The Principle of Administrative Law and Judicial Application Based on E-commerce Model

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Objectives: As a principle that controls the rational exercise of administrative power, the principle of proportionality is adopted by other legal systems because of its reasonable structure and effective control of administrative power. Methods: In this paper, in the information technology environment of mobile internet and based on the e-commerce model, the proportional principle of administrative law and its judicial application were studied. Results: Mainly the principle of proportionality in administrative law was introduced into the e-commerce negotiation system. A specific example in the context of e-commerce was selected to simulate the entire automatic negotiation process. Conclusion: The simulation experiment results were analyzed and summarized, which shows the advantages of the automatic negotiation mechanism proposed in this paper.

Key words: e-commerce; proportional principle; justice; security
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At present, with the rapid development of information technology centered on computer networks and the rapid spread of the Internet in the world, human society has entered the era of information networks. Due to its high efficiency, borderlessness, timelessness and low cost, e-commerce has been valued by governments and business circles around the world [1]. The emergence and expansion of e-commerce has not only triggered a broad and profound revolution in the field of human society and the legal system, but also brought opportunities and challenges to our society [2]. In order to comply with the changes of the times and promote the development of e-commerce, many policies and new laws are formulated by countries around the world and the international community [3]. However, the laws and regulations are complicated, by which, it is more complicated to be applied to the specific negotiation process [4]. Therefore, in this paper, based on Multi-Agent, an automated negotiation mechanism for electronic commerce which applies the principle of proportion in administrative law was developed.

E-commerce refers to commercial activities carried out by using various communication methods [5]. The impact and challenge of e-commerce on traditional legal rules are all-round, including private law issues such as civil and commercial law and economic law, as well as public law issues such as criminal law, procedural law and administrative law [6]. With the popularization of Internet technology and the development of e-commerce, the supervision of traditional network commodity quality and safety faces new problems and challenges. The severe network commodity security situation has caused serious damage and many potential threats to the health rights of large-scale online commodity consumers [7]. In-depth research on the regulatory issues in the special field of online commodity security regulation and the special regulatory body of third-party platforms for online commodity trading are rarely conducted by scholars [8]. Based on the principle of proportionality in administrative law, a learning mechanism is introduced in the process of generating automatic negotiation strategies to improve the efficiency of negotiation. A dynamic Q-learning algorithm that has been successfully applied in the robot soccer game (same as the multi-agent system field) is applied to the research background of this paper. In addition, the multi-attribute utility theory is used to evaluate the negotiation proposal, and the step of generating the proposed strategy based on dynamic Q-learning is given.

METHODS

Dynamic Q-learning Algorithm

The rapid spread of the Internet lies in its natural advantages. Firstly, the market is broader and Internet search is not affected by national borders. Secondly, the transaction is more convenient, which means that you can operate, buy, and pay online directly, anytime and anywhere. Besides, cashless payment can be realized. Thirdly, it is cheaper and does not require transportation to the designated location, and does not result in opportunity costs. Lastly, the price is more transparent, so don't worry about being cheated by the retailer. When searching for products in the search box, all seller information that sells the product will be displayed. At present, China's basic e-commerce model should be divided into several types of e-commerce models such as B2B, B2C, C2C, C2B and A2A. The most representative of these is the B2B and B2C modes. The picture below shows the development of China's representative B2C model, and various types of e-commerce are developing rapidly. Among them, the O2O model represents a very rapid growth of the take-out platform (Figure 1, Figure 2).

Figure 1
Chinese Internet Websites Monthly Monitor Chinese E-Commerce Websites Monthly Audience Arrival Rate Data Statistics

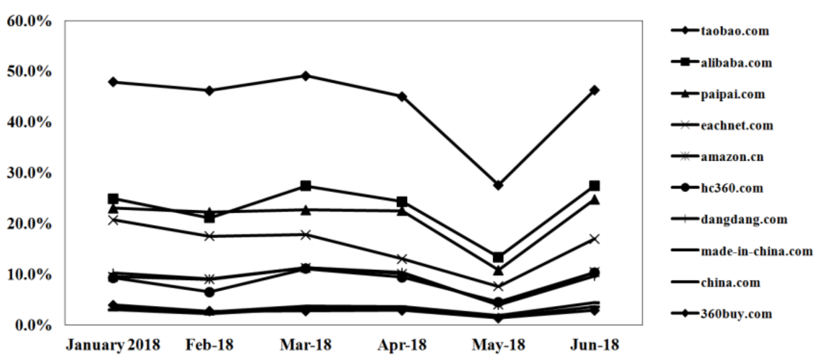
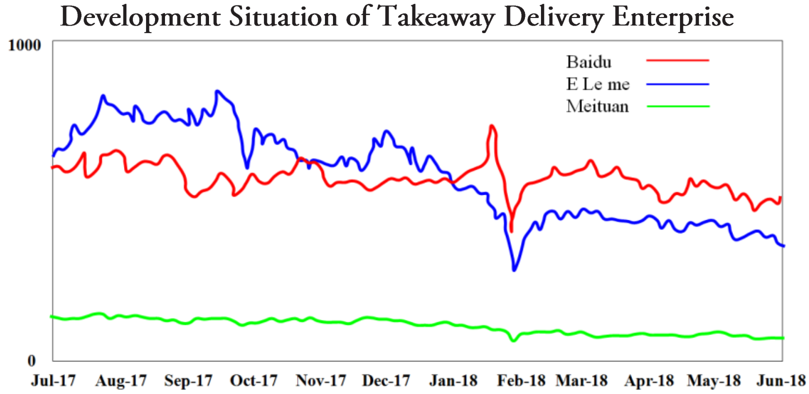


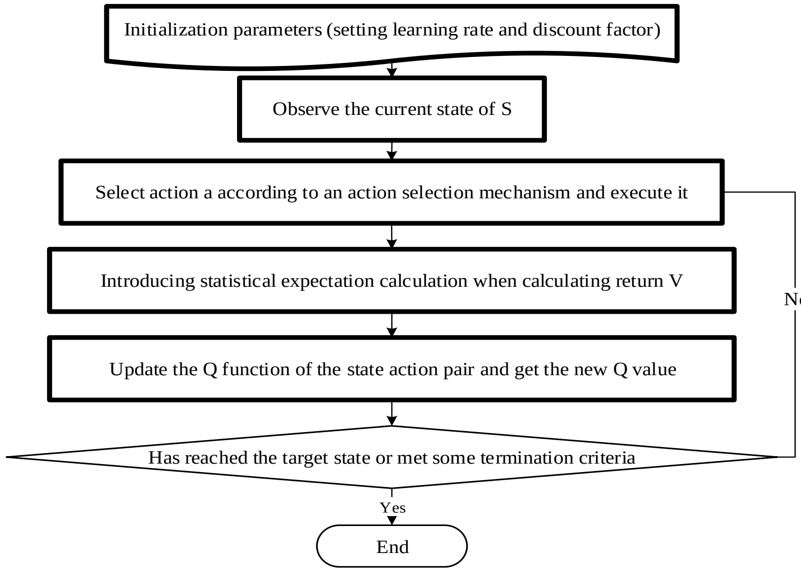
Figure 2
Development Situation of Takeaway Delivery Enterprise



In China, e-commerce is developing rapidly, it is necessary for the construction of administrative law system to be improved to ensure the healthy and sustainable development of e-commerce. However, the laws and regulations are complicated, by which it is more complicated to be applied to the specific negotiation process. Therefore, based on Multi-Agent and traditional Q-learning algorithm, an automated negotiation mechanism for electronic commerce which applies the principle of proportion in administrative law is developed. The traditional q-learning algorithm is based on the markov process model (MDP) [9]. In the Markov process model, the transformation of the environmental state does not change with time, but defined by the transition probability function [10]. Therefore, it is necessary to use dynamic Q-learning technology to solve the problems caused by environmental dynamic changes [11]. In the process of multi-agent automatic negotiation, multiple agents conduct learning activities, and each agent's behavior strategy changes according to the status of self-learning [12]. Since there are other agents in the environment, in this dynamic environment, the transition probability function will be changed with time [13]. In this case, the MDP model is no longer applicable. However, through the current research, many existing reinforcement learning algorithms applied to multi-agent systems are still based on the MDP model [14]. Although typical algorithms in reinforcement learning Q-learning and Bayesian learning methods or genetic algorithms are applied by some scholars, most of the improved algorithms are only suitable for learning in static environments [15]. The process of automatic negotiation is dynamic, so the improvement of the Q-learning algorithm should focus on adapting it to a dynamic negotiation environment [15]. By reading a large amount of literature, a dynamic Q-learning algorithm that has been successfully applied in robot soccer is selected and applied to the many-to-many attribute automatic negotiation. The reasons for the selection are as the follows. Firstly, the ultimate goal of the improvement of the Q-learning algorithm is to adapt it to a dynamically changing automated negotiation environment, which happens to be met by the dynamic Q-learning selected in this paper. Robot soccer is another research hotspot in the field of multi-agent. These two application backgrounds belong to the dynamic multi-agent system research field, and there are commonalities in the environment, so there is no need to worry about the inapplicability problem. Second, this algorithm has proven to be convergent. See the literature for a detailed algorithm for the proof of convergence.

In a multi-agent system, multiple agents will affect each other, which must be taken into account in the solution of multi-agent system problems. In the multi-agent system, the current environmental state has many influencing factors. In addition to the current state, the action of the Agent itself or other Agents will also cause changes in the environment. Because of the dynamic nature of multi-agent systems, MAS cannot be described by MDP. Therefore, traditional Q-learning based on MDP cannot be directly applied in multi-agent systems. In order to apply the Q-learning algorithm in the multi-agent system, the key is to improve the environment model that the traditional Q-learning depends on. Because the Agent's actions are applied to the environment, the Multi-Agent system loses its closure. The same function and state successor of the Q-learning algorithm in multi-agent can no longer be represented by $r(s,a)$ and $S' = \delta(S,a)$. Therefore, combined with statistical methods, the traditional Q-learning algorithm is improved by Guo Rui. By referring to the dynamic Q-learning algorithm proposed by him, this algorithm is applied to the field of automatic negotiation. In a multi-agent system, the process of transitioning the system from the current state to the next state is determined by the actions of the various agents in the MAS. The strategy of other agents is to learn the learning objectives of the Agent. If the strategy of other Agents is unknown, then the successor function can't be determined. In most cases, the behavior of other agents follows a certain strategy. And this strategy is a strategy that obeys a random behavior with a certain probability distribution. The basic flow of the dynamic Q-learning algorithm is shown in Figure 3:

Figure 3
Flow Chart of Dynamic Q- Learning Algorithm



Negotiation strategy generation based on dynamic Q-learning algorithm

In the early 1990s, relatively low-level development languages such as C++ and Java were used by users to develop complex system simulations. Due to the lack of a dedicated development platform, it is necessary for model developers to have high computer expertise and technology. In 1995, the Swarm platform was introduced, and since then, the complexity system simulation platform, which includes standard modeling frameworks and class libraries, has been continuously developed by professionals. In order to save the user's coding work, the platform internal function is allowed to be called, which pushes the agent-based complexity system simulation to another level and expands its application in various research fields. Swarm and LOGO are two representatives of a proprietary platform based on Agent modeling. Swarm only provides a dedicated class library during the modeling process, while the LOGO family provides users with a complete development environment, represented by StarLogo and NetLogo. NetLogo is originally launched by Uri Wilensky and is continuously developed by CCL. It is a programming language based on StarLogoT, but the user interface is redesigned and many new features are added. The early Logo language control turtles are insufficient, which is improved by NetLogo and the number of turtles controlled in the subject-based modeling is increased, reaching tens of thousands of scales. In order to control the behavior of individuals, it is necessary for researchers to issue instructions to a large number of independent entities (Agents), and then, it is possible for macroscopic models and micro-individual behavior to be connected.

NetLogo is a platform system that can run independently. It provides users with many libraries, which can be called at the time of encoding. The top left corner of the Run Interface customer area is three tabs, namely, Interface, Information, and Routines. Tabs can be switched between pages. In the automatic negotiation strategy generation process, when using the dynamic Q-learning algorithm, it is usually necessary to first consider how to determine the agent state space S, the action space set A of the agent, and the return value r of the environment feedback. The generation process of the negotiation strategy is shown by definition 1, definition 2 and definition 3. Definition 1: The proposal received by the definition agent is called s. As in formula (1), it can be thought of as an n-tuple:

$$s = (x_1, x_2, \dots x_j, \dots x_n) \quad (1)$$

In formula (1), $x_j^{'}$ represents the value of the negotiating attribute j of the item. The state space S is a collection of all s at different stages. The best strategy expected by the negotiating agent in the process of automatic negotiation is represented by s*. Definition 2: The current Agent changes or maintains the value of the negotiation attribute j is defined as the action of the Agent, represented by a. The essence of action a is the strategy currently adopted by the negotiation agent. A is a collection of all actions ^ of the negotiation agent. Definition 3: The return value during the negotiation process is defined as r:

$$r = \sum_{j \in J} w_i v(x_i) \quad (2)$$

$v(x_i)$ is used to represent the scoring function of the Agent negotiation attribute j value x_j (Mentioned in the automatic negotiation formalization model in Chapter 3). During the negotiation, the counteroffer sent by the negotiating party Agent to the negotiating party is made on the basis of the previous round of proposal made by the negotiation party Agent. Therefore, the negotiation function's scoring function $v(x_i)$ can be used to evaluate the attribute value given by the negotiating opponent Agent. The reward value is then determined by using the overall attribute evaluation value.

At the beginning of the learning behavior, through continuous trial and error, the action strategy is selected by the agent with learning behavior, and the behavior strategies of other agents in the MAS are learned and counted. Through continuous learning, agents with learning behaviors gradually recognize the behavior strategies of other agents, and their effective behavior strategies are gradually established. After many learning behaviors, the excessive change of other Agent behavior strategies in MAS is given a small probability of recognition, and the main learning energy should be placed on the large probability events in other previo us Agent behavior strategies.

In the process of automatic negotiation, the learning behavior is mainly reflected in the process of generating the negotiation strategy. The following is the step of generating the strategy of the negotiation agent in the negotiation. In the initialization phase, $\forall s \in S, \forall a \in A, Q_0(s,a) = 1, a_0 = 1, \gamma = 0.9$. In the stage state in which the agent conducts automatic negotiation, the current best behavior a is selected by the negotiating agent according to one's own preference. At this time, there are many optional policy action a of the agent. At the moment t in the negotiation, the environment changes to a new state s'. The action a_{other} sent by the other party's agent can be received by the negotiating agent. If the negotiating agent is satisfied with the proposal sent by the current negotiating party, the proposal is accepted. At this point, the proposal converges to the state s*. If not, proceed to the next round of negotiations, that is, go to step (2) to continue the negotiation process. The process of generating an automatic negotiation strategy for agents with learning behavior is mainly introduced, including the proposed utility evaluation mechanism, dynamic Q-learning algorithm and the generation process of negotiation proposals. The innovation lies in application innovation, and a dynamic Q-learning algorithm that has been proved to be convergent and effective by the algorithm is applied to the field of e-commerce automatic negotiation. The reason for choosing this algorithm is explained. The algorithm steps and applicability of dynamic Q filial piety are introduced. Finally, the flow of applying this algorithm in the process of automatic negotiation strategy generation is obtained.

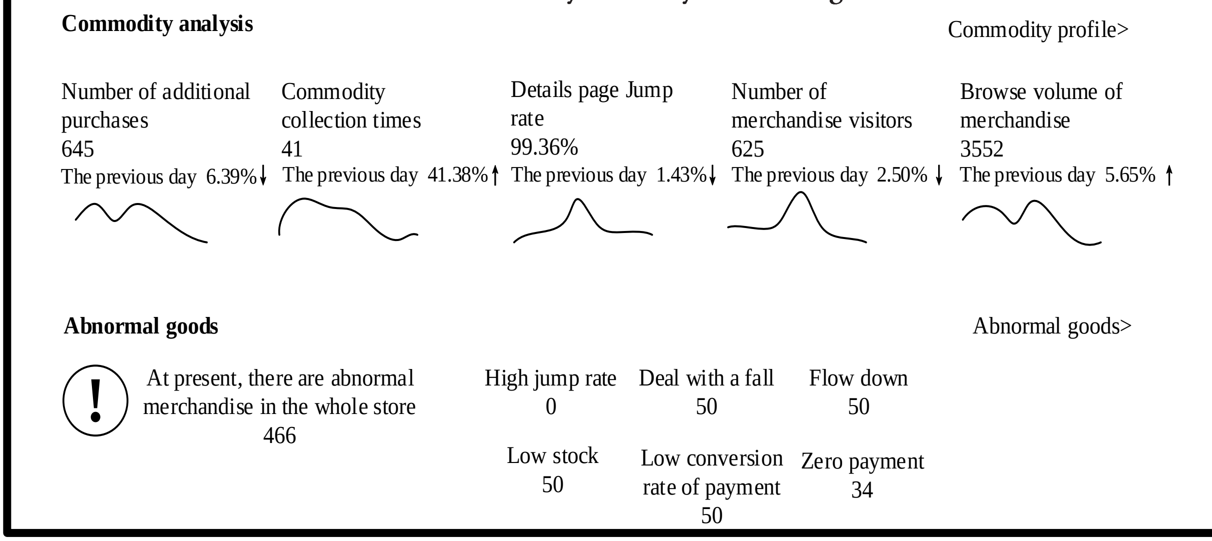
RESULTS

E-commerce Negotiation Background

E-commerce negotiation participants in the market include multiple buyer agents and multiple seller agents. The attributes of e-commerce negotiations include the price of goods, the quality of goods and services, and the characteristics of goods, which all have corresponding utility functions. At the same time, Agents involved in e-commerce negotiations have certain limits on the acceptable range of these three attribute values. The e-business negotiation strategy is that the buyer's agents and the seller's agents all adopt the dynamic q-learning algorithm mentioned in chapter 4 to produce the e-business negotiation strategy. In the process of e-commerce negotiation, the e-commerce negotiation proposal that is repeatedly exchanged is the action choice after the learning behavior. About the time, both parties to the e-commerce negotiation have their own e-commerce negotiation time limits.

In the experiment, a simulated distributed environment is built. Due to conditional restrictions, simulating multiple seller agents is done by only one computer, and multiple stores are registered with one IP address. The specific information of the store is shown below. For dynamic Q-learning, there are two experimental parameters that need to be set in advance. That is, the learning rate α and the discount value γ. In the process of exploring this paper, a large amount of information about learning algorithms is read. It can be concluded that the learning rate mainly affects the speed at which the e-commerce negotiation agent adapts to the environment. However, in practical applications, the speed cannot be pursued blindly. The combined effect of the final result of e-commerce negotiations should also be considered. Too fast e-commerce negotiations can lead to poor e-commerce negotiations. The learning rate taken in this trial is 0.5, by which can ensure that the e-commerce negotiation agent has a better response in the general dynamic e-commerce negotiation environment. At the same time, relatively good e-commerce negotiation results can be obtained.

Figure 4
Network Commodity Anomaly Monitoring Tool



The discount value mainly affects the convergence speed of the algorithm. The smaller the discount value, the faster the convergence of learning, and the faster the e-commerce negotiation ends. On the contrary, the greater the discount value, the e-commerce negotiation agent is more inclined to consider long-term benefits because it pays more attention to future benefits. In this case, a better e-commerce negotiation transaction can be better accomplished by the Agent. The convergence of learning is slower. In this paper, considering the speed of learning convergence and the effectiveness of the final e-commerce negotiation, the discount value was set to 0.9. Table 1 shows the e-commerce negotiation parameter settings of some agents in the simulation environment.

Table 1
Initial Settings for Negotiation Parameters

Negotiant participant	Negotiation attributes	Acceptance interval of attribute values	Initial proposed value	Attribute weight
Seller1	commodity price	50100	100	0.3
	Service quality	30-70	30	0.2
	Commodity characteristics	20-70	20	0.5
Seller2	commodity price	50-100	100	0.3
	Service quality	40-90	40	0.5
	Commodity characteristics	40-90	40	0.2
Seller3	commodity price	50-100	100	0.4
	Service quality	50-100	50	0.4
	Commodity characteristics	40-70	40	0.2
Buyer1	commodity price	40-65	40	0.2
	Service quality	40-70	70	0.6
	Commodity characteristics	35-60	60	0.2
Buyer2	commodity price	40-90	40	0.4
	Service quality	50-100	100	0.4
	Commodity characteristics	40-70	70	0.2
Buyer3	commodity price	20-80	20	0.1
	Service quality	60-100	100	0.4
	Commodity characteristics	70-100	100	0.5

Table 1
Initial Settings for Negotiation Parameters

E-commerce Negotiation Process and Experimental Results

The Agent e-commerce negotiation process with learning behavior and the Agent e-commerce negotiation process without learning behavior are simulated separately. The non-learning behavior e-commerce negotiation agent's proposal generation process is based on its own pre-set of the e-commerce negotiation attribute transaction value range. After the other party's proposal is received, it is compared with its own value range. If it reaches the satisfaction level of its own party, the other party's proposal is accepted and the e-commerce negotiation is ended. If not, some pre-set concessions are used to adjust their offer. The images of data clustering and classification in the experiment are as the follows:

Figure 5
Clustering Tool

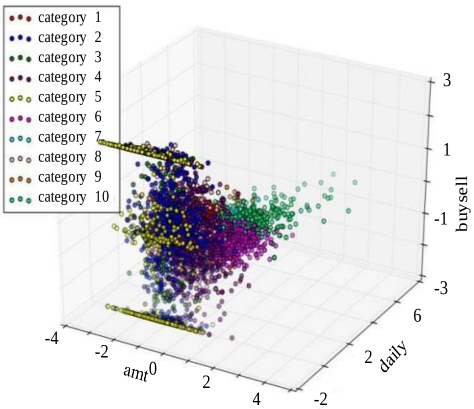
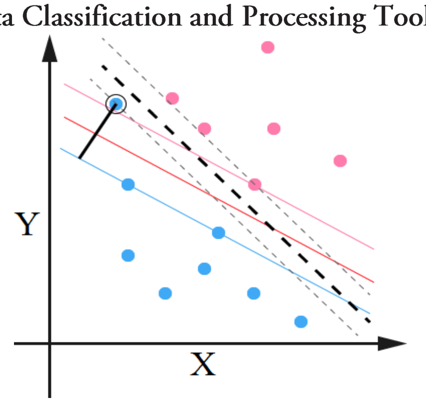
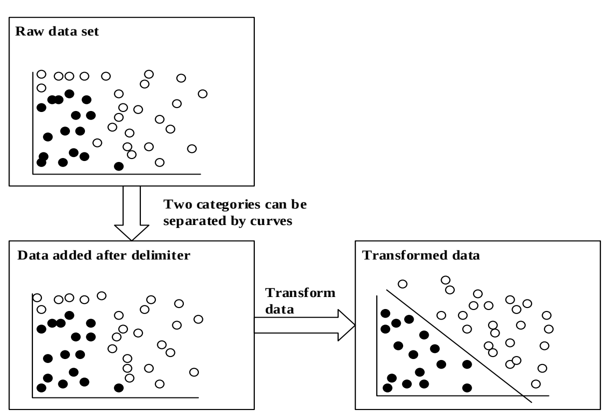


Figure 6
Data Classification and Processing Tools



Support vector machine



In the process of counter-proposal generation, the agent with learning behavior continuously uses the dynamic Q-learning method to learn the behavior of the other party, and then the original proposal is updated. The new counter-proposal is generated. The multi-attribute joint utility detailed in the previous section is used to calculate the utility of both parties. During the experimental run, the data is observed and recorded. In addition, buyerl and sellerl e-commerce negotiation process is analyzed in detail. After 14 interactions, the buyer agent with the learning behavior and the seller Agent (55, 56, 35) reached a deal. And the results of e-commerce negotiations are within the scope of acceptance of the attributes of the Agents. Therefore, the transaction is successful. When the experimental parameters are the same as the initial proposed values, the e-commerce negotiation process is recorded, and the number of e-commerce negotiations and utility are calculated. The joint utility of the buyer and seller who reached the transaction is calculated according to the method described in the previous section. Similarly, the utility calculation result of the e-commerce negotiation agent without learning behavior is 0.69. Thirty sets of experimental data are recorded separately, and the utility of each set of experiments is compared with the number of e-commerce negotiations when the transaction is concluded. The results are as shown in Table 2, Figure 7, Table 3, and Figure 8:

Table 2
Overall Utility Results

Number of experimental groups	Negotiation Agent has learning behavior.	Negotiation Agent no learning behavior
1	0.75	0.7
2	0.69	0.63
3	0.81	0.55
4	0.43	0.39
5	0.51	0.52
6	0.77	0.49
7	0.61	0.49
8	0.85	0.66
9	0.41	0.43
10	0.33	0.29
11	0.73	0.59
12	0.55	0.53
13	0.76	0.71
14	0.39	0.33
15	0.82	0.75
16	0.67	0.58
17	0.62	0.59
18	0.5	0.63
19	0.77	0.66
20	0.66	0.44
21	0.52	0.48
22	0.72	0.56
23	0.58	0.25
24	0.76	0.43
25	0.35	0.2
26	0.73	0.46
27	0.69	0.55
28	0.62	0.45
29	0.44	0.39
30	0.52	0.48

Figure 7
Comparison of Overall Utility

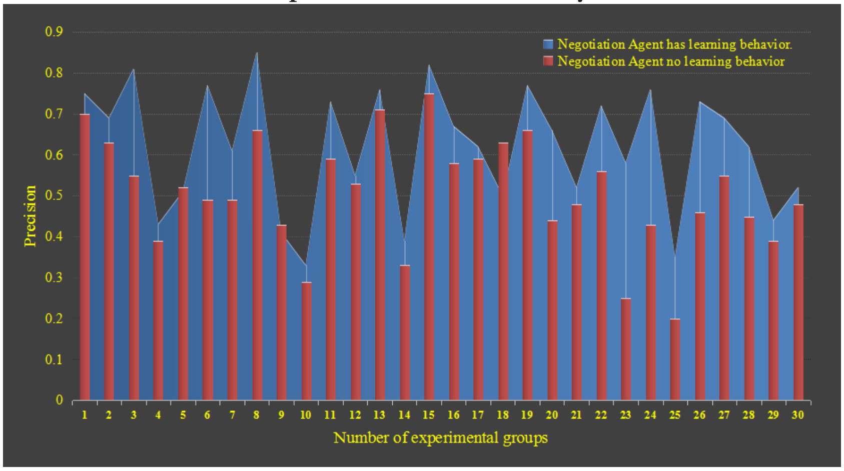


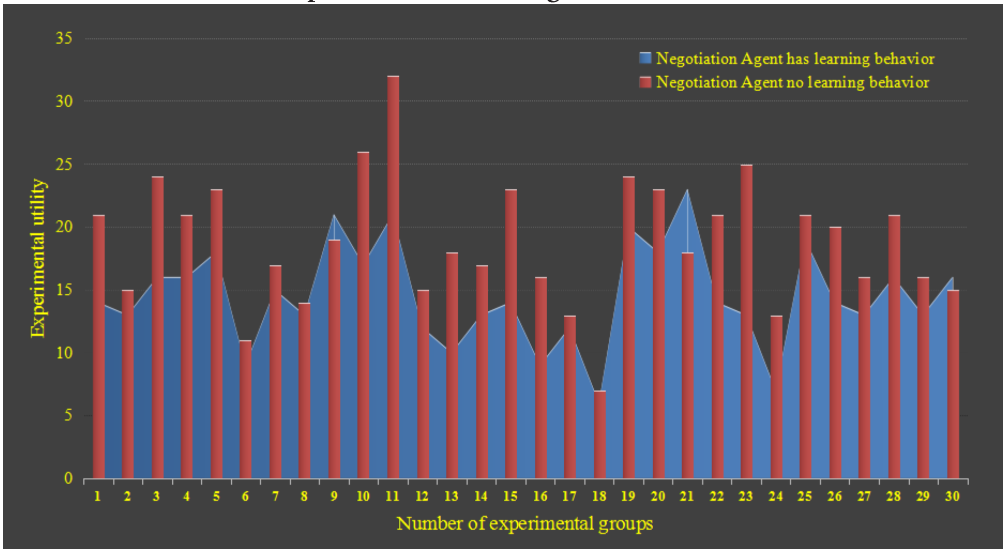
Table 3
Results of Negotiation

Number of experimental groups	Negotiation Agent has learning behavior	Negotiation Agent no learning behavior
1	14	21
2	13	15
3	16	24
4	16	21
5	18	23
6	9	11
7	15	17
8	13	14
9	21	19
10	17	26
11	21	32
12	12	15
13	10	18
14	13	17
15	14	23
16	9	16
17	12	13
18	6	7
19	20	24
20	18	23
21	23	18

Table 3
Results of Negotiation

22	14	21
23	13	25
24	7	13
25	19	21
26	14	20
27	13	16
28	16	21
29	13	16
30	16	15

Figure 8
Comparison Chart of Negotiation Times



It can be seen from the experimental results that if each buyer Agent and each seller Agent involved in the negotiation do not learn during the negotiation process, although most of the negotiations can be concluded in the end, there are still too many rounds of negotiation, the negotiation efficiency is low, and the utility value of the negotiation result is relatively small. If the buyer agents and the seller agents involved in the negotiation are engaged in the negotiation, and the joint utility value of the result is relatively large, the number of negotiations in the transaction process is relatively small, which saves the negotiation time and improves the efficiency of automatic negotiation. This proves that the design of a series of automatic negotiation mechanisms proposed in this paper is feasible, and a better negotiation result can be obtained in a shorter time. A concrete example is simulated. According to the comparison of experimental results, it is concluded that the automatic negotiation mechanism can improve the overall effectiveness of the negotiation and reduce the number of negotiations. This proves that the mechanism proposed in this paper is feasible and relatively superior.

DISCUSSION

Based on the e-commerce model, the proportional principle of administrative law and its judicial application were studied. It is mainly to introduce the principle of proportionality in administrative law into a set of e-commerce negotiation system, and automatically negotiate many-to-many attributes as research objects. According to the characteristics of multi-attribute automatic negotiation, a formal model of multi-attribute automatic negotiation was proposed. Due to the intelligent, learning and other advantages of Agent, the classic contract network protocol was extended by using multi-agent technology in the automatic negotiation of e-commerce, and a negotiation protocol more suitable for learning multi-attribute automatic negotiation was designed. In the process of automatic negotiation, the Agent must abide by the action execution rules set in the agreement. The multi-attribute utility theory was used to evaluate the negotiation proposal, and the step of generating the proposed strategy based on dynamic Q-learning was obtained. Besides, multi-attribute utility theory was adopted to measure automated negotiation results. Through the analysis of simulation experiment results, while reducing the negotiation time, the overall effectiveness of the negotiation results can be improved by the learning-type automatic negotiation mechanism proposed in this paper.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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