Price Competition with Particle Swarm Optimization Learning Algorithm:

An Agent-Based Artificial Model

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Abstract: This study instructs an artificial price competition market to examine the impact of capacity constraints on the behavior of packers. Results show when there are cattle left for the lowest bidder after all other packers finishing their procurement, the capacity constraints make the price lower than the perfect competition level.

Key Words: fed cattle market, agent-based model, particle swarm optimization, oligopsony,

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Introduction

In the vertical product supply chain, processors procure from upstream producers and sell product to downstream industries or consumers. For example, in the fed-cattle market, packers purchase fed cattle from producers and then sell processed boxed beef to retailers. For the past decades, the packing industry has consolidated and the four-firm concentration has grown to around 80% in 2003 (GIPSA, 2005).

This high concentration rate in the meat packing industry arouses the concern about market power of packers over feeders and numerous studies have been made on it. The empirical results of studies do not suggest uncompetitive behavior for packers (Azzam and Anderson, ; Muth, Liu, Koontz, and Lawrence, 2007). Koontz and Garcia show that the market power of packers is small and decreasing with time. Since most empirical studies are based on the time series data and have to consider the effects of technology improvement, demand changing and concentration at the same time, it causes difficulty to study the effect of a single variable on market power. To study the oligopsony market, the type of behaviors that the participants actually follow play an important role. According to game theory, there are two mainly kinds of marketing strategies for oligopsony firms, price competition and quantity competition. Under the price competition mechanism, agents use price as a strategy and try to procure as many cattle as possible until then reach a capacity constraint (Levitan and Shubik, 1972). Under the quantity competition, agents believe their purchasing quantity will affect the market price and use quantity as a marketing strategy.

Once procurement reaches their planned number, they will stop purchasing any more. Xia and Sexton (2004) adopt a theoretical duopsony model and assume packers use quantity strategies. This model predicts a much larger market power than the empirical estimation. This suggests that their assumption may not be the main mechanism of fed cattle market.

One possible explanation of the discrepancy between empirical and theoretical results is that pricing strategy of packers play an important role in this market. Quantity competition assumes each producer decides how much to produce and then the total supply determines the price with consumers' aggregate demand (Maskin and Tirole, 1987). Price competition is more like an auction market in that the highest bidder gets the supply first until it reaches its capacity. Majerus compares quantity vs. price competition in his paper with differentiated products and concludes that the latter is harsher than the former (1988).

For the fed cattle market, if there is more than one packer bidding in a feedlot, the higher bidder will get the cattle first. There are 4 large processing firms and many small processors and this makes it difficult for a single firm to use quantity as a main strategy. Anderson et al (1999) use an experimental method called packer-feeder game to study the trading behaviors of agents. In this game people act as packers and feeders, packers have convex cost function and bid cattle from feeders. But because of high cost, time limit, and heterogeneous learning ability of people, it is costly to test the long run equilibrium. In addition, their study and other packer-feeder games make a realistic environment and contain many other features such as quality, feeding time and captive supply besides bidding strategy, which makes it difficult to differentiate the effect of one variable from the other.

Based on the above analysis, we set up a basic artificial price competition market to study the trading behavior of packers. This artificial model simulates the dynamic interaction between packers and feeders under different economic environments. Under price competition market structure, packers make bidding price strategy simultaneously. If feeders have complete information about packers' bidding price, they will only sell products to the current highest bidder. In this simulation, we also let packers have learning ability to change their marketing strategy based on their history performance and market information.

Compared to experimental simulation, this agent-based model is easy and economical to test effects of each variable by changing the environment conditions, population and properties/parameters of participants. Past research using agent-based models in economics have used genetic algorithm (GA) (Vriend, J. N., 1998) and reinforcement leaning algorithm (RL) (Kutschinski, E., Uthmann, T. and Polani, D., 2003). GA is mainly used in simple quantity competition artificial market, like Vriend's work. But this algorithm has been proved too slow to use in the more complex market considered here. When modeling price competition market, the RL lets agents increase or decrease prices by a small value, and if the current return is higher than the previous one, the agents will replace the last action. Because of this strategy feature, the previous market simulations with RL only allow part of the agents to change their strategies at one time or agents cannot distinguish the effect of return come from change of its own strategy or the environment. This restriction makes RL difficult to model the more realistic market in which all agents continually adjust their strategies simultaneously.

To avoid the above problems of GA and RL , this study adopts Particle Swarm Optimization

(PSO) algorithm. PSO is a stochastic optimization technique developed by Eberhart and Kennedy (1995) and can be used for a social optimization problem. Each individual agent's strategy can be evaluated by a fitness function and the problem has its own paralleled structures in which each individual can learn. The asynchronous best strategies of one agent in every parallel structure are called local best solutions and the best fit strategy among all parallel structures at the current simulation step is called global best. Every agent continuously uses PSO algorithm searching for better solutions in each parallel structure. Movements through the search space are guided by these local and global successes, with the population usually converging.

This research simulates the price competition behavior of packers with an artificial fed cattle market and also uses particle swarm optimization algorithm to model the packers learning. We examine the effect of processors' capacity constraint on the equilibrium market price.

Methods and Data

In this study, we deal with the case of packers procuring fed cattle for processing from feeders. First we use an artificial market without packers' capacity constraint to illustrate the market mechanism and then consider the effects of adding capacity constraints.

Market Mechanism without Packers' Capacity Constraint

Consider a homogeneous product market with M packers and N feeders. The number of packers is much less than the number of feeders ($M << N$). Assume that packers process products that will be sold in the retail market and the marginal cost for processing is constant for all processors. The marginal value equals the selling price minus the marginal processing cost. To focus our research on the games between packers and feeders in this market, we assume the final product boxed beef price, the processing rate and the marginal processing cost for one cattle are constant and then the derived price of before processing cattle R is constant, too. Then the marginal revenue is constant and equals R . Each buyer uses bidding price ratio as its choice variable as equation (1) shows.

$$x = p / R \tag{1}$$

here x is defined as price ratio, p is bid price, R is buyer's the marginal revenue. At the beginning of each simulation step, packers use the price ratio and R to set bid prices simultaneously.

In this section, we suppose that none of the packers has a capacity constraint and that the highest bidder will purchase all available supply and the remaining packers will not buy anything. If more than one packer bids the highest price, they split the supply quantity. That is, given $(p_i)_{i \in M}$, if there are l packers that bid the same highest price, the procurement of buyer i is

$$q_i = \frac{S(p_i)}{l} \text{ if } p_{i_1} = p_{i_2} = \ldots = p_{i_l} > p_{i'} \text{ for all } i' \in M \tag{2}$$

We assume all feeders are homogeneous and have the same supply function and assume there is a time delay between production and marketing. Then feeders have to make their production decision based on the market information of the previous time period and make selling decisions based on the current market. Their production function and supply function are $q_j^p(t) = p^H(t-1) - [q_j^p(t-1) - q_j^s(t-1)]$ and $q_j^s(t) = \min\{q_j^p(t), p^H(t)\}$, here the subscripts p, s and H indicate production, sold and highest respectively. This means after production, the current storage is the same as the highest price of last time period. This study assumes feeders have no cost or time delay to get the bid price information of all packers. Under this perfect information market for feeders, they will only sell their products to the highest bidders. If the current highest bid price $p^H(t)$ is not less than $p^H(t-1)$, then seller will sell all its production quantity $q_j^p(t)$, else it will sell $q_j^s(t) < q_j^p(t)$ and hold the product left to next time period. Here we assume the storage cost is small enough to be neglected.

Market Mechanism with Packers' Capacity Constraint

In the real world, packing firms have processing capacity constraints. The market price competition level with firms' capacity constraint may be different from the level without it. In this section, we assume the artificial market structure is the same as the previous one except packers have capacity constraints. The highest bidder gets the supply first to its capacity. Then the next highest bidder makes the procurement and so on.

To model the depth of oligopsony market structure caused by packers' capacity, we define the processor's capacity ratio in equation (3).

$$\kappa = K/(R \times N) \tag{3}$$

here κ is the capacity ratio, K is the processing capacity of the packer, R is the marginal revenue of one processor and also the supply level of producers under the perfect competition price level, N is the total number of feeders. For example, if in perfect competition market all producers supply 10000 products and the capacity of processor i is 3000, its capacity ratio κ_i equals 0.3 here. Since we assume all processors are homogenous then their capacity ratios are the same. In this simulation, we change the packers' κ and compare the results of them to see how the capacity constraint affects the price level.

Particle Swarm Optimization Algorithm

Schoeman and Engelbrecht (2006) adapt PSO with a niching algorithm for dynamic environments. In the fed cattle market, packers face a changing economic environment since all packers continuously update their market strategies. In this research, since we assume all agents do not have cooperation then we adjust PSO algorithm and only allow each agent to learn from their own experience.

We set up K parallel markets and each agent has its own clones in every market. We call one clone of an agent a particle. If there are 4 agents and 20 parallel markets, each agent has 20 clones and there are 80 particles in this simulation structure. Although having the same behavior rules, one agent and its K clones may take a different market strategy since the initialized random values are different. In the simulation, packers dynamically change their marketing strategy with the PSO algorithm but feeders are price takers and simply sell their products to the current highest bidders. Then in the following paragraph we only state the PSO algorithm for packers.

Each particle chooses a price ratio value x as a strategy parameter, $x \in [0,1]$, and each strategy parameter is normalized at the beginning of the simulation. Each particle has an evolutionary velocity, $v \in [-1,+1]$, which determines the change of the particle. The changes of particles are influenced by the location of the best solutions achieved by the particle itself, $p_{i,k}^{l} \in [0,1]$ for k^{th} particle, and by the whole population, $p_i^g \in [0,1]$. The superscripts l and g indicate local and global, the subscripts k and i indicate k^{th} parallel market and i^{th} agent respectively. Profit function $\pi(x_{i,k})$ is used to value the performance of each position x, Table 1 shows the pseudo code of the PSO algorithm.

In every simulation step, the particle of the i^{th} packer in k^{th} parallel market can be updated by the following equations:

$$x_{i,k}(t+1) = x_{i,k}(t) + v_{i,k}(t) \tag{4}$$

and

$$v_{i,k}(t+1) = w(t)v_{i,k}(t) + c_1 u_1 (p^l_{i,k}(t) - x_{i,k}(t)) + c_2 u_2 (p^g_{i,k}(t) - x_{i,k}(t)) \tag{5}$$

where x is the price ratio value, v is the velocity vector, $u \in [0,1]$ are uniformly distributed random numbers, c_1 and c_2 are learning factors, w is an inertia weight parameter, $p^l_{i,k}$ and p^g_i are local best and global best particles.

The following equations (6) and (7) indicate how to choose $p^l_{i,k}$ and p^g_i among all parameters of agent i. The best local chooses from the best performance history parameters $p_{i,k}(t')$, as equation (6) shows.

$$p_{i,k}(t) = \arg\max \pi(p_{i,k}(t'), x_{i,k}(t)) \tag{6}$$

here $t' = t-1, t-2, ..., t-10$. And the best global parameter is elected from the best local parameters.

$$p^g_{i,k}(t) = \arg\max(\sum_{k=1}^{K} \pi_k(p^l_{i,k}(t))/K) \tag{7}$$

here $k = 1,2,...,K$ and K is the total number of parallel markets.

Chatterjee and Siarry (2006) state that the inertia weight w in (4) is critical for the PSO's convergence behavior. A large inertia weight provides a larger exploration but a smaller one fine-tuning the current search area. So it is worth making a compromise, e.g. w start with a higher value at the beginning and then decreasing with iterations:

$$w(t) = 0.4 + \frac{t_{\max} - t}{2 \cdot t_{\max}} \tag{8}$$

where $t_{\max}$ is the maximum number of iterations and t is the current iteration. c_1 and c_2 are set equal 2 respectively.

Simulation Procedure

Packers select independently the prices they bid for the product simultaneously and can learn from their own experiences. With a homogeneous product, supply will go to the current highest bidder first. If more than one buyer bids the same price, then a sharing rule must be assumed.

We set up 20 parallel markets and each market contains the same agents. Each buyer use the best fitness bidding in one market as best local and its own best performance in all parallel markets as best global. The best global differs by packer.

(i) There are 20 parallel markets. There are *M* packers and *N* feeders act as independent agents and trade in each market at the same time. Each buyer may have a different trading strategy in each parallel market and evolves according to time respectively and chooses the best local parameter as the best global parameter.

(ii) In each market, randomly initialize x_i and v_i for all i. We choose the price ratio $x_{i,k} \in U[0,1]$ and $v_i = 0$ for all i and $k = 1,\ldots,K$.

(iii) While the market is not converged, each buyer continuously uses the function (4) and (5) to update the new bidding price.

(iv) Use the history p_i and g to test the best local parameters following equation (6). In this game, all packers change their marketing strategies with time going by. Since the performance of current pricing strategy and the past best local choice are under different economic environments, it is reasonable to retest the past locals. Then for each buyer, we retest the performance of 10 history local parameters under the current market environment, and choose the best fit as the best local parameter of this iteration from both these 10 history local parameter and the current parameter.

(v) To choose the best performance parameter for one buyer, we test each best current local parameter in all 20 parallel markets holding other agents' current strategies unchanged and choose the one that gives the highest average return, This means it will give the highest expected return and be chosen as the global best parameter, as function (7) shows.

This study introduces a new method to agricultural economics, an agent-based model, which can be used to simulate the behavior of participants with different characteristics under a complex market environment. The model is programmed with JAVA language and it is easier to test effects of different types of contracts, number of market participants, level of market information, etc.

Results

The artificial market in this research tests the above theory with a market without packers' capacity constraints and test the effect of processors' capacity constraint on the price level when constraints exist.

Market without capacity constraint

In this section we study the optimal pricing strategies of packers under the assumption that processors do not have a processing capacity constraint.

Figure 1 shows the simulation results with no processing capacity constraints. The result in Figure 1 (a) is under the monopoly assumption and there is only one processor in the market. Since there is no other competitor, this processor tries to maximize its profit and sets the price at the monopoly level. With more processors joining the market, as far as they win cattle with a bid lower than the marginal revenue *R*, they will make a profit. Since the highest bidder gets the entire product, these processors continually increase their bidding and drive the market price up to the perfect competition level. From Figure 1 (b) to (d), more competitors in the market will cause the price to reach the perfect competition level more quickly. If processors number is more than 3, the price evolves to perfect competition level nearly immediately.

Market with capacity constraint

The results in Figure 2 and Figure 3 show that if all processors have a chance to procure some input, which means $\sum_{i=1}^{M-1} \kappa_i < 1$ and that after the first packer get its entire requirement, there is still a probability that there are some cattle left for the other packer in the market. Then the lower bidder can earn a profit with a price lower than the perfect competition price level. This causes the market price to be lower than the perfect competition price level. If there is any processor left with no procurement, the market price will be driven to the perfect competition price level.

The results in Figure 2 come from a duopsony market. In Figure 2(a), when the capacity ratio of one packer is 0.9, the competition is not as harsh as Figure 1(b) shows and the market price is already lower than the perfect competition level. When capacity constraints tighten, the market price gets lower. Figure 3 shows how the equilibrium price level changes after more packers join the market. When four packers compete in the market, the capacity rate is 0.25, as Figure 3 (b) shows, the total processing capacity is near to the perfect competition supply level. Figure 3 (c) and 3 (d) shows that once each packer's κ gets lower than 0.25, the market price level becomes less than the perfect competition level and the market power gets larger as κ decreases.

Figure 2 and Figure 3 show how capacity constraints affect the price evolution and the market price level. Compared to the results without a capacity constraint, we can see that a capacity constraint weakens price competition. If the capacity constraint level is relatively higher, the price distortion from the perfect competition level is less than theoretical quantity competition results. While if the capacity constraint level is very low, the market power of processors is even more severe than with quantity competition market.

[Place Figure 2 Approximately Here]

[Place Figure 3 Approximately Here]

Conclusions

This research studies the price competition behavior for processors and illustrates how the capacity constraint of processors caused market price to be distorted from perfect competition level. Market power is a topic of great concern and the results of this research provide potential for discussion. In addition, particle swarm simulation is used to simulate market and study the learning behavior of economic agents.

From above discussion, we find that if after $N-1$ buyers get all their required products and some supply is left for the lowest bidder, the price level has the chance to be lower than the perfect competition level. Or else in order to make positive profit, the lowest bidder will increase their bidding and compete with the 2nd lowest bidder which drives the market price to the perfect competition level. Once the total capacity of $N-1$ buyers is less than the perfect competition supply level, the market price evolves lower than the perfect competition price. And after this threshold, with the capacity gets smaller, the market power depth gets deeper.

In addition, this research assumes that suppliers have zero storage cost and the products are imperishable. If there is no capacity constraint, suppliers can always sell out their products and the perishable assumption affects the results shown in Figure 1. While if there is capacity constraint and products are perishable and only can be stored for short time periods associated with a high cost, the products can be looked upon as sunk cost and the market price level may be volatile instead of converging to a consistent point. Under extreme situation, if suppliers produce a huge quantity that is much more than the requirement of processors in the current time period, buyers can purchase these products with a very low price. This problem needs to be studied in future.

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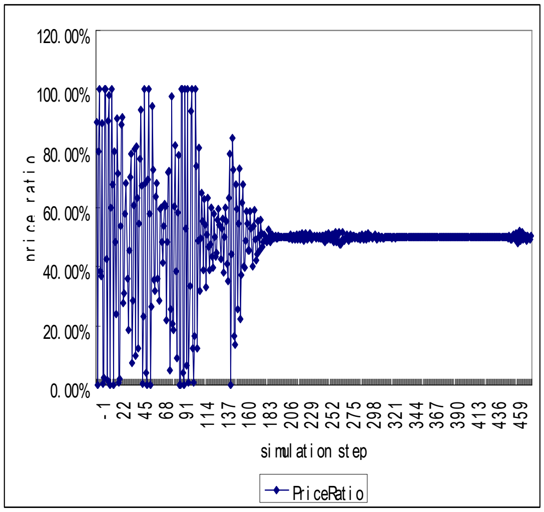
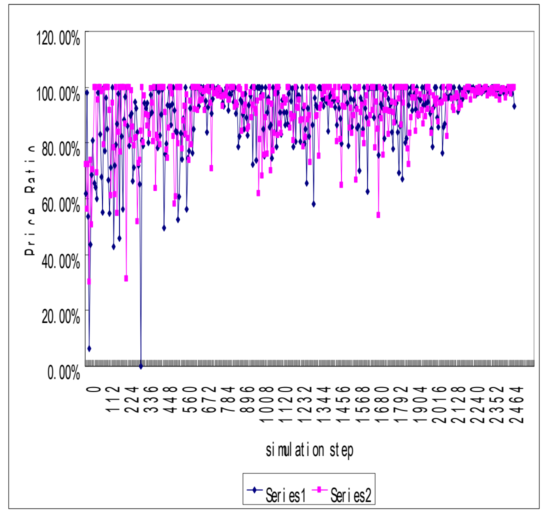
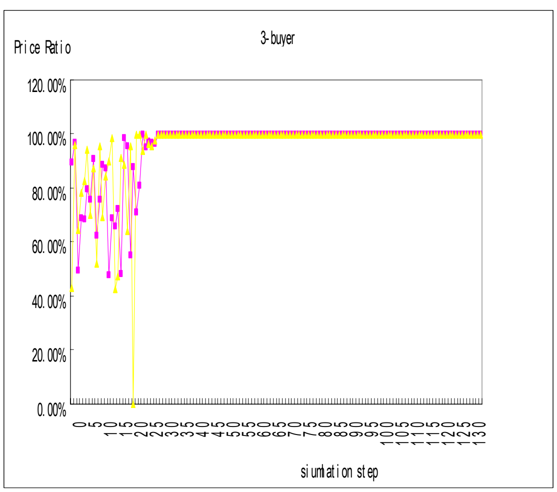


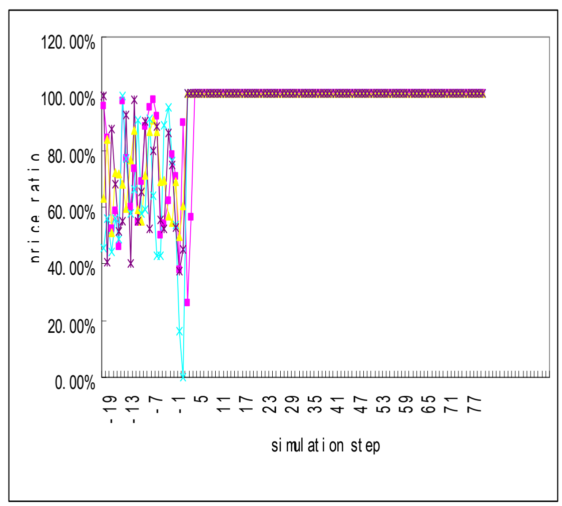
(a) Monopoly Market



(b) Price Competition with 2 Processors

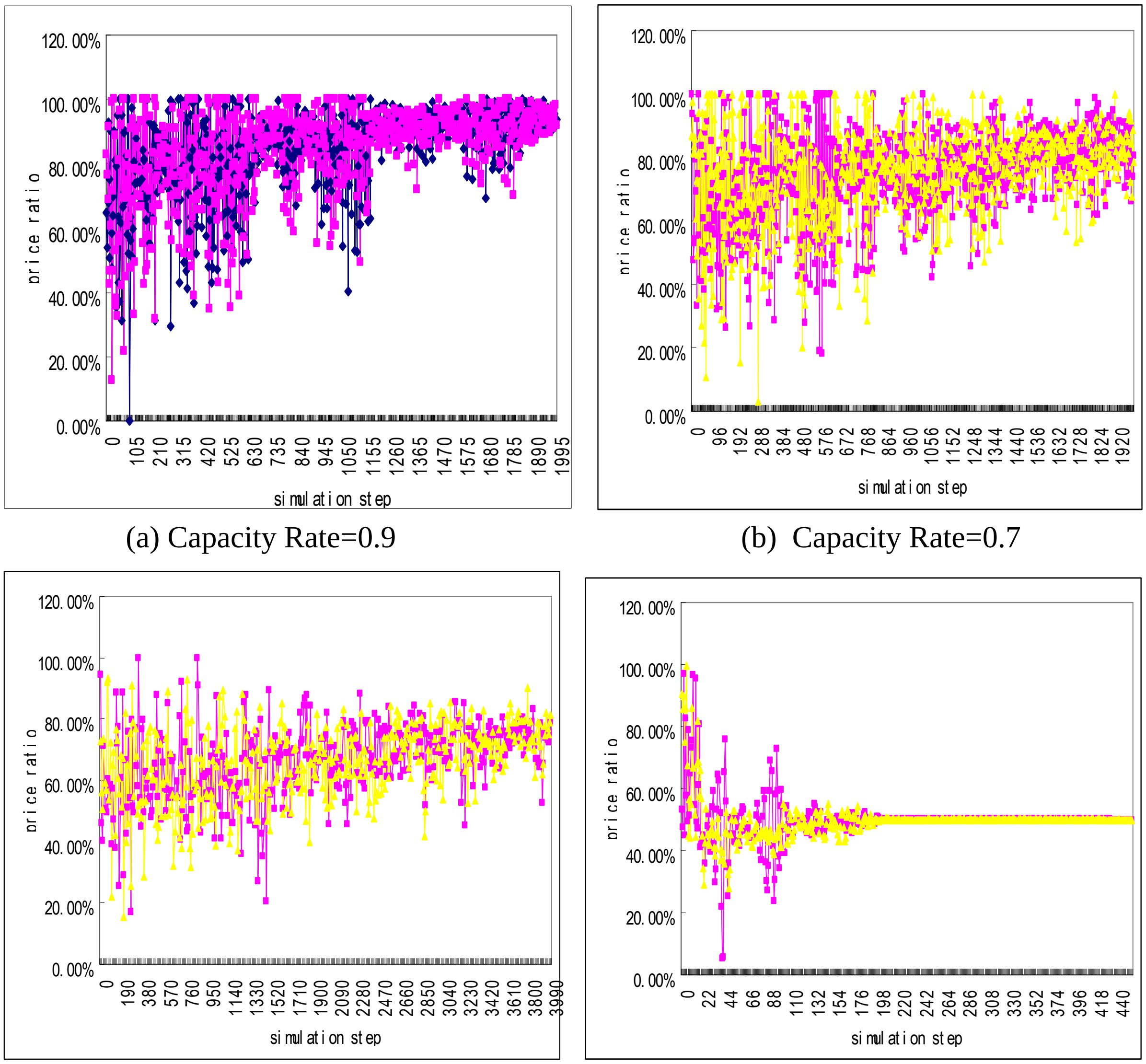


(c) Price Competition with 3 Processors



(d) Price Competition with 4 Processors

Figure 1 Processors' Price Competition Behavior without Capacity Constraint



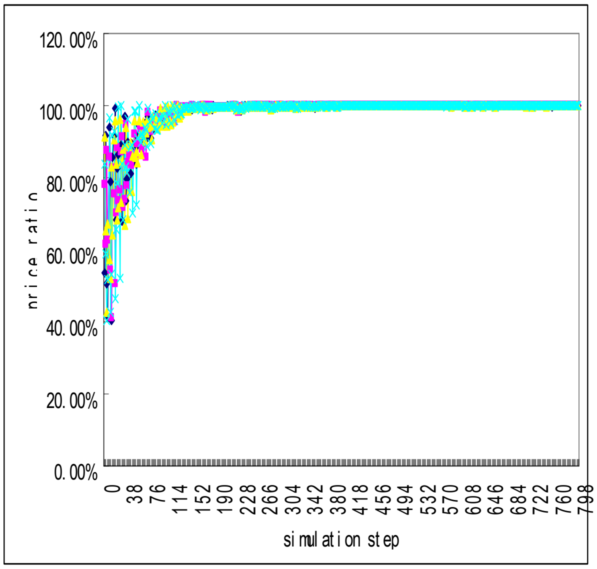
(a) Capacity Rate=0.9

(b) Capacity Rate=0.7

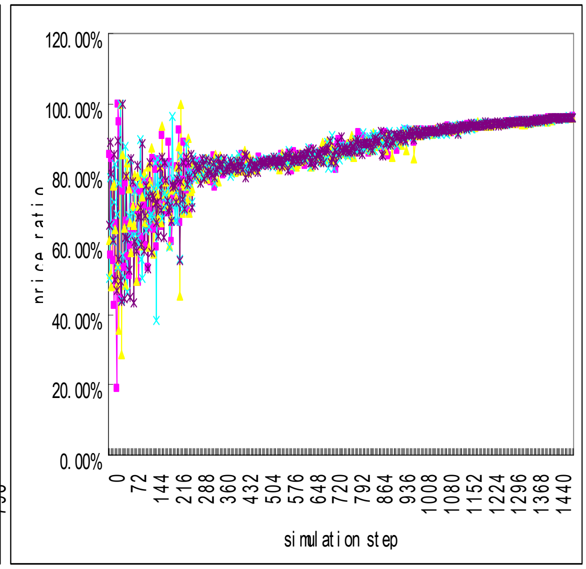
(c) Capacity Rate=0.5

(d) Capacity Rate=0.25

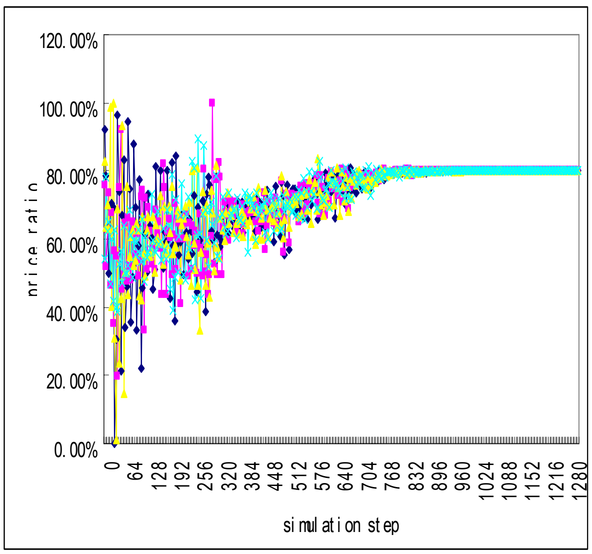
Figure 2 Two Processors' Price Competition Behavior with Capacity Constraint



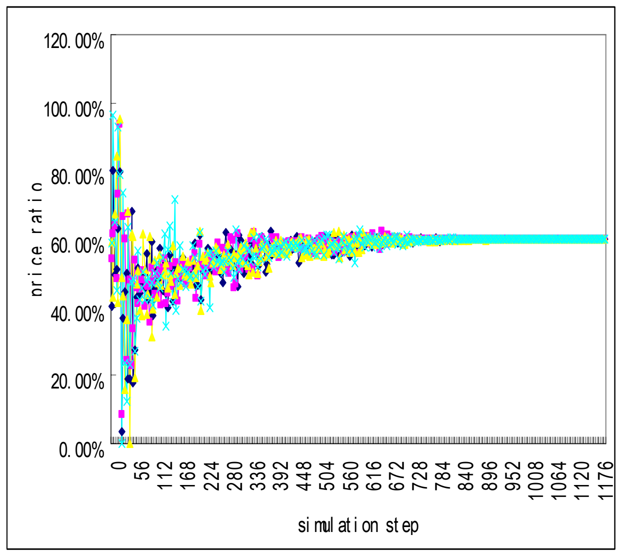
(a) Capacity Rate=0.35



(b) Capacity Rate=0.25



(c) Capacity Rate=0.20



(d) Capacity Rate=0.15

Figure 3 Four Processors' Price Competition Behavior with Capacity Constraint