# Pricing Mechanism Design and Simulation Based on Swarm Intelligence

**Sun Jun-yan**[1, 2]

[1]*Faculty of Mechanical and Precision Instrument Engineering, Xi'an University of Technology, Xi'an 710048, Shaanxi, China*

[2]*Faculty of Mechanical and Electronic Engineering, Shanxi University of Science and Technology, Xi'an 710021, Shaanxi, China*

**Fu Wei-ping**

*Faculty of Mechanical and Precision Instrument Engineering, Xi'an University of Technology, Xi'an 710048, Shaanxi, China*

**Wang Wen**

*Faculty of Mechanical and Precision Instrument Engineering, Xi'an University of Technology, Xi'an 710048, Shaanxi, China*

**Wang Fang**

*Faculty of Business, Beijing Wuzi University, Beijing 101149, China*

Abstract
Particle swarm optimisation (PSO) was used to simulate pricing mechanisms and the evolution of enterprises on the conditions of information interaction based on a multi-agent modelling method. By taking maximum consumer utility as the fitness function, the learning model of dynamic pricing for enterprises was established, and simulated on the Swarm platform. The simulation results showed that: the designed model can significantly improve consumer utility, and can help consumers to predict price changes of enterprises. Parameter simulation showed that: increasing numbers of

enterprises can improve market competition and reduce optimal price, so as to increase consumer utility value; enterprises focus on one learning ability while ignoring another, and the consumer utility value will be favourable. However, the desired value can be obtained in a shorter period by using social learning and self-learning abilities. This study may provide a reference for pricing of enterprises and price forecasting by consumers.

Key words: PRICING MECHANISM, MULTI-AGENT MODELING, PSO ALGORITHM, SWARM PLATFORM

## 1. Introduction

With increasingly fierce market competition in a buyer's market, how to set a predictable dynamic price model for enterprises which can not only prevent the entry of potential manufacturers, but also maximise their own interests is problematic. Therefore, the unnecessary loss of enterprises caused by blindly lowering price can be avoided. This has been one of key strategies in any enterprise [1-3]. Enterprises need to set prices based on consumer demand, and research pricing mechanisms to allow for real-time dynamic adjustment to maintain and expand market position. Pricing mechanisms have been extensively explored worldwide. Gallego and van Ryzin proposed the classical GVR model: assuming that product demand is sustainable, the optimal solution can be obtained with a given function[4]. Feng and Gallego extended the above model, and studied the problems concerning the optimal times for price reductions and increases[5]. Bitran and Mondschein studied periodic pricing models that can only adjust the price $K$ times[6]. The price does not increase with time; while customer arrival rate and customer retention price change with time. Pricing models considering consumer behaviour have been investigated by Popescu and Wu[7]. Their research considered the reference-dependent behaviour, by assuming that the update mechanism for the reference price is regarded as an exponential smoothing model, it is inferred that the optimal pricing strategy of an enterprise will be developed into a stable price by monotonic convergence under dynamic pricing over an infinite period. Caro and Martinez de Albeniz studied product and price competition in the presence of satisfactory effects[8]. Zhang analysed the effects of consumer expectations on potential sales of a product according to the consumer utility function[9]. Guan combined the effects of strategic behaviour and reference price to describe the dynamic pricing strategy of retailers under the influence of historical and expected prices, and established a multi-stage dynamic pricing strategy model[10]. The conclusion shows that ignoring the effect of consumer strategic behaviour and price referencing exerts a significant negative effect on retailers.

A pricing mechanism is actually a process of continuous adjustment and optimisation. The PSO algorithm is a simple, efficient swarm intelligence algorithm[11]: when solving optimisation problems using PSO, the solution to the problem corresponds to the position of particles in the search space, the particles can adjust their flight direction and speed to maintain overall optimality based on their own experience (*i.e.* individual optimisation points are used) and other experiences (*i.e.* global optimisation points)[12]. Therefore, the pricing mechanism of an enterprise can be optimised by PSO algorithm. For a complex adaptive system (CAS), consumers choose products according to their own needs, and enterprises adjust product price in accordance with consumer choice, so enterprise, consumer, and market environment constitute an evolved CAS. The individuals in the system can influence its own and other individuals: when consuming, consumers always choose the product which can bring about the expected maximum utility for them. When determining the price of a product, the enterprise should adjust their price strategy to meet consumer demand for maximum utility. The aforementioned concepts can dynamically interact with each other in real-time according to environmental changes, and thus have independence and adaptability. Agent-based modelling (ABM) is one of the most dynamic and influential methods used in research into complex systems under the guidance of CAS theory[13]. Swarm is a standard computer simulation modelling tool set developed by the Santa Fe Institute: it is based on multi-agent modelling methods and its purpose is to build a shared computer platform through simulation. Using the Swarm development platform, researchers can focus on the research work and the construction of the model itself rather than the manufacturing tools. At present, Swarm has been widely used in many fields [14-18].

Through the design of the dynamic pricing mechanism using PSO, this research performs simulation analysis with an ABM approach. First, by taking the consumer as the main object, under the condition of dynamic pricing, consumers can perceive all external information. The optimal price dynamic adjustment model is established in an attempt to maximise consumer utility[19]. The Swarm simulation platform is used to verify the validity and applicability of the dynamic pricing model. Finally, how to realise profit maximisation in a business by self-learning and social learning, is analysed so as to avoid blind pricing and vicious competition.

## 2. Design of a pricing mechanism using PSO algorithm

### 2.1. Theoretical assumptions of the model

Combining real market assumptions, the model is established as follows:

Hypothesis 1: Same kind of consumers. It is assumed that consumers have the same ability to consume.

Hypothesis 2: Information symmetry. Enterprises and consumers can both receive accurate information about products on the market.

Hypothesis 3: Single scale quality. A scalar $m$ can be used to express the quality of a product. Product quality is classified by one of five grades *1, 2, 3, 4, 5* (5 being optimal), according to the quality level in ascending order. It is assumed that the product quality of the enterprises in the selected segments is subject to a uniform distribution of $U(3,4)$.

Hypothesis 4: Each consumer can only buy products from a given enterprise (such as enterprise $i$ ($i$ = 1, 2, …, $n$), the price of the product is $V_i$, the quantity is $Q_i$. The disposable income of a consumer is $I$, the leftover money after purchasing the product is $S_i$.

Hypothesis 5: The enterprises in the same segment of the market only produce a certain kind of product. Competition arises between enterprises in the same market segment only.

Hypothesis 6: In time *t*, each enterprise can continuously adjust their product prices within the period according to privately owned information and external information acquired by themselves.

Hypothesis 7: No game relationship is found among enterprises $i$ ($i$ = 1, 2, …, $n$). There are only information exchanges and mutual study in the absence of collusion.

Hypothesis 8: Each enterprise $i$ ($i$ = 1, 2, …, $n$) is independent of the other and is subject to a normal distribution.

Hypothesis 9: Each enterprise and each consumer are all rational with risk neutral preferences.

### 2.2. The change of dynamic pricing of enterprises based on PSO

According to the description of the PSO algorithm, *n* enterprises are taken as a group, among them, enterprise $i$ is a particle in *d*-dimensional space, the speed vector is $X_i=(X_{i1},X_{i2},......X_{id})$, and the position vector $V_i=(V_{i1},V_{i2},......V_{id})$. This research investigates the dynamic pricing mechanism of enterprises, and focuses on price attributes, so $d$ = 1. The price of enterprise $i$ in period $t$ is $V_i^t$, the speed vector $X_i^t$ is the range of change in price within time $t$. Enterprise $i$ will use its own private information and pricing strategies of other enterprises to modify the existing speed $V_i^t$ and price $X_i^t$. This leads to new rounds of changes to speeds and prices, the process reflects the learning and interaction between particles within the group. In time, the enterprises continue to adjust their prices, resulting in multiple transformations of speed and price. In the $t$-$th$ transformation, business enterprise $i$ makes the price at $t+1$ through adjustment according to their current flight speed and current price.

$$X_i^{t+1}=wX_i^t+c_1r_1(\mathrm{p}_i^{best}-V_i^t)+c_2r_2(\mathrm{p}_g^{best}-V_i^t) \quad (1)$$

$$V_i^{t+1}=V_i^t+X_i^{t+1} \quad 1\le i\le n \quad (2)$$

$$\mathrm{p}_i^{best}=\mathrm{p}_i^t,\quad \mathrm{p}_g^{best}=\min \mathrm{p}_i^{best} \quad (3)$$

In (1), $w$, as an inertial factor, reflects the extent to which enterprise $i$ recognises current price, which is the inertia performance of the enterprise; $c_1$ and $c_2$ are positive constants, called acceleration factors which represent the self-learning, and social learning, abilities of enterprise $i$. $r_1$ and $r_2$ are random numbers on the interval [0,1], $p_i^t$ represents the lowest price of enterprise $i$ at period $t$, and $p_g^{best}=\min p_i^{best}$ indicates the lowest price of all enterprises in period $t$. After observing the behaviours of other enterprises, enterprise $i$ adjusts its price: because the cost prices and strategies of different enterprises are different, and their price floors are also different, to reflect the heterogeneity of an enterprise, the sum of the initial price and a random number $r$ are used to represent the price floor of the enterprise.

Based on the formula for price changes, it is found that the speed of the enterprise is composed of three parts: current speed, best price (individual history), and best price (group history). The price adjustment rules use the PSO algorithm to simulate the process of learning and interaction between enterprises, which can be summarised as the evolution process of an enterprise's price strategy: based on private information and external information received through self-learning and social learning, as well as the existing price strategy, enterprises adjust their price strategies, to change the price and finally set a relatively stable price through the presence of the population. As a result, the whole industry can be optimised.

**2.3. Design of a dynamic pricing mechanism**

Considering a buyers' market that takes consumers as its centre, a dynamic pricing adjustment mechanism is established with the goal of maximising consumer utility.

The utility function of the consumer is usually used to represent a function of consumer utility and the combination of the goods (*i.e.* the product mix). Consumers buy products to benefit from the application and value thereof, and to satisfy their desires to a certain extent. That is to say, under their existing conditions, they always expected to obtain maximum profit. The utility function is considered to be related to the commodity price vector $V$, the consumption quantity (commodity quantity vector) $Q$, consumer budget constraint $S$, and other economic variables. This research considers that the utility function of a consumer is closely related to the application value $f$ of a product, and the quantity of the purchased product and the number of the rest of disposable income determines the size of the utility function. The consumer utility function can be expressed as:

$$U = U(\mathrm{f}, \mathrm{Q}, \mathrm{S}).$$

From Hypothesis 4, the income constraint condition of a consumer is $VQ + S = I$. Meanwhile, enterprises aim to realise long-term development when pursuing interests, so price will not be lower than cost. Assuming the cost is $C$, then: $V > C$. The mathematical model for maximising the utility function for consumers is as follows:

$$\begin{cases} U = U(\mathrm{f}, \mathrm{Q}, \mathrm{S}) \\ s.t \quad VQ + S = I \\ \qquad V > C \end{cases} \tag{4}$$

Remove the restriction condition and substitute (4) into this utility function, we obtain max $U(\mathrm{f}, \mathrm{Q}, \mathrm{S}) = \max \mathrm{U}(\mathrm{f}, \mathrm{Q}, \mathrm{I} - \mathrm{VQ})$.

According to the Douglas (Cobb-Douglass) utility function, the appropriate coordinate system is chosen to fit the utility function which can be written as follows:

$$\mathrm{U}(\mathrm{f}, \mathrm{Q}, \mathrm{I} - \mathrm{VQ}) = \mathrm{Af}^{\alpha} Q^{\beta} + K(\mathrm{I} - \mathrm{VQ}) \qquad (\mathrm{A} > 0, \mathrm{K} > 0, 0 \le \alpha \le 1, 0 \le \beta \le 1, \alpha + \beta = 1) \tag{5}$$

Assuming that each consumer only buys one product, $\mathrm{Q} = 1, \beta = 0, \alpha = 1$. The application value is expressed as the product quality-price ratio, that is $f = m / V$. The simplified model is given by

$$\mathrm{U}(\mathrm{f}, \mathrm{I} - \mathrm{V}) = \mathrm{Af} + K(\mathrm{I} - \mathrm{V}) = \mathrm{Am} / \mathrm{V} + K(\mathrm{I} - \mathrm{V}) \qquad (\mathrm{A} > 0, \mathrm{K} > 0, \mathrm{V} > \mathrm{C}) \tag{6}$$

According to the analysis thereof, the consumer utility function is positively related to the quality of the purchased goods, and negatively related to the price of the commodity: it is thus realistic.

By taking the utility maximisation, as expected by consumers as a target, the dynamic pricing model using the PSO algorithm is:

$$\begin{cases} \max \left\{ U(\mathrm{f}, \mathrm{I} - \mathrm{V}_i^t) \right\} = Am_i / \frac{1}{n} \sum_{i=1}^{n} \mathrm{V}_i^t + K(\mathrm{I} - \sum_{i=1}^{n} \frac{1}{n} \mathrm{V}_i^t) \\ s.t \quad A > 0, K > 0 \\ \qquad V_i > C_i \quad i = 1, 2, ..., n \end{cases} \tag{7}$$

$$X_i^{t+1} = wX_i^t + c_1 r_1 (\mathrm{p}_i^{best} - V_i^t) + c_2 r_2 (\mathrm{p}_g^{best} - V_i^t) \tag{8}$$

$$V_i^{t+1} = V_i^t + X_i^{t+1} \qquad 1 \le i \le n \tag{9}$$

$$\mathrm{p}_i^{best} = \mathrm{p}_i^t, \quad \mathrm{p}_g^{best} = \min \mathrm{p}_i^{best} \tag{10}$$

Formula (7) shows that consumers choose products from $n$ enterprises and tend to compare the utility of different enterprises. The ultimate goal is to maximise their utility. The two lines of (7) represent constraint conditions within which consumers aim to maximise their own utility. Formulae (8) to (10) indicate the evolutionary process of enterprise pricing based on the PSO algorithm. The enterprises conduct a new round of valuation according to current pricing as recognised by themselves and their market. Through dynamic updating of the pricing information of other enterprises, the lowest price set by an enterprise is acquired, so as to achieve the maximisation of consumer utility. Given the pull characteristics of the consumer market, the PSO algorithm is used to simulate the change of enterprise pricing and form a relatively stable price, which finally yields maximal consumer utility. This provides guidance to enterprises as to rational pricing thus avoiding a loss of customers or revenue caused by blind pricing. It also provides a stable industry chain. The specific steps in the PSO algorithm model are as follows:

Step 1 Randomly initialise the speed and position of particles.

Step 2 Calculate the fitness function values for each particle.

Step 3 Compare the fitness of a particle with its fitness in the best position experienced so far: if this is smaller, it will be the best position for the particle.

Step 4 Compare the fitness of each particle with the fitness of the particle with the best position in the population: if it is smaller than the latter, it will be the best position for the population.

Step 5 According to (8), conduct iteration to update the particle speeds and positions.

Step 6 Return to Step 2 if the maximum number of iterations and the minimum threshold of the adaptive value are not achieved.

**3. Simulation results and analysis of the enterprise dynamic pricing adjustment model**

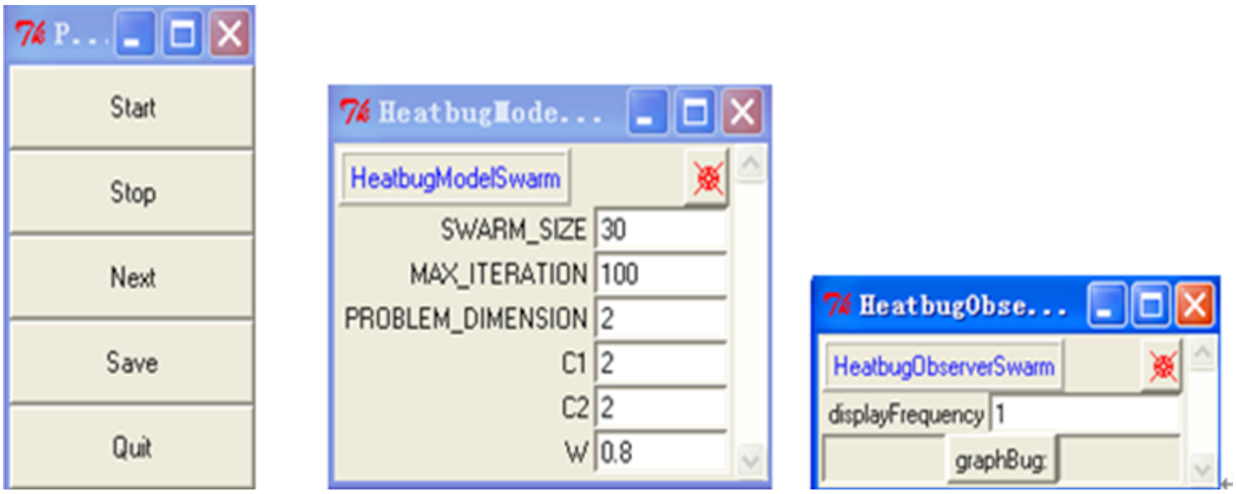
In the Swarm simulation platform, the selection of the main variables, the construction of the file types and the preparation of the main program are important. Based on the multi-agent modelling method, the learning mechanism built using the PSO algorithm is adopted. The structure of the simulation model used here is shown in Table 1.

**3.1. Standard start panel**

After running the program on the Swarm simulation platform, three standard start panels pop up as shown in Figure 3. Among them, the total control panel controls the start, operation, and end of the whole program. The initial parameter settings panel can display and change the related parameters, including group size, the number of iterations, the space dimension, the acceleration factor, and the inertia factor. The initial parameter settings panel of the observer's Swarm displays frequency.

**Table 1.** Swarm simulation model structure based on PSO based pricing mechanism

| File types | Filename | Main functions |
|---|---|---|
| Define PSO | HeatBug.java | HeatBug realises the implementation of PSO, and mainly defines the enterprise price change rules. |
| Define consumer utility function | ProblemSet.java | ProblemSet defines the consumer utility function and the relevant parameters. |
| Define main program Swarm | HeatbugModelSwarm.java | HeatbugModelSwarm sets the systematic parameters in the model, which can be displayed to the user, and modified to compare results obtained under different parameters. |
| Define observer Swarm | HeatbugObserverSwarm.java | Heatbug-ObserverSwarm collects and displays results. Its tasks mainly include the visualisation of the results of the processing, and output of results in chart form. |
| Main program | StartHeatbugs.java | StartHeatBugs.Java is a subsidiary file and function used as a selector, which simplifies the code length. It is conducive to the programming of ModelSwarm and ObserverSwarm. |
| Define position | Location.java | Location defines the position variables that are called by the HeatBug. |
| Define speed | Velocity.java | Velocity class defines the speed variable that is called by the HeatBug. |




(a) (b) (c)

**Figure 1.** The three pop-up panels
(a) Total control panel, (b) Initial parameter settings panel, (c) Initial parameter settings panel of Swarm observers

**3.2. Simulation result**

The initial parameters of the model are as follows: the initial price is 20, the cost is 8, the product quality of each enterprise is distributed U (3, 4), the inertia factor $w = 0.8$; the acceleration factor $c_1 = 0.2$ $c_2 = 0.2$; random numbers $r_1$ and $r_2$ are subject to a uniform distribution $U(0,1)$, consumer income $I = 25$; the simulation time is Current Time = 0, the simulation time will be incremented by one after undergoing each simulation period; in real cases, the number of enterprises in the same segment market is limited, and the number of enterprises is $n = 20$.

To investigate the changes in price and the utility of consumers, the dynamic change curve of the lowest price set by the group of enterprises, and the changes in the consumer utility function, are given. With increasing simulation time, enterprises adjust their prices according to the PSO price adjustment rules, and obtain the best price for all enterprises in the next round, so that the dynamic change in optimal price for the enterprise group is obtained. Besides, the change in optimal price can cause changes in the utility curve.

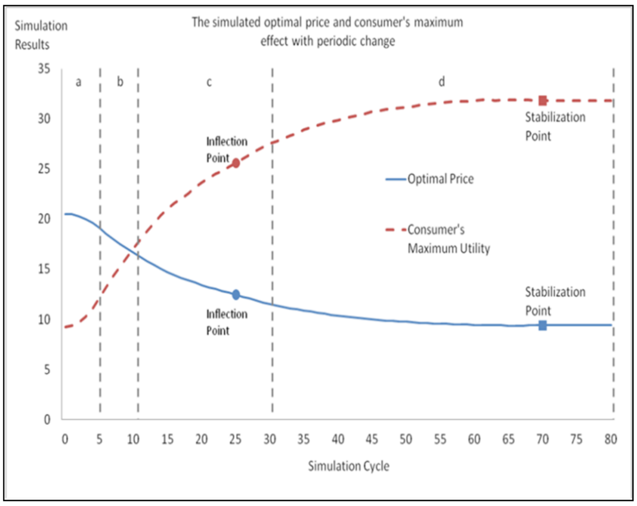



**Figure 2.** Simulated optimal price and consumer maximum effect with periodic change(a shows the change over the first five cycles; b shows the change over the fifth to 10th cycle; c shows the change over the 10th to 30th cycles; d shows the change over the 30th to 80th cycles)

Based on the changes in the two curves shown in Figure 2, it can be seen that the change in consumer utility, and the trend of change in the highest price given by the enterprise group are mutually opposed: a decreasing maximum price of the enterprise group caused an increase in consumer utility, which was consistent with the model established. From areas a and b in Figure 2, it can be seen that the lowest price of enterprise groups and consumer income change rapidly at the beginning of the simulation, and in time in area c in Figure 2, the lowest price of enterprise groups and consumer income growth slowdown after 25 cycles (see the inflection point marked). The learning curve is convex, after 70 cycles. The curve tends to be stable as shown in area d in Figure 2. The highest valuation and consumer utility showed stable trends. As shown in the process from the price learning of the enterprise group to table pricing, enterprise groups are initially formed in the first 25 cycles with fierce competition. The learning and changes in price and consumer utility growth are faster. With stability among enterprise groups, and at the lowest price limit, the price of learning, changes thereto, and consumer utility growth slowdown after 45 cycles. With the maturity and stability of the industry, the price of the enterprise group, and the utility of consumers tend to be stable. The simulation results are consistent with actual price change trends. It was concluded that, to pursue maximum utility, consumers should buy when the price of the enterprise group is stable.

### 3.3. Parameter analysis of price strategy model

The variations of two parameters which are the number of enterprises and their learning ability are mainly considered.

#### 3.3.1. Changes in the number of enterprises

By changing only the number of enterprises, while other parameters remain unchanged, the simulation results for $n$ = 15 and $n$ = 5 are as shown in Table 2. Through comparison thereof, the final price of the enterprise group at $n$ = 20 is the highest; while the utility of the consumer is the lowest; however, at $n$ = 15, the final price of the enterprise group reduces, and the utility of consumers increases. This shows that with increasing $n$, competition among enterprises is fiercer, and more external information is received by each enterprise. To win customers, enterprises will lower their prices, and the utility of consumers will increase. This shows that increasing the number of enterprises will strengthen market competition and further enhances the utility of consumers.

**Table 2.** The influence of the number of enterprises on optimal price and maximum consumer utility

| Number of enterprises $n$ | Price expectation | Consumer maximum utility |
|---|---|---|
| 5 | 15.61283 | 26.34388314 |
| 15 | 8.673331 | 33.43454414 |

To clarify the relationship between $n$, the optimal price, and consumer utility, the relationship between different $n$ values and the aforementioned two parameters, was analysed (Figure 3). The increase in $n$ resulted in the decrease of optimal price of the enterprise and rising consumer utility. As the number of enterprises reached a certain level ($n$ > 20), the optimal price and the utility value to the consumer remained unchanged, which indicated that more enterprises cannot increase consumer utility.

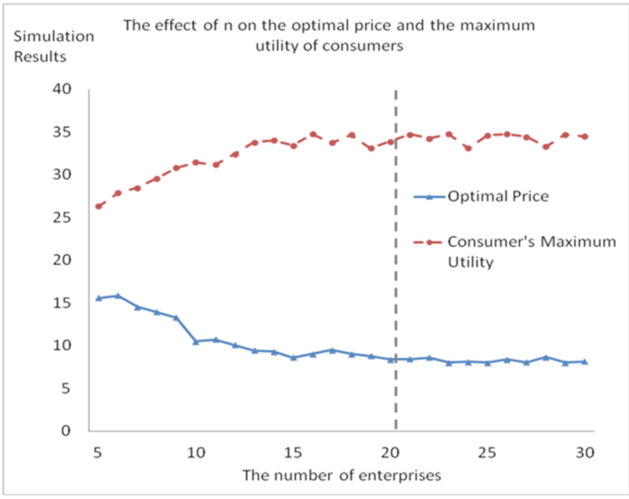



**Figure 3.** The effect of $n$ on optimal price and maximum consumer utility

From the above, enterprise pricing strategy is summarised thus: in the early stage, enterprises may adopt a strategy to improve their competitiveness and reduce their price, to increase the market entry threshold, prevent potential competition, and finally obtain maximum profit by reducing prices to maximise consumer utility. After the market matures, industry competition tends to be stable, and there is not as much room for price cuts. In these circumstan- ces, an enterprise can reduce product costs and improve product quality, with the appropriate increase in price to avoid malicious peer-competition, and maximise profits.

### 3.3.2. Change in learning ability

(1) Change in social learning ability

When setting $n = 20$, and $c_1 = 0.2$, only the social learning ability of enterprises is changed (Figures 4 and 5).

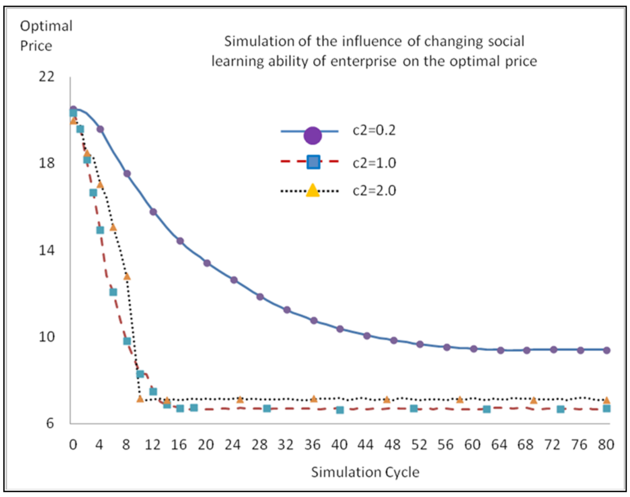



**Figure 4.** Simulation of the influence of changing social learning ability of an enterprise on optimal price

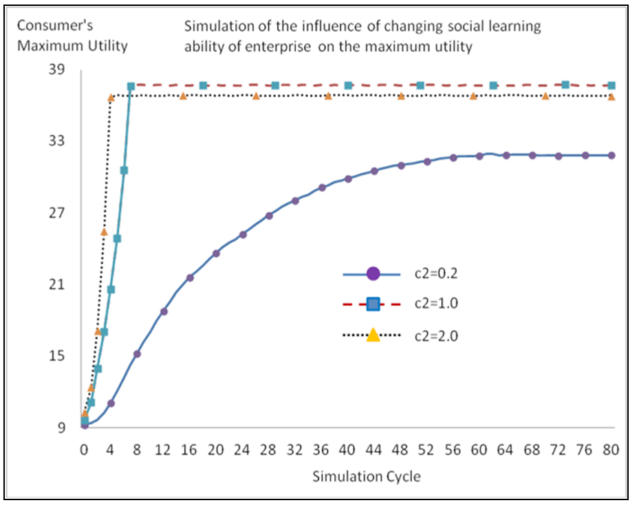



**Figure 5.** Simulation of the influence of changing social learning ability of an enterprise on maximum utility

Figures 4 and 5 show the simulation results for $c_2 = 1.0$ and $c_2 = 0.2$. When $c_2 = 1.0$, the final price of the enterprise group becomes smaller, the utility of the consumer increases, and the simulation time required to reach a stable value decreases; the optimal price and the consumer's maximum utility change little at $c_2 = 2.0$ and $c_2 = 1.0$, but the simulation time of the average time decreases more markedly. Results show that when the social learning ability became stronger, the enterprise and a consumer's ability to respond to market information improved. This results in less time being needed for the optimisation of price, and consumer maximum utility.

By comparing Figures 4 and 5, it is found that as $c_2$ increases from 0.2 to 1.0, the price learning curve gradually changes from convex to stable at a fixed rate. This shows that with the increase of the social learning ability of the enterprise group, the rate of price decline changes in ascending order, and the utility of consumers continues to increase. As the learning ability of the price further increases, namely, $c_2 > 1.0$, the price learning curve changes to convex from the previous linear form, which shows that an increasing social learning ability among enterprises causes a price decreases and that consumer utility also declines to some extent.

Statistical data on the influence of social learning ability on the time to stability of the market price, the final price, and the maximum utility of consumers, are shown in Table 3.

As shown in Table 3, as $c_2$ increases from 0.2 to 1, the time to market stability is greatly reduced, the final price of the product also significantly decreases, and the maximum utility of consumers increases. As the learning ability changes from 1.0 to 2.0, the time to market stability continues to be reduced; however, a strong social learning ability did not cause lower prices and greater consumer maximum utility. From the above analysis, an enterprise should fully investigate all legitimate external information when pricing.

**Table 3.** The influence of the change of social learning ability on optimal price and the maximum utility of consumers

| Social learning ability | Time to market stability | Final price | Consumer maximum utility |
|---|---|---|---|
| $c_2 = 0.2$ | 70 | 9.414749 | 31.85361 |
| $c_2 = 1.0$ | 8 | 6.641528 | 37.65166 |
| $c_2 = 2.0$ | 4 | 7.08563372 | 36.7094057 |

(2) Change in self-learning ability

When setting $n = 20$, and $c_2 = 0.2$, only an enterprise's self-learning ability is changed (Figures 6 and 7).

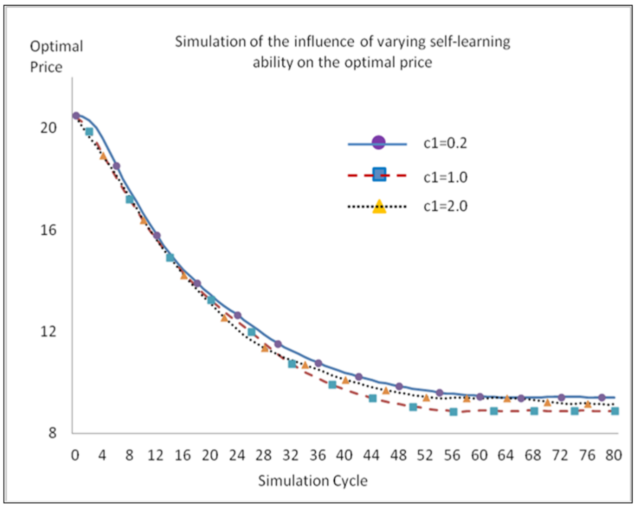



**Figure 6.** Simulation of the influence of varying self-learning ability on optimal price

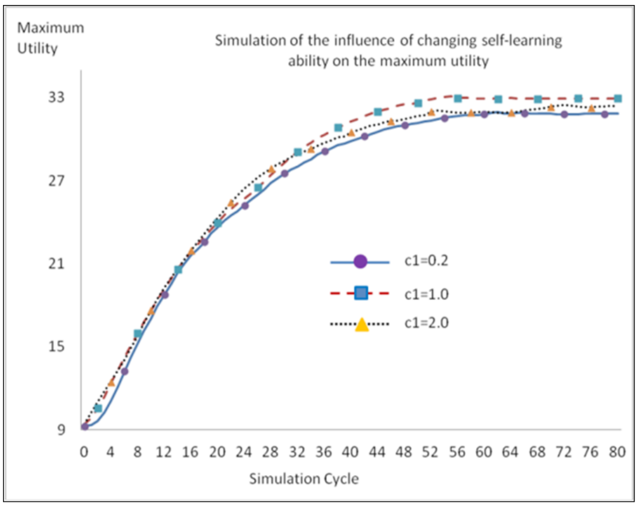



**Figure 7.** Simulation of the influence of changing self-learning ability on maximum utility

Figures 6 and 7 show that the change in learning ability has little effect on the optimal price and consumer's utility. Table 4 lists statistical data pertinent to the influence of self-learning ability on the time to market stability, final price, and maximum consumer utility.

**Table 4.** The influence of changes in social learning ability on optimal price and the maximum utility of consumers

| Social learning ability | Time to market stability | Final price | Consumer maximum utility |
|---|---|---|---|
| $c_1 = 0.2$ | 70 | 9.414749 | 31.85361 |
| $c_1 = 1.0$ | 65 | 8.876187 | 32.9622 |
| $c_1 = 2.0$ | 50 | 8.662043 | 33.46807 |

From Table 4, with increasing self-learning ability, market stability, and the final price of the product, gradually falls while the maximum utility value to consumers increases slightly: the influence of self-learning ability is not evident.

These results in the lower limit set for price in each enterprise, which causes small difference between the lowest price of each enterprise and existing price, weakening the effect of self-learning ability. In addition, enterprises update their prices on the basis of external information available about the market. Comparatively speaking, the effect of social learning ability is more prominent, this can weaken self-learning ability.

(3) Summary

By changing the values of $c_1$, $c_2$, and by further analysis of the learning ability of enterprises, the results show that a price strategy model based on the PSO algorithm can achieve the desired results, and that the utility of the consumer can be improved significantly when enterprises focus more on one learning ability and neglect others; however, only when enterprises comprehensively utilise two learning abilities, can the final price of goods sold by an individual enterprise be obtained in a short period in these simulations: this is more conducive to the enterprise winning customers.

## 4. Summary

A multi-agent modelling based simulation method, taking the utility function of consumers as the biggest fitness function, was used to establish a price strategy model and enterprise price strategy learning mechanism by PSO algorithm. The result of Swarm analysis shows that increasing the number of enterprises will reduce the price of the enterprise group, and lead to increasing consumer utility. However, when the number of enterprises exceeds 20, the optimal price of the enterprise group and the utility of consumers does not change. The simulation results for the learning ability of enterprises show that compared to social learning ability, the influence of self-learning ability is not obvious; as enterprises strengthen a single learning ability, the decrease in the final price of enterprise groups and increasing consumer utility will be found after the simulation, and for a longer time.

The simulation analysis of the pricing model based on this multi-agent modelling method can provide a reference for pricing strategy among enterprises, and price prediction by consumers. This work establishes its model by assuming that consumers have the same spending power. It cannot reflect the influence of individual differences in price strategy, and it is recommended that this be the subject of future research.

**Acknowledgements**

This work was supported by the National Natural Science Foundation, China (No. 11072192), and the Shaanxi Province Fund for Industrial Technology Research Projects, China (No. 2015GY118).

**References**

1. Jen-Ming Chen, Chia-I Chang (2013) Dynamic pricing for new and remanufactured products in a closed-loop supply chain. *International Journal of Production Economics,* 146(1), p.p.153-160
2. B. Denkena, A. Nemeti (2013) Stock Market Related Pricing Mechanisms for the Tool and Mould Manufacturing Industry. *Procedia CIRP*, 12, 2013, p.p.414-419.
3. Michèle Breton, Mohammed Kharbach (2012) Transportation and storage under a dynamic price cap regulation process. *Energy Economics*, 34(4), p.p.918-929.
4. Gallego G, Van Ryzin G (1994) Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science*, 40(8), p.p. 999-1020.
5. Feng Y, Gallego G. (1995) Optimal Starting Times for End-of-Season Sales and Optimal Stopping Times for Promotional Fares. *Management Science*. 41(8), p.p. 1371-1391.
6. Bitran GR, Mondschein SV. (1997) Periodic Pricing of Seasonal Products in Retailing. *Management Science*. 43(l), p.p. 64-79.
7. Popescu I, Wu Y. (2007) Dynamic Pricing Strategies with Reference Effects. *Operations Research*, 55(3), p.p.413-429.
8. Caro F, Martinez-de-Albeniz V. (2012) Product and Price Competition with Satiation Effects[J]. *Management Science*, 58(7), p.p.1357-1373.
9. Zhang Jiangyi, Liu Ning, Liu Yachen (2015) Real Estate Projects Dynamic Pricing Decision Analysis Consided Consumer Expectations. *Operation and Management*, No.4, p.p.136-139.
10. Guan Zhenzhong, REN Jianbiao (2014) Optimal Dynamics Pricing in the Presence of Strategic Consumers *Systems Engineering Theory and Practice*, No.8, p.p.2018-2024.
11. M.R. Tanweer, S. Suresh, N. Sundararajan (2016) Dynamic Mentoring and Self-Regulation Based Particle Swarm Optimization Algorithm for Solving Complex Real-World Optimization Problems. *Information Sciences*, 326(1), p.p.1-24.
12. Vahid Hosseinnezhad, Mansour Rafiee, Mohammad Ahmadian, Mohammad Taghi Ameli (2014) Species-Based Quantum Particle Swarm Optimization for Economic Load Dispatch. *International Journal of Electrical Power & Energy Systems*, 63, p.p.311-322.
13. Kamalendu P, Bill Karakostas (2014) A Multi Agent-Based Service Framework for Supply Chain Management. *Procedia Computer Science*, 32, p.p.53-60.
14. M.V. Dileep, Surekha Kamath, Vishnu G. Nair (2015) Particle Swarm Optimization Applied to Ascent Phase Launch Vehicle Trajectory Optimization Problem. *Procedia Computer Science*, 54, p.p.516-522.
15. Jitendra Agrawal, Shikha Agrawal (2015) Acceleration Based Particle Swarm Optimization for Graph Coloring Problem. *Procedia Computer Science*, 60, p.p.714-721.
16. A.I. Awad, N.A. El-Hefnawy, H.M. Abdel_kader (2015) Enhanced Particle Swarm Optimization for Task Scheduling in Cloud Computing Environments. *Procedia Computer Science*, 65, p.p.920-929.
17. Elnaz Davoodi, Mehrdad Tarafdar Hagh, Saeid Ghassem Zadeh (2014) A hybrid Improved Quantum-behaved Particle Swarm Optimization–Simplex Method (IQPSOS) to Solve Power System Load Flow Problems. *Applied Soft Computing*, 21, p.p.171-179.
18. M.J. Mahmoodabadi, Z. Salahshoor Mottaghi, A. Bagheri (2014) HEPSO: High Exploration Particle Swarm Optimization. *Information Sciences*, 273, p.p.101-111.
19. Michael Scholz, Verena Dorner, Markus Franz, Oliver Hinz (2015) Measuring Consumers' Willingness to Pay with Utility-Based Recommendation Systems. *Decision Support Systems*, 72, p.p.60-71.