

Research on Adaptive Concession Strategies in Argumentation-based Negotiation

Guorui Jiang

The Economics & Management School
Beijing University of Technology,
Beijing, China, 100124
e-mail: jiangr@bjut.edu.cn

Bo Hao

The Economics & Management School
Beijing University of Technology,
Beijing, China, 100124
e-mail: kujoir@emails.bjut.edu.cn

Abstract—The paper discusses an application of multi-agent based on theory of argumentation-based on negotiation, and provides adaptive concession strategy model for beginning a negotiation. Firstly, this paper defines hypotheses of model and a frame of negotiation based on argumentation. Secondly, for comparing purpose, two generating models of concession strategy are also studied as: model based on time constraint and model based on opposite's preferences, the process of demonstration and result of experiment has been shown that the latter designed by PSO-RBFNN (RBF Neural Network optimized by Particle Swarm Optimization) algorithm has better abilities of learning and reasoning, which is dominant strategy in bilateral negotiations, and has a certain feasibility and application value.

Keywords-Multi-Agent; Self-Learning; Argumentation-based Negotiation; Adaptive Concession Strategies.

I. INTRODUCTION

In the process of e-commerce industrialization, Multi-Agent technology is crucial to the big change of e-commerce, and negotiation as a process of dynamic interaction is considered to be an important factor in multi-agent system. At present, some researches in the technology of automated negotiation based on multi-agent have been pursued and some achievements have also been developed. These researches often have been made in many different aspects, which are the design and implementation of automated negotiation system, the model of negotiation support system and the key technologies in automated negotiation based on multi-agent, etc. In accordance with difference of research methods, three types of negotiation have been presented, which are the negotiation based game theory, the negotiation based on heuristic algorithm and the negotiation based on argumentation, respectively. In recent years, argumentation-based negotiation has been accepted as a promising alternative to game-theoretic or heuristic-based negotiation [1]. In a argumentation-based negotiation, the problem of conflict must be brought up because of the different beliefs between buyer and seller, so that one of the main goals of negotiation is to make one negotiator agent has the ability to infer opposite negotiator's thinking, and revise own belief through learning opposite's preferences during the process of interaction to avoid negative dialogue between both parties, which make agent be able to adjust

negotiation strategies to changing environment. Up to this point, the problem of adaptive strategy has become a new topic in the field of argumentation-based negotiation.

While many researchers had developed some achievements in the field of adaptive negotiation strategies, there are two main problems with current researches, which are largely based on on-line learning. Usually, the large numbers of negotiated transaction records in history are not used effectively. At the same time, the mechanism of argumentation are not fully introduced into current most adaptive negotiation strategies. Consequently, if a negotiator can offer a proposal with argumentation based on concession strategies according to opposite's preferences reasoned from negotiating records in history, then persuasiveness of the proposal will be improved and process of negotiation will be advanced effectively. In this paper, the generating model of concessional strategies in the argumentation-based negotiation is discussed. Firstly, the paper defines hypotheses of model and a frame of argumentation-based negotiation. Secondly, the model based on time constraint and model based on opposite's preferences are presented respectively, and the latter designed by PSO-RBFNN algorithm can be demonstrated to be dominant strategy in a negotiation. Finally, the model based on opposite's preferences which can be proved to have a certain feasibility and application value via experiment.

II. MODEL HYPOTHESES AND FRAMEWORK

The paper will conduct the research on adaptive concession strategies in argumentation-based negotiation based on the following hypotheses and framework.

A. Model Hypotheses

Hypothesis 1. Agent is completely selfish, i.e., agent will pursue individual maximum utility.

Hypothesis 2. Agent has limited rationality, i.e., agent can change the mental state of the other party through offering proposal with argumentation.

Hypothesis 3. Agent with incomplete information don't know the other Agent's preference information, i.e., one agent will can not directly control other agent unless through negotiating between both parties.

Hypothesis 4. Time is precious to both parties.

Hypothesis 5.The both negotiating parties are sincere to reach agreement through negotiations, that is to say there isn't deceit during negotiation process.

Hypothesis 6.The failure of the negotiation is the worst result of negotiations between both parties.

B. Framework

In the accordance with hypotheses above, a framework of bilateral multi-issue negotiation based on argumentation is constructed (see Figure 1), which make agents have ability of self-learning. For example, in a negotiation, if there is a obvious differences between information of buyer agent(a_i)'s order and expectation of seller agent(a_j) after the seller agent offers a proposal, then a_i asks a_j to accept the proposal, but a_j will can not accept it in order to keep individual utility at maximum. Meanwhile, intermediary agent can acquire a_i 's satisfaction degree of issue in the proposal through neural network module, and then the satisfaction degree will be transformed into the information that understood by a_j through the model of output processing. Further, a_j can acquire the preference condition of the buyer according to the received information, generate concessional strategy, and determine the content of argumentation to improve the persuasiveness of new proposal and advance the process of negotiation.

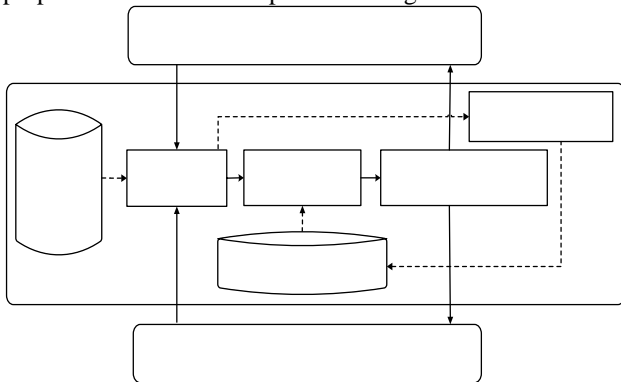


Figure 1. Framework of argumentation-based Negotiation where dotted line show the training process of network, and solid line show the reasoning process of network.

Negotiator Agent (Seller/Buyer Agent): During the process of negotiation, Negotiator Agent make seller and buyer acquire data information that reflect interaction event in negotiation, and carry out some action that affect the negotiation process.

Intermediary Agent: Intermediary Agent is introduced into this research in order to ensure authenticity of the interaction event and avoid fraud in negotiating environment, which make Negotiator Agent acquire more effective and operational information from Intermediary Agent compared with information obtained directly from the opposite negotiator.

Negotiation Case Base: This base is used for storing finished negotiating records in history, and Intermediary

Agent can take advantage of these records to learn negotiators' private information (e.g., preference) .

Knowledge Base: This base is used for storing negotiators' private information for different negotiating mission, in which one negotiating mission is stored for each record, and each record includes the important parameters needed by Neural Network Module.

Training and Learning Module: Finished negotiating records stored in Negotiation Case Base can be processed in this module. This processing is also the process of learning negotiators' private information to adjust the important parameters needed by Neural Network Module, and results will be put into Knowledge Base.

Neural Network Module: During the process of negotiation, Neural Network Module can obtain important parameters of neural network from Knowledge Base, and then reason negotiators' private information through processing input data information (have been pretreated through Pretreatment Module) from Negotiator Agent.

Pretreatment Module: The input data from Negotiation Case Base or Negotiator Agent can be normalized in this module so that input data fit the constraints of format required by Neural Network Module and Training and Learning Module.

Output Processing Module: Through this module, negotiators' private information reasoned by Neural Network Module will be transferred into the information easily unstandable for Negotiator Agent.

III. CONCESSION STRATEGIES IN ARGUMENTATION-BASED NEGOTIATION

Next this paper will discuss adaptive concession strategy model in argumentation-based negotiation.

A. Parameters Settings

1) Let $Ag\{a_1, a_2, a_3, \dots, a_t\}$ denotes negotiator agents vector, where a_t is the negotiator agents, t is the number of Agent, i.e., "t=2" denotes bilateral negotiation.

2) Let $r, r \in N$ denotes the current round of negotiation. Let R denotes time constraint of negotiation. One negotiator offer a proposal and the opposite offer a counter-proposal, or the one side agent only sends "Accept", which denotes completing a round of negotiation and then let $r = r + 1$. Let r_{end} denotes the total rounds of completed negotiation. Therefore the following conditions hold $0 \leq r \leq r_{end} \leq R$.

3) Let $Q = \langle q_s, q_x \rangle$ denotes the information of negotiating mission participated by both agents in a negotiation, where q_s consists of main information of negotiation mission, e.g., the name and identity of goods, etc. The elements in $q_x = \langle q_{x1}, q_{x2}, q_{x3}, \dots, q_{xu} \rangle$ denotes u issues of the goods involved in the negotiation.

4) Let $C(a_i, r, q_x) = \langle c(a_i, r, q_{x1}), c(a_i, r, q_{x2}), \dots, c(a_i, r, q_{xn}) \rangle, a_i \in Ag, 0 \leq r \leq r_{end}$ denotes the issues vector of Agent a_i in the (r)th round, where $c(a_i, r, q_{xu})$ denotes the value of issue.

5) Let $C_r(a_i, q_x) = C(a_i, r, q_x), a_i \in Ag, q_x \in Q, 0 \leq r \leq r_{end}$ denotes the vector of issues in current round of negotiation, where $c_r(a_i, q_{xu}) \in C_r(a_i, q_x)$ represents the current value of issue q_{xu} .

6) Let $C_{rend}^h(a_i, q_x) = C(a_i, r_{end}, h, q_x), a_i \in Ag, q_x \in Q, 0 \leq r_{end} \leq R, 1 \leq h \leq n$ denotes the vector of final deal agreed by both parties during the (h)th negotiated transaction in history, where n is the number of negotiated transaction about goods Q in history, and $c_{rend}^h(a_i, q_{xu}) \in C_{rend}^h(a_i, q_x)$ represents the final value of issue q_{xu} in the (h)th negotiated transaction in history.

B. Description of Definition

Definition 1(Satisfaction Degree). A contrast of buyer's feelings generated by purchasing a goods and their own expectation (preference), which is a relative concept. It can be used to assist the seller to investigate the match condition between seller's goods and buyer's expectation, and can also be quantized through reasoning in accordance with initial information of goods' issues. The range of satisfaction degree is $[0,1]$, and the greater value, the better degree of satisfaction.

Definition 2(Preference Coefficient). Representing a negotiator's favorable attitude toward negotiating goods. A negotiator can sort the important degree of negotiating issues in accordance with own expectation. The sorting order can reflect the needs, interests and hobbies of negotiators. The range of preferences coefficient is $[0,1]$, the greater value, the more important for negotiators.

The formal description of satisfaction degree and preferences coefficient is as follows.

1) Let $S(a_i, r^h, q_x) = \langle s(a_i, r^1, q_{x1}), s(a_i, r^2, q_{x2}), \dots, s(a_i, r^n, q_{xn}) \rangle, a_i \in Ag, h=1,2,\dots,n$ denotes the vector of satisfaction degree about single issue q_{xu} during the (h)th negotiated transaction in history, where n is the number of negotiated transaction about goods Q in history.

2) Let $s(a_i, r, q_{xu}), a_i \in Ag$ denotes the value of the satisfaction degree about issue q_{xu} in current round of negotiation.

3) Let $S(a_i, r^h, \sum q_{xu}) = \langle s(a_i, r^1, \sum q_{xu}), s(a_i, r^2, \sum q_{xu}), \dots, s(a_i, r^n, \sum q_{xu}) \rangle, a_i \in Ag, h=1,2,\dots,n$ denotes the vector of satisfaction degree about all issues $\sum q_{xu}$ during the (h)th negotiated transaction in history.

4) Let $s(a_i, r, \sum q_{xu}), a_i \in Ag$ denotes the value of the satisfaction degree about all issues $\sum q_{xu}$ in current round of negotiation.

5) Let $\alpha_{q_x} = \{\alpha_{q_{x1}}, \alpha_{q_{x2}}, \dots, \alpha_{q_{xn}}\}$ denotes the information of preferences about issue q_{xu} , where $\alpha_{q_{xu}}$ is the preference coefficient of issue q_{xu} , which is acquired through reasoning based on negotiated transaction records about issue q_{xu} in the past. $\alpha_{q_{x1}} < \alpha_{q_{x2}} < \dots < \alpha_{q_{xn}}$ can be explained that a negotiator agent will lay too much stress on the value of issue q_{xu} , while just the opposite for q_{x1} .

C. Concession Strategies

In a argumentation-based negotiation, no matter which form of argumentation (Reward, Threat, Defense) is presented [6], negotiator agent should consider to make concession on proposal at first. During the process of practical negotiation, a concession strategy based on time constraints may make negotiator loss opportunities for reaching an agreement because both sides are in a hurry to complete negotiation within the time constraint, while concession strategy based on opposite's preferences can help negotiator agent to have a definite object in view generate new proposal in accordance with the least action principle of belief revision, which will improve the efficiency of negotiation. This strategy is dominant strategy in a bilateral negotiation. By compared with concession strategy based on time constraint, the concession strategy based on opposite's preference has the high feasibility and application value. This conclusion will be formalized through the following propositions.

Under Hypothesis 1, agent will pursue individual maximum utility. The individual utility of a negotiator agent a_i in the r th round of negotiation is as follow,

$$U_r(a_i, q_x) = \sum U_r(a_i, q_{xu})$$

where $U_r(a_i, q_{xu})$ represents the utility what Agent a_i acquire from the value of issue q_{xu} .

But if take the inherent correlation between two issues into consideration (e.g., price and quality: the higher price, the better quality), then can be corrected through introducing a correlative coefficient as show below,

$$U_r(a_i, q_x) = \sum_{u \in K} U_r(a_i, q_{xu}) + \sum_{u \in G} U_r(a_i, q_{xu})(1 + \sum \eta)$$

where K is independent set of issues, G is the set of issues associated with other issues, η is the correlative coefficients. Besides, the utility value of single issue can be clarified as the following formula,

if the utility value of single issue increases with the increase of $c_r(a_i, q_{xu})$, then the formula is

$$U_r(a_i, q_{xu}) = (c_r(a_i, q_{xu}) - c^{\min}(a_i, q_{xu})) / (c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

if the utility value of single issue decreases with the increase of $c_r(a_i, q_{xu})$, then the formula is

$$U_r(a_i, q_{xu}) = (c^{\max}(a_i, q_{xu}) - c_r(a_i, q_{xu})) / (c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

where $c^{\min}(a_i, q_{xu})$ represents the minimum value of issue q_{xu} what agent a_i would accept, $c^{\max}(a_i, q_{xu})$ represents the maximum value of same issue what opposite negotiator agent would accept that is considered by agent a_i . Then the Lemma can be presented through analyzing as show below.

Lemma 1. In the generating models of concession strategy based on single time constraint, the individual utility value of agent ($U_r(a_i, q_x)$) will increase with the increase of the value of single issue ($U_r(a_i, q_{xu})$).

Proof. The following conditions hold in accordance with

$$\begin{aligned} U_r(a_i, q_x) &= f(U_r(a_i, q_{xu})|_{u \in K}, U_r(a_i, q_{xu})|_{u \in G}) \\ &= \sum_{u \in K} U_r(a_i, q_{xu}) + \sum_{u \in G} U_r(a_i, q_{xu}) (1 + \sum \eta) \\ &= \sum_{u \in K} U_r(a_i, q_{xu}) + \sum_{m=1}^u U_r(a_i, q_{xm}) + \sum_{m=1}^u \sum_{n \neq m} U_r(a_i, q_{xm}) U_r(a_i, q_{xn}) \eta_{mn} + \sum_{n=1}^u U_r(a_i, q_{xn}) \end{aligned}$$

Demanding $U_r(a_i, q_x)$ on the $U_r(a_i, q_{xu})|_{u \in K}, U_r(a_i, q_{xm})$ and $U_r(a_i, q_{xn})$ partial derivatives as follow,

$$\begin{aligned} \frac{\partial U_r(a_i, q_x)}{\partial U_r(a_i, q_{xu})|_{u \in K}} &= 1 > 0 \\ \frac{\partial U_r(a_i, q_x)}{\partial U_r(a_i, q_{xm})} &= 1 + \sum_{\substack{m=1 \\ n \neq m}} U_r(a_i, q_{xn}) \eta_{mn} > 0 \\ \frac{\partial U_r(a_i, q_x)}{\partial U_r(a_i, q_{xn})} &= \sum_{\substack{m=1 \\ n \neq m}} U_r(a_i, q_{xm}) \eta_{mn} + 1 > 0 \end{aligned}$$

therefore,

$$\begin{aligned} \frac{\partial f(U_r(a_i, q_{xu})|_{u \in K}, U_r(a_i, q_{xu})|_{u \in G})}{\partial U_r(a_i, q_{xu})|_{u \in K}} &> 0 \\ \frac{\partial f(U_r(a_i, q_{xu})|_{u \in K}, U_r(a_i, q_{xu})|_{u \in G})}{\partial U_r(a_i, q_{xu})|_{u \in G}} &> 0 \end{aligned}$$

The process above indicates the individual utility function ($f(U_r(a_i, q_{xu})|_{u \in K}, U_r(a_i, q_{xu})|_{u \in G})$) is a increasing function for $U_r(a_i, q_{xu})$, i.e., $U_r(a_i, q_x)$ will increase with the increase of $U_r(a_i, q_{xu})$. Proof finished.

Further, the following proposition hold in accordance with and .

Proposition 1. At the beginning of a negotiation, the initial proposal given by a negotiator agent is the proposal that make the individual utility value of negotiator reach maximum. The initial proposal is the following,

if the utility value of single issue increases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r=1}(a_i, q_{xu}) = c^{\max}(a_i, q_{xu})$$

if the utility value of single issue decreases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r=1}(a_i, q_{xu}) = c^{\min}(a_i, q_{xu})$$

Proof. Under Hypothesis 1, negotiator agent will pursue individual maximum utility. In the generating models of concession strategy based on single time constraint, the individual utility value of a negotiator agent is relevant to the current round of negotiation and the value of issue q_{xu} . Obviously, at the beginning of negotiation, if let

$$c_{r=1}(a_i, q_{xu}) = \begin{cases} c^{\max}(a_i, q_{xu}), & \text{Utility of single issue increases with the increase of } c_r \\ c^{\min}(a_i, q_{xu}), & \text{Utility of single issue decreases with the increase of } c_r \end{cases}$$

then $U_{r=1}(a_i, q_{xu}) \equiv 1$ according to and , i.e., the utility value of single issue reaches maximum, at the same time, the individual utility value of agent a_i can also reach maximum in accordance with Lemma 1. Up to this point, and are proved to be reasonable. Proof finished.

Proposition 2. In the generating model of concession strategy based on single time constraint, the negotiator agent should generate new proposal in next round of negotiation($C_{r+1}(a_i, q_x) < C_r(a_i, q_{x1}), C_{r+1}(a_i, q_{x2}), \dots, C_{r+1}(a_i, q_{xu}) >$) when the negotiation comes to a deadlock, where $c_{r+1}(a_i, q_{xu})$ is as follows,

if the utility value of single issue increases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r+1}(a_i, q_{xu}) = c_r(a_i, q_{xu}) - \xi(r) (c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

if the utility value of single issue decreases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r+1}(a_i, q_{xu}) = c_r(a_i, q_{xu}) + \xi(r) (c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

where $\xi(r)$ is the time strategy function based on single time constraint.

Proof. Time is precious to both parties from Hypothesis 4. When both parties can not reach an agreement after the current round of negotiation(r), one negotiator agent firstly

need to reduce the individual utility value ($U_r(a_i, q_x)$) in order to break a deadlock and complete negotiation within time constraint (R), So the negotiator should make concession in certain issues. The new proposal should be made certain concession based on the value of issue ($c_r(a_i, q_{xu})$) in the current round of negotiation, which meet the description about limited rationality of agent in Hypothesis 2. Besides, the individual utility value reduction through concession should be as small as possible after each round of negotiation in order to make the individual utility of negotiator keep on a high level.

In accordance with Lemma 1, the individual utility value reduction of agent relates to the utility value reduction of single issue. So the individual utility value reduction can be determined by the utility function of single issue, see Figure 2, where the solid lines denote the utility function of single issue, the utility value reduction of single issue (ΔU) depends on the length of line segment d , d is determined by $c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu})$ (i.e. AB) and the time strategy function ($\xi(r)$) based on single time constraint, i.e., $d = \xi(r)|OB - OA| = \xi(r)(c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu})) = |c_{r+1}(a_i, q_{xu}) - c_r(a_i, q_{xu})|$. Further, and are proved to be reasonable through combining with typical time strategies in the process of a practical negotiation (uniform, radical and conservative).

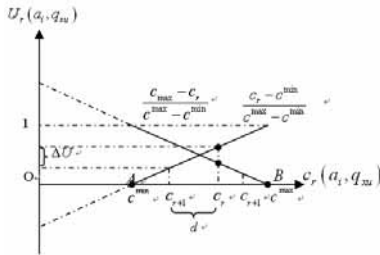


Figure 2

In particular, three typical time strategy function can be used in a negotiation based on single time constraint, as follows,

1) *Uniform type*. It is the time strategy function that make uniform concession with advance of negotiating process, e.g., $\xi(r) = \frac{1}{R}$.

2) *Radical type*. It is the time strategy function that make monotonic increasing concession with advance of negotiating process, e.g., $\xi(r) = \frac{1}{2^{(R-r)}}$, $2 \leq r \leq R$.

3) *Conservative type*. It is the time strategy function that make monotonic decreasing concession with advance of negotiating process, e.g., $\xi(r) = \frac{1}{2^{(r-1)}}$, $2 \leq r \leq R$.

Proof finished.

Proposition 3. In the model of concession strategy based on opposite's preferences, when the negotiation come to a deadlock, one negotiator agent can deduce the opposite's preferences from negotiated transaction records in history, and then determine issue and floting value of

concession in the next round of negotiation according to the opposite's preferences. $c_{r+1}(a_i, q_{xu})$ is as follows,

if the utility value of single issue increases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r+1}(a_i, q_{xu}) = c_r(a_i, q_{xu}) - E(c_{r_{end}}^h)(c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

if the utility value of single issue decreases with the increase of $c_r(a_i, q_{xu})$, then

$$c_{r+1}(a_i, q_{xu}) = c_r(a_i, q_{xu}) + E(c_{r_{end}}^h)(c^{\max}(a_i, q_{xu}) - c^{\min}(a_i, q_{xu}))$$

where $E(c_{r_{end}}^h)$ denotes step size of concession.

Proof. The both parties are sincere to reach agreement through negotiations, and there is not deceit during negotiation process from Hypothesis 5. Besides, in accordance with Hypothesis 3, the negotiator agent with incomplete information don't know the opposite's preferences information, and the preferences information can be acquired only through learning and reasoning based on negotiated transaction records in history. In the negotiation, if one negotiator agent can determine own behaviors according to the opposite's preferences, determine issue of concession and step size of concession, and further generate a new proposal with argumentation, then deceit in the negotiation can be avoided. In particular, after determining the issue of concession, $E(c_{r_{end}}^h)$ can be classified into two categories, relative step size of concession and absolute step size of concession, which are formally represented as follow,

1) *Relative step size of concession*,

$$E(c_{r_{end}}^h) = \frac{\sum_{h=h-k}^h c_{r_{end}}^h(a_i, q_{xu})}{k}$$

denotes the average concessional range of the issues' value ($c_{r_{end}}(a_i, q_{xu})$) of k records before the (h)th negotiated transaction records in hitory, where $1 \leq h-k < h \leq n$.

2) *Absolute step size of concession*,

$$E(c_{r_{end}}^h) = \frac{c_{r_{end}}^{h=last}(a_i, q_{xu}) - c_{r_{end}}^{h=first}(a_i, q_{xu})}{n}$$

where $c_{r_{end}}^{h=last}(a_i, q_{xu})$ denotes the value of issue q_{xu} in final round of the (h)th negotiated record in history, $c_{r_{end}}^{h=first}(a_i, q_{xu})$ denotes the value of issue q_{xu} in first round of the (h)th negotiated record in history, n denotes the length of negotiated records in history which must meet the following condition, $n > 3$.

Besides, when a negotiation come to a deadlock, one negotiator agent can sort the preference coefficient of all issues after determining opposite's preferences of all issues, make concession in the certain issue with minimal priority among $\alpha_{q_{x1}}, \alpha_{q_{x2}}, \dots, \alpha_{q_{xu}}$ according to principle of utility maximization, and then offer a new proposal in the next round of negotiation. If the new proposal is rejected, then the agent can adjust the proposal according to following steps,

1) Determining whether the preference coefficient ($\alpha_{q_{xu}}$) of certain issue (q_{xu}) has minimum priority or not, if so, the issue with the second-smallest priority will be used as new issue of concession.

2) The belief of issue with the second-smallest priority should be revised according to function of concession; the negotiator agent should make concession the issue with the second-smallest priority.

Facts show that agent can acquire much more individual utility if the agent comply strictly with the process of revising belief[5]. Up to this point, and is proved to be reasonable.

Besides, the value of every element in the preference coefficient set is determined by satisfaction degree in historical negotiated transaction records, so this paper will fit the mapping relation from satisfaction degree to preferences coefficient through PSO-RBFNN with the ability of approximation to random nonlinear functions in order to adapt to environmental changes.

IV. EVALUATION OF MODEL

The main task of this concessional strategy model is to determine the opposite's preferences to help agent to generate proposal with argumentation and further advance the process of negotiation. The preferences information can be acquired through PSO-RBFNN, so the neural network module in Figure 1 is the core module in the framework of argumentation-based negotiation. And this paper will select the following simulation experiment to demonstrate the feasibility of this module design.

A. Training

Firstly, using a group of historical negotiated transaction records(including 21 records) that have been normalized as training samples of the RBF neural network. And only 4 typical issues (i.e., price, warranty, delivery date and method of payment) will be involved in the following experiment

In the training samples, the values of the 4 issues are used as input($c_{end}^h(a_i, q_{x1}), c_{end}^h(a_i, q_{x2}), c_{end}^h(a_i, q_{x3})$ and $c_{end}^h(a_i, q_{x4})$), i.e., there are 4 input neurons, the satisfaction degree of each issue and the global satisfaction degree of 4 issues are used as

output($s(a_i, r_{end}^h, q_{x1}), s(a_i, r_{end}^h, q_{x2}), s(a_i, r_{end}^h, q_{x3}), s(a_i, r_{end}^h, q_{x4})$ and $s(a_i, r_{end}^h, \sum q_{xu})$), i.e., there are 5output neurons. So the structure of the neural network is "4-l-5", and l is the number of hidden nodes which can be adjusted during the process of learning. Optimum parameters of this neural

network are searched by using PSO algorithm to improve speed and accuracy of training. The convergence situation of key parameters is as shown in Figure 3 (via Matlab2010). The MMSE (Minimum Mean-Square Error) decreases with the increase of iteration times, finally the error converge to 10^{-3} in the 40462th generation. Then the RBF neural network that is used to fit negotiators' preferences can be constructed by using these optimum key parameters.

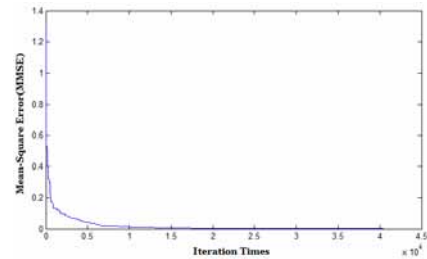


Figure 3 Process of parameters convergence

B. Testing

A group of testing samples including 11 records (see Table 1) are inputted into the neural network. The comparison between predictive output and ideal output of the testing samples is shown in Figure 4.

TABLE 1 TESTING SAMPLES

No.	q_{x1}		q_{x2}		q_{x3}		q_{x4}		P.S				
	d	χ	d	χ	d	χ	d	χ	q_{x1}	q_{x2}	q_{x3}	q_{x4}	Whole
1	300	0	6	0	7	0	1	0	0.87	0.25	0.14	0.2	0.471
2	290	0.25	12	0.33	1	1.00	1	0	0.9	0.5	1	0.2	0.73
3	280	0.50	24	1	3	0.67	1	0	0.93	1	0.33	0.2	0.758
4	280	0.50	18	0.67	2	0.83	2	0.33	0.93	0.75	0.5	0.4	0.737
5	280	0.50	6	0	1	1	3	0.67	0.93	0.25	1	0.85	0.732
6	275	0.63	24	1	3	0.67	1	0	0.95	1	0.33	0.2	0.766
7	275	0.63	12	0.33	1	1	1	0	0.95	0.5	1	0.2	0.75
8	270	0.75	18	0.67	3	0.67	3	0.67	0.96	0.75	0.33	0.85	0.76
9	265	0.88	18	0.67	2	0.83	4	1	0.98	0.75	0.5	1	0.817
10	265	0.88	12	0.33	1	1	3	0.67	0.98	0.5	1	0.85	0.827
11	260	1	18	0.67	1	1	4	1	1	0.75	1	1	0.925

In Table 1, q_{x1}, q_{x2}, q_{x3} and q_{x4} represent price, warranty, delivery date and method of payment, respectively. d and χ represent original value and normalized value. P.S represents predictive output. In column of payment method, "1~4" represent delivery on pay(D.O.P), upfront payment, credit card and pay on delivery(P.O.D), respectively.

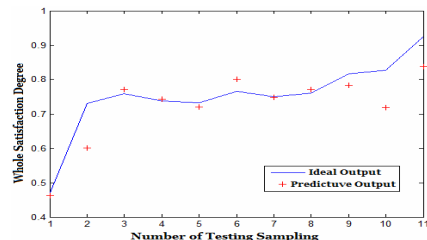


Figure 4 Comparison between predictive output and ideal output
In accordance with the output result of testing samples above, when the ideal(actual) output value of whole satisfaction degree is beyond 0.7, the predictive output value

of whole satisfaction degree is also beyond 0.7, thus the predictive effect is good. Besides, the preferences' characteristics shown in the testing samples are similar to the preferences' characteristics shown in the training samples, e.g., the whole satisfaction degree decreases with the increase of price, the buyer negotiator set a high value on other issues when the price has begun to level off. So the effect of simulation for preferences is good, this model has a certain feasibility and application value. Then negotiator agent can sort the preferences coefficient of all issues after determining opposite negotiator's preferences information, result as follows, $\alpha_{q_{x3}} < \alpha_{q_{x4}} < \alpha_{q_{x2}} < \alpha_{q_{x1}}$. Next, agent can determinate concessional issue (q_{x3}) through adhering to principle of individual utility maximization, and make concession on the issue in accordance with the model of concession strategy based on opposite's preferences mentioned above, further generate a new proposal with argumentation and advance the process of negotiation.

V. RELATED WORK

In recent years, there is an increasing amount of works on adaptive strategy in negotiation. Richter, Klusch and Kowalczyk suggested an adaptive strategy that bases on multistage fuzzy decision making. The bilateral negotiation strategies can allow agent to adapt its negotiation strategies and improve its individual payoffs by constructing a modelling of individual preferences as fuzzy goal and fuzzy constraints [4]. Wong and Wang proposed an ontology-mediated approach to organize the agent-based supply chain negotiation. Through equipping the agents with sophisticated negotiation knowledge that is structured by the usage of ontology, agents' negotiation behaviors will be more adaptive to various negotiation environments [5]. A number of researchers had attempted to use machine learning methods to optimal adaptive interaction strategies and their researches have several similarities to our own (e.g., each negotiator agent is given ability to reason opposite negotiator's private information). Oliverira and Rocha designed a virtual market and generate negotiation proposal by using a continuous reinforcement learning algorithm to enable agents to adjust themselves to the changing environment, including the opponent agents [6]. Sim and Guo presented a method that use the synergy of Bayesian learning (BL) and genetic algorithm (GA) to determine an agent's optimal strategy in negotiation (N) with incomplete information, called BLGAN. One agent can learn opponent's research price (RP) and deadline through BL, reduce the size of search space for GA, then search and generate a optimum strategy at each negotiation round [7]. Although there are several similarities, our research differs in that we construct a concessional strategy model designed

by PSO-RBFNN to allow negotiator agent to reason opposite negotiator's preferences information, determine concessional issues and adapt negotiation strategies.

VI. CONCLUSION AND FUTURE WORK

This paper proposes some hypotheses that support argumentation-based negotiation at first, then presents the generating model of concessional strategy based on single time constraint and the model based on opposite's preferences, respectively, the process of demonstration and result of experiment show that the latter designed by PSO-RBFNN has better abilities of learning and reasoning, which is dominant strategy in bilateral negotiations, and has a certain feasibility and application value. But the research in this paper is only a preliminary result, there are a lot of works to do in the future, and the emphasis is on appliance of the model to the environment of practical business negotiation. In addition, how to introduce the factor of credit and trust into the model mentioned above to evaluate argumentation based on negotiation transaction records in history is also an important research direction in the future.

ACKNOWLEDGMENT

This research has been sponsored by NSFC Grant #71071005, 70940005.

REFERENCES

- [1] P. Philippe, R. Hollands, I. Rahwan, F. Dignum, and L. Sonenberg. An empirical study of interest-based negotiation. *Journal of Autonomous Agents and Multi-Agent Systems*, 2011, Vol.22, No.2, pp. 249-288.
- [2] L. Amgoud and H. Prade. *Formal handling of threats and rewards in a negotiation dialogue*. New York, NY, USA: ACM Press, 2005, pp. 529-536.
- [3] RYK. Lau. Context-sensitive text mining and belief revision for intelligent information retrieval on the Web. *Journal of Web Intelligence and Agent Systems*, 2003, Vol.1, No.1, pp. 1-22.
- [4] J. Richter, M. Klusch, and R. Kowalczyk. A multistage fuzzy decision approach for modelling adaptive negotiation strategies. *Proceeding of IEEE International Conference on Fuzzy Systems*, 2010, pp.1-8.
- [5] G. Wang, T. Wong, and X. Wang. Research on multi-lateral multi-issue negotiation based on hybrid genetic algorithm in e-commerce. *Proceeding of 2nd IEEE International Conference on Information and Financial Engineering*, 2010, pp. 706-709.
- [6] E. Oliverira and A. Rocha. Agents advanced features for negotiation in electronic commerce and virtual organisation formation process. In: Dignum F Sierra C(eds): *Agent Mediated Electronic Co-mmerce*, The European AgentLink Perspective, Lecture Notes in Computer Science, Springer, 2001, pp. 78-97.
- [7] K. Sim and Y. Guo, and B. Shi. BLGAN: Bayesian learning and genetic algorithm for supporting negotiation with incomplete information. *Proceeding of IEEE Transactions On Systems, MAN, And Cybernetics Part B: Cybernetics*, Vol. 39, No. 1, February 2009, pp.198-211.