Exploring Business Models and Dynamic Pricing Frameworks for SPOC Services

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Abstract. MOOCs provide irreplaceable opportunities of making high-quality courses accessible to everybody. However, MOOCs are often criticized for lacking sustainable business models, and academic research for business strategies for MOOCs is also a blind spot currently, especially for the B2B markets. As the primary B2B business model, *SPOC services* can help the institutional users to improve their in-classroom teaching outcomes, as well as bring considerable revenue to the MOOC platforms. In this work, we formulate the economic model and pricing strategy for SPOC services in a theoretical way and further present the future work of applying our model in real markets.

1 Introduction

MOOCs bring an unprecedented revolution to the worldwide higher education of producing high-quality online courses and make them accessible to everybody. At the same time, universities can also adopt flipped classroom learning to improve the teaching quality of the on-campus education by using *SPOCs* (i.e. *Small Private Online Courses*) through various blended teaching and learning methodologies. MOOC is an ecosystem involving efforts from many parties. The *MOOC platforms* are the core of the ecosystem. Every MOOC platform is a marketplace where *MOOC producers* (usually universities) deliver their MOOCs and corresponding education services to the *users*. The users in the MOOC ecosystem consist of both *Internet users* and *institutional users*. From an industrial perspective, the profitability and financial stability of the MOOC platforms become a critical problem associated with the sustainable development of the entire MOOC ecosystem.

As we know, the B2C (i.e., business-to-customer) services are the basic business models for MOOC platforms of making money from the Internet users with a *freemium* strategy: Where the basic materials of MOOCs are open and free to all users, and the MOOC platforms also offer fee-based *online value-added services* to the users including the *Verified Certificates*, *Specializations*, *Online Micro Masters*, *Advanced Placement* (i.e. AP) courses and so forth. However, for some MOOC platforms, both the completion rate (i.e., the percentage of the users to pass the basic requirement of a course) and the paying rate (i.e., the percentage of users to pay for value-added services such as verified certificates) is not promising[1]. These MOOC platforms can hardly sustain by only providing

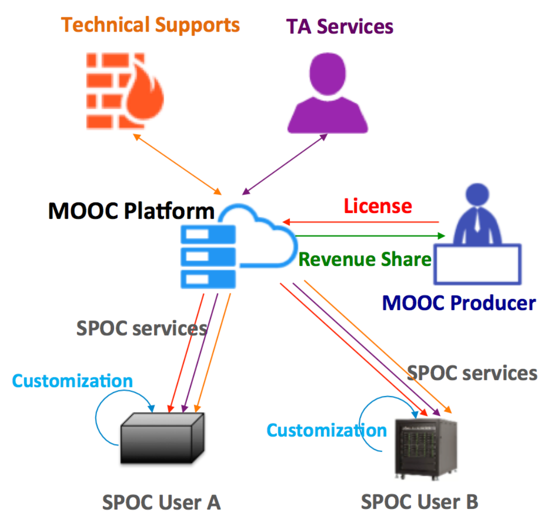

Fig. 1. Business model and market structure for the SPOC services.

value-added services to the Internet users. In China, some MOOC platforms (e.g., xuetangX, icourse163) make profits by providing B2B (i.e., business-to-business) education services to institutional users (e.g., universities, professional training institutions, etc) by sub-licensing MOOC contents and on-campus SPOC platforms. In this work, we focus on the B2B services, which attract less attention from both the industries and academics, but also play an important role in the MOOC ecosystem, and sometimes bring more revenue to some early-stage MOOC platforms than B2C services. In the B2B *course sub-licensing* market, the MOOC platform is the seller in the market, and buyers are *institutional users* with the demand of using the MOOC materials from the platform and deploy them as SPOCs for purposes of blended learning.

In practice, the sub-licensing services always exist in the pattern of *SPOC services* by allowing the *institutional users* to import MOOC materials from the platform and use them as SPOCs with blended teaching and learning approaches. To guarantee the quality of service, the *SPOC services* are dynamic and highly customized, and a user's demand is a *bundle* of education services including MOOC contents, teaching assistant services, SaaS services, technical supports and so forth. We illustrate the business model and market structure for the SPOC services in Figure 1. On one hand, each institutional user pays for a bundle of customized education services and the MOOC platform makes revenue from the services. On the other hand, as the copyrights of the licensed MOOCs do not belong to the platform, the MOOC platform should get sub-licensing approvals from the MOOC producers and share revenue with them.

To the best of our knowledge, this is the first work to study the business model and pricing strategy for the SPOC services with economic models. As the users' demands are dynamic, we design interactive business process and dynamic pricing framework to analyze the SPOC services, and further present the profit maximization strategy for the MOOC platform by formulating an integer programming with resource capacity constraints.

In this work, we propose a theoretical model to analyze the business process and pricing strategy for SPOC services, and also present ideas of applying our model in the MOOC industry. The rest of the paper is organized as follows: We first review related work in Section 2. We formulate the theoretical model for the dynamic pricing framework and business process of the SPOC services in Section 3. To solve the optimization problem, We present the theoretical analysis to maximize the MOOC platform's total profits through combinatorial auction mechanisms in Section 4. We then give ideas of applying our model in practice in Section 5. Finally, we present the directions of our future work and conclude the paper in Section 6.

2 Related Work

SPOC (i.e., Small Private Online Course) refers to another version of a MOOC (i.e., Massive Open Online Course) which localizes the instances of a MOOC on campus through business-to-business contexts. The concept of the SPOC is initiated in the University of California Berkeley by Armando Fox [2]. Soon after that, Chinese pioneers start to deploy the SPOC services and apply blended learning methodologies on campus from 2013 [3]. To the best of our knowledge, this work is the first to study the business model and dynamic pricing framework with theoretical analysis for SPOC services. In [1], we analyze the flat-rate pricing strategies for B2C markets with both theoretical models and data-driven analysis. [4] presents the ideas of involving adaptive learning into the business model design of MOOCs. There are also discussions on future trends of business development of MOOCs from the industry. For instance, [5] shows the latest experience of finding niche and business model for MOOC in 2016.

To analyze the business models for the B2B services, there have been lots of research done in the area of resource allocation using auction models. One early work dates back to [6], where they use the combinatorial auction to deal with the problem of airport time slot allocation by utilizing the concept of shadow price. Recent work such as [7], designs a heuristic greedy deterministic auction as well as a randomized linear optimization based auction for allocating wireless spectrum in secondary network. The authors in [8] present a discriminative second price auction technique to motivate users in peer-to-peer video-on-demand streaming applications. [9] presents a reverse auction framework to motivate the smartphone users to join mobile crowdsourcing applications. The authors in [10] show how we can deal with resource provisioning in cloud computing with an online combinatorial auctions framework. These studies bring us inspirations of applying various mechanisms to optimize the MOOC B2B market.

We further study the theoretical methodologies for auction mechanism design. [11] shows the strong links between combinatorial auction and Lagrangian-based decomposition. The authors in [12] utilize mixed integer programming to manage general combinatorial auction problems efficiently. [13] presents a new family of preference elicitation algorithms to prevent bidders to bid on all combinations. In another way, [14] shows how to use boosting to automatically modifying existing mechanisms to increase expected revenue. [15] exhibits three approximation algorithms for the allocation problem in combinatorial auctions with different ratios under different assumptions. [16] dives deeper into the question of whether polynomial-time truthful mechanisms for combinatorial auctions are provably weaker in terms of approximation ratio than non-truthful ones. We use some of the above-mentioned techniques to improve the performance of our combinatorial auction model.

3 Modeling the SPOC services

In this section, we analyze the business model of the SPOC services by using an auction-based pricing framework. In the auction-based market, each user attaches a bid to her *bundle* that signifies her willingness to pay for the SPOC services, and then the MOOC platform decides whether to accept this bundle. If yes, the MOOC platform makes a contract with the user under a dynamic pricing mechanism; if no, the business negotiation between the user and the platform continues.

Then we formulate the B2B market with one MOOC platform as the seller within a certain period (e.g. a semester, or a fiscal year). There is a total of C courses with sub-licensing approvals which can be used as *SPOCs*. We use $[X] = \{1, 2, \ldots, X\}$ to denote the set of X elements throughout the paper, and therefore $[C] = \{1, 2, \cdots, C\}$ is the set of sub-licensing courses. For each course $c \in [C]$, the MOOC platform provides SaaS services, teaching assistant services, technical support, and other education services. Due to the resource capacity constraint (e.g., the limited number of TAs, or limited computational resources of the SPOC platform) for each course, course c can support at most q_c students from all the SPOCs. There are N users in the market, and the business process is a series of negotiations between the users and the platform. We assume that each user-platform negotiation completes within K steps, otherwise the negotiation fails. In the k-th step ($k \in [K]$) of the negotiation, the user $n \in [N]$ submits a bid with a bundle $B_{n,k}$ of SPOC services and her valuation $v_{n,k}$ (i.e., willingness to pay) to the bundle. Each bundle $B_{n,k}$ contains a vector of C integers indicating the enrollments for the C courses, and we denote the number of enrollments for the SPOC c in bundle $B_{n,k}$ as $s_{n,k,c}$. If the negotiation terminates in K' rounds and $K' < K$, then let $B_{n,k} = \{0, 0, \cdots, 0\}$ and $x_{n,k} = 0$ for all $K' < k \leq K$. In the following analysis, we first consider the offline setting, where we know the information for all the bids of each user in advance, and we take all the data of $B_{n,k}$ as the input.

We further consider two types of cost to deploy and operate the SPOC services: The *capital cost* is the expenditures to support the basic features of SPOCs (e.g. the cost to build the customized SPOC platform), and we denote the capital cost for bundle $B_{n,k}$ as $d_{n,k}$, which is not associate with each SPOC; The *operational cost* is the cost to operate and support each SPOC including the TA's labor cost, video traffics cost and so forth, and we denote the *operational cost* for the course c in bundle $B_{n,k}$ as $\omega_{n,k,c}$.

The platform need a *decision algorithm* $\mathcal{A}$ to decide whether to accept a bid and a pricing mechanism $\mathcal{P}$ to maximize the total profit from all the users. We use $\mathcal{R}$ to denote the current resource capacity which is a vector of C integers indicating the remaining capacities for the C courses. The decision algorithm $\mathcal{A}$ is a function of $B_{n,k}$, $v_{n,k}$ and $\mathcal{R}$. We use the binary variable $x_{n,k}$ to denote whether bundle $B_{n,k}$ is accepted by the platform, so we have:

$$x_{n,k} = \mathcal{A}(B_{n,k}, v_{n,k}, \mathcal{R}) = \begin{cases} 1 \text{ Accept} \\ \\ 0 \text{ Reject} \end{cases} \qquad \forall k \in [K], n \in [N]$$

Let $p_{n,k} = \mathcal{P}(B_{n,k}, v_{n,k}, \mathcal{R})$ denote the price for bundle $B_{n,k}$, then we formulate the profit maximization strategy for the platform by using an integer programming as follows:

$$\text{maximize:} \sum_{n\in[N],k\in[K]} (p_{n,k} - d_{n,k} - \sum_{c\in[C]} \omega_{n,k,c}) \cdot x_{n,k} \tag{1}$$

s.t.

$$\sum_{k\in[K]} x_{n,k} \leq 1, \quad \forall n \in [N]; \tag{2a}$$

$$\sum_{k\in[K]} \sum_{n\in[N]} s_{n,k,c} \cdot x_{n,k} \leq q_c, \quad \forall c \in [C]; \tag{2b}$$

$$x_{n,k} \in \{0,1\}, \quad \forall n \in [N], \forall k \in [K]. \tag{2c}$$

The objective function (1) is the total profits gained by the MOOC platform. Constraint (2a) means that each buyer wins at most one bundle of the SPOC services and constraint (2b) is the resource capacity constraint, showing that the total enrollments of each course are smaller than its capacity.

4 Combinatorial Auction Mechanisms

In this section, we present combinatorial auction mechanisms to solve the offline problem to optimize the MOOC platform's total profits, where we know all the information for the bids of each user (i.e, $B_{n,k}, \forall n, \forall k$) in advance.

To maximize the platform's total profits from the *bundled education services*, the combinatorial auction mechanisms are promising techniques to fit our settings. In a typical one round combinatorial auction, there are n bidders, each of them will bid for k bundles of items. Then the outcome (i.e., total profits in our settings) of this auction (x, p) will be decided by a specific mechanism, where $x_{i,k}$ is the allocation for bidder i and bundle k and $p_{i,k}$ is the price that bidder i should pay for bundle k. In our setting, the courses and services represent the items to be sold in the general combinatorial auction setting, and each institutional user bids for several bundles of services (i.e., at most k bundles). Constraints come from the limits of teaching assistants, computing resources and so on. In this work, We apply three combinatorial mechanisms: the *VCG Mechanism*, the *Virtual Valuation Mechanism*, and the *Shadow Price Mechanism*.

4.1 VCG Mechanism

We first apply the famous VCG mechanism [17] in our setting. VCG mechanism employs an allocation rule to maximize the social warfare, i.e. the sum of all the valuations of users who win the bidding bundles. The formulation of allocation rule is as follows:

$$\begin{aligned} \max \quad & \sum_{n \in [N]} \sum_{k \in [K]} v_{n,k} x_{n,k} \\ \text{s.t.} \quad & \textit{Constraints (2a) - (2c)} \end{aligned}$$

Then the payment p_i for each bidder i by VCG mechanism is:

$$p_i = \sum_{j \neq i} \sum_{k \in [K]} v_{j,k} \tilde{x}_{j,k} - \sum_{j \neq i} \sum_{k \in [K]} v_{j,k} x_{j,k}$$

where

$$\tilde{x}_{j,k} = \arg\max_{x_{j,k}} \sum_{j \neq i} \sum_{k \in [K]} v_{j,k} x_{j,k}$$

The intuition of the above mechanism is that we set the price of the SPOC services to one particular bidder as the decrease of all the other bidders' gain due to the participation of this bidder. Note that VCG auctions are generally computational intractable, existing work such as [18] incorporate the use of VCG-style pricing with exploited greedy allocation schemes.

4.2 Virtual Valuation Mechanism

VCG Mechanism may not be optimal in respect of the seller's revenue. Inspired by Myerson mechanism [19] for the optimal single item auction, and the authors of VVCA (virtual valuation combinatorial auction) [14] further introduce two kinds of virtual valuation forms to boost seller's revenue in combinatorial auction. Instead of maximizing the sum of all the real valuations of users who won the bidding bundle, the allocation is decided by maximizing the sum of all the virtual valuations. Then the price is decided by calculating the decrease of other bidders' virtual gain due to the participation of this bidder.

VVCA mechanisms is parameterized by a bunch of preset parameters μs and λs, corresponding to the bidder weighting technique and allocation boosting technique respectively: the former assign priorities to bidders with higher valuations, while the latter assign priorities to a specific bundle for a bidder. The allocation is computed by solving:

$$\begin{aligned} \max \quad & \sum_{n\in[N]}\sum_{k\in[K]}(\mu_n v_{n,k}x_{n,k}+\lambda_{n,k}x_{n,k}) \\ \text{s.t.} \quad & \textit{Constraints (2a) - (2c)} \end{aligned}$$

where μ are positive real numbers. The payment rule is

$$p_i = \frac{1}{\mu_i}\left(\sum_{j\neq i}\sum_{k\in[K]}(\mu_j v_{j,k}\tilde{x}_{j,k}+\lambda_{j,k}\tilde{x}_{j,k}-\mu_j v_{j,k}x_{j,k}-\lambda_{j,k}x_{j,k})-\sum_{k\in[K]}\lambda_{i,k}x_{i,k}\right)$$

where

$$\tilde{x}_{j,k} = \arg\max_{x_{j,k}}\left(\sum_{j\neq i}\sum_{k\in[K]}\mu_j v_{j,k}x_{j,k}+\lambda_{j,k}x_{j,k}\right)$$

The intuition is that we substitute the valuations in VCG to virtual valuations here. Then we determine the parameters λ and μ by using numerical methods such as hill-climbing to maximize the seller's expected revenue.

4.3 Shadow Price Mechanism

The main idea of the Shadow Price Mechanism [6] is to determine a shadow price for each available resource using the optimal Lagrangian multiplier of the primal integer program, and determine the bid rejection prices (D_R) and bid acceptance prices (D_A) using two pseudo-dual programs.

$$\begin{aligned} \min & \sum_{x^*_{n,k}=0} y_{n,k} && \\ \text{s.t.} & \sum_c w_c s_{n,k,c} \le v_{n,k} && \forall x^*_{n,k}=1 \\ & y_{n,k} \ge v_{n,k} - \sum_c w_c s_{n,k,c} && \forall x^*_{n,k}=0 \\ & y_{n,k} \ge 0 && \forall x^*_{n,k}=0 \\ & w_c \ge 0 && \end{aligned}$$

Here $x^*_{n,k}$ is the optimal solution to the primal integer program, and the set of lower bound prices is w^*_c, and we denote the exceeding price of a rejected bundle comparing to the market price as $y_{n,k}$.

$$\begin{aligned}
\min & \sum_{x^*_{n,k}=1} y'_{n,k} & \\
\text{s.t.} & \sum_c u_c s_{n,k,c} \geq v_{n,k} & \forall x^*_{n,k}=0 \\
& y'_{n,k} \geq \sum_c u_c s_{n,k,c} - v_{n,k} & \forall x^*_{n,k}=1 \\
& y'_{n,k} \geq 0 & \forall x^*_{n,k}=1 \\
& u_c \geq 0 &
\end{aligned}$$

Here the set of upper bound prices is u^*_c, and we also denote the exceeding price of a rejected bundle comparing to the market price as $y'_{n,k}$.

Then the allocation rule has the following properties: (i) if a bid is greater than the sum of its component values in the set $\{u^*\}$, then it is accepted. (ii) if a bid is less than the sum of its component values in the set $\{w^*\}$, then it is rejected. (iii) all bids between are determined by considering the primal integer program regardless of the shadow prices.

The pricing strategy is to set the price for any bidder whose bundle k is accepted in the solution of the primal problem to the sum of the shadow prices for the resources in the package.

4.4 Examples

Now we give an example to show why VVCA mechanism can generate higher revenue than VCG mechanism. Consider the following scenario, there are three bidders $\{A, B, C\}$ and two items $\{P, Q\}$, the valuation of bidders to bundles are listed below:

$$v_{A,\{P\}} = 5,\ v_{B,\{Q\}} = 1,\ v_{C,\{P,Q\}} = 16$$

Then with VCG mechanism, the allocations are decided by solving the following integer programming:

$$\max \quad 5 \cdot x_{A,\{P\}} + x_{B,\{Q\}} + 16 \cdot x_{C,\{P,Q\}} \tag{3}$$

s.t.

$$x_{A,\{P\}} + x_{C,\{P,Q\}} \leq 1 \tag{4a}$$

$$x_{B,\{Q\}} + x_{C,\{P,Q\}} \leq 1 \tag{4b}$$

$$x_{A,\{P\}},\ x_{B,\{Q\}},\ x_{C,\{P,Q\}} \in \{0, 1\} \tag{4c}$$

A simple enumeration of the feasible solutions gives the optimal solution

$$x_{A,\{P\}} = x_{B,\{Q\}} = 0,\ x_{C,\{P,Q\}} = 1$$

So the final allocation would be give item $\{P, Q\}$ to C. Now we compute what price would C pay. Without the presence of C, we have the integer programming:

$$\max \quad 5 \cdot x_{A,\{P\}} + x_{B,\{Q\}} \tag{5}$$

s.t.

$$x_{A,\{P\}} \leq 1 \tag{6a}$$

$$x_{B,\{Q\}} \leq 1 \tag{6b}$$

$$x_{A,\{P\}},\ x_{B,\{Q\}} \in \{0, 1\} \tag{6c}$$

The optimal solution would be

$$\tilde{x}_{A,\{P\}} = \tilde{x}_{B,\{Q\}} = 1$$

So the price C needs to pay is the decrease of social ware-fare due to the presence of himself, which is

$$\begin{aligned} P_c &= \big(\tilde{x}_{A,\{P\}} \cdot v_{A,\{P\}} + \tilde{x}_{B,\{Q\}} \cdot v_{B,\{Q\}}\big) \\ &\quad - \big(x_{A,\{P\}} \cdot v_{A,\{P\}} + x_{B,\{Q\}} \cdot v_{B,\{Q\}}\big) \\ &= (1 \cdot 5 + 1 \cdot 1) - (0 \cdot 5 + 0 \cdot 1) \\ &= 6 \end{aligned}$$

Thus the revenue of VCG mechanism would be 6. Then we show how VVCA would boost the revenue of above VCG mechanism. The main idea is to use virtual valuations to bring down the difference of valuations between strong bidders and weak bidders, thus creating an artificial competition to extract more revenue from strong bidders. We assign the following λ, μ:

$$\mu_C = 0.5,\ \lambda_{B,\{Q\}} = 1$$

Now the integer programming would become:

$$\begin{aligned} \max \quad & 5 \cdot x_{A,\{P\}} + x_{B,\{Q\}} + x_{B,\{Q\}} + 0.5 \cdot 16 \cdot x_{C,\{P,Q\}} \\ \text{s.t.} \quad & \textit{Constraints (4a) - (4c)} \end{aligned}$$

Without the presence of C, we have:

$$\begin{aligned} \max \quad & 5 \cdot x_{A,\{P\}} + x_{B,\{Q\}} + x_{B,\{Q\}} \\ \text{s.t.} \quad & \textit{Constraints (6a) - (6c)} \end{aligned}$$

The optimal solution would still be

$$x_{A,\{P\}} = x_{B,\{Q\}} = 0,\ x_{C,\{P,Q\}} = 1$$

$$\tilde{x}_{A,\{P\}} = \tilde{x}_{B,\{Q\}} = 1$$

The difference lies in the price that C would pay:

$$
\begin{aligned}
p'_C &= \frac{1}{\mu_C}\left(\tilde{x}_{A,\{P\}} \cdot v_{A,\{P\}} + \tilde{x}_{B,\{Q\}} \cdot v_{B,\{Q\}} + \lambda_{B,\{Q\}}\tilde{x}_{B,\{Q\}} \cdot v_{B,\{Q\}}\right) \\
&- \frac{1}{\mu_C}\left(x_{A,\{P\}} \cdot v_{A,\{P\}} + x_{B,\{Q\}} \cdot v_{B,\{Q\}}\lambda_{B,\{Q\}}x_{B,\{Q\}} \cdot v_{B,\{Q\}}\right) \\
&= \frac{1}{0.5}(1 \cdot 5 + 1 \cdot 1 + 1 \cdot 1 \cdot 1) - \frac{1}{0.5}(0 \cdot 5 + 0 \cdot 1 + 1 \cdot 0 \cdot 1) \\
&= 14
\end{aligned}
$$

Thus the revenue of VVCA mechanism would be 14, which is much higher than the revenue of VCG mechanism, i.e., 6.

5 Business Process in the MOOC Industry

In the previous discussion, we only consider the offline setting for the combinatorial auction in only one round. In practice, the business process of the user-platform negotiation is *online*, indicating that the platform must give quick (or even instant) response to the user when she submits a bid. Moreover, the response message to the user is interactive, including not only the result of whether the bid is accepted or not, but also the reasons of why the bid is rejected, or even suggestions on the combinations of $B_{n,k}$ and $v_{n,k}$. For instance, a bid may be rejected due to the low valuation, or unmet resource capacities for some SPOCs. When the user receives the message, she will adjust her bid by reducing the demand or increasing the valuation to the bundle in the next step of negotiation. We further present Algorithm 1 to demonstrate the business process of the user-platform negotiation in a systematic way.

To solve the online setting of the problem, we apply the iterative combinatorial auctions in [20], and further use the *iBundle* mechanism [21] for detailed analysis.

iBundle maintains *ask prices* on bundles, which is the lowest price at which a bundle may be sold, and also the *provisional allocation*, which is the possible allocation for the current bids. The process goes through multiple rounds, in each round a bidder can submit bids on bundles, where at most one bid will be chosen. A bid is called competitive if it is at or above the current ask price. A bidder is called competitive if at least one of his bids is competitive. Then a winner-determination algorithm computes the provisional allocation to maximize the seller's revenue. iBundle terminates when each competitive bidder receives a bundle in the provisional allocation. Otherwise, prices are increased by a preset parameter ϵ above the bid price on all bundles that receive a bid from some losing bidder in the current round and the allocation and new prices are provided as feedback to bidders. On termination, the provisional allocation becomes the final allocation, and the bidders pay their final bid prices.

Algorithm 1: Negotiation between user n and the platform

Initialization: Set $t = 1$ and $flag = 0$. Suppose the current status of resource capacity is $\mathcal{R}$.
while $t \leq T$ **do**
  (a) User n submits his bids $(B_{n,k}, v_{n,k})$ to the platform.
  (b) The platform calculates $x_{n,k}$ and $p_{n,k}$, and sends the response message to the user.
  (c) **If** *accepted*, **then** the negotiation succeeds, update $\mathcal{R}$, set $flag = 1$, and **break**. **Else** (i.e. *rejected*) the negotiation continues with $t = t + 1$.
end
If $flag = 0$, **then** the negotiation fails.

6 Conclusion Remarks

In this work, we focus on analyzing the business model and pricing strategy for the SPOC services, and maximize the MOOC platform's total profits by using combinatorial auctions. We present formulations and solutions for both the one-round offline scenario, and also the iterative multi-round scenario. We present several mechanisms for the allocation rules and pricing strategies.

Working in the MOOC industry for the past four years, we have gained valuable marketing experience of selling MOOC and SPOC services. For the B2C services, we can directly get sales data from the online purchasing records and use data-driven approaches to better analyze the real market. For the SPOC services, we successfully deploy the services to 125 real institutional users, including 90 universities, 20 corporations, 7 high schools and 8 government organizations. Even though there are no automatic ways to collect sales data for SPOC services, we can use the *Customer Relationship Management* (i.e. *CRM*) system to keep track of the marketing data and the business process. It is also practical to conduct surveys to the key users to better understand the buyers' behavior. We will apply these methodologies in the MOOC industry to improve the marketing performance of the models in our future work.

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