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Multi-agent-based Simulation Model for the Limited Rational Pricing Behavior of Natural Gas Suppliers in Online Transaction Markets

Xiang Xie[1,a], Heting Jia[2,b,*], Hanya Chen[3,c], Kai Pan[1,d], Liming Huang[4,e], Shixu Li[5,f]

[1]*China Petroleum Planning and Engineering Institute, Beijing, China*
[2]*School of Economics and Management, Dalian University of Technology, Dalian, China*
[3]*School of Economics and Management, Beijing University of Chemical Technology, Beijing, China*
[4]*China National Petroleum Corporation Hunan Sales Branch, Changsha, China*
[5]*Dalian PetroChina Kunlun Gas Co., Ltd, Dalian, China*
[a]*xiexiang11@petrochina.com.cn*, [b]*jiaheting@foxmail.com*, [c]*chenhanya0201@163.com*, [d]*pankai1988@petrochina.com.cn*, [e]*huangliming@petrochina.com.cn*, [f]*lishixu@petrochina.com.cn*
[*]*Corresponding author*

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Abstract: The simulation method based on multi-agent agents is a common approach for analyzing market equilibrium in online trading markets. The accurate simulation of natural gas quotation decision-making by intelligent agents is crucial to ensuring the consistency of simulation results with market phenomena. To enable intelligent agents to effectively describe the real quotation strategies of natural gas suppliers across diverse and complex market environments, we developed a natural gas supplier intelligent agent quotation model incorporating limited rationality features through an analysis of bidding strategy characteristics and psychological mechanisms. This model encompasses capacity segmentation and quotation strategy space construction based on multiple psychological accounts, as well as a reinforcement learning model for domain search within the strategy space that reflects cautious adjustment and gradual trial-and-error psychology. Through this approach, our model successfully simulates the limited rationality in the quotation behavior of natural gas suppliers. Finally, we validated the effectiveness of our limited rationality intelligent agent model using an illustrative example and analyzed its impact on market equilibrium.

1. Introduction

Currently, China is actively advancing the reform and development of the electricity spot market while also launching an online trading market for natural gas[1]. In the short-term market-based allocation, there is a growing diversity in trading methods and products, which contributes to the discovery of the true price of natural gas, facilitates rational resource allocation, and ensures timely price transmission[2]. This will create more favorable conditions for the market-based reform of natural gas prices.

In the context of the natural gas trading market, agent-based market simulation is an effective method for market analysis [3-4]. For instance, references [5] and [6] utilize multi-agent reinforcement learning algorithms to comprehensively consider pricing mechanism characteristics and game equilibrium situations, analyzing how pricing mechanisms are selected in the spot market. References [7] and [8] employ agent-based model simulation methods to investigate issues related to uneven fund allocation and imbalanced costs in the imbalance market. Reference [9] introduces a probability reinforcement learning algorithm to examine the behavior of intelligent agents utilizing line congestion as a means of exerting market power. Reference [10] proposes a non-zero-sum stochastic game theory model based on reinforcement learning algorithms for evaluating the market power of electricity suppliers in day-ahead markets.

There are few agent-based simulations of the natural gas market. Therefore, effectively simulating actual bidding behavior is crucial for analyzing simulation results and aligning them with real market phenomena. Statistical analysis of China's online natural gas market's actual bidding data reveals a tendency to increase bid prices in the strategies employed by city gas enterprises, industrial gas users, and natural gas power generation companies. The distinction lies in the extent of this behavior. However, existing agent models based on algorithms such as RE (Roth-Erev), Q-learning, experience-weighted attraction (EWA), and neural network-combined Q-learning fail to accurately simulate the bid-raising behavior adopted by power generation enterprises during bidding decisions.

Research on economic hold-up (bidding up prices) mainly focuses on three aspects: the first is the empirical analysis and market power monitoring of economic hold-up behavior. For example, studies such as [11-12] and [13] show that economic hold-up behavior in the markets of Australia and New Zealand has certain universality, while study [14] shows that economic hold-up behavior occurred in the Zhejiang electricity market during the first round of electricity reform. The second is the construction of economic hold-up strategies by generators and their impact on the market. For example, studies [15] and [16] show that generators with certain access location advantages can use economic hold-up strategies to cause congestion in transmission lines and raise node prices, thereby profiting. The third is the economic explanation of economic hold-up behavior. Studies [17] and [18] explain economic hold-up behavior from the perspective of behavioral economics [19], indicating that economic hold-up behavior may arise from the multi-account phenomenon of generators' decision-making in uncertain environments, where different capacity segments are assigned different objectives and risk attitudes, and therefore, completely different bidding strategies are adopted for capacity segments with similar cost differences[20].

There is a lack of modeling economic hoarding behavior based on the multi-mental account theory in the agent-based simulation equilibrium analysis model. Therefore, considering the characteristics and psychological mechanisms of economic hoarding strategies, a pricing model for intelligent entities with limited rationality features was developed. This includes a model for constructing the strategy space based on multi-mental account capacity segmentation and quoting strategy, as well as a reinforcement learning model for searching the strategy space domain that can reflect cautious adjustment and gradual trial-and-error psychology. This effectively simulates the limited rational quoting behavior of natural gas suppliers.

2. Framework for analyzing the equilibrium in online transaction markets using intelligent agents

The simulation method for online transaction markets based on multi-agent agents typically follows a two-layer structure. The upper layer represents the bidding decision process of natural gas suppliers, with each supplier being modeled as an individual agent. These agents evaluate alternative bidding strategies within the bidding space using market information, pipeline constraints, historical bidding experiences, and other factors to select a strategy according to specific rules before submitting the corresponding bid curve to the online trading market. The lower layer is responsible for clearing in the online trading market; here, clearing agents use bidding decisions and market boundaries to clear transactions and communicate these results back to natural gas supplier agents for further decision-making. Optimized bid information from natural gas suppliers and competitor winning data are exchanged between layers as interaction data that undergo continuous optimization to simulate evolutionary changes in market dynamics.

The development of the intelligent agent bidding module is crucial, as it directly impacts the variation in simulation outcomes. This module primarily comprises the bidding strategy space and the bidding strategy selection learning components.

2.1. Analysis of Critical Modules for Constructing an Gas Supplier Intelligent Agents

Previous studies on quoting curve construction can be broadly categorized into two groups: one involves using a linear function (aP+b) as the quoting curve, where different values of a or b are employed to establish the quoting strategy space; the other approach utilizes a step-type quoting curve, initially creating segmented quoting curves based on marginal cost and then generating the quoting strategy space by multiplying each segmented quoting curve by the same factor. Fundamentally, both methods construct the quoting strategy space in a similar manner.

The pricing strategy commonly adopted by natural gas suppliers is the economic retention strategy, which involves submitting high prices for the end portion of the capacity bid curve to achieve a bidding advantage[21-22], and submitting opportunity costs or marginal costs for the remaining capacity portion. The difference between pricing strategies lies in the proportion of high prices.The above two methods are evidently inadequate in describing genuine economic retention strategies. Theoretically, the traditional decision-making theory based on fully rational individuals in classical economics also struggles to depict the aforementioned economic retention behavior.

In the process of simulating market evolution, intelligent agents are required to re-evaluate and select new bidding strategies based on their learning from current and historical clearing results. In traditional RE, Q-learning, and EWA algorithms, the selection of new strategies is randomized across the entire set of alternative solutions according to learned probabilities. This approach may lead to significant differences between selected bidding strategies in consecutive rounds, which can be beneficial from an optimization standpoint for identifying a globally optimal equilibrium point. However, as rational decision-makers with bounded rationality, individuals typically do not make drastic changes to their bidding strategies but rather adjust them cautiously while gradually exploring the market. It is evident that the existing method for selecting new bidding strategies in the learning process fails to capture this bounded rational behavior. Consequently, the subsequent section proposes novel solutions addressing these two existing issues in research.

2.2. Building the Quoting Strategy Space Based on Multiple Mental Accounts

One of the primary challenges in agent simulation involves establishing an alternative strategy space that corresponds to real-world bidding decisions, enabling agents to make decisions during iterative simulations.

When employing economic retention strategies for bidding, the auction volume capacity is typically categorized into three parts. The first part (OA) usually represents the minimum output capacity of the unit, often reported as a single segment with a very low value (even a negative price floor), to ensure that this portion of gas volume is awarded during the clearing process and to mitigate potential losses for the gas supplier in case of unsuccessful bids. The second part (LA) generally comprises a larger capacity divided into multiple segments, each reporting its marginal cost, aiming to secure supply profits when gas prices exceed marginal costs and avoid losses when prices fall below marginal costs. The third part (HA) denotes the economic retention capacity, often represented as a single segment at a high price (even reaching the price ceiling), intended to further elevate prices through economic retention during periods of tight supply and generate supernormal profits while mitigating excessive retention costs by maintaining this portion of gas volume small or unawarded in normal clearing processes.

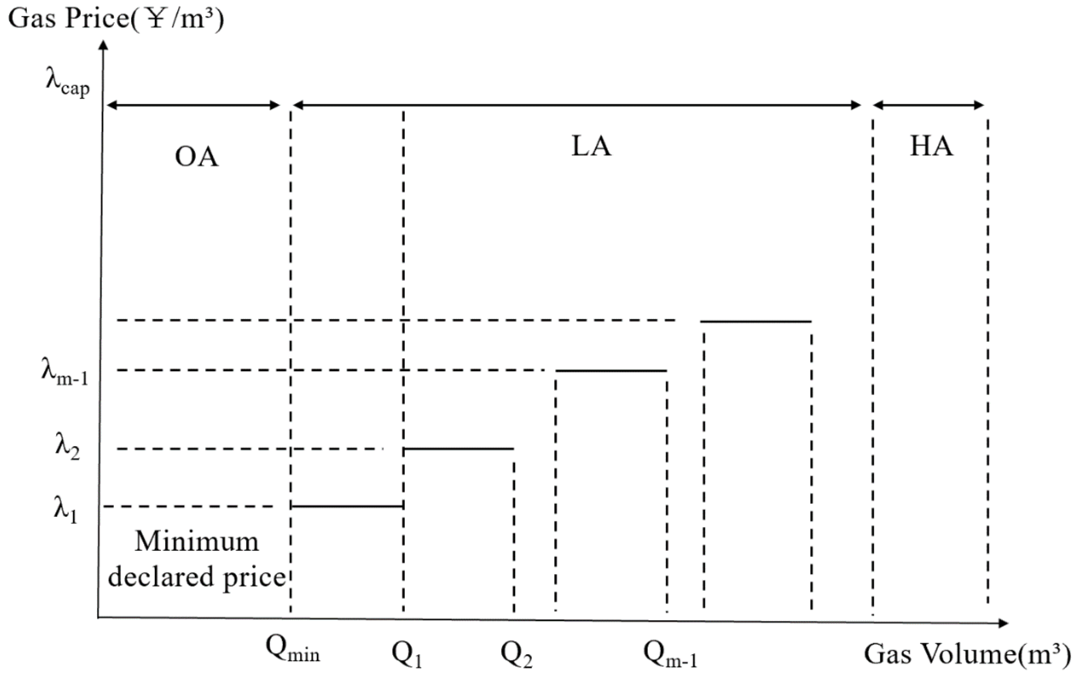

Figure 1: Segmented ladder bidding curve.

The natural gas suppliers have implemented a price-taker strategy (i.e., reporting opportunity costs or marginal costs) for the OA and LA capacity segments, while employing a price-setter strategy (i.e., reporting prices significantly above marginal costs) for the HA capacity segment.

Segmented differential quoting is a typical decision behavior stemming from the limited rationality of humans in highly uncertain environments. Balancing safety and potentiality in offers represents a common decision-making psychology. Behavioral economists have observed that due to individuals' inherent "limited rationality," characterized by restricted abilities to acquire, process, and judge information, cognitive biases are inevitable in their perception and assessment of market information; most individuals are conscious of their own cognitive limitations. Consequently, decision-makers naturally perceive the need for a low-risk protected safe portion within their asset portfolio and a risk-taking segment designed for wealth creation. This approach fulfills people's simultaneous requirements for safety and potentiality while mitigating risks arising from cognitive biases. The phenomenon of making distinct decisions on assets based on factors such as source, location, and use is referred to as the multi-mental accounting phenomenon. Within different mental accounts, individuals often adopt varying risk attitudes and decision strategies.

In the context of economic hedging strategies, natural gas suppliers allocate the OA and LA capacity segments to a safety account, thereby implementing a price acceptor strategy. Meanwhile, they assign the HA capacity segment to a speculative account, thus employing a price setter strategy. Essentially, economic hedging strategies involve natural gas suppliers partitioning the entire capacity into two distinct psychological accounts with different objectives and subsequently adopting varying risk attitudes and pricing strategies.

Based on the aforementioned analysis and empirical evidence from literature [11], economic holding behavior emerges as a prevalent pricing strategy frequently employed by gas power generation enterprises in their quoting decisions. Economic holding results in a substantial upward shift in the total supply curve, leading to a market clearing price that significantly surpasses the supplier's marginal cost during peak gas consumption periods.

After analyzing the above, it can be concluded that the economic retention strategy is a method through which gas enterprises acknowledge their own limited rationality and implement a "rational" pricing approach, widely utilized in their actual pricing decision-making process. To accurately simulate the genuine pricing behavior of gas enterprises within intelligent agent simulations, this section establishes a framework for pricing strategies tailored to limited-rational intelligent agents based on the pricing curve depicted in Figure 1. This framework can be acquired and employed by these intelligent agents.

Based on the segmentation of holding capacity in the aforementioned pricing curve, we can establish M+1 pricing strategies as outlined in Equation 1. Specifically, the 0th pricing strategy corresponds to a holding capacity of 0, indicating that all M segments are reported at marginal cost; the 1st pricing strategy pertains to a holding capacity corresponding to the last segment, while the remaining 1~M-1 segments are reported at marginal cost. This process continues iteratively, resulting in the construction of M+1 pricing strategies representing the strategy space for intelligent agent selection.

$$\boldsymbol{S} = \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ s_m \\ s_M \end{bmatrix} = \begin{bmatrix} \lambda_1 & \cdots & \lambda_M \\ \vdots & \ddots & \vdots \\ \lambda_{cap} & \cdots & \lambda_{cap} \end{bmatrix} \tag{1}$$

where S represents the strategy space of M + 1 bidding strategies; s_m represents the m-th bidding strategy, where the holding capacity is the last m periods, with $s_m \in$ S; $\lambda_1, \lambda_2 .. \lambda_M$. represents the marginal cost of each gas consumption segment; and λ_{cap} is the upper limit of the market price that the online transaction market allows bidders to submit.

3. Reinforcement learning model based on neighborhood searches

This paper is based on RE algorithm and EWA algorithm, and the quotation strategy space constructed in the above section is the research object. Under the premise that natural gas suppliers only have limited rationality, a risk-avoidance reinforcement learning model based on neighborhood search is constructed. The specific steps are as follows.

3.1. Set the initial tendency coefficient of each quotation strategy

When the clearing market price is the price ceiling, the gas profit of each strategy is taken as the initial tendency coefficient of each strategy, as shown in the following equation (2). Obviously, the larger the retention capacity of each strategy at this time, the smaller the profit of natural gas suppliers, the smaller the initial inclination coefficient, and the smaller the selection probability. The purpose of setting the initial propensity coefficient in this way is to simulate more cautious economic holding behavior by gas suppliers to test the market.

$$R_m(\mathrm{t}=0) = \lambda_{\mathrm{cap}}(Q_{\max} - \mathrm{m} \cdot \Delta\mathrm{Q}) - \mathrm{F}(Q_{\max} - \mathrm{m} \cdot \Delta\mathrm{Q}), \mathrm{m} = 0, \ldots, \mathrm{M} \tag{2}$$

Where: R_m is the initial tendency coefficient of the M-th bidding strategy of the gas supplier; t=0 means initial; $Q_{\max}$ is the maximum pipeline constraint of gas supplier. $\Delta\mathrm{Q}$ is the size of the capacity segment; $\mathrm{m}\cdot\Delta\mathrm{Q}$ is the retention capacity under this strategy. $Q_{\max}-\mathrm{m}\cdot\Delta\mathrm{Q}$ is the winning capacity under this strategy. $\mathrm{F}(Q_{\max}-\mathrm{m}\cdot\Delta\mathrm{Q})$ represents the gas cost at this selected capacity.

3.2. Set the initial tendency coefficient of each quotation strategy

Typical correlation analysis allows the study of the linear correlation between the column vectors of two matrices themselves. And the method is not limited to the analysis of the correlation between individual vectors, but extends the analysis to two sets of variables, each containing a number of vectors.

In theory, the selection of the initial quotation strategy can be made in many ways, such as setting the selection probability according to the initial inclination coefficient as the traditional learning algorithm, and then making random selection according to the probability. It can also be an artificial initial pricing strategy.

3.3. Learning from market clearing results

The natural gas supplier intelligent agent will submit the quotation curve corresponding to the selected quotation strategy to the market for online transaction market clearance, and calculate the profit according to the winning result. The formula for calculating the profit of gas suppliers is as follows:

$$\pi(t)=Q(t)\alpha(t)-F[Q(t)] \tag{3}$$

Where: $\pi(t)$ is the profit of the gas supplier when the t round market is cleared; $\alpha(t)$ is the system marginal gas price of the T-round clearance; $Q(t)$is the t round actual bid gas consumption of the suppliers; $F[Q(t)]$ is the operating cost corresponding to the bid for gas consumption by the round t gas supplier. Then the agents corrects the propensity coefficient of each quotation strategy based on the resulting profit.

$$R_m(t)=\begin{cases}(1-f)R_{m_w}(t-1)+e_w\pi_m(t-1) \\ \qquad m=m_w \\ (1-f)R_m(t-1)+e_1\pi_m(t-1) \\ \qquad m\neq m_w\end{cases} \tag{4}$$

Where: $R_m(t)$ is the tendency coefficient of the m bidding strategy of the natural gas supplier in the t round; m_w is the selected bidding strategy; f is the empirical forgetting parameter; we encourage metrics for successful experiences; e_1 indicates the encouraged parameter of failure experience. Among them, the first formula represents the correction of the selected quotation strategy, and the second formula represents the correction of the unselected quotation strategy.

Then, the selection probability of each quotation strategy is calculated according to the inclination coefficient obtained from equation (4).

$$C_m(t)=\frac{e^{Rm(t)/c}}{\sum_{m=0}^{M+1}e^{Rm(t)/c}} \tag{5}$$

Where, $C_m(t)$ is the selection probability of the m-th bidding strategy of the natural gas supplier in the t-th round of bidding; c is the preference coefficient, which determines the degree of influence of the initial propensity coefficient on the probability coefficient.

After obtaining the selection probability of each quotation strategy shown in equation (5), the traditional method generally selects a new quotation strategy randomly among all M+1 quotation strategies according to the probability to enter the next round of clearing.

However, in the actual quotation decision, the random selection of the quotation strategy is likely to lead to the new selection of the strategy and the current strategy is very different, it is likely to lead to a large change in profits, which is different from the normal decision-making constantly small adjustments to gradually test the market practice. To solve this problem, this paper proposes a selection method for selecting a new bidding strategy within the field of the current strategy, that is, if the current strategy is m, the new strategy will be randomly selected within the three strategies M-1, m, and m +1 according to the selection probability, as shown in Formula (6) below.

$$S(t) = \begin{cases} \{S_m, S_{m+1}\}, \quad m = 0 \\ \{S_{m-1}, S_m, S_{m+1}\}, m \neq 0, m \neq M \\ \{S_{m-1}, S_m\}, \quad m = M \end{cases} \tag{6}$$

Where, $S(t)$ is the domain quotation strategy space of the supplier's round t quotation; S_m is the quotation policy selected in the previous round. S_{m-1} and S_{m+1} are the bidding policies adjacent to S_m. After the domain policy space is determined, the selection probability of all bidding strategies in the neighborhood is normalized to select a new bidding strategy. The normalized probability model is as follows:

$$C_m^1(t) = \frac{C_m(t)}{\sum_{m-1}^{m+1} C_m(t)} \tag{7}$$

Where $C_m^1(t)$ is the probability after the normalization of each quotation strategy in the domain quotation strategy space during the unit's round t quotation, and the upper corner mark 1 represents the normalization.

Finally, the selection probability after normalization is used to judge whether the agent's bidding decision-making behavior reaches convergence. If the selection probability of a certain bidding strategy exists in all agents in the system is greater than the convergence coefficient, it is considered convergence. If it does not converge, it is randomly selected as a new quotation strategy in the domain space according to the selection probability, and it returns to step (3) to continue iteration until convergence. The convergence determination formula as follows, where δ is a given convergence precision.

$$C_m^1(t) \geq \delta, \quad s_m \epsilon S \tag{8}$$

3.4. Example simulation and analysis

In the parameters of the gas supplier agent, set the preference coefficient c to 2000, the experience forgetting parameter f to 0.03, the success experience encouragement parameter we to 0.95, the failure experience encouragement parameter e_1 to 0.95, the convergence accuracy δ to 99%, and the maximum number of simulation rounds to 2000. If more than 2000 iterations do not converge, the experiment is considered not convergent. As can be seen from Figure 2, the market clearing price fluctuated continuously in the first 170 rounds, gradually stabilized after 161 rounds, and finally converged to 2.946 ¥/m ^{3}after about 350 rounds of learning.

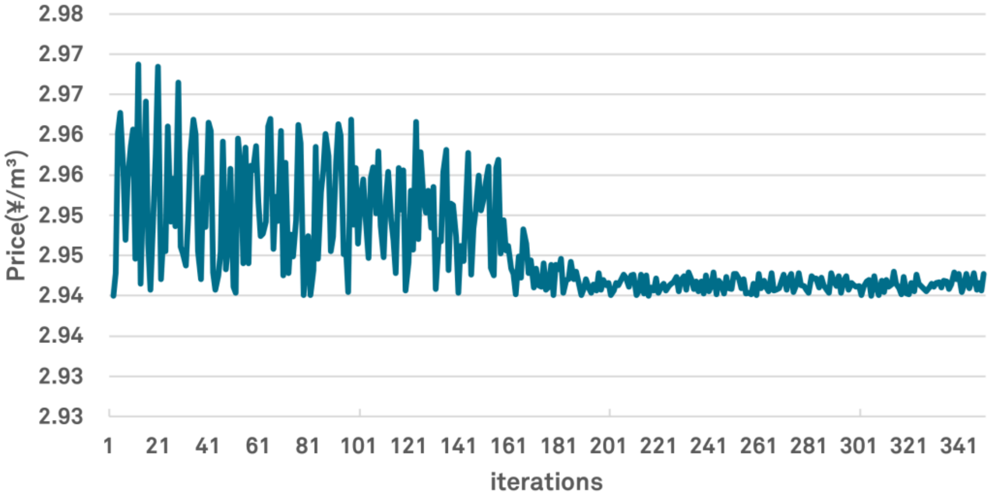

Figure 2: Market clearing price curve

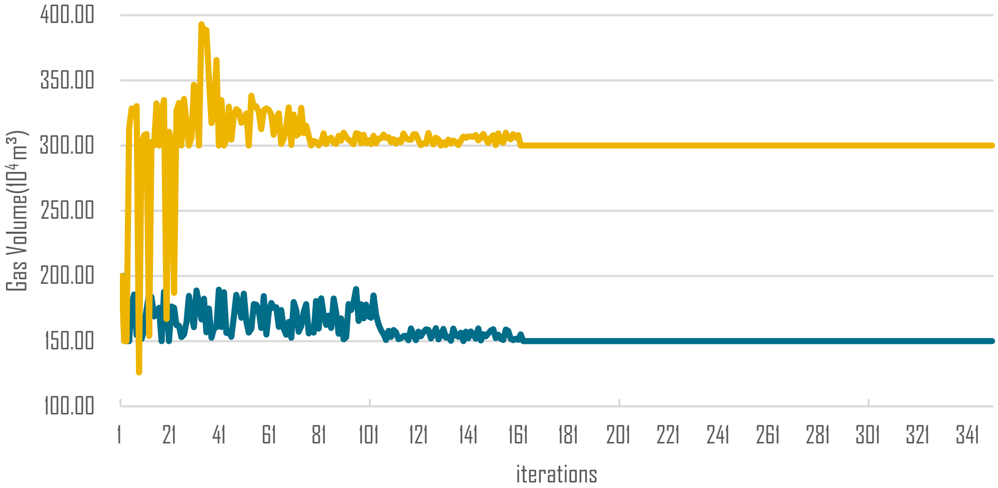

Figure 3: Gas consumption auction volume

Figure 3 shows the evolution process of the bidding game for a gas supplier with different costs. In the first 100 rounds of bidding, gas consumption enterprises with high cost have tried to reduce the holding capacity many times in order to increase the revenue by expanding the bid volume. However, due to the high cost, reducing the holding capacity will reduce the gas price but reduce the revenue, and finally convergence to the larger holding capacity strategy. Then, in the subsequent learning adjustment, the retention capacity is gradually reduced to increase the bid volume and increase the profit, and finally converges to a smaller retention capacity strategy. In the whole evolution process of the game, enterprises with small gas supply cost have less retention and low cost, so the initial bid power is high. In the first 95 rounds, enterprises constantly try to improve the economic retention capacity, expecting to reduce the market price to obtain excess returns. However, the increase of economic retention will lead to the reduction of the bid capacity, but the profit reduced.

4. Conclusions

In order to make the simulation results of spot market clearing based on multi-agents more consistent with the real market phenomenon, and fully consider the finite rationality of human as the decision maker, a natural gas supplier agent quotation model with finite rationality characteristics is constructed, including: the quotation strategy space model based on multi-psychological accounts and the reinforcement learning model based on the domain search of strategy space. Theoretical analysis and simulation results show that:

1) Economic retention strategy is a quotation strategy commonly adopted by natural gas suppliers. Natural gas suppliers often bid high prices for the capacity segment with a low probability of winning the bid in history to carry out economic retention, so as to obtain higher expected retention income at a very low holding cost. The psychological essence of this phenomenon is multi-psychological accounts, that is, the natural gas supplier divides the entire capacity into two psychological accounts with different purposes, and puts the capacity segment that is often won into the safety account to declare the marginal cost, while the capacity segment that is not often won into the potential account to speculate through economic retention.

2) Due to the economic retention strategy of natural gas suppliers, the simulated market clearing price tends to converge to the upper price limit when the load is high and converge to the marginal cost of the system when the load is low.

3) When the overall market cost is high, even if the gas consumption is low, the market price will converge to the marginal cost, but there will still be some natural gas suppliers adopt the partial capacity continuity strategy, rather than the full use of marginal cost quotation. This is because the capacity held by natural gas suppliers is often those that cannot win the bid, the cost of holding is very low, and once other rivals also use the retention strategy to test the market, it will form a high price to obtain additional profits. This means that the market monopolized by large enterprises is more likely to reach tacit collusion with competitors to jointly push up market prices, but as gas consumption decreases, the probability of tacit collusion is gradually reduced.

4) Compared with the traditional method in the global space, the new method of selecting the new quotation strategy in the domain space during the learning process of the agent is more in line with the decision psychology of carefully adjusting the strategy and gradually testing the market when making decisions in the face of uncertainty, and will also lead to more stable market convergence.

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