

Optimal Allocation of Online Content Combination Pricing under Mixed Revenue Mode

Yue Yao, Yan Cheng, and Yingying Xie

Abstract—The development of Internet makes the rapid expansion of the business model based on providing online content service to online users. In recent years, the promotion of the payment model has brought new profit increasing point for content service providers. Single-on-demand payment and bundling subscription payment are widely used payment methods. If the two modes are combined, the service providers will often get more benefits. So in the mixed revenue model, online content service providers need to decide how to set a reasonable price for each charge mode in order to maximize expected revenue. In this paper, the user's value estimation model is constructed based on time preference theory and loss aversion theory. Furthermore, the variable neighborhood search algorithm is used to simulate and verify the optimal pricing strategy of various charging model combinations.

Index Terms—Online content, loss aversion, time preference, mixed revenue.

I. INTRODUCTION

Online content is a digital product [1], which is transmitted through the Internet. Service providers often supported by online advertising revenue and given away online content for free. However, with the strengthening of intellectual property protection, service providers must pay high copyright fees to obtain the exclusive right of content distribution. In the traditional profit model, advertising revenue gradually cannot be offset royalties [2], so operators are still exploring an effective paid content service model. On the one hand, online content has a long tail niche attributes; on the other hand, the Pareto effect is reflected in the revenue distribution. Specifically, according to the praetor law, paid content should target the vital few customers that generates 80 percent of the revenue. However, long tail theory shows that a large number of small demands together occupy a considerable market share, long tail niche products will generate huge profits especially when the marginal cost is extremely low [3].

Currently, the paid content service model is divided into two categories: (1) Pay Per Usage (PPU) mode: single-on-demand payment model. For example, MANGO TV implements long tail theory, which charges 5¥ for a single on-demand movie. (2) Subscription Fee (SF) mode: a one-time payment, then you can enjoy unlimited number of online contents in a certain period. For example, iQIYI's

subscription fee is 19.8¥ per month, and the amount of online consumption during the subscription period is not limited. In fact, the long tail theory is not contradictory to the Pareto law and the long tail theory is a deep excavation, complementation and improvement of the Pareto law. Online paid content can include not only best sellers, but also long tail niche products. This requires the online content charging model to meet the differentiated needs of consumers and maximize the benefits of VIP customers and niche customers. Therefore, some operators have further refined the subscription model and introduced a time difference-based subscription fee Usage (SFU) model. The diversification of the charging model gives consumers more choices, but it also triggers the revenue competition between different payment models. If the pricing of various models is not well allocated, it may reduce the total revenue level. For example, under certain market conditions, lowering the price of a monthly subscription service may result in some users abandoning the annual or quarterly payment model. In this regard, online content providers need to explicit "what kind of correct combination of pricing should be allocated under dynamic market demand conditions?"

The difficulty of the above problem is that the service providers need to understand the customer's value evaluation for different payment models. In the SFU mode, the customer pay-for instantly and delay consumption, while in the PPU mode, it is the instant payment and consumption, which makes value evaluation model not only involve the customer's value judgment on the content product, but also involves: (1) the customer's consumption time preference, because some customers' perception of the current consumption value is far greater than the value perception of future consumption, while others' value judgments are less affected by the consumption delay time; (2) the customer's loss aversion level [4], [5]. Due to the uncertainty of the final consumption quantity, many customers are worried that the cost of each consumed product in the SFU mode is even higher than the unit price of the product in the PPU mode, thereby generating a loss of value perception. With a strong sense of loss, consumers tend to circumvent uncertain risks, which reduces their value judgment for the SFU model. Based on this, it is worthwhile to discuss which combination of pricing can bring the greatest revenue to content service providers under market demand conditions.

Therefore, this paper will study: (1) applying the time preference theory and loss aversion theory to construct the customers' value estimation model, making the value estimation model conform to the characteristics of the mixed revenue model; (2) using the variable domain search algorithm to solve the optimized allocation of mixed revenue mode. The results can help online content service providers

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optimize the pricing allocation of mixed revenue model, and analyze which market conditions are suitable for mixed revenue model or single revenue model.

II. VALUE FUNCTION OF CONSUMER CHOICE BEHAVIOR

A. Value Discount Based on Time Preference

Due to the timeliness of online content, the consumer's interest level will gradually decrease over time, and the perceived value of the consumer will be reduced. As a result, the consumers pay more attention to the current content than the long-term attention of the same content. Therefore, according to the time preference theory, the hyperbolic discount model [3] is used to describe the consumer's value perception.

$$v(x, t) = \frac{v(x)}{1+\zeta \times t} \quad (1)$$

where $v(x, t)$ represents the value perception of the consumers' consumption content x for the delay time t , and $v(x)$ represents the consumer's value evaluation for the content product x . ζ is the index discount rate, and $\zeta \in (0,1)$.

B. Loss Aversion

Owing to the uncertainty of the actual consumption in the future, customers often worry that the usage is too small in the SFU mode, which leads to the actual cost of each content product is higher than the product price in the PPU mode. This kind of worry makes the consumer exist economic loss perception. So, let λ denote the loss aversion coefficient, and $\lambda \in [0,1]$. Under the subscription strategy, if the customer feels that the fee has been paid but not consumed to the content product x , then the perceived loss value is higher than its value perception of the product itself. Let $Los(x)$ denote the loss function, then:

$$Los(x) = (1 + \lambda)v(x) \quad (2)$$

C. Customer's Value Estimation Model

For the convenience of discussion, symbolic conventions as follows:

- 1) Let N denote the total amount of online content provided by the service website, and M is the total number of users.
- 2) The subscription terms will stipulate an expiration date, and T indicates the validity period.
- 3) Different types of customers have different value estimation models for different payment models. So, let c denote the customer type identifier, and b_c denote the proportion of each type of customer.
- 4) Let p_{PPU} denote the undifferentiated unit price of each content product in PPU mode, and p_{SFU} denote the price under subscription mode (SFU).
- 5) In the PPU mode, the estimated usage of the consumer is affected by the content unit price p_{PPU} , so that $n_c(p_{PPU})$ is the maximum usage amount when the price is p_{PPU} .
- 6) In the SFU mode, $n_{c,SFU}$ represents the maximum consumption estimated by customer c .

1) Value estimation in PPU mode

In the PPU mode, the customer pays instantly and

consumes instantly, there is no value discount for delayed consumption, and there is no loss aversion psychology. In this model, customer's consumption is primarily influenced by its highest value assessment of content products and the level of valuation differences for different content products.

Let $v_{c,0}$ denote the highest value estimate of customer c for online content. Suppose the customer always consumes the content product with high estimated value, so let $i=1, 2, \dots$ denotes the order identifier of content products, and $v_{c,i}$ denotes the value estimate of the customer c for the i -th content products, and $v_{c,1} > v_{c,2} > \dots > v_{c,\infty}$. Suppose that customer c estimates the value of content products in the order of consumption is evenly decreasing, and the decline rate is written as α_c . Obviously, the parameter combination $(v_{c,0}, \alpha_c)$ reflects the value estimation characteristics of customer c in PPU mode. The estimated value of the i -th content product can be calculated as:

$$v_{c,i} = \max\{0, v_{c,0} \times (1 - \frac{i \times \alpha_c}{N})\} \quad (3)$$

According to expression (3): $v_{c,0} \times (1 - \frac{n_c(p_{PPU})}{N} \times \alpha_c) = p_{PPU}$, then:

$$n_c(p_{PPU}) = N \times \frac{1}{\alpha_c} \times (1 - \frac{p_{PPU}}{v_{c,0}}) \quad (4)$$

Let $v_c(p_{PPU})$ denote the value estimate of customer c for the PPU mode whose price is p_{PPU} , then:

$$v_c(p_{PPU}) = \sum_{i=1}^{n_c(p_{PPU})} v_{c,0} \times (1 - \frac{i \times \alpha_c}{N}) \quad (5)$$

2) Value estimation in SFU mode

In the SFU mode, the user is divided into G categories according to consumption, and the center of gravity of each type is taken as the maximum consumption quantity $n_{c,SFU}$ of the class. Value discounting occurs as consumers evaluate the subscription plan. When the customer estimates the consumption is $n_{c,SFU}$, the average time interval for the consumption of the $n_{c,SFU}$ content products in time T is $T/n_{c,SFU}$. The delayed consumption time of the i -th content product is $t_i = (i - 1) \times T/n$, then the value discounted by the customer c to the i -th content product is $\frac{1}{1+\zeta \times t_i} \times v_{c,i}$.

Meanwhile, customers have loss aversion. When the maximum usage estimated by customer c is $n_{c,SFU}$, the actual cost per unit of product is: $p_{SFU}/n_{c,SFU}$. If $p_{SFU}/n_{c,SFU} < p_{PPU}$, the customer's experience is the best; if $p_{SFU}/n_{c,SFU} > p_{PPU}$, the customer will have a sense of loss. Different types of customers have different levels of loss aversion, so that λ_c represents the coefficient of degree of loss of customer c , and we have from (2) that:

$$Los(n_{c,SFU}) = \begin{cases} (1+\lambda_c)(\frac{p_{SFU}}{n_{c,SFU}} - p_{PPU}) & \text{if } \frac{p_{SFU}}{n_{c,SFU}} > p_{PPU} \\ 0 & \text{else} \end{cases} \quad (6)$$

Let $v_c(p_{SFU})$ denote the value estimate of customer c for SFU, and according to equation (1)-(4):

$$v_c(p_{SFU}) = \sum_{i=1}^{n_{c,SFU}} \frac{1}{1+\zeta_c \times t_i} \times v_{c,i} - Los(n_{c,SFU}) \quad (7)$$

D. Decision-Making Utility for Customer Segmentation and Consumption Choices

In the mixed revenue model, the value preference characteristics of customer c can be described as a vector $(v_{c,0}, \alpha_c, \zeta_c, \lambda_c)$. The parameters $(v_{c,0}, \alpha_c)$ reflect the overall preference of customer c for the online content, while the parameters ζ_c and λ_c reflect the value preference of the customer in the face of uncertain future consumption. Clustering customer feature vectors $(v_{c,0}, \alpha_c, \zeta_c, \lambda_c)$ according to the principle of similarity can subdivide the customer group into C categories, and make the integer c ($c=1, 2, \dots, C$) represents the identity of the customer segment. Therefore, the utility of different payment models satisfies the equations:

Let $u_c(p_{PPU})$ indicate the decision utility of the c -type customer to select the PPU mode, then:

$$u_c(p_{PPU}) = v_c(p_{PPU}) - p_{PPU} \times n_c(p_{PPU}) \quad (8)$$

Let $u_c(p_{SFU})$ indicate the decision utility of the c -type customer to select the SFU mode, then:

$$u_c(p_{SFU}) = v_c(p_{SFU}) - p_{SFU} \quad (9)$$

III. OPTIMAL ALLOCATION OF ONLINE CONTENT REVENUE MODEL

A. Comparison of the Revenue of Three Types of Charging Modes in Two Products

For the convenience of discussion, it is assumed that there are only two content products. In the pay-per-usage (PPU) model, website operators treat the same type of content as a homogeneous product, and then make undifferentiated pricing of the content product. The revenue principle of various charging modes is shown in Fig. 1.

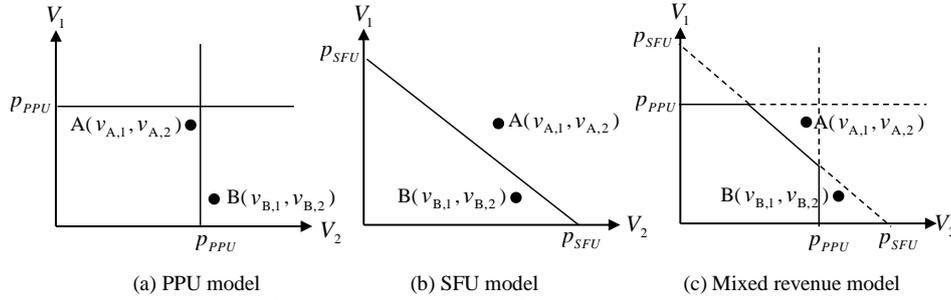


Fig. 1. Comparison of the revenue of the three charging models.

In Fig. 1, the ordinate V_1 represents the consumer's estimate of the value of the content product 1, and the abscissa V_2 represents the consumer's estimate of the value of the content product 2. p_{PPU} indicates the undifferentiated unit price of online content in PPU mode and p_{SFU} indicates the subscription price in SFU mode. $A(v_{A,1}, v_{A,2})$ indicates that there is a customer A whose value for content product 1 is estimated to be $v_{A,1}$ and the value for product 2 is estimated to be $v_{A,2}$. In the same way, $B(v_{A,1}, v_{A,2})$ represents the value estimate of content products 1 and 2 of customer B.

1) According to Fig. 1(a), in the PPU model, customer A doesn't purchase any content products when $v_{A,1} < p_{PPU}$ and $v_{A,2} < p_{PPU}$. While $v_{B,1} < p_{PPU}$, $v_{B,2} > p_{PPU}$, customer B will only purchase product 2. Obviously, the operators' revenue is p_{PPU} .

2) As shown in Fig. 1(b), due to $v_{A,1} + v_{A,2} > p_{SFU}$ and $v_{B,1} + v_{B,2} < p_{SFU}$, customer A will subscribe product 1 and 2, however, customer B will purchase nothing. This is clearly that the operators' revenue is p_{SFU} .

3) Fig. 1(c) shows that in the mixed revenue model, customer A will subscribe two products when $v_{A,1} + v_{A,2} > p_{SFU}$; customer B only choose the product 2 because of $v_{B,1} + v_{B,2} < p_{SFU}$ and $v_{B,2} > p_{PPU}$. In this case, the revenue that the operator will receive is $2p_{SFU} + p_{PPU}$.

B. Optimal Allocation of Single Revenue Model

Currently, the number of paid users for online content is small, and most users are less willing to pay. In this case, it is assumed that only the PPU model or the subscription-only payment model SFU is provided, and the decision-making revenue level under the single payment mode is first

understood. Whether it can meet the dual needs of operators and consumers at the same time. The choice of revenue level and revenue model is influenced by the structure of various segments of customers in the market, so let b_c ($0 \leq b_c \leq 1, b_1 + b_2 + \dots + b_c = 1$) represents the proportion of category c customers to the total customer base.

1) Optimal allocation model for PPU

According to the consumer surplus theory, consumers perceive purchase utility by comparing reservation price with product price. And the consumer purchases the product if and only if his perceive utility is nonnegative. Without considering the markdown anticipation, Gallego's customer purchase probability model is widely used in the field of revenue management models [6]:

$$Pr = \begin{cases} e^{-p/v} & v \geq p \\ 0 & \text{else} \end{cases} \quad (10)$$

where p is the price of the product, and v is the reservation price of the product, which is a sort of value threshold for a given consumer and for the online content.

If only the PPU mode is provided, service providers need to determine an optimal undifferentiated unit price p_{PPU} . For different types of customers, their perceived value for online content products is different so that the value estimates are not the same and corresponding purchase probability not be the same. The content service providers' revenue is in the same way. Therefore, we must fully consider the impact of different customer types on the optimization model. Based on this, according to the aforesaid parameter variables and

formula (10), the consumer purchase probability in a single PPU mode can be obtained as the formula (11), where β is the adjustment coefficient, ensuring purchase probability take value in [0,1].

$$Pr_1 = \beta \times \sum_{i=1}^N e^{-\frac{p_{PPU}}{v_{c,i}}} \quad (11)$$

Thus, the decision optimization model of the PPU mode is written as the equation (12), in which μ indicates the user arrival rate:

$$\max \sum_{c=1}^C b_c \times p_{PPU} \times \mu \times M \times Pr_1 \quad (12)$$

2) Optimal allocation model for SFU

If only the SFU mode is provided, which there are a variety of selectable types, such as monthly payment, quarterly payment, annual payment, etc. Therefore, the consumer needs to makes proper purchase choices by comparing the payment price to best meet their needs. And the operator needs to determine the different optimal subscription price p_{SFU} according to the bundled time. At the same time, according to formula (10), the probability of consumer purchase in a single SFU mode can be obtained:

$$Pr_2 = \beta \times e^{-\frac{p_{SFU}}{v_{c(SFU)}}} \quad (13)$$

The other parameter variables are the same as those in the PPU mode, so the decision optimization model for the SFU mode is:

$$\max \sum_{c=1}^C b_c \times p_{SFU} \times \mu \times M \times Pr_2 \quad (14)$$

C. Optimal Allocation of Mixed Model

In the mixed revenue model, consumers need to compare the consumption utility under various charging modes. The larger the utility, the greater the probability that consumers will accept. According to the expression (8)-(9), if $u_c(p_{PPU}) < 0$ and $u_c(p_{SFU}) < 0$, the consumer purchase probability is zero; otherwise, the consumer may make a purchase decision. When the consumer decides to purchase, he also needs to choose PPU mode or SFU mode. In this case, the purchase probability of the PPU mode and the SFU mode are affected by the utilities respectively.

In the case where both the PPU mode and the SFU mode exist simultaneously, consumers generally make choices based on utility. Due to the loss of aversion psychology and value discount, SFU mode may enable consumers to acquire higher utility levels. However, if consumers can't watch the sufficient quantity of online contents, the final utility value they obtained even lower than the utility value in the PPU mode. Therefore, consumers' respective purchase probability is interactional whether they choose the PPU mode or the SFU mode. So, in the mixed revenue model, the purchase probabilities of the two modes are:

$$Pr_1' = Pr_1 \times (1 - Pr_2) \quad (15)$$

$$Pr_2' = Pr_2 \times (1 - Pr_1) \quad (16)$$

Base on formulas (15)-(16), the probability that the

consumer does not choose to pay for online contents is:

$$Pr_{no} = 1 - Pr_1' - Pr_2' \quad (17)$$

According to the formulas (11)-(17), the decision optimization model under the mixed revenue model is:

$$\max \sum_{c=1}^C b_c \times p_{PPU} \times \mu \times M \times Pr_1' + \sum_{c=1}^C b_c \times p_{SFU} \times \mu \times M \times Pr_2' + \sum_{c=1}^C b_c \times 0 \times \mu \times M \times Pr_{no} \quad (18)$$

So the mixed decision optimization model can be simplified as:

$$\max \sum_{c=1}^C b_c \times \mu \times M \times (p_{PPU} \times Pr_1' + p_{SFU} \times Pr_2') \quad (19)$$

IV. SIMULATION AND ANALYSIS

A. Variable Neighborhood Search Algorithm

The variable neighborhood search algorithm [8] is a new heuristic algorithm, especially outstanding for large-scale combinatorial optimization problems' solution. The basic thinking is that changing the neighborhood structure set in the search process to expand the search scope and obtain the local optimal solution. Then, based on the local optimal solution, the system changes the neighborhood structure set to expand the search range and find another local optimal solution until the target requirements are met. Due to the advantages and convenience of the variable neighborhood search algorithm, the algorithm is applied to solve this model. The algorithm steps are as follows:

Step 1: Initialization. Select the set of neighborhood structures $N_k (k=1, 2, \dots, k_{max})$, that will be used in the search; find an initial solution x ; choose a stopping condition.

Step 2: Repeat the following until the stopping condition is met:

Step 2.1: Set $k=1$;

Step 2.2: Until $k=k_{max}$, repeat the following steps:

Step 2.2.1: Shaking. Generate a point x' at random from the k^{th} neighborhood of x .

Step 2.2.2: Local search. x' as initial solution; denote with x_1^* the so obtained local optimum.

Step 2.2.3: Update. If this local optimum is better than the incumbent, then set $x=x_1^*$, and continue the search with N_i , otherwise, set $k=k+1$.

B. Basic Market Parameters

This paper takes the video website as an example to analyze. Assume that the video service subscription period $T=30$, the total number of customers is $M=100$, other feature parameters are shown in Table I. Among them, the customer who has a high judgment on the value of the online content is also estimated to consume a large amount of consumption, and vice versa. The number of high-end customers who overestimate the value of contents and the number of low-end

customers who underestimate the value of contents are relatively small, with mid-end customers accounting for the market. At the same time, according to the Spence-Merrilee's single cross conditional theorem, it can be inferred that the more high-end consumers, the greater the value estimation of the bundling sales [7]. Essentially, subscription is also a type of bundling sale. So we make the following provision: the customers with a higher value estimation for online content have lower loss aversion level and discount level.

TABLE I: CUSTOMER'S FEATURE PARAMETERS

c	b_c (%)	$v_{c,0}$ (¥) (PPU)	$v_{c,0}$ (¥) (SFU)	$n_{c,SFU}$	ζ_c	λ_c
1	24.7	6.5	27	20	0.01	0.10
2	18.1	6	25	18	0.02	0.30
3	16	5.5	22	15	0.03	0.50
4	21.4	5	20	12	0.04	0.70
5	15	4.5	17	10	0.05	0.90
6	4.8	4	15	8	0.06	1.00

C. Experimental Results and Analysis

According to the consumer's time preference and loss aversion, this paper establishes the optimal configuration model under the single charging mode and the mixed income mode, uses the variable neighborhood search algorithm, and uses Matlab software to simulate the model. The optimal pricing of PPU and SFU modes is obtained through experiments, and the benefits are compared. At the same time, the mixed benefits based on PPU and SFU are obtained.

1) Single revenue model results analysis

From the experimental results as shown in Fig. 2(a) and Fig. 2-b, we can see the difference in pricing and returns under the single revenue model. Fig. 2(a) shows the website revenue curve diagram when only the PPU mode is provided. The return trend rising up at the beginning and declining in late, and the situation reached a high point at 122.3¥ when the optimal price is 5.07¥, which is very close to the current single-on-demand pricing of major video websites. It can also prove the effectiveness of the optimization model established in this paper. Fig. 2(b) is a graph which illustrates the benefits of the video website when only the SFU subscription model is available. The yield curve also starts to fall sharply after reaching the highest point, and the monthly price corresponding to the highest yield point of 294¥ is 20.6¥, which is slightly higher than the actual price quoted by the video website. Comparing the highest revenue in both cases, it can be found that the return of single SFU model is twice as much as the return of single PPU model in the 30-day video service subscription period.

The figures lead us to the conclusion that:

(a) It is clear that the single PPU model has the lowest level of return. Because in the PPU mode, the customer decides to purchase by comparing the undifferentiated unit price and its' value estimate for various content products. However, there are large differences in the estimated value of online content among various types of customers in Table I. When operator set content product unit price in the PPU mode, it cannot adapt to the difference in value perceptions of various types of customers, which is not conducive for the website operator to fully extract the consumer surplus.

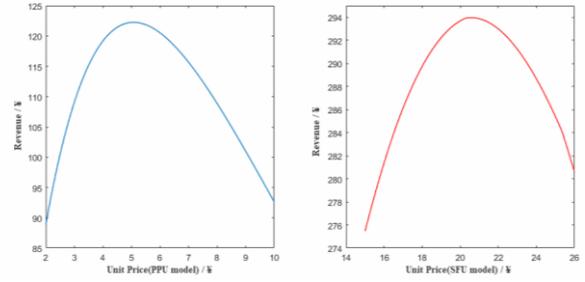


Fig. 2. (a) Video website revenue in PPU model; (b) Video website revenue in SFU model.

(b) The benefit of SFU mode in the experiment is slightly higher than that of PPU mode. The reason is that the proportion of low-end customers in Table I is lower, and there are more customers with larger demand $n_{c,max}$. When evaluating the utility of the SFU model, the customer incorporates all possible future consumption $n_{c,max}$ into the purchasing utility, and uses $p_{SFU}/n_{c,max}$ to replace the unit price of the product, thereby psychologically lowering the unit price of the product. However, due to the loss of aversion and value discounting, some customers will also abandon the SFU mode, so the revenue of the SFU mode are only slightly improved compared to the PPU mode.

2) Mixed revenue model results analysis

As shown in Fig. 3(a) and Fig. 3(b), the mixed revenue model is compared with the PPU mode and the SFU mode. It can be found that the benefit effect of the mixed revenue model is significantly better than the single PPU mode or the SFU mode. By comparing Fig. 3(a) with Fig. 3(b), we can see that the benefit level of online video sites providing different types of charging methods is: w (mixed revenue mode) $>$ w (single SFU mode) $>$ w (single PPU mode).

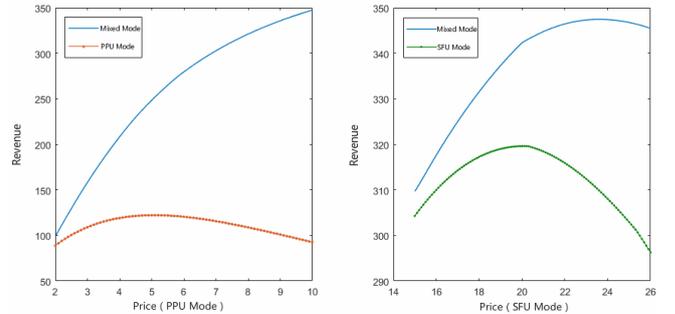


Fig. 3. (a) Comparison of revenue between mixed model and PPU model; (b) Comparison of revenue between mixed model and SFU model.

Combining the respective revenue advantages of the PPU mode and the SFU mode, Fig. 4 is obtained, which shows the profit level of the video website under the mixed revenue mode. The overall trend of the profit level is rising gradually with some slight fluctuation. The results show that the mixed revenue mode obtains the maximum return of 372.2¥ when the price is 10¥ in PPU mode and 20.1¥ in SFU mode. In this case, the consumer's purchase probability is 0.12 and 0.28 respectively. Compared with the website revenue under the single charging mode, it can be clearly seen that the profits obtained by the mixed revenue model is larger than the profits of the PPU mode and the SFU mode. As can be seen, the mixed revenue model can provide appropriate product services for customers with different value estimation, at the

same time, it also can take into account the value discount and loss aversion of consumers. Based on the consideration of consumer's behavior characteristics and psychological adaptation level, mixed mode can allocate a reasonable price for each bundling strategy to make full use of their profitability, furthermore, the website service providers can obtain the maximum revenue.

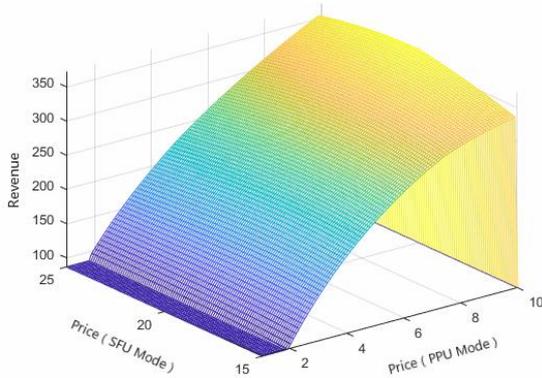


Fig. 4. Video website revenue under mixed revenue model.

V. CONCLUSION

This paper proposes an online content bundling pricing decision optimization model and model solution algorithm based on quantity difference. On the basis of considering the relationship between the customer's time preference level, loss aversion and the value perception of online contents, the influence of the customer's choice behavior of different product types on the profitability of the service provider is analyzed, and the large-scale combination optimization is solved through the variable neighborhood search algorithm. The results show that the mixed revenue model based on the quantity difference can bring more benefits to the online content service provider than the single payment model.

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