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Study on the Customer Choice for Electricity Contract and Relevant Impact on the Retail Market

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Abstract

The introduction of smart meter technology and electricity retail tariffs plays an important role in the open electricity retail market, and the most widely used retail pricing in the current market is the Time-of-Use (ToU) Pricing tariffs. However, the diversity of ToU tariffs brings more complexity to the choices of electricity customers. Therefore, a retail ToU pricing tariff decision-making model based on customer satisfaction and neighbor influence from social network is proposed. The model first needs to extract features and create profiles for each customer, and establish a customer satisfaction model based on the electricity price tariff characteristics and customer characteristics, which comprehensively considers the satisfaction of customers in four dimensions: electricity consumption, electricity consumption habits, electricity expenditure, and household electrification degree. Secondly, using a small-world network model to simulate the information dissemination process between customers, while considering the weight of neighbors' opinions and prediction of the customer's electricity demand response, a dynamic social interaction model is established. When customers come into tariff with new price information, they will evaluate their satisfaction with the new tariff and compare it with the original tariff, and simulate their decision-making behavior of whether to switch the tariff by setting two customer decision strategies. Under this model, customer decisions will be simulated which can change with customer inner satisfaction and social network influence, and the market share of different electricity price tariffs will also dynamically change accordingly.

Keywords: ToU price tariff, customer profiles, customer satisfaction, social network, decision-making

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Chapter 1

Introduction

1.1 Background

With the deepening of electricity marketization reform in various countries around the world, the opening up of the retail electricity market has become a key component of the reform. The introduction of smart meter technology and the promotion of dynamic electricity prices are crucial for incentivizing customers to respond to price fluctuations. This not only helps to balance electricity demand and supply, but also improves the operational reliability of the power system. In the mature retail electricity market, customers can independently choose the appropriate package based on their energy consumption, for example, the Choose Texas Power website [**1**] and Autorità di Regolazione per Energia Reti e Ambiente (ARERA) website [**2**] provide this service to customers.

However, the retail electricity market offers various electricity price packages to customers, including fixed-cost, time-based ladder, and real-time pricing schemes. For example, Iren provides customers with different options, such as "Iren Placet Luce Casa Prezzo Fisso", "Iren Extra Large Luce Verde Variabile", and "Iren Revolution Luce Verde Variabile". Overly complex and diverse retail packages have brought difficulties to customers in understanding, bringing more complexity to their independent choices.

Time-of-Use (ToU) pricing, as a mainstream pricing mechanism, has been proven to effectively reduce electricity demand during peak hours by implementing different pricing strategies at different time periods during the day, with an expected reduction range of 3% to 6% [**3**] . Currently, more and more customers in North America, Australia, and Europe have started installing smart meters and adopting ToU pricing, with Italy implementing it as a mandatory policy.

In addition, with the development of social media, information dissemination among different customers is becoming more widespread. customers will obtain different information from dynamic social networks, such as family, friends, social media, and advertisements, to learn about different electricity retailers and different kinds of pricing packages. This will influence the psychology of customers and enable customers to continuously adjust their electricity consumption behavior based on their electricity price demand elasticity. Therefore, the electricity demand of customers will not be directly controlled and predicted, and the selling strategy of fixed pricing plans of electricity retailers cannot completely eliminate the uncertainty risk caused by demand fluctuations.

Therefore, retailers not only need to grasp the electricity consumption of customers in different periods, but also need to distinguish customer clusters, understand their consumption patterns, and provide diversified electricity package services to reduce risks while pursuing profits. These are the challenges that retailers have been facing in the development of smart grids [**4**].

1.2 Objective

The purpose of this study is to build a retail ToU pricing customer decision-making model based on customer psychological satisfaction and dynamic social influence, and to study how customers can autonomously choose the appropriate ToU tariff among numerous tariffs options.

The research approach mainly starts from the perspective of customers, and establishes a customer satisfaction model based on multiple dimensions such as average daily electricity consumption, average daily electricity consumption habits, average daily electricity expenditure, and household electrification level. Moreover, considering the influence of neighbors on customers in social networks, a small-world network is established to simulate the information dissemination. Using electricity price demand elasticity of each customer to predict their electricity demand response, so customer satisfaction will continue to be updated after social interaction model. Finally, in order to simulate the subjectivity and randomness of decision-making in real life as much as possible, the customer decision model including two different decision strategies is proposed to simulate whether customers will change the decision-making behavior of Tariff.

1.3 Literature Review

For electricity retailers, how to develop electricity pricing packages, optimize the price, attract potential customers, and expand their market share is becoming a research hotspot in the electricity retail market. Relevant studies have also conducted extensive research on the design of electricity retail packages from the perspectives of customer energy consumption characteristics [**5**], demand response [**6**], and electricity purchase decisions [**7**][**8**].

In the field of ToU package pricing strategies, existing research mainly focus on the development of pricing optimization algorithms. For example, in [**9**] a ToU pricing method based on game theory has been proposed, which constructs a utility function between customers and electricity retailers and uses reverse induction to determine the Nash equilibrium point, in order to develop differentiated pricing strategies for different customer groups. In [**10**] Gaussian mixture model clustering method has been used to design ToU prices based on changes in energy prices and load demand. In [**11**] and [**12**] the optimization methods for ToU pricing from the perspective of intuitionistic fuzzy logic and uncertainty in demand price elasticity have been explored. Data mining techniques have been used in [**13**] to extract customer load characteristics to customize ToU prices.

In the field of helping customers find better packages, one of the value-added services of electricity retailers is to help customers understand the complex electricity tariff mechanism and recommend existing electricity pricing packages to customers. Most of the existing packages recommendation methods are based on the rating prediction of different types of customers on the package, and recommend customers according to the package rating. For example, a hierarchical clustering method of customers based on differentiated feature extraction has been proposed, which classifies customers according to whether their energy consumption level and power consumption behavior are changeable and pushes packages for different types of customers [**14**]. In [**15**] a customer feature subset filtering algorithm based on weighted incremental item coverage has been designed, determined the customer similarity by the customer's known score on the package, and then used the collaborative filtering recommendation algorithm to predict the target customer's score on the package in the feature subset. customer portraits based on customers' electricity consumption in different seasons and working/non-working days has been constructed, classifies customers using fuzzy c-means method, and recommends packages with the highest purchase frequency for similar customers to target customers [**16**]. Zhang Cai et al. [**17**] takes the duration of household appliances as the power consumption characteristics of residential customers, and recommends electricity pricing packages for target customers according to the package price scores of similar customers; On this basis, they proposed a package recommendation method based on Bayesian hybrid collaborative filtering, which uses Bayesian probability matrix decomposition algorithm to deal with the problem of missing data of customers' household appliances [**18**]. It can be seen that most of the existing researches extract customer characteristics based on power consumption, electrical appliance information or package rating score. However, according to the measures for the administration of electricity retailers [**19**] issued by the national development and Reform Commission and the energy administration, electricity retailers can query their historical electricity consumption data only after obtaining the authorization of the agent customer. For potential electricity customers, considering data privacy and customer wishes, it is difficult for electricity retailers to obtain their historical electricity consumption data or customers' explicit rating score of specific packages.

Although these studies have made progress in the pricing strategy and recommended package strategy of electricity retailers, the above studies do not fully consider the psychological factors such as individual acceptance and consumption preferences of different price packages from the perspective of customers, and do not consider the impact of neighborhood opinions in dynamic social networks. At present, the research on customer decision-making process is still blank. The impact of neighbor behavior on individuals in social networks is an important issue in social sciences and network analysis. Research shows that in social networks, individuals tend to imitate the behavior of their neighbors, and the homogeneity of the network ultimately leads to the consistency of views and behaviors. In [**20**] it reveals that individuals often establish connections with people with similar tastes and preferences. In terms of behavior habits, it shows the propagation mode of health behaviors such as obesity in social networks [**21**]. In the process of customer decision-making, the research of Bollinger et al. [**22**] shows that the impact of social networks is also significant, including brand choice, product preference, etc., which are affected by other members of the network. Considering the clustering and small world characteristics of social networks, the small world network model has become an ideal tool for simulating information dissemination due to its high clustering coefficient and short average path length [**23**][**24**].

1.4 Overall Structure

- **Chapter 2** introduce the overall framework for this study, establish the customer satisfaction model and determine the sensitivity analysis of the parameters, build the customer social interaction model with small-world network and build the customer decision-making model with two different strategies.

- **Chapter 3** collect customers data, ToU tariffs data and process data.
- **Chapter 4** simulate different cases with different parameters settings.
- **Chapter 5** summarize the results and present the future works.

Chapter 2

Methodology

2.1 Framework

This study constructed a retail ToU tariff package decision-making model based on customer psychological satisfaction and dynamic social influence. The parameter settings of the model depend on customer data and ToU tariffs, fully considering individual uniqueness from the customer's perspective to simulate the psychological satisfaction of each customer and quantify the impact of social influence on their decision-making. The overall method architecture is shown in Figure 2.1, which includes the data layer and the model layer.

- **Data layer**

In the data layer, customer data and ToU tariffs data are first collected. Secondly, the main focus is on processing customer data. The first step in data processing is to extract customer features, including income level, number of household appliances, number of rooms, and smart meter load data. The second step is to collect customer smart meter load data and obtain the average daily load curve of the customer. The third step is to consider the above customer features and classify customers using the k-means method. For the ToU tariff, it refers to implementing different electricity pricing strategies during different time periods such as day, night, and peak, with each customer having an initial ToU tariff.

- **Model layer**

In the model layer, first, based on the customer features and pricing strategies of the ToU tariffs obtained from the data layer, a customer satisfaction model is established by comprehensively considering factors such as average daily electricity consumption, average daily electricity consumption habits, average daily electricity expenditure, and household electrification level. This model takes into account the characteristics of each customer and can quantify the psychological satisfaction that the ToU tariff brings to each individual.

Secondly, this study uses small-world network to simulate the information dissemination process between customers in the real world, considering the influence of neighbor opinions on individual customers, and constructs a social interaction model for electricity customers. The social interaction model is set as follows: when customers learn about new tariff information during the social process with neighbors, they predict their electricity consumption habits under the new tariff based on their electricity price elasticity demand. They evaluate their satisfaction with the new tariff based on the new average daily electricity consumption, new electricity consumption habits, new average daily electricity expenditure, and new household electrification level. Then, they add the influence of neighbor opinions and update their satisfaction with all the packages they have encountered.

The third model in the model layer is the customer decision-making model. This study proposes two decision-making strategies. The first one is that customers only use the satisfaction of each tariff updated by the social interaction model as a measurement standard, and choose the ToU tariff with the highest satisfaction. The second strategy is for customers to consider economic benefits in addition to psychological satisfaction, such as calculating changes in monthly electricity bills, penalty fees, and ToU tariff replacement fees, before deciding whether to replace the ToU tariff. This study conducted simulations and analyses on these two decision-making strategies, respectively.

Throughout the overall framework of this study, customer decisions will vary with customer psychological and social influences, and the number of customers for different packages will also dynamically change. In subsequent chapters, each model will be elaborated in detail.

2.2 Customer Satisfaction Model

This study comprehensively considers four key dimensions for each customer: average daily electricity consumption, average daily electricity consumption habits, average daily electricity expenditure, and household electrification level, to comprehensively quantify the psychological satisfaction of customers with the electricity price package they choose.

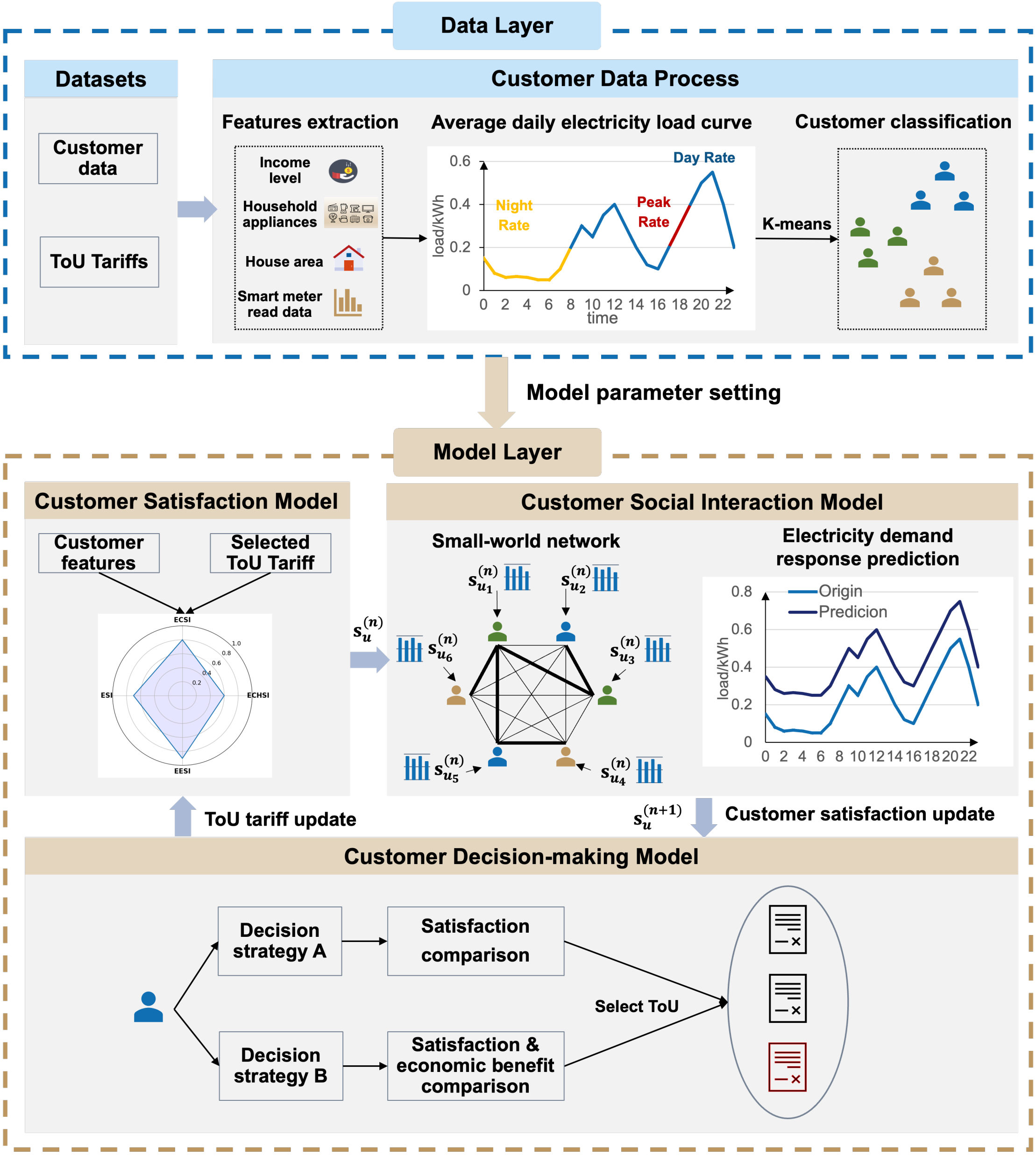


Figure 2.1: Overall framework

Firstly, the dimension of average daily electricity consumption evaluates the satisfaction of customers with the amount of electricity they consume. Satisfaction increases with the increase of electricity consumption, but the marginal utility that increases at the same time decreases. Secondly, the dimension of average daily electricity consumption habits reflects the user's recognition of their electricity consumption habits, including the choice of electricity consumption time and the implementation of energy-saving measures. Thirdly, the average daily electricity expenditure is an indicator that measures the amount of change in customer electricity expenditure. Finally, under the premise of constant total energy consumption, the higher the degree of household electrification, the higher the customer satisfaction.

In addition, considering that each customer's income level, housing area, number of household appliances, average daily load curve, etc. are different, when quantifying satisfaction for each customer, corresponding parameter values in the model will be set based on their characteristics.

2.2.1 Electricity Consumption Satisfaction Index

1. **ECSI modelling**

This study uses an exponential function to quantify customer satisfaction with their electricity consumption (ECSI, Electricity Consumption Satisfaction Index). customer u_k initially chose package c_i, and after choosing a new package c_j, their electricity consumption will change in response to changing price, and so their satisfaction with electricity consumption will also change, which is shown in 2.1:

$$s_{u_k,c_j}^{ECSI} = \frac{1}{T}\sum_{t=1}^{T}\left[1 - e^{-\lambda_{1,u_k}\left(\frac{d_{u_k,c_j,t}}{d_{u_k,c_i,t}}\right)}\right] \tag{2.1}$$

In the formula presented: U denotes the set of electricity customers, represented as $\{u_1, u_2, \ldots, u_N\}$, where N indicates the number of users; C represents the set of electricity tariff packages, denoted as $\{c_1, c_2, \ldots, c_M\}$, with M indicating the number of packages. For each customer $u_k \in U$ and each tariff $c_i \in C$, $f(u_k) = c_i$ indicates that customer u_k has selected tariff c_i. The term $d_{u_k,c_j,t}$ represents the load of customer u_k at time t after selecting tariff c_j, while $d_{u_k,c_i,t}$ represents the load at time t under the previous tariff c_i, with their ratio reflecting the degree of change in electricity consumption following the tariff switch. T denotes the total number of time intervals considered for analysis.

In summary, this ECSI function models the satisfaction from electricity consumption by comparing the change in electricity consumption before and after the package change, which is consistent with the marginal effect. If the electricity consumption under a new tariff is zero, the ECSI for that customer is zero; as consumption increases, satisfaction also increases, asymptotically approaching 1.

2. **Sensitivity analysis of ECSC**

The parameter λ_{1,u_k}, referred to as the Electricity Consumption Sensitivity Coefficient (ECSC), quantifies customer u_k's sensitivity to changes in electricity consumption; a larger value implies that even minor changes in electricity usage significantly impact the user's perceived satisfaction.

To better understand the impact of ECSC on ECSI, this study conducted a sensitivity analysis of ECSC. The analysis aimed to reveal the trends in ECSI at various ECSC values, thereby assessing the sensitivity of the ECSI model to changes in electricity usage and its robustness in prediction. The results of the sensitivity analysis are depicted in Figure 2.2, where the horizontal axis represents the ratio of electricity consumption post-tariff change to pre-tariff change, and the vertical axis represents the ECSI values. As electricity consumption increases, ECSI gradually increases. The green, orange, and blue curves correspond to ECSC values of 1, 2, and 3, respectively, illustrating how ECSI varies with changes in electricity consumption. It is observed that at a constant ratio of electricity consumption change, a lower ECSC results in reduced sensitivity to changes in electricity usage, causing a slower approach to an ECSI of 1; conversely, a higher ECSC leads to increased sensitivity, facilitating a quicker convergence to 1. Future this study will involve setting the ECSC based on the number of household appliances a customer possesses; customers with a higher number of appliances will be assigned a lower ECSC, whereas those with fewer appliances will have a higher ECSC.

2.2.2 Electricity Consumption Habit Satisfaction Index

1. **ECHSI modelling**

Customer electricity consumption habits are intricately linked to their lifestyle and comfort. Before switching electricity tariff plans, customers arrange their electricity usage in a manner that best suits their established habits, during which their satisfaction with these habits is at its maximum. Upon switching to a new tariff plan, customers adjust their electricity usage habits, resulting in a new user load curve. This study employs the Euclidean distance to measure

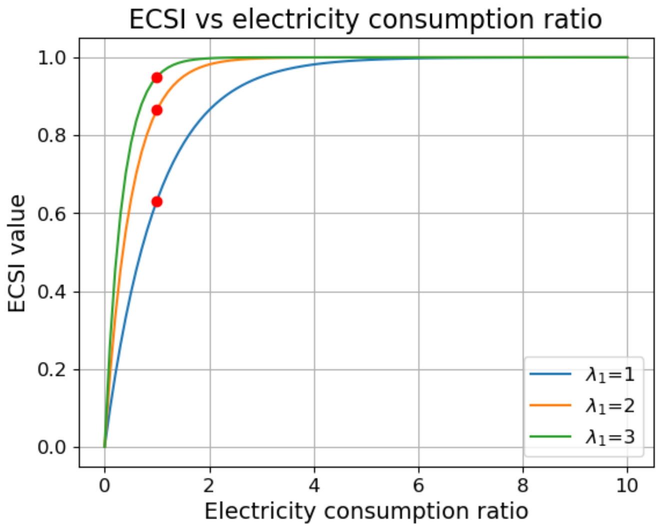


Figure 2.2: Sensitivity analysis of ECSC

the similarity between the new and original load curves, thereby defining the Electricity Consumption Habit Satisfaction Index (ECHSI). For a customer u_k initially choosing tariff c_i and subsequently switching to a new tariff c_j, the ECHSI is defined as follows in (2.2):

$$s_{u_k,c_j}^{ECHSI} = e^{-\lambda_{2,u_k}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(d_{u_k,c_j,t}-d_{u_k,c_i,t})^2}} \tag{2.2}$$

The above ECHSI function estimates the degree of satisfaction decline due to changes in electricity consumption habits by calculating the similarity between load curves before and after a tariff change. If the customer's electricity consumption habits under the new tariff remain identical to those under the previous tariff, the satisfaction score is the highest, set at 1. This reflects a stable and habitual lifestyle. Conversely, extensive adjustments in electricity consumption habits may indicate a necessary adaptation of lifestyle, which can lead to a decrease in satisfaction. This is consistent with the psychological preference for stability, a well-documented phenomenon in psychology that suggests drastic changes in habits often result in reduced satisfaction [**25**].

2. **Sensitivity analysis of ECHSC**

The parameter λ_{2,u_k}, specific to customer u_k, is termed the Electricity Consumption Habit Sensitivity Coefficient (ECHSC). It models the sensitivity of customer u_k to differences in electricity consumption patterns. To better understand the impact of ECHSC on the ECHSI, this study conducted a sensitivity analysis of ECHSC. The results, depicted in Figure 2.3, use the Euclidean distance on the horizontal axis to represent the similarity in electricity usage habits before and after changing the tariff plan, and the ECHSI values on the vertical axis. It is observed that when there is no change in electricity usage habits, the ECHSC reaches a maximum of 1, and it decreases as the magnitude of habit changes increases.

Additionally, the blue, orange, and green curves in the graph respectively represent the variations in ECHSI with changes in electricity usage habits at ECHSC values of 1, 2, and 3. A lower ECHSC implies a lower sensitivity to changes in electricity usage habits, leading to a slower decrease in ECHSI; conversely, a higher ECHSC indicates a higher sensitivity, leading to a faster decrease in ECHSI. When the magnitude of habit changes is constant, customers with a smaller ECHSC exhibit higher internal ECHSI.

Future this study will involve setting the ECHSC based on the number of household appliances a customer possesses; customers with more appliances will be assigned a lower ECHSC, indicating less sensitivity to changes in electricity usage habits, while those with fewer appliances will have a higher ECHSC, indicating greater sensitivity.

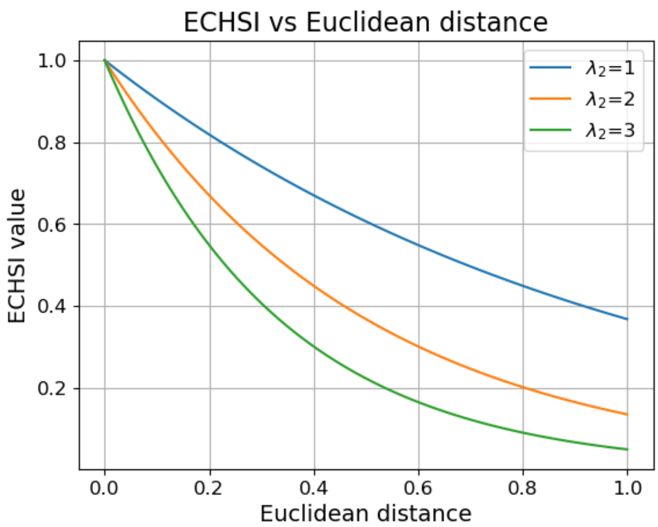


Figure 2.3: Sensitivity analysis of ECHSC

2.2.3 Electricity Expenditure Satisfaction Index

1. **EESI modelling**

   In the field of energy economics, the Engel coefficient is a crucial economic indicator used to measure the proportion of a specific expenditure relative to total income, reflecting the importance of that expenditure to the customer. Drawing inspiration from the concept of the Engel coefficient, this study uses the ratio of electricity expenditure required after changing to a new tariff plan to that required by the previous plan as the independent variable for the Electricity Expenditure Satisfaction Index (EESI). The specific expression for the EESI function is as shown in 2.3:

   $$s_{u_k,c_j}^{EESI} = e^{-\lambda_{3,u_k}\left(\frac{C_{u_k,c_j}}{C_{u_k,c_i}}\right)} \tag{2.3}$$

   In the equation, C_{u_k,c_j} represents the average daily electricity expenditure incurred by customer u_k after selecting tariff plan c_j, and C_{u_k,c_i} denotes the average daily electricity expenditure for customer u_k under the previous tariff plan c_i.

   The Electricity Expenditure Satisfaction Index (EESI) function simulates the satisfaction derived from changes in electricity expenditure by comparing the expenditures before and after changing tariff plans. If the electricity expenditure under the new plan is zero, the EESI for the customer reaches its maximum value of 1; as the proportion of electricity expenditure increases, satisfaction shows an exponential decay, eventually tending towards 0.

2. **Sensitivity analysis of EESC**

   The parameter λ_{3,u_k} is defined as the Electricity Expenditure Sensitivity Coefficient (EESC), which models the sensitivity of customer u_k to increases in electricity expenditure and the corresponding decrease in satisfaction. To better understand the impact of EESC on the Electricity Expenditure Satisfaction Index (EESI), this study conducted a sensitivity analysis of EESC. The results of the sensitivity analysis, as depicted in Figure 2.4, show the ratio of electricity expenditure required after changing the tariff plan to that under the original plan on the horizontal axis and the EESI values of the customers on the vertical axis. It is evident that as the ratio of electricity expenditure increases, EESC gradually decreases.

Furthermore, the blue, orange, and green curves in the graph respectively represent the trends in EESI with EESC values of 0.1, 0.2, and 0.3. A smaller EESC implies a lower sensitivity to increases in electricity expenditure, resulting in a slower decline in EESI; conversely, a larger EESC indicates a higher sensitivity, leading to a faster decline in EESI. When electricity expenditures are constant, customers with smaller EESC values experience higher internal EESI.

The later cases study will involve setting the EESC based on the income levels of customers. Customers with higher income levels will be assigned a lower EESC, indicating less sensitivity to changes in electricity expenditure, whereas those with lower income levels will have a higher EESC, indicating greater sensitivity.

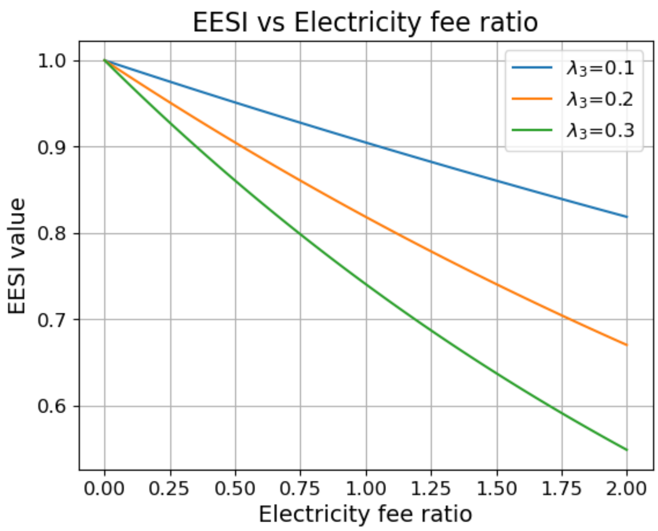


Figure 2.4: Sensitivity analysis of EESC

2.2.4 Electrification Satisfaction Index

1. **ESI modelling**

Electrification level refers to the proportion of electrical energy consumption within the total energy consumption in a defined area (such as a country, region, or individual household). To measure the impact of electrification level on customer satisfaction, this study calculates the ratio of average monthly electrical energy consumption to the average total monthly energy consumption (including both electrical and natural gas consumption). This ratio serves as the independent variable for the Electrification Satisfaction Index (ESI) function, reflecting the modernization level of household energy usage and simulating customer satisfaction with electrification. The expression for the ESI function is as follows:

$$s^{ESI}_{u_k,c_j} = \left[1 - e^{-\lambda_{4,u_k}\left(\frac{Ele_{u_k,c_j}}{Ele_{u_k,c_j}+Gas_{u_k,c_j}}\right)}\right] \tag{2.4}$$

$$Ele_{u_k,c_j} = 30 \times \sum_{t=1}^{T} d_{u_k,c_j,t} \tag{2.5}$$

$$Energy_{u_k} = Gas_{u_k,c_j} + Ele_{u_k,c_j} = Gas_{u_k,c_i} + Ele_{u_k,c_i} \tag{2.6}$$

In Equation 2.4, Ele_{u_k,c_j} represents the average monthly electrical energy consumption of customer u_k after switching to the new tariff plan c_j. This value is calculated as described in Equation 2.5, namely, 30 days multiplied by the average daily load. Equation 2.6 asserts that the total monthly energy consumption for customers remains constant; Gas_{u_k,c_i} and Gas_{u_k,c_j} respectively represent the average monthly natural gas consumption of customer u_k before and after switching tariff plans.

This study assumes that after customers change their tariff plans, the household's average total monthly energy consumption remains unchanged, but the relative consumption of electricity and natural gas is adjusted accordingly to maintain a constant total energy consumption. Under this premise, when electricity consumption approaches zero (with an increase in natural gas consumption), indicating a very low level of electrification, user satisfaction tends towards zero; conversely, as electricity consumption increases (and natural gas consumption decreases) reflecting a higher degree of electrification, customer satisfaction increases.

2. **Sensitivity analysis of ESC**

The parameter λ_{4,u_k} is defined as the Electrification Sensitivity Coefficient (ESC), which quantifies customer u_k's sensitivity to changes in household electrification. To better understand the impact of the ESC on the ESI of customers, this study conducted a sensitivity analysis of the ESC. The results of this analysis, as depicted in Figure 2.5, illustrate that as the degree of electrification increases following a tariff change, the ESC progressively rises.

Furthermore, the blue, orange, and green curves in the graph respectively represent the trends in ESI at ESC levels of 1, 2, and 3. A lower ESC indicates a reduced sensitivity to changes in the degree of electrification, resulting in a slower increase in ESI; conversely, a higher ESC implies greater sensitivity, leading to a faster increase in ESI. At a constant level of electrification, customers with a higher ESC exhibit a higher internal ESI.

Future this study will involve setting the ESC based on the number of household appliances a customer possesses; customers with a larger number of appliances will be assigned a higher ESC, indicating greater sensitivity to changes in electrification. This further implies that for customers with more appliances, an equivalent increase in electrification results in a greater increase in satisfaction compared to those with fewer appliances.

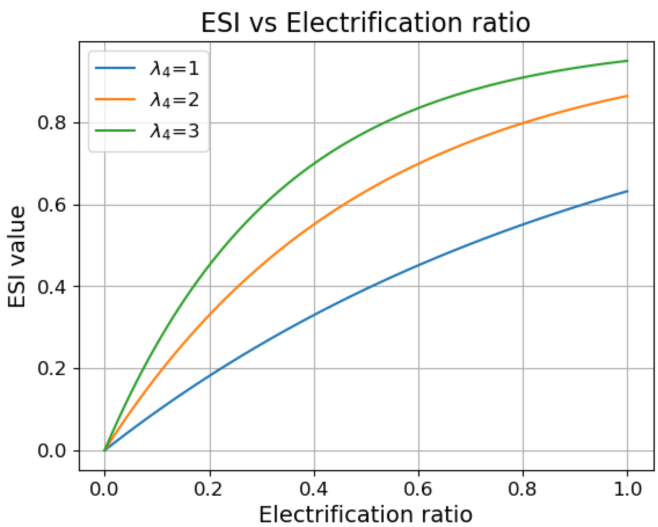


Figure 2.5: Sensitivity analysis of ESC

2.2.5 Customer Satisfaction Model

To comprehensively assess individual customer satisfaction with electricity tariff plans, this study employs a series of customer-specific weighting parameters δ_i, where $\delta_i \in [0, 1]$, to weight satisfaction across various dimensions. This approach reflects the differing levels of importance that users place on each dimension. The satisfaction model for customer u_k with the tariff plan c_j is structured as followed equation:

$$s_{u_k,c_i} = \delta_{1,u_k} s_{u_k,c_i}^{ECSI} + \delta_{2,u_k} s_{u_k,c_i}^{ECHSI} + \delta_{3,u_k} s_{u_k,c_i}^{EESI} + \delta_{4,u_k} s_{u_k,c_i}^{ESI} \tag{2.7}$$

$$\delta_{1,u_k} + \delta_{2,u_k} + \delta_{3,u_k} + \delta_{4,u_k} = 1 \tag{2.8}$$

Within this framework, the weighting parameter δ_{i,u_k} reflects the relative importance that customer u_k places on the satisfaction for the i-th dimension. By adjusting these weighting parameters, the composite satisfaction can flexibly reflect each customer's preferences and needs. For instance, customers in better economic conditions may focus more on electricity usage and habits, and they often have more resources to invest in home electrification improvements, such as installing solar panels and electric vehicle charging stations, to enhance their quality of life and home energy efficiency. Consequently, δ_{1,u_k}, δ_{2,u_k}, and δ_{4,u_k} are assigned higher values. Conversely, customers with lower income might focus more on electricity expenditure, hence δ_{3,u_k} is relatively higher.

If there are M tariffs, then the satisfaction scores of customer u_k for these tariffs can be represented as a column vector $\mathbf{s}_{u_k}$ given by:

$$\mathbf{s}_{u_k} = \begin{bmatrix} s_{u_k,c_1} \\ s_{u_k,c_2} \\ \vdots \\ s_{u_k,c_M} \end{bmatrix}$$

where each s_{u_k,c_i} is the satisfaction value for tariff c_i, for $i = 1, 2, \ldots, M$.

2.3 Customer Social Interaction Model

In open electricity markets, customer choices regarding electricity tariff plans are influenced not only by individual factors such as electricity consumption, usage habits, expenditure, and the degree of electrification, but also by social influences within their network of neighbors. The *Social Influence Model* [**26**] is a framework used to analyze and quantify how individuals are influenced by others within social networks. This model considers the dynamic nature of social ties and influence over time, emphasizing the propagation and diffusion of influence among individuals in social networks. In various fields such as marketing, public policy, sociology, and psychology, dynamic social influence models can assist in analyzing and predicting changes in individual or collective behaviors. This study incorporates this model to explore how electricity customers make purchasing decisions for electricity plans under the influence of their social networks.

Initially, this study will employ a small-world network to simulate the real-world process of information interaction among users, such as learning about different electricity retailers and tariff plans through relatives, friends, social media, and advertisements. Subsequently, considering the weighted opinions of neighbors [26] and the impact of customer autonomy, a dynamic customer social interaction model will be constructed.

2.3.1 Small-world Network

Social relationships can be depicted using a network model where nodes represent decision-makers and edges represent the informational interactions between individuals. In the real world, individuals are more likely to interact and be influenced by their immediate neighbors, hence displaying characteristics of a small-world network with high clustering coefficients and short path lengths.

Utilizing the small-world network can effectively simulate the complex social structures formed by electricity users in real life, including local dense connections and random cross-regional contacts. This allows for the rapid propagation of views on electricity tariff plans within the network, effectively simulating the process of opinion formation and change within groups. The small-world network, initially proposed by Watts and Strogatz, is centered around random reconnections, hence the original model is referred to as the WS model. This study generates a Small-World Network using the following steps:

1. Construct a nearest neighbor coupled network: Assume the network contains N nodes, each node i is connected to its K nearest neighbors, forming what is known as the nearest neighbor coupled network, where each link is referred to as a short edge.

2. Random reconnection: For each node i, disconnect the short edges based on a reconnection probability p ranging from 0 to 1. Using a random number generator, select nodes not yet connected to node i to establish new connections, thereby forming new long edges. During this process, ensure that no two nodes are connected by more than one edge, and no node is connected to itself. When p is small, the generated network retains characteristics of a small-world network.

2.3.2 Electricity Demand Response Prediction

In the small-world network, when customers are exposed to information about new tariffs through information dissemination, they predict their electricity demand response under the new tariff based on the price structure at different times of day, referencing their demand response under their existing plan. This study introduces the concept of price elasticity of demand [**27**] to construct the electricity demand response prediction model, which is based on changes in pricing during different periods of the day is expressed in 2.9, 2.10 and 2.11:

$$\Delta d^{\text{day}}_{u_k,c_j} = \Delta p^{\text{day}}_{u_k,c_j} \cdot \epsilon_{u_k} \tag{2.9}$$

$$\Delta d^{\text{night}}_{u_k,c_j} = \Delta p^{\text{night}}_{u_k,c_j} \cdot \epsilon_{u_k} \tag{2.10}$$

$$\Delta d^{\text{peak}}_{u_k,c_j} = \Delta p^{\text{peak}}_{u_k,c_j} \cdot \epsilon_{u_k} \tag{2.11}$$

The electricity demand response prediction model represented by Δd indicates the expected changes in electricity consumption during day, night, and peak periods. These changes are based on the price variations Δp of the new tariff relative to the original tariff and the price elasticity of demand ϵ_{u_k} for customer u_k. The price elasticity of demand ϵ_{u_k} is set within the range $[-1.56, -0.33]$. In this study, the price elasticity of demand of each customer will be determined by the number of household appliances and the specific value can be found in Table 2.1.

Table 2.1: Price elasticity of demand related to number of household appliances

Household appliances number	ϵ_{u_k}
Low (≤ 5)	[-0.74,-0.33]
Middle (> 5 and ≤ 8)	[-1.15,-0.74]
High (> 8)	[-1.15,-1.56]

Thus, the average daily electricity cost for customer u_k under the initial tariff plan c_i is calculated as follows:

$$C_{u_k,c_i} = d^{\text{day}}_{u_k,c_i} \cdot p^{\text{day}}_{u_k,c_i} + d^{\text{night}}_{u_k,c_i} \cdot p^{\text{night}}_{u_k,c_i} + d^{\text{peak}}_{u_k,c_i} \cdot p^{\text{peak}}_{u_k,c_i} \tag{2.12}$$

Similarly, the predicted average daily electricity cost for customer u_k under the new tariff plan c_j based on the initial plan c_i is as follows:

$$C_{u_k,c_j} = d^{\text{day}}_{u_k,c_j} \cdot p^{\text{day}}_{u_k,c_j} + d^{\text{night}}_{u_k,c_j} \cdot p^{\text{night}}_{u_k,c_j} + d^{\text{peak}}_{u_k,c_j} \cdot p^{\text{peak}}_{u_k,c_j} \tag{2.13}$$

In summary, the electricity consumption, usage habits, expenditure, and level of electrification obtained from the electricity demand response prediction model will serve as inputs to the customer satisfaction model. This will enable the calculation of customer satisfaction predicted for the new tariff plan.

2.3.3 Dynamic Social Interaction Model

Given that individuals are more likely to interact and be influenced by their immediate neighbors, this study integrates the current satisfaction of customers with different tariff plans and the opinions of their neighbors in each round of information dissemination. A dynamic social influence model [**28**] has been developed to simulate the evolving satisfaction of customers within social networks concerning various tariff plans. The satisfaction level for user u_k at iteration $n+1$ is updated according to the model:

$$\mathbf{s}_{u_k}^{(n+1)} = \begin{cases} \alpha_{u_k}\mathbf{s}_{u_k}^{(n)} + \beta_{u_k}\mathbf{s}_{\mathcal{N}(u_k)}^{(n)} & \text{if } \mathbf{s}_{\mathcal{N}(u_k)}^{(n)} \neq 0 \\ \mathbf{s}_{u_k}^{(n)} & \text{otherwise} \end{cases} \tag{2.14}$$

$$\alpha_{u_k} + \beta_{u_k} = 1 \tag{2.15}$$

In Equation 2.14, $\mathbf{s}_{u_k}^{(n)}$ represents the column vector of customer u_k's satisfaction levels with various tariffs in the n-th round of information dissemination, which includes the satisfaction with the currently chosen tariff as well as the predicted satisfaction values for other newly encountered plans as mentioned in Section 2.3.2. $\mathcal{N}(u_k)$ denotes the set of neighbors of customer u_k, and $\mathbf{s}_{\mathcal{N}(u_k)}^{(n)}$ represents the neighbors' satisfaction levels with various tariffs. The parameters α_{u_k} and β_{u_k} quantify the autonomy coefficient and neighbor influence coefficient of customer u_k, respectively, and the summation of the two coefficients is 1.

As information is disseminated in each round, customer u_k interacts with their neighbors $\mathcal{N}(u_k)$. If a neighbor's satisfaction level for a tariff is not zero, customer u_k's satisfaction $\mathbf{s}_{u_k}^{(n+1)}$ will be updated based on their previous state $\mathbf{s}_{u_k}^{(n)}$ and the influence from their neighbors $\mathbf{s}_{\mathcal{N}(u_k)}^{(n)}$. If a neighbor's satisfaction level for a tariff is zero, then the customer's satisfaction for that plan remains unchanged.

Considering the clustering characteristics of social networks on information dissemination, the willingness of customers to receive information from their neighbors depends on the similarity between them, denoted as ω, where $\omega \in [0,1]$. In this study, after extracting customer features, the K-means algorithm [**29**] is employed to cluster these features. It is hypothesized that customers within the same category are more likely to accept information; conversely, the greater the differences between customer categories, the lower their willingness to accept information.

Furthermore, during each round of information interaction, neighbors will only recommend the tariff plans they are currently using. Based on the neighbors' recommendations and the customers' willingness to accept, the average influence of neighbors' opinions is defined as the weighted average of all opinions encountered by the customer in each round of information dissemination. The neighbor opinion influence model is defined as follows:

$$s_{\mathcal{N}(u_k),c_i}^{(n)} = \frac{\sum_{u_l \in \mathcal{N}(u_k), f(u_l)=c_i} s_{u_l,c_i}^{(n)} \cdot \omega_{u_k,u_l,c_i}^{(n)}}{\sum_{u_l \in \mathcal{N}(u_k), f(u_l)=c_i} \omega_{u_k,u_l,c_i}^{(n)}} \tag{2.16}$$

Within each cycle of information interaction, the willingness of user u_k to accept the opinions of neighbor u_l is continuously updated. If the neighbor has a positive influence, the customer's receptivity to that neighbor's opinion will increase in the subsequent interaction round; conversely, it will decrease if the influence is negative. The update rule for the weight $\omega_{u_k,u_l,c_i}^{(n+1)}$ between customers u_k and u_l concerning tariff c_i is defined as follows:

$$\omega_{u_k,u_l,c_i}^{(n+1)} = \begin{cases} \omega_{u_k,u_l,c_i}^{(n)} \cdot (1+\eta) & \text{if } s_{u_k,c_i}^{(n)} - s_{u_l,c_i}^{(n)} < 0 \\ \omega_{u_k,u_l,c_i}^{(n)} \cdot (1-\eta) & \text{if } s_{u_k,c_i}^{(n)} - s_{u_l,c_i}^{(n)} > 0 \\ \omega_{u_k,u_l,c_i}^{(n)} & \text{if } s_{u_k,c_i}^{(n)} - s_{u_l,c_i}^{(n)} = 0 \end{cases} \tag{2.17}$$

In Equation 2.17, η is the learning rate of the customer's willingness to receive neighbors' opinions, which is set to 0.1 in this study.

2.4 Customer Decision-making Model

According to behavioral economics theory, individuals exhibit bounded rationality in reality, deviating from the optimal responses assumed by traditional economic theory when making economic decisions. Even when aware of the utility-maximizing solution, they may fail to make optimal decisions due to psychological factors, willpower, environmental influences, and other reasons. In recent years, behavioral economics theory has been widely applied in areas such as demand response, microgrid energy trading, and residential energy conservation. To incorporate customer psychological factors and social influences as comprehensively as possible, this study, building on updated customer satisfaction derived from a dynamic customer social model, proposes a customer decision model to simulate customer behavior in choosing tariff plans within a continuous information dissemination environment.

2.4.1 Decision Strategy A

After each round of information interaction, customers only consider their satisfaction with each tariff and choose the tariff with the highest satisfaction. The model is as Equation 2.18:

$$f_{u_k}^{(n+1)} = \arg\max_{c_i} s_{u_k,c_i}^{(n+1)} \tag{2.18}$$

2.4.2 Decision Strategy B

After each round of information interaction, customers consider not only their satisfaction with each tariff but also evaluate the economic benefits of changing tariffs. This study introduces a switching fee F, a breach of contract fee P during the tariff term, and the monthly economic benefit $B_{c_i \to c_j}$ from switching from tariff c_i to c_j. Furthermore, borrowing from the concept of the 'Break-even Period,' this research proposes a "Cost Recovery Lock-in Period" L_{u_k,c_j}, which is the time it takes for customer u_k to offset the incurred fees through monthly savings from the new tariff.

The specific decision steps are as follows:

1. First, identify the tariff with the highest satisfaction. If this tariff is the one currently chosen by the customer, no change is made. If the tariff with the highest satisfaction is different, proceed to the second step.

2. Next, the customer assesses whether switching to the tariff with the highest satisfaction will result in monthly savings on electricity expenses. If there are savings, they opt to switch and calculate the "Cost Recovery Lock-in Period" for the new tariff. If not, move to the third step.

3. Then, compare the percentage increase in satisfaction with the percentage increase in costs, where the increased costs include the switching fee, penalty for breach of contract, any additional electricity costs, and the unrecouped costs within the remaining "Cost Recovery Lock-in Period" of the original plan. If the increase in satisfaction outweighs the cost increase, the customer switches to the new tariff. If not, they retain their current tariff.

The specific algorithm of decision-making process for changing tariffs is shown in Algorithm 1.

Algorithm 1 Decision-making process for changing tariffs.

▷ Identify the plan with the highest satisfaction level
if $c_i = \arg\max_{c_i} s_{u_k}^{(n+1)}$ **then**
  $f_{u_k}^{(n+1)} \leftarrow c_i$ ▷ keep tariff c_i unchanged
  $L_{u_k,c_i}^{(n+1)} \leftarrow L_{u_k,c_i}^{(n)} - 1$ ▷ Cost Recovery Lock-in Period update
else
  $c_j = \arg\max_{c_j} s_{u_k,c_j}^{(n+1)}$
  if The economic benefit $B_{c_i \to c_j} \leq 0$ **then**
    if $L_{u_k,c_i}^{(n)} = 0$ **then**
      ▷ compare the increase in satisfaction with the increase in costs
      if $\frac{s_{u_k,c_j}^{(n+1)} - s_{u_k,c_i}^{(n+1)}}{s_{u_k,c_i}^{(n+1)}} > \frac{F+P+|B_{c_i \to c_j}|}{30 \times C_{u_k,c_i}}$ **then**
        $f_{u_k}^{(n+1)} = c_j$ ▷ change tariff to c_j
        $L_{u_k,c_j}^{(n+1)} = 0$ ▷ Cost Recovery Lock-in Period set to 0
      else
        $f_{u_k}^{(n+1)} = c_i$ ▷ keep tariff c_i unchanged
        $L_{u_k,c_j}^{(n+1)} = 0$ ▷ Cost Recovery Lock-in Period set to 0
      end if
    end if
  else
    ▷ compare the increase in satisfaction with the increase in costs
    if $\frac{s_{u_k,c_j}^{(n+1)} - s_{u_k,c_i}^{(n+1)}}{s_{u_k,c_i}^{(n+1)}} > \frac{F+P+|B_{c_i \to c_j}|+L_{u_k,c_i}^{(n)} \times |B_{c_m \to c_i}|}{30 \times C_{u_k,c_i}}$ **then**
      $f_{u_k}^{(n+1)} = c_j$ ▷ change tariff to c_j
      $L_{u_k,c_j}^{(n+1)} = 0$ ▷ Cost Recovery Lock-in Period set to 0
    else
      $f_{u_k}^{(n+1)} = c_i$ ▷ keep tariff c_i unchanged
      $L_{u_k,c_j}^{(n+1)} = L_{u_k,c_i}^{(n)} - 1$ ▷ Cost Recovery Lock-in Period update
    end if
  end if
end if

Chapter 3

Data preparation

For customer data, this study mainly focuses on household customers and refers to the Irish CER smart meter project [**30**]. This project installed smart meters for 4232 household customers and collected smart meter data every 30 minutes from July 2009 to December 2010. In order to gain a deeper understanding of customers' electricity consumption patterns, participants were also invited to fill out a detailed survey questionnaire, which included the socio-economic background of residents (such as employment situation, socio-economic status), housing characteristics (such as building area, number of bedrooms), and household appliance usage (such as the number of washing machines and refrigerators). In the process of data cleaning and filtering, this study ultimately selected 1620 household customers as samples, which not only have complete smart meter readings, but also include complete questionnaire data and initial allocation of electricity price package information.

For the selection of time of use electricity pricing packages, this study also refers to the Irish CER smart meter project. In order to encourage customers to transfer some of their electricity consumption from the peak electricity demand period of the day, this project proposes a time of use electricity pricing package, which divides the electricity consumption time of the day into three different prices. In addition, the project also initially allocated different electricity price packages to customers to study the impact of price changes on consumer behavior.

3.1 Customer Dataset

Firstly, collect and process customer data.

3.1.1 Customer Features

To make customer characteristics more intuitive and easy to interpret, this study first assigned a limited number of category labels to each feature. Table 3.1 lists the selected customer characteristics for this study, and counts the selected category labels and the number of customers associated with each feature. These characteristics are mainly divided into three categories: customer income level, number of rooms, and number of household appliances.

Among them, income level can be used to quantify the sensitivity of customers to changes in electricity expenses and the proportion of satisfaction generated from this to total satisfaction. The number of rooms can be used to estimate the average annual natural gas consumption of customers, and specific data can be found in Table 3.2. The number of household appliances can be used to quantify the sensitivity coefficients in functions such as satisfaction with electricity consumption, satisfaction with electricity habits, and satisfaction with electrification.

Table 3.1: Summary of customer features

Category	Class labels	Customers number
Income level		
AB	1	248
C1	2	419
C2	3	288
DE	4	621
F	5	44
Number of bedrooms		
1	1	19
2	2	140
3	3	695
4	4	572
5+	5	194
Number of household appliances		
Low (≤ 5)	1	585
Middle ($5 <$ and ≤ 8)	2	874
High (> 8)	3	161

Table 3.2: Summary of customer gas cunsumption

Number of bedrooms	Annual gas consumption (kWh) [31]
1	5500
2	8250
3	11000
4	13750
5+	16500

3.1.2 Customer Electricity Loads

For the processing of customer smart meter data, in order to accurately describe their electricity consumption habits, this study avoids Christmas, New Year holidays, summer vacations, etc. Firstly, the electricity consumption data for each customer in February is taken, and then the average value of the data is taken to calculate the average daily load curve for each customer. Figure 3.1 shows the electricity consumption data of the first 5 customers every half hour of the day. It can be seen that each customer has different electricity consumption and habits.

In order to further analyze the electricity consumption types of customers, divide the day into three time periods, calculate the average electricity consumption of customers in each time period, and identify the time period with the highest average electricity consumption. If the average electricity consumption of the customer is the highest during that period, the customer will be divided into the types of electricity consumption for that period. Figure 3.2 clearly shows the electricity consumption of each customer at different time periods, with different colors representing different types of customers. In addition, Table 3.3 shows the number of customers corresponding to each type of electricity consumption. It can be found that the vast majority of customers belong to the Peak type, with only 31 customers belonging to the Night type.

3.1.3 Customer Classification

To describe the profile of electricity customers, this study use clustering algorithms to classify their 5 features including customer income level, number of rooms, number of household appliances, daily electricity consumption and customer electricity consumption type. The clustering results also provide a reference basis for formulating corresponding electricity pricing packages for different types of customers.

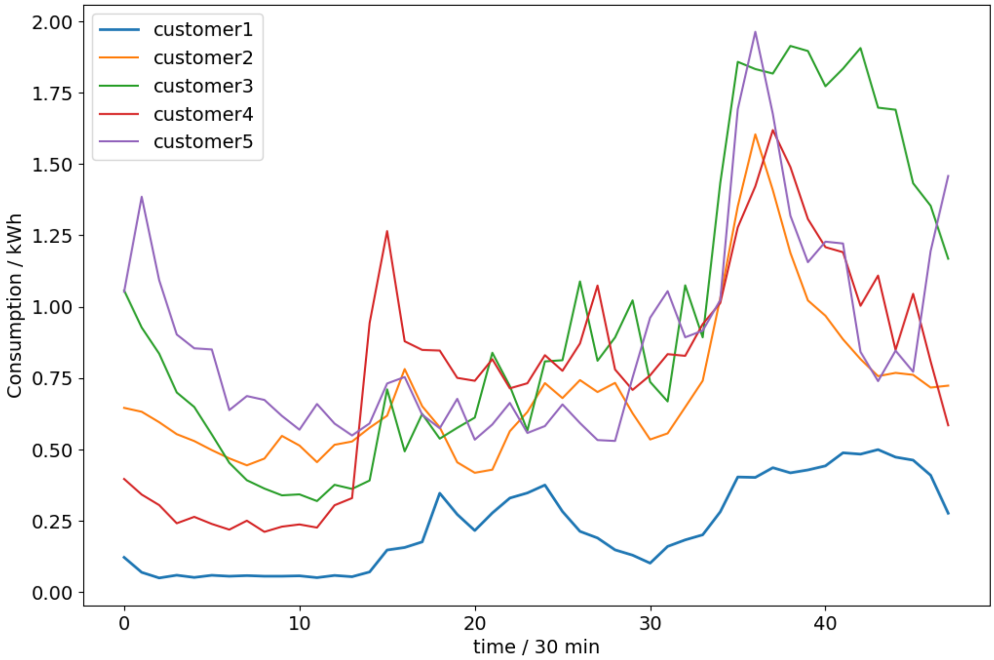


Figure 3.1: First 5 customers average daily load curve

Table 3.3: Summary of customer electricity consumption types

Time period	Type	Customers number
08:00 – 17:00 19:00 – 23:00	Day	233
23:00 – 08:00	Night	31
17:00 – 19:00	Peak	1356

Considering the complexity of the algorithm, this study selects the K-means algorithm for clustering analysis. K-means algorithm is an iterative unsupervised learning method. By dividing data points into a predetermined number of clusters, each data point is more similar to other data points in the same cluster. The following are the steps for customer feature recognition based on K-means clustering:

1. Normalize the each feature data of customers, the normalized data is:

$$X = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3.1}$$

Where x_{max} is the maximum value of customer feature data and x_{min} is the minimum value.

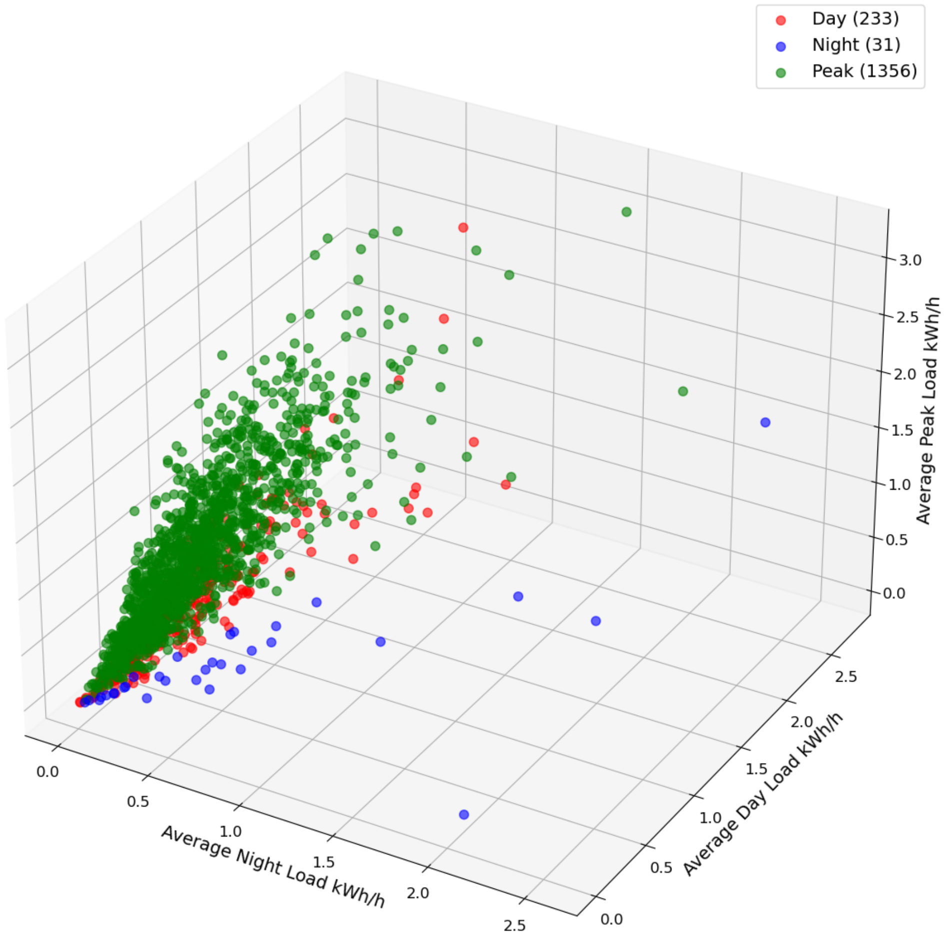


Figure 3.2: Customer electricity consumption types

2. Determine the optimal number of clusters through Silhouette coefficient:

$$si(i) = \frac{b(i) - a(i)}{max\,\{a(i), b(i)\}} \tag{3.2}$$

Where $a(i)$ is the average distance between sample point i and all other data points in the same cluster, which is used to quantify the cohesion between sample data within a cluster. $b(i)$ is the smallest mean distance of sample point i to all points in any other cluster, which is used to quantify the separation between sample data between clusters. The value of the Silhouette coefficient is between [-1,1], and the closer it approaches 1, the better the cohesion and separation are.

The Silhouette scores for different numbers of clusters can be found in Figure 3.3. It can be seen that the Silhouette coefficient decreases with the increase of clusters number. Although the Silhouette coefficient of the cluster amount 5 is about 0.35, considering the customer data is 5-dimension so this study use the cluster amount 5 for later analysis.

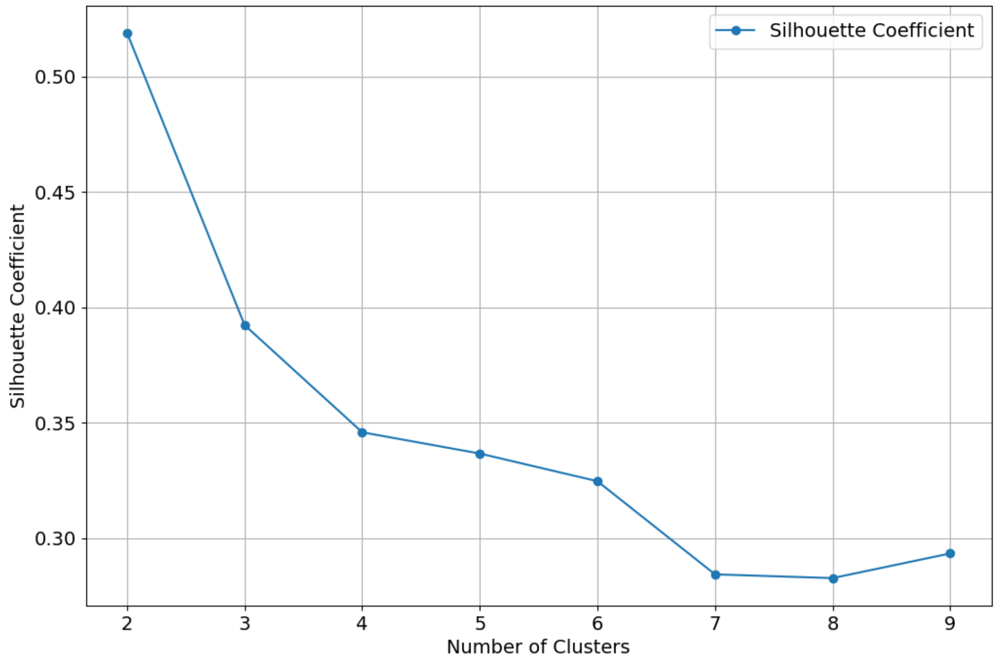


Figure 3.3: Silhouette scores for different numbers of clusters

After K-means clustering is completed, due to the fact that customer data is 5-dimensional and cannot be visualized, the PCA (Principal Component Analysis) algorithm [**32**] is used to reduce the latitude to 2-dimensional. The clustering effect is shown in Figure 3.4, where the distribution of the number of customers in each cluster is relatively uniform, with values of 263, 432, 226, 355 and 343, respectively. In order to compare the characteristics of each cluster of customer more clearly, Figure 3.5 displays the feature values of each cluster center. It can be seen that only cluster2 customers belong to the Day electricity consumption type, while others are of the Peak type.

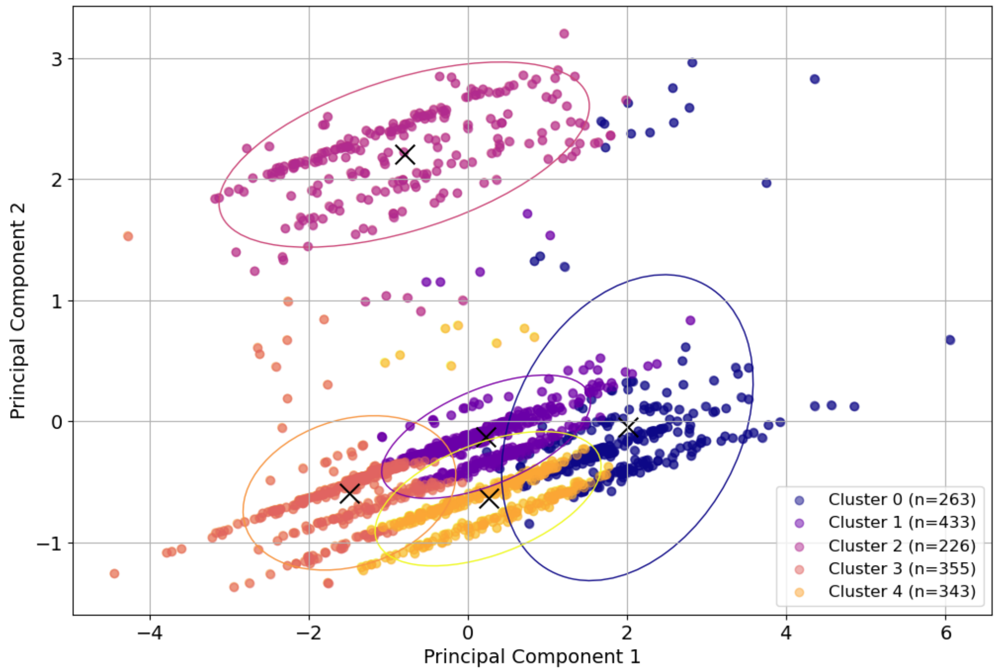


Figure 3.4: K-Means clustering results with k=5

3.2 ToU Tariffs

Another important data is the ToU tariffs, which also refers to the Irish CER smart meter project.

3.2.1 Pricing Rates

The following Table 3.4 shows 5 different ToU tariffs, which offer different ToU general unit charges for the actual units of electricity in different time periods. It is observed that Tariff A has the lowest price for Peak hours, while Tariff D and Tariff E have almost twice as many Peak hours as Tariff. Meanwhile, Tariff D has the lowest prices for both Day and Night time slots.Tariff B and Tariff C have relatively small differences between tariffs for different time slots.

3.2.2 Initial Allocation of Tariffs

In real life, customers will choose electricity pricing tariffs based on their electricity demands at different time periods of the day, but the initial allocation of tariffs has already been made to customers in the Irish CER smart meter project. The initial allocation of personnel for each electricity price tariff is shown in Table 3.5. It is

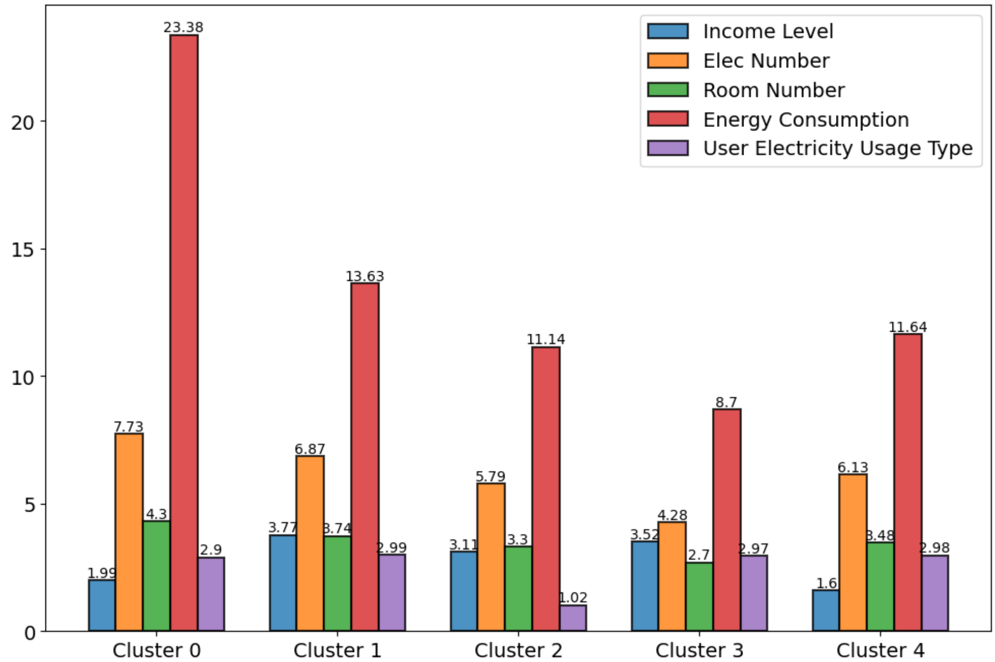


Figure 3.5: Cluster centers comparison across features

Table 3.4: Price structure of different Tariffs

Period	Time slot	Tariff-A €/kWh	Tariff-B €/kWh	Tariff-C €/kWh	Tariff-D €/kWh	Tariff-E €/kWh
Day	08:00 – 17:00 19:00 – 23:00	0.14	0.135	0.13	0.125	0.14
Night	23:00 – 08:00	0.12	0.11	0.10	0.09	0.10
Peak	17:00 – 19:00	0.20	0.26	0.32	0.38	0.38

obvious that Tariff C initially had the highest number of customers, followed by Tariff A and Tariff E. The number of customers for Tariff B and Tariff D is similar. In addition, there were 35 customers with missing tariff data. This study assumed that these 35 customers were not initially assigned a tariff, but in subsequent social simulations, customers would make decisions about the tariff.

In addition, in order to more intuitively display the distribution of customer

Table 3.5: Initial tariff distribution

Tariff type	Number of customers
Tariff-A	428
Tariff-B	175
Tariff-C	450
Tariff-D	173
Tariff-E	359
No tariff	35
	total = 1620

types in each tariff, Figure 3.6 and Figure 3.7 show the heatmap of the distribution of customer numbers of different customer clusters and different electricity consumption types in each tariff under the initial allocation of tariffs respectively. From the customer cluster perspective, it can be seen that the number of customers initially assigned to Tariff A, Tariff C, and Tariff E is higher than Tariff B and Tariff C. However, there is no obvious pattern in the distribution of customer in each tariff. From the customer electricity consumption type perspective, almost every type of customer is evenly distributed across various tariffs. Relatively speaking, whether it is Day customers or Peak customers, the number of customers initially assigned to Tariff A, Tariff C, and Tariff E is higher than Tariff B and Tariff C.

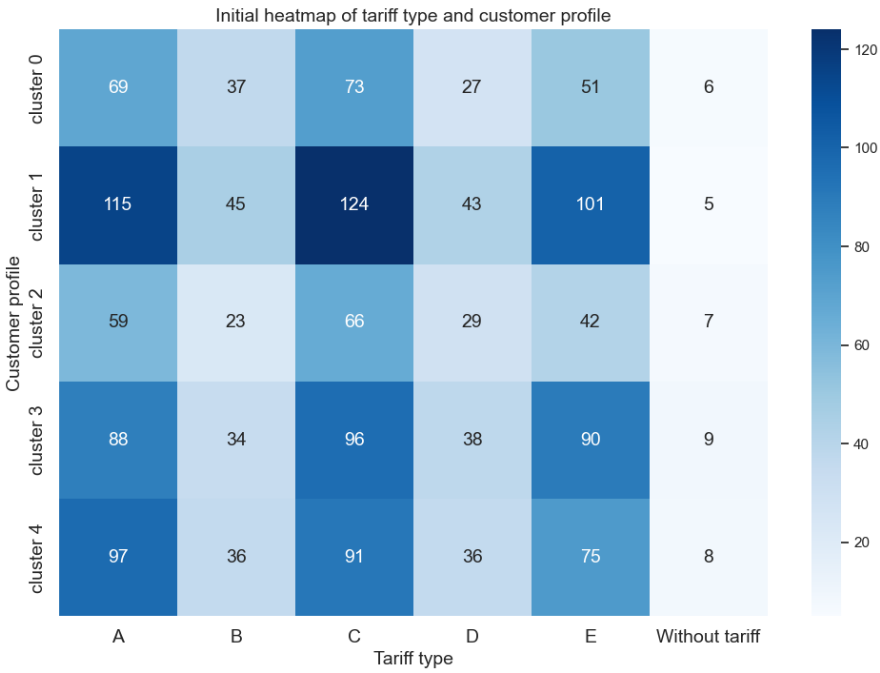


Figure 3.6: Initial heatmap of tariff types and customer profiles

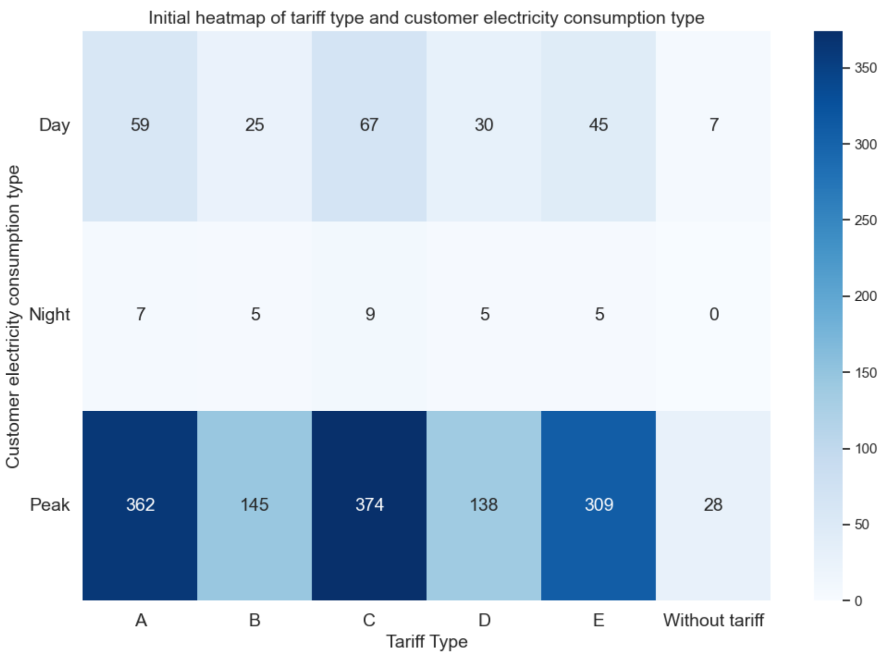


Figure 3.7: Initial heatmap of tariff types and customer electricity consumption types

Chapter 4

Cases Study

For the initial value setting of model parameters, this study follows two methods: the first is to cite data from existing literature, and the second is to use reasonable logical reasoning. Below, a detailed introduction to the parameter setting results for each model will be introduced.

4.1 Parameter and Scenario Settings

4.1.1 Parameter Settings: Customer Satisfaction Model

Due to sensitivity testing of sensitivity parameters in the customer satisfaction model conducted in Section 2.2, this study set sensitivity coefficients in each dimension of the satisfaction model based on the characteristics of each customer. The specific setting results are shown in Table 4.1 and Table 4.2:

Table 4.1: Sensitivity coefficients related to number of household appliances

Household appliances number	λ_1	λ_2	λ_4
Low (≤ 5)	3	3	1
Middle (> 5 and ≤ 8)	2	2	2
High (> 8)	1	1	3

The weight parameters for each dimension in the satisfaction model represent the degree of importance that customers place on each dimension. Due to the fact that the description of the level of importance itself is a fuzzy judgment with many subjective factors, this study assigns values to each category of customers based on their own characteristics. According to the classification of customers in Section

Table 4.2: Sensitivity coefficients related to income level

Income level	λ_3
1	0.01
2	0.02
3	0.03
4	0.04
5	0.05

3.1.3, there are a total of 5 types of customers. The following is a fuzzy description of these 5 types of customers:

- **Cluster 0**: With a high income level, a large number of appliances and rooms, the daily electricity consumption is very high, and the peak electricity consumption occurs during peak hours. Assuming that this type of customer places the highest importance on electricity consumption, followed by electricity usage habits, electricity expenses, and electrification levels.

- **Cluster 1** With a lower income level, a higher number of appliances and rooms, daily electricity consumption is higher, and peak electricity consumption occurs during peak hours. Assuming that this type of customer places the most emphasis on electricity expenses, followed by electricity consumption, with the lowest emphasis on electricity expenses and electrification levels.

- **Cluster 2** Moderate income level, moderate number of appliances, moderate number of rooms, low daily electricity consumption, and peak electricity consumption during the Day period. Assuming that this type of customer places the highest emphasis on electricity usage habits, followed by electricity bill expenses, electricity usage habits, and electrification levels.

- **Cluster 3** Income level is below average, with fewer appliances and rooms, resulting in lower daily electricity consumption and peak electricity consumption during peak hours. Assuming that this type of customer places the highest importance on electricity expenses, followed by electricity usage habits, electrification level, and electricity consumption.

- **Cluster 4** Higher income level, more electrical appliances, moderate number of rooms, higher daily electricity consumption, peak electricity consumption during peak hours. Assuming that this type of customer values electricity consumption the most, followed by the degree of electrification, electricity usage habits, and electricity bill expenses.

Based on the above 5 fuzzy descriptions, determine the parameter values of customer importance for each dimension, as shown in the Table 4.3:

Table 4.3: A satisfaction weight evaluation method based on fuzzy logic

Customer cluster	$[\delta_1,\delta_2,\delta_3,\delta_4]$
Cluster 0	$[0.8, 0.1, 0.05, 0.05]$
Cluster 1	$[0.3, 0.05, 0.6, 0.05]$
Cluster 2	$[0.15, 0.5, 0.3, 0.05]$
Cluster 3	$[0.1, 0.3, 0.4, 0.2]$
Cluster 4	$[0.4, 0.2, 0.1, 0.3]$

4.1.2 Parameter Settings: Small-world Network

The parameters that need to be determined for a small world network include the number of neighbors and the probability of reconnection. The reasonable setting of these two parameters can ensure that the small world network has a high clustering coefficient and an average short path length. This study refers to the Facebook social network [**33**], which has a cluster coefficient of 0.605 and a shortest path length of 3.69. This study included a total of 1620 customers, each representing a node. In order to simulate the real social network as much as possible in the small world network, the number of neighbors and reconnection probability were continuously adjusted in the simulation to make the clustering coefficient and shortest path length as close as possible to the Facebook social network.

Figure 4.1 shows the simulation results of adjusting the number of neighbors from 21 to 30 when the fixed reconnection probability is 0.05. It can be observed that when the number of neighbors is 23, the clustering coefficient of the network is 0.61, and the shortest path is 3.67, which is close to the Facebook social network. Figure 4.2 shows the simulation results of adjusting the reconnection probability from 0.01 to 0.1 when the fixed number of neighbors is 23. The results show that when the reconnection probability is 0.05, the clustering coefficient of the network is 0.61, and the shortest path strength is 3.7.

Therefore, in this study, the reconnection probability parameter for the small-world network was set to 0.05, and the number of neighbors parameter was set to 23.

After setting the parameters of the small-world network, Figure 4.3 shows the network connections of these 1620 customers, where nodes represent each customer and different colors represent the initial allocation tariff for each customer.

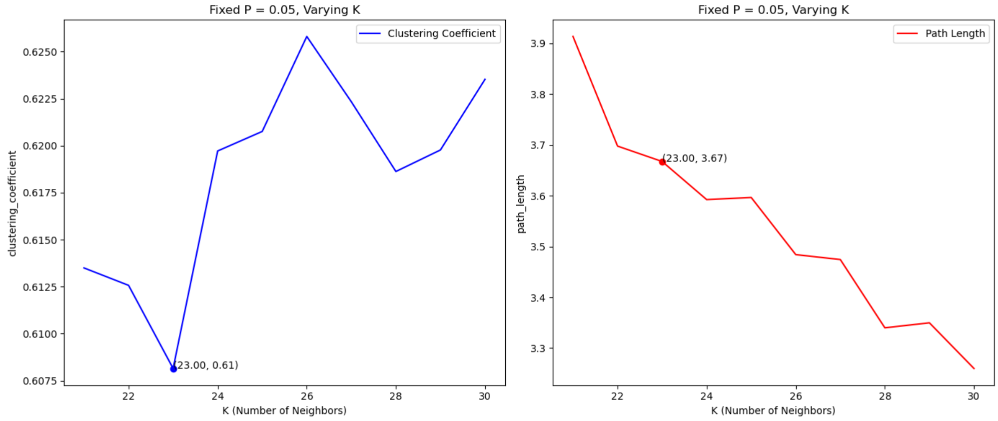


Figure 4.1: Neighbor number determination

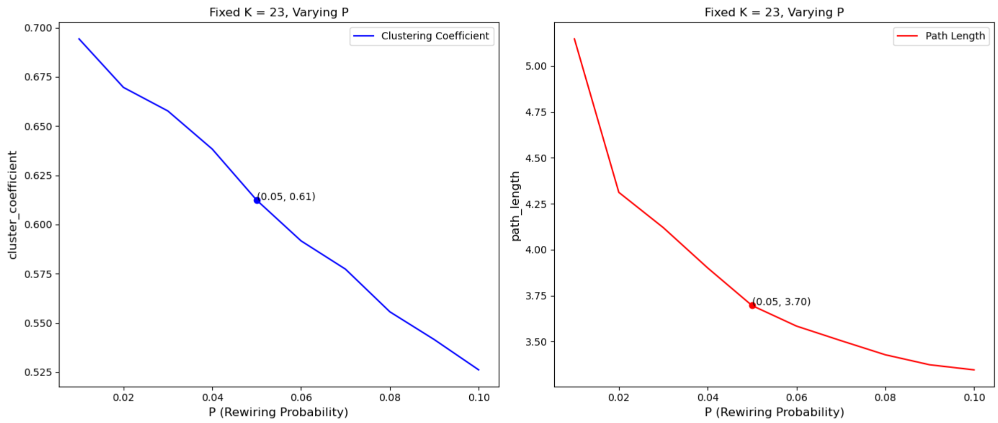


Figure 4.2: Reconnection probability determination

4.1.3 Parameter Settings: Customer Decision-making Model

In decision strategy B, as customers need to consider not only satisfaction but also economic benefits when making a decision to change tariffs, the switching fees, default fees, and tariff terms for changing tariffs need to be set, as shown in the Table 4.4.

4.1.4 Simulation Scenarios Setting

In order to investigate the effects of neighbor influence coefficient and satisfaction weight on customer decision-making, this study conducted a univariate comparative analysis experiment. The specific simulation case number is shown in Figure 4.4. Each row represents adjusting the neighbor influence coefficient when the

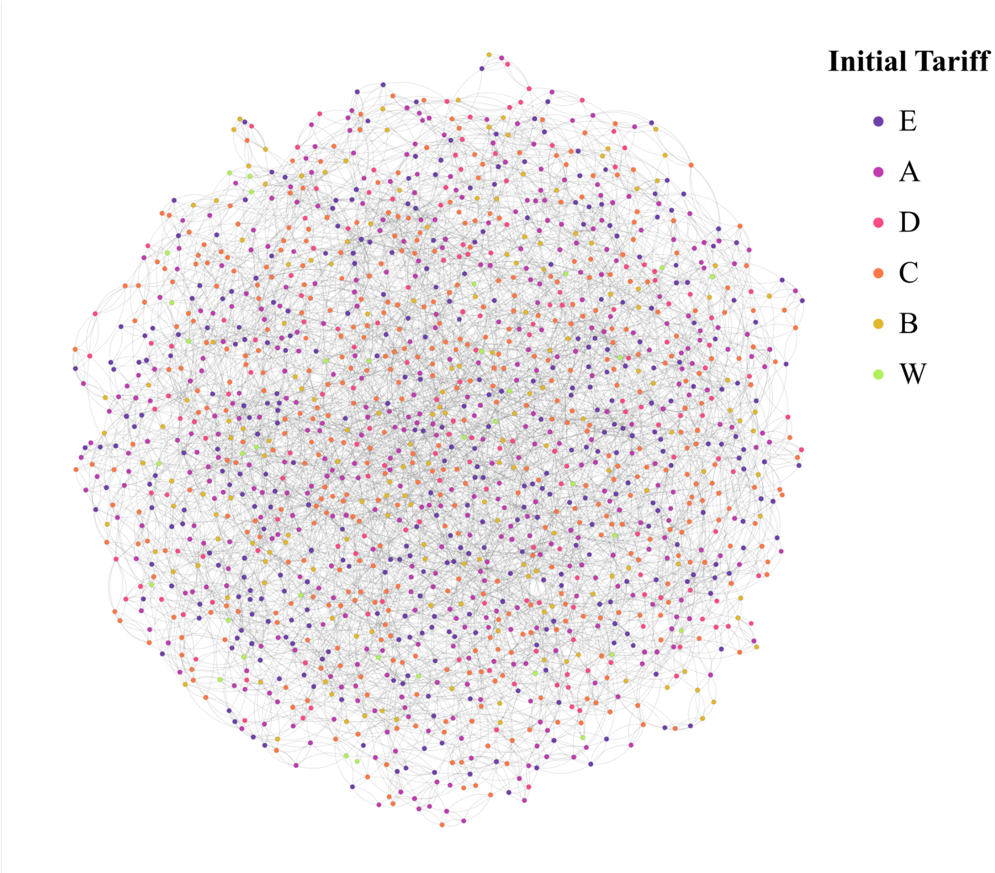


Figure 4.3: Small-world network of 1620 customers with initial tariff allocation

Table 4.4: Decision model paramters

Parameters	Values
Switch fee F	30 (€)
Penalty for breach of contract P	30 (€)
Tariff contract period	12 months

satisfaction weights are fixed, where the neighbor influence coefficient is set to 5 levels: 0, 0.3, 0.5, 0.7, and 1, respectively. Each column represents adjusting the satisfaction weight parameters when fixing the neighbor influence coefficient, and the setting of the satisfaction weight parameters are based on Table 4.3.

- **Case1-#__HighLoad__**β means setting all customers to have the same satisfaction weights parameter as Cluster 0 customers.

- **Case2-#_LowIncome_**β means setting all customers to have the same satisfaction weights parameter as Cluster 1 customers.
- **Case3-#_DayType_**β means setting all customers to have the same satisfaction weights parameter as Cluster 2 customers.
- **Case4-#_LowAppliance_**β means setting all customers to have the same satisfaction weights parameter as Cluster 3 customers.
- **Case5-#_HighAppliance_**β means setting all customers to have the same satisfaction weights parameter as Cluster 4 customers.
- **Case6-#_Uniform_**β means setting the satisfaction weights parameter for all customers to be the same and evenly distributed.
- **Case7-#_ClusterType_**β indicates that each type of customer will be set according to the satisfaction weights parameter in Table 4.3.

The specific simulation case number is shown in Figure 4.4. And all the above cases will be simulated under two different decision-making strategies.

Satisfaction weights $[\delta_1, \delta_2, \delta_3, \delta_4]$	Neighbor influence coefficient $\beta = 0$	Neighbor influence coefficient $\beta = 0.3$	Neighbor influence coefficient $\beta = 0.5$	Neighbor influence coefficient $\beta = 0.7$	Neighbor influence coefficient $\beta = 1$
Cluster0: [0.8, 0.1, 0.05, 0.05] Cluster1: [0.8, 0.1, 0.05, 0.05] Cluster2: [0.8, 0.1, 0.05, 0.05] Cluster3: [0.8, 0.1, 0.05, 0.05] Cluster4: [0.8, 0.1, 0.05, 0.05]	Case1-1_HighLoad_$\beta = 0$	Case1-2_HighLoad_$\beta = 0.3$	Case1-3_HighLoad_$\beta = 0.5$	Case1-4_HighLoad_$\beta = 0.7$	Case1-5_HighLoad_$\beta = 1$
Cluster0: [0.3, 0.05, 0.6, 0.05] Cluster1: [0.3, 0.05, 0.6, 0.05] Cluster2: [0.3, 0.05, 0.6, 0.05] Cluster3: [0.3, 0.05, 0.6, 0.05] Cluster4: [0.3, 0.05, 0.6, 0.05]	Case2-1_LowIncome_$\beta = 0$	Case2-2_LowIncome_$\beta = 0.3$	Case2-3_LowIncome_$\beta = 0.5$	Case2-4_LowIncome_$\beta = 0.7$	Case2-5_LowIncome_$\beta = 1$
Cluster0: [0.15, 0.5, 0.3, 0.05] Cluster1: [0.15, 0.5, 0.3, 0.05] Cluster2: [0.15, 0.5, 0.3, 0.05] Cluster3: [0.15, 0.5, 0.3, 0.05] Cluster4: [0.15, 0.5, 0.3, 0.05]	Case3-1_DayType_$\beta = 0$	Case3-2_DayType_$\beta = 0.3$	Case3-3_DayType_$\beta = 0.5$	Case3-4_DayType_$\beta = 0.7$	Case3-5_DayType_$\beta = 1$
Cluster0: [0.1, 0.3, 0.4, 0.2] Cluster1: [0.1, 0.3, 0.4, 0.2] Cluster2: [0.1, 0.3, 0.4, 0.2] Cluster3: [0.1, 0.3, 0.4, 0.2] Cluster4: [0.1, 0.3, 0.4, 0.2]	Case4-1_LowAppliance_$\beta = 0$	Case4-2_LowAppliance_$\beta = 0.3$	Case4-3_LowAppliance_$\beta = 0.5$	Case4-4_LowAppliance_$\beta = 0.7$	Case4-5_LowAppliance_$\beta = 1$
Cluster0: [0.4, 0.2, 0.1, 0.3] Cluster1: [0.4, 0.2, 0.1, 0.3] Cluster2: [0.4, 0.2, 0.1, 0.3] Cluster3: [0.4, 0.2, 0.1, 0.3] Cluster4: [0.4, 0.2, 0.1, 0.3]	Case5-1_HighAppliance_$\beta = 0$	Case5-2_HighAppliance_$\beta = 0.3$	Case5-3_HighAppliance_$\beta = 0.5$	Case5-4_HighAppliance_$\beta = 0.7$	Case5-5_HighAppliance_$\beta = 1$
Cluster0: [0.25 0.25 0.25 0.25] Cluster1: [0.25 0.25 0.25 0.25] Cluster2: [0.25 0.25 0.25 0.25] Cluster3: [0.25 0.25 0.25 0.25] Cluster4: [0.25 0.25 0.25 0.25]	Case6-1_Uniform_$\beta = 0$	Case6-2_Uniform_$\beta = 0.3$	Case6-3_Uniform_$\beta = 0.5$	Case6-4_Uniform_$\beta = 0.7$	Case6-5_Uniform_$\beta = 1$
Cluster0: [0.8, 0.1, 0.05, 0.05] Cluster1: [0.3, 0.05, 0.6, 0.05] Cluster2: [0.15, 0.5, 0.3, 0.05] Cluster3: [0.1, 0.3, 0.4, 0.2] Cluster4: [0.4, 0.2, 0.1, 0.3]	Case7-1_ClusterType_$\beta = 0$	Case7-2_ClusterType_$\beta = 0.3$	Case7-3_ClusterType_$\beta = 0.5$	Case7-4_ClusterType_$\beta = 0.7$	Case7-5_ClusterType_$\beta = 1$

Figure 4.4: Cases setting

4.2 Simulation Scenarios: Decision Strategy A

Under decision strategy A, the customer's decision only depends on the satisfaction of tariff.

4.2.1 Fixed [δ_1,δ_2,δ_3,δ_4], different β

In order to investigate the impact of neighbor influence coefficient β on customer decisions, this study continuously adjusted the neighbor influence coefficient under setting all the customers with the fixed satisfaction weights. Due to a large number of simulation results, **Case1-#_HighLoad_**β (the first row in Figure 4.4) is selected as an example for analysis in this section.

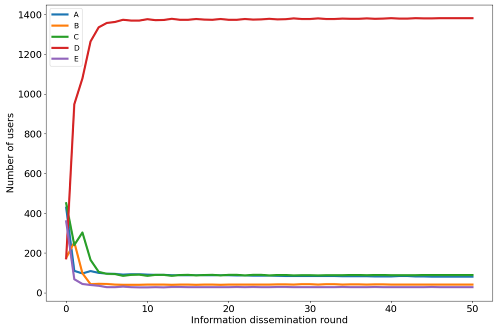
Figure 4.5 shows the trend of the number of customers in each tariff with 50 times of information dissemination under different neighbor influence coefficients, which are 0,0.3,0.5,0.7 and 1. Where the blue line is for tariff A, the orange line is for tariff B, the green line is for tariff C, the red line is for tariff D, and the purple line is for tariff E.

1. β=**0**

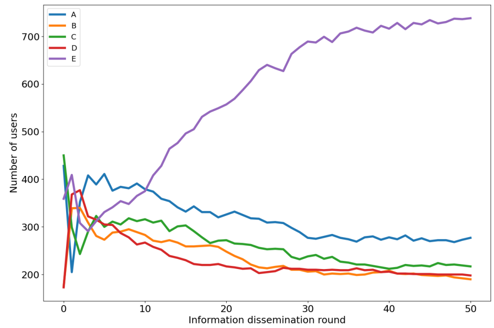
   Figure 4.5 (a) shows that initially, customers' choices of tariff are relatively scattered, and after the initial fluctuation, the number of customers of tariff D increases rapidly and remains stable, while the number of customers of other tariffs decreases and tends to 0. When the neighbor influence coefficient is 0, customers' choices are based solely on their initial preferences. Since there is no neighbor influence, each customer makes the decision independently, but tariff D may have a surge in the number of customers due to the lowest Day and Night price that are more in line with the electricity needs of the majority of customers.

2. β=**0.3**

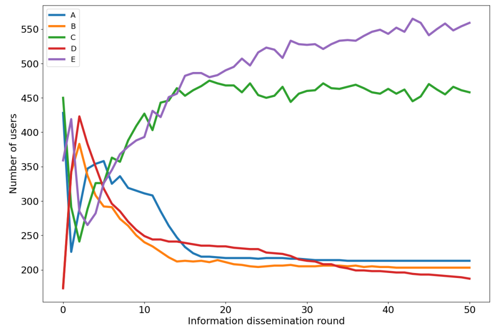
   Figure 4.5 (b) shows that the number of customers in tariff E gradually increases after initial fluctuations, while the number of customers in tariffs A, B, C and D tends to decrease and stabilize. The smaller neighbor influence coefficients make customers start to refer to their neighbors' choices when making decisions, but still retain some personal preferences. When the weight



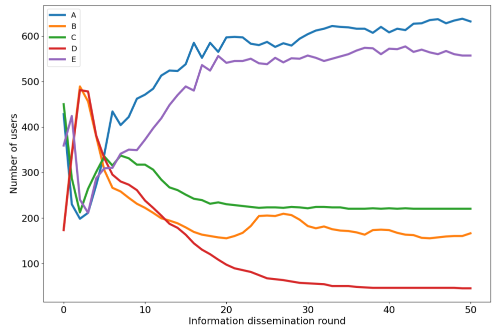
(a) Case1-1_ClusterType_β=0



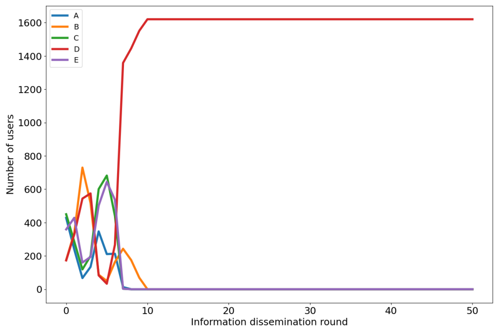
(b) Case1-2_ClusterType_β=0.3



(c) Case1-3_ClusterType_β=0.5



(d) Case1-4_ClusterType_β=0.7



(e) Case1-5_ClusterType_β=1

Figure 4.5: Case1-#__HighLoad__β: customer numbers change with decision strategy A

of electricity consumption satisfaction is set to the maximum, tariff E may have an advantage in electricity consumption and attracts some customers, and the choices of these customers further influence the decisions of other customers.

3. β**=0.5**

Figure 4.5 (c) shows a significant increase in the number of customers for tariffs C and E. However, the increase for tariff E is smaller than that in Figure 4.5 (b), while the number of customers for the other tariffs gradually decreases. As the neighbor influence coefficient increases to 0.5, the neighbor's choice starts to play a more important role in customer decision making. Customers are more inclined to choose the tariffs chosen by their neighbors, creating a more pronounced herd effect.

4. β**=0.7**

Figure 4.5 (d) shows that the number of subscribers of tariffs A and E increases, especially tariff A grows significantly, while the number of subscribers of other tariffs gradually decreases. The herd effect is further enhanced with higher neighbor influence coefficients. Customers are more likely to be influenced by their neighbors' choices, leading to a concentration of choices.

5. β**=1**

Figure 4.5 (e) shows that the number of customers for tariff D peaks rapidly, far exceeding the other tariffs and occupying essentially all customers. When the neighborhood influence coefficient is 1, customers' choices are completely dependent on their neighbors' choices. At this point, the herd effect reaches its extreme, and customers no longer base their preferences on their own, but completely imitate their neighbors.

In the early stage of information dissemination, due to the lowest Day and Night tariffs, some customers choose tariff D, and these choices are quickly passed on and influence their neighbors, causing more customers to choose tariff D. This choice is self-reinforcing when more and more customers choose tariff D. Customers who see that most of their neighbors choose tariff D will be more inclined to follow this choice as the optimal choice. The initial choice and the self-reinforcing herd effect causes the number of customers of tariff D to increase rapidly and become the choice of almost all customers after reaching a certain threshold. This result resembles that when the neighbor influence coefficient is 0, suggesting that the lowest Day and Night tariffs that tariff D has make it the most popular choice in both extreme cases, whether in the case of independent or herd decision making.

In summary, as the neighbor influence coefficient increases, the herd effect gradually increases, and customers' choices tend to be consistent and less dependent on initial preferences. At the beginning of information dissemination, the number of customers of each tariff fluctuates a lot, which may be due to customers' incomplete information in the initial decision-making stage, resulting in unstable choices. After the number of information dissemination rounds increases, the number of subscribers of each tariff tends to stabilize, which indicates that customers' choices gradually solidify and the effect of neighbor influence reaches equilibrium. Certain tariffs attract a large number of customers under different neighbor influence coefficients due to their specific advantages (e.g., price, features, or promotional strategies) and become the final dominant choices, reflecting the importance of product advantages and initial market strategies in market competition.

4.2.2 Fixed β, different $[\delta_1,\delta_2,\delta_3,\delta_4]$

In order to investigate the impact of satisfaction weights $\delta_1,\delta_2,\delta_3,\delta_4$ on customer decisions, this study continuously adjusted the satisfaction weights under setting all the customers with the fixed neighbor influence coefficient. Due to a large number of simulation results, **Case#-1_#_β=0** (the first column with β=0 in Figure 4.4) is selected as an example for analysis in this section.

Figure 4.6 shows the trend in the number of customers for the five tariffs with different satisfaction weight settings at a fixed neighborhood influence factor of 0. First of all, the simulation results of each case are that the number of customers of each tariff fluctuates a lot at the beginning of the information interaction, and the number of customers of each tariff tends to stabilize after the number of information dissemination rounds increases.

Figure 4.6 (a) - (f) show that when the 4-dimensional satisfaction weights for each type of customer are set to be the same, the relationship between the satisfaction weights is:

(a) $\delta_1 > \delta_2 > \delta_3 = \delta_4$
Finally tariff D has the largest number of customers and almost monopolizes the market.

(b) $\delta_3 > \delta_1 > \delta_2 = \delta_4$
The number of customers of final tariff A reaches the maximum, followed by tariff D.

(c) $\delta_2 > \delta_3 > \delta_1 > \delta_4$
The final tariff A reaches the largest number of customers and almost monopolizes the market.

(d) $\delta_3 > \delta_2 > \delta_4 > \delta_1$
The trend of the number of customers is similar to that of the graph in (c).

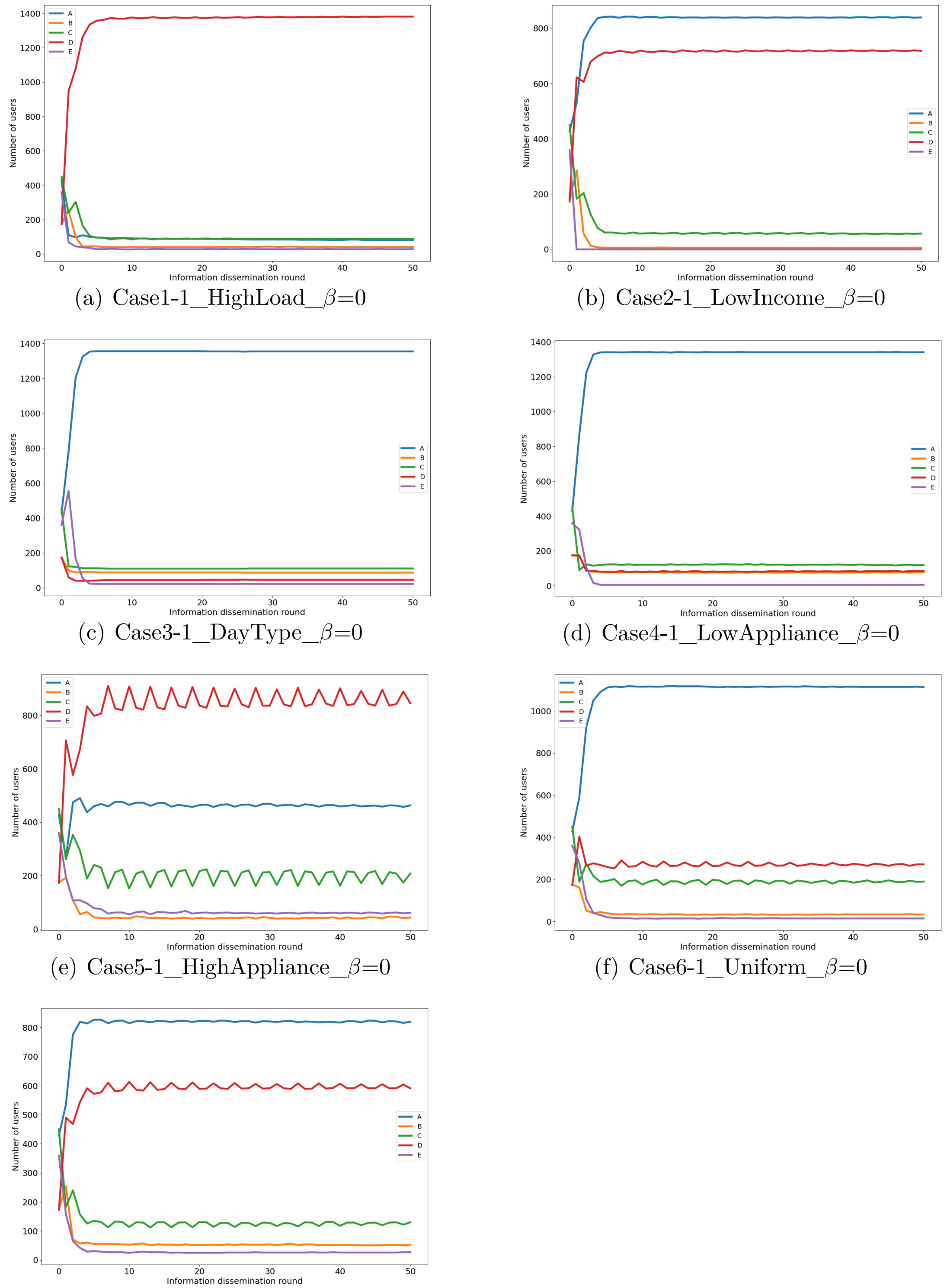
(e) $\delta_1 > \delta_4 > \delta_2 > \delta_3$
Finally the number of customers in tariff D reaches the maximum, but the number of customers appears to have an approximate periodic fluctuation, and the trend of the fluctuation is opposite to that of tariff C.

(f) $\delta_1 = \delta_4 = \delta_2 = \delta_3$
The number of customers of tariff A finally reaches the largest number of customers, and the number of customers of tariffs D and C shows approximate cyclical fluctuations, and the fluctuation tendency is opposite to each other.

Figure 4.6 (g) shows that when the 4-dimensional satisfaction weights of each type of customer are set differently according to the customer portrait of that type of customer, the trend of the number of customers is similar to that of the graph in (b), and the number of customers of tariff D and tariff C appears to fluctuate approximately periodically with opposite fluctuation trends, which indicates that the two tariffs appear to be in a competitive relationship.

In order to quantify the impact of each of the four dimensions (electricity consumption, electricity usage habits, electricity expenditure and degree of electrification) on the customer's final decision, this study uses the Random Forest model to perform a feature importance analysis, where the larger the value of the feature importance, the greater the impact of the dimension on the customer's choice of the tariff.

Table 4.5 counts the number of customers of each tariff after 50 rounds of information interaction under different satisfaction weight settings, and then does the feature importance analysis of the satisfaction weights according to the distribution



(a) Case1-1_HighLoad_β=0

(b) Case2-1_LowIncome_β=0

(c) Case3-1_DayType_β=0

(d) Case4-1_LowAppliance_β=0

(e) Case5-1_HighAppliance_β=0

(f) Case6-1_Uniform_β=0

(g) Case7-1_ClusterType_β=0

Figure 4.6: Case#-1_#_β=0 : customer numbers change with decision strategy A

of the number of customers using the Random Forest model, and the results are shown in Figure 4.7. It can be seen that if customers are most concerned about electricity consumption, they will give priority to tariffs A and D. If customers are most concerned about electricity expenditure, they will give priority to tariff A. If customers are most concerned about electricity consumption habits, they will give priority to tariff B. If customers are most concerned about electrification, they will give priority to tariffs C and E. Combined with the trend of the number of customers in the Figure 4.6, most customers are still more concerned about electricity consumption and electricity expenditure when there is no influence of their neighbors, so more choose tariff A and D.

Table 4.5: Case#-1_#_β=0 : customer distribution after 50 rounds

Case with β=0	$[\delta_1,\delta_2,\delta_3,\delta_4]$	A	B	C	D	E
Case1-1_HighLoad	$[0.8, 0.1, 0.05, 0.05]$	81	41	89	1381	28
Case2-1_LowIncome	$[0.3, 0.05, 0.6, 0.05]$	839	6	57	718	0
Case3-1_DayType	$[0.15, 0.5, 0.3, 0.05]$	1354	87	111	46	22
Case4-1_LowAppliance	$[0.1, 0.3, 0.4, 0.2]$	1340	74	118	83	4
Case5-1_HighAppliance	$[0.4, 0.2, 0.1, 0.3]$	463	43	208	845	61
Case6-1_Uniform	$[0.25, 0.25, 0.25, 0.25]$	1113	33	189	271	14
Case7-1_ClusterType	(varies by cluster)	820	52	130	591	27

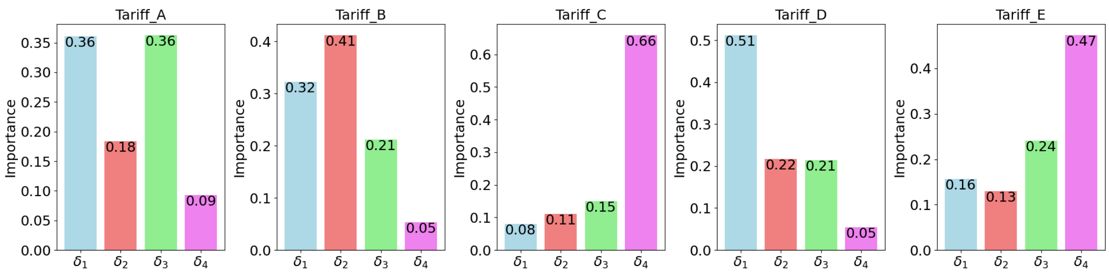


Figure 4.7: Case#-1_#_β=0 : importance of satisfaction weights

4.2.3 Behaviour Analysis of Customer 1002

In order to further analyze the customer's decision-making behavior throughout the information interaction process, this study selected in Case7-2_ClusterType_β=0.3

and customer 1002 as the object of analysis, whose initial tariff is E.

Table 4.6 summarizes the characteristics of customer 1002 and the model parameter settings corresponding to this customer profile, which include a satisfaction model sensitivity parameters based on the number of household appliances and income level of the customer, an average annual natural gas consumption based on the number of rooms of the customer, the satisfaction weight parameters based on the fact that the customer profile belongs to Cluster3, and the customer's electricity consumption classification as Peak.

Table 4.6: Profile of customer 1002

Features of customer 1002	**Parameters setting**
Household appliances number: 3	λ_1=3,λ_2=3,λ_4=1, ϵ=[-0.74,-0.33]
Income level: 4	λ_3=0.04
Room number: 3	Annual gas consumption: 11000kWh
Electricity consumption type: Peak	-
Customer profile: Cluster3	δ_1=0.1,δ_2=0.3,δ_3=0.4,δ_4=0.3

First, customer 1002 has an initial tariff of E. Through customer social interaction model simulation, this customer is exposed to neighbors and receives information about new tariffs. The left part of figure 4.8 shows the number of neighbors that the first ten customers meet in the first round of information interaction, and the right part of figure 4.8 counts the number of different tariffs that the ten customers are exposed to in the first round of information interaction. It can be seen that customer 1002 meets 20 neighbors in the first round of information interactions and is exposed to 2 tariffs E, 4 tariffs D, 7 tariffs C, 2 tariffs B, and 5 tariffs A.

Secondly, when a neighbor recommends a tariff to customer 1002, customer 1002 will predict their own electricity load curve under the recommended tariff based on their electricity price demand elasticity, calculate their satisfaction with the recommended tariff based on the predicted electricity load curve, and add their own satisfaction to the influence of neighbor opinions to obtain their satisfaction with the recommended tariff. Therefore, the customer's satisfaction matrix will be updated. Then, the customer will determine whether to change the tariff based on decision A.

Figure 4.9 clearly shows the information of the neighbor nodes that 1002 encounters in the first ten rounds of information interaction, and different colors

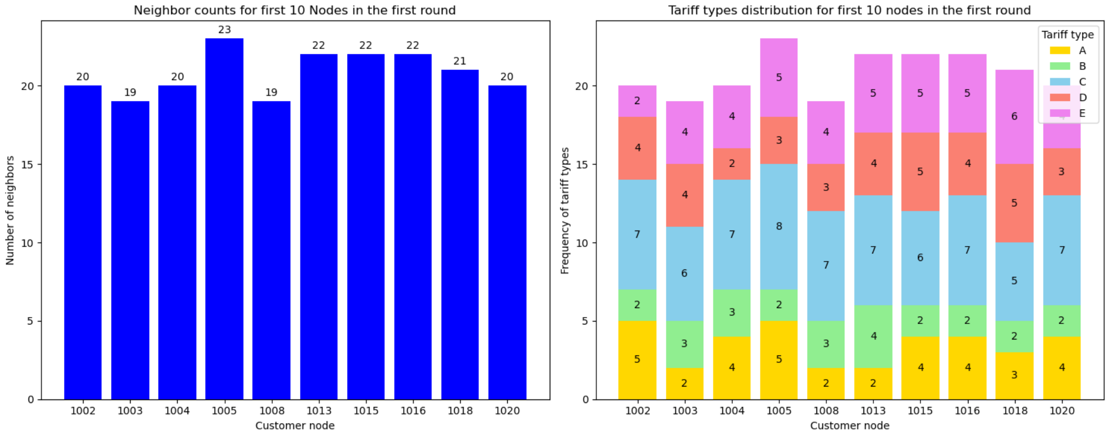


Figure 4.8: Information interaction in the first round

indicate different tariffs. It can be found that customer 1002 changes from tariff E to tariff B after the first round of information interaction, and the number of neighbors choosing tariff B increases. And then customer 1002 changes from tariff B to tariff C after the second round of information interaction, the number of neighbors choosing tariff C also increases.

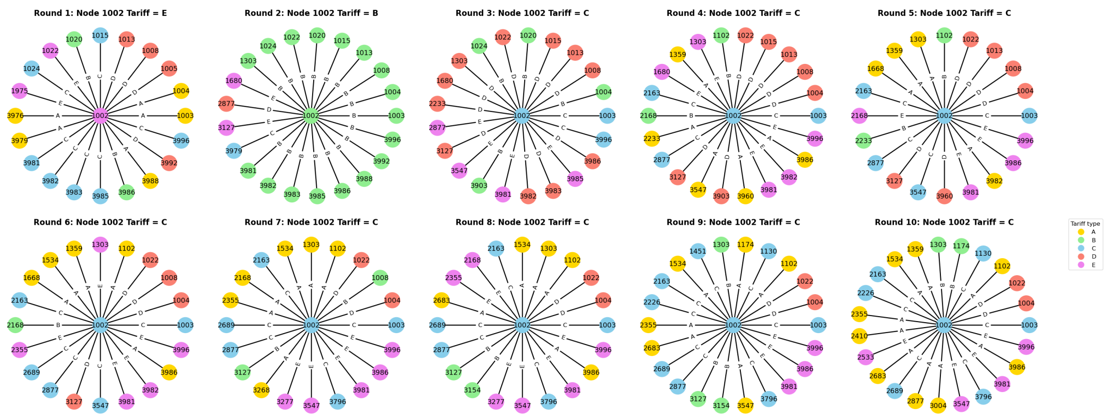


Figure 4.9: Information interaction in the first 10 rounds of customer 1002

Figure 4.10 summarizes the tariff selection of customer 1002 in 50 rounds of information interactions, and it can be seen that the customer has remained unchanged after changing to tariff C. Figure 4.11 shows the change of satisfaction matrix of customer 1002 in 50 rounds of information interaction, where the green line is representing tariff C. It can be seen that after the second round of information interaction, the customer's satisfaction with tariff C has been kept to a maximum.

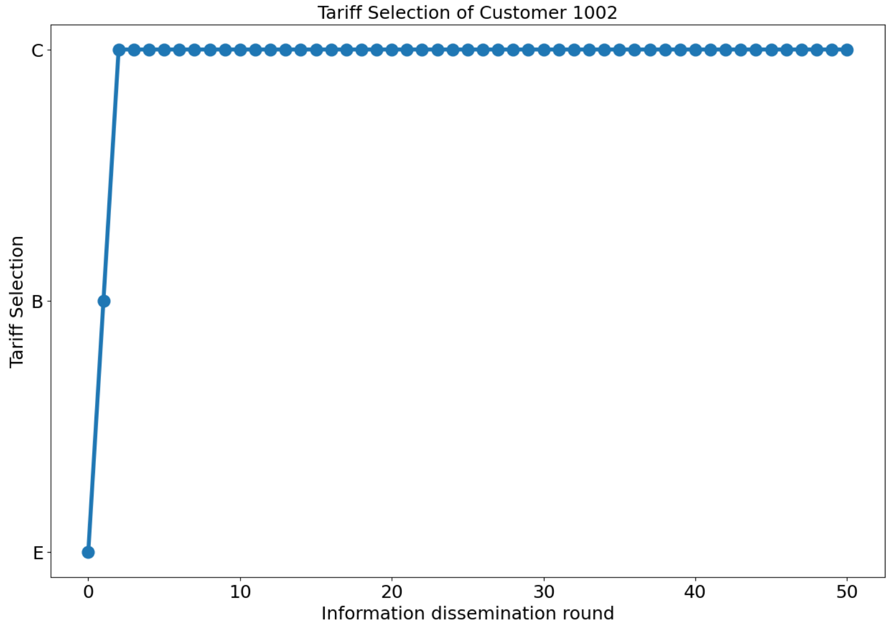


Figure 4.10: Tariff selection of customer 1002

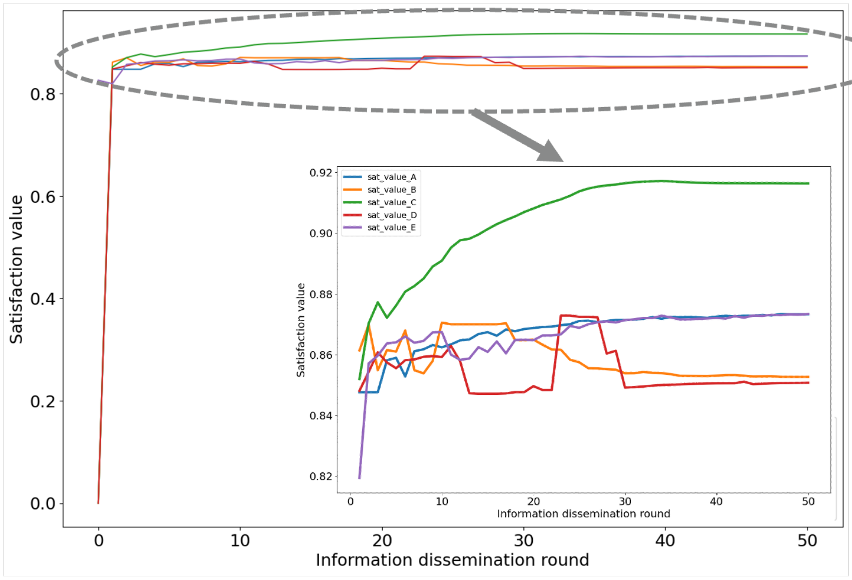
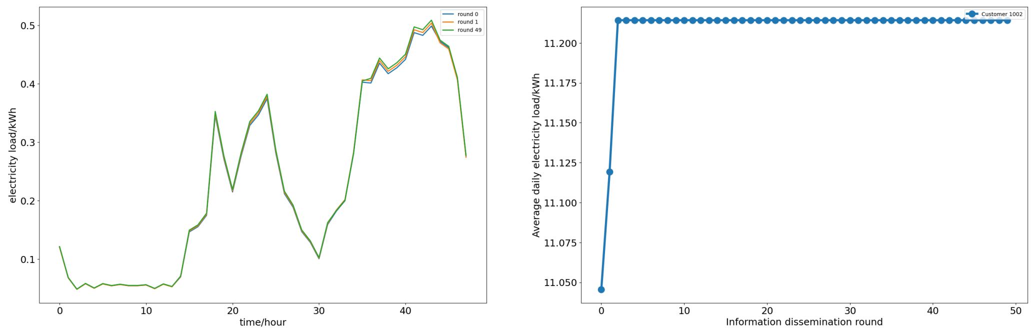


Figure 4.11: Satisfaction value with the five tariffs of customer 1002

Figure 4.12 (a) illustrates the change in the average daily electricity load curve for customer 1002 after after changing the tariff twice. The customer's electricity load curve changes slightly after switching to another tariff according to the customer's electricity price demand elasticity. Figure 4.12 (b) shows the average daily load increases from 11.02kWh to approximately 11.12kWh and then increases to 11.22kWh. This suggests that customer 1002 is switching to tariff C due to an increase in electricity consumption, which brings about an increase in satisfaction at the same time.



(a) Average daily electricity load curve (b) Average daily electricity load

Figure 4.12: Electricity consumption of customer 1002

4.3 Simulation Scenarios: Decision Strategy B

Under decision strategy B, the customer's decision depends on the satisfaction of tariff and economic benefits.

4.3.1 Fixed $[\delta_1,\delta_2,\delta_3,\delta_4]$, different β

In order to investigate the impact of neighbor influence coefficient β on customer decisions, this study continuously adjusted the neighbor influence coefficient under setting all the customers with the fixed satisfaction weights. Due to a large number of simulation results, **Case1-#_HighLoad_**β is selected as an example for analysis in this section. The simulation results of **Case2-#_HighLoad_**β to **Case7-#_HighLoad_**β can be found in Appendix.

Moreover, this study will analyze simulation results from three perspectives: changes in customer numbers, distribution of different customer profile types in different tariffs, and distribution of different customer electricity consumption types in different tariffs.

1. **Changes in customer numbers**

   The left part of the Figure 4.13 shows the trend of the number of customers in each tariff tariff after 50 rounds of information interaction under different neighbor influence coefficients. The right part enlarges the results of the first 4 rounds of information interaction. The blue line represents tariff A, the orange line represents tariff B, the green line represents tariff C, the red line represents tariff D, and the purple line represents tariff E. The numbers in the left figure represent the number of tariff customers after 50 rounds of information interaction and the percentage change compared to the initial value, while the numbers in the right figure represent the number of tariff customers after the first round of information interaction and the percentage change compared to the initial value.

   It is clear from the Figure 4.13 that no matter how large the neighborhood influence coefficient is set, the number of customers for tariffs C and E decreases rapidly in the initial phase, while the number of customers for tariffs A, B, and D increases rapidly. This may indicate that tariffs A, B, and D are more preferred by neighbor opinions in the initial stage of information interaction, or due to the type of customer's electricity time period these tariffs have more advantages in the eyes of the customer.

   Furthermore, compared to the initial fluctuations, it is evident from the distribution of customer numbers after 50 rounds of information interaction that although the number of customers for tariffs A, B, and D ultimately increased, and tariffs C and E ultimately decreased, the degree of fluctuation became smaller and smaller. This indicates that although some tariffs may seem more advantageous at the beginning, as more information is exchanged and influence accumulates among customers, their choices gradually stabilize, reflecting a saturation state of information in the network.

   A more detailed analysis of different neighborhood influence coefficients is presented below.

   (a) β**=0**

      Firstly, in the first figure on the left, the number of customer in each tariff has changed after the first three rounds of information interaction, especially after the first round of information interaction, but has remained stable thereafter, which is because after the first round of information interaction, customers are exposed to new tariff information through their neighbors. Based on the information obtained from each tariff, customers will judge their satisfaction with each tariff and the economic benefits of changing it, thus making a decision on whether to change the tariff. Due to the setting of the small-world network neighbor parameter to 23, which is much larger than the number of tariffs 5, customers can obtain information about all tariffs after the first three rounds of information interaction. Therefore, almost from the fourth round of information interaction, customers will not be exposed to new tariff information, and their satisfaction with these five tariffs will not be affected by neighbor opinions, resulting in no further changes in customer decisions.

From the first figure on the right, it can be seen that after the first round of information interaction, the number of customer in tariff D increased the most, reaching 265.32%. Secondly, the number of customer under tariff A remains unchanged, because the number of incoming and outgoing tariff customers is the same, not because no one chooses tariff A. Tariff B, C, and E are all showing a downward trend, but the most obvious one is tariff E, where the number of customer has decreased by 98%. This indicates that when the satisfaction weight of all customers for electricity consumption is set to the maximum, most customers have a strong initial preference for tariff D, while their initial preference for tariff E is the weakest. This is because the Day and Night period prices of tariff D are the lowest, while the overall price of tariff E is relatively high compared to other tariffs.

The simulation results indicate that when the neighbor influence coefficient is 0, customers only make decisions based on their initial preferences, and neighbor opinions do not affect their decisions.

(b) β=**0.3-0.7**

From the second, third, and fourth graphs on the left, it can be seen that as the neighbor influence coefficient increases from 0.3 to 0.7, after 50 rounds of information interaction, the number of customers is more evenly distributed among various tariffs. This indicates that as the neighbor influence coefficient increases, customers are more susceptible to the influence of neighbor opinions, and their decisions tend to choose the common choices in the community. Especially under the strong neighbor influence coefficient of 0.7, customers are more likely to choose the tariff chosen by the majority, forming a clear herd effect.

(c) β=**1**

In the gray circle of the last figure on the left, it can be seen that when the neighbor influence coefficient reaches its maximum value of 1, compared to smaller neighbor influence coefficients, the number of customer in the five tariffs showed significant fluctuations in the first few rounds of information interaction, and gradually stabilized after about the 10th round. This indicates that customers' choices of tariffs are almost entirely influenced by the opinions of their neighbors. Especially evident are tariff A, D, and E. Under specific conditions where there is no influence from neighbors, tariff D is the most popular. As the influence of neighbors increases, the number of customer in tariff D decreases, tariff A becomes the most popular, and tariff E reduces to the least popular. As the influence of neighbors increases to 1, tariff E actually goes from least popular to most popular. This indicates that as the influence of neighbors increases, customers will weaken their initial preferences and make general choices towards the community, especially in the extreme case of β=1, where customers' decisions are almost entirely dependent on their neighbors' choices.

2. **Distribution of customer profile types in tariffs**

The left part of the Figure 4.14 shows the distribution of the initial number of customers in the five clusters under the five tariffs, showing that the distribution of the five clusters of customers is relatively even at the beginning and there is no obvious concentration trend. For example, cluster 0 has distributions of 69, 37, 73, 27, and 51 for tariffs A, B, C, D, and E, respectively.

The right part shows the heatmap of customer distribution when the neighbor influence coefficient factor is 0, 0.3, 0.5, 0.7 and 1 respectively.

(a) β=**0-0.3**

When the neighbor influence coefficient is 0, each type of customer chooses tariff D. When the neighbor influence coefficient increases to 0.3, the customers' choices start to be influenced by their neighbors. At this point, Cluster 2 customers are more likely to concentrate on tariff D because the peak electricity consumption of cluster 2 customers is concentrated in the Day time hours, and tariff D has the lowest Day time electricity price. Customers in the other clusters (whose electricity consumption is of the Peak type) are more concentrated in tariff A, which has the lowest Peak hour price. This suggests that with some neighbor influence, different clusters of customers start to show their own choice preferences, with the preference for tariffs stemming more from the customer's electricity consumption type.

(b) β=**0.5**

When the neighborhood influence coefficient is further increased to 0.5, there is still a significant difference in the choices of different clusters of customers, with customers in cluster 2 still choosing mainly tariff D, while customers in the other clusters are more likely to choose tariff A. However, compared to the low neighborhood influence coefficients, the number of customers in the different clusters is more evenly distributed among the tariffs, which suggests that the increase in the neighborhood influence leads to a greater tendency to choose the tariffs that are more popular in the neighborhood. This suggests that increased neighborhood influence makes customers more likely to choose the more popular tariffs in the neighborhood.

(c) β=**0.7-1**

When the neighborhood influence coefficient increases to 0.7, customer choices converge further, but there is still some cluster variation. Finally, when the neighborhood influence coefficient increases to 1, customers' choices are almost completely influenced by their neighbors, with a greater concentration on tariff E. This indicates that, in the extreme case, customers' decisions are almost completely dependent on the choices of their neighbors, which creates an obvious herd effect.

3. **Distribution of customer electricity consumption types in tariffs**

In order to further explore the factors determining customer preferences, this study categorizes customers into Day, Night, and Peak from the perspective of the type of electricity consumption so as to analyze the distribution of the number of customers in these three categories under different tariffs.

The Figure 4.15 on the left shows the initial distribution of the number of customers in these three categories under the five tariffs. It can be seen that the distribution of the three types of customers at the initial stage is relatively even, indicating that without the influence of neighbors, different types of customers do not have a clear preference for the choice of tariffs. For example, the distributions of Peak type customers on tariffs A, B, C, D and E are 362, 145, 374, 138 and 309, respectively.

The right part shows the heat map of customer distribution when the neighbor influence coefficient is 0, 0.3, 0.5, 0.7 and 1 respectively.

(a) β=**0-0.3**

When the neighborhood influence coefficient is 0, customers choose tariffs mainly based on their initial preferences. Each type of customer chooses tariff D more often.This indicates that tariff D becomes the first choice of most customers in the absence of neighbor influence. When the neighbor influence coefficient increases to 0.3, Day and Night customers are more likely to focus on tariff D, which is the lowest priced tariff during Day and Night hours, while Peak customers are more likely to focus on tariff A, which is the lowest priced tariff during Peak hours, indicating that the choices of different types of customers begin to diverge as the neighbor influence increases.

(b) β=**0.5**

When the neighbor influence coefficient is further increased to 0.5, Day and Night customers will still concentrate on tariff D, while Peak customers will still concentrate on tariff A. At this point, customers' choices are more obviously influenced by their neighbors, but they still retain some initial preferences. This suggests that a moderate intensity of neighbor influence can induce customers to find a balance between initial preference and neighbor choice.

(c) β=**0.7**

When the neighbor influence coefficient increases to 0.7, customer choices tend to be more evenly distributed. Although Day and Night category customers are still concentrated in tariff D, in general, different categories of customers are more evenly distributed across tariffs. This reflects the fact that higher Neighborhood Influence Coefficients make customers more inclined to choose the more popular tariffs in their neighborhoods, reducing the differences between categories.

(d) β=**1**

When the neighbor influence coefficient reaches 1, customers' choices are almost completely influenced by their neighbors, showing a strong herd effect. customers in the Day and Night categories significantly deviate from their initial preferences in their choices, with more of them choosing tariff E, while Peak customers are mainly concentrated in tariffs A and E. This indicates that, in the extreme case, the customers' decisions are completely reliant on the choices of their neighbors, and their initial preferences are basically no longer play a role.

In summary, the neighbor influence coefficient has a significant effect on the distribution of customers across tariffs. As the neighbor influence coefficient increases, customers' choices are gradually influenced by their neighbors, showing the herd effect. However, different clusters of customers respond differently to neighbor influence, which may be related to their specific needs and preferences caused by different electricity consumption type. At lower neighborhood influence coefficients, customers make decisions mainly on the basis of their own initial preferences, while as neighborhood influence coefficient increases, customers' choice patterns converge, the influence of initial preferences gradually diminishes, and the choices of different categories of customers become more balanced, creating a clear herd effect.

4.3.2 Fixed β, different [δ_1,δ_2,δ_3,δ_4]

In order to investigate the impact of satisfaction weights δ_1,δ_2,δ_3,δ_4 on customer decisions, this study continuously adjusted the satisfaction weights under setting all the customers with the fixed neighbor influence coefficient. In Section 4.2.2, we summarized the relative importance of each dimension for the selection of a particular tariff in the absence of neighbor influence. In this section, **Case#-2_#_β=0.3** (the column with β=0.3 in Figure 4.4) is selected as an example to examine the impact of each dimension on customer decision-making. The simulation results of other columns in Cases setting Figure 4.4 can be found in Appendix.

Figure 4.16 shows the trend in the number of customers for the five tariffs with different satisfaction weight settings at a fixed neighborhood influence factor of 0.3. Firstly, it can be seen that the trends in the number of customers are very similar regardless of the satisfaction weight setting. A rapid redistribution of the number of customers occurs after several times of information interaction, and the number of customers of each tariff tends to stabilize as the number of information interactions increases. In addition, in all cases, after 50 rounds of information interactions, both tariff A and tariff E show great volatility, with tariff A becoming the most popular and tariff E becoming the least popular, in addition to relatively small fluctuations in the number of customers in tariffs B, C, and D. Except for figure (c), all other figures show a trend of rapid increase in the number of customers in tariffs A, B, and D and a rapid decrease in the number of customers in C and E after the first few information interactions, and in figure (c), only tariff A shows an increase in the number of customers, while all other tariffs show a decrease in the number of customers. Since only Case3-2 has the satisfaction weights according to the customer's type of electricity consumption, it shows that the type of electricity consumption has a great influence on the customer's decision, and this conclusion coincides with the previous section 4.3.1.

Overall, the satisfaction weights have less influence on the final customer decision when the neighbor influence coefficient is larger than 0.

4.3.3 Behaviour Analysis of Customer 1002

In order to further compare the results of the two decision strategies, this study selected in Case7-2_ClusterType_β=0.3 and customer 1002 as the object of analysis, which is the same with Section 4.2.3.

Since the settings for the small-world network parameters are the same, the information about the neighbors that the customer 1002 meets in the information interaction remains Figure 4.8.

Figure 4.17 clearly shows the information of the neighbor nodes that 1002 encounters in the first ten rounds of information interaction, and different colors indicate different tariffs. It can be found that customer 1002 changes from tariff E to tariff B after the first round of information interaction, and the number of neighboring neighbors choosing tariff B increases.

Figure 4.18 summarizes the tariff selection of customer 1002 in 50 rounds of information interactions, and it can be seen that the customer has remained unchanged after changing to tariff B. Figure 4.19 shows the change of satisfaction matrix of customer 1002 in 50 rounds of information interaction, where the yellow line is representing tariff B. It can be seen that after the first round of information interaction, the customer's satisfaction with tariff B reaches the maximum and lasts until roughly 12 rounds, and then between 20 rounds although the satisfaction with tariff B is not the maximum, considering the economic factors such as handling fee for changing tariffs, default fee, etc., the customer still keep tariff B unchanged.

Figure 4.20 shows the change in the electricity load curve of customer 1002, after switching to tariff B, the customer's electricity load curve changes slightly according to the customer's electricity price demand elasticity, and the average daily load increases from 11.02kWh to approximately 11.12kWh.

In sammry, comparing the results of tariff selection under the two decision conditions of customer 1002, it can be seen that under the premise of considering the customer's satisfaction with each tariff, and then adding the customer's consideration of economic benefits, the customer becomes relatively more rational, which will lead to a decrease in the frequency of the customer's replacement of tariffs.

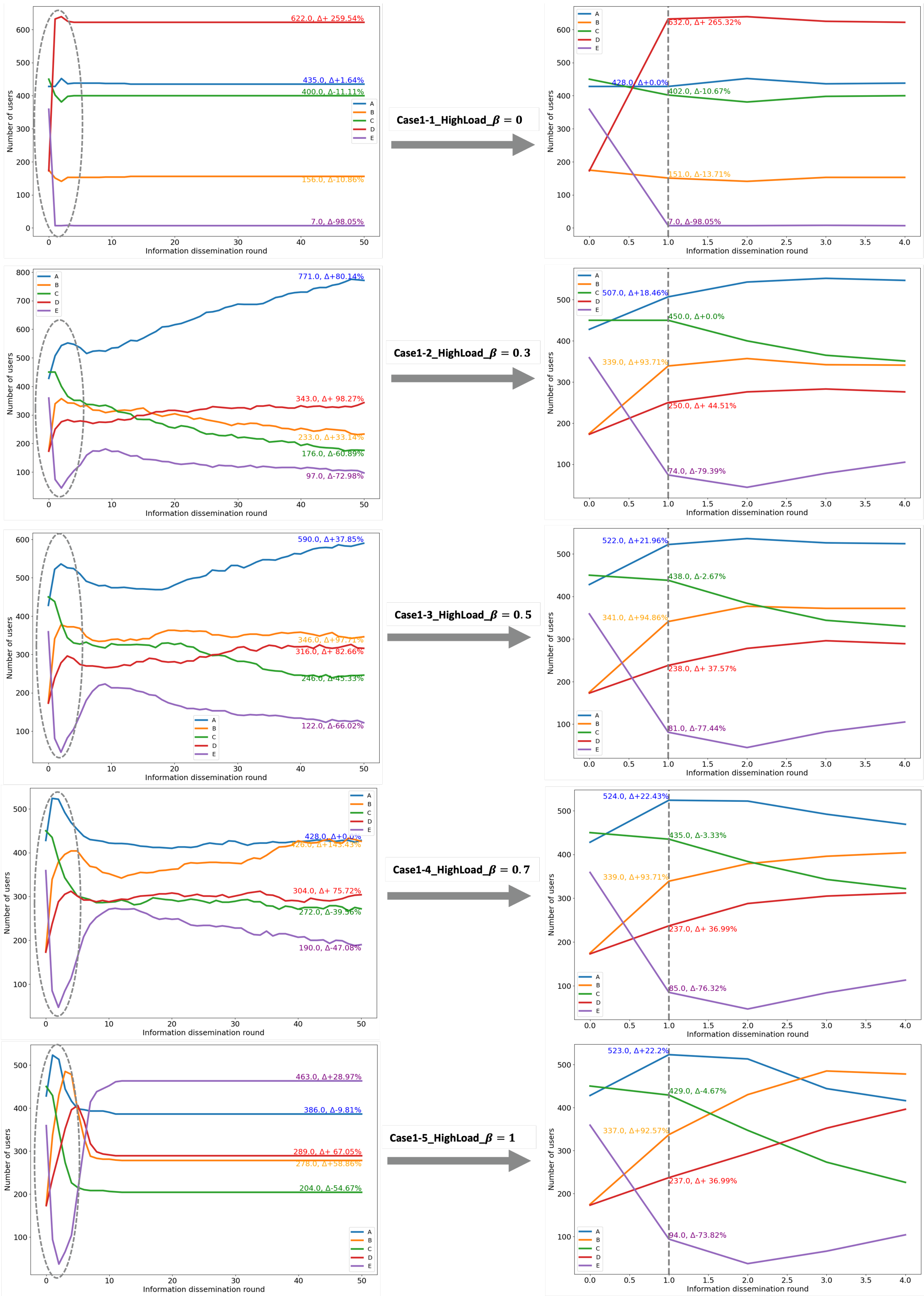


Figure 4.13: Case1-#_HighLoad_β: customer numbers change with decision strategy B

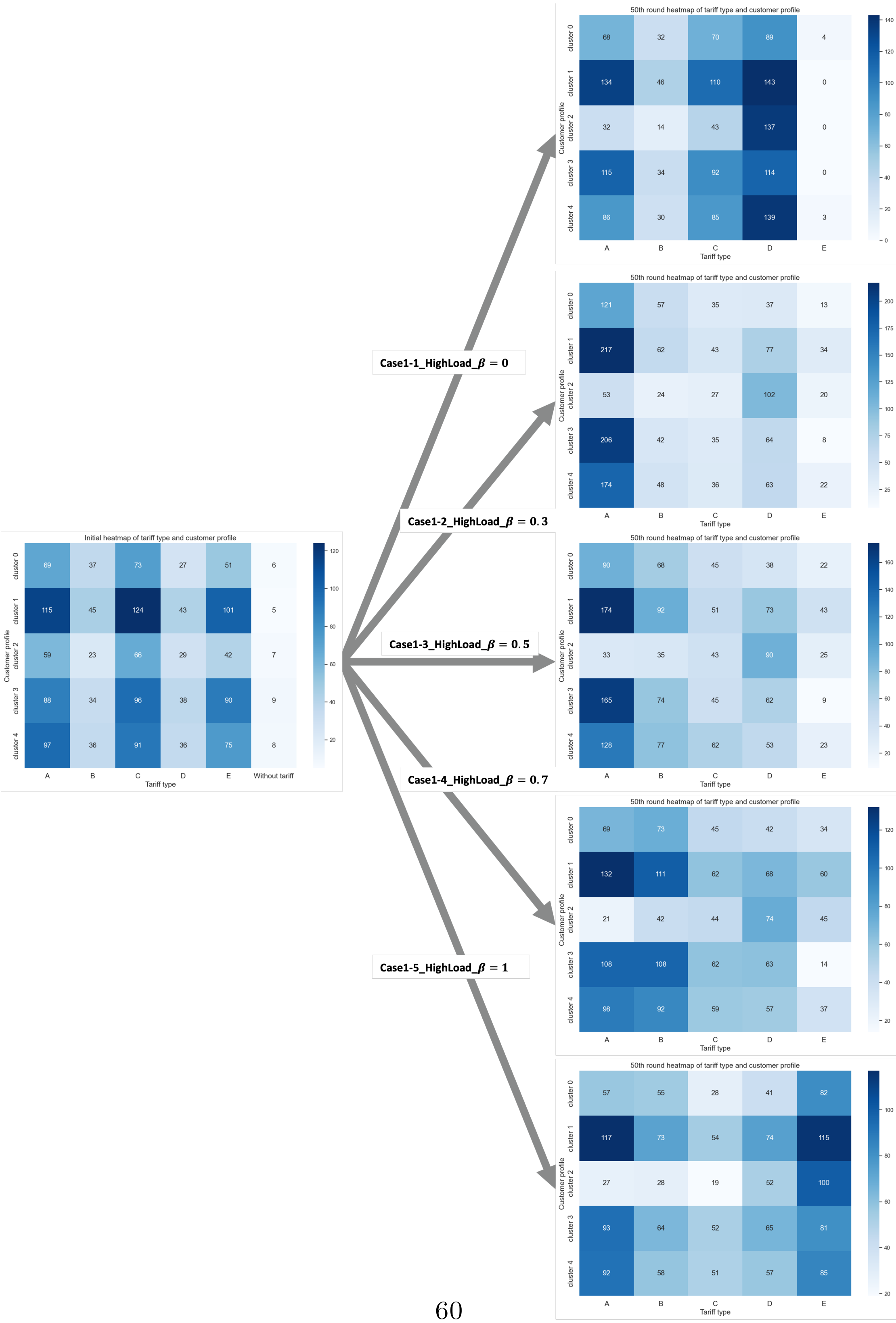


Figure 4.14: Case1-#_HighLoad_β: distribution of customer profile clusters with decision strategy B

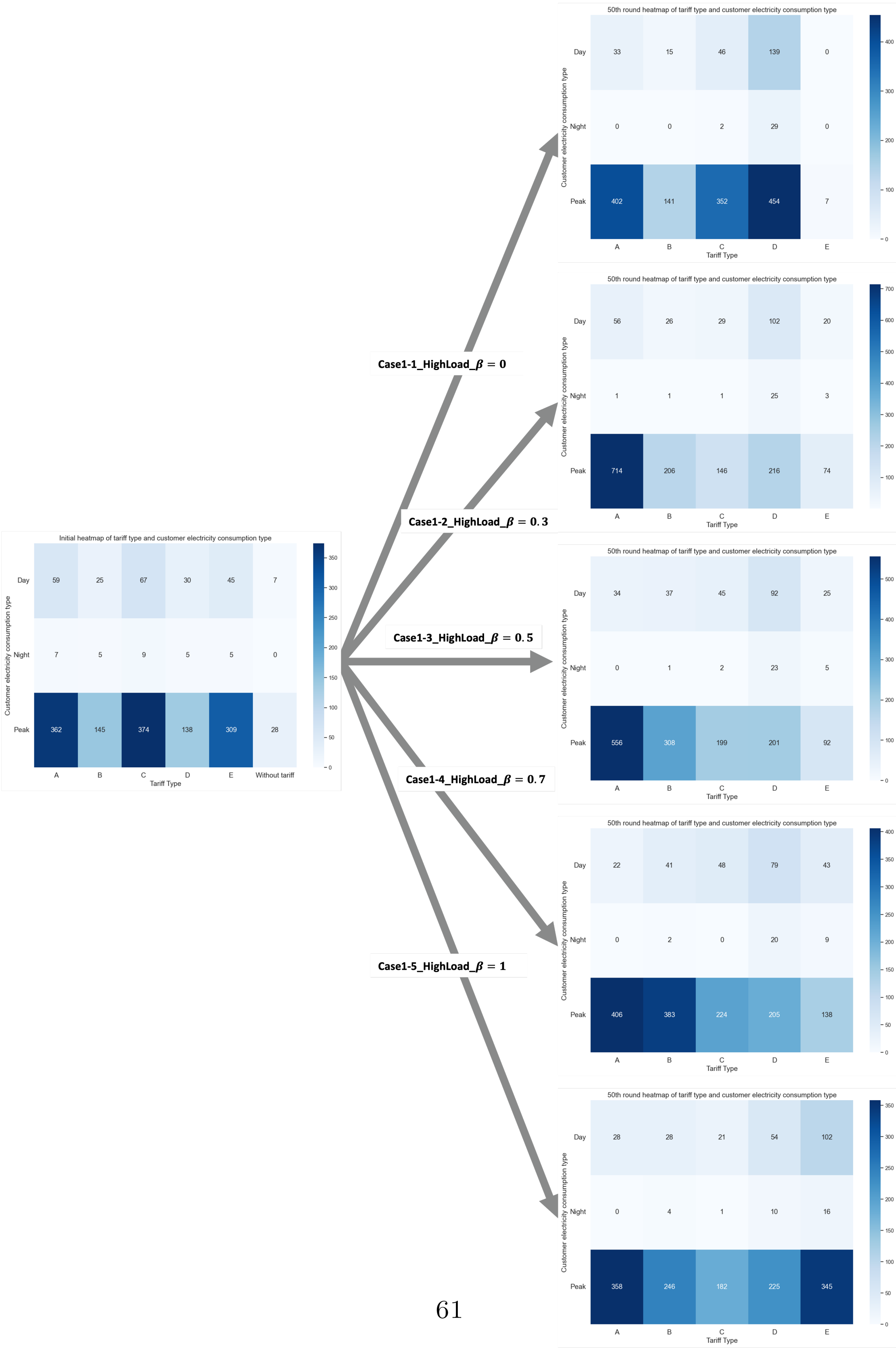
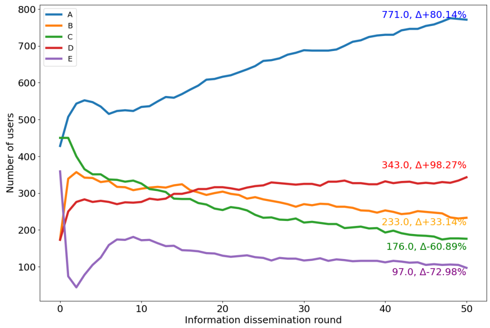
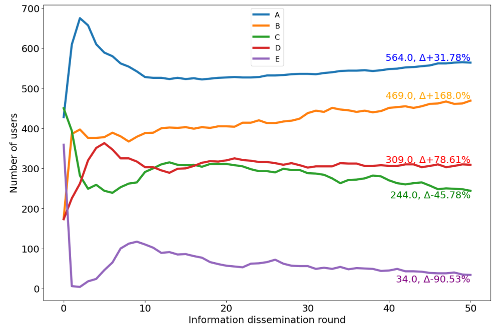


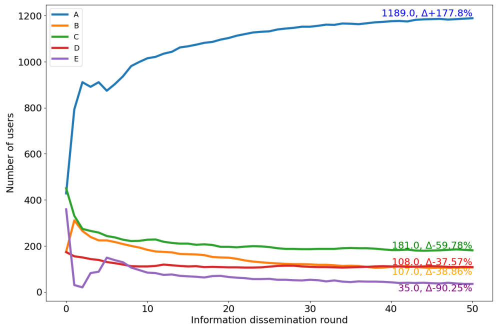
Figure 4.15: Case1-#_HighLoad_β: distribution of customer electricity consumption types with decision strategy B



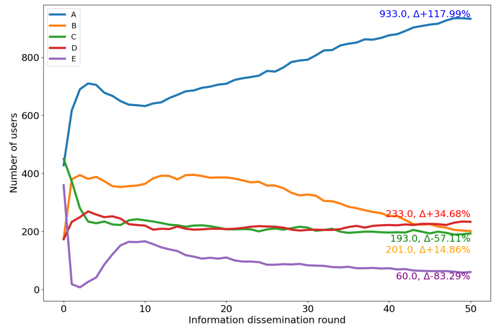
(a) Case1-2_HighLoad_β=0.3



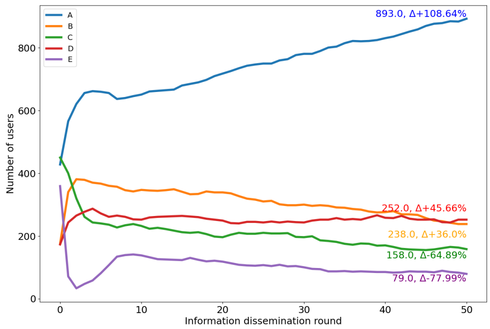
(b) Case2-2_LowIncome_β=0.3



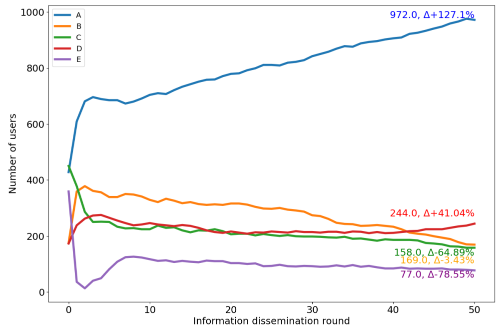
(c) Case3-2_DayType_β=0.3



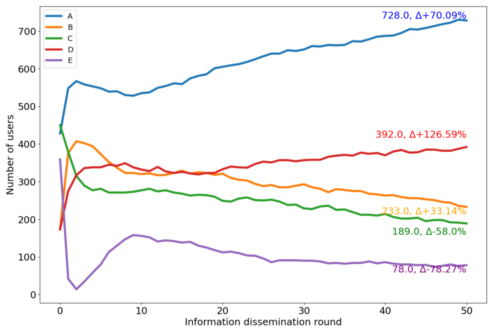
(d) Case4-2_LowAppliance_β=0.3



(e) Case5-2_HighAppliance_β=0.3



(f) Case6-2_Uniform_β=0.3



(g) Case7-2_ClusterType_β=0.3

Figure 4.16: Case#-2_#_β=0.3 : customer numbers change with decision strategy B

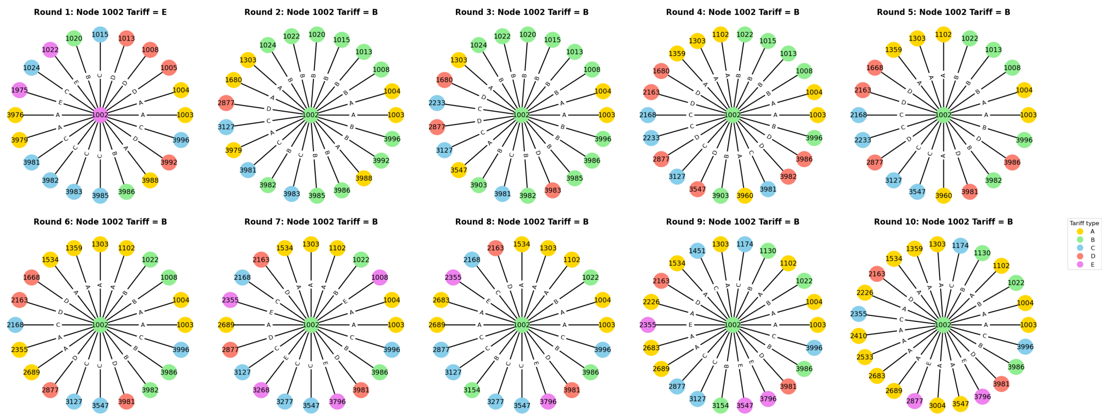


Figure 4.17: Information interaction in the first 10 rounds of customer 1002

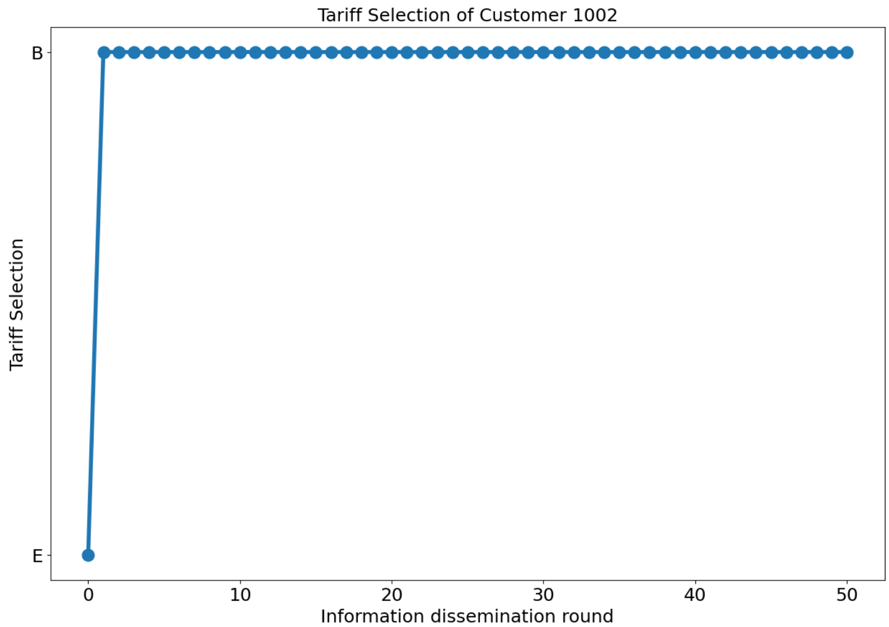


Figure 4.18: Tariff selection of customer 1002

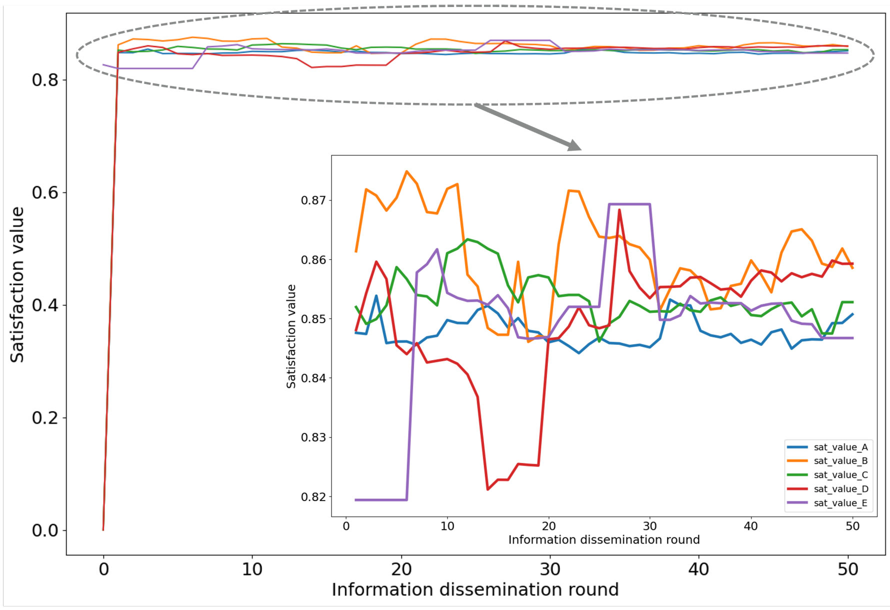
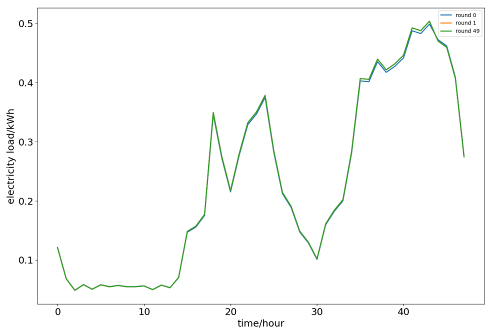
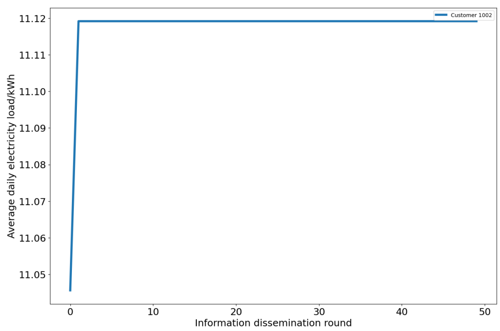


Figure 4.19: Satisfaction value with the five tariffs of customer 1002



(a) Average daily electricity load curve



(b) Average daily electricity load

Figure 4.20: Electricity consumption of customer 1002

Chapter 5

Conclusion

5.1 Summary

In this study, a retail TOU tariff decision-making model based on customer psychological satisfaction and dynamic social influence has been built, which consists of 3 main parts, customer satisfaction model, customer social interaction model and customer decision-making model.

Firstly, a customer satisfaction model is built based on the price data of TOU tariffs and customer characteristics obtained from the data layer, taking into account customers' average daily electricity consumption, average daily electricity consumption habits, average daily electricity expenditure, and household electrification level. The model takes into account the characteristics of each customer and can quantify for each individual the psychological satisfaction that the electricity price tariff brings to them. Then this study uses the small-world network to simulate the information dissemination process between customers in the real world, and considers the impact of neighbors' opinions on individual customers to construct a social interaction model for electricity customers. The social interaction model is set up as follows, when customers learn about the new tariff information during the social process, they predict their electricity consumption habits under the new tariff based on their tariff elasticity demand, assess their satisfaction with the new tariff based on their new average daily electricity consumption, electricity consumption habits, average daily electricity expenditure, and household electrification level, and then superimpose the influence of their neighbors' opinions to update their satisfaction matrix including all the tariffs they have come across. In the customer decision-making model, this study proposes two decision-making strategies, the first one is that customers only use the satisfaction of each tariff after being updated by the social interaction model as a measure to choose the electricity tariff with the highest satisfaction; the second one is that customers also consider the economic benefits based on psychological satisfaction, such as by calculating the change in monthly electricity expenditure, liquidated damages, and the handling fee for changing tariffs, before deciding whether or not to change the tariff.

Secondly, in order to carry out parameter sensitivity analysis of the model, different simulation cases have been designed in this study. Under the decision strategy of A and B, fix the neighbor influence coefficient and adjust the satisfaction weights to different combinations, as well as fix the satisfaction weights and adjust the neighbor influence coefficient, and calculate the trends of customer number changes under 5 tariffs.

The results show that social network has a significant impact on customer decisions. In the early stage of information dissemination, the number of customers under each tariff fluctuates greatly, which may be due to the unstable choice of customers caused by incomplete information in the initial decision-making stage, and the choice of customers tends to be stable with the exchange of more information among customers, reflecting that the information in the network has reached a "saturation state".

Different neighbor influence coefficients have significant effects on the distribution of customers in different tariffs. As the neighbor influence coefficient increases, customers' choices are gradually influenced by their neighbors, showing the herd effect. However, different categories of customers respond differently to neighbor influence, which may be related to their specific needs and preferences. At lower neighbor influence coefficients, customers make decisions mainly based on their own initial preferences, while at higher neighbor influence coefficients, customers' choice patterns converge, forming an obvious herd effect.

In addition, when the neighbor influence coefficient is 0, the relative importance of different dimensions of satisfaction weights on the choice of a particular tariff is not the same. However, as the neighbor influence coefficient increases, the influence of satisfaction weights on the final customer decision gradually diminishes. Moreover, comparing the two decision-making strategies, customers become more rational and change tariffs less frequently when the consideration of economic benefits is increased.

Overall, this study quantifies both the psychological aspects of customers and the information interaction in social networks, builds the decision-making behaviors of customers on electricity tariffs, and conducts a sensitivity analysis of parameters such as satisfaction weights and neighbor influence coefficients in the model.

5.2 Future Work

This study primarily examines how customers in social networks make tariff choices influenced by their neighbors. Future research can integrate multi-agent large models to consider the role of electricity suppliers in dynamically adjusting their tariffs based on market share fluctuations. Additionally, it is crucial to explore the extra influence of suppliers' marketing efforts on tariff choices. Employing reinforcement learning to simulate the behavior of both suppliers and consumers will provide a more comprehensive understanding of market dynamics and decision-making processes.

Furthermore, future studies can focus on the perspective of prosumers in the energy community, incorporating more economic principles to further refine the satisfaction model, customer social interaction model, and decision-making model. This approach will deepen the understanding of market mechanisms and support the development of more effective market strategies.

Appendix A

Decision Strategy A

A.1 Fixed [δ_1,δ_2,δ_3,δ_4], different β

A.1.1 Case2-#_Lowincome_β

A.1.2 Case3-#_DayType_β

A.1.3 Case4-#_LowAppliance_β

A.1.4 Case5-#_HighAppliance_β

A.1.5 Case6-#_Uniform_β

A.1.6 Case7-#_ClusterType_β

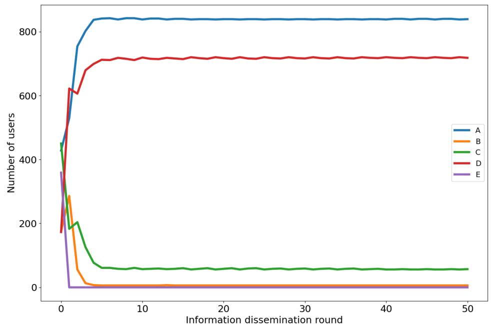
A.2 Fixed β, different [δ_1,δ_2,δ_3,δ_4]

A.2.1 Case#-2_#_β=0.3

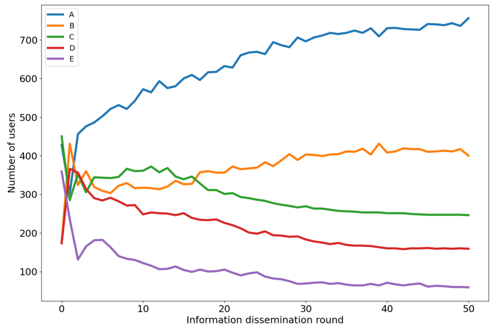
A.2.2 Case#-3_#_β=0.5

A.2.3 Case#-4_#_β=0.7

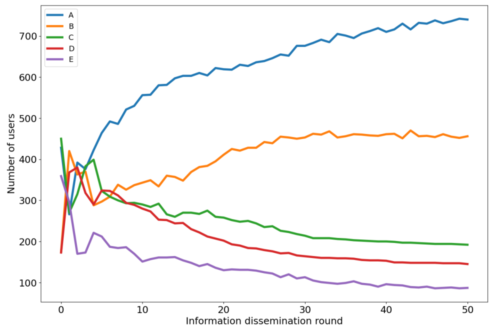
A.2.4 Case#-5_#_β=1



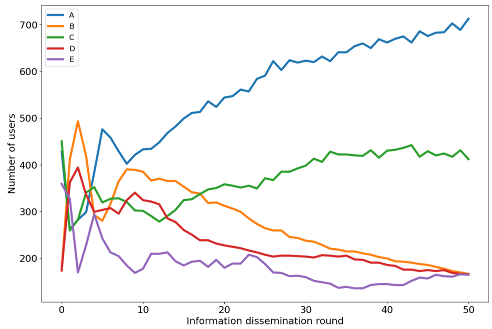
(a) Case2-1_Lowincome_β=0



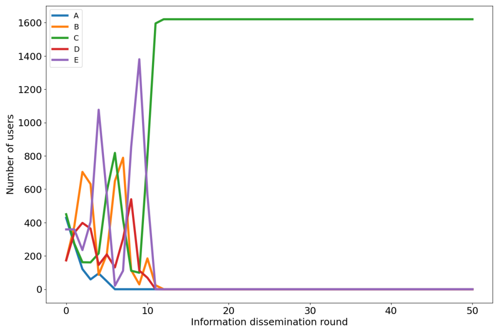
(b) Case2-2_LowIncome_β=0.3



(c) Case2-3_Lowincome_β=0.5

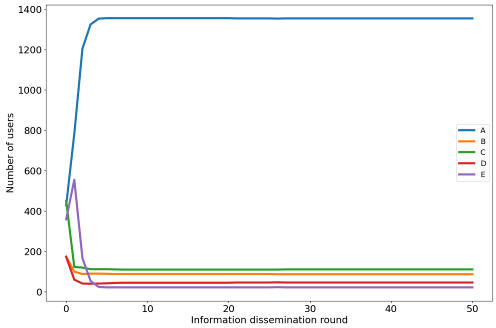


(d) Case2-4_Lowincome_β=0.7

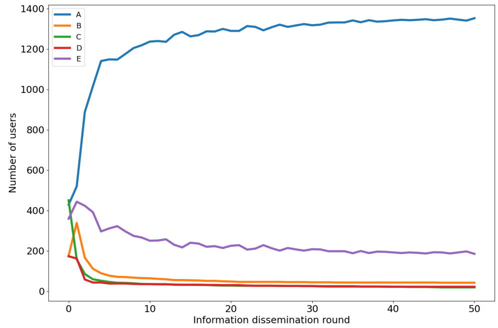


(e) Case2-5_Lowincome_β=1

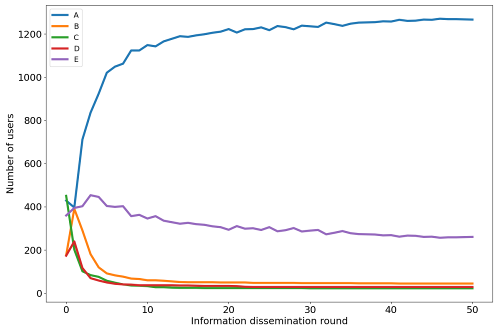
Figure A.1: Case2-#_Lowincome_β: changes in customer number with decision strategy A



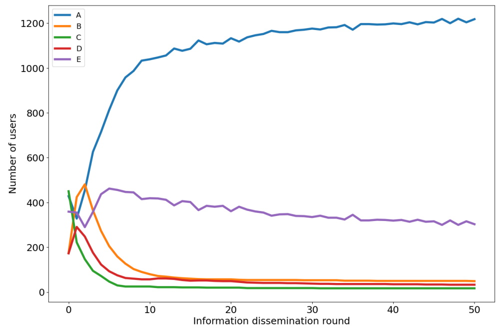
(a) Case3-1__DayType__β=0



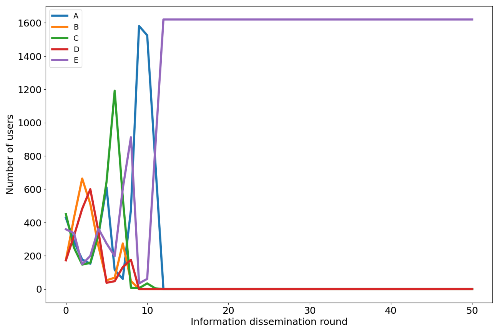
(b) Case3-2__DayType__β=0.3



(c) Case3-3__DayType__β=0.5

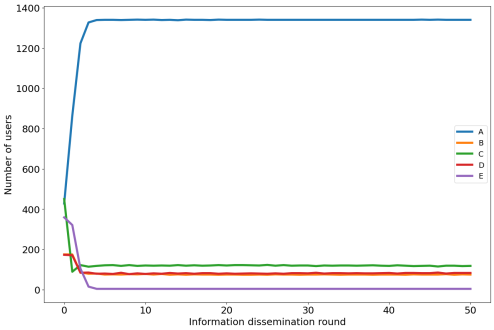


(d) Case3-4__DayType__β=0.7

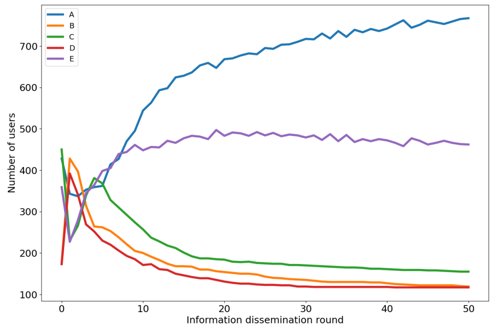


(e) Case3-5__DayType__β=1

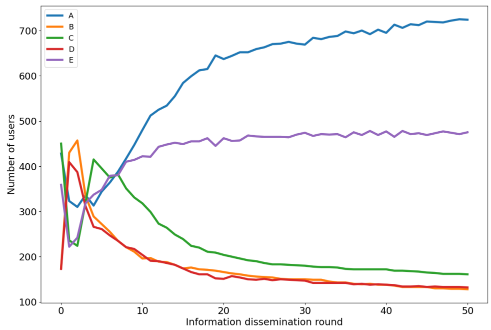
Figure A.2: Case3-#__DayType__β: changes in customer number with decision strategy A



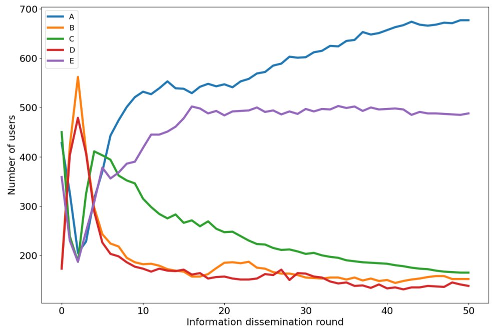
(a) Case4-1_LowAppliance_β=0



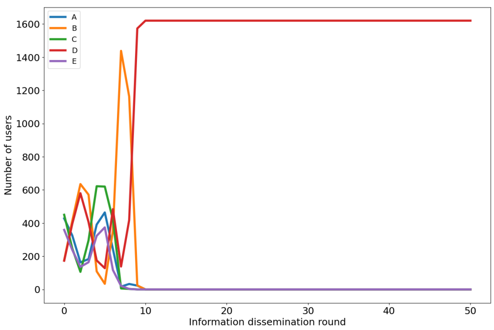
(b) Case4-2_LowAppliance_β=0.3



(c) Case4-3_LowAppliance_β=0.5

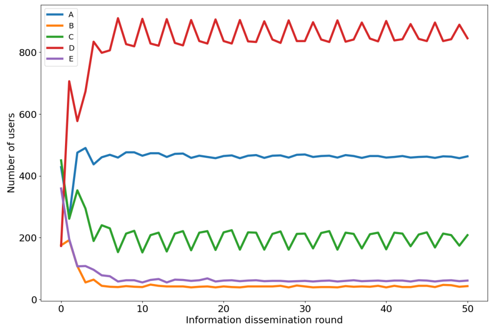


(d) Case4-4_LowAppliance_β=0.7

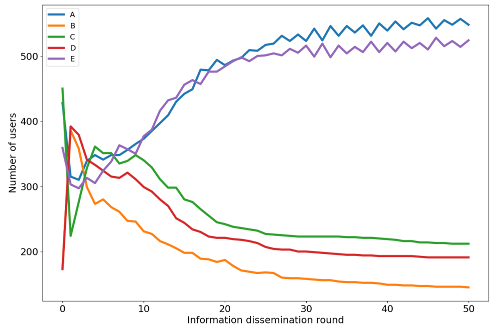


(e) Case4-5_LowAppliance_β=1

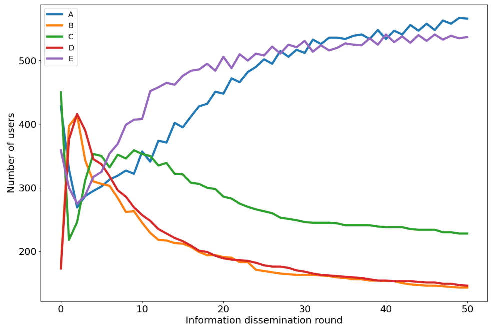
Figure A.3: Case4-#_LowAppliance_β: changes in customer number with decision strategy A



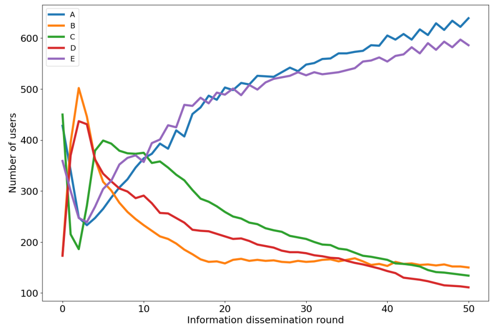
(a) Case5-1_HighAppliance_β=0



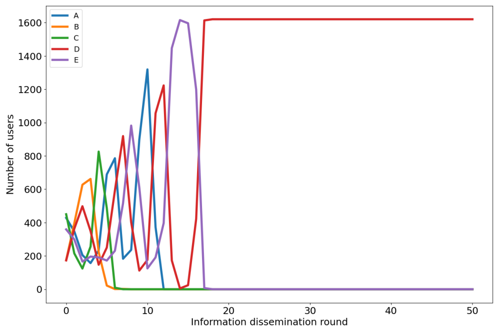
(b) Case5-2_HighAppliance_β=0.3



(c) Case5-3_HighAppliance_β=0.5

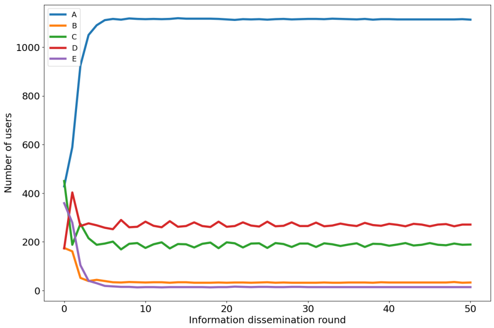


(d) Case5-4_HighAppliance_β=0.7

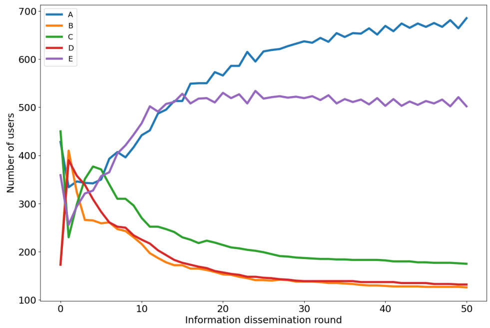


(e) Case5-5_HighAppliance_β=1

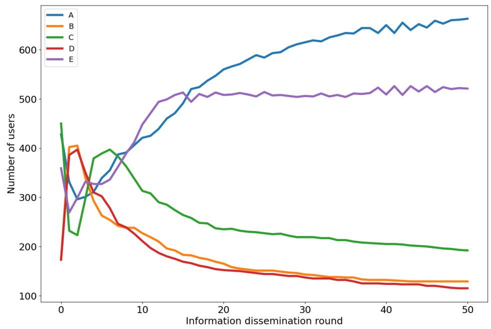
Figure A.4: Case5-#_HighAppliance_β: changes in customer number with decision strategy A



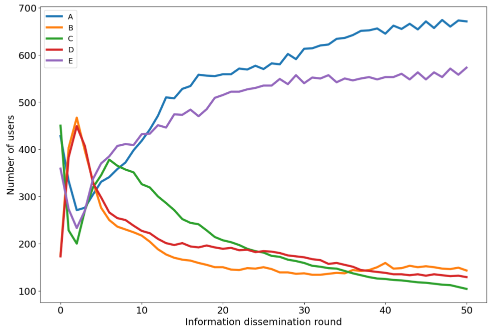
(a) Case6-1_Uniform_β=0



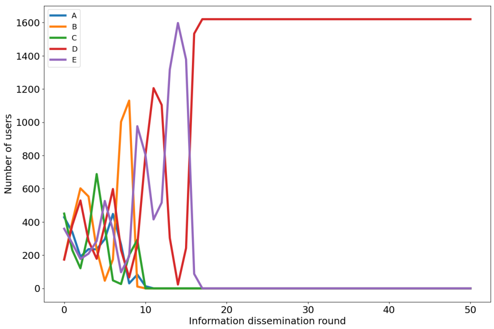
(b) Case6-2_Uniform_β=0.3



(c) Case6-3_Uniform_β=0.5

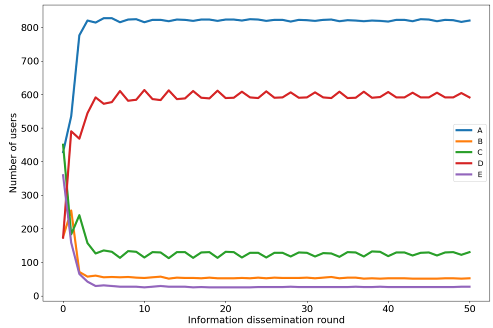


(d) Case6-4_Uniform_β=0.7

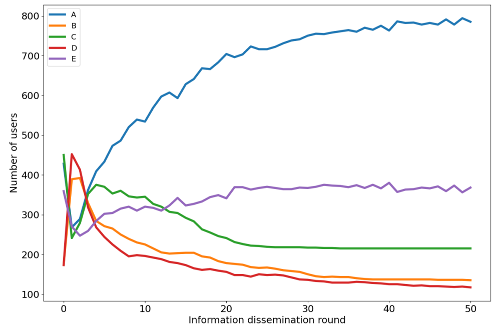


(e) Case6-5_Uniform_β=1

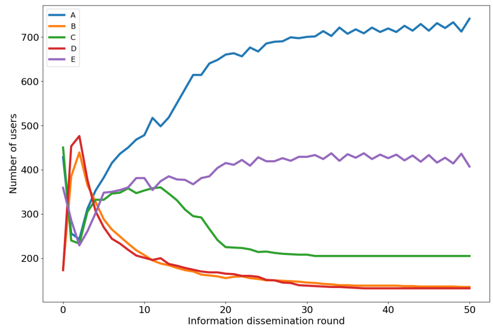
Figure A.5: Case6-#_Uniform_β: changes in customer number with decision strategy A



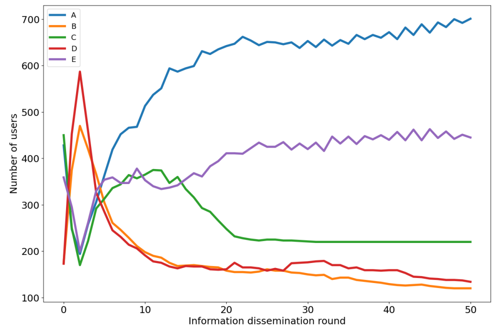
(a) Case7-1_ClusterType_β=0



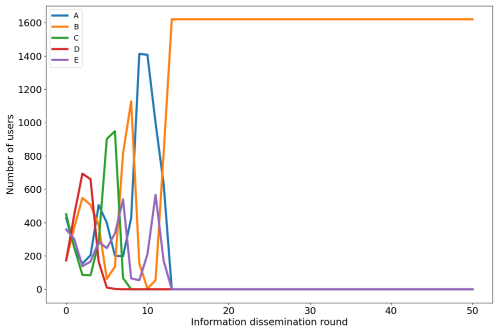
(b) Case7-2_ClusterType_β=0.3



(c) Case7-3_ClusterType_β=0.5

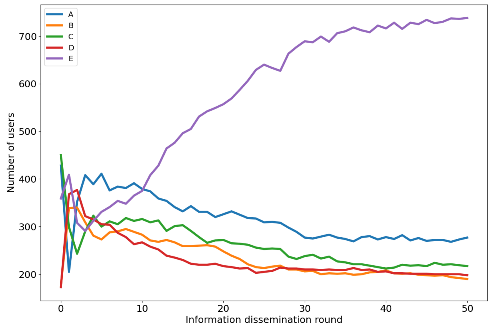


(d) Case7-4_ClusterType_β=0.7

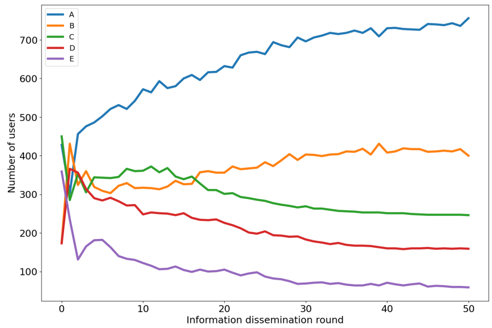


(e) Case7-5_ClusterType_β=1

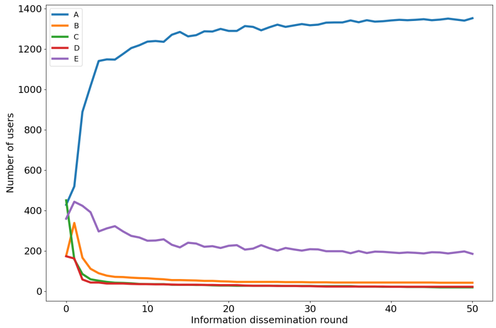
Figure A.6: Case7-#_ClusterType_β: changes in customer number with decision strategy A



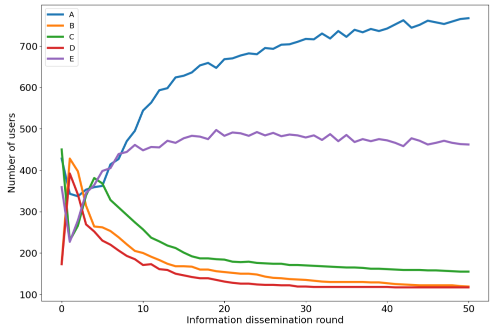
(a) Case1-2__HighLoad__β=0.3



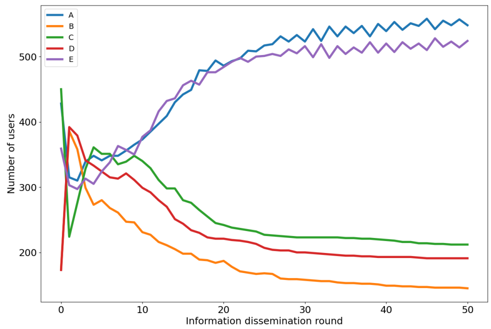
(b) Case2-2__LowIncome__β=0.3



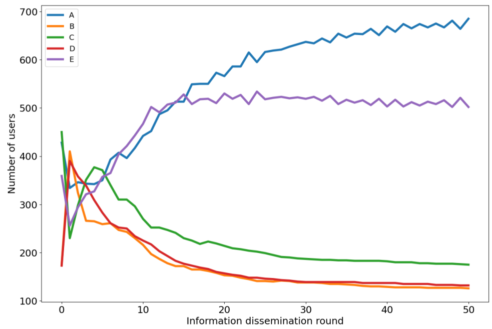
(c) Case3-2__DayType__β=0.3



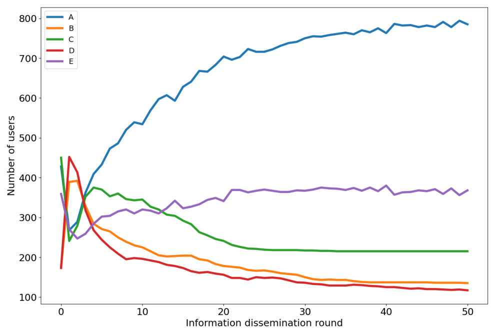
(d) Case4-2__LowAppliance__β=0.3



(e) Case5-2__HighAppliance__β=0.3

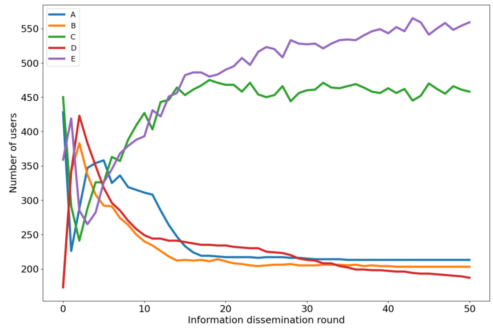


(f) Case6-2__Uniform__β=0.3

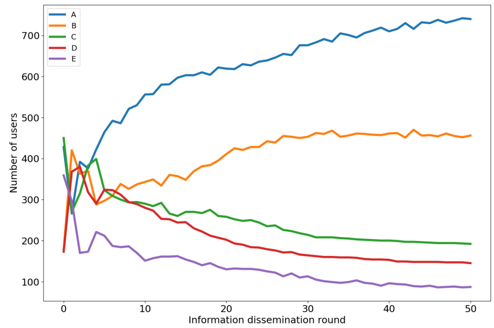


(g) Case7-2__ClusterType__β=0.3

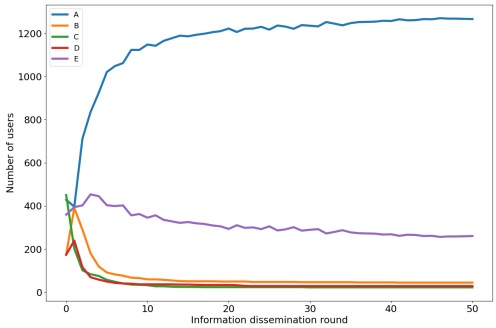
Figure A.7: Case#-2__#__β=0.3 : customer numbers change with decision strategy A



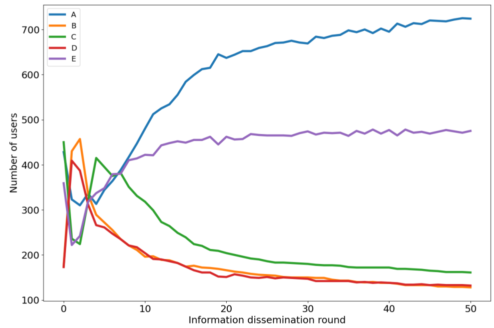
(a) Case1-3_HighLoad_β=0.5



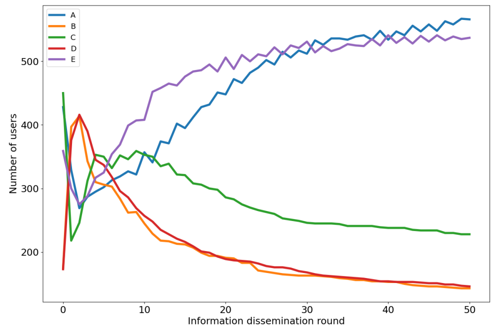
(b) Case2-3_LowIncome_β=0.5



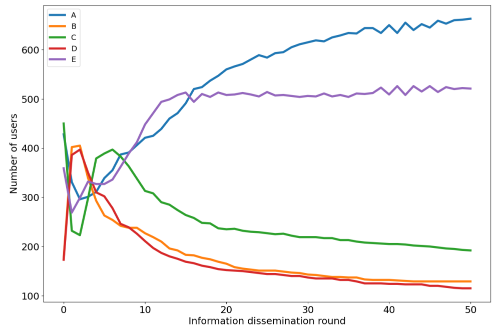
(c) Case3-3_DayType_β=0.5



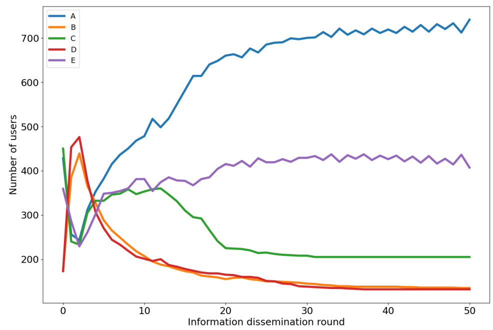
(d) Case4-3_LowAppliance_β=0.5



(e) Case5-3_HighAppliance_β=0.5

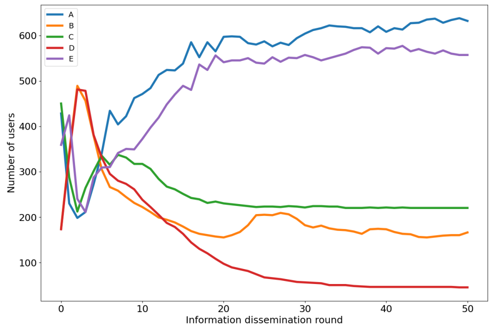


(f) Case6-3_Uniform_β=0.5

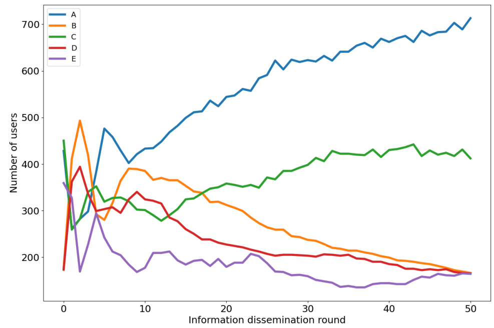


(g) Case7-3_ClusterType_β=0.5

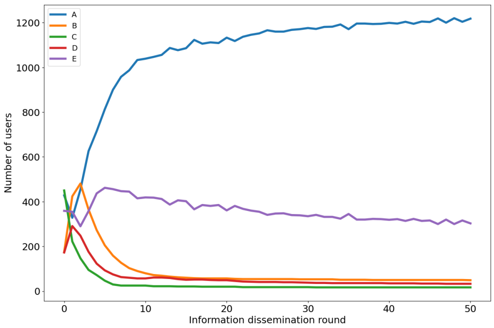
Figure A.8: Case#-3_#_β=0.5 : customer numbers change with decision strategy A



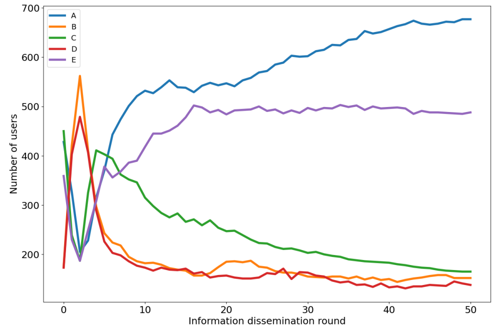
(a) Case1-4_HighLoad_β=0.7



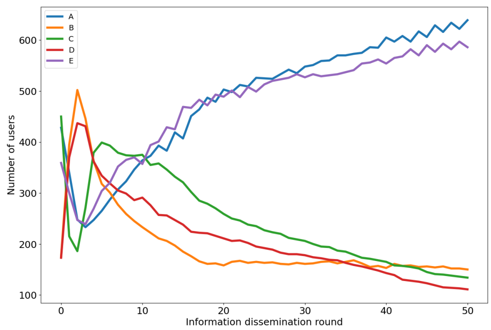
(b) Case2-4_LowIncome_β=0.7



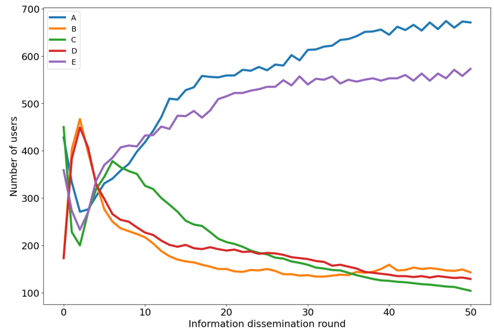
(c) Case3-4_DayType_β=0.7



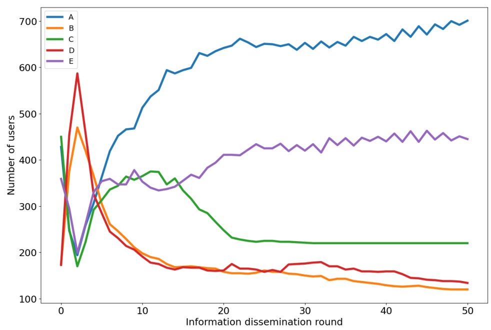
(d) Case4-4_LowAppliance_β=0.7



(e) Case5-4_HighAppliance_β=0.7

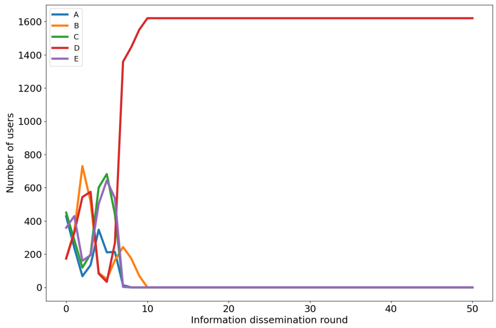


(f) Case6-4_Uniform_β=0.7

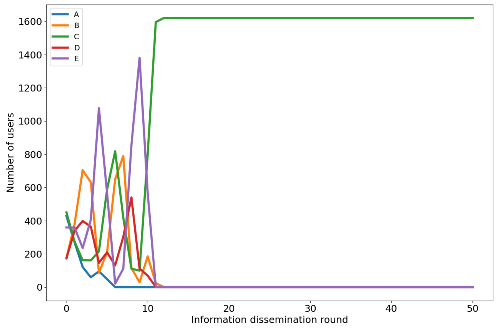


(g) Case7-4_ClusterType_β=0.7

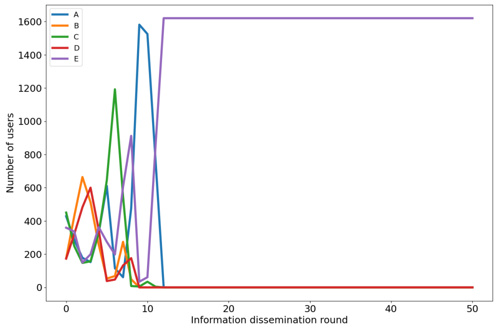
Figure A.9: Case#-4_#_β=0.7 : customer numbers change with decision strategy A



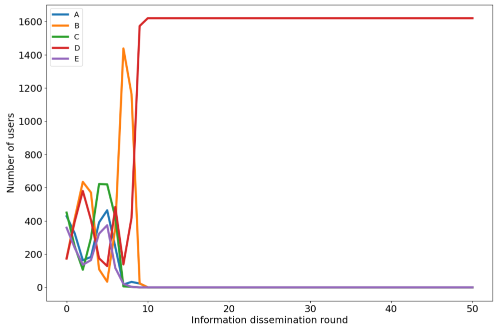
(a) Case1-5_HighLoad_β=1



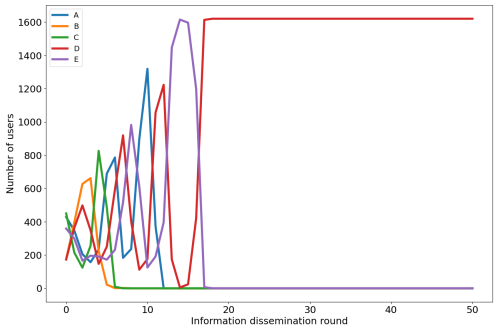
(b) Case2-5_LowIncome_β=1



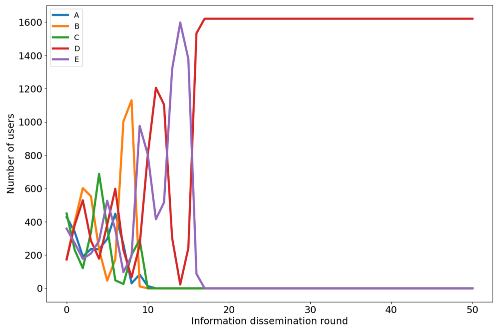
(c) Case3-5_DayType_β=1



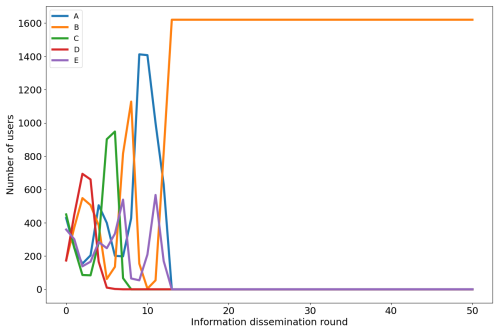
(d) Case4-5_LowAppliance_β=1



(e) Case5-5_HighAppliance_β=1



(f) Case6-5_Uniform_β=1



(g) Case7-5_ClusterType_β=1

Figure A.10: Case#-5_#_β=1 : customer numbers change with decision strategy A

Appendix B

Decision Strategy B

B.1 Fixed [δ_1,δ_2,δ_3,δ_4], different β

B.1.1 Case2-#_LowIncome_β

B.1.2 Case3-#_DayType_β

B.1.3 Case4-#_LowAppliance_β

B.1.4 Case5-#_HighAppliance_β

B.1.5 Case6-#_Uniform_β

B.1.6 Case7-#_ClusterType_β

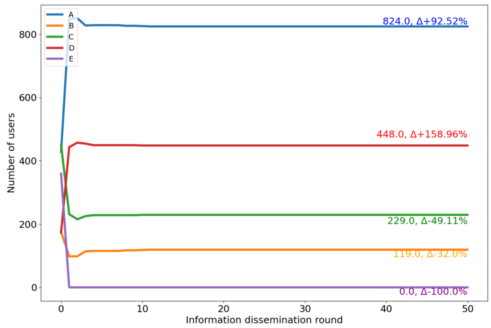
B.2 Fixed β, different [δ_1,δ_2,δ_3,δ_4]

B.2.1 Case#-1_#_β=0

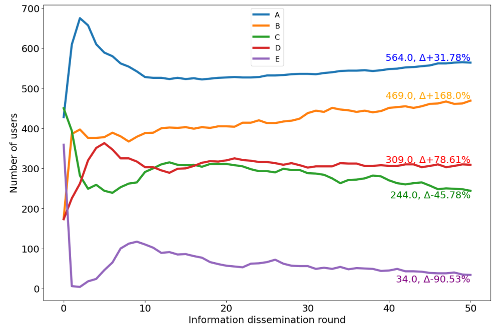
B.2.2 Case#-3_#_β=0.5

B.2.3 Case#-4_#_β=0.7

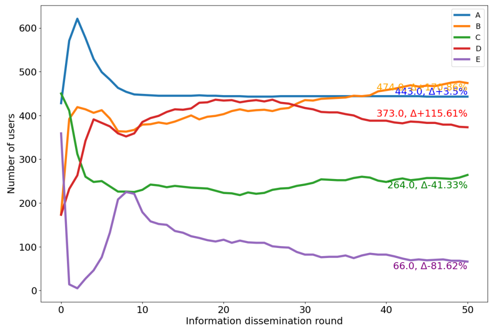
B.2.4 Case#-5_#_β=1



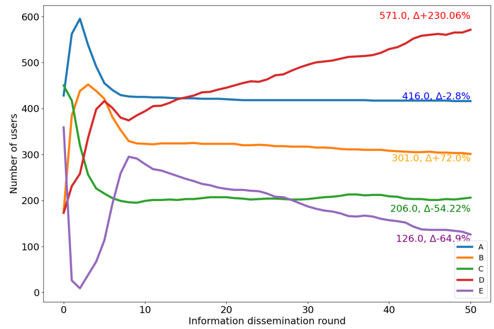
(a) Case2-1_Lowincome_β=0



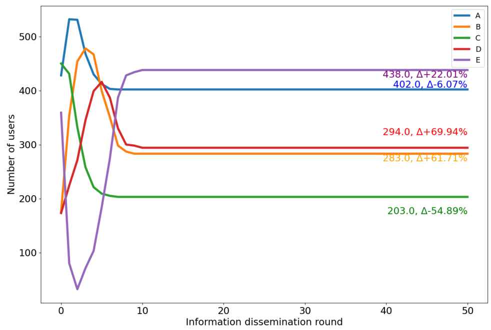
(b) Case2-2_LowIncome_β=0.3



(c) Case2-3_Lowincome_β=0.5

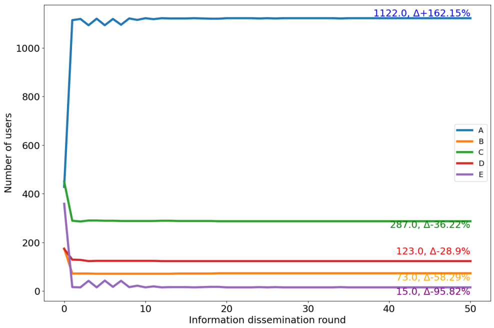


(d) Case2-4_Lowincome_β=0.7

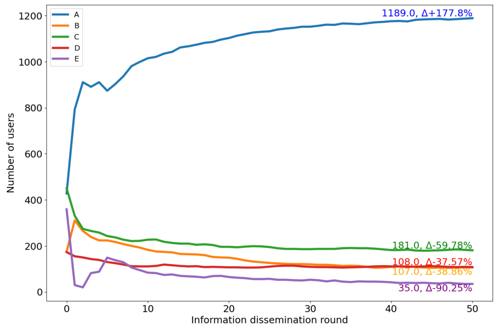


(e) Case2-5_Lowincome_β=1

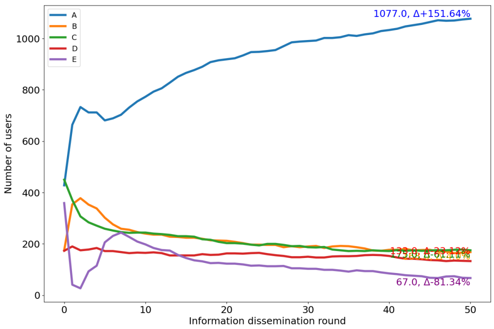
Figure B.1: Case2-#_Lowincome_β: changes in customer number with decision strategy B



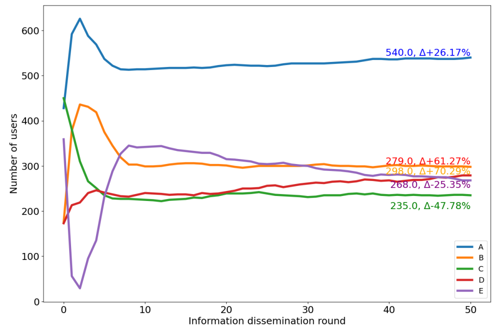
(a) Case3-1__DayType__β=0



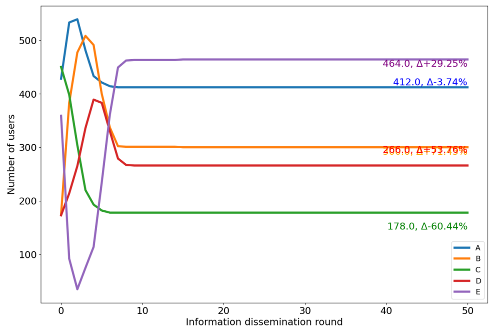
(b) Case3-2__DayType__β=0.3



(c) Case3-3__DayType__β=0.5

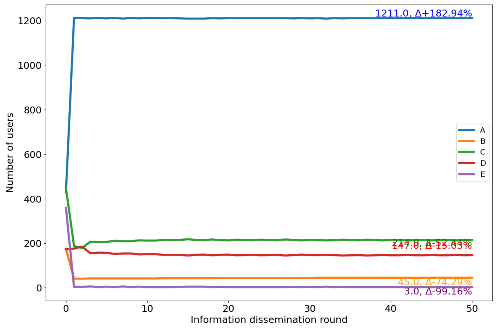


(d) Case3-4__DayType__β=0.7

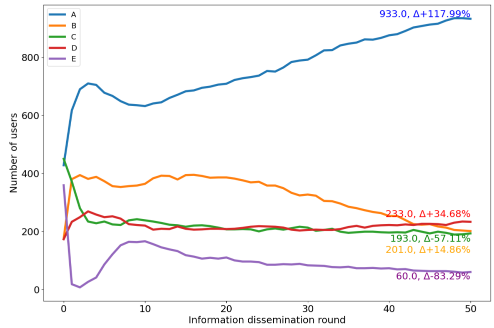


(e) Case3-5__DayType__β=1

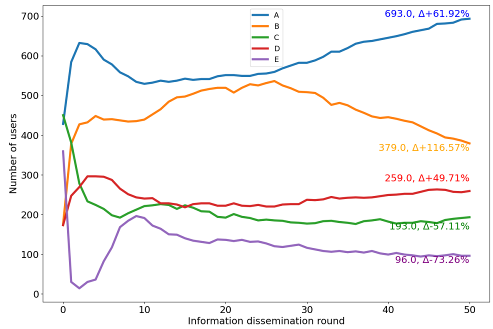
Figure B.2: Case3-#__DayType__β: changes in customer number with decision strategy B



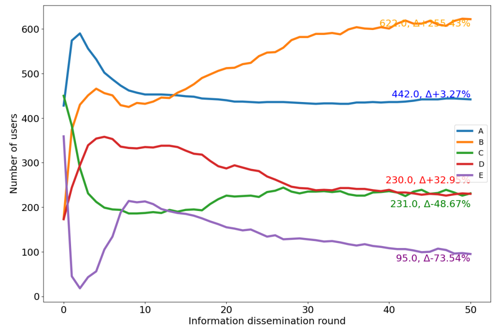
(a) Case4-1_LowAppliance_β=0



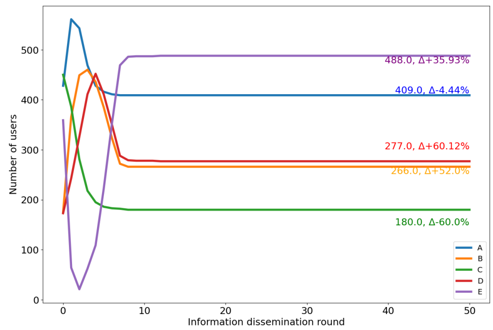
(b) Case4-2_LowAppliance_β=0.3



(c) Case4-3_LowAppliance_β=0.5

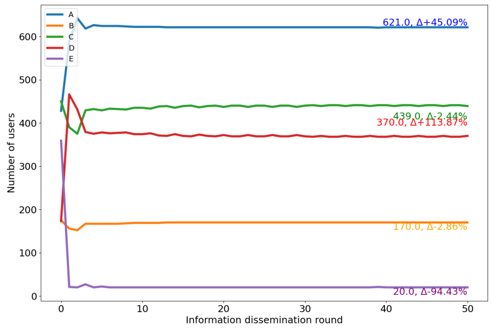


(d) Case4-4_LowAppliance_β=0.7

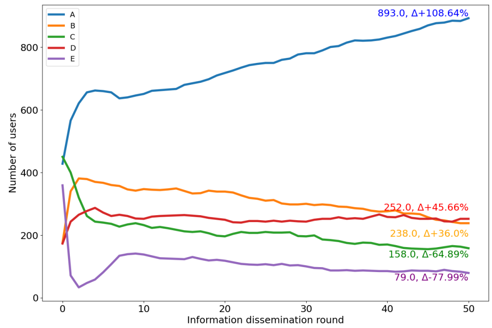


(e) Case4-5_LowAppliance_β=1

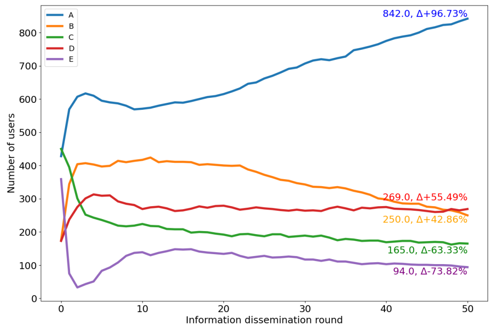
Figure B.3: Case4-#_LowAppliance_β: changes in customer number with decision strategy B



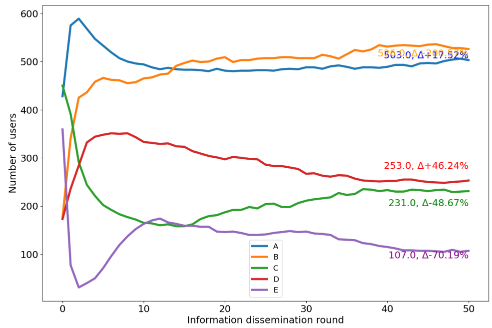
(a) Case5-1_HighAppliance_β=0



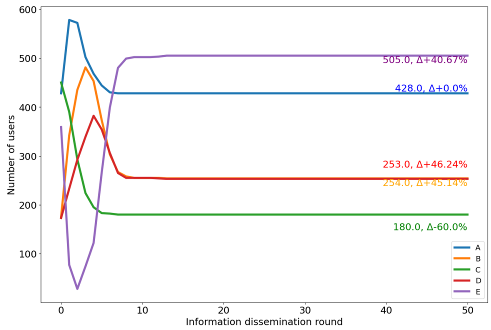
(b) Case5-2_HighAppliance_β=0.3



(c) Case5-3_HighAppliance_β=0.5

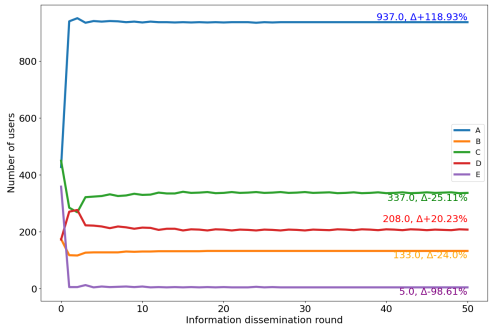


(d) Case5-4_HighAppliance_β=0.7

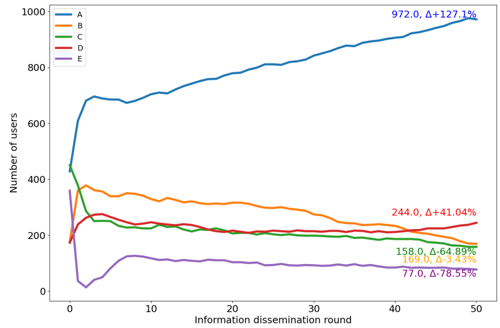


(e) Case5-5_HighAppliance_β=1

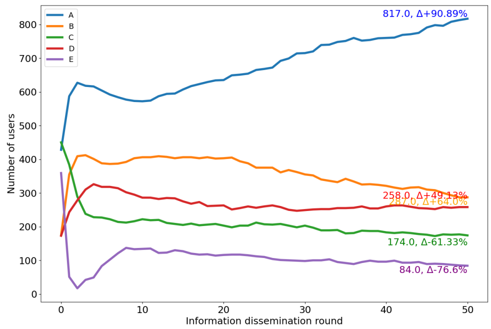
Figure B.4: Case5-#_HighAppliance_β: changes in customer number with decision strategy B



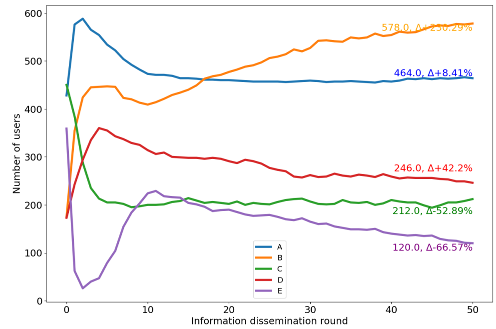
(a) Case6-1_Uniform_β=0



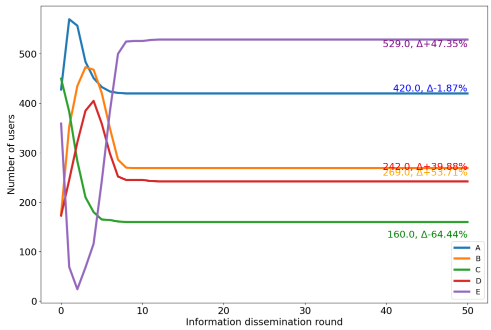
(b) Case6-2_Uniform_β=0.3



(c) Case6-3_Uniform_β=0.5

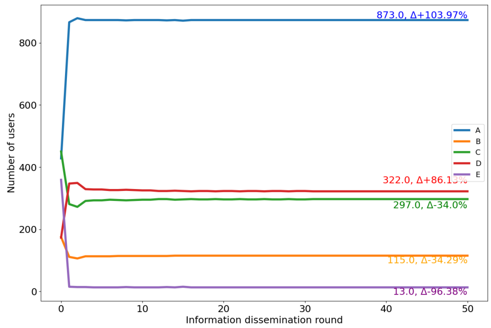


(d) Case6-4_Uniform_β=0.7

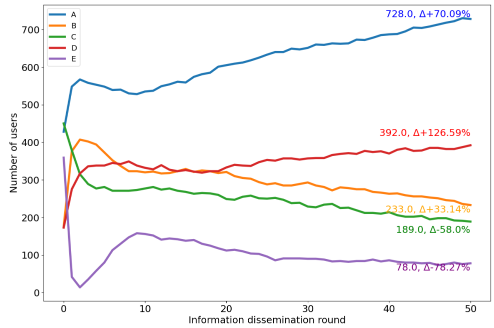


(e) Case6-5_Uniform_β=1

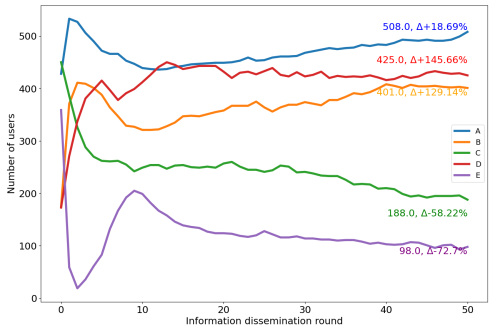
Figure B.5: Case6-#_Uniform_β: changes in customer number with decision strategy B



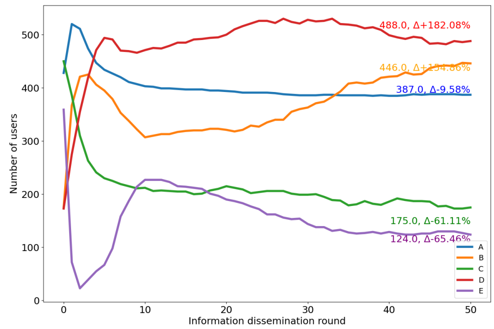
(a) Case7-1_ClusterType_β=0



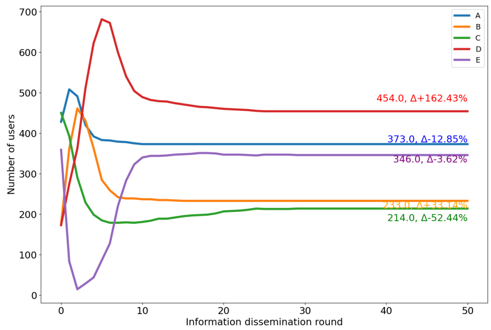
(b) Case7-2_ClusterType_β=0.3



(c) Case7-3_ClusterType_β=0.5

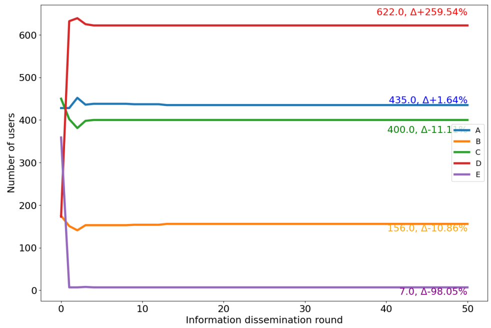


(d) Case7-4_ClusterType_β=0.7

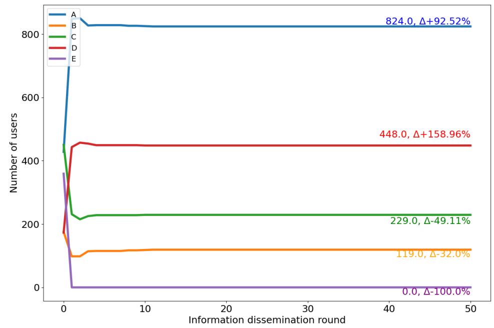


(e) Case7-5_ClusterType_β=1

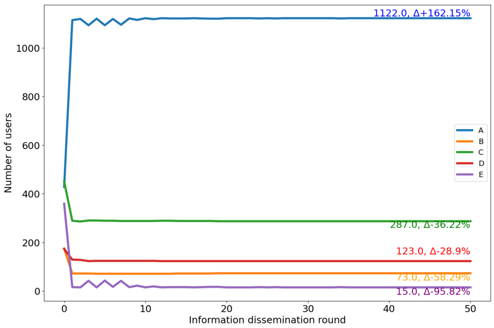
Figure B.6: Case7-#_ClusterType_β: changes in customer number with decision strategy B



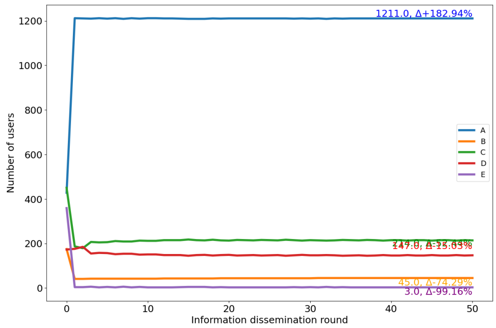
(a) Case1-1_HighLoad_β=0



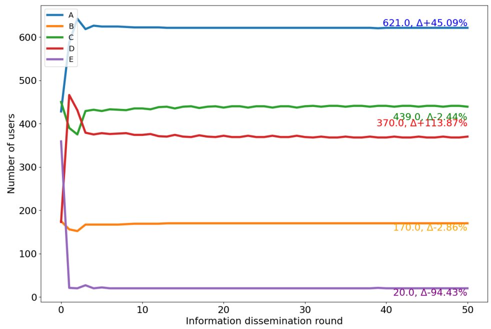
(b) Case2-1_LowIncome_β=0



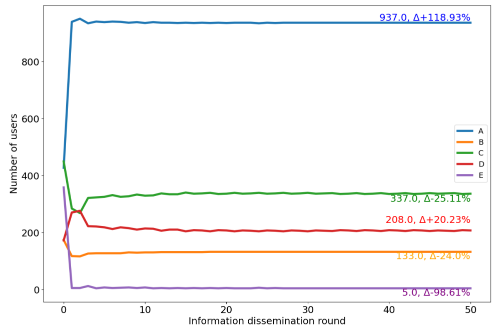
(c) Case3-1_DayType_β=0



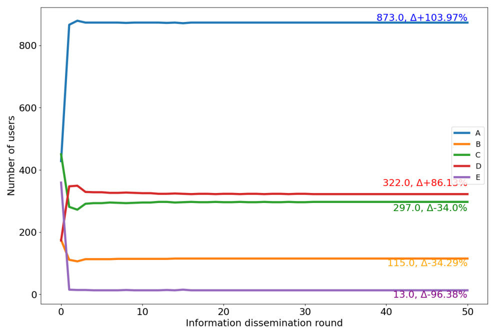
(d) Case4-1_LowAppliance_β=0



(e) Case5-1_HighAppliance_β=0

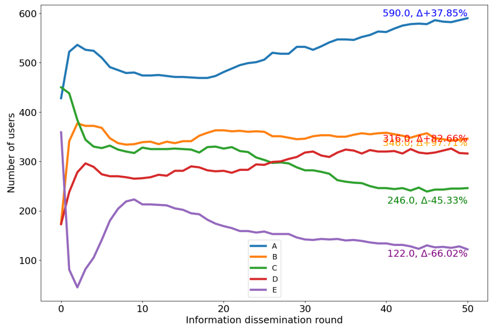


(f) Case6-1_Uniform_β=0

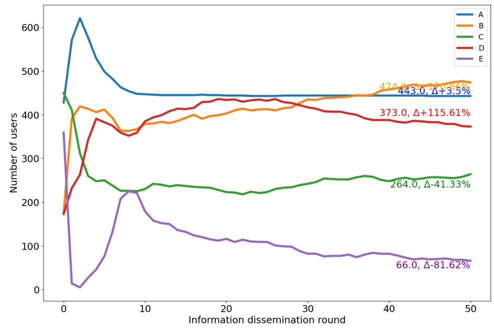


(g) Case7-1_ClusterType_β=0

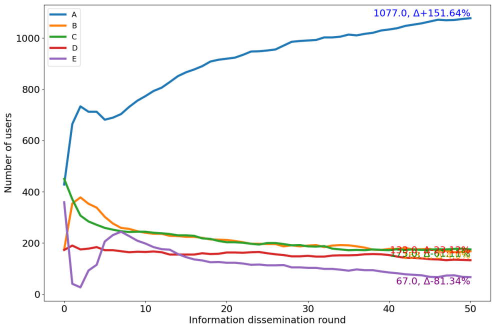
Figure B.7: Case#-1_#_β=0 : customer numbers change with decision strategy A



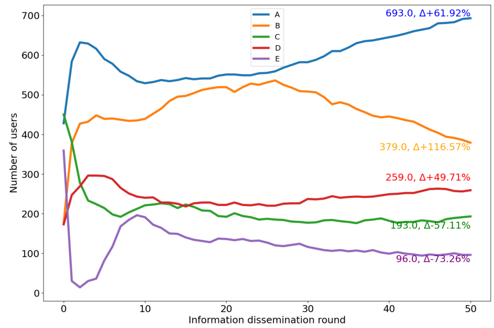
(a) Case1-3_HighLoad_β=0.5



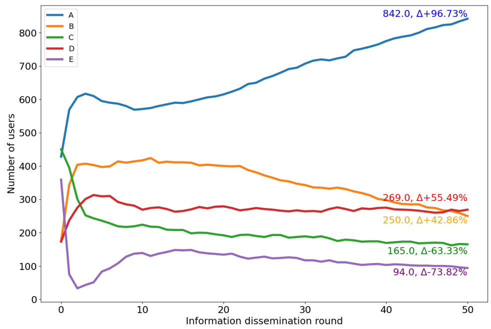
(b) Case2-3_LowIncome_β=0.5



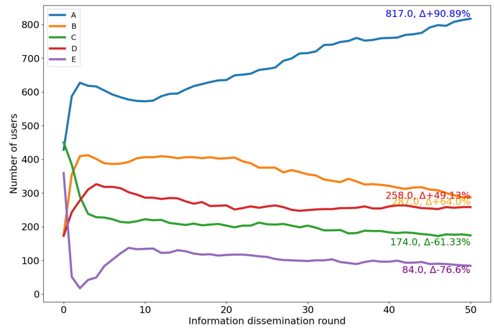
(c) Case3-3_DayType_β=0.5



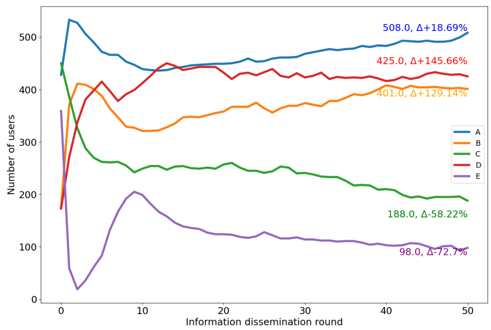
(d) Case4-3_LowAppliance_β=0.5



(e) Case5-3_HighAppliance_β=0.5

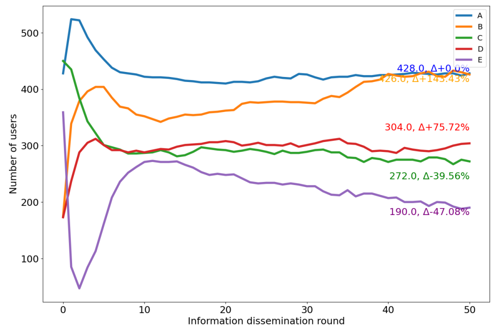


(f) Case6-3_Uniform_β=0.5

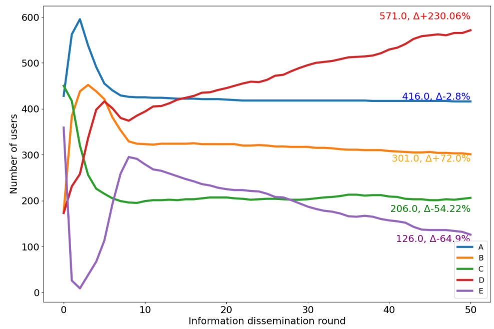


(g) Case7-3_ClusterType_β=0.5

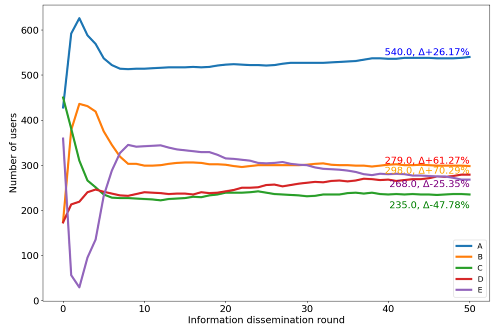
Figure B.8: Case#-3_#_β=0.5 : customer numbers change with decision strategy B



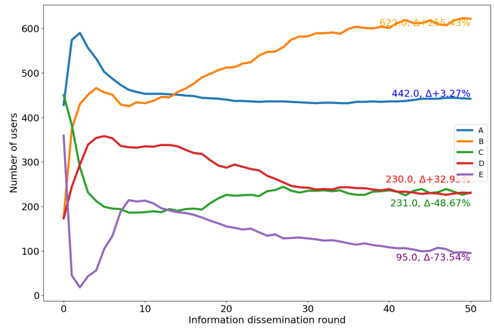
(a) Case1-4_HighLoad_β=0.7



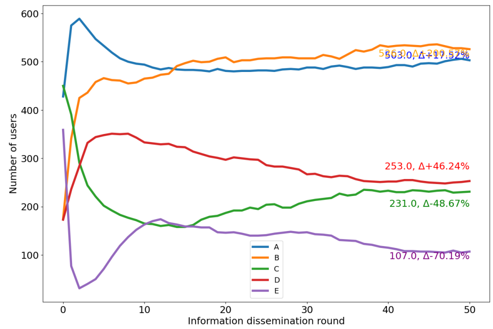
(b) Case2-4_LowIncome_β=0.7



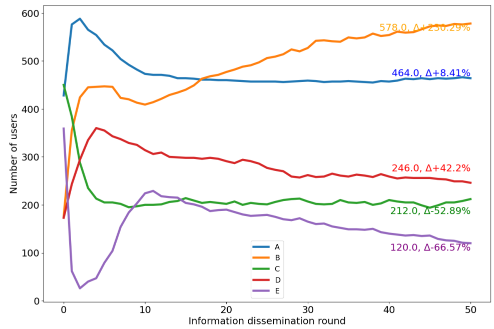
(c) Case3-4_DayType_β=0.7



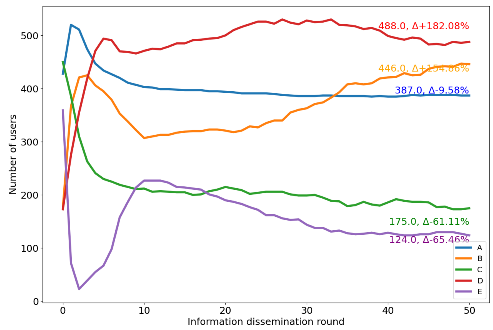
(d) Case4-4_LowAppliance_β=0.7



(e) Case5-4_HighAppliance_β=0.7

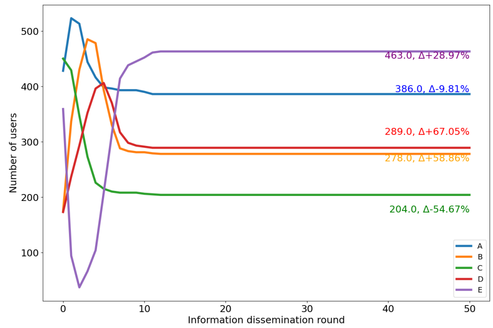


(f) Case6-4_Uniform_β=0.7

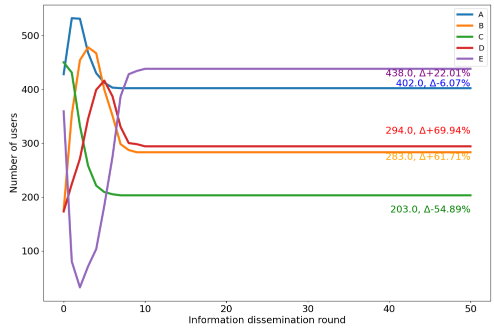


(g) Case7-4_ClusterType_β=0.7

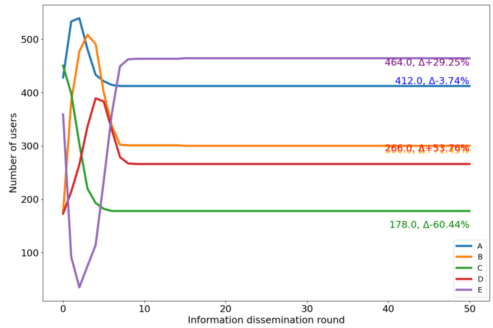
Figure B.9: Case#-4_#_β=0.7 : customer numbers change with decision strategy B



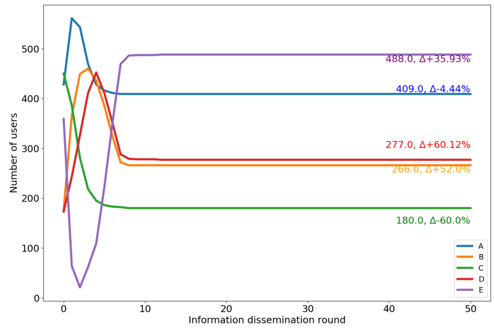
(a) Case1-5_HighLoad_β=1



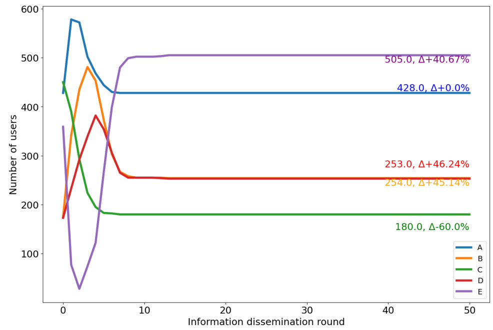
(b) Case2-5_LowIncome_β=1



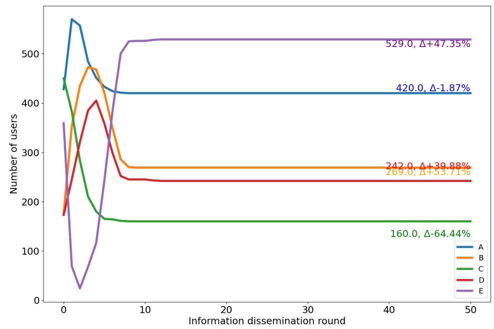
(c) Case3-5_DayType_β=1



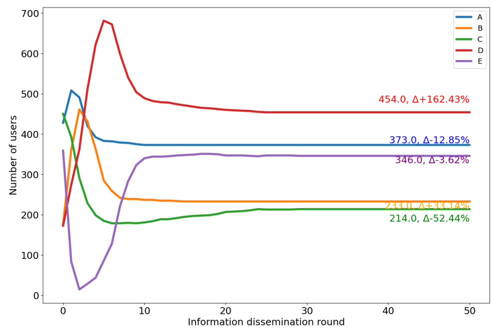
(d) Case4-5_LowAppliance_β=1



(e) Case5-5_HighAppliance_β=1



(f) Case6-5_Uniform_β=1



(g) Case7-5_ClusterType_β=1

Figure B.10: Case#-5_#_β=1 : customer numbers change with decision strategy B

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