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Output of Multi-intelligent Simulation Building Products Based on the Needs of Smart Cities

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Abstract: In the traditional market, the price of a product is mainly determined by the cost of the product itself and the relationship between supply and demand of the product in the market. Product price has always been an important link between producers and consumers. Compared with traditional products, construction products have distinctly different characteristics in terms of economy and technology. Therefore, this article adopts the multi-agent simulation model to study the output of construction products based on the needs of smart cities, and conducts advanced research on the pricing of construction products, which not only has very important academic value, but also has important practical significance. This paper uses Anylogic simulation software to define the attributes and behavior rules of the agent, abstract the agents in the system, define the attributes and behavior rules of the agent, combine the characteristics of the pricing of building products, and use the multi-agent modeling method for construction enterprises and consumption the person conducts multi-agent modeling. The test proves that when the initial price is equal to 12, no matter in the scale-free network or the small world network, no matter which pricing strategy the construction company adopts, when there are pirated products, the number of consumers using construction products is greater than when there is no piracy. This shows that the use of multi-intelligence simulation models to study the output of construction products can not only improve the product pricing level of construction companies, but also promote the vigorous development of my country's construction industry.

1. Introduction

Social development has entered the age of technology and efficiency. While the government and enterprises are overly pursuing efficiency in the process of economic construction, they ignore or even neglect the nature of social development. As a result, although the current urban construction is changing with each passing day, the level of urbanization is rapid. However, problems in urban development are frequent and serious. In particular, the output of multi-intelligence simulation building products cannot meet the needs of people at all, resulting in a significant decline in people’s happiness and satisfaction with urban life. Facing the current disconnect between high-level technology and low-quality public services, people can't help but think about how to better improve the output of multi-smart simulation building products. In this way, smart cities are ready to emerge and become the current stage that can improve services. A bright spot to meet the needs of the people.

In the environment of rapid economic development, the relationship between supply and demand of products on the market is not stable. At the same time, because construction products play an important role in the development of smart cities, the pricing strategy of construction products becomes more diversified and complicated. This is quite different from the traditional product pricing strategy based on cost. The pricing of construction products and what effective pricing strategy to adopt has become an urgent problem that construction product providers need to solve. Therefore, studying the pricing strategy of construction products is of great significance for guiding construction product manufacturers to formulate attractive pricing strategies.

In recent years, scholars at home and abroad have used mathematical modeling, computational economics, and other methods to study the pricing of construction products in terms of pricing, installation basis, consumer surplus, and social welfare, and have drawn corresponding research conclusions. Hashem I PROPOSED that accurate state estimation is the basis for the normal operation of the distribution network, and it has a essential position in the power system. Taking into account the complex and changeable state of the distribution network, according to the complementary theory of intelligent algorithms, a distribution network state estimation model based on the multi-intelligence optimization algorithm is constructed. Establish an objection function to describe state changes, use genetic algorithm to estimate the state, use ant colony algorithm to correct the state value of the distribution network, and conduct simulation tests through the network. The results show that the model can effectively integrate genetic algorithm and ant colony algorithm, effectively describe the characteristics of change, and help improve the estimation accuracy. The result is better than other estimation models, and the result can provide valuable information for allocation. However, his research did not clearly propose how to solve the optimal distribution network state estimation model [1]. Wang T uses an agent-based computational economics simulation method to simulate the video game console market composed of game console manufacturers, game software developers, and consumers, and explores the video game console market with indirect network effects. Research shows that due to the strong indirect network effects in the video game console market, game console manufacturers can gain more market share by adopting penetration pricing strategies. The experimental results lack more data to support whether penetration pricing strategies can gain more market share. Many market shares are still in doubt [2]. Menouar H used a two-period model to discuss the monopoly pricing of durable goods with network effects. The research shows that when the network effect of durable goods is weak, its monopoly pricing still satisfies the coarse dynamics, and monopolists lose some market power; when the network effect of durable goods is stronger, its monopoly pricing no longer satisfies the Coase dynamics. Monopoly companies can use penetration pricing strategies to ingest consumer surplus. When information products have network effects, they can give away low-end versions of information products for free to expand their network value and become information products. A basic strategy of the supplier, but his research has stricter assumptions on the diffusion network of network effect software products, which is quite different from the actual situation [3].

This article is going to study the pricing strategy of construction products. Pricing strategy is one of the important parts of organization theory. The pricing strategy of construction products is also an important part of construction industry and construction economics. The decision-making method of building product pricing is the focus of this article. The utility of building products increases with the increase in the number of adopters. In response to this situation, this article uses Anylogic simulation software to build a multi-agent model of building product pricing. Research on the pricing strategy adopted by construction companies to maximize profits, and how consumers can adjust their own reservation prices according to the status of other consumers. Therefore, the research on the pricing strategy of construction products has important theoretical value for enriching and developing the relevant theories of construction economics.

2. Output of Multi-intelligent Simulation Building Products

2.1. Consumer and Construction Product Enterprise Agent Behavior Rules

In diffusion, consumers may hold two attitudes of purchase and rejection. According to information processing theory, individual decision-making is mainly based on external environmental information, through their own thinking and judgment, and based on this, a conceptual model of consumer purchase and rejection decision-making behavior is constructed [4-5], as shown in Figure 1.

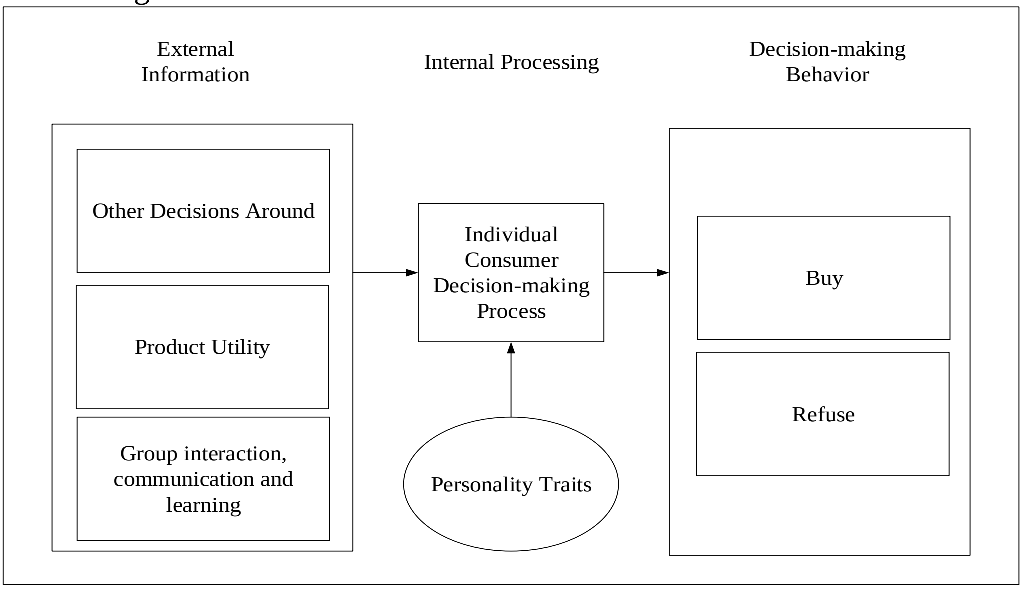

Figure 1: Conceptual model of consumer purchase and refusal decision behaviour

(1) Behavioral Rules of Building Product Enterprise Agent

The construction product enterprise collects statistics on the sales and profit data of construction products every certain period and decides the product sales price for the next period according to the analysis results of the previous period's sales volume and profit, as shown in Equation 1 [6].

$$P_{t+1} = P_t(1+\lambda_t) \tag{1}$$

Where λ_t is the product price adjustment factor.

When calculating the cost of a construction product company, only its operating costs are considered, including daily operating expenses such as employee wages, employee benefits, taxes, advertising costs, office space rent, etc. Therefore, the profit of the construction product company during each operating cycle is:

$$Z_t = Q_t * P_t - O_t \tag{2}$$

The total profit of the construction product company in the entire operating cycle is:

$$Z=\sum_{t=1}^{T}\left(Q_t*P_t-O_t\right)=\sum_{t=1}^{T}Z_t \tag{3}$$

1) Profit-based dynamic pricing strategy

$$\gamma_t=\begin{cases}0, & Z_t\geq Z_{t-1}\\ uniform(-0.032{,}0.032), & Z_t<Z_{t-1}\end{cases} \tag{4}$$

In Formula 4, when the current period's profit is greater than or equal to the previous period's profit, the construction product company will keep the next period's product price unchanged to seek a stable profit return, and the price adjustment factor is zero; when the current period's profit is less than the previous period's profit, the construction product company will change the next product price to increase profits [7-8].

2) Dynamic pricing strategy based on sales volume

$$\gamma_t=\begin{cases}0.05, & Q_t>Q_{t-1}\\ -0.05, & Q_t<Q_{t-1}\\ 0, & Q_t=Q_{t-1}\end{cases} \tag{5}$$

In Formula 5, when the sales volume of the current period is greater than the sales volume of the previous period, the construction product company will increase the price of the next period product to seek higher profits. When the sales volume of the current period is less than the sales volume of the previous period, the construction product company will reduce the price of the next period product to increase the sales volume. When the current sales volume is equal to the previous sales volume, the construction product company will keep the price of the next product unchanged [9-10].

3) Fixed pricing strategy

Fixed pricing strategy is one of the simplest pricing methods. No matter how the profit and sales change, construction product companies always sell construction products at the initial price.

(2) Consumer Agent Rules

When consumers are potential adopters of construction products, that is, when consumers are in a state of not purchasing construction products, the consumer’s reserved price is determined by the sum of the basic utility of the construction product and the network utility [11]; when the consumer is the adopter of construction products, that is, when consumers are in the state of buying construction products, consumers will not have the motivation and willingness to buy construction products. The formula for calculating the consumer reserve price is shown in Equation 6.

$$r_{i,t}=\begin{cases}d_i+n_, & S_i=SP\\ 0_, & S_i=SA\end{cases} \tag{6}$$

The utility n_i of a building product is determined by the characteristics of the building product and the number of consumers adopting the building product. The number of adopters has a greater impact on the utility of the building product. The calculation formula for the utility n_i of the building product is shown in Equation 7.

$$n_i=a+\theta*\sum h_i^a \tag{7}$$

In Equation 7, a represents the part of the utility determined by the characteristics of the building product. The utility of this type of building product will be greater than that of the general building product. h_i^a indicates that consumer i has adopted construction products, and θ is the impact factor.

This model assumes that there are N consumers in the market, and each consumer has complete information on the price of construction products. When the reservation price of the consumer is greater than or equal to the sales price of the construction product, the consumer will buy the construction product, and the potential, state of the adopter changes to the state of the adopter [12-13]; when the consumer's reserved price is less than the selling price of the building product, the consumer will not buy the building product, continue to wait and see the market, and the status remains as a potential adopter state, consumer agent behavior rules are shown in Equation 8.

$$Adopt = \begin{cases} Ture, & r_{i,t} \geq P_t \\ False, & r_{i,t} < P_t \end{cases} \tag{8}$$

Among them, adopt represents the decision-making behavior of consumer intelligence to purchase construction products. When the building product reaches its life cycle, the consumer agent in the adopter state will abandon the building product and change from the adopter state to the potential adopter state again [14].

2.2. Calculation of Evaluation Index Combination Weight Based on Entropy Method

(1) Analytic hierarchy process for weight

The traditional analytic hierarchy process usually uses the nine-scale method to determine the judgment matrix. When the scale is used to judge the relative importance of the indicators, it is difficult to make accurate judgments due to many choices. The traditional analytic hierarchy process still has a large amount of calculation, which is prone to errors and reduces the amount of calculation [15-16].

1) Build a hierarchical structure

The hierarchical structure includes the target layer, the criterion layer, and the indicator layer. In the new smart city evaluation problem, the first-level indicators in the evaluation index system are used as the target layer, and the second-level indicators and the third-level indicators are, respectively, used as the criterion layer and the indicator layer.

2) Construct comparison matrix

The elements in the comparison matrix reflect the relative importance of each index. The comparison matrix obtained by the three-scale method in this paper is A.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & a_{ij} & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{9}$$

Among them, a_{ij} represents the importance of the i index relative to the j index, and n is the order of the comparison matrix.

3) Calculate the ranking index

The ranking index can be obtained by calculating the comparison result of the i index and other indexes and summing them separately, denoted by h_i.

$$h_i = \sum_{j=1}^{n} a_{ij} \tag{10}$$

4) Construct a judgment matrix

According to the calculated ranking index h_i, the judgment matrix B is constructed. The element b_{ij} in the matrix B can be obtained by Formula 11:

$$b_{ij} = \frac{h_i - h_j}{h_{\max} - h_{\min}}(q-1)+1 \tag{11}$$

In Formula 11, $h_{\max} = \max(h_i)$, $h_{\min} = \min(h_i)$, $q = \frac{h_{\max}}{h_{\min}}$. Due to the complexity of the consistency test, the consistency test method has various defects. Now the weight value of the index is obtained by constructing the quasi-optimal matrix of the judgment matrix and solving its eigenvalues and eigenvectors [17].

5) Find the quasi-optimal matrix of the judgment matrix

Suppose the quasi-optimal matrix of the judgment matrix is B', then the element b_{ij}' in the matrix B' can be obtained by Formulas 12 and 13:

$$b_{ij} = 10^{c_{ij}} \tag{12}$$

$$c_{ij} = \frac{1}{n}\sum_{k=1}^{n} \lg \frac{b_{ik}}{b_{jk}} \tag{13}$$

The matrix C formed by c_{ij} is the optimal transfer matrix. Transform the standardized value of each evaluation index in the standardized matrix $Y = (x_{ij}')_{m\times n}$ to calculate the contribution Z_{ij} of the j index and the i evaluation object:

$$Z_{ij} = x_{ij}' / \sum_{i=1}^{m} x_{ij}' \tag{14}$$

Calculate the information entropy of each indicator:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} Z_{ij} \ln Z_{ij} \tag{15}$$

Among them, when defining $Z_{ij} = 0$, $Z_{ij} \ln Z_{ij} = 0$. Calculate information entropy redundancy:

$$d_j = 1 - e_j \tag{16}$$

Calculate indicator weight:

$$\omega = d_j / \sum_{j=1}^{n} d_j = (1-e_j)/(n - \sum_{j=1}^{n} e_j), j = 1,2,\cdots,n \tag{17}$$

2.3. Smart City Information Security Risk Identification

(1) Smart City Information Security Risk Subject

It is the responsibility of government departments to provide public services to the society. Our country's smart city construction is developing rapidly, and information technology has penetrated into all aspects of smart city construction. The government urgently needs to transform its functions to meet various challenges and improve government management and service capabilities. At the same time, in the process of building a smart city, the government should take the initiative to take the initiative, and various government departments should work together to build a smart city and build a modern Chinese city[18-19]. However, from the government's point of view, the relevant departments of smart cities should actively cooperate to avoid information islands, so as to realize the mutual sharing of data among various departments within the government, reduce the government's financial pressure, and improve the efficiency of administrative staff. Smart city construction is a large process involving all aspects of city construction. The role of enterprises related to smart city construction is the actual builder of smart cities, which can not only provide solutions for the government's smart city construction, but also manage and use smart city platforms. Therefore, the government should take the public as the starting point, break the division of administrative management, and follow the top-level design of the government to rationally guide enterprises in the development and construction of smart cities, ensure information security, effectively improve the public's lifestyle and living standards, and ensure that the public there is a better service experience [20-21].

(2) Information security risk manifestation of smart cities

The perception layer of the Internet of Things mainly obtains data at all levels of the city through various technologies, and is the primary link of the smart city technology system; the network communication layer is the channel for data transmission and an important neural network of the smart city, which mainly connects data. Disperse and isolate the data; the data and service support layer turns information into knowledge through high-level sharing, research, judgment, and analysis, which is the basic guarantee for providing smart services; the smart application layer integrates the above useful information and related emerging technologies to form a human-centered smart services are applied to various fields of smart cities [22-23]. In the perception layer of the Internet of Things, the smart city information system takes the Internet of Things as the core, realizes the perception of the city through sensor technology, and means and accesses a variety of external devices, regardless of the environment, quantity or method. Attackers can easily obtain smart city information security data by destroying or illegally manipulating sensing devices, leading to information leakage or information forgery and tampering, resulting in economic losses.

(3) Formation mechanism of public satisfaction with public information services in smart cities

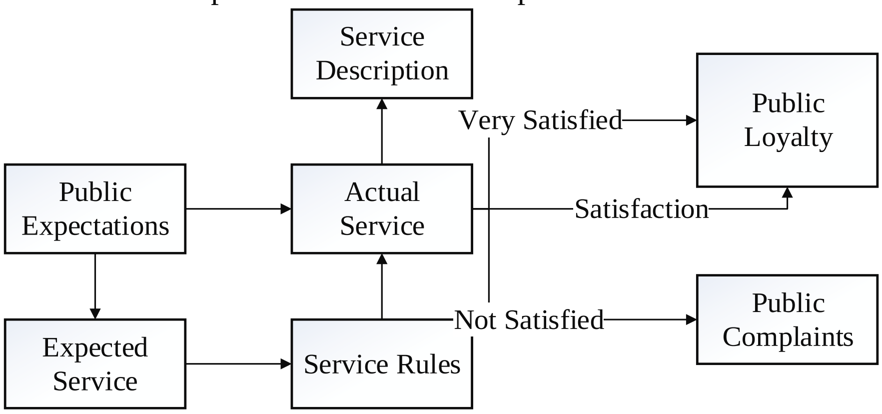

Figure 2: Diagram of the formation mechanism of smart city public information services

The initial goal of building a smart city and creating an information service system is to meet the public's demand for quality information services. When the public is evaluating public information services, the public will always expect to continuously improve public information services to meet their service needs. Therefore, the method of optimizing all services with quantitative cost is essential [24-25]. The general service management that adopts the gap nature in the research of public information services is also applicable. This is precisely because of the imaginary gap before and after the use of public information services, which makes the public have two attitudes of satisfaction and dissatisfaction with public information services, which together constitute the current formation mechanism of public information service satisfaction, as shown in Figure 2.

3. Experimental Design of Multi-intelligence Simulation Building Product Output

3.1. Design of Multi-Agent Model for Building Product Pricing

In the market, consumers have different preferences, and each consumer has its own reserved price for the construction product, that is, the highest price that each consumer is willing to pay for the construction product is different. Before purchasing a product, it is assumed that the consumer's reservation price is known. When the consumer's reservation price is higher than or equal to the selling price of the product, the consumer will buy the product. When the consumer's reservation price is lower than the product, if there is no piracy in the market, consumers will continue to wait and see the market, waiting for companies to reduce prices or carry out promotional activities before buying; if there is piracy in the market, consumers will buy or copy the pirates version with a certain probability for products, construction companies dynamically adjust product prices in a certain period to achieve their business goals. For the agent in the abstract system, we use Anylogic simulation software to define the agent’s attributes and behavior rules, abstract the agent in the system, define the agent’s attributes and behavior rules, combine the characteristics of building product pricing, and use multi-agent construction modeling method performs multi-agent modeling for construction companies and consumers.

3.2. Model Running Steps

According to the characteristics of construction product pricing, model assumptions, and the attributes and behavior rules of the aforementioned agents, the model operation steps are designed as follows:

Step 1: Initialize the parameters and variables used, including the initial attribute values of the construction enterprise agent and the consumer agent, and the initial price of the construction product;

Step 2: At the beginning of each operating cycle, each consumer agent in the state of a potential adopter decides whether to purchase the construction product according to its own reservation price and the current construction product price. When the reservation price of the consumer agent is greater than or equal to the price of the construction product, the consumer agent will purchase the construction product, and its state will change from the potential adopter state to the adopter state, and its reservation price will become zero; when the reservation price of the consumer agent is less than the price of the construction product, the consumer agent will not take any action, and its status is still a potential adopter. After all consumer agents used have completed the adoption decision-making behavior, the consumer agent that is still in the state of potential adopters will reset its own reservation price according to the number of neighbors in the state of adopters in its connected network. At the same time, the model will count the number of consumer agents using construction products in the period, that is, the sales volume of construction products.

Step 3: At the end of each operating cycle, the construction enterprise intelligent body will calculate the profit of the current period based on the sales and prices of construction products, and the operating cost of the current period, and make decisions based on the sum of the current profit and the previous profit and the consumer's reserved price sales price of construction products for the next period.

Step 4: During the operation of the model, when the construction product reaches its life cycle, the consumer agent in the adopter state will change the potential adoption state and obtain its reserve price.

Step 5: When the model running time reaches the end time, the model stops running, collects relevant statistical data, and analyzes the results.

3.3. Simulation Model Implementation

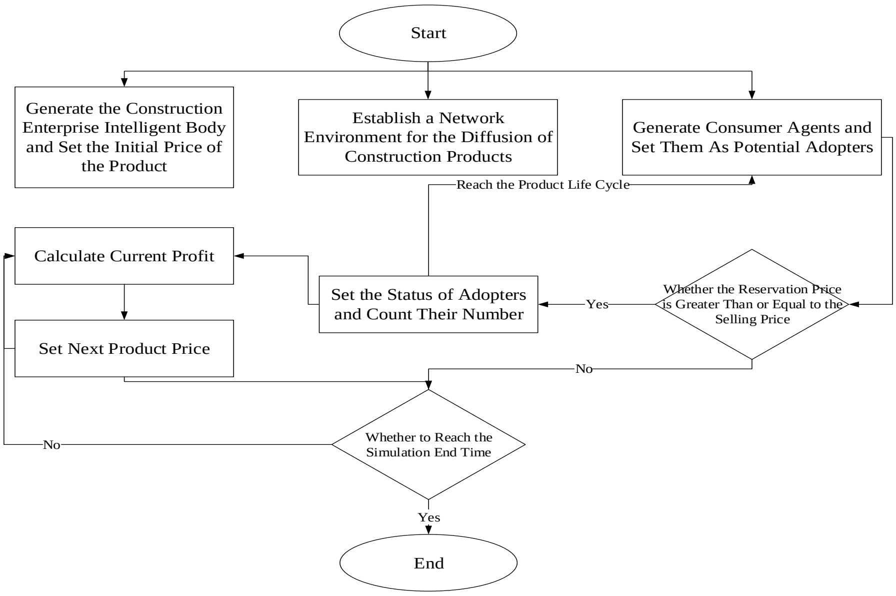

Figure 3: Simulation flow chart

According to the operating steps of the multi-agent model of building product pricing, combined with multi-agent modeling and simulation methods, the simulation process of the model is established. Before the simulation model starts to run, first generate the construction enterprise agent and the consumer agent, and set the initial price of the construction product and the initial state of the consumer agent. The initial state of the consumer agent is the state of potential adopters. Establish a diffusion network for construction products. The diffusion network is divided into two types: small-world networks and scale-free networks. After the simulation model starts to run, at the beginning of each operating cycle, the consumer agent judges whether to buy the building product based on the reserved price and the selling price. If the reserved price is greater than or equal to the selling price, the consumer agent will purchase the building product and the state changes, if it is the status of adopters and counts the number of adopters; if the reserved price is less than the selling price, the consumer agent will not take any action, and the status is still the status of potential adopters. At the end of each operating cycle, the construction enterprise agent calculates the current profit based on the number of adopters and the current product sales price, and sets the next product price. After reaching the product life cycle, the consumer agent in the adopter state will abandon the already adopted building products, and the state will change to the potential adopter state again. Check whether the simulation and time is reached. If the end time is not reached, continue the agent's decision-making behavior; if the simulation end time is reached, the simulation model stops running. The model simulation process is shown in Figure 3.

3.4. Simulation Model Organization Structure

In the simulation model, the organizational structure between the construction enterprise agent and the consumer agent is shown in Figure 4.

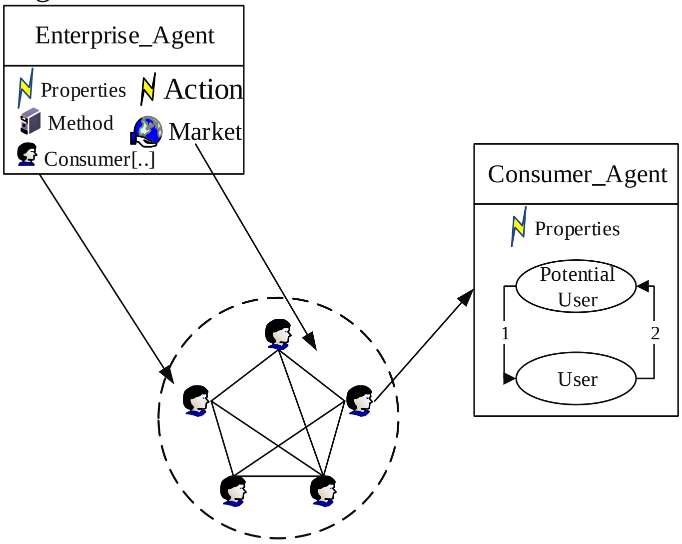

Figure 4: Simulation model organization chart

In Figure 4, the consumer agent is encapsulated in the construction enterprise agent. The blue villain represents the consumer agent, and the connection between the blue villains represents the connection network of the consumer agent, which is the diffusion network of construction products.

3.5. Statistical Data Processing Method

SPSS23.0 software was used for data processing, and the count data was expressed in percentage (%), k is the number of data in this experiment, σ^2 is the variance of all survey results, and P<0.05 indicates that the difference is statistically significant. The formula for calculating reliability is shown in Equation 18.

$$a = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma^2}\right) \tag{18}$$

4. Output of Multi-intelligent Simulation Building Products

4.1. Simulation Test

Before the start of the experiment, we set the consumer's intelligent body activity area to be 200*200 square area. The small gray dots are used to indicate consumer agents in the state of potential adopters, the small blue squares indicate consumer agents in the state of adopters, and the thin solid gray lines indicate the connection between consumer agents. Set the time unit of the simulation experiment to a week, and the simulation duration is 50 weeks. The result is shown in Figure 5.

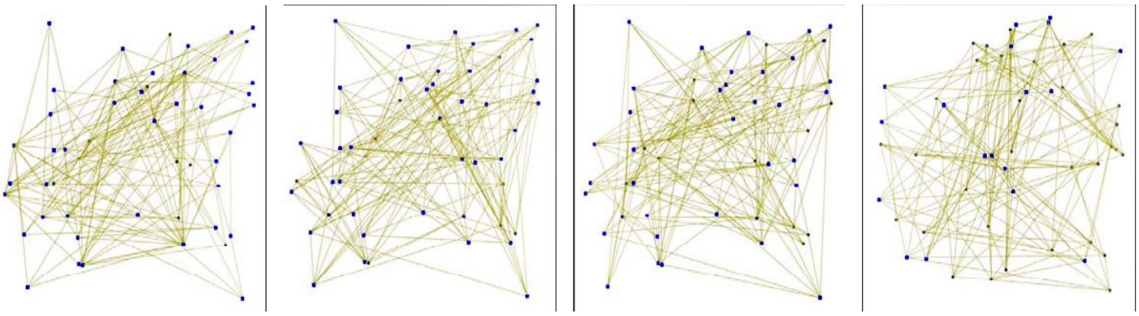

Figure 5: Simulation model runtime state

Figure 5 shows the runtime state of the simulation experiment containing 50 consumer agents, respectively, showing the runtime state of the simulation model under the scale-free network, small-world network, random network, and regular network.

4.2. Multi-Agent Model Analysis of Construction Product Pricing Piracy

(1) Analysis of the impact of diffusion network topology on pricing strategy

The same pricing strategy has different effects under different diffusion networks. Figure 6 shows the profit and sales volume of three different pricing strategies under scale-free network, small-world network, random network, and regular network.

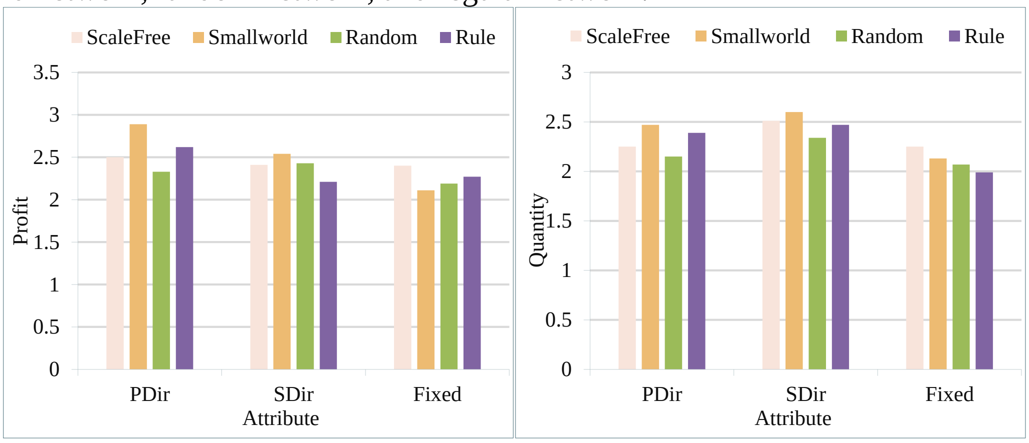

Figure 6: Profit and sales when the initial price is equal to 15

It can be seen from Figure 6 that when the initial price is fixed, the profit and sales volume of the dynamic pricing strategy based on profit and the dynamic pricing strategy based on sales volume in the small world network are higher than those in other networks, while the fixed pricing strategy is in the small world network. The profit and sales volume under the network are lower than those under other networks. At the same time, since the biggest feature of the scale-free network is that the node degree distribution is a power-law distribution, and the node degree distribution of the small-world network is Poisson distribution, the scale-free network and the small-world network are better than the analysis effect of the multi-intelligence simulation model. Random network and regular network.

Table 1 and Table 2, respectively, show the change trend of profit and sales in each period under the scale-free network and the small world network.

Table 1: Changes in profit per period under different diffusion networks

Period		0	20	40	60	80	100
	PDir	1.00	1.09	2.24	2.62	3.12	3.43
ScaleFree	SDir	1.00	1.07	2.02	2.49	2.77	2.83
	Fixed	5.00	1.33	2.42	2.79	3.02	3.37
	PDir	1.00	0.22	1.74	2.39	2.95	3.13
SmallWorld	SDir	1.00	0.20	2.53	2.74	2.86	2.99
	Fixed	5.00	0.05	1.78	2.69	3.11	3.52

Table 2: Changes in sales in each period under different diffusion networks

Period		0	20	40	60	80	100
	PDir	1750	1750	2500	2750	3000	3000
ScaleFree	SDir	1300	1500	2000	2500	2500	2500
	Fixed	5000	1250	2250	2500	3000	3000
	PDir	1750	1000	2500	2750	3000	3000
SmallWorld	SDir	1300	750	1750	2250	2500	2500
	Fixed	5000	750	1500	2500	3000	3000

It can be seen from Table 1 and Table 2 that in the early stage of the simulation model operation, the profits and sales volume of the three pricing strategies are in a declining stage; in the middle of the simulation model operation, the profits and sales volume of the three pricing strategies are in the rising stage, and the rate of increase gradually decrease, especially the change range of the dynamic pricing strategy based on sales volume has decreased more clearly; in the middle and late stages of the simulation model operation, the profits and sales volume of the three pricing strategies tend to a stable state; at the end of the simulation model operation, Under the scale-free network, the profit per period of the profit-based dynamic pricing strategy shows a slow upward trend, and the profit per period is greater than the other two fixed strategies, while the sales volume per period is in a steady state, and the sales volume per period is low in the other two pricing strategies; in the small world network, the profit per period of the fixed pricing strategy shows a slow upward trend, and the profit per period is greater than the other two fixed strategies; in the two diffusion networks, dynamic pricing based on sales volume the profit and sales volume of each period of the strategy fluctuates up and down, and the amplitude of the vibration decreases with the passage of simulation time. The average sales volume per period is greater than the other two pricing strategies.

(2) Analysis of the influence of initial price on pricing strategy

Figures 7 and 8 show the profit and sales volume of three different pricing strategies under the scale-free network and the small-world network, respectively.

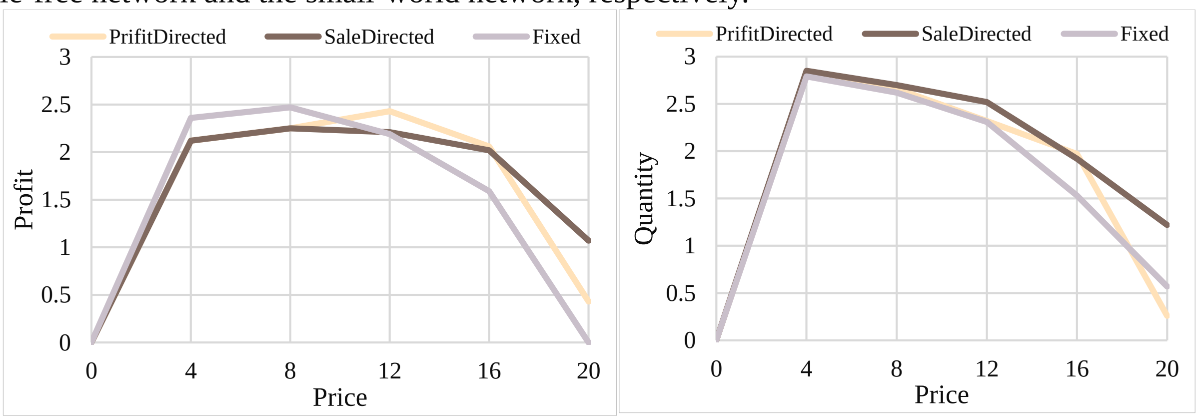

Figure 7: Profit and sales under the scale-free network

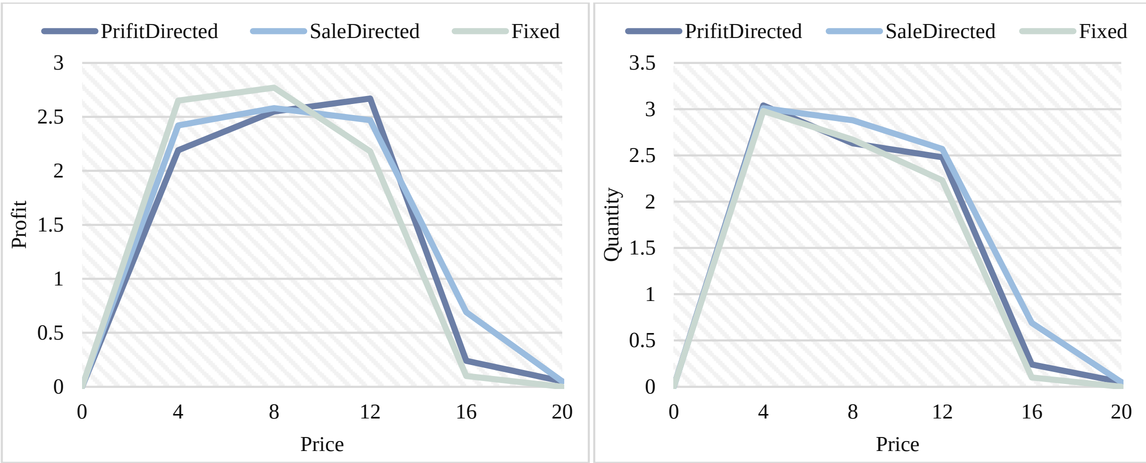

Figure 8: Profit and sales under the small world network

Figure 7 shows that, under the scale-free network, when the initial price is less than 12, the profit of the fixed pricing strategy is the largest and the sales volume is the smallest; when the initial price is between 12 and 16, the profit of the dynamic pricing strategy based on the profit is the largest, the sales volume is between the fixed pricing strategy and the sales-based dynamic pricing strategy. The fixed pricing strategy has the smallest profit and sales volume; when the initial price is between 16 and 20, the sales volume-based dynamic pricing strategy has the largest profit and sales volume..

Figure 8 shows that, under the small world network, when the initial price is less than 12, the profit of the fixed pricing strategy is the largest, and the sales volume of the three pricing strategies is basically the same; when the initial price is between 12 and 15, the profit-based profit of the dynamic pricing strategy is the largest, and the sales volume is between the fixed pricing strategy and the dynamic pricing strategy based on sales volume. The profit and sales volume of the fixed pricing strategy are the smallest; when the initial price is between 15 and 20, the dynamic pricing strategy based on sales volume, the profits and sales of the company are the largest, and the profits and sales of the fixed pricing strategy are the smallest.

4.3. Impact of Piracy on Pricing Strategy

Figure 9 and Figure 10, respectively, show the profit and sales volume of three different pricing strategies when there is piracy under the scale-free network and the small-world network.

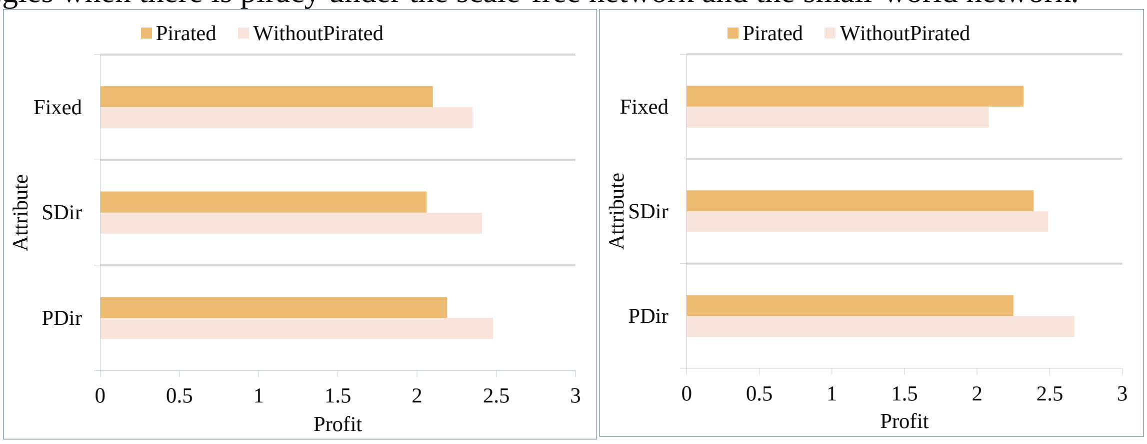

Figure 9: The impact of piracy on profits

It can be seen from Figure 9 that when the initial price is equal to 12, under the scale-free network, no matter what pricing strategy is adopted, the profit of the construction enterprise when there is piracy is less than the profit when there is no piracy; while under the small world network, when adopting a profit-based dynamic pricing strategy and a sales volume-based dynamic pricing strategy, the profit of the construction company when there is pirated products is less than the profit when there is no piracy. When using a fixed pricing strategy, the profit of the construction company when there is pirated product is greater than that when there is no piracy profit.

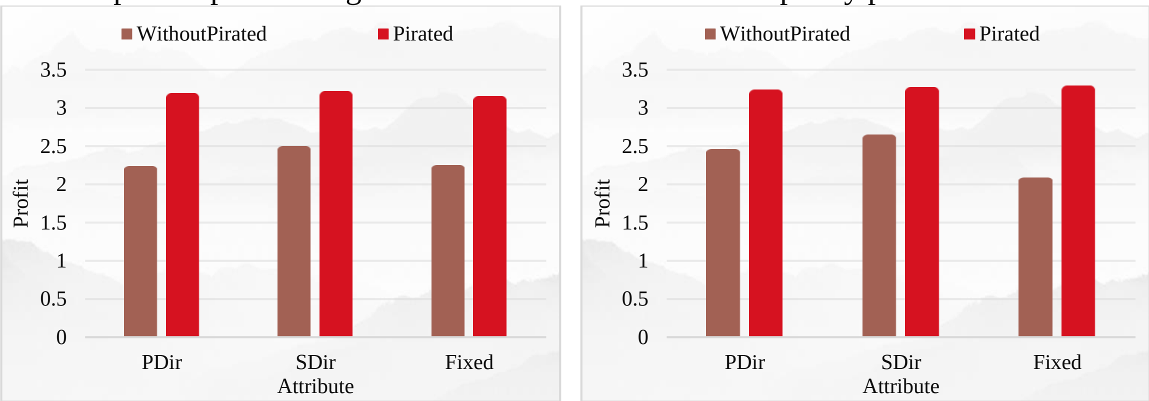

Figure 10: The impact of piracy on social welfare

It can be seen from Figure 10 that when the initial price is equal to 12, regardless of the scale-free network or the small-world network, no matter which pricing strategy the construction company adopts, when there are pirated products, the use of construction products (including genuine construction products and the number of consumers of pirated construction products is greater than the number of consumers when there is no piracy. It can be seen that piracy can increase social welfare.

5. Conclusions

Product price is a bridge between producers and consumers, a means to allocate social resources among different stakeholders, and is one of the core research contents of economics. Compared with traditional products, construction products have different characteristics in terms of economy and technology. The pricing theories and methods studied in the past are mainly aimed at the pricing of traditional products, and there is relatively little involved in the pricing of special products such as construction products. Research on the pricing of construction products not only has certain academic value, but also has great practical significance for improving the product pricing level of construction enterprises and promoting the vigorous development of my country's construction industry. This paper uses the multi-intelligence simulation model to study the output of construction products, uses Anylogic simulation software to realize the construction of the multi-agent model of construction product pricing, analyzes consumer market behavior rules and interaction methods, and proposes three different construction products for pricing strategy, different simulation experiments were designed, sensitivity analysis was conducted on the results of simulation experiments, and the initial pricing of construction products was studied through three design parameter optimization experiments, and the best initial values of the three pricing strategies were determined. Disadvantages: This article assumes that there is only one construction company in the entire market, which is somewhat different from the actual market environment. Future research work can introduce market competition mechanisms into the multi-agent model of building product pricing and study the pricing issues of construction companies in the presence of competitors.

References

[1] Hashem I A T, Chang V, Anuar N B, et al. The role of big data in smart city [J]. International Journal of Information Management, 2016, 36(5):748-758.
[2] Wang T, Bhuiyan M Z A, Wang G, et al. Big Data Reduction for a Smart City's Critical Infrastructural Health Monitoring [J]. IEEE Communications Magazine, 2018, 56(3):128-133.
[3] Menouar H, Guvenc I, Akkaya K, et al. UAV-Enabled Intelligent Transportation Systems for the Smart City: Applications and Challenges [J]. IEEE Communications Magazine, 2017, 55(3):22-28.
[4] Centenaro M, Vangelista L, Zanella A, et al. Long-range communications in unlicensed bands: the rising stars in the IoT and smart city scenarios [J]. IEEE Wireless Communications, 2016, 23(5):60-67.
[5] Rath M, Pati B. Communication Improvement and Traffic Control Based on V2I in Smart City Framework [J]. International Journal of Vehicular Telematics & Infotainment Systems, 2018, 2(1):18-33.
[6] Samee S, Vengatesan K, Bhaskar M S, et al. Smart City Automatic Garbage Collecting System for a Better Tomorrow [J]. International Journal of Pure and Applied Mathematics, 2017, 114(9):455-463.
[7] Gretzel Z C K U, Cacho, Andréa, Mendes-Filho L, et al. Mobile tourist guide supporting a smart city initiative: a Brazilian case study [J]. International Journal of Tourism Cities, 2016, 2(2):164-183.
[8] Kim, Kwi-Gon. Evolution of Climate Resilience and Low-Carbon Smart City Planning: A Process [J]. 2018, 10.1007/978-3-319-59618-1(Chapter 1):1-76.
[9] Burini F, Cortesi N, Gotti K, et al. The Urban Nexus Approach for Analyzing Mobility in the Smart City: Towards the Identification of City Users Networking [J]. Mobile Information Systems, 2018, 2018(PT.2):6294872.1-6294872.17.
[10] Sarma S, Sunny S A. Civic entrepreneurial ecosystems: Smart city emergence in Kansas City [J]. Business Horizons, 2017, 60(6):843-853.
[11] Kim H, Mokdad L, Ben-Othman J. Designing UAV Surveillance Frameworks for Smart City and Extensive Ocean with Differential Perspectives [J]. IEEE Communications Magazine, 2018, 56(4):98-104.
[12] Daely P T, Reda H T, Satrya G B, et al. Design of Smart LED Streetlight System for Smart City with Web-Based Management System [J]. IEEE Sensors Journal, 2017, 17(18):6100-6110.
[13] Joachim V D B, Viaene S, Scholl H J. Unveiling smart city implementation challenges: The case of Ghent [J]. Information Polity, 2016, 21(1):1-15.
[14] Liu X, Zeng Y, Zhang T, et al. Parallel Brain Simulator: A Multi-scale and Parallel Brain-Inspired Neural Network Modeling and Simulation Platform [J]. Cognitive Computation, 2016, 8(5):967-981.
[15] Reynaud Q, Sabouret N, Haradji Y, et al. Simulation de l'activité humaine Une étude sur le réalisme multi-niveau [J]. Revue d'Intelligence Artificielle, 2018, 32(2):137-137,197-221.
[16] S, Kara, W, et al. Economic and environmental value stream map (E~2VSM) simulation for multi-product manufacturing systems [J]. International journal of sustainable engineering, 2016, 9(6):354-362.
[17] Qi, Guo, Shumei, et al. Study on gradational optimization of oil reservoir streamline field based on an artificial intelligence algorithm [J]. Journal of Petroleum Exploration and Production Technologies, 2019, 9(2):1295–1306.
[18] Andersson, Staffan, Olofsson, et al. Calibration of low-rise multifamily residential simulation models using regressed estimations of transmission losses [J]. Journal of building performance simulation, 2016, 9(3/4):304-315.
[19] Bouguessa Beddar H, Saadia N, Mansour M. Energy control in a hybrid residential building using MAS: A case study in Algiers [J]. Journal of Ambient Intelligence and Smart Environments, 2018, 10(6):461-480.
[20] Groenewolt A, Schwinn T, Nguyen L, et al. An interactive agent-based framework for materialization-informed architectural design [J]. Swarm intelligence, 2018, 12(2):155-186.
[21] Steele R, Jaimes L G. Crowdsensing sub-populations in a region [J]. Journal of Ambient Intelligence & Humanized Computing, 2019, 10(4):1453-1462.
[22] Ma L. Construction of intelligent building sky-eye system based on multi-camera and speech recognition [J]. International journal of speech technology, 2020, 23(1):23-30.
[23] Wei-Chih, Wang, Tymur, et al. Conceptual cost estimations using neuro-fuzzy and multi-factor evaluation methods for building projects [J]. Journal of Civil Engineering and Management, 2017, 23(1):1-14.
[24] Mazuroski W, Berger J, Oliveira R C L F, et al. An artificial intelligence-based method to efficiently bring CFD to building simulation [J]. Journal of Building Performance Simulation, 2018, 11(5-6):1-16.
[25] Jalalimanesh A, Haghighi H S, Ahmadi A, et al. Multi-objective optimization of radiotherapy: distributed Q-learning and agent-based simulation[J]. Journal of Experimental & Theoretical Artificial Intelligence, 2017, 29(5):1071-1086.