \max U_{user} = \sum_{t=1}^{T} (U_g^t + U_d^t + U_h^t + U_c^t) \\ s.t.(8), (10) \ldots (17) \end{cases} \tag{21}$$

5. Case Study

5.1. Basic Data

In order to further illustrate the influence of herd mentality on the flexible load scheduling of community users, a community building with 7 commercial and residential buildings is taken as an example to verify the scheduling strategy proposed in this paper. Each building is equipped with roof PV, and the installed capacity ranges from 50 kWp to 100 kWp. The time-of-use electricity price in the community is shown in Figure 5. The scheduling time period T is 24 h and the time interval Δt is 1 h. The maximum proportion of shiftable load of all users is 30%. The value of M is assumed to be a random number between [0.04, 0.1] based on the herd mentality utility generated by the selected users for the demand response. c_{gc}^t penalty price is 2 yuan/kWh. The parameters of ES installed by users are shown in Table 2. The user's load forecast curve and PV forecasting are shown in Figure 5.

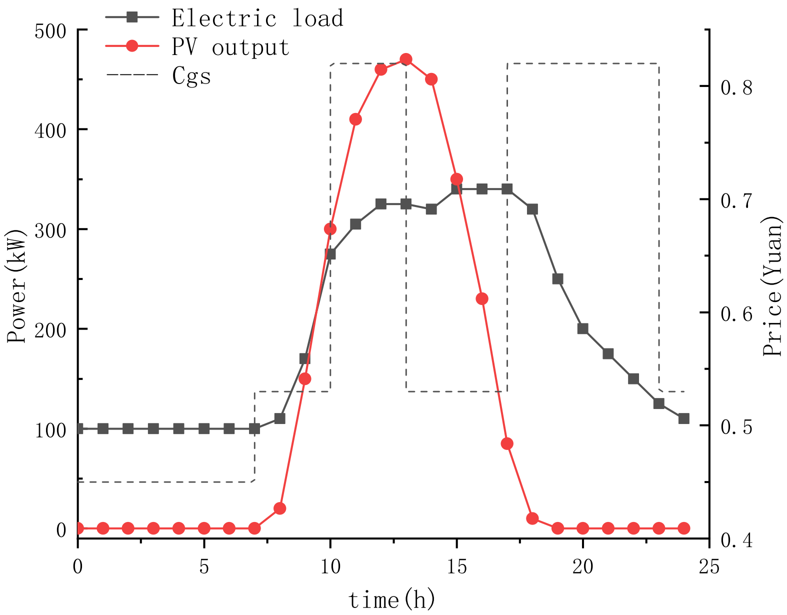

Figure 5. Power and price curves of all users in a day.

Table 2. Energy storage parameters.

Parameter	Value
Initial ES	20%
Lower limit of ES	10%
upper limit of ES	90%
ES capacity	40 kW

5.2. Analysis of Flexible Load Scheduling Results Considering Herd Mentality

It is assumed that users 1–4 will share some energy habits in the information center, and users 5 to 7 are users with a strong awareness of autonomous energy use. Therefore, the preference coefficients of users 1–4 are set to 10, and the preference coefficients of users 5–7 are set to 80, 90, and 100, respectively. According to Equation (21), the load usage of each user in the community is calculated, as shown in Figure 6.

As shown in Figure 6, the flexible load usage of users 1–4 is more concentrated in the morning from 1:00 to 6:00 and from 11:00 to 14:00 noon. According to the electricity price information in Figure 5, it can be seen that the electricity price is at the lowest value at this time, and users 1–4, as users who actively respond to the community, are more willing to shiftable loads such as electric vehicles to this period to obtain additional subsidies. Users' flexible loads are used more from 11:00 to 14:00 because the PV output is large at noon, and users can use energy according to their wishes without being restricted by electricity prices. In addition, it can be seen from Figure 6 that the energy usage habits of users 5–7 are similar to those of users 1–4. This phenomenon can determine that users 5–7 may have a herd mentality and change their decision-making.

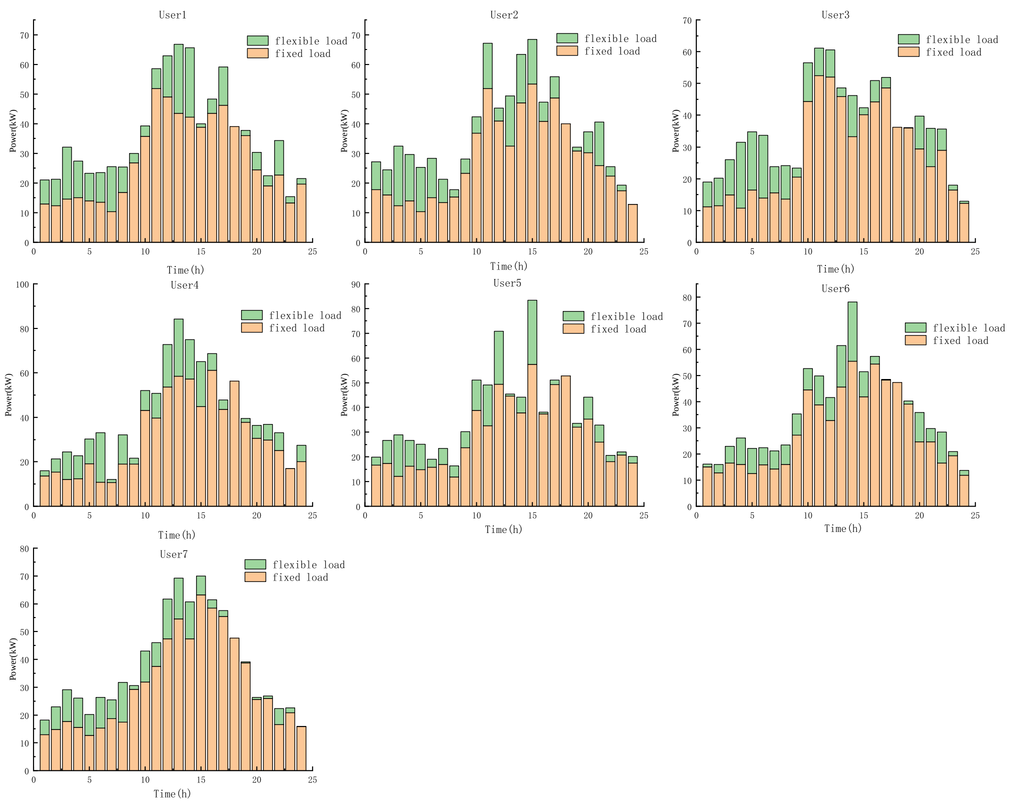

Figure 6. Power distribution for households in community under herd mentality.

In order to further analyze the influence of herd mentality on user response decision-making, the flexible load usage of users 5–7 is calculated and compared with the flexible load usage of users 5–7 without considering herd mentality and the flexible load usage of users 5–7 under ideal conditions of community managers. A comparative analysis is carried out, as shown in Figure 7.

Through the analysis, it can be seen that in the actual dispatching, users 5–7 flexible load use did not reasonably arrange their energy consumption according to the electricity price guidance information, and the flexible load use is relatively balanced. However, under the influence of herd mentality, users 5–7 transferred the flexible load from 18:00–24:00 to 1:00–6:00, indicating their energy consumption habits have changed. The electrical behavior is more in line with the manager's scheduling expectations for flexible load, and users' enthusiasm to participate in demand response is improved.

In addition, considering that users 1–4 also intensively use flexible load from 11:00 to 14:00 at noon, the above results cannot prove that users 5–7 produce herd behavior during this period. Therefore, this paper judges whether there is a herd mentality by calculating the Euclidean distance of load of users 1–4. The smaller the Euclidean distance is, the more similar the behavior between users is, and vice versa. The Euclidean distance is shown in Figure 8. Combined with the analysis of users' energy use behavior in Figure 6, it can be seen that the Euclidean distance between users 1–4 is smaller in the morning when users 1–4 concentrate on using flexible load, and this phenomenon may have a greater influence on the energy use behavior of users 5–7. Based on the analysis of herd mentality, it is more likely that users will change their energy use habits if other users have similar energy use behaviors. In addition, users 1–4 also use flexible load at noon, which does not necessarily produce the herd mentality; on the one hand, due to the higher tariffs at this time, customers 1–4 are unlikely to actively use flexible load, which may be due to the existence of a certain percentage of PV surplus; on the other hand, the possibility of herd mentality is weakened by the large variation in users' energy use behavior.

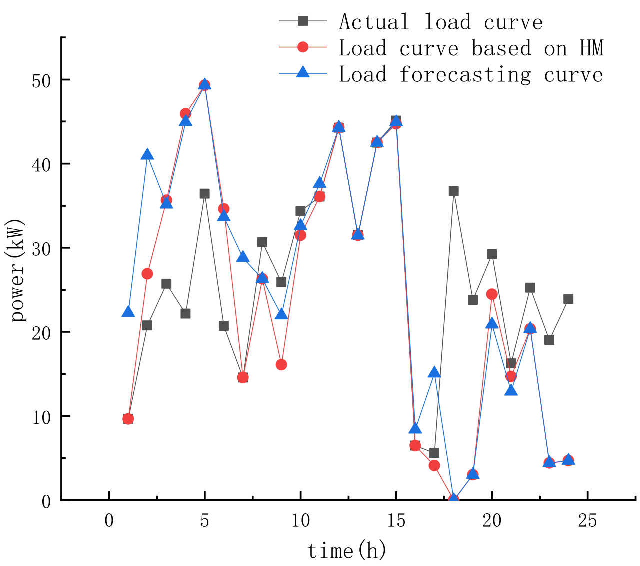

Figure 7. Curve of flexible load.

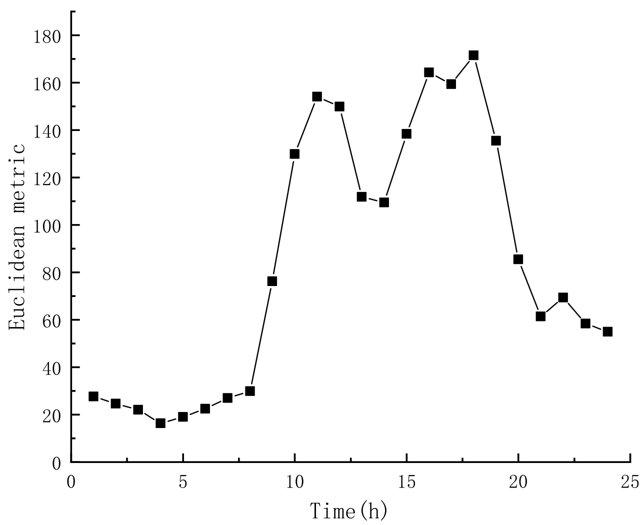

Figure 8. Euclidean metric.

5.3. Analysis of Random Flexible Load Scheduling Results Considering Influence of Herd Mentality

The above example analyses the specific impact of herd behavior on users 5–7. However, users' willingness to respond is often uncertain in actual situations, and community scheduling is uncontrollable. Therefore, in order to further analyse the impact of user response uncertainty on community scheduling, it is still assumed that users 1–4 actively participate in demand response, and their preference coefficient is set to 10; users 5–7 respond according to their wishes, and their energy preference coefficient fluctuates randomly in the range of [50, 150], and 100 scenarios are randomly generated to simulate the situation that users 5–7 respond according to their wishes. Considering the randomly generated graphs without data pre-processing to get a set of unordered data, which is not helpful for this paper, for this reason, the data is processed, and the user responses in 100 scenes are arranged from smallest to largest. The results are shown in Figures 9 and 10.

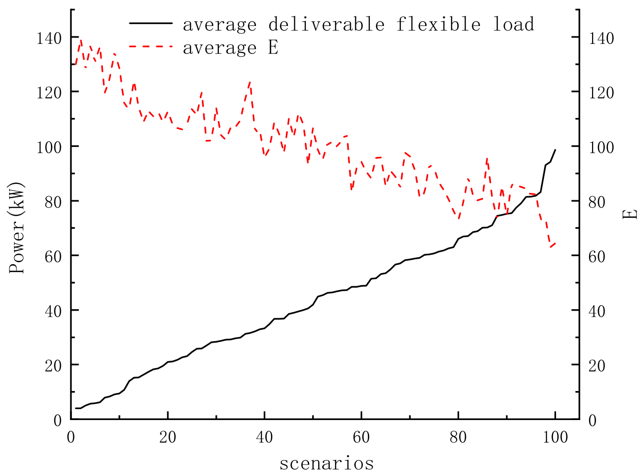

Figure 9. Relationship between random energy consumption preference and FL under 100 scenarios.

It can be seen from Figure 9 that when users 5–7 have a strong energy use willingness, they hardly respond to the community's demand response instructions, indicating that the herd effect has not changed their energy use habits. Their willingness to function decreases and their enthusiasm for participating in community demand response gradually increases due to the influence of herd mentality. The above phenomenon is consistent with the reality; the stubborn users are less motivated to participate in demand response, while the less determined users are more likely to follow the trend and increase their enthusiasm to join in the demand response.

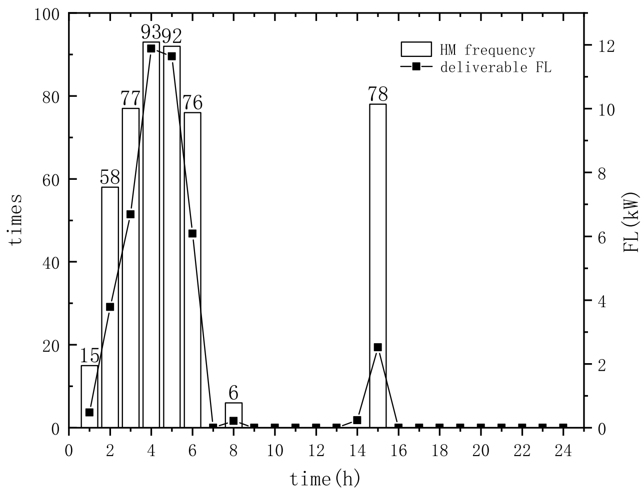

Figure 10. The number of HM and increased FL under 100 scenarios.

Figure 10 shows the herd behavior of users 5–7 in 100 random scenarios. The bar graph represents the number of conformity behaviors, and the line graph represents the average increased dispatchable flexible load in the community at this time. Figure 10 shows that users have herd behavior at 1:00–8:00 and 15:00, and herd behavior is not obvious at other times. The reason is that, on the one hand, due to the low electricity price at this time, users will consider transferring part of the load to this period in order to obtain additional income. Compared with other periods, the usage of flexible load is more intuitive at this moment, which may have a more significant impact on users 5–7. Although users 5–7 also had the phenomenon of herd mentality at 15:00, the effect was not noticeable. Combining with the information in Figure 5, it can be preliminarily judged that the herd mentality effect has limited influence on their behavior at this time.

6. Conclusions and Prospect

This paper regards the herd mentality of community users as an important factor affecting their participation in demand response behavior. Aiming at the problem that the response effect is not in line with expectations and the user's response ability is limited due to the willingness of community users to use energy independently, a flexible load optimisation scheduling strategy based on the user's herd mentality is proposed. The calculation example results show that:

(1) If the herd mentality strategy is implemented correctly, it will minimize the impact of the uncertainty of customers' willingness to use energy on the community's flexible load dispatching and positively guide the community's customers to participate in demand response behavior.

(2) Using the Nash social welfare function to model the herd mentality of the uncertainty of user demand response, under the action of the user's herd mentality, it can guide some users with strong autonomy in electricity consumption to change their energy consumption habits, which can give full play to the community's flexible load participation needs potential to respond.

(3) According to the calculation results, it is known that the demand response will better play the role of peak and valley reduction.

In this paper, only the shiftable flexible load among users is considered in the calculation, and the user's reducible load is not taken into account. The authors will jointly consider the effects of both shiftable and reducible load in the follow-up study. In addition to the herd mentality, the peer effect within the community may also trigger different effects, and we will continue to pay attention to the influence of social psychology on users' demand response behavior.

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Abbreviations

The following abbreviations are used in this manuscript:

DFR	Distributed Flexible Resources
CM	Community Manager
DR	demand Response
HM	Herd Mentality
SWF	Social Welfare Function
PV	Photovoltaic
CV	Comfomsit Value
ES	Energy Storage
FL	Flexible Load
Δt	Unit Time
U_{user}	Total User's Utility
U_1	Utility Gained by Users Engaged in Other Activities
U_g^t	Electricity Charges at time t
U_d^t	Energy Consumption Utility at time t
U_c^t	Community Penalty Utility at time t
U_h^t	Community Herd Mentality Utility at time t
c_{gs}^t	Time of Use Price at time t
c_{gc}^t	Penalty Price at time t
b_n	User n Personal Benefits
q_n^t	Herd Mentality Utility Coefficient Normalized at time t
d	Flexible Load Changed Due to Herd Mentality
P_e^t	Electric Load at time t
P_v^t	PV Forecast at time t
P_s^t	Deliverable Flexible Load at time t
P_z^t	Non-deliverable Flexible Load at time t
P_{sl}^t	Shiftable Load at time t
P_{ec}^t	Charge load at time t
P_{ed}^t	Discharge load at time t
E	Preference Coefficient
M	Herd Mentality Coefficient
Q	Total Shiftable Load in a Period
$\overline{W}$	Up Limit of Flexible Load
$\underline{W}$	Lower Limit of Flexible Load
$\overline{P_{sl}}$	Up Limit of Shiftable Load
$\underline{P_{sl}}$	Lower Limit of Shiftable Load
η	ES Loss
SOC	ES State
ComfomsitValue	The Utility of User's Herd Mentality
Deliverable Flexible Load	Flexible Load Used under the Influence of Community Information
Non-deliverable Flexible Load	Flexible Load Used by Users according to Preference

Appendix A

The questionnaire is given here. Except for the basic information, the rest of the information is set with five options according to the Likert scale standard.

Table A1. This is a questionnaire.

ITEMs
1. age 2. Education 3. gender 4. When I see that most of the neighbors are involved in demand response, what is your choice? 5. The more people in the community who participate in demand response, the more I want to participate, do you agree? 6. Do you choose to stand your ground when your opinion is contrary to most people's? 7. When you know that some neighbors are used to charging electric cars in the early morning but you are used to charging in the afternoon, what is your choice? 8. In daily consumption, I like to be consistent with most of the people around me, do you agree with this point of view? 9. Are you affected by your neighbour's energy usage information? 10. When you learned that your neighbors were involved in demand response, would you consider participating? 11. Do you share information about your energy use with people?

Q4–Q11 Comply with the Likert Scale Statistical Requirements: 1 = strongly disagree (strongly repulsive); 5 = strongly agree (active participation).

Table A2. Basic information of the scale.

Constructs	Items	Frequency	Percentage
gender	Male	102	48.6%
	Female	108	51.4%
Education	Junior high school and below	33	15.7%
	High school	71	33.8%
	Undergraduate	67	31.9%
	Graduate and above	39	18.6%
Age	under 20	24	11.4%
	20–30	34	16.2%
	30–40	48	22.9%
	40–50	42	20%
	50–60	51	24.3%
	over 60	11	5.2%

Energy storage is being used in communities to increase community energy dispatch flexibility. Users' energy storage usage is shown in Figure A1.

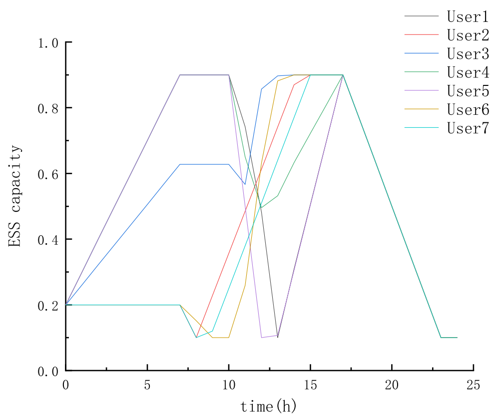

Figure A1. Curve of energy storage capacity.

The statistical information of the community user questionnaire is shown in Figure A2.

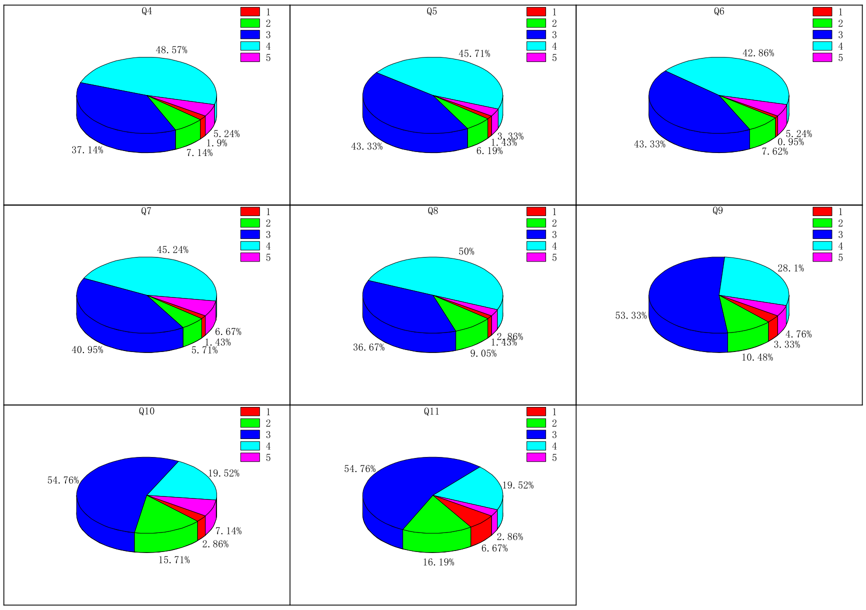

Figure A2. The response information for questions 4–11.

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