Can a P2P File-Sharing Network Become an e-Marketplace?

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Abstract

The prevalence of P2P technology contributes the ease of file-sharing, but it also brings some problems such as free-riding and copyright infringement. To solve these problems, many researchers have proposed incentive mechanisms. At the same time, some applications and business models based on P2P technology are developed. However, those new business models would not allow users redistribute files which they have downloaded. This study proposes a new business model which adopts a reselling mechanism to distribute contents on P2P networks. Users who have downloaded contents from peers other than the author peer can resell them by paying a portion of reselling gains as the royalty to the author. Content providers and consumers may re-price shared contents dynamically via incremental learning. This study aims to verify that authors can gain more through P2P reselling model than through client/server architecture, and we will investigate into the factors which influence this possibility.

Keywords: Peer-to-Peer, Reselling mechanism, Multi-Agent Simulation, Dynamic pricing.

1. Introduction

Peer-to-Peer technology enables computers around the world to directly share resources like CPU processing capability, disk storage, contents, etc. However, because of the lack of proper incentive mechanisms, a majority of users download files via P2P networks but very few people contribute contents in return, which render to the free-riding problem. In 2000, an experiment conducted on Gnutella shows that approximately 66% of peers shared no files and 73% shared ten or fewer files, while top 1% represents approximately 37 % of the total files shared and top 20% represents 98% of the total files [1]. Another study in 2005 shows that 85% of peers share no files and 86% share 10 or fewer files [2]. Free riding has increased significantly since then. Moreover, the distribution of unauthorized contents on P2P networks hinders the productive uses of P2P technology. Over the past years, extensive transactions of copyright-infringed files on P2P networks have severely damaged record brands [3]. In consequence, IFPI (International Fédération Phonographique Industrie) started to fight back against the tendency towards illegal downloading. IFPI first canvassed US Congressmen for the adoption of a forbidding P2P Act. Subsequently, IFPI brought suits against software companies and large-volume-illegal-file providers. The record brands even added DRM (Digital Right Management) technology on CDs, which is used to protect music from transforming into digital format. Meanwhile, Apple Company took the lead in launching online music service, which allows consumers to legally download music with specific format to their iPods or iTunes. After the success of iPod, several online music services emerged in Taiwan, such as KKBOX, Kuro and ezPeer, noted that Kuro and ezPeer provided their services over P2P network architecture, while the service of KKBOX uses DRM to protect the music files from illegal copies over client/server architecture. Nevertheless, the same illegal downloading happened on Kuro and ezPeer.

The responsibility of software companies has not been clear and definite until US Supreme Court pronounced that whoever distributes equipments, by which others might facilitate copyright infringement, should be in charge of others' copyright infringement. This sentence has caused a lot of famous P2P technology companies go bankrupt, *e.g.*, eDonkey and limewire, or has driven them to find another way out. In 2003, IFPI in Taiwan made an accusation against Kuro and ezPeer. They forced Kuro and ezPeer to provide a legitimate platform which would not ease the copyright infringement, or they should take charge of the copyright infringement of their members. At this moment, the declaration of the alignment between Warner

Bros. and well-known P2P software, BitTorrent, was catching mass attention indeed, which implied that a new business model apparently came into a reality.

However, the possibility of a content distribution channel based on P2P networks still remains questionable. A concrete business model needs to answer questions, such as how the digital content is priced and whether the downloaded files can be redistributed.

This study proposes a business model which adopts a reselling mechanism to distribute contents on P2P networks. Users who have downloaded contents from other peers can resell them by paying a portion of reselling gains as the royalty to these peers. Content providers and consumers may re-price shared contents dynamically via incremental learning. Besides, this study aims to verify that authors can gain more through P2P reselling model than through client/server architecture, and we will investigate into the factors which influence this possibility.

2. Literature review

We will first review the literatures on the current economic issues of P2P network and related techniques used in this study.

2.1. Peer-to-Peer network

P2P technology takes advantage of the resources owned by hosts on the Internet, such as CPU processing capability, storage, contents and user participation, to enable various applications [4]. Some famous examples are MSN, SETI@home and KaZaA. In addition, P2P technology presents the advantages of distributed systems that save the expense of constructing centralized computation and storage facilities. Many researches have investigated business-oriented applications based on P2P technology, for example, marketing [5], enterprise application integration [6], B2BI [7], workflow [8], and the distribution channel of digital-stored goods [9]. At present, the hottest application of P2P is file-sharing.

Nevertheless, P2P technology has several drawbacks of management. Because P2P is free from the central control unit, the access to P2P is unmanageable. The development of trust among users becomes the key to the business applications of P2P. Some researches studied the construction of trust on P2P networks [10]. The payment on P2P networks also needs to be noticed. Arora et al. proposed the framework of CasPaCE to ensure the security of transactions and payments under P2P context [11].

The lack of appropriate management makes people distribute unauthorized copyrighted files via P2P software easily. This problem influences many industries, especially music industry, which incurs many debates. P2P indeed beats CD sales of music industry [12]. Clark (2000) pointed out that the estimate of annual CD sales loss caused by online music will reach \$3.1 billions by 2005 [13]. The piracy on P2P decreases consumers' willingness of CD purchasing to 65% [14].

Accordingly, the Recording Industry Association of America (RIAA) did a great effort to protect copyright from infringement. However, the effort of RIAA conflicts with the intention of P2P software developers, the normal use of legal music consumers, and the privacy-protected obligation of ISPs [15].

From the perspective of policy makers, it is important to design a mechanism for distributing information goods, to balance the interest between copyright-owners and Internet users. Researchers recognized that existing business models need to be modified behind P2P appearance [16]. Hui and Png suggested that people use P2P software for business [17].

Researchers have also started to investigate the design of e-commerce architectures under P2P contexts, which provide the details of transaction procedures and information transitions [18-20]. However, most of them lack the ability of file-sharing. Hence, Grimm and Nutzel proposed a business model which allows users to redistribute downloaded files and share the profit [21]. Under this model, consumers have two choices: *free downloading* and *purchasing*. Once a peer pays for downloading, it will have the right of redistribution automatically, and it can gain commission from redistribution. Courcoubetis and Antoniadis identified several important parameters on P2P business models, including reputation, cost, utility, and degree of competition [22].

However, the described redistribution model doesn't allow users to price their downloaded files. This study combines the concept of royalty with redistribution as a new reselling mechanism. Content providers will price their products and set royalties, which are drawn from consumers' reselling revenue. Consumers will be able to set reselling prices for their downloaded files, and some of their revenue from reselling will be drawn as royalties. Consumers in the proposed reselling mechanism are more autonomous, and have more motivation to purchase files.

In addition, Lang and Vragov developed the monopolistic pricing mechanism for distributing digital contents on P2P [23]. Their study revealed that the distribution by P2P networks will be more profitable than by a client/server platform as P2P networks present stronger incentives for users to redistribute digital contents. But this pricing mechanism looks for an optimal price via optimization process, which needs giant computation and complete information about users. This study aims to find the optimal price via incremental learning.

2.2. Radial basis function network (RBFN)

Radial Basis Function Networks (RBFN) is a neural network technique, containing an input layer, a hidden layer, and an output layer. In the output layer, with an unknown function $y(x)$: $R^d \to R$, a RBFN can approximate $y(x)$ with a set of d-dimensional radial basis functions. These radial basis functions are centered on centroids, which can be treated as the nodes of the hidden layer. Therefore, the transformation from the input space to the hidden-unit space is nonlinear, whereas the transformation from the hidden-unit space to the output space is linear.

Suppose that we want to use a set of m radial basis functions $\psi(x)$, centered on the centroids c_j to approximate $y(x)$, where $j = 1, 2,...,m$. $\varphi(x)$ can be defined as φ: $R^d \to R$: $\varphi = \varphi(\|x - c\|)$ where $\|.\|$ denotes the Euclidean norm, $c_j \in R^d$. Then we can get the estimation of $y(x)$, denoted by $\hat{y}(x)$, representing a linear combination of the radial basis function $\psi(x)$: $\hat{y}(x) = \sum_{j=1}^{m} \theta_j \phi(\| x - c_j \|)$, where θ_j is a weight factor. A radial basis function is a Gaussian function typically, *i.e.*, $\varphi(\|x - c_j\|) = \exp(-\frac{\| x - c_j \|^2}{\sigma_j^2})$, where σ_j is the width factor of the j^{th} unit in the hidden layer.

Chen, Cowan and Grant proposed an alternative learning procedure for RBFN based on the Orthogonal Least Squares (OLS) method [24]. The procedure chooses radial basis function centers one by one in a rational way until an adequate network has been constructed. Each selected center maximizes the increment to the explained variance of the desired output and does not suffer numerical ill-conditioning problems. The orthogonal least-squares learning strategy provides a simple and efficient way for fitting radial basis function networks.

The main advantage of RBFN is that it can solve both linear and nonlinear problems by fast learning and reducing sensitivity to the order of presenting training data. Lin, Huang & Yang adopted RBFN to automatically model multi-attribute utility function of a peer [25]. A multi-attribute utility function may be either linear or nonlinear. Rapidly modeling a user's utility function is important to many agent applications.

This study builds a preference model for each peer to make decisions, in which a peer's preference is usually determined by many decision attributes. We combine weighted utility of decision attributes into a conjoint model and adopt RBFN to formulize the multi-attribute utility function.

2.3. Semi-Markov decision process (SMDP)

Many sequential decision making problems can be modeled as Semi-Markov Decision Processes (SMDPs) embedded on continuous time semi-Markov processes (SMPs) [26].

Suppose a random variable, state, X_n takes values in a countable set $\wp$, and a random variable, time, T_n takes values in $\Re^+ = [0,\infty]$, such that $0 = T_0 \le T_1 \le T_2...$. The stochastic process $(X, T) = \{X_n, T_n : n \in N\}$ is said to be a Markov renewal process (MRP) with state space $\wp$, when for all $n\in N$, $j\in \wp$, and $t\in \Re^+$, the following condition is satisfied:

$$P\{X_{n+1} = j, T_{n+1} - T_n \le t \mid X_0,..., X_n; T_0,..., T_n\} = P\{X_{n+1} = j, T_{n+1} - T_n \le t \mid X_n\}$$

Define a process $Y = \{Y_t : t \in \Re^+\}$, where $Y_t = X_n$, if $T_n \le t \le T_{n+1}$. The process is called a semi-Markov process associated with the MRP (X,T). Clearly, decision epochs in SMDPs are not restricted to discrete time epochs but are all time epochs at which the system enters a new decision making state. That is, the system may change several times during two decision epochs.

This study formulates the author's and the reseller's decision processes as SMDPs; however, the computation of the immediate reward is quite difficult. Thus, we adopt reinforcement learning to solve this problem.

2.4. Temporal-difference learning (TD learning)

Sutton (1988) introduced Temporal Difference (TD) learning approach to solve the problem of *learning-to-predict*, which uses past experience with an incompletely known system to predict its future behavior [27]. For instance, through experience one might learn to predict for particular chess positions whether they will lead to a win, for particular cloud formations whether there will be rain, or for particular economic conditions how much the stock market will rise or fall. An important advantage of prediction learning is that its training examples can be taken directly from the temporal sequence of ordinary sensory input; no special supervisor or teacher is required. TD learning is a class of incremental learning procedures specialized for prediction. Whereas conventional prediction learning methods are driven by the error between predicted and actual outcomes, TD learning are similarly driven by the error or difference between temporally successive predictions, with which learning occurs whenever there is a change in prediction over time. TD learning requires less memory and peak computation than conventional methods, but produces more accurate predictions.

2.5. Leader-follower incentive game

In the P2P file sharing network with a reselling mechanism, the relationship between the content provider and consumers can be modeled as a leader-follower incentive game. In this game, the leader would act by his/her policy and seek to maximize his/her profit. Each follower chooses one of actions to respond to the leader. Similarly, every follower's goal is to gain maximum for himself. Therefore, when a leader is making decision, s/he is thinking what actions the followers would take, and what action s/he should take to respond to the followers' reactions. S/he tries to find the optimal answer to this question. To make decisions, the followers would both observe the leader's action and consider the other followers' responses to leader's action. Thus, followers will wait leader's decision and compete with other followers.

For example, in a supply chain, the provider decides the wholesale price, and the retailers would consider the other retailers' prices and decide their retailing prices. For the leader, his wholesale price is the best price he can find to maximize his/her profit.

2.6 Swarm

The Swarm project was started in 1994 by Chris Langton, then at Santa Fe Institute (SFI) in New Mexico. It is currently based at the non-for-profit organization, Swarm Development Group, which is also based in Santa Fe, New Mexico. Their aim is to develop both a vocabulary and a set of standard computer tools for the development of multi-agent simulation models (so-called ABMs, short for Agent-Based Models).

Swarm is designed to help researchers build models in studying complex systems. A researcher has to give contents to "agents," possibly by thinking of them as honey bees, investors, trees, or bugs. One research goal of Swarm is to discern overall patterns that emerge from these detailed behaviors at the individual level.

A Swarm simulation proceeds in discrete time steps. Agents are created and then interact according to a scheduling mechanism. As the simulation proceeds, agents update their instance variables and may be asked to report their states to the observer swarm layer of the simulation. The core of Swarm contains two categories of swarms: the model swarm and the observer swarm. The model swarm encapsulates the simulated model. Everything in the model swarm corresponds to an object in the world being modeled. The model swarm contains a schedule of activities on the model. A model swarm consists of a set of inputs and outputs. The inputs to the model swarm are model parameters such as the number of agents and the length of the observed period, etc. The outputs of the model swarm are the observables of the model, the author's price, and the royalty, etc.

In Swarm computer simulations, those observation objects are placed in an observer swarm. The most important object in an observer swarm is the model swarm that is being studied as shown in Figure 1. The model swarm is one component of the observer. Other observer objects can then input data into the model swarm (setting simulation parameters, for instance) and read data out of the model swarm (collecting statistics of the behavior of agents). (For more details, visit the official web site of Swarm, http://www.swarm.org/, and the Swarm user guide, http://pj.freefaculty.org/Swarm/Beta/SwarmUserGuide/userbook.html)

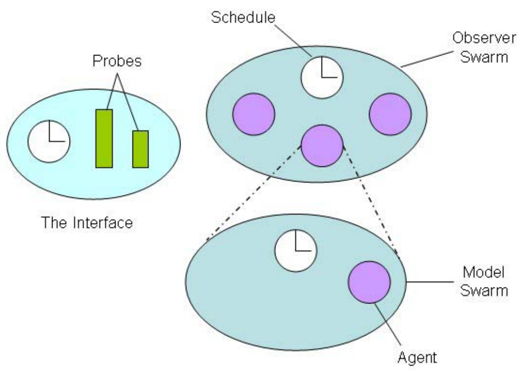

Figure 1. Nested hierarchy of Swarms

3. A new P2P business model of online music industry

This study proposes a new P2P business model of online music industry and aims to verify the proposed model is more profitable than one based on client/server architecture.

3.1 Model overview

We start the model with a scenario shown in Figure 2 that an online music provider offers the online music through a P2P network. The consumers of this online music provider may download music files from either the provider or the other consumers who have already downloaded the music files. A consumer who downloads music files from the provider or other consumers needs to pay the fees to these music sources. A provider of a music file needs to pay the loyalty to the origin peer if the provider downloaded the file from the origin peer. A provider which may be the original source or secondary distributor can decide the price of the music file.

The relation between an original provider and its consumers as well as between distributors and end consumers can be seen as leader-follower incentive games. The utility function of downloading decision of a consumer can be accomplished by RBFN. The pricing issue, including reselling price, and the royalty issue can be modeled by SMDPs and TD Learning approaches.

To verify that a new business model of online music distribution on P2P networks is more profitable than one based on client/server architecture, we construct a simulation platform used to model peers' transactions on P2P networks. In the simulation, peers are autonomous to make decisions, and the roles agents play can be categorized into provider and consumer. A provider acts as a leader who prices his/her products at each decision epoch, and a consumer who wants to resell what s/he has downloaded plays as a follower who decides his/her reselling price with the reselling mechanism.

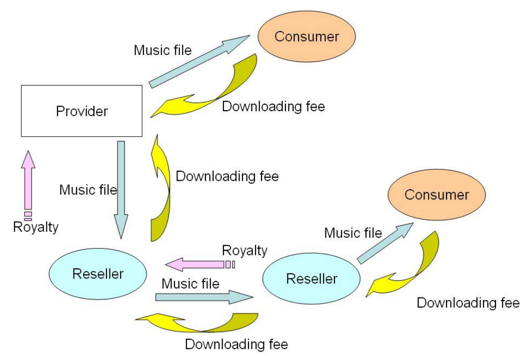

Figure 2. Model overview

We describe the details of agent behaviors, including downloading decisions, price and royalty decisions, and reselling decisions in Section 3.2. The relationship of agents is described in Section 3.3, and the procedure of agent interaction is in Section 3.4.

3.2 Agents

We first construct agents in the simulation. When agents decide to sell or download contents, they invoke their peers on P2P networks. Thus, in the simulation, agents are not always on the P2P network. Agents can make decisions autonomously. Depending on the role agents play in the simulation, they make different decisions. An agent of a content provider makes price and royalty decisions, and an agent of a consumer makes downloading and reselling decisions. The details of these decisions are presented in the following.

3.2.1 Price and royalty decisions

The content provider repeatedly monitors the market situation, changes the product price and royalty, and tries to find the optimal pair (price and royalty) which brings him/her the largest revenue. This problem could be formed as a semi-Markov Decision Process (SMDP) described in Section 2.3. Figure 3 presents the provider's decision as a SMDP. Because the optimization method for SMDP needs complete information about the participants in the market, which is impossible to obtain in the real world, we consider TD learning method described in Section 2.4, which learns to predict by past experience.

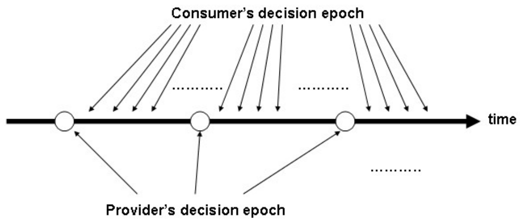

Figure 3. Provider's decision as SMDP

For the prediction of price and royalty, we keep one TD network for each decision. In our implementation of TD learning model, we use the current market information and the provider's action (price or royalty) as inputs, and the output is the provider's profit. The market information consists of the popularity of MP3, the potential market of MP3, and the price or royalty of MP3 (depending on the purpose of TD learning). Figure 4 presents the implementation of TD learning model.

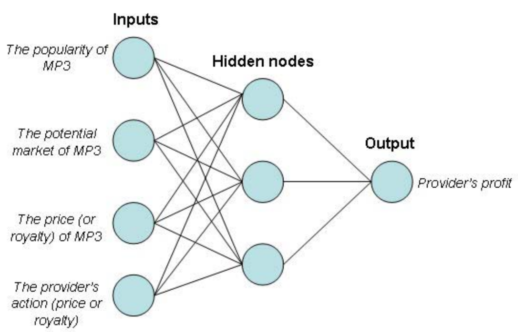

Figure 4. Implementation of TD Learning model

The popularity of MP3 is defined as (the number of current downloaders − the number of prior downloaders) divided by the number of prior downloaders, and the potential market for MP3 is calculated by the following function based on the original Bass Diffusion Model; that is, $\dfrac{[p+q\times N(t)/m]\times[m-N(t)]}{m}$,where p is the coefficient of innovation, q is the coefficient of imitation, $N(t)$ is the cumulative number of consumers at time t, and m is the fixed market size.

At the beginning of TD learning, the provider uses the training data to train the weight of TD learning model, and then collects the current market information as the input data. Next, the provider decides the best action to respond to the current situation. In return, the provider records the market information and the profit gained by the action. At next decision epoch, it repeats this procedure. After few times (we called "learning periods"), the provider uses the recorded data to re-train the weight of TD learning model. This procedure iterates until the end of observation period.

3.2.2 Downloading decision

To make a downloading decision, each consumer needs to assign the utility value to available products. The utility value consists of many attributes. Conventionally, we assign utility value to products by utility functions. In the simulation, we use RBFN described in Section 2.2 to formulate a consumer's utility function.

To implement RBFN, we use the product information as input, and the output is the utility value of the product. The product information consists of the price, the royalty, the download speed, the popularity, and the potential market.

A consumer first collects the product information as the input data, and then assigns utility values to products shared by other peers. A consumer chooses the product with the highest utility value to compare with their acceptable utility value in mind. If the utility of the product is higher than that in their minds, they will download the product. At each decision epoch, consumers repeatedly make downloading decisions until they decide to download.

3.2.3 Reselling decision

Once a consumer decides to download, he may also consider reselling the downloaded file. To resell the downloaded file, the peer of a consumer needs to decide a reselling price to the file, and s/he compares the reselling price with the acceptable price in mind. S/he will resell the product when the value is higher than that in mind. The goal of his/her reselling files is similar to the provider's, and s/he repeatedly re-prices the product like the provider does as well. Therefore, a reselling decision could be formed as a SMDP, and we can use TD learning method to find the best reselling price.

Here we only use TD learning to predict reselling price, so that we keep one TD network. The inputs are the market information and the action (reselling price), and the output is the reselling profit.

A consumer who downloads a file will

repeatedly make the reselling decision at each decision epoch, no matter they are resellers or not. The algorithm of reselling decision is similar to that in Section 3.2.1, and it is described in Figure 5.

1. Using the training data to train the weight of TD learning model.
2. Starting to price the product.
   - 2.1 Collecting the market information as the input data.
   - 2.2 Using TD learning to find the reselling price.
   - 2.3 Comparing the price with the acceptable price in mind. If the price is higher than that in mind, consumers start to resell and the reselling price is the value gained by TD learning.
   - 2.4 Recording the market information and the reselling price.
   - 2.5 Repeating step 2 until the learning periods are over.
3. Using the recorded data to re-train the weight of TD learning.
4. Go back to step 2 until the observation periods are over.

Figure 5. Algorithm of reselling decision

3.3 The relationship of agents

The relationship among these participants can be formulated by the concept of “leader-follower incentive game”. In the simulation, the roles played by agents can be categorized into the leader and followers; *i.e.*, the content provider plays the leader, while the resellers play the followers. The content provider repeatedly monitors the state situation, and tunes product price and royalty. The resellers decide their reselling prices respectively. Some of the reselling revenue will be taxed as royalty set by the leader. Followers repeatedly review their situation and change their price as well. The content provider is a monopolist, and consumers compete with each other.

3.4 The procedure of agent interaction

In the simulation, the content provider and resellers repeatedly review the current market situation and tunes their prices and royalties, respectively. Consumers search product information from the provider and resellers. They evaluate all the available candidates and decide whether to download or not and where to download (from the provider or resellers). Once consumers decide to download, they need to decide whether to resell. They might choose not to resell, and just to be consumers. The reselling decision won’t be changed until the next decision epoch.

4. Experimental design

Simulative experiments are based on the following context. There is an online MP3 aggregator, which distributes MP3 media made by singers. The aggregator pays a fixed amount of money as loyalty to these singers to exchange the exclusive authorization to distribute their songs. The aggregator has two different channels to access MP3 consumers: one is based on client/server architecture, and the other is based on P2P networks. The former is commonly used for current aggregators, such as iTunes and KKBOX, etc.; the latter is the proposed business model in this study. An aggregator may be interested in knowing which channel is more profitable, and how they influence the profitability. To conduct experiments, we specify variables in Section 4.1, market settings in Section 4.2, and the experimental design in Section 4.3.

4.1 Variables

Variables used for the experimentation are categorized into three types: environmental, behavioral, and dependant variables.

In the multi-agent simulation for online music market, players such as aggregator, resellers, and end users, are modeled as agents. Environmental variables denote contexts which agents exist. We first consider the size of agent population, noted as AMOUNT_OF_AGENTS, which is the base of downloaders and resellers. Next, we denote an MP3 product life time as OBSERVED_PERIOD. Due to that the aggregator and resellers re-price by incremental learning, the length of learning time may influence the profitability via dynamic pricing. We finally consider λ value used by TD(λ) learning algorithm, denoted as LAMBDA, which implies the percentage of one’s past experiences used in prediction. The environmental variables are summarized in Table 1.

The roles of an agent play are categorized into an aggregator or a consumer. A consumer’s and aggregator’s behavior variables are specified in Tables 2 and 3, respectively. The simulative experiments will observe such variables as shown in Table 4.

Table 1. Summary of environmental variables

Variable Name	Description	Values
AMOUNT_OF_AGENTS	The size of agent population	100, 500, 1000, 2000
OBSERVED_PERIOD	MP3 product life time	15, 30, 45
LAMBDA	The percentage of one's past experiences used in prediction	0.1, 0.3, 0.6, 0.9

Table 2. A consumer's behavioral variable

Variable Name	Description	Values
THRESHOLD_OF_ PURCHASING	One's lowest acceptable utility of downloading MP3.	0.1, 0.3, 0.6, 0.9
THRESHOLD_OF_ RESELLING	One's lowest acceptable price of reselling MP3.	0.1, 0.3, 0.6, 0.9
BANDWIDTH_OF_ AGENT	The network bandwidth provided by a consumer when he wants to resell MP3.	1M bps, 10M bps, 50M bps, 100M bps

Table 3. An aggregator's behavioral variables

Variable Name	Description	Values
CONTRACT_COST	The cost of gaining the exclusive distribution right from singers.	500, 1000, 2000, 3000
BANDWIDTH_OF_ AGGREGATOR	The bandwidth provided by the aggregator.	1M bps, 10M bps, 50M bps, 100M bps
INITIAL_PRICE	The initial price of MP3.	$5, $20, $35, $50
INITIAL_ROYALTY	The initial royalty of MP3.	0.1, 0.3, 0.6, 0.9

Table 4. Dependent variables

Variable Name	Description
TOTAL_AMOUNT_OF_DOWNLOADER	The final number of downloaders
AVERAGE_AMOUNT_OF_RESELLER	The average number of resellers during an MP3 product life time
AGGREGATOR_TOTAL_REVENUE	The total revenue of aggregator
AVERAGE_RESELLER_REVENUE	Each reseller's average revenue
AVERAGE_ RESELLER_PRICE	Average reselling price during an MP3 product life time
AVERAGE_AGGREGATOR_PRICE	Average aggregator's price during an MP3 product life time
AVERAGE_ROYALTY	Average royalty during an MP3 product life time

4.2 Market settings

Assuming that consumers in general behave one of three types of risk attitude toward purchasing: risk seeking, risk averse, and risk neutral. For each type of consumers, we have asked students to answer assumptive questions to fill out the utility value for each item, and then collect their preferences as training data of RBFN and TD learning.

By this data, we tune some scores to compose different ratios of these three types of consumers to form four different market environments to denote different compositions of prospect consumers as shown in Table 5.

4.3 Experimental design

The experimentation aims to identify which behavioral variables significantly influence dependent variables on P2P and client/server networks, respectively. Thus, we examine the effect of one behavioral variable, and each behavior variable is set four values for four experiments, respectively. Therefore, we have four results for each behavior variable. We conduct ANOVA to verify whether four different values of each behavioral variable have different influences on dependant variables across four market settings. Moreover, we verify whether four different marketing settings have different influences on dependant variables across four values of one behavioral variable. These experiments are also conducted for the client/server context in order to compare the performance between P2P and client/server networks. Finally, we compare the aggregator's revenue of P2P distribution channel with that of client/server architecture.

Table 5. Market settings

Market Setting	Ratio of Three Types of Consumers
Market 1	33.3% risk seeker, 33.3% risk Averter, and 33.3% risk neutral.
Market 2	60% risk seeker, 20% risk averter, and 20% risk neutral.
Market 3	60% risk neutral, 20% risk seeker, and 20% risk averter.
Market 4	60% risk averter, 20% risk seeker, and 20% risk neutral.

5. Experimental results and analysis

This section will present the experimental results and analyze them corresponding to variables specified in Section 4.

5.1 Effects of environmental variables

We examined whether the environmental variables influence the dependant variables. We found that the amount of agents only significantly affects the amount of total downloaders, average amount of resellers, and the aggregator's revenue, as we expected. Based on this finding, the following experiments are conducted under the market size with 100 agents.

The ANOVA test on experimental results under various λ values for TD(λ) learning, and shows that there are no significant influences on dependant variables. Thus, in the following experiments, λ is set to 0.5.

5.2 Summary of experimental results

The results of experiments in P2P

distribution channel are described as follows: (1) the average aggregator's price is influenced by the threshold of purchasing, (2) the amount of total downloaders is influenced by the threshold of purchasing and a consumer's network bandwidth, (3) the average amount of resellers is influenced by the threshold of reselling, an aggregator's initial royalty, and a consumer's network bandwidth, an aggregator's revenue is influenced by the threshold of purchasing and the threshold of reselling, and (4) both of the average reseller's revenue and reseller's price are influenced by the threshold of reselling.

The results of experiments in client/server distribution channel are described as follows: (1) the amount of total downloaders is influenced by the threshold of purchasing and an aggregator's network bandwidth, and (2) an aggregator's total revenue is influenced by the aggregator's bandwidth.

The results show that, in P2P distribution channel, the average aggregator's price is influenced by the initial royalty, and the average reseller's revenue is influenced by contract cost. Revenue gained from both channels differ insignificantly except for contract set at \$2000, aggregator's network bandwidth set at 100M bps, initial price set at \$20, and threshold of purchasing set at 0.3 that the client/server network outperforms significantly P2P networks. However, the P2P network outperforms significantly client/server when the aggregator's network bandwidth set as 1M bps.

6. Conclusion

This study proposes a new business model which adopts a reselling mechanism to distribute contents on P2P networks. Users who have downloaded contents from a peer can resell them by paying a portion of reselling gain as royalty to the peer. The provider and consumers may re-price shared contents dynamically via incremental learning from market feedback. This study also aims to verify that authors of digital goods can gain more through the P2P reselling model than through the client/server architecture.

This study adopted Swarm as a multi-agent simulation platform to model peer networks as agent interactions in the real world. An agent which acts as a content provider makes price and royalty decisions, and the other agents who play as consumers make downloading and reselling decisions. The provider-consumer relationship is similar to the leader-follower incentive game, where the consumers do not make re-selling price decision until the provider have made the price decision.

In the experimentation, each simulation is designed for each value of behavioral variables in four market settings. Then, we conducted ANOVA test to analyze the experimental results to answer the following questions:

1. Do different values of the environmental variable influence the dependant variables?

With ANOVA test, we found that environmental variables do not influence the dependant variables. Thus, we set those variables as constants.

*2. Is **threshold of purchasing** important to both distribution channels?*

From the results of ANOVA, in P2P channel, a consumer's lowest acceptable utility of downloading MP3 really influences those dependant variables and the average number of resellers during an MP3 product life time. However, in the client/server architecture, it only influences the final number of downloaders. We inference that this results may result from some other variables that have higher weights than a consumer's lowest acceptable utility of downloading MP3 files in the client/server architecture.

*3. Is **contract cost** important to both distribution channels?*

Both channels would not be influenced by the cost of gaining the exclusive distribution right from singers, because the cost is a fixed cost and more users share less cost by each one. Thus, we set the cost of gaining the exclusive distribution right from singers as a constant.

*4. Is **provider's bandwidth** important to both distribution channels?*

From ANOVA test, the bandwidth provided by the aggregator only influences the amount of total downloaders in the client/server architecture because the quality of service of client/server architecture depends on the speed. Consumers prefer faster service, so that the network bandwidth becomes the key to success.

*5. Is **provider's initial price** important to both distribution channels?*

Both channels are not influenced by the initial price for MP3, because of the dynamic pricing scheme. Agents re-price periodically, so that the effect of the initial price for MP3 is weakened.

*6. Is **the threshold of reselling** important for a content provider on a P2P distribution channel?*

Four dependant variables, the average number of resellers during an MP3 product life time, the total revenue of an aggregator, each reseller's average revenue, and the average reselling price during an MP3 product life time, are influenced by a consumer's lowest acceptable price of reselling MP3. The reason is that the core of a reselling mechanism is the participation of resellers. The preference of reselling is undoubtedly the key to a P2P network with reselling mechanism.

7. Is a consumer's network bandwidth important for a content provider on P2P distribution channel?

From ANOVA test, the final number of downloaders, and the average number of resellers during an MP3 product life time are influenced by the network bandwidth provided by a consumer when s/he resells MP3 files.

8. Is aggregator's initial royalty important for a content provider on P2P distribution channel?

From ANOVA test, the average number of resellers during an MP3 product life time is influenced by the initial royalty of MP3. We can certainly assert that the initial royalty of MP3 is important to the amount of total downloaders.

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