Agent-based simulation of competitive and collaborative mechanisms for mobile service chains

Guoyin Jianga,b, Bin Hua,a,*, Youtian Wanga

a School of Management, Huazhong University of Science and Technology, Hubei Wuhan 430074, China
b School of Information Management, Hubei University of Economics, Hubei Wuhan 430025, China

A R T I C L E   I N F O
Article history:
Received 28 June 2008
Received in revised form 13 September 2009
Accepted 19 September 2009

Keywords:
Multi-agent system
Mobile service chains
Competitive mechanism
Collaborative mechanism
Agent evolution algorithm

A B S T R A C T
A new paradigm for a mobile service chain’s competitive and collaborative mechanism is proposed in this study. The main idea of the proposed approach is based on a multi-agent system with optimal profit of the pull, push, and collaborative models among the portal access service provider (PASP), the product service provider (PSP), and the mobile service provider (MSP). To address the running mechanism for the multi-agent system, an integrated system framework is proposed based on the agent evolution algorithm (AEA), which could resolve all these modes. To examine the feasibility of the framework, a prototype system based on Java-Repast is implemented. The simulation experiments show that this system can help decision makers take the appropriate strategies with higher profits. By analyzing the expectations and variances (or risks) of each player’s profit, the interaction between and among entities in the chain is well understood. It is found that in the situation where a collaborative mechanism is applied, the performance of players is better as compared to the other two situations where a competitive mechanism is implemented. If some constraints are applied, the risk will be kept at a low level.

© 2009 Elsevier Inc. All rights reserved.

doi:10.1016/j.ins.2009.09.014

1. Introduction

With the development of the Internet and communication technology, e-commerce has been rapidly growing in China. The report 2007–2008 China’s Internet Shopping Development, released by iResearch Consulting Company (http://www iresearch.com.cn/html/Default.html), shows that the market of China’s Internet shopping reached ¥56.1 billion in 2007 and is predicted to reach ¥406 billion in 2011. Along with the traditional online shopping, a new technology-driven commerce, mobile commerce (m-commerce), has emerged. M-commerce can be viewed as a subset of e-commerce [7], which is further stimulated by the explosion of mobile technology [4]. For instance, the introduction of third-generation (3G) mobile communication technology allows higher transmission rates on cell phones and personal digital assistants (PDAs), and various kinds of mobile applications have become popular. Mobile devices can provide people with games, Internet surfing and even stock market transaction [3]. According to a survey conducted by iResearch Consulting Company, the m-commerce market will have been growing rapidly in the next five years, and will reach ¥7.6 billion by the end of 2010.

M-commerce is generally defined as a process of conducting information inquiries and/or business transactions using mobile devices via mobile communications. Combining the portability of mobile devices with mobile communications, m-commerce provides users with the benefit of flexibly retrieving information via the Internet [21]. As compared to the large number of mobile phone users, the number of m-commerce consumers in China is still smaller. People in the academe and
businesses argue that m-commerce is not only a simple extension of e-commerce [27] because it has its own technological infrastructure, business models, and value chains. It also produces new value for consumers. Therefore, theory and practice about m-commerce are required. Increasing research has been done on m-commerce in various fields each year [28]; however, these studies have been mainly focused on qualitative macro description or empirical study. Research performed on the perspective insights into and the theoretical framework of m-commerce will essentially help decision makers in this field [30].

The basis of the m-commerce service chain is traditional supply chain theories. However, it is different from the traditional one in the following four aspects. (1) The participating entities in the mobile service chain are the portal access provider, the product service provider (PSP), the mobile service provider (MSP), and others. (2) The information in the m-commerce chain is highly shared, especially when collaborative systems, such as the Workflow system, Enterprise Resource Planning (ERP), Office Automation (OA), are used by participating entities. (3) The inventory level of m-commerce is lower, and even a zero inventory could be achieved if an entity can be mobile in the entire chain during the transaction. (4) Response to customers could be faster in m-commerce if the efficiency in business flow is improved.

Collaboration allows organizations to improve their efficiency and the quality of their business activities [22]. The collaborative supply chain has been recognized as a significant process because it creates an opportunity in the supply chain management [11]. An effective collaboration mechanism in a supply chain could share incomes among the supply chains and eventually improve operations. This collaboration mechanism could be driven not only by the coordination of physical flows but the use of different kinds of information flow in the supply chain as well, including demand, capacity, inventory, and scheduling [14].

A large volume of literature has been devoted to collaborative supply chains. In order to resolve the problems on collaboration and information sharing, various approaches have to be taken, including framework, optimization, simulation, and multi-agent, which are described in the following. (1) Framework research approach. Gilmour [13] proposed a strategic model describing a framework that could be used to evaluate the supply chain process. Based on the business processes within a supply chain, Gruat et al. [14] suggested a general framework which has been instantiated and validated in an industrial case study. These models are structural frameworks based on a business process approach and can only describe qualitative characteristics, but not quantitative ones. (2) Optimization-based approach. Maturana and Norrie [25] gave a mathematical model dealing with information sharing in the operational aspect. This approach is very practical in addressing specific problems, such as inventory designing and logistics transportation optimization. However, it described the models in a static way, and is inflexible in discussing multi-phase and multi-period behaviors. (3) Simulation-based approach. Simulation-based approaches could describe the dynamic process of a supply chain with different rules and steps [15]. Lau et al. [19] recommended a framework to investigate the effect of information sharing in production on supply chain performance. Zhang and Zhang [42] explored a simulation approach to model business processes and performances in a multi-tier supply chain. However, this simulation approach relies on running models with pre-specified parameters and rules, thus lacking in agility. (4) Multi-agent based approach. This approach deals with collaboration and information-sharing problems [34]. The participating entities in the supply chains are typically modeled as agents. Each entity has its own goals under certain conditions. Forget et al. [10] proposed a computational agent model using different planning strategies, where the planning decisions are supported by a distributed agent-based system. (5) Case-based approach. Based on examining the impact of environmental collaborative activities on manufacturing performance, Vachon and Klassen [37] made empirical analyses. Emberson and Storey [8] presented collaborative buyer–supplier examples drawn from multi-field cases examining customer-responsive supply chains. This approach could be used to analyze the physical environment; however, the results would be affected by the reliability and validity of each case or sample. (6) Integrated approach. Each of these approaches can describe a different decision problem in supply chains. The integration of these approaches is a better strategy to deal with some complex decision problems in the real world. Kwon [18] integrated multi-agent simulation and case-based method to represent collaboration mechanism in the supply chain. In order to describe the reactive and dynamic collaboration among the participating entities, Laua et al. [20] proposed a centralized fuzzy framework to reflect the environmental changes and translate them to a new level using agents’ autonomous reaction.

Available literature shows that there are few studies examining the e-supply chain and the mobile service chain. (1) Qualitative model and framework research approach. Yao et al. [40] proposed possible strategies for an e-retailer to reveal more real information from the supplier. Swaminathan et al. [34] reviewed the relevant analytical models in e-business and supply chain management. Eng [9] gave some insights into the qualitative nature of mobile supply chain management (mSCM). Manthou et al. [24] proposed a virtual e-chain model which presents a supply chain collaboration framework. (2) Simulation-based approach. Wang and Liu [38] examined an agent-mediated approach and integrated the on-demand e-business supply chain. This supply chain allowed agents to interact with one another to achieve compatibility and harmony among the different operations of all services. This literature analyzed the collaborative relationship and the interaction strategies among participating entities in a service chain under e-commerce. However, they did not discuss the collaboration mechanism under an uncertain demand and a real-time and dynamic environment.

Unfortunately, the competitive and collaborative decision problems in a mobile service chain are subject to the uncertainty decision environment, including price, demand, inventory, and production quantity. Traditionally, scholars have focused on the uncertainties degree are low [18]. However, a service chain may experience uncertainties in both high supply and high demand. The traditional approaches may have limited applicability because analytical solutions are prohibitive, or even impossible. The model becomes considerably complicated as these uncertainties create increased complexities.
The decision problem in a mobile service chain is also a real-time decision problem, and the entity in service chains needs a real-time response to others' request. This decision process is a continuous, multi-period, and multi-phase process. However, the traditional qualitative and mathematic-analytical method is too intricate to resolve this decision problem. Therefore, there is strong motivation for the conduct of further research in this area.

Our objective is to contribute in addressing the aforementioned research gap by presenting a mathematical model, exact algorithm, simulation decision system, and analysis method for a competitive and collaborative decision problem in a mobile service chain. This will be of significance in reality as it makes the decision maker determine the optimal price in real time, identify the quantity of inventory, and realize production with the maximum profit and minimum costs. This study will discuss the mobile sale mode [41], in which the demand is typically uncertain with a changing market price for the furnished goods on Web sites. The inventory level of the portal Web site is very low, and even nil. The push, pull, and collaboration operation modes are applied on the sale process. In the push mode, PSP initiatively supplies products to the portal service provider according to the previous order information. The quantity of products received by the portal service provider will depend on the price and the inventory. In the pull mode, the portal service provider orders products from PSP. PSP will then supply products for the portal service provider based on the production and the inventory. In the collaboration mode, all parties share one inventory and make decisions altogether. This simulation approach not only describes the dynamic behaviors but also allows real-time, decentralized, interactive, and collaborative decisions [20]. We use the agent-based simulation to represent the communication among entities in the service chain. The optimization approach could describe the uncertainty variables. Genetic algorithms (GAs) are attractive in terms of their potential in solving complex problems; however, as for the multi-phase and multi-period models, the computational efficiency of traditional GA cannot meet the need in real time. In order to increase the computational performance of GA, we propose an agent evolution algorithm (AEA) to determine the optimal solution for these models. Given the different preferences of the decision maker, the game analytical method is applied to discuss the equilibrium strategy for decision combination.

This paper is organized as follows. In Section 2, the decision problems in mobile service chains are introduced. In Section 3, three profit optimization models are described, including two competition models initiated by the portal access service provider (PASP) and product service provider (PSP), and one collaboration model. In Section 4, the process is presented using Eclipse and Java to code the multi-phase and multi-period profiting game system in a mobile service chain. In the end, by comparing and analyzing the simulation results in different experimental scenarios, conclusions are provided.

2. The competitive and collaborative decision problems in mobile service chains

There are many types of mobile commerce, such as B2C mobile commerce, B2B mobile commerce, and so on. The present research will focus on B2C mobile sale mode only. In this mode, the retailers can sell books, clothes, and any other stuff via mobile service Web sites. One representative m-commerce service Web site in China is Hubei Mobile (http://wap.e159.com). The mobile service sale chain is illustrated in Fig. 1.

The mobile sale process includes the following four steps. First, mobile users select the goods via their mobile devices on the Web site of the portal access service, then place their orders. The Web site of the portal access service checks orders, confirms the valid ones, and asks for payment. This may be completed by deducting the users' cell phone fees or through other ways. In the third step, MSP will organize the goods. Finally, the product provider will confirm the orders based on the inventory and the production, and distribute the goods to the mobile users.

![Fig. 1. The mobile sale mode.](image)
In this process, each operation mode shows different results by each entity in the mobile service chain. The operation mode can be generalized into three categories: (1) Pull operation mode. The pull mode is initiated by PASP. PASP determines the price according to the previous prices and the market demand, and then the service chain processes start. (2) Push operation mode: The push mode is sponsored by PSP. PSP supplements the goods for PASP based on the previous orders from the latter, then PSP prices the goods, and service chain processes start. (3) Collaborative operation mode: The goal of this mode is to maximize the total profits in the service chain by coordinating among all entities. In this paper, we discuss the optimal profit decision in three modes about selling price, inventory, ordering quantity, profit, and risk.

In an uncertain environment, in order to model the single-product, multi-phase, multi-period decision problem in mobile service chains, the following assumptions are considered in this paper:

1. The selling price and the customer demand are random variables with a correlation.
2. The maximum inventory and the production capability are clear.
3. The minimum profits of PASP, PSP, and MSP are known.

Based on the above assumptions, we propose three multi-period and multi-phase profit operation models. The objective is to maximize profit and minimize costs simultaneously.

3. Modeling

All the firms or entities in the service chain try to achieve maximum profit by increasing the income, charging compensation, and decreasing the cost in different fields. PASP is in the whole process. They have to decide the amount to order from the PSP. PSP is in the inventory and the production process, while MSP is in the service operation. The sale price that PASP bids is a main concern for the supplier. The decision made by PASP has an indirect effect on MSP’s income. In this section, we will propose mathematical models for the pull, the push, and the collaborative modes, respectively. The notations used in this paper are listed as follows:

\[
\begin{align*}
P &= P(e, t): \text{product selling price for PASP at time } t \\
P &= P(s, t): \text{product selling price for PSP at time } t \\
S &= S(e, t): \text{product selling quantity for PASP at time } t \\
S &= S(s, t): \text{product selling quantity for PSP at time } t \\
\text{Inv} &= \text{Inv} : \text{unit inventory cost of PASP at time } t \\
\text{Inv} &= \text{Inv} : \text{unit inventory cost of PSP at time } t \\
\text{Inv} &= \text{Inv} : \text{inventory quantity of PASP at time } t \\
\text{Inv} &= \text{Inv} : \text{inventory quantity of PSP at time } t \\
\text{Cap}_{-i} &= \text{Cap}_{-i} : \text{inventory capacity of PASP at time } t \\
\text{Cap}_{-i} &= \text{Cap}_{-i} : \text{inventory capacity of PSP at time } t \\
\text{Cap}_{-prd} &= \text{Cap}_{-prd}: \text{production capacity of PSP} \\
\text{Total}_{-Dem}(t) &= \text{Total market demand at time } t \\
\text{Dem}(e, t) &= \text{Market demand quantity in the portal access service Web site at time } t \\
\text{Prd}(s, t) &= \text{Unit cost of each product at time } t \\
\text{Pre}(e, t) &= \text{Attraction degree at time } t \\
\text{Cs}(e, t) &= \text{Unit compensation while the portal access provider cannot satisfy customer demand at time } t \text{ (i.e., some Web site return integral to the consumer for compensation)} \\
\text{O}_{-uc}(e, t) &= \text{Unit order cost of the portal access provider at time } t \\
\text{O}(e, t) &= \text{Order quantity of the portal access provider at time } t \\
\text{Cod}(e, t) &= \text{Unit compensation cost of PSP out of stock at time } t \\
\text{M}_{-uc}(m, t) &= \text{Unit service charge of the mobile service for the consumer at time } t \\
\text{M}_{-fc}(m, t) &= \text{Fixed information service charge for the consumer at time } t \\
\text{M}_{-tc}(m, t) &= \text{Total service cost of the mobile service for the consumer at time } t 
\end{align*}
\]

3.1. The pull mode initiated by PASP

In the multi-phase competitive mechanism, PASP spontaneously makes the decision on the basis of initialized parameters in the first phase, and then makes the order to PSP. In the second phase, the product or service provider receives the order from PASP, and then decides on the production quantity and the selling price.

3.1.1. The optimization profit model for PASP

PASP actively makes the decision \(P(e, t)\) and \(O(e, t)\) based on \(\text{Dem}(e, t), \text{Inv}(e, t-1), S(e, t-1)\) and \(\text{Mc}(m, t)\), and then places the order to PSP. The optimal profit model is as follows:
Maximize profit \( P(e, t), O(e, t) = P(e, t) * S(e, t) + (O(e, t) - S(s, t)) * C_3(e, t) \)

Minimize cost \( P(e, t), O(e, t) = P(s, t) * S(s, t) + \text{Inv}(e, t) * \text{Inv}(e, t) + (\text{Dem}(e, t) - S(e, t)) * C_3(e, t) + M_{uc}(m, t) * S(e, t) + O_{uc}(e, t) * O(e, t) \)

\[
\begin{align*}
\text{Dem}(e, t) & \leq \text{Pre}(e, t) * \text{Total}(e, t) \\
S(e, t) & = \min \{\text{Dem}(e, t), \text{Inv}(e, t - 1) + O(e, t)\} \\
P(e, t) & \geq P(s, t) \\
\text{Inv}(e, t) & \leq \text{Cap}(e)
\end{align*}
\]

where \( a \) is the attraction intensity, and \( b \) and \( c \) are the random parameters.

\[
M_{uc} = f(S(e, t)) = u * e^{v/w}
\]

where \( u \) is the service charge discount, and \( v \) and \( w \) are the random parameters.

In Model (1), \( P(e, t), O(e, t), \) and \( S(s, t) \) are the unknown decision variables. \( S(s, t) \) and \( P(s, t) \) are provided by the product provider. We substitute \( O(e, t - 1) \), \( P(s, t - 1) \) for \( S(s, t) \) and \( P(s, t) \), respectively. Therefore, \( (P(e, t) \) and \( O(e, t)) \) are the optimal solutions to Model (1). After the calculation of \( S(s, t) \) and \( P(s, t) \) in Model (5), the profit will be recalculated based on all data at time \( t \).

3.1.2. The optimal profit model for PSP

After PSP receives the order from PASP, \( O(e, t), Prd(s, t) \), and \( P(s, t) \) can be calculated based on \( \text{Inv}(s, t - 1), O(e, t) \). Its optimal profit model is described as follows:

Maximize profit \( S(e, t) = P(s, t) * S(s, t) + O_{uc}(e, t) * O(e, t) \)

Minimize cost \( S(e, t) = Prd(s, t) * \text{Cop}(s, t) + \text{Inv}_{uc}(s, t) * \text{Inv}(s, t) + (O(e, t) - S(s, t)) * C_3(e, t) \)

\[
\begin{align*}
\text{Prd}(s, t) & \leq \text{Cap}_{prd} \\
\text{Inv}(s, t) & \leq \text{Cap}_{i(s)} \\
\text{Inv}(s, t - 1) & \leq S(s, t) \\
S(s, t) & = \min \{O(e, t), \text{Inv}(s, t - 1) + \text{Prd}(s, t)\}
\end{align*}
\]

where

\[
\text{Inv}(s, t) = \text{Inv}(s, t - 1) + \text{Prd}(s, t) - S(s, t).
\]

From Model (5), we can obtain an optimal solution \( (\text{Prd}(s, t), P(s, t)) \). \( S(s, t) \) is calculated from Eq. (7). On the basis of \( S(s, t) \) and other parameters, we can generate a real optimal profit for PSP by the objection function of Model (1).

\[
S(s, t) = \min \{O(e, t), \text{Inv}(s, t - 1) + \text{Prd}(s, t)\}
\]

3.1.3. The optimal profit model for MSP

The goal of MSP is to maximize profits by increasing sale commissions \( (M_{uc}(m, t) * S(e, t)) \) and information service charges \( (M_{fc}(m, t)) \), and minimizing the costs in service operation \( (M_{tc}(m, t)) \). Its profit model can be expressed as follows:

Maximize profit \( f(m, t) = M_{uc}(m, t) * S(e, t) + M_{fc}(m, t) + M_{tc}(m, t) \)

\[
\begin{align*}
\text{Profit}(f(m, t)) & \geq \min \text{Profit}(f(m, t))
\end{align*}
\]

Generally, \( M_{uc}(m, t), M_{fc}(m, t), \) and \( M_{tc}(m, t) \) are the constants, and \( S(e, t) \) can be calculated by Model (1). With all the known variables in Model (8), the profit can be calculated by the objection function as the subject condition is satisfied.

3.2. The push mode initiated by PSP

This competitive mechanism is the same multi-phase problem as the pull mode. In the first phase, PSP makes the decision on the production quantity and selling price on the basis of the initialized parameters, and then dynamically provides supply information to PSP. In the second phase, e PASP makes the decision on the basis of the given price, and then makes order to PSP.
3.2.1. The profit function of PSP

PSP decides \(Prd(s, t)\) and \(P(s, t)\) according to \(Inv(s, t - 1), O(e, t)\). Its optimal profit model is described as follows:

\[
\begin{align*}
\text{Maximize profit}(S(e, t)) &= P(s, t) * S(e, t) + O(e, t) * O(e, t) \\
\text{Minimize cost}(S(e, t)) &= Prd(s, t) * Cop(s, t) + Inv,uc(s, t) * Inv(s, t) + (O(e, t) - S(s, t)) * Cod(e, t)
\end{align*}
\]

\[
\begin{align*}
\text{s.t.} \quad & Prd(s, t) \leq Cap,prd \\
& Inv(s, t) \leq Cap,i(s) \\
& Inv(s, t - 1) \leq S(s, t) \\
& S(s, t) = \min\{O(e, t), Inv(s, t - 1) + Prd(s, t)\}
\end{align*}
\]

where

\[
Inv(s, t) = Inv(s, t - 1) + Prd(s, t) - S(s, t).
\]

In Model (9), \(P(s, t), Prd(s, t),\) and \(O(e, t)\) are the unknown variables decided by the portal provider. In order to perform the calculation, \(O(e, t - 1)\) is used to substitute for \(O(e, t)\). Therefore, \((P(s, t), Prd(s, t))\) is an optimal solution in Model (9). After calculating \(O(e, t)\) by Model (11), we should recalculate the profit based on all the data at time \(t\).

3.2.2. The profit model of PASP

PASP decides on \(P(e, t)\) and \(O(e, t)\) on the basis of \(Dem(e, t), Inv(e, t - 1), S(e, t), P(s, t),\) and \(Mc(m, t)\), and then places orders to PSP. The following shows this optimal profit model:

\[
\begin{align*}
\text{Maximize profit}(P(e, t), O(e, t)) &= P(s, t) * S(e, t) + (O(e, t) - S(s, t)) * Cod(e, t) \\
\text{Minimize cost}(P(e, t), O(e, t)) &= P(s, t) * S(s, t) + Inv,uc(e, t) * Inv(e, t) + (Dem(e, t) - S(e, t)) * Cs(e, t) + Mc * S(e, t) + O,uc(e, t) * O(e, t)
\end{align*}
\]

\[
\begin{align*}
\text{s.t.} \quad & Dem(e, t) \leq Pre(e, t) * Total,Dem(t) \\
& S(e, t) = \min\{Dem(e, t), Inv(e, t - 1) + S(s, t)\} \\
& P(e, t) \geq P(s, t) \\
& Inv(s, t) \leq Cap,i(e)
\end{align*}
\]

where

\[
Inv(e, t) = Inv(e, t - 1) + S(s, t) - S(e, t),
\]

\[
Pre(e, t) = a * e^{b/c},
\]

where \(a\) is the attraction intensity, and \(b\) and \(c\) are the random parameters.

\[
M,uc = f(S(e, t)) = u * e^{v/w},
\]

where \(u\) is the service charge discount, and \(v\) and \(w\) are the random parameters.

From Model (11), we can obtain the optimal solution \((P(e, t), O(e, t))\), and then recalculate the profit for the portal provider on the basis of all data at time \(t\).

3.2.3. The profit model of MSP

In the push mode, the profit model can be expressed as follows:

\[
\begin{align*}
\text{Maximize profit}(f(m, t)) &= M,uc(m, t) * S(e, t) + M,fc(m, t) - M,tc(m, t) \\
\text{s.t.} \quad & \text{Profit}(f(m, t)) \geq \text{Min Profit}(f(m, t))
\end{align*}
\]

3.3. Collaboration mechanism

In order to gain a larger market share for the existing products or services in the collaborative service chain, information sharing is important in order to reduce costs. The main goal is to maximize the total service chain profit by coordinating all entities. Therefore, all participating entities in the service chain should join and make decisions to improve their existing products or services. They will share total profit and risk according to the contract. We consider one collaborative scenario in which all the entities participate in decision making on the product quantity and price. One inventory quantity is required without middle pricing. From the above discussion, we develop the following mathematical model:

\[
\begin{align*}
\text{Maximize profit}(P(e, t), Prd(s, t), f(m, t)) &= P(e, t) * S(e, t) \\
\text{Minimize cost}(P(e, t), Prd(s, t), f(m, t)) &= Prd(s, t) * Cop(s, t) + Inv,uc(s, t) * Inv(s, t)
\end{align*}
\]

\[
\begin{align*}
\text{s.t.} \quad & Dem(e, t) \leq Pre(e, t) * Total,Dem(t) \\
& S(e, t) = \min\{Dem(e, t), Inv(e, t - 1) + S(s, t)\} \\
& P(e, t) \geq Prd(s, t) \\
& Inv(s, t) \leq Cap,i
\end{align*}
\]
4. Implementation

4.1. Agent and multi-agent system

Agents are either separate computer programs or distinct parts of a program used to represent social actors. They may be individuals, organizations such as companies, or governments. Agents are programmed not only to react to the located computation environment but also to pass information to one another. An agent has the basic features of autonomy, sociability, and reactivity. It also has the following characteristics [12]:

1. Perception. An agent can perceive its environment, including the presence of other agents in its vicinity.
2. Performance. An agent is capable of performing, motioning, communicating, and acting.
3. Policy. An agent can interact with others according to the rules, heuristics, or strategies.

Agent-based models (ABMs) are computational models used to describe the populations of interacting agents [5]. They are composed of interacting agents within an environment. As simulation techniques, they can be used in a situation where it is impossible to treat complicated and inaccessible targets under rigorous conditions. In addition, the collection of real-life data, especially multi-period data, is difficult.

Agent-based modeling can easily be introduced to simulate human activity because human actors and organizations themselves can be considered as agent oriented, while the individual can be the artificial personal agent [33]. In particular, the application of an agent-based approach helps increase the matching between the information system and the human organization supported by the multi-agent systems (MAS).

4.2. The agent-based simulation system framework and the solution procedure

4.2.1. Simulation system framework

There are five major agents in this system: the portal access service provider agent (PASPA), the product service provider agent (PSPA), the mobile service provider agent (MSPA), the collaborative service agent (CSA), and the master control agent (MCA). The system framework is shown in Fig. 2.

The functions of each agent are as follows. PASPA receives the customer’s orders and sells the products with enough inventories; otherwise, it will place the orders to PSPA. PSPA then decides on the production quantity based on the orders. In the meantime, it will maximize the profit by increasing the income and reducing the cost of inventories and the cost of products. MSPA provides wireless service to PASPA, tries to maximize profit by increasing sale commissions and charging information services, and minimizes the costs in service operation. CSA will coordinate with PASPA, PSPA, and MSPA to gain high overall service profit by sharing information and reducing cost. MCA, a master agent, will allocate the communication properly among agents according to the pull, push, and collaborative mechanisms.

4.2.2. The running procedure of the simulation system

4.2.2.1. Overall running procedure.

Step 1: Each profit optimal model is initiated.
Step 2: MCA allocates the communication properly according to the user’s parameters.

![Fig. 2. Framework of the agent-based simulation system for the mobile service chain.](image-url)
Step 3: Check the stopping criteria. If the stop criteria are met, then go to Step 8, or else continue to the next step.
Step 4: If CSA receives the communication properly, it will first run, and then go to Step 7. Otherwise, it will continue to the next step.
Step 5: If PASPA receives the communication properly, it will acquire the following parameters: PSPA’s price at time \( t \), the market demand function, and MSP’s cost function at time \( t \). The optimal solution for Model (1) can be obtained by using AEA. The solution includes the optimal product price on the Web site, the sale quantity, and the order quantity. This order information will be submitted to PSPA. If PSPA receives the communication properly, it will obtain the quantity ordered by PASPA. The optimal solution can be similarly obtained using AEA. The solution would include the product price, the sale quantity, and the product quantity. The sales information is then submitted to PASPA.
Step 6: PASPA/PSPA amends the profit value on the basis of the actual value. MSPA calculates the profit value, and then goes back to Step 3.
Step 7: According to the latest inventory, the demand function, the production capability, and other parameters, CSA searches for the optimal profit, and then goes back to Step 3.
Step 8: The end.

4.2.2.2. Agent evolution algorithm (AEA). Most algorithms are designed to find the set of Pareto optimal solutions for solving optimization problems. In this regard GAs are considered effective tools in solving complex problems. GAs have been successfully applied in various areas [1,2,6,16,17,32,36]. In traditional GAs, those individuals generating children are usually selected according to their fitness value. However, in multi-phase and multi-period problems, the global optimal solution space may be so large that the computation might increase exponentially with the problems, thus resulting in an evident decrease in system performance owing to the long computation time. Therefore, the selection of the best global optimal solution space will possess a considerably cognitive burden [39]. The natural selection is only induced in a local space where the chromosome can interact with neighbors. In other words, natural evolution is a local behavior. The information can be globally shared only after a process of diffusion, which is similar to cellular automata [23,35]. An agent is a physical or logical entity that can interact with others, pass information, and react on the received messages. An agent can represent the GAs’ individual, and the searching algorithm is designed as AEA.

In AEA, all agents exist in a lattice environment (L) based on a regular square grid of agents, which represent chromosomes. The size of \( L, m \times n \) (where \( m, n \) are integer), is the number of agents, that is, the population. Each grid of \( L \) is called an agent grid, which can interact with Moore neighbors (the neighbor cells of \( (i,j) \)). There are eight neighbor cells around each agent grid, as shown in Fig. 3.

**Definition 1.** An agent grid \( A_{ij} \) in \( L \) has a fixed structure, \( A_{ij} = \{ID, LOC, Nb_{ij}, CHRO, FIT\} \), where

- (1) \( ID \) is the agent’s identifier.
- (2) \( LOC \) is the location of the agent grid in \( L \), which is a tuple \( \{i,j\} \).
- (3) \( CHRO \) is the binary code of the chromosome. A vector \( \mathbf{e} = \{e_1; e_2; \ldots; e_l\} \) is used as a chromosome representing the solution to optimize the problem \( (e_t = 0 \text{ or } 1) \). Assuming that the number of unknown variables is \( x \), \( l \) equals \( 8 \times x \). For example, in Model (1), the unknown variables are \( p(e,t) \) and \( s(s,t) \), then \( l = 16 \).
- (4) Assuming that the agent located at \( (i,j) \) is represented as \( L_{ij}, i = 1, 2, 3 \ldots m; j = 1, 2, 3 \ldots n \), the Moore neighbors of \( L_{ij} \) are defined as follows:

\[
Nb_{ij} = \begin{cases} 
(Li - 1, j; Li - 1, j - 1; Li - 1, j + 1; Li, j - 1; Li, j + 1; Li + 1, j - 1; Li + 1, j; Li + 1, j + 1), & i \neq 1 \text{ or } n,
(Lm, j - 1; Lm, j + 1; Lm, j + 1; Lm, j - 1; Lm, j - 2; Lm, j - 1; Lm, j + 1), & i = 1, j \neq 1 \text{ or } n,
(Lm - 1, j; Lm - 1, j - 1; Lm - 1, j + 1; Lm, j - 1; Lm, j + 1; Lm, j - 1; Lm, j + 1; Lm, j - 1; Lm, j + 1), & i = m, j \neq 1 \text{ or } n,
(Li - 1, 1; Li - 1, n; Li - 1, 2; Li, n; Li, n; Li + 1, n; Li + 1, 2), & i \neq 1 \text{ or } m, j = 1,
(Li - 1, n; Li - 1, n - 1; Li - 1, n - 1; Li, n - 1; Li, n - 1; Li + 1, n - 1; Li + 1, n), & i \neq 1 \text{ or } m, j = n.
\end{cases}
\]

\[
\begin{array}{cccc}
A_{1,1} & A_{1,2} & \ldots & A_{1,n} \\
A_{2,1} & A_{2,2} & \ldots & A_{2,n} \\
\vdots & \vdots & \ddots & \vdots \\
A_{m,1} & A_{m,2} & \ldots & A_{m,n}
\end{array}
\]

Fig. 3. Agent lattice of AEA.
FIT is the fitness value of CHRO. The regret value of CHRO is converted from binary to decimal \(f\), and then the fitness function of CHRO is calculated by the following equation:

\[
FIT = \frac{f_{\text{max}} - f + \varepsilon}{f_{\text{max}} - f_{\text{min}} + \varepsilon} + f_{\text{min}},
\]

where \(\varepsilon \in (0, 1), f_{\text{max}}, \) and \(f_{\text{min}}\) represent the maximal and minimal values of \(f\) in the current \(L\), respectively.

Reproduction process: We generate a random binary vector \(e\) from this region until a feasible one is accepted as a chromosome. The fitness of the feasible chromosome is between \([0, 255]\). By repeating the above process \(m \times n\) (the numbers of agent lattice) times, we have the \(m \times n\) initial feasible chromosomes \(e1, e2, \ldots, e(m \times n)\), and then we calculate all the structure parameters for each agent grid.

Each agent has both competition and cooperation behaviors. The neighborhood competition operator and the neighborhood crossover operator are used to realize the behaviors of competition and cooperation, respectively. The mutation operator realizes the behaviors using the knowledge. Assuming that the three operators are performed on the agent grid located at \((i, j)\), \(L_{ij}\), we denote \(\text{MaxNbi}_j\) as the agent with maximum fitness among the neighbors of \(L_{ij}\) (i.e., \(\text{MaxNbi}_j \in N_{bi}\)). If the \(FIT_{ij}\) of \(L_{ij}\) satisfies Formula 19, it will still live in the agent lattice. Otherwise, it will die, and the grid will be replaced by the child agent grid with the probability \(p_c\), where the parameter \(p_c\) is the probability of crossover operation. A crossover operation process could be expressed as follows:

\[
FIT_{ij} < FIT(\text{MaxNbi}_j).
\]

Crossover operation: A random number \(U(0, 1)\) could be generated from the open interval \((0, 1)\). If \(U(0, 1) < p_c\), the chromosome of \(L_{ij}\), \(e1\) and the chromosome of \(\text{MaxNbi}_j\), \(e2\) are taken as parents, then a one-point crossover operated on \(e1\) and \(e2\) is applied to produce two children \(y1\) and \(y2\). If both children are feasible, \(e1\) is replaced by the better one of them. The one-point crossover is a commonly used method for crossover proceeding in three steps. Two newly reproduced strings are first selected from the reproductve mating pool. Then a position along the two strings is randomly selected. The third step is to exchange all characters following the crossing point. In AEA, this operation is performed between \(L_{ij}\) and \(\text{MaxNbi}_j\) to achieve cooperation on both sides.

Mutation operation: This operation enhances the capability of GAs to find near-optimal solutions. Mutation is the occasional alternation of a value at a particular string position. This is an insurance policy against the permanent loss of any simulation, the first agent is updated. Then one of its neighbors will compete with its neighbors, until all agents in the lattice have been stimulated to take part in the competition.

Steps for AEA

Note: \(L^t\) represents the agent lattice in the \(t\)th generation, and \(L^{t/u}\) is the mid-lattice between \(L^t\) and \(L^{t+1}\); \(u\) is the number of agent grid in the lattice; \(\text{MaxF}^t\) is the best agent in \(L^0, L^1, L^2, \ldots, L^t\), and \(L\text{MaxF}^t\) is the best agent in \(L^t\). \(FA\) is the agent grid that has the initial competition right.

Step 1: Initialize \(L^0, 0 \to t\).
Step 2: The agent grid \(L_{ij}\) is initialized with the competition right, \(L_{ij} \to FA, v=1\), and updates \(L^t\).
Step 3: Do dynamic neighboring competitive selection processing for agent grid \(L_{ij}\), obtain \(L^{t+1/u}\) and \(N_{bi}\).
Step 4: For \(FA\), do crossover processing on it.
Step 5: For \(FA\), do mutation processing on it, and obtain \(L^{v/u}\).
Step 6: If \(v\) is equal to or less than \(u\), then update \(L^{t+1}\), and go to Step 7. Otherwise, one of \(N_{bi}\) obtains the competition right (which has never obtained the competition right), \(v+1\) \(\to v\), then go to Step 3.
Step 7: Find \(L\text{MaxF}^t\) in \(L^{t+1}\). If fitness \((L\text{MaxF}^t) > \text{fitness}(\text{MaxF}^t)\), then \(L\text{MaxF}^t \to \text{MaxF}^t\).
Step 8: If the stop criterion is satisfied, then output \(\text{MaxF}^t\) and stop; otherwise, \(t+1\) \(\to t\), go to Step 2.

4.2.3. System implementation

4.2.3.1. Introduction of Repast and Eclipse. In this research, the Recursive Porous Agent Simulation Toolkit (Repast) [29] and Eclipse are adopted to implement the agent-based simulation models for the above proposed mobile service chains. Repast is a free open source toolkit. It has been widely used in the theory of complex systems, including social simulation, economic system simulation, and physical system simulation system. It is a SWARM-LIKE simulation toolkit, but it is superior to SWARM in many respects [31]. The Repast implementation steps are discussed in detail in [29], including the source code for example.

Eclipse is an extensively used and powerful integrated development environment. Free and available for Linux and Windows, Eclipse provides a convenient platform to develop Repast models. It provides a programming studio, which includes a Java-specific editor, graphical displays of the running program and package management, and a debugger.
4.2.3. System–user interface. In Fig. 4, the Repast simulation system interface is given, which includes the following five partition sections:

(a) The control menu is located at the top. The menu items include starting operation, stepping operation, pausing operation, initializing operation, and so on.
(b) The right side is the parameters interface. In this system, we use one parameter mode to represent the selected operation mode.
(c) The upper left is display interface 1, which could distribute the three types of agents. If the agent works, the color will be changed.
(d) The bottom left is display interface 2 displaying the diffusion of the agent grid in the lattice of AEA.
(e) The bottom right is the statistical curve interface, which will display the profit of the three parties in the mobile service chain at every tick.

5. Simulation experiments

5.1. Comparison of AEA and m-GA

The profit optimization models (1), (5), (8), (9), (11), (15), and (16) are a class of multi-period optimal models. The previous solutions at time \( t = 1 \) would affect the present solutions at time \( t \), and the computational time of a single period has an effect on the total computational time. Therefore, the efficiency and effectiveness of the optimization algorithms for the profit optimization models described above should be taken into consideration.

Numerical experiments have been performed to test the effectiveness and efficiency of the agent evolution algorithms (AEA). Model (20) is selected to test and demonstrate the reliability and convergence capability of the presented algorithm. This model is a simple case of Model (1). Based on Michalewicz’s approach,[26], the genetic algorithm (m-GA) is presented using Java program language. Both AEA and m-GA with the same GA parameters \( p_c = 0.9 \) and \( p_m = 0.01 \) were run on the same operation platform, a personal computer with a 2.4 GHz CPU and 1 GB memory. In order to obtain more information on these algorithms, each test problem was divided into three numerical experiments given different population sizes. The numerical experiments were all run 10 times.

Maximize profit

\[
\text{Maximize profit}(P(e,t), O(e,t)) = P(e,t) \times S(e,t)
\]

Minimize cost

\[
\text{Minimize cost}(P(e,t), O(e,t)) = 20 \times S(s,t) + 2 \times (100 + S(s,t) - S(e,t)) + (500 - 10 \times P(e,t) - S(e,t)) \times 0.1 \times \text{Math.exp}(1/(P(e,t)) + 1) - O(e,t) \times 0.1
\]

\[
\text{s.t.}
\begin{align*}
& P(e,t) > 0 \\
& S(e,t) = \text{Min}\{500 - 10 \times P(e,t), 100 + S(e,t)\} \\
& P(e,t) \geq 20 \\
& S(s,t) = O(e,t)
\end{align*}
\]

(20)
It is very important to conduct the experiments with a reasonable population in order to ensure the maximum profit and the minimum computation time. As shown in Table 1, the AEA method in Model (1) has better results than those of m-GA with the same computation time. With an increasing population, a slight increase in the average optimal profit is observed. A significant increase in the average computation time is also obtained.

5.2. Simulation for the mobile service chain

5.2.1. The experiment scenarios

**Hypothesis 1.** Customer demand is an uncertain function in the mobile service chain, and PASP has knowledge of this function.

**Hypothesis 2.** In the service chain, each participating entity has finite rationality and reasonably bids for long-term cooperation.

In this system, the demand function is an anti-demand function shown as follows:

\[ \text{Dem}(t) = a - b \times p(t), \]

where \( a \) is the maximum demand of the customers, and \( b \) represents the sensitivity coefficient. Other parameters are given in Table 2.

The operation platform is a PC with a CPU frequency of 2.4 GHz and a memory of 1 GB. The initial agent number of AEA is 200, generation = 150, \( p_c = 0.9 \), and \( p_m = 0.01 \).

5.2.2. Simulation results and numerical analysis

5.2.2.1. The mode initiated by PASP

PASP first analyzes the market and acquires two online pricing strategies for the products: a low-price conservative strategy and a high-price optimistic strategy. Then PASP places the orders to PSP. The price offered by the product provider should be lower than the online price. Otherwise, PASP will terminate the cooperation owing to the absence of profits. The pricing strategy matrix is shown in Table 3, and the simulation results are displayed in Fig. 5.

Fig. 5a–d illustrates the maximum profit of all the entities when the four strategy portfolios are taken at the initiative of PASP. From the trend of change shown in Fig. 5a, we can observe that the maximum profit of each participant in the service chain fluctuates with time. PASP's profit is in the first place, while PSP's profit falls into the second place. This indicates that PASP has the advantage of the greatest fluctuation during the process, while MSP is in a follow-suit participant position. MSP will obtain the least profit corresponding to its contribution. When PASP places the order, PSP would make decisions according to the previous data. PASP would adjust its profit according to the reality in the end, resulting in a negative profit shown

<table>
<thead>
<tr>
<th>Population size</th>
<th>m-GA AOP</th>
<th>ACT</th>
<th>AEA AOP</th>
<th>ACT</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>3218.08</td>
<td>220.2</td>
<td>3231.943</td>
<td>297.3</td>
</tr>
<tr>
<td>200</td>
<td>3225.25</td>
<td>770.2</td>
<td>3234.404</td>
<td>352.5</td>
</tr>
<tr>
<td>400</td>
<td>3225.512</td>
<td>2979.8</td>
<td>3234.896</td>
<td>387.5</td>
</tr>
</tbody>
</table>

Note: ACT (the average computation time) in millisecond; AOP (average optimal profit).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( \text{Cap}_j(e) )</th>
<th>( \text{Cap}_j(s) )</th>
<th>( \text{In}_v \mu_c(e, t) )</th>
<th>( \text{In}_v \mu_c(s, t) )</th>
<th>( \text{Cap}_{\text{prd}} )</th>
<th>( \text{Prd}(s, t) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>50</td>
<td>200</td>
<td>2</td>
<td>1</td>
<td>250</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pricing strategy matrix for the pull mode.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PASP</strong></td>
</tr>
<tr>
<td>Conservative</td>
</tr>
<tr>
<td>((P(s, t - 1) \sim 25, 10 \sim P(e, t)))</td>
</tr>
<tr>
<td>((P(s, t - 1) \sim 50, 10 \sim P(e, t)))</td>
</tr>
</tbody>
</table>

Note: The (conservative, optimistic) is a moderate optimistic strategy profile.
in Fig. 5b and c. To further investigate the fluctuation and the difference in maximum profit of all entities, the following simulation data in Table 4 could be helpful for analysis.

The expectations and variances of profit in a service chain in 100 period phrases are shown in Table 4. Total profit is the sum profit of all three providers. Exp and Dvar represent expectation and variance, respectively. The expectation profit is analyzed to make a contrast among all providers. The variance of profit is taken into consideration in order to compare the accompanying risk. The remaining issue is how to choose the optimal strategy. Decision makers want to maximize their profit as well as their opponent’s in the preference risk range. Based on the above ideas, we found that if PSP chooses the conservative strategy, it would choose the optimistic strategy without risk according to the principle of maximum profit. The profit of PASP will reach 1210.627. On the contrary, if both PASP and PSP want the same optimistic strategy, the profit of PASP would be 653.941. Considering the maximum profit, PASP would first take the conservative strategy, and then PSP would take the optimistic one. As a result, (conservative, optimistic) would be the equilibrium solution to the game.

If the risk is taken into consideration, profit maximization would be realized with a lower risk. If PASP prefers low risk, it would make a pricing based on the opponent’s risk preference. This means that if PSP also prefers a low risk, PASP would choose the conservative strategy, while PSP would take the same strategy. The profit of PSP would be 404.913 with a risk...
of 493.954, which is lower than 754.256 when it chooses the optimistic strategy. If PASP takes the optimistic strategy, PSP would choose the conservative one, and the profit of PASP will be 1387.229. The risk of 598.248 corresponding to the conservative strategy is lower than that of 988.568 in the optimistic strategy. In order to keep the risk lower, both PASP and PSP would choose the same conservative strategy. Therefore, (conservative, conservative) would be the game’s available equilibrium for PASP. On the contrary, if the opponent has a higher risk preference, (optimistic, optimistic) would be the best solution. In the same way, if PASP’s risk preference is high, whereas PSP’s is low, (optimistic, conservative) would be the equilibrium solution. Otherwise, (conservative, optimistic) would be the equilibrium solution when PSP’s risk preference is low.

5.2.2.2. The mode initiated by PSP. If PSP is the initiator, the conservative and the optimistic product pricing strategies will be followed by PSP. The combination of these pricing strategies is shown in Table 5. The simulation results are illustrated in Fig. 6, and the simulation data are summarized in Table 6.

Table 5
Pricing strategy matrix for the push mode.

<table>
<thead>
<tr>
<th>PASP</th>
<th>PSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>( (P(s, t) \sim 25, 10 \sim P(e, t - 1)) )</td>
</tr>
<tr>
<td>Optimistic</td>
<td>( (P(s, t) \sim 50, 25 \sim P(e, t - 1)) )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PASP</th>
<th>PSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>( (P(s, t) \sim 25, 10 \sim 25) )</td>
</tr>
<tr>
<td>Optimistic</td>
<td>( (P(s, t) \sim 50, 25 \sim 50) )</td>
</tr>
</tbody>
</table>

Note: The (conservative, optimistic) is a moderate optimistic strategy profile.

Fig. 6. The profit simulation results in the push mode (100 periods).
Table 6 shows that the possible game equilibrium solution is (optimistic, conservative) if no risk is taken into consideration for every game participating entity. This means that PASP would adopt the optimistic pricing strategy with a profit of 701.193 when PSP takes a conservative pricing strategy with a profit of 643.313. If the risk is considered, PASP will pursue the maximum profit and the lowest risk. If both PSP and PASP have a low risk preference, (conservative, conservative) would be the final game equilibrium solution; otherwise, (conservative, optimistic) would be the game’s equilibrium solution. If PSP prefers a high risk, while PASP prefers a low risk, (optimistic, optimistic) would be the game’s equilibrium solution. Otherwise, (optimistic and conservative) would be the game’s equilibrium solution.

5.2.2.3. Collaborative mechanism. In the collaborative situation, every participating entity in the service chain can share information in a mobile business environment. Therefore, all participating entities can be considered as a whole. Many functions
of the participating entities can be integrated, including PASP’s stock. Some function departments can be divided among participating entities, and the main competition functions or departments are retained. In this situation, the collaborative workflow system and the ERP system are applied; the product suppliers can obtain real-time feedback on the product sale. This feedback would in turn enable suppliers to optimize the products and improve the services. The suppliers could obtain true information on PASPs’ inventory, and predict and replenish products in time, which would significantly reduce PASPs’ inventory, even to the zero level. PASPs’ efforts could be spared and channeled toward maintaining and optimizing business services. This would in turn stimulate customer response, reduce feedback time, and lower information asymmetry and distortion. As a result, the participating entities can join together to decide on the state of collaboration, especially on the pricing strategy, in order to optimize the service chains and maximize the total profit.

If all participating entities in the mobile services chain could cooperate, the total profit of the service chain would be maximized, resulting in the decrease of risk. By taking the appropriate allocation mechanism and payment, the parties could share both risk and surplus profit. This is consistent with the current practice in China. As an example, China Hubei E-Mobile (e159), a mobile electronic commerce company founded by Hubei Company of China Mobile Co., cooperates with Team 6688, a Web site management and operation team led by Mr. Juntao Wang and is number 1 in the China electronics business sector. Their products and services are provided to major cooperating retailers, such as Wuhan ZhongBai Group Co., Carrefour China Inc., and many other retailers. They distribute products from a nearby retail warehouse or distribution points, take advantage of logistics, and improve their service responsibility to customers. They also deal with payment themselves by developing E Yuan business to facilitate network payments. This payment system integrates the E Yuan account with cell phone bills, which is fairly convenient for payment.

5.2.2.4. Comparative analysis. By analyzing the above three types of working mechanisms, it is found that in a collaborative situation with an optimistic pricing strategy, the total profit would be the maximum, which exceeds the sum profit of the two competition states. The stricter the constraints, the smaller the risk to the service chain. By taking conservative pricing, the profit of the collaboration mechanism in the loose constraint is between the portal provider-initiated mechanism and the products/service-initiated mechanism. However, in an intensified restraint situation, the profit of collaboration is much higher than that of the total of the two competition situations.

If all participating entities in the mobile services chain could cooperate, the total profit of the service chain would be maximized, resulting in the decrease of risk. By taking the appropriate allocation mechanism and payment, the parties could share both risk and surplus profit. This is consistent with the current practice in China. As an example, China Hubei E-Mobile (e159), a mobile electronic commerce company founded by Hubei Company of China Mobile Co., cooperates with Team 6688, a Web site management and operation team led by Mr. Juntao Wang and is number 1 in the China electronics business sector. Their products and services are provided to major cooperating retailers, such as Wuhan ZhongBai Group Co., Carrefour China Inc., and many other retailers. They distribute products from a nearby retail warehouse or distribution points, take advantage of logistics, and improve their service responsibility to customers. They also deal with payment themselves by developing E Yuan business to facilitate network payments. This payment system integrates the E Yuan account with cell phone bills, which is fairly convenient for payment.

6. Conclusions

In this study, we proposed an effective approach based on agent-based simulation with an improved genetic algorithm-agent evolution algorithm (AEA). AEA has a fast searching procedure to find the best solutions for multi-phase and multi-period decisions of mobile service chain entities. We implemented the simulation system in Java based on Repast and used the game analysis method based on the simulation system. The results obtained enabled the decision makers of mobile service chains in competition and collaboration state to choose the best pricing and product strategy for maximum profits. There are three contributions of this study. (1) Under an actual mobile business environment, two competition models (i.e., the model initiated by PASP and that initiated by PSP) and one collaboration model are proposed. (2) Based on the Agent Evolution Algorithm and multi-agent system mechanism, a decision support simulation system for multi-phase pricing game is designed and implemented. The simulation system can support decision makers in solving dynamics, uncertainty, and real-time decision problems in the mobile sale business. (3) The interactive pricing mechanism among various participating entities is described by analyzing the experiment results. We further compared the profits and risks of competitive and collaborative working mechanisms. The results show that regardless of the type of competition, the average profit of the competition mechanism is much lower than that of the cooperative mechanism. By applying reasonable constraints, the risk could be reduced in the cooperative mechanism as well.

Acknowledgements

We would like to thank the Editor-in-Chief Professor Witold Pedrycz and all the anonymous referees for their many helpful suggestions and insightful comments, which have significantly improved the content and presentation of the paper. This work is supported by National Natural Science Foundation of China (Nos. 70731001, 70671048).

<table>
<thead>
<tr>
<th></th>
<th>Total profit (loose)</th>
<th>Total profit (strict)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exp</td>
<td>Dvar</td>
</tr>
<tr>
<td>Conservative</td>
<td>1044.26</td>
<td>793.826</td>
</tr>
<tr>
<td>Optimistic</td>
<td>2638.1</td>
<td>1521.043</td>
</tr>
</tbody>
</table>

Fig. 7a–d shows the profit results in slack and tight or limited condition. In the scenario, the conservative price range is from 10 to 25, and the optimistic price range is from 25 to 50. The comparative results are summarized in Table 7. From the table above, we can see that with tighter constraint conditions, the total profit of the service chain will increase with a lower risk. The collaboration effect would also be better.
References


