Accepted Manuscript

Title: A Multi-Demand Negotiation Model Based on Fuzzy
Rules Elicited via Psychological Experiments

Author: Jieyu Zhan Xudong Luo Cong Feng Minghua He

PII: S1568-4946(17)30422-2
DOI: http://dx.doi.org/doi:10.1016/j.asoc.2017.07.013
Reference: ASOC 4341

To appear in: *Applied Soft Computing*

Received date: 26-1-2017
Revised date: 12-6-2017
Accepted date: 5-7-2017

Please cite this article as: Jieyu Zhan, Xudong Luo, Cong Feng, Minghua He, A Multi-Demand Negotiation Model Based on Fuzzy Rules Elicited via Psychological Experiments, *<![CDATA[Applied Soft Computing Journal]]>* (2017), http://dx.doi.org/10.1016/j.asoc.2017.07.013

A Multi-Demand Negotiation Model Based on Fuzzy Rules Elicited via Psychological Experiments

Jieyu Zhan[a], Xudong Luo[a,*], Cong Feng[a], Minghua He[b]

[a]Institute of Logic and Cognition, Sun Yat-sen University, Guangzhou, China.
[b]School of Engineering and Applied Science, Aston University, UK

Abstract

This paper proposes a multi-demand negotiation model that takes the effect of human users' psychological characteristics into consideration. Specifically, in our model each negotiating agent's preference over its demands can be changed, according to human users' attitudes to risk, patience and regret, during the course of a negotiation. And the change of preference structures is determined by fuzzy logic rules, which are elicited through our psychological experiments. The applicability of our model is illustrated by using our model to solve a problem of political negotiation between two countries. Moreover, we do lots of theoretical and empirical analyses to reveal some insights into our model. In addition, to compare our model with existing ones, we make a survey on fuzzy logic based negotiation, and discuss the similarities and differences between our negotiation model and various consensus models.

Keywords: automated negotiation, fuzzy logic, bargaining game, preference, agent

1. Introduction

A negotiation problem is a communication process among a number of agents about how to allocate profit, goods, resources and so on among them [1, 2, 3]. It is one of the most common phenomena in our daily life [4]. Therefore, since Nash built the first mathematical model of negotiation [5], various models have been proposed in various areas, such as economics [6, 7, 8, 9], political science [10, 11, 12], management science [13, 14, 15], sociology [16, 17, 18], and especially artificial intelligence [1, 19, 20, 21, 22, 23]. In the area of artificial intelligence, most of the studies about negotiation focus on handling one demand with one or multiple attributes in continuous domains. There are many examples of this kind, such as how to divide a pie [24], negotiation in an accommodation renting scenario [2], wage negotiation between employers and employees [25], negotiation of multiple dependent issues based on hypergraph utility [26], using BLGAN strategy and its extension for dealing with consecutively-conceding opponents [27] or multifarious opponents [28] in one-shot negotiation, finding agents' optimal strategies in bilateral negotiation with uncertain information about

*Corresponding author
Email address: louxd3@mail.sysu.edu.cn (Xudong Luo)

one-sided uncertain reserve prices [29], trade-off making for generating counter offer [30, 31], and multi-strategy selection [32] in negotiation. The utility functions of demand in these examples are continuous.

In contrast, little work deals with multiple demands in discrete domains. However, in real life it is very common that people negotiate multi-demand in discrete domains. For example, in a congress, different parties often bargain many political demands that are in discrete domains; in collective design problems, agreements must be reached by a group of stakeholders with different discrete demands; in a problem of real estate investment, some investors demand to build large houses using environmentally friendly but expensive material, while some demand to build small houses using cheap materials; and a group of friends want to organise a trip to a variety of places (the places are the demands in this case). Moreover, there are often many inconsistencies among different people concerned with different demands. In the problems of this kind, it is hard to elicit numerical utilities and then do quantitative analyses [33, 34].

Moreover, most of negotiation models and systems just focus on the optimisation and stabilisation of a negotiation's agreement, but ignore human users' psychological characteristics [35, 36, 37, 38, 39] (although some studies [40, 41, 32, 4] did not). Nonetheless, sometimes it is necessary to reflect such human factors in negotiation models for a number of reasons. Firstly, a faithful negotiation model should also capture such aspects, *i.e.,* the outcome or final decision should reflect users' individual emotions or affective factors, such as attitudes towards risk, patience and so on [42, 43, 44]. This is because a negotiating agent should accurately model its user, including the user's preference, utility, way of thinking, emotion and so on; otherwise it is hard for the human user to delegate his negotiation task to the agent [45, 3]. Of course, if a user could choose the best negotiating agent to obtain the highest profit for him/her, it would not matter whether the user can be modelled well or not. However, the problem is: how can a user judge whether a negotiation system is the best or not? For example, in the domain of e-commerce, when a negotiating agent acts on behalf of a human, it is actually spending the money of its human owner. Thus, if the human user cannot judge whether the system is the best or not, the safest way is to let the agent be accurately aware of his interests, preferences and prejudices, and then do that job for him automatically to save him both time and energy as much as possible. Thus, in this way the deal made might not be better but at least not worse. Otherwise, it is not very possible for the human user to trust the agent and delegate his/her negotiation task to the computer system.

For instance, in a negotiation for dividing 100 pounds between two, the fair solution is to give each 50 pounds. However, one who is greedy might feel unsatisfied with the solution, thinking he could get more if he holds his position more strongly during the course of the negotiation; while another, who would be satisfied with 40 pounds, might feel more than happy with 50 pounds. In this case, the greedy user, of course, wants the negotiating agent to reflect his greedy nature and to try his luck to get more than 50 pounds. Actually, if the other side was satisfied with 40 pounds, the greedy one could get 60 pounds, and thus he will definitely not think the fair solution of 50 each is good. As a result, such a user would not delegate the negotiation task to a negotiating agent that can only gain 50 pounds for him/her.

Also, some psychological experiments confirm that human factors play important roles in negotiation. For example, Rothman and Northcraft discover that one human negotiator's expressed emotional ambivalence can foster integrative outcomes [46]. And Kleef et al. investigate the interpersonal effects of anger and happiness in negotiations [47]. Their experiments show that participants make more concession to an angry opponent than to a happy one, because participants use the emotion information to identify the opponents' limits and accordingly they adjust their demands. By using a hypothetical negotiation scenario and a computer-mediated negotiation simulation, Adam et al. find that expressing anger elicited larger concessions from European and American negotiators, but smaller concessions from Asian and Asian American negotiators [48]. Kleef et al. study more social effects of emotions in negotiation, such as disappointment, guilt, worry and regret [43]. They conducted several experiments in a computer-simulated negotiation. One experiment shows that participants make more concessions when the other displayed supplication emotions, and conceded less when the other displayed appeasement emotions (especially guilt). Another experiment shows that disappointment and guilt are moderated by the perceivers dispositional trust: negotiators with high trust conceded more to a disappointed counterpart than to a happy one, while those with low trust are unaffected. Hareli et al. implement an experiment to find two other factors relevant to negotiation: a negotiator's power, and their counterparts' emotional reaction to the negotiation [49]. Their findings show that at the beginning of a negotiation, the power is an important factor, but the informative value of emotion information takes precedence over time. Thus, when automated agents are employed to negotiate with people [50, 51] or train human negotiators [52, 53], it is necessary to put human personality traits into account in designing such negotiating agents [54, 55, 56].

To address these problems, in this paper we develop a negotiation model, in which each negotiating agent has two preference orderings over his demands: one for reflecting its human user's taste without considering any information about the negotiation, while the other for reflecting not only his user's own taste but also his thinking about which demand should be insisted on or given up earlier. Thus, his attitude to risk can be tasted out by comparing the two preferences. Moreover, in our model, a negotiating agent's preference can be changed during the course of a negotiation according to its user's psychological factors about risk, patience and regret. Thus, a fuzzy logic system is employed to calculate the degree to which the preference should be changed dynamically as per these psychological factors during the course of a negotiation.

Actually, the distinction between the two preferences is intuitive because in some negotiation processes negotiators choose to hide their real purpose and preference. For example, in a political negotiation, on the one hand, each party is in favour of policies (demands) that ensure their own supporters' interest; on the other hand, they try their best to win votes or reach an agreement with other parties even though this may be at the price of policies they espoused. For example, a party has to latch onto environmental issues to win votes even though it prefers establishing new factories to getting more profit. This may form two kinds of preferences about policies: one is a negotiator's real preference, and the other can be regarded as a strategic one for the negotiation.

What is more, some empirical studies support our conjecture of distinguishing two kinds of demand preferences. In fact, Derlega et al. reveal that in hypothetical negotiation situations, international students from collectivism countries (*e.g.*, China and

Japan) are more willing to make concessions when their opponent is an inside-group one (*e.g.*, a friend) than an outside-group one (*e.g.*, a stranger) [57]. In another simulated selling-buying task [58], people in a cooperative relationship set lower selling prices, and thus are more willing to let their partners take possession of the object; but it is less likely for people in competitive relationships to do so. From these studies, we can clearly see that each negotiator could have two preferences: one reflects his own taste and the other reflects his thinking of his negotiating opponents.

In short, the motivation of our negotiation system is three-fold. Firstly, most work on automated negotiation is in continuous domains, but discrete domains is in need. Secondly, on the one hand, existing negotiation models in discrete domains consider little about human factors' influence upon automated negotiation although they are necessary; one the other hand, those studies that put human factors into consideration are not about negotiation in discrete domains. Thirdly, it might be not complete idea to change preference structure during negotiation, but it has been rarely implemented in any automated negotiation system in discrete domains. To address the problems of these three aspects, in this paper we present a method for automated multi-demand negotiation with dynamic preference structure over discrete domains by taking into account human-like negotiation factors such as risk, patience and regret.

More specifically, our work advances the state of the art in the field of automated negotiation in the following aspects. (i) We introduce the concept of dynamic preference into negotiation models in discrete domains to reflect a negotiator's adaptability during the course of a negotiation, so that negotiation success rate, efficiency and quality can be increased significantly. (ii) We design a new algorithm for multi-demand negotiation, which works with public information of demand but private information about demand preferences that will be updated during the course of a negotiation. (iii) We identify, using lots of psychological experiments, a set of fuzzy logic rules which can be used to update negotiating agents' preferences in each negotiation round according to their degree of regret, initial attitude to risk, and patience. (iv) We theoretically show how users' psychological characteristics about regret, risk and patience influence their preference structures during the course of a multi-demand negotiation, and under which conditions an agreement can be reached. (v) We carry out computer simulation experiments to analyse the rationale for the choice of action function in our model, the influence of input parameters in the fuzzy system, as well as the negotiation success rate, efficiency and quality of our method. And (vi) to compare our model with existing ones, we make a survey on fuzzy logic based negotiation, and discuss the similarities and differences between our negotiation model and various consensus models.

The rest of the paper is organised as follows. Section 2 defines our negotiation model and its agreement concept. Section 3 presents our fuzzy logic system and the psychological experiment that elicits its fuzzy logic rules. Section 4 reveals some properties of our model. Section 5 illustrates our model by a political example. Section 6 presents our experimental analyses. Section 7 benchmarks our model with a previous one. Section 8 discusses the related work to confirm our contribution to the research field of automated negotiation. Finally, Section 9 concludes the paper with future work.

Table 1: Key notational conventions

Notation	Meaning
N	the set of the players
D_i	the initial demand set of negotiating agent i
$D_i^{\pm}$	the conflicting demand set of negotiating agent i in D_i
$D_i^{(\lambda)}$	the demand set of negotiating agent i in λ-th round
$D_i^{(1,\lambda)}$	the set of the demands that negotiating agent i prefers the most in round λ
$D_i^{(H_i(\lambda),\lambda)}$	the set of the demands that negotiating agent i prefers the least in round λ
d	demand
$\mathcal{L}$	a propositional language
$\succcurlyeq_i^{(0)}$	negotiating agent i's original demand preference ordering
$\succcurlyeq_i^{(1)}$	negotiating agent i's initial dynamic demand preference ordering
$\succcurlyeq_i^{(\lambda)}$	negotiating agent i's dynamic demand preference ordering in the λ-th round
$\mathcal{A}_i$	negotiating agent i's action function
FLS	a fuzzy logic system for calculating the preference change degree
G	a negotiation procedure
$H_i(\lambda)$	the height of the hierarchy of negotiating agent i in the λ-th round demand set
SCS	the simultaneous concession solution
DSCS	the dynamically simultaneous concession solution
$A(G)$	the agreement of procedure G
$A_i(G)$	the outcome of negotiating agent i
$A_{DSCS}(G)$	the agreement of procedure G by DSCS
$A_{SCS}(G)$	the agreement of procedure G by SCS
ϑ_i	the regret degree of negotiating agent i
ρ_i	the patience descent degree of negotiating agent i
γ_i	the initial risk degree of negotiating agent i
ζ_i	the preference change degree of negotiating agent i
$n_{c,i}$	the number of consistent demands of negotiating agent i in D_i
$n_{r,i}^{(\lambda)}$	the number of remaining consistent demands of bargainer i in the λ-th round
$l_i(d)$	the level of d in agent i's original preference hierarchy
$l_i^{(1)}(d)$	the level of d in agent i's initial dynamic preference hierarchy
$l_i^{(\lambda)}(d)$	the level of d in the dynamic preference hierarchy in the λ-th round

2. Negotiation model

This section defines our negotiation model and its solution concept. For convenience, we summarise our main notational conventions in Table 1.

Firstly, we recall the concept of a total pre-order [59]:

Definition 1. *Let $\succcurlyeq$ be a binary relation on a non-empty set D. Then $\succcurlyeq$ is a total pre-order on D if it satisfies the following properties:*

(i) completeness: $\forall \phi, \psi \in D$, $\phi \succcurlyeq \psi$ or $\psi \succcurlyeq \phi$;

(ii) reflexivity: $\forall \phi \in D$, $\phi \succcurlyeq \phi$; and

(iii) transitivity: $\forall \phi, \psi, \theta \in D$, if $\phi \succcurlyeq \psi$ and $\psi \succcurlyeq \theta$, then $\psi \succcurlyeq \theta$.

Now we introduce the concept of our negotiation model as follows:

Definition 2. *The input of a negotiation is a tuple of $(N, \{D_i, \succcurlyeq_i^{(0)}, \succcurlyeq_i^{(1)}\}_{i\in N})$, where:*

(i) $N = \{1, \cdots, n\}$ *is the set of all the negotiating agents;*

(ii) D_i *is the demand set of negotiating agent i, in which each demand is expressed in a propositional language, denoted as* $\mathcal{L}$*, consisting of a finite set of literals;*

(iii) $\succcurlyeq_i^{(0)}$ *is negotiating agent i's original demand preference ordering, which is a total pre-order on* D_i*; and*

(iv) $\succcurlyeq_i^{(1)}$ *is negotiating agent i's initial dynamic demand preference ordering, which is a total pre-order on* D_i*.*

In the above definition, the negotiating agents' demands are represented by logical literals, rather than compound statements with connectives $\{\neg, \vee, \wedge, \rightarrow, \leftrightarrow\}$. This is because in real negotiation scenarios, it is more common and easier to express opinions on individual things than collective things. For instance, if a party's position stands for two policies a and b, it is better to explain its attitude to these policies one by one, so that the voters can understand their propositions more clearly. Although a party could express a statement like $a \vee b$, which means the party supports at least one of the policies, we do not take the compound statements into consideration in this paper, but our work can still cover the most common situations in real life.[1]

In the above definition, we suppose that before a negotiation, each negotiating agent has two preference orderings over his demands: (i) the original one, which just reflects his own favourites in his mind without considering whether or not an agreement can be reached; and (ii) the initial dynamic one, which reflects not only his own taste but also his thinking about which demand should be given up earlier or insisted on during the negotiation. As we argued in the introduction section, some empirical studies (*e.g.*, [57, 58]) show that sometimes it is necessary to distinguish two kinds of demand preferences in negotiation: one reflects his own taste and the other reflects his thinking of his negotiating opponents.

It should be noted that in this paper we just have an assumption that each agent has the knowledge of others' demands and so what demands of it are inconsistent with others' demands. However, they do not know how much an opponent prefers his/her demands. That is, they do not know the preferences of each other. This is because if an agent reveals its preference information, it will lose its competitive advantage on the opponent [60, 61, 62, 63] and so it should not do that.

In the following, we will define the process of a negotiation of this kind. Firstly, we introduce the concept of a negotiating agent's demand preference hierarchy as follows:

Definition 3. *Let* $(D_i^{(\lambda)}, \succcurlyeq_i^{(\lambda)})$ *be negotiating agent i's dynamic preference structure in the* λ*-th round of negotiation, in which* $D_i^{(\lambda)}$ *refers to the demand set of negotiating agent i in the* λ*-th round of negotiation and* $\succcurlyeq_i^{(\lambda)}$ *refers to negotiating agent i's dynamic demand preference ordering in the* λ*-th round. Particularly,* $\succcurlyeq_i^{(1)}$ *is negotiating agent*

[1] Of course, it may be worthy studying the situation of compound statements, but the issue is beyond the scope of this paper.

i's initial dynamic demand preference ordering. Then $\{D_i^{(1,\lambda)}, \cdots, D_i^{(H_i(\lambda),\lambda)}\}$ *is called negotiating agent i's demand preference hierarchy if* $\forall j, k \in \{1, \cdots, H_i(\lambda)\}$,

(i) $D_i^{(\lambda)} \neq \emptyset$;

(ii) $D_i^{(\lambda)} = D_i^{(1,\lambda)} \cup \cdots \cup D_i^{(H_i(\lambda),\lambda)}$;

(iii) $D_i^{(j,\lambda)} \cap D_i^{(k,\lambda)} = \emptyset$ *if* $j \neq k$;

(iv) $\forall d_i, d_i' \in D_i^{(j,\lambda)}, d_i \succcurlyeq_i^{(\lambda)} d_i'$ *and* $d_i' \succcurlyeq_i^{(\lambda)} d_i$;

(v) $\forall d_i \in D_i^{(j,\lambda)}, d_i' \in D_i^{(k,\lambda)}, d_i \succcurlyeq_i^{(\lambda)} d_i'$ *if* $j \leqslant k$; *and*

(vi) $\forall j \leqslant H_i(1), D_i^{(j,1)} \neq \emptyset$.

Here $D_i^{(j,\lambda)}$ *is called the j-th level of negotiating agent i's demand preference hierarchy in the* λ*-th round of negotiation, and* $H_i(\lambda)$ *is called the height of the demand preference hierarchy of negotiating agent i in the* λ*-th round of negotiation.* $\forall d \in D_i$*, let* $l_i^{(\lambda)}(d)$ *denote the level of d in the dynamic preference hierarchy in the* λ*-th round.*

Clearly, in the above definition, the highest level is $D_i^{(1,\lambda)}$, and the lowest level is $D_i^{(H_i(\lambda),\lambda)}$. In the following definition, in round λ, "move demand $d^{\pm}$ down one or two levels" means to move $d^{\pm}$ from its current level in $\{D_i^{(1,\lambda)}, \cdots, D_i^{(H_i(\lambda),\lambda)}\}$ down one or two levels.

Definition 4. *For each negotiating agent i, its negotiation processor is a tuple of* $(FLS, \mathcal{A}, \mathcal{U})$*, where:*

(i) *FLS is a fuzzy logic system for calculating the preference change degree.*

(ii) $\mathcal{A}_i$ *is negotiating agents' action function defined as follows:*

$$\mathcal{A}_i(\zeta, d_i^{\pm}, \lambda) = \begin{cases} \textit{move } d_i^{\pm} \textit{ down two levels from its current level in round } \lambda \\ \qquad \textit{if } \zeta \geqslant \tau_1 \wedge l_i^{(\lambda)}(d_i^{\pm}) \leqslant H_i(1) - 2, \\ \textit{move } d_i^{\pm} \textit{ down one level from its current level in round } \lambda \\ \qquad \textit{if } (\tau_1 > \zeta \geqslant \tau_2 \wedge l_i^{(\lambda)}(d^{\pm}) \leqslant H_i(1) - 1) \vee \\ \qquad\quad (\zeta \geqslant \tau_1 \wedge l_i^{(\lambda)}(d_i^{\pm}) = H_i(1) - 1), \\ \textit{do nothing} \\ \qquad \textit{otherwise}, \end{cases} \tag{1}$$

where ζ *is the preference change degree,* τ_1 *and* τ_2 *are pre-determined thresholds,* $d_i^{\pm}$ *belongs to the set of the negotiating agent i's conflicting demand set* $D_i^{\pm}$ *(in which each element* $d_i^{\pm}$ *is inconsistent with one demand* d_j *of at least another negotiator,* i.e., $d_i^{\pm} \wedge d_j \to \bot$ *because d is a single atom), and* λ *means the* λ*-th round of the negotiation procedure.*

(iii) *$\mathcal{U}_i$ is negotiating agent i's update function. Let the dynamic preference structures of negotiating agent i in the λ-th and $(\lambda+1)$-th rounds be $(D_i^{(\lambda)}, \succcurlyeq_i^{(\lambda)})$ and $(D_i^{(\lambda+1)}, \succcurlyeq_i^{(\lambda+1)})$, respectively. Then update function $\mathcal{U}_i$ is given by:*

$$(D_i^{(\lambda+1)}, \succcurlyeq_i^{(\lambda+1)}) = \mathcal{U}(D_i^{(\lambda)}, \succcurlyeq_i^{(\lambda)}), \tag{2}$$

where

$$D_i^{(\lambda+1)} = D_i^{(\lambda)} - \{\underline{d}_i\}, \tag{3}$$

where $\underline{d}_i$ is defined as follows:

(a) *if $\exists d_i \in D_i^{(H_i(\lambda),\lambda)} \bigcap D_i^{\pm}$, then $\underline{d}_i \in D_i^{(H_i(\lambda),\lambda)} \bigcap D_i^{\pm}$ such that $\forall d_i \in D_i^{(H_i(\lambda),\lambda)} \bigcap D_i^{\pm}$, $l_i^{(1)}((\underline{d}_i)) \succcurlyeq_i^{(1)} l_i^{(1)}(d_i)$, and*

(b) *if $\nexists d_i \in D_i^{(H_i(\lambda),\lambda)} \bigcap D_i^{\pm}$, then $\underline{d}_i \in D_i^{(H_i(\lambda),\lambda)} \backslash D_i^{\pm}$;*

and $\succcurlyeq_i^{(\lambda+1)}$ is defined as follows:

(a) *$\forall d_i, d_i' \in D_i^{(j,\lambda+1)}, d_i \succcurlyeq_i^{(\lambda+1)} d_i'$ and $d_i' \succcurlyeq_i^{(\lambda+1)} d_i$, and*

(b) *$\forall d_i \in D_i^{(j,\lambda+1)}, d_i' \in D_i^{(k,\lambda+1)}, d_i \succ_i^{(\lambda+1)} d_i'$ if $j < k$,*

where $D_i^{(j,\lambda+1)}$ and $D_i^{(k,\lambda+1)}$ are in $\{D_i^{(1,\lambda+1)}, \cdots, D_i^{(H_i(\lambda+1),\lambda+1)}\}$, which is obtained by applying action function (1) to $\{D_i^{(1,\lambda)}, \cdots, D_i^{(H_i(\lambda),\lambda)}\}$.

According to the above definition, after the λ-th round, the dynamic demand preference structure of negotiating agent i, $(D_i^{(\lambda)}, \succcurlyeq_i^{(\lambda)})$, will be updated to a new one, $(D_i^{(\lambda+1)}, \succcurlyeq_i^{(\lambda+1)})$, by a certain action chosen according to action function (1), where its input (*i.e.*, preference change degree ζ) is determined by fuzzy logic system FLS (see Section 3 for the detailed discussion). More specifically, the updating consists of two key steps: (i) give up one demand by formula (3); and (ii) revise preference by action function (1).

The reason why we choose function (1) is explained by experiments in Section 6. That is, if action function (1) is used in our fuzzy logic based model, it can guarantee not only a high success rate of negotiation but also a high efficiency when the numbers of conflicting demands and negotiating agents are increased. Moreover, the thresholds of the preference change degrees (*i.e.*, τ_1 and τ_2) in function (1) are used to reflect the intuition that when a preference change degree is higher than τ_1, it is high enough to make more change of the preference structure, while when a preference change degree is lower than τ_2, it is low enough to make no change of the preference structure. The thresholds may be different from people to people and from problem to problem, so its elicitation will be a significant problem that needs to be tackled, but it is beyond the scope of this paper. However, in this paper, without losing generality, in the relevant calculation we just set $\tau_1 = 0.7$ and $\tau_2 = 0.3$ (a special setting of the thresholds of preference change degrees).

A negotiation procedure consists of the negotiation input and process. Formally, we have:

Definition 5. *A negotiation procedure is a tuple of* (I, P)*, where:*

(i) $I = (N, \{D_i, \succcurlyeq_i^{(0)}, \succcurlyeq_i^{(1)}\}_{i \in N})$ *is the input of the negotiation; and*

(ii) $P = (FLS, \mathcal{A}, \mathcal{U})$ *is the negotiation processor of each agent.*

Generally speaking, an agreement should satisfy the intuitive properties as follows: (i) there are no conflicting demands in the agreement; and (ii) all the negotiating agents should accept all of each other's demands when they have no conflicting demands with each other; (iii) there are no agreements when one of the negotiating agents cannot bargain any more because he gave up all his demands; and (iv) if after the λ-th round of negotiation all the demands of all the negotiating agents have become logically consistent, it is unnecessary to carry out any further concession. Formally, we have:

Definition 6. *For negotiation* $G = (I, P)$*, let negotiating agent i's demand set in the* $\underline{\lambda}$*-th round be* $D_i^{(\underline{\lambda})}$*. Then*

$$A(G) = \bigcup_{i \in N} D_i^{(\underline{\lambda})} \tag{4}$$

is an agreement among all the negotiating agents of negotiation G if:

(i) consistency: $A(G) \nvdash \perp$*;*

(ii) collective-rationality: if $\bigcup_{i \in N} D_i \nvdash \perp$*, then* $\forall i \in N, A(G) = \bigcup_{i \in N} D_i$*;*

(iii) non-empty: $\forall i \in N$*,* $D_i^{(\underline{\lambda})} \neq \emptyset$*; and*

(iv) minimum-concession: $A(G) \cup \{d_i, \cdots, d_{|N|}\} \vdash \perp$*, where* d_i *is the demand that agent i gives up after the* $(\underline{\lambda} - 1)$*-th round.*

In this paper, the concept of an agreement defined as the above is also called a *dynamically simultaneous concession solution* (DSCS) to reflect the nature that in each round each agent dynamically changes their preferences and at the same time concedes off one demand simultaneously.

3. Fuzzy logic system

This section will discuss our fuzzy logic system FLS. Specifically, we discuss first the input parameters of the fuzzy logic system, then we discuss the fuzzy variables used in the fuzzy rules, following by the psychological experiment for eliciting the fuzzy rules, and finally the fuzzy inference method. The reason why we use fuzzy reasoning to represent the generation of preference change degree is that based on natural language it is conceptually easy to understand fuzzy logic. It is intuitive for users to express their reasoning about how their regret, patience and risk attitude influence their preference change degree through linguistic terms, rather than precise numbers.

3.1. Input parameters

Our fuzzy logic system is used to calculate a degree to which a negotiating agent should change his preference. This calculation mainly depends on three human cognitive factors: regret degree, patience descent degree, and initial risk degree. In this subsection, we will discuss how to calculate the three parameters.

3.1.1. Regret degree

In Longman English Dictionary Online,[2] *regret* is defined as "sadness that you feel about something, especially because you wish it had not happened". Thus, in our problem of multi-demand negotiation, when a negotiating agent regrets, it is because the agent gives up some preferred or consistent demands (which all the negotiating agents want). However, by our negotiation process, the effect of the first possibility is less obvious than the second one because negotiating agents give up the least preferred demands at the beginning. Thus, we can depict a negotiating agent's regret degree through the second character. That is, (i) the more consistent demands a negotiating agent has given up, the more he regrets; (ii) if no consistent demands have been given up during a negotiation, the regret degree is the lowest; and (iii) if all consistent demands have been given up during the course of a negotiation, the regret degree is the highest. Thus, formally we have:

Definition 7. *Given a negotiation procedure $G = (I, P)$, let $n_{c,i}$ be the number of consistent demands of negotiating agent i in D_i (consistent demands refer to the demands that have no contradiction with others' demands), and $n_{r,i}^{(\lambda)}$ be the number of remaining consistent demands of negotiating agent i after the λ-th round of negotiation. A function $f_i^{(\lambda)}$ is the regret degree function of negotiating agent i after λ-th round of negotiation if it satisfies:*

(i) if $n_{r,i}^{(\lambda)} \geqslant n_{r,i}^{(\lambda')}$ then $f_i^{(\lambda)}(n_{r,i}^{(\lambda)}) \leqslant f_i^{(\lambda)}(n_{r,i}^{(\lambda')})$;

(ii) $\forall n_{r,i}^{(\lambda)}$, $f_i^{(\lambda)}(n_{r,i}^{(\lambda)}) \geqslant f_i^{(\lambda)}(n_{c,i})$; and

(iii) $\forall n_{r,i}^{(\lambda)}$, $f_i^{(\lambda)}(n_{r,i}^{(\lambda)}) \leqslant f_i^{(\lambda)}(0)$.

It is easy to check that given negotiation procedure $G = (I, P)$, the following formula defines a regret degree of negotiating agent i after the λ-th round:

$$\vartheta_i^{(\lambda)}(n_{r,i}^{(\lambda)}) = \frac{n_{c,i} - n_{r,i}^{(\lambda)}}{n_{c,i}}. \tag{5}$$

3.1.2. Patience descent degree

In Longman English Dictionary Online, *patience* is defined as: (i) "the ability to continue waiting or doing something for a long time without becoming angry or anxious"; and (ii) "the ability to accept trouble and other people's annoying behaviour

[2] http://www.ldoceonline.com/dictionary/regret_2

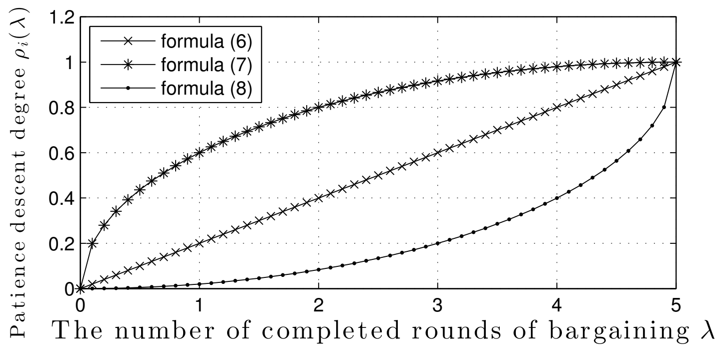

Figure 1: Three patience descent degree functions

without complaining or becoming angry". Thus, the calculation of patience descent degree should reflect the phenomenon that in real life, when a thing is going on, the more time is spent, the less patient the persons involved will become. Therefore, if we use *patience descent degree (ρ)* to represent how much the patience of a negotiating agent will be after every round of a negotiation, it should reflect: (i) the more rounds completed, the less patient a negotiating agent; (ii) at the beginning of a negotiation, a negotiating agent is the most patient; and (iii) at the end of a negotiation, a negotiating agent is the most impatient. Thus, formally we have:

Definition 8. *A function f_i is the patience descent degree function of negotiating agent i if it satisfies:*

(i) $\forall \lambda, \omega \leqslant |D_i|$, *if* $\lambda \leqslant \omega$ *then* $f_i(\lambda) \leqslant f_i(\omega)$*;*

(ii) $\forall \lambda \leqslant |D_i|$, $f_i(\lambda) \geqslant f_i(0)$*; and*

(iii) $\forall \lambda \leqslant |D_i|$, $f_i(\lambda) \leqslant f_i(|D_i|)$,

where $|D_i|$ is the number of negotiating agent i's demands.

It is easy to check that given negotiation procedure $G = (I, P)$, the patience descent degree of negotiating agent i after the λ-th round can be calculated in the following three ways:

$$\rho_i(\lambda) = \frac{\lambda}{|D_i|}, \tag{6}$$

$$\rho_i(\lambda) = \frac{\sqrt{\lambda(2|D_i| - \lambda)}}{|D_i|}, \tag{7}$$

$$\rho_i(\lambda) = 1 - \frac{\sqrt{|D_i|^2 - \lambda^2}}{|D_i|}, \tag{8}$$

where λ is the number of completed rounds of negotiation and D_i is negotiating agent i's demand set.

The difference among formulas (6)-(8) is in the aspects of the descent rates of patience. Formula (6) reflects that a negotiating agent's patience declines in a constant speed during a negotiation. Formula (7) reflects that a negotiating agent's patience declines swiftly first and then slows down during a negotiation. And formula (8) reflects the reverse situation, *i.e.,* a negotiating agent's patience declines slowly and speeds up during a negotiation. For example, Figure 1 shows the difference among the three patience descent degree functions in the case of $|D_i| = 5$.

3.1.3. Initial risk degree

In Longman English Dictionary Online, *risk* is defined as "the possibility that something bad, unpleasant, or dangerous may happen". Therefore, we can assume: (i) if a negotiating agent has a high risk attitude, it will put all the conflicting demands at the top level of its preference hierarchy because by the simultaneous concession in our negotiation process, it may get most of its conflicting demands if its opponent is risk-averse, but it may break the negotiation if its opponent is risk-seeking; (ii) on the contrary, it can show its low risk attitude when it puts all its conflicting demands at the lowest level of its initial dynamic preference hierarchy; (iii) if it does not change the preference, it is risk neutral; (iv) if a negotiating agent moves up one of its conflicting demands but keeps others unchanged, it shows a higher degree of risk; and (v) if a negotiating agent moves down one of its conflicting demands but keeps others unchanged, it shows a lower degree of risk. Thus, formally we have:

Definition 9. *Given a negotiation procedure $G = (I, P)$, let $L_i = \{$mapping $l_i : D_i \to \mathbb{N}\}$ and $L_i^{(1)} = \{$mapping $l_i^{(1)} : D_i \to \mathbb{N}\}$ be the sets of all the possible original preference hierarchies of agent i and all the possible initial dynamic preference hierarchies of agent i, respectively. Then $\forall d \in D_i$, $\forall l_i \in L_i$, $\forall l_i^{(1)} \in L_i^{(1)}$, $l_i(d)$ and $l_i^{(1)}(d)$ denote the level of d in an original preference hierarchy and an initial dynamic preference hierarchy, respectively. A function f_i is the initial risk degree function of negotiating agent i with respect to $l_i^{(1)}$ if it satisfies:*

(i) if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)'}(d^{\pm}_{i,j}) = 1$, then $\forall l_i^{(1)} \neq l_i^{(1)'}$, $f_i(l_i^{(1)'}(d)) \geqslant f_i(l_i^{(1)}(d))$;

(ii) if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)'}(d^{\pm}_{i,j}) = H_i$, then $\forall l_i^{(1)} \neq l_i^{(1)'}$ $f_i(l_i^{(1)'}(d)) \leqslant f_i(l_i^{(1)}(d))$;

(iii) if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)}(d^{\pm}_{i,j}) = l_i(d^{\pm}_{i,j})$, $\max\{f_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} \neq 0$ and $\min\{f_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} \neq 0$, then

$$f_i(l_i^{(1)}(d)) = \frac{\max\{f_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} + \min\{f_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\}}{2};$$

(iv) if $\exists d'^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)}(d'^{\pm}_{i,j}) < l_i^{(1)'}(d'^{\pm}_{i,j})$, $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $d^{\pm}_{i,j} \neq d'^{\pm}_{i,j}$, $l_i^{(1)}(d^{\pm}_{i,j}) = l_i^{(1)'}(d^{\pm}_{i,j})$, then $f_i(l_i^{(1)}(d)) > f_i(l_i^{(1)'}(d))$; and

(v) if $\exists d'^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)}(d'^{\pm}_{i,j}) > l_i^{(1)'}(d'^{\pm}_{i,j})$, and $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $d^{\pm}_{i,j} \neq d'^{\pm}_{i,j}$, $l_i^{(1)}(d^{\pm}_{i,j}) = l_i^{(1)'}(d^{\pm}_{i,j})$, then $f_i(l_i^{(1)}(d)) < f_i(l_i^{(1)'}(d))$.

In the above definition, actually $l_i^{(1)}$ represents an initial dynamic preference hierarchy of agent i, and the difference between $l_i^{(1)}$ and $l_i^{(1)'}$ is that agent i maps different preference levels to its demands in the initial dynamic preference hierarchy. The idea of evaluating a negotiating agent's risk degree is to compare its initial dynamic preference hierarchy to the original preference hierarchy. The basic assumption is that if the more a negotiating agent insists on conflicting but unimportant demands, the more risk-seeking it is; and if the more a negotiation agent concedes conflicting but important demands, the more conservative it is.

The following theorem presents a specific formula for calculating the initial risk degree:

Theorem 1. *An initial risk degree function of negotiating agent i can be given by:*

$$\gamma_i(l_i^{(1)}(d)) = \begin{cases} \dfrac{\sum_{d^{\pm}_{i,j}\in D^{\pm}_i}(l_i(d^{\pm}_{i,j})-l_i^{(1)}(d^{\pm}_{i,j}))}{\left|\sum_{d^{\pm}_{i,j}\in D^{\pm}_i} l_i(d^{\pm}_{i,j})-\left|D^{\pm}_i\right|\right|} & \text{if } \sum_{d^{\pm}_{i,j}\in D^{\pm}_i}(l_i(d^{\pm}_{i,j})-l_i^{(1)}(d^{\pm}_{i,j}))>0, \\ \dfrac{\sum_{d^{\pm}_{i,j}\in D^{\pm}_i}(l_i(d^{\pm}_{i,j})-l_i^{(1)}(d^{\pm}_{i,j}))}{\left|\sum_{d^{\pm}_{i,j}\in D^{\pm}_i} l_i(d^{\pm}_{i,j})-\left|D^{\pm}_i\right|H_i\right|} & \text{if } \sum_{d^{\pm}_{i,j}\in D^{\pm}_i}(l_i(d^{\pm}_{i,j})-l_i^{(1)}(d^{\pm}_{i,j}))<0, \\ 0 & \text{otherwise}, \end{cases} \tag{9}$$

where $D^{\pm}_i$ is the conflicting demand set of negotiating agent i in D_i.

Proof. Let $D^{\pm}_i = \{d^{\pm}_{i,1}, \ldots, d^{\pm}_{i,|D^{\pm}_i|}\}$.

(i) If $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i(d^{\pm}_{i,j}) = 1$, then $\max\{\gamma_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} = 0$ and if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)'}(d^{\pm}_{i,j}) = 1$, then $\gamma_i(l_i^{(1)'}(d)) = 0$. Therefore, $\forall l_i^{(1)} \neq l_i^{(1)'}$, $\gamma_i(l_i^{(1)'}(d)) \geqslant \gamma_i(l_i^{(1)}(d))$. Otherwise, $\max\{\gamma_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} = 1$, and thus if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)'}(d^{\pm}_{i,j}) = 1$, then

$$\begin{aligned} \gamma_i(l_i^{(1)'}(d)) &= \frac{(l_i(d^{\pm}_{i,1})-1)+\cdots+(l_i(d^{\pm}_{i,|D^{\pm}_i|})-1)}{\left|\sum_{d^{\pm}_{i,j}\in D^{\pm}_i} l_i(d^{\pm}_{i,j})-\left|D^{\pm}_i\right|\right|} \\ &= 1. \end{aligned}$$

Therefore, we still have $\forall l_i^{(1)} \neq l_i^{(1)'}$, $\gamma_i(l_i^{(1)'}(d)) \geqslant \gamma_i(l_i^{(1)}(d))$.

(ii) If $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i(d^{\pm}_{i,j}) = H_i$, then $\min\{\gamma_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} = 0$ and if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l_i^{(1)'}(d^{\pm}_{i,j}) = H_i$, then $\gamma_i(l_i^{(1)'}(d)) = 0$. Therefore, for any $l_i^{(1)} \neq l_i^{(1)'}$, $\gamma_i(l_i^{(1)'}(d)) \leqslant \gamma_i(l_i^{(1)}(d))$. Otherwise, $\min\{\gamma_i(l_i^{(1)}(d)) \mid l_i^{(1)} \in L_i^{(1)}\} = -1$, and thus if

$\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l^{(1)'}_i(d^{\pm}_{i,j}) = H_i$, then

$$\begin{aligned}\gamma_i(l^{(1)'}_i(d)) &= \frac{(l_i(d^{\pm}_{i,1}) - H_i) + \cdots + (l_i(d^{\pm}_{i,|D^{\pm}_i|}) - H_i)}{\left|\sum_{d^{\pm}_{i,j} \in D^{\pm}_i} l_i(d^{\pm}_{i,j}) - \left|D^{\pm}_i\right| H_i\right|} \\ &= -1.\end{aligned}$$

Therefore, we still have $\forall l^{(1)}_i \neq l^{(1)'}_i$, $\gamma_i(l^{(1)'}_i(d)) \leqslant \gamma_i(l^{(1)}_i(d))$.

(iii) By formula (9), if $\max\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\} \neq 0$ and $\min\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\} \neq 0$, then $\max\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\} = 1$ and $\min\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\} = -1$, thus $\frac{\max\{\gamma_i(l^{(1)}_i(d)) | l^{(1)}_i \in L^{(1)}_i\} + \min\{\gamma_i(l^{(1)}_i(d)) | l^{(1)}_i \in L^{(1)}_i\}}{2} = 0$. And if $\forall d^{\pm}_{i,j} \in D^{\pm}_i$, $l^{(1)}_i(d^{\pm}_{i,j}) = l_i(d^{\pm}_{i,j})$, then $\gamma(l^{(1)}_i(d)) = 0$. Therefore, we have

$$\gamma(l^{(1)}_i(d)) = \frac{\max\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\} + \min\{\gamma_i(l^{(1)}_i(d)) \mid l^{(1)}_i \in L^{(1)}_i\}}{2}.$$

(iv) If $\exists d'^{\pm}_{i,j} \in D^{\pm}_i$ such that $l^{(1)}_i(d'^{\pm}_{i,j}) < l^{(1)'}_i(d'^{\pm}_{i,j})$ and $\forall d^{\pm}_{i,j} \in D^{\pm}_i$ such that $d^{\pm}_{i,j} \neq d'^{\pm}_{i,j}$, $l^{(1)}_i(d^{\pm}_{i,j}) = l^{(1)'}_i(d^{\pm}_{i,j})$, then

$$\sum_{d^{\pm}_{i,j} \in D^{\pm}_i} (l_i(d^{\pm}_{i,j}) - l^{(1)}_i(d^{\pm}_{i,j})) > \sum_{d^{\pm}_{i,j} \in D^{\pm}_i} (l_i(d^{\pm}_{i,j}) - l^{(1)'}_i(d^{\pm}_{i,j})).$$

Therefore, by formula (9), we have $\gamma_i(l^{(1)}_i(d)) > \gamma_i(l^{(1)'}_i(d))$.

(v) If $\exists d'^{\pm}_{i,j} \in D^{\pm}_i$ such that $l^{(1)}_i(d^{\pm'}_{i,j}) > l^{(1)'}_i(d^{\pm'}_{i,j})$ and $\forall d^{\pm}_{i,j} \in D^{\pm}_i$ such that $d^{\pm}_{i,j} \neq d'^{\pm}_{i,j}$, $l^{(1)}_i(d^{\pm}_{i,j}) = l^{(1)'}_i(d^{\pm}_{i,j})$, then

$$\sum_{d^{\pm}_{i,j} \in D^{\pm}_i} (l_i(d^{\pm}_{i,j}) - l^{(1)}_i(d^{\pm}_{i,j})) < \sum_{d^{\pm}_{i,j} \in D^{\pm}_i} (l_i(d^{\pm}_{i,j}) - l^{(1)'}_i(d^{\pm}_{i,j})).$$

Therefore, by formula (9), we have $\gamma_i(l^{(1)}_i(d)) < \gamma_i(l^{(1)'}_i(d))$. □

3.2. Fuzzy linguistic terms of fuzzy variables

The meanings of these parameters' linguistic terms are as follows. The *low* regret degree (RD) indicates that a negotiating agent only regrets a little for the demands given up in the previous round. The *medium* regret degree means that a negotiating agent regrets giving up the demands in the previous round. And the *high* regret degree means that a negotiating agent regrets very much giving up the demands in the previous round, and so most likely changes the preference ordering because it causes many consistent demands lost. Similarly, we can understand the linguistic terms of the other two parameters: patience descent degree (PDD) and initial risk degree (IRD).

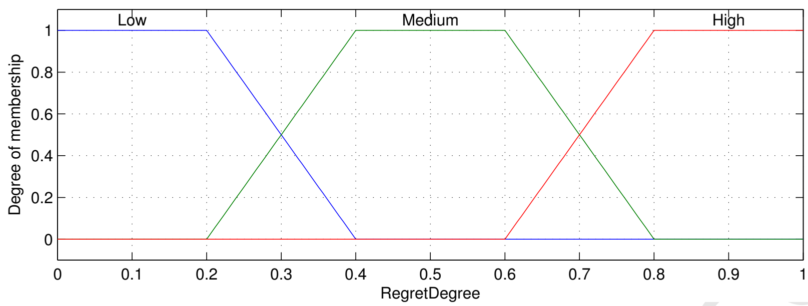

Figure 2: The membership functions of various linguistic terms of Regret Degree

These linguistic terms can be modelled by the fuzzy membership function as follows:

$$\mu(x) = \begin{cases} 0 & \text{if } x \leqslant a, \\ \frac{x-a}{b-a} & \text{if } a \leqslant x \leqslant b, \\ 1 & \text{if } b \leqslant x \leqslant c, \\ \frac{d-x}{d-c} & \text{if } c \leqslant x \leqslant d, \\ 0 & \text{if } x \geqslant d. \end{cases} \tag{10}$$

The reason for our choice of formula (10) is as follows. Its parameters a, b, c and d can reflect well that different people could set the membership function of the same linguistic term differently. For example, when $a = b = c < d$, it reflects a decreasing tendency; when $a < b = c = d$, it reflects an increasing tendency; when $a < b = c < d$, it reflects a tendency that is increasing between a and b, decreasing between c and d; and when $a < b < c < d$, it reflects a tendency that is increasing between a and b, reaching the maximum level between b and c, and decreasing between c and d [45].

For convenience, we denote formula (10) as $\mu(x)$=(a, b, c, d). Thus, the linguistic terms of regret degree (RD) can be represented as:

$$\mu_{low\ RD}(\vartheta) = (-0.2, 0, 0.2, 0.4), \tag{11}$$
$$\mu_{medium\ RD}(\vartheta) = (0.2, 0.4, 0.6, 0.8), \tag{12}$$
$$\mu_{high\ RD}(\vartheta) = (0.6, 0.8, 1, 1.2). \tag{13}$$

Similarly, we can have:

$$\mu_{low\ PDD}(\rho) = (-0.2, 0, 0.2, 0.4), \tag{14}$$
$$\mu_{medium\ PDD}(\rho) = (0.2, 0.4, 0.6, 0.8), \tag{15}$$
$$\mu_{high\ PDD}(\rho) = (0.6, 0.8, 1, 1.2); \tag{16}$$
$$\mu_{low\ IRD}(\gamma) = (-1.4, -1, -0.6, -0.2), \tag{17}$$
$$\mu_{medium\ IRD}(\gamma) = (-0.6, -0.2, 0.2, 0.6), \tag{18}$$
$$\mu_{high\ IRD}(\gamma) = (0.2, 0.6, 1, 1.4); \tag{19}$$

Table 2: Fuzzy rules

1	If *regret degree* is *Low* then *preference change degree* is *Low*.
2	If *regret degree* is *Medium* then *preference change degree* is *Medium*.
3	If *regret degree* is *High* then *preference change degree* is *High*.
4	If *patience descent degree* is *Low* then *preference change degree* is *Low*.
5	If *patience descent degree* is *Medium* then *preference change degree* is *Medium*.
6	If *patience descent degree* is *High* then *preference change degree* is *High*.
7	If *initial risk degree* is *Low* then *preference change degree* is *High*.
8	If *initial risk degree* is *Medium* then *preference change degree* is *Medium*.
9	If *initial risk degree* is *High* then *preference change degree* is *Low*.

$$\mu_{low\ CD}(\zeta) = (-0.2, 0, 0.2, 0.4), \tag{20}$$
$$\mu_{medium\ CD}(\zeta) = (0.2, 0.4, 0.6, 0.8), \tag{21}$$
$$\mu_{high\ CD}(\zeta) = (0.6, 0.8, 1, 1.2). \tag{22}$$

We draw the membership functions of the three linguistic terms of regret degree in Figure 2 and the figures of the membership functions of other inputs and outputs are similar. The setting of the parameters (*i.e.*, a, b, c and d) of each linguistic terms is based on our experimental results, which will be discussed in Section 3.3.

3.3. Psychological experiment

We calculate a preference change degree from a negotiating agent's *regret degree*, *patience descent degree*, and *initial risk degree* by the fuzzy rules as shown in Table 2. There Rule 1 means that if a negotiating agent does not lose too many consistent demands, which makes him regret just a little, then his desire to change his preference ordering is low. Similarly, we can understand other rules. The relations between the rules' inputs and output are shown in the left column of Figure 3. We can see that overall the preference change degree increases with the increase of the regret degree and the patience descent degree in an upward trend, while decreases with the increase of the initial risk degree in a downward trend.

These fuzzy rules were established by a psychological survey with 40 human subjects. Empirically, 30 is the minimal sample size required to conduct such a statistical analysis, while more than 50 is pointless [64, 45]. Therefore, it was reasonable to choose 40 (18 females and 22 males). They ranged in age from 19 to 40, and varied in careers and educational levels. All the subjects volunteered to participate and complete the questionnaires, which consisted of the following four parts:

3.3.1. Risk Orientation Questionnaire

This uses 12 items to assess individuals' risk propensity and cautiousness [42]. That is, to ask a subject to choose an appropriate number, in-between 1 and 7, to indicate how much he/she agrees with the following statements (1 means totally disagree, then the numbers from 2 to 6 indicate the agreement degrees that become gradually stronger, and 7 means totally agree):

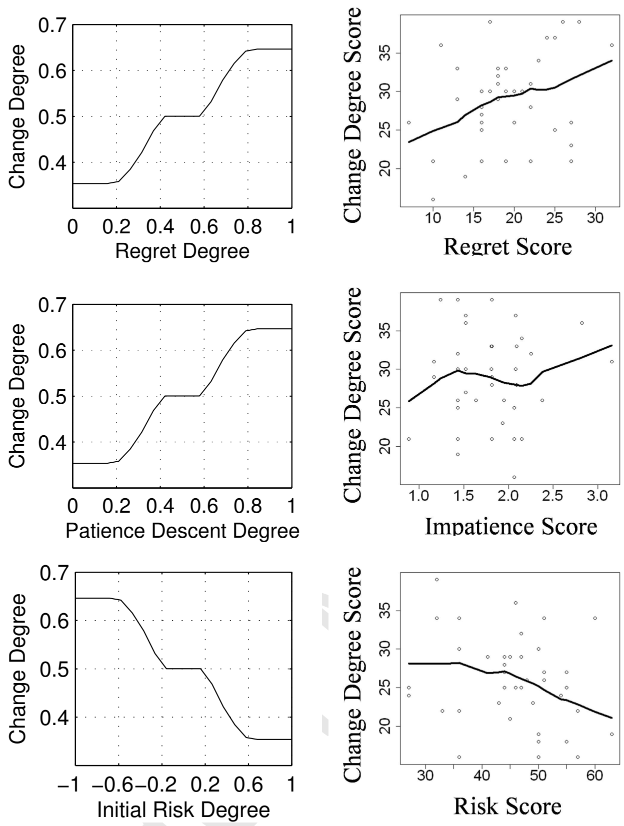

Figure 3: The relations between the preference change degree and the three parameters in our fuzzy logic system (the first column) and in psychological experiments (the second column)

1) I am very careful when making and implementing a plan.
2) My motto is “Nothing ventured, nothing gained”.
3) I do not like to make a risky decision.
4) As long as a task is very interesting, regardless of whether or not I am able to conduct it well, I will try it.
5) I do not like to take a risk at the cost of what I have, I would rather stay safe in everything.
6) Even though I knew it had not been a good choice, I still decided to gamble.
7) I often set myself smaller goals at work, so I can more easily achieve them.
8) Even though most people disagree with me, I will still air my own ideas.
9) I always make decisions after careful thinking.
10) I sometimes like to do things for others to show my ability even though there will be the risk of error.
11) I often imagine the negative consequences of my actions.
12) I would rather take a great risk in order to succeed.

3.3.2. Regret Scale

This consists of 5 items designed to assess how subjects deal with decision situations after the decision has been made, specifically the extent to which they experience regret [65]. That is, to choose a number, in-between 1 and 7 (1 means totally disagree, then the numbers from 2 to 6 indicate the gradually stronger agreement degree, and 7 means totally agree), to indicate how much a subject agrees with the following statements:

1) Once I have made a decision, I will not regret it.
2) After making a decision, I would like to know what would have happened if I had chosen another.
3) When I find that other options could bring better results, I feel very frustrated although the outcomes brought by the current selection are also good.
4) I will always think of the opportunities missed when I am thinking how well I live now.
5) I always gather information about other options when I have to make a decision.

3.3.3. Delay-discounting rate

This assesses a subject's patience level by offering a human subject a series of choices between immediate but less rewards and larger but delayed rewards as follows [66]:

1) \$30 now vs. \$85 14 days later;
2) \$40 now vs. \$55 25 days later;
3) \$67 now vs. \$85 35 days later;
4) \$34 now vs. \$35 43 days later;
5) \$15 now vs. \$35 10 days later;
6) \$32 now vs. \$55 20 days later;
7) \$83 now vs. \$85 35 days later;
8) \$21 now vs. \$30 75 days later;
9) \$48 now vs. \$55 45 days later;
10) \$40 now vs. \$65 70 days later;
11) \$25 now vs. \$35 25 days later;
12) \$65 now vs. \$75 50 days later;
13) \$24 now vs. \$55 10 days later;
14) \$30 now vs. \$35 20 days later;
15) \$53 now vs. \$55 50 days later;
16) \$47 now vs. \$60 50 days later;
17) \$40 now vs. \$70 20 days later;
18) \$50 now vs. \$80 70 days later;
19) \$45 now vs. \$70 35 days later;
20) \$27 now vs. \$30 35 days later;
21) \$16 now vs. \$30 35 days later.

3.3.4. Maximisation Scale Short

This uses 6 items to assess individuals' tendency to optimise decisions, and that people with a tendency to optimise their decision are less likely change their original decisions [67]. That is, ask a subject to choose an appropriate number, in-between 1 and 7 (1 means totally disagree, then the numbers from 2 to 6 indicate the agreement degrees that is gradually stronger, and 7 means totally agree), to indicate how much he/she agrees with the following statements:

1) No matter how much I am satisfied with my current job, I am always looking for a better opportunity.
2) No matter what I do, I will finish it up to the highest standard.
3) When I am watching TV, even though I am now quite satisfied with the current programme, I will still search for other channels to see whether or not there is a better one.

Table 3: Regression analysis results. Here β is the standardised regression coefficient; $S.E.$ is the standard error of the estimate; and p is the significant level of the t-test.

	β	S.E.	t value	p
Intercept	-12.38	6.59	-1.88	0.07
Regret degree	0.36	0.17	2.12	0.04
Impatience	1.18	2.16	0.55	0.59
Risk degree	-0.17	0.10	1.66	0.10

4) Shopping is very difficult for me because I always try to find the most appropriate things for me.
5) I am never satisfied with the second best choice.
6) I always think it is very difficult for me to help a friend to choose a gift in a shop.

A multi-regression analysis [68] is conducted to test the effect of the risk attitude, the regret degree and the patience level on how individuals approach their decision. The analysis results are reported in Table 3. The regret degree is significantly relevant to the tendency to change their decisions (*i.e.*, β =0.36 and p=0.04). Those, who experience more regret after the decision has been made, are more likely to change their decisions. Risk attitude is marginally related to the preference change degree (*i.e.*, β =-0.17 and p=0.10). Those, who prefer a higher level of risk, tend to insist on their original decisions. The patience level is also positively relevant to the preference change degree (*i.e.*, β =1.18 and p=0.59).

As shown in the right column of Figure 3, according to the experiment results, we draw three scatter plots for ζ's change with the regret degree, the patience descent level, and the risk attitude, respectively. The curve was superimposed on each scatter plot using the scatter smoother function $lowess()$ of the MASS package in the R system for statistical analysis. Compared with the left column of Figure 3, we can see our fuzzy rules well reflect the result of these psychological experiments.

3.4. Fuzzy inference method

We employ standard fuzzy inference method [69, 70].

The following definition is about the fuzzy logic implication of the well-known Mamdani method [70].

Definition 10. *Let A_i be a Boolean combination of fuzzy sets $A_{i,1}, \cdots, A_{i,m}$, where $A_{i,j}$ is a fuzzy set defined on $U_{i,j}$ $(i = 1, \cdots, n;\ j = 1, \cdots, m)$, and B_i be fuzzy set on U' $(i = 1, \cdots, n)$. Then when the inputs are $\mu_{A_{i,1}}(u_{i,1}), \cdots, \mu_{A_{i,m}}(u_{i,m})$, the output of fuzzy rule $A_i \to B_i$ is fuzzy set B'_i defined as follows:*

$$\forall u' \in U', \mu_i(u') = \min\{f(\mu_{A_{i,1}}(u_{i,1}), \cdots, \mu_{A_{i,m}}(u_{i,m})), \mu_{B_i}(u')\}, \tag{23}$$

where f is obtained through replacing $A_{i,j}$ in A_i by $\mu_{A_{i,j}}(u_{i,j})$ and replacing "and", "or", and "not" in A_i by "min", "max", and "$1-\mu$", respectively. And the output of all rules $A_1 \to B_1, \cdots, A_n \to B_n$, is fuzzy set M, which is given by:

$$\forall u' \in U', \mu_M(u') = \max\{\mu_1(u'), \cdots, \mu_n(u')\}. \tag{24}$$

Thus, by formulas (23) and (24), the output of all these rules in Table 2 is fuzzy set M defined as: $\forall u' \in U'$,

$$\begin{aligned}\mu_M(\zeta) = \max\{&\min\{\mu_{low\ RD}(\vartheta), \mu_{low\ CD}(\zeta)\},\\ &\min\{\mu_{medium\ RD}(\vartheta), \mu_{medium\ CD}(\zeta)\},\\ &\min\{\mu_{high\ RD}(\vartheta), \mu_{high\ CD}(\zeta)\},\\ &\min\{\mu_{low\ PDD}(\rho), \mu_{low\ CD}(\zeta)\},\\ &\min\{\mu_{medium\ PDD}(\rho), \mu_{medium\ CD}(\zeta)\},\\ &\min\{\mu_{high\ PDD}(\rho), \mu_{high\ CD}(\zeta)\},\\ &\min\{\mu_{low\ IRD}(\gamma), \mu_{high\ CD}(\zeta)\},\\ &\min\{\mu_{medium\ IRD}(\gamma), \mu_{medium\ CD}(\zeta)\},\\ &\min\{\mu_{high\ IRD}(\gamma), \mu_{low\ CD}(\zeta)\}\}.\end{aligned} \tag{25}$$

By Definition 10, the result that we get is still a fuzzy set. To defuzzify the fuzzy set, we need the following centroid method [71]:

Definition 11. *The centroid point u_{cen} of fuzzy set M given by formula (24) is:*

$$u_{cen} = \frac{\int_{U'} u' \mu_M(u')\,\mathrm{d}u'}{\int_{U'} \mu_M(u')\,\mathrm{d}u'}, \tag{26}$$

or

$$u_{cen} = \frac{\sum_{j=1}^{n} u_j \mu_M(u_j)}{\sum_{j=1}^{n} \mu_M(u_j)}. \tag{27}$$

Actually, u_{cen} above is the centroid of the area that is circled by the curve of membership function μ_M and the horizontal ordinate.[3]

4. Properties

This section will reveal some properties of our model.

4.1. The influence of regret, patience and risk

In this subsection, we will discuss how a negotiating agent's psychological factors of regret, patience and risk influence the preference change degrees according to the fuzzy rules.

[3]Some people may challenge the robustness of these fuzzy inference methods, but the problem is out of the scope of this paper. We just apply the well-known fuzzy logic methods into automated negotiation. Of course, in the future we can study what will be resulted if using different fuzzy inference methods for our negotiation problem.

Table 4: Original and dynamic preference hierarchies of Parties 1 and 2

Level	Party 1		Party 2	
	original	dynamic	original	dynamic
1	EHI	CJO	¬LR, CJO	¬LR, CJO,¬RT
2	CJO, LPAV, MR	EHI, ¬LR	¬FHC, ¬RT	¬FHC, ¬EHI
3	¬RMB, ¬LR	LPAV, IEI	¬EHI, RMB	RMB, ¬LRAV, IEI
4	IEI, BHR, ¬ FHC	MR, BHR, ¬FHC	¬LRAV, IEI	¬ MR
5	RT	¬RMB, RT	BHR, ¬MR	BHR

Theorem 2. *Suppose after a negotiation round, a negotiating agent has regret degree ϑ, patience descent degree ρ, and initial risk degree γ, and thus gets the corresponding preference change degree of ζ through our FLS. Then:*

(i) If $\vartheta \geqslant 0.8$ then $\forall\rho \in [0,1], \gamma \in [-1,1]$, $\zeta \geqslant 0.5$; and if $\vartheta \leqslant 0.2$ then $\forall\rho \in [0,1], \gamma \in [-1,1]$, $\zeta \leqslant 0.5$.

(ii) If $\rho \geqslant 0.8$ then $\forall r_1 \in [0,1], \gamma \in [-1,1]$, $\zeta \geqslant 0.5$; and if $\rho \leqslant 0.2$ then $\forall\vartheta \in [0,1], \gamma \in [-1,1]$, $\zeta \leqslant 0.5$.

(iii) If $\gamma \geqslant 0.6$ then $\forall\vartheta \in [0,1], \rho \in [0,1]$, $\zeta \leqslant 0.5$; and if $\gamma \leqslant -0.6$ then $\forall\vartheta \in [0,1], \rho \in [0,1]$, $\zeta \geqslant 0.5$.

Proof. Firstly we prove property (i). When $\vartheta \in [0.8,1]$, by the definitions of $\mu_{low\ RD}$ (*i.e.*, formula (11)), $\mu_{medium\ RD}$ (*i.e.*, formula (12)), and $\mu_{high\ RD}$ (*i.e.*, formula (13)), we can get $\mu_{low\ RD}(\vartheta) = \mu_{medium\ RD}(\vartheta) = 0$ and $\mu_{high\ RD}(\vartheta) = 1$. By formula (23), the outputs of the first three rules in Table 2 are $\mu_1(\zeta) = 0$, $\mu_2(\zeta) = 0$, and $\mu_3(\zeta) = \mu_{high\ CD}(\zeta)$, respectively. Now we want to find out the minimum of μ_{cen}. Because of $\rho \in [0,1]$ and $\gamma \in [-1,1]$, when the assignment of ρ or γ changes, the shape of $\mu_M(\zeta)$ may change. More specifically, by formulas (24) and (26) we have the following cases:

1) In the case of $\rho \in [0,0.2]$ and $\gamma \in [0.6,1]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2-5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.4, \\ 0 & \text{if } 0.4 \leqslant \zeta \leqslant 0.6, \\ 5\zeta-3 & \text{if } 0.6 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

2) In the case of $\rho \in [0,0.2]$ and $\gamma \in [0.4,0.6]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2-5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.1+0.5\gamma, \\ 1.5-2.5\gamma & \text{if } 0.1+0.5\gamma \leqslant \zeta \leqslant 0.9-0.5\gamma, \\ 5\zeta-3 & \text{if } 0.9-0.5\gamma \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

3) In the case of $\rho \in [0, 0.2]$ and $\gamma \in [0.2, 0.4]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.3, \\ 5\zeta - 1 & \text{if } 0.3 \leqslant \zeta \leqslant 0.5 - 0.5\gamma, \\ 1.5 - 2.5\gamma & \text{if } 0.5 - 0.5\gamma \leqslant \zeta \leqslant 0.5 + 0.5\gamma, \\ 4 - 5\zeta & \text{if } 0.5 + 0.5\gamma \leqslant \zeta \leqslant 0.7, \\ 5\zeta - 3 & \text{if } 0.7 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

4) In the case of $\rho \in [0, 0.2]$ and $\gamma \in [-0.2, 0.2]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.3, \\ 5\zeta - 1 & \text{if } 0.3 \leqslant \zeta \leqslant 0.4, \\ 1 & \text{if } 0.4 \leqslant \zeta \leqslant 0.6, \\ 4 - 5\zeta & \text{if } 0.6 \leqslant \zeta \leqslant 0.7, \\ 5\zeta - 3 & \text{if } 0.7 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

5) In the case of $\rho \in [0, 0.2]$ and $\gamma \in [-0.4, -0.2]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.3, \\ 5\zeta - 1 & \text{if } 0.3 \leqslant \zeta \leqslant 0.5 + 0.5\gamma, \\ 1.5 + 2.5\gamma & \text{if } 0.5 + 0.5\gamma \leqslant \zeta \leqslant 0.5 - 0.5\gamma, \\ 4 - 5\zeta & \text{if } 0.5 - 0.5\gamma \leqslant \zeta \leqslant 0.7, \\ 5\zeta - 3 & \text{if } 0.7 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

6) In the case of $\rho \in [0, 0.2]$ and $\gamma \in [-0.6, -0.4]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.1 - 0.5\gamma, \\ 1.5 + 2.5\gamma & \text{if } 0.1 - 0.5\gamma \leqslant \zeta \leqslant 0.9 + 0.5\gamma, \\ 5\zeta - 3 & \text{if } 0.9 + 0.5\gamma \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

7) In the case of $\rho \in [0, 0.2]$ and $\gamma \in [-1, -0.6]$, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.4, \\ 0 & \text{if } 0.4 \leqslant \zeta \leqslant 0.6, \\ 5 - 3\zeta & \text{if } 0.6 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } 0.8 \leqslant \zeta \leqslant 1; \end{cases}$$
$$u_{cen} = 0.5.$$

Similarly, we can discuss the other cases where ρ is in $[0.2, 0.3]$, $[0.3, 0.4]$, $[0.4, 0.6]$, $[0.6, 0.7]$, $[0.7, 0.8]$, and $[0.8, 1]$, respectively. Finally we can find that when $\rho \in [0, 0.2]$ or $\gamma \in [0.6, 1]$, $\mu_{cen} = 0.5$, which is the maximum. Therefore, if $\vartheta \geqslant 0.8$ then $\forall \rho \in [0, 1], \gamma \in [-1, 1], \zeta \geqslant 0.5$.

If $\vartheta \in [0, 0.2]$, by the definitions of $\mu_{low\ RD}$ (*i.e.*, formula (11)), $\mu_{medium\ RD}$ (*i.e.*, formula (12)), and $\mu_{high\ RD}$ (*i.e.*, formula (13)), we can get $\mu_{medium\ RD}(\vartheta) = \mu_{high\ RD}(\vartheta) = 0$ and $\mu_{low\ RD}(\vartheta) = 1$. By formula (23), the outputs of the first three rules in Table 2 are $\mu_1(\zeta) = \mu_{low\ CD}(\zeta), \mu_2(\zeta) = 0$, and $\mu_3(\zeta) = 0$, respectively. By formulas (24) and (26) as well as the other 6 rules in Table 2, similar to the above discussion, we know that when $\rho \in [0.8, 1]$ or $\gamma \in [-1, -0.6]$, $\mu_{cen} = 0.5$, which is the maximum. We choose an appropriate case where $\rho = 1$ and $\gamma = -1$ to calculate the maximum value. In this case, we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.4, \\ 0 & \text{if } 0.4 \leqslant \zeta \leqslant 0.6, \\ 5\zeta - 3 & \text{if } 0.6 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } \zeta \geqslant 0.8. \end{cases}$$

And by formula (26), we have:

$$u_{cen} = \frac{\int_0^1 \zeta \mu_M(\zeta)\, \mathrm{d}\zeta}{\int_0^1 \mu_M(\zeta)\, \mathrm{d}\zeta} = 0.5.$$

Therefore, if $\vartheta \leqslant 0.2$ then $\forall \rho \in [0, 1], \gamma \in [-1, 1], \zeta \leqslant 0.5$.

Similarly, we can prove properties (ii) and (iii) of this theorem. □

This theorem reveals that when a parameter is higher or lower than a certain threshold, the preference change degree can be controlled within a certain range (higher or lower than a mid-value, *i.e.*, 0.5 in our fuzzy system). This is in accord with our intuitions, *i.e.*, when a negotiating agent regrets his preference changing extremely, even though he is patient and risk-seeking, likely he is very unwilling to insist on his original preference.

4.2. Agreement Existence

We now discuss the agreement existence of our negotiation procedures. In the discussion of this subsection, we use formulas (5), (6), and (9) as the regret degree, patience descent degree and initial risk degree functions, respectively.

Firstly, the following theorem states that no matter how different the attitudes of risk, regret and patience that the negotiating agents possess, if they have at least two demands in common, they can reach an agreement.

Theorem 3. *In a bilateral negotiation procedure G, if $\forall i \in N_i$, $\exists\ d_{i,1}, d_{i,2} \notin D_i^{\pm}$ such that $l^{(1)}(d_{i,1}) \neq l^{(1)}(d_{i,2})$, then $A_{DSCS}(G) \neq \varnothing$.*

Proof. Firstly, similar to the discussion in the proof of Theorem 2, we can prove that when $\vartheta = 0.3$, $\rho \in [0, 0.2]$ and $\gamma \in [0.6, 1]$, the value of μ_{cen} is the minimum. We choose an appropriate situation where $\vartheta = 0.3$, $\rho = 0$ and $\gamma = 1$ to calculate the minimum value. In this situation, by formulas (24) and (26), we have:

$$\mu_M(\zeta) = \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2 - 5\zeta & \text{if } 0.2 \leqslant \zeta \leqslant 0.3, \\ 0.5 & \text{if } 0.3 \leqslant \zeta \leqslant 0.7, \\ 4 - 5\zeta & \text{if } 0.7 \leqslant \zeta \leqslant 0.8, \\ 1 & \text{if } \zeta \geqslant 0.8; \end{cases}$$

$$u_{cen} = \frac{\int_0^1 \zeta \mu_M(\zeta)\, \mathrm{d}\zeta}{\int_0^1 \mu_M(\zeta)\, \mathrm{d}\zeta} = 0.31 > 0.3.$$

Therefore, if regret degree $\vartheta \geqslant 0.3$, no matter what the patience descent degree and the initial risk degree are, the corresponding preference change degree is not less than 0.3.

Secondly, we prove the theorem by using the above conclusion. Suppose the negotiation procedure reaches no agreements. Then by Definition 6, there does not exist a $\underline{\lambda}$ such that $\forall i \in N, D_i^{(\underline{\lambda})} \neq \emptyset, \underline{\lambda} < |D|_{min}$, where $|D|_{min}$ is the minimum of demand amount among all negotiating agents' demand sets. That is, before the end of the negotiation process, there is at least one negotiating agent who has at least one demand inconsistent with each other. However, this situation is impossible in our assumption because when the negotiation procedure continues to the above situation, at least one negotiating agent has to give up all his consistent demands. Nevertheless, let us consider the situation where a negotiating agent has given up $m-1$ consistent demands (m is the total number of his consistent demands). By the formula of calculating regret degree (*i.e.*, formula (5)), we know regret degree ϑ of the negotiating agent in this round is $\frac{m-1}{m}$. Since

$$\min\{\frac{m-1}{m} \mid m \in \mathbb{N}\} = \frac{1}{2} \geqslant 0.3,$$

we have $\vartheta \geqslant 0.3$. Hence, we know the corresponding preference change degree $\zeta \geqslant 0.3$. Therefore, by action function (1), $\forall i \in N_i$, if $\exists d_i^{\pm} \in D_i^{\pm}$ such that $l^{(d)}(d_i^{\pm}) \leqslant H_i(1) - 1$, demand $d_i^{\pm}$ will be downgraded and the left consistent demand will be not given up by our negotiation protocol after preference updating. Therefore, it is impossible that at the end of the negotiation process there is at least a negotiator who has at least a demand inconsistent with others'. Hence, $A_{DSCS}(G) \neq \emptyset$. □

It seems that if there is at least one non-conflicting demand in the demand sets of all agents, there will be an agreement. However, in our negotiation model, two non-conflicting demands are needed to achieve an agreement because in our model, different agents may have difference preferences on demands and rank them in different hierarchies, but which is private information, so that the non-conflicting demand may be given up by all the agents in the earlier stage of a negotiation in our model.

The following theorem states that no matter how different personalities the negotiating agents own, if they have at least one demand in common and one of them is not at their low levels of preference hierarchies, but in the middle or high levels, then an agreement can be reached finally.

Theorem 4. *In a bilateral negotiation procedure G, if* $\forall i \in N_i, \exists d_i \notin D_i^{\pm}$ *such that*

$$|\{d_j \mid d_j \in D_i, l^{(1)}(d_j) > l^{(1)}(d_i)\}| > \lceil \frac{|D|_i}{3} \rceil,$$

then $A_{DSCS}(G) \neq \emptyset$.

Proof. Similar to that of Theorem 3, we can prove that if $\rho \geqslant 0.3$ then $\forall r_1 \in [0, 1], \gamma \in [-1, 1]$, $\zeta \geqslant 0.3$. Suppose the negotiation procedure reaches no agreements. Then by Definition 6, there does not exist a $\underline{\lambda}$ such that $\forall i \in N, D_i^{(\underline{\lambda})} \neq \emptyset, \underline{\lambda} < |D|_{min}$, where $|D|_{min}$ is the minimum of demand amount among all negotiating agents' demand sets. That is, before the end of the negotiation process, there is at least one negotiating agent who has at least one demand inconsistent with each other. However, this situation is impossible in our assumption because when the negotiation procedure continues to round $\lceil \frac{|D|_i}{3} \rceil$, $\rho_i(\lceil \frac{|D|_i}{3} \rceil) = \frac{\lceil \frac{|D|_i}{3} \rceil}{|D|_i} \geqslant 0.3$. Thus, by the above inference the corresponding preference change degree ζ will be not less than 0.3. Therefore, by action function (1), $\forall i \in N_i$, if $\exists d_i^{\pm} \in D_i^{\pm}$ such that $l^{(d)}(d_i^{\pm}) \leqslant H_i(1) - 1$, demand $d_i^{\pm}$ will be downgraded and the left consistent demands will not be given up by our negotiation model after preference updating. Therefore, it is impossible that in the last round of the negotiation procedure there is at least a negotiating agent who has at least one demand inconsistent with others', *i.e.*, $\nexists i \in N, \exists d_i \in D_i^{(\lambda)}, \exists j \neq i, d_i \wedge D_j^{(\lambda)} \vdash \perp$. Hence, $A_{DSCS}(G) \neq \emptyset$. □

5. Example

In this section, we will illustrate our negotiation model through a political example. Suppose two political parties are negotiating over some policies that will be written into new planning. Party 1 supports economical housing investment (EHI), raising taxes (RT), medical reform (MR), building high-speed railways (BHR), creating job opportunities (CJO), increasing education investment (IEI), and lengthening paid annual vacation (LPAV); but opposes rescuing major bank (RMB), fighting with hostile country (FHC), and land reclamation (LR). Party 2 supports RMB, BHR, CJO and IEI; but opposes EHI, RT, LPAV, MR, FHC and LR. That is, their demand sets are:

$$D_1 = \{\text{EHI, RT, BHR, CJO, IEI, LPAV, MR}, \neg\text{RMB}, \neg\text{FHC}, \neg\text{LR}\},$$
$$D_2 = \{\text{RMB, BHR, CJO, IEI}, \neg\text{EHI}, \neg\text{RT}, \neg\text{LPAV}, \neg\text{FHC}, \neg\text{LR}, \neg\text{MR}\}.$$

As shown in Table 4, two parties have their original preferences over their own policies, which just reflect their own voters' favourites rather than the other side's situation. Nonetheless, when going to the negotiation, they will worry about their conflicting demands and thus adjust the preferences to form initial dynamic ones, hoping to avoid reaching no agreements, whilst keeping as many of their highly preferred demands as possible. In this example, Party 1 demands RT but Party 2 demands ¬RT, which is a contradiction. Therefore, RT is an element of party 1's conflicting demand set and ¬RT is an element of party 2's one. Similarly, we can get

$$D_1^{\pm} = \{\text{EHI, LPAV, MR}, \neg\text{RMB}, \text{RT}\},$$
$$D_2^{\pm} = \{\neg\text{EHI}, \neg\text{LPAV}, \neg\text{MR}, \text{RMB}, \neg\text{RT}\}.$$

From Table 4, by formula (9), Party 1's initial risk degree is:

$$
\begin{aligned}
&\gamma_1 \\
=&\frac{(l_1(EHI)-l_1^{(1)}(EHI))+(l_1(LPAV)-l_1^{(1)}(LPAV))+(l_1(MR)-l_1^{(1)}(MR))+(l_1(\neg RMB)-l_1^{(1)}(\neg RMB))+(l_1(RT)-l_1^{(1)}(RT)}{|(l_1(EHI)-5)+(l_1(LPAV)-5)+(l_2(\neg MR)-5)+(l_1(\neg RMB)-5)+(l_1(RT)-5)|} \\
=&\frac{(1-2)+(2-3)+(2-4)+(3-5)+(5-5)}{\left|(1-5)+(2-5)+(2-5)+(3-5)+(5-5)\right|} \\
=&-0.5.
\end{aligned}
$$

Similarly, by formula (9), we can obtain:

$$
\begin{aligned}
&\gamma_2 \\
=&\frac{(l_2(\neg RT)-l_2^{(1)}(\neg RT))+(l_2(\neg EHI)-l_2^{(1)}(\neg EHI))+(l_2(RMB)-l_2^{(1)}(RMB))+(l_2(\neg PLAV)-l_2^{(1)}(\neg PLAV))+(l_2(\neg MR)-l_2^{(1)}(\neg MR))}{|(l_2(\neg RT)-1)+(l_2(\neg EHI)-1)+(l_2(RMB)-1)+(l_2(\neg LPAV)-1)+(l_2(\neg MR)-1)|} \\
=&\frac{(2-1)+(3-2)+(3-3)+(4-3)+(5-4)}{\left|(2-1)+(3-1)+(3-1)+(4-1)+(5-1)\right|} \\
=&0.33.
\end{aligned}
$$

Party 1 downgrades the conflicting demand of EHI from the top level to the second level, downgrades LPAV from the second level to the third level, and downgrades the other conflicting demands MR and ¬RMB. Therefore, Party 1 is somewhat risk-averse. On the other hand, Party 2 is risk-seeking, because it moves up its conflicting demands ¬RT, ¬EHI, ¬LPAV and ¬MR when changing the original preference to the initial dynamic one.

Suppose Party 2 is more patient than Party 1. Then Party 1 uses formula (7) and Party 2 uses formula (8) as their patience descent degree functions, respectively. Now we show how the problem is solved by using our dynamically simultaneous concession process. During the negotiation, the changes of preference and parameters are shown in Tables 5 and 6, respectively.

More specifically, there are two steps in the first round of negotiation. Firstly, as shown in Table 4, there are some contradiction in demands of Parties 1 and 2, so each of them chooses one demand (conflicting demands have priority) on the lowest level in their dynamic preferences and gives up a demand, *i.e.*, Party 1 gives up RT and Party 2 gives up BHR. After the first step of the first round, the dynamic preference structure will be updated into a new one, by simultaneous concession, as shown in the first row (denoted as Round 1) in the left sub-table of Table 5. Secondly, by the parameters' functions (*i.e.*, formulas (5) and (7)-(9)), we can obtain:

$$
\begin{aligned}
&\vartheta_1 = \frac{0}{5} = 0, \;\; \rho_1 = \frac{\sqrt{1 \times (2 \times 10 - 1)}}{10} = 0.436; \\
&\gamma_1 = -0.5, \;\; \vartheta_2 = \frac{1}{5} = 0.2, \\
&\rho_2 = 1 - \frac{\sqrt{10^2 - 1^2}}{10} = 0.005, \;\; \gamma_2 = 0.33.
\end{aligned}
$$

Thus, according to fuzzy rules in Table 2, based on the Mamdani method (see Definition 10), we can obtain:

Table 5: Dynamic negotiation proceeding

	Rank	Party 1	Party 2
Round 1	1	CJO	¬LR, CJO, ¬RT
	2	¬LR, EHI	¬FHC, ¬EHI
	3	LPAV, IEI	RMB, IEI, ¬LPAV
	4	¬FHC, MR, BHR	¬MR
	5	¬RMB	
Round 2	1	CJO	¬LR, CJO
	2	¬LR	¬FHC, ¬RT
	3	IEI, EHI	IEI, ¬EHI
	4	¬FHC, BHR, LPAV	RMB, ¬LPAV
	5	MR	
Round 3	1	CJO	¬LR, CJO
	2	¬LR	¬FHC
	3	IEI	IEI, ¬RT
	4	¬FHC, BHR, EHI	¬EHI
	5	LPAV	RMB
Round 4	1	CJO	¬LR, CJO
	2	¬LR	¬FHC
	3	IEI	IEI
	4	¬FHC, BHR	¬RT
	5	EHI	RMB

	Rank	Party 1	Party 2
Round 1*	1	CJO	¬LR, CJO
	2	¬LR	¬FHC,¬RT
	3	IEI, EHI	IEI, ¬EHI
	4	¬FHC, BHR, LPAV	RMB, ¬LPAV
	5	MR, ¬RMB	¬MR
Round 2*	1	CJO	¬LR, CJO
	2	¬LR	¬FHC
	3	IEI	IEI, ¬RT
	4	¬FHC, BHR, EHI	¬EHI
	5	MR, LPAV	RMB, ¬LPAV
Round 3*	1	CJO	¬LR, CJO
	2	¬LR	¬FHC
	3	IEI	IEI
	4	¬FHC, BHR	¬RT
	5	EHI, LPAV	¬EHI, RMB
Round 4*	1	CJO	¬LR, CJO
	2	¬LR	¬FHC
	3	IEI	IEI
	4	¬FHC, BHR	
	5	EHI	¬RT, RMB

Table 6: Parameters

parameters	Round 1	Round 2	Round 3	Round 4
$(\vartheta_1, \vartheta_2)$	(0, 0.2)	(0, 0.2)	(0, 0.2)	(0, 0.2)
(ρ_1, ρ_2)	(0.436, 0.005)	(0.600, 0.020)	(0.714, 0.046)	(0.800, 0.200)
(γ_1, γ_2)	(-0.5, 0.33)	(-0.5, 0.33)	(-0.5, 0.33)	(-0.5, 0.33)
(ζ_1, ζ_2)	(0.474, 0.331)	(0.474, 0.331)	(0.5, 0.331)	(0.5, 0.331)

$$
\begin{aligned}
\mu_{M,1}(\zeta) = \max\{ & \min\{\mu_{low\ RD}(0), \mu_{low\ CD}(\zeta)\}, \min\{\mu_{medium\ RD}(0), \mu_{medium\ CD}(\zeta)\}, \\
& \min\{\mu_{high\ RD}(0), \mu_{high\ CD}(\zeta)\}, \min\{\mu_{low\ PDD}(0.436), \mu_{low\ CD}(\zeta)\}, \\
& \min\{\mu_{medium\ PDD}(0.436), \mu_{medium\ CD}(\zeta)\}, \min\{\mu_{high\ PDD}(0.436), \mu_{high\ CD}(\zeta)\}, \\
& \min\{\mu_{low\ IRD}(-0.5), \mu_{high\ CD}(\zeta)\}, \min\{\mu_{medium\ IRD}(-0.5), \mu_{medium\ CD}(\zeta)\}, \\
& \min\{\mu_{high\ IRD}(-0.5), \mu_{low\ CD}(\zeta)\}\} \\
= & \begin{cases} 1 & \text{if } 0 \leqslant \zeta \leqslant 0.2, \\ 2-5x & \text{if } 0.2 \leqslant \zeta \leqslant 0.3, \\ 5x-1 & \text{if } 0.3 \leqslant \zeta \leqslant 0.4, \\ 1 & \text{if } 0.4 \leqslant \zeta \leqslant 0.6, \\ 4-5x & \text{if } 0.6 \leqslant \zeta \leqslant 0.7, \\ 5x-3 & \text{if } 0.7 \leqslant \zeta \leqslant 0.75, \\ 0.75 & \text{if } 0.75 \leqslant \zeta \geqslant 1. \end{cases}
\end{aligned}
$$

Then, by formula (26) we have:

$$\zeta_1 = u_{cen,1} = \frac{\int_0^1 \zeta \mu_M(\zeta)\,\mathrm{d}\zeta}{\int_0^1 \mu_M(\zeta)\,\mathrm{d}\zeta} = 0.474.$$

Similarly, we can obtain $\zeta_2 = 0.331$ in this round. Thus, according to their action function (*i.e.*, formula (1)), their initial dynamic preferences are updated into new ones as shown in the first row (denoted as Round 1*) in the right sub-table of Table 5. Since Party 1's preference change degree is higher than 0.3 but lower than 0.7, according to the second branch of action function (1) it chooses "move down the conflicting demand one level" in the first round for EHI, ¬LPAV, MR, and ¬RMB, and according to the third branch of action function (1) leaves the others unchanged. And Party 2's preference change degree is also higher than 0.3 but lower than 0.7, so according to the second branch of action function (1), it chooses "move down the conflicting demand one level" for ¬RT, ¬EHI, RMB, ¬LPAV, and ¬MR, and according to the third branch of action function (1), it leaves the others unchanged.

Similarly, in the first step of the second round, Party 1 gives up ¬RMB and Party 2 gives up ¬MR. After the first step, their preferences are shown in Round 2. In this round, by formulas (5) and (7)-(9), we can obtain $\vartheta_1 = 0$, $\rho_1 = 0.6$, $\gamma_1 = -0.5$, $\vartheta_2 = 0.2$, $\rho_2 = 0.02$, and $\gamma_2 = 0.33$, respectively. Then $\zeta_1 = 0.474$ and $\zeta_2 = 0.331$. Thus, according to the second branch of action function (1) both parties choose "move down the conflicting demand one level" for EHI and LPAV (Party 1) and ¬RT, ¬EHI, RMB, and ¬LPAV (Party 2). According to the third branch of action function (1), they leave the others unchanged.

In the first step of the third round, Party 1 gives up MR and Party 2 gives up ¬LPAV. After the first step, their preferences are shown in Round 3. In this round, by formulas (5) and (7)-(9), we can obtain $\vartheta_1 = 0$, $\rho_1 = 0.714$, $\gamma_1 = -0.5$, $\vartheta_2 = 0.2$, $\rho_2 = 0.046$, and $\gamma_2 = 0.33$, respectively. Then $\zeta_1 = 0.5$ and $\zeta_2 = 0.331$. According to action function (1), EHI of Party 1 and ¬RMB, ¬RT, and ¬EHI of Party 2 decline one level in this round.

In the first step of the fourth round, Party 1 gives up LPAV and Party 2 gives up ¬EHI. After the first step, their preferences are shown in Round 4. In this round, by formulas (5) and (7)-(9), we can obtain $\vartheta_1 = 0$, $\rho_1 = 0.8$, $\gamma_1 = -0.5$, $\vartheta_2 = 0.2$, $\rho_2 = 0.2$, and $\gamma_2 = 0.33$, respectively. Then $\zeta_1 = 0.5$ and $\zeta_2 = 0.331$. Thus according to the third branch of action function (1), Party 1 chooses "do nothing" for all conflicting demands in this round and according to the second branch of action function (1), party 2 moves down ¬RT one level and according to the third branch of action function (1) it leaves the others unchanged.

The negotiation procedure ends after the 4th round because both of the parties have nothing in contradiction.

From Table 5, we can see that by our dynamically simultaneous concession method, the outcome of the negotiation procedure is:

$$A_{DSCS,1}(G) = \{\text{CJO}, \neg\text{LR}, \text{IEI}, \neg\text{FHC}, \text{BHR}, \text{EHI}\},$$
$$A_{DSCS,2}(G) = \{\neg\text{LR}, \text{CJO}, \neg\text{FHC}, \text{IEI}, \neg\text{RT}, \text{RMB}\}.$$

Therefore, their agreement is:

$$\begin{aligned} A_{DSCS}(G) &= A_{DSCS,1}(G) \cup A_{DSCS,2}(G) \\ &= \{\text{CJO}, \neg\ \text{LR}, \text{IEI}, \neg\text{FHC}, \text{BHR}, \text{EHI}, \neg\text{RT}, \text{RMB}\}. \end{aligned}$$

6. Experimental analyses

In order to reveal some insights into our model, we do lots of simulation experimental analysis in this section, which can be divided into two parts. In Section 6.1, we do experiments to explain why we just consider the downgrading direction in action function (1) in our model. In Section 6.2, we do experiments to analyse how the negotiating agents' attitudes of risk affect the outcome of a negotiation procedure.

6.1. Comparison with other action functions

This subsection presents the experiment of justifying why we choose formula (1), rather than the following ones, as the action function of a negotiating agent:

$$\mathcal{A}_i'(\zeta) = \begin{cases} \text{move } d^{\pm} \text{ down two levels from its current level in round } \lambda \\ \qquad \text{if } \zeta \geqslant 0.8 \wedge l_i^{(\lambda)}(d^{\pm}) \leqslant H_i(1) - 2, \\ \text{move } d^{\pm} \text{ down one level from its current level in round } \lambda \\ \qquad \text{if } (0.8 > \zeta \geqslant 0.6 \wedge l_i^{(\lambda)}(d^{\pm}) \leqslant H_i(1) - 1) \vee (\zeta \geqslant 0.8 \wedge l_i^{(\lambda)}(d^{\pm}) = H_i(1) - 1), \\ \text{move } d^{\pm} \text{ up two levels from its current level in round } \lambda \\ \qquad \text{if } \zeta < 0.2 \wedge l_i^{(\lambda)}(d^{\pm}) \geqslant 3, \\ \text{move } d^{\pm} \text{ up one level from its current level in round } \lambda \\ \qquad \text{if } (0.2 \leqslant \zeta < 0.4 \wedge l_i^{(\lambda)}(d^{\pm}) \geqslant 2) \vee (\zeta < 0.2 \wedge l_i^{(\lambda)}(d^{\pm}) = 2) \\ \text{do nothing} \\ \qquad \text{otherwise;} \end{cases} \tag{28}$$

$$\mathcal{A}_i''(\zeta) = \begin{cases} \text{move } d^{\pm} \text{ up two levels from its current level in round } \lambda \\ \qquad \text{if } \zeta < 0.3 \wedge l_i^{(\lambda)}(d^{\pm}) \geqslant 3, \\ \text{move } d^{\pm} \text{ up one level from its current level in round } \lambda \\ \qquad \text{if } (0.3 \leqslant \zeta < 0.7 \wedge l_i^{(\lambda)}(d^{\pm}) \geqslant 2) \vee (\zeta < 0.3 \wedge l_i^{(\lambda)}(d^{\pm}) = 2), \\ \text{do nothing} \\ \qquad \text{otherwise,} \end{cases} \tag{29}$$

where $D_i^{\pm}$ is the conflicting demand set of negotiating agent i in D_i, $d^{\pm} \in D_i^{\pm}$, and λ means the λ-th round of the negotiation procedure. The difference among the action functions (1), (28) and (29) is that action function (1) just considers the downgrading direction of updating preference, action function (29) just considers the upgrading direction, and action function (28) considers both directions.

On the Matlab platform, we conduct two experiments to see how different action functions influence the outcomes when the number of conflicting demands and negotiating agents change, respectively. In both experiments, we run the negotiation model 1,000 times under the setting that every negotiating agent's action function is the same (action function (1) or action function (28) or action function (29)), and the fuzzy rules are those in Table 2.

In the first experiment, we randomly generate 10 demands on different preference levels for two negotiating agents and arbitrarily label P (in-between 0 and 10) of them

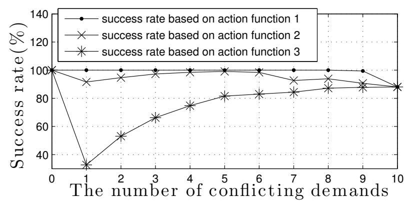

Figure 4: Success rate over the number of conflicting demands

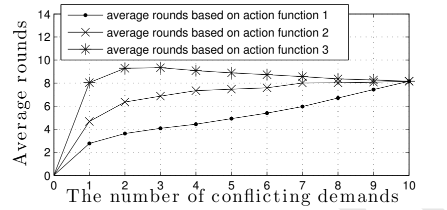

Figure 5: Average rounds of reaching agreements over the number of conflicting demands

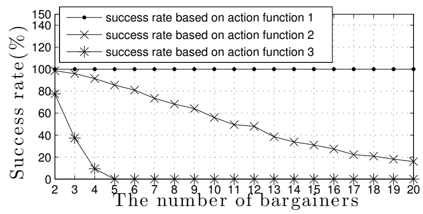

Figure 6: Success rate over the number of bargainers

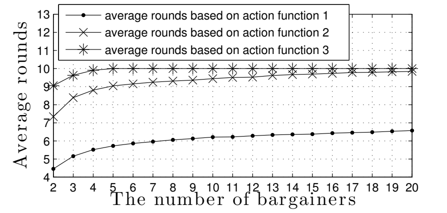

Figure 7: Average rounds of reaching agreements over the number of bargainers

as the conflicting ones. The negotiation is carried out in our fuzzy logic based model but based on action functions (1), (28), and (29), respectively. From Figure 4, we can see that the success rate of the model with action function (1) always keeps high when the conflicting demands are less than 10. However, the success rate of the one with action function (28) increases first and then decreases, and is lower than that of the one with action function (1) in all situations, especially when the number of conflicting demands is low or high, and the success rate of the model with action function (29) is the lowest one in all situations. Moreover, Figure 5 shows that in the model with action function (1), the average number of rounds in reaching agreements are the lowest.

In the second experiment, we randomly generate 10 demands in different preference levels for *M* negotiating agents (in-between 2 and 20) and arbitrarily select 4 of them as the conflicting ones among all the negotiators. The negotiation will proceed until there are no conflicting demands, respectively. From Figure 6, we can see the model with action function (1) can maintain a high success rate of negotiation even when the number of negotiating agents increases, while the success rate will obviously decrease with the other two with action function (28) and action function (29). And Figure 7 shows that the model with action function (1) can also keep lower rounds when reaching agreements.

Therefore, according to the experiments, we have:

Observation 1. *If action function (1) is used in our fuzzy logic based model, it can guarantee not only a high success rate of negotiation but also a high efficiency when the numbers of conflicting demands and negotiating agents are increased.*

Here we should note that giving-up the upgrading direction change does not mean giving-up the representation of attitude towards risk, but just adjusting the method to improve the outcomes, because the attitude towards risk can also be represented by the preference change degree, and different preference change degrees lead to different

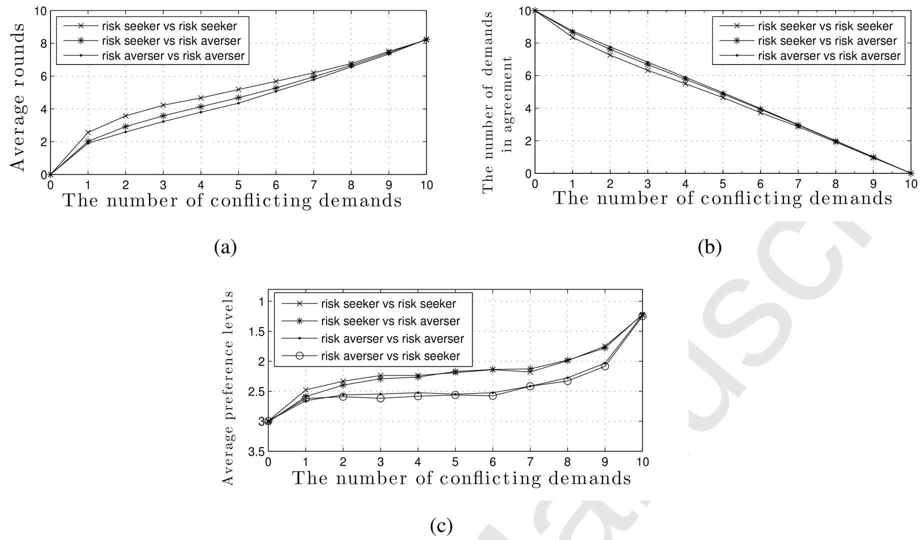

Figure 8: Average rounds of reaching agreements, the number of demands in agreement, the average preference levels of remaining demands in the first negotiating agent's outcome with the number of conflicting demands about effect of risk degree.

actions.

6.2. The influence of negotiating agents' attitude towards risk

This subsection will experimentally analyse how negotiating agents' attitudes towards risk influence the outcome of a negotiation procedure.

We will use the measure of the average level number of remaining demands in a negotiating agents' outcome in initial dynamic preference. A smaller average level number means a higher average level (*i.e.*, a negotiating agent gains more of what he prefers) and a large average level number means a lower average level (*i.e.*, a negotiating agent gains less of what he really wants). In this experiments, we run the negotiation 1,000 times under the setting that every negotiating agent's action function is formula (1) and the fuzzy rules are those in Table 2.

We do three experiments to investigate the effect of attitude towards risk in three dimensions: (i) the average rounds to achieve agreements; (ii) the number of demands in agreement; and (iii) the average preference levels of remaining demands in certain negotiating agent's outcome. We randomly generate 10 demands on 5 preference levels for two negotiating agents and arbitrarily label N (changing from 0 to 10) of them as their conflicting ones.

In the first and second experiments, the negotiation is carried out in the fuzzy logic based model where both negotiating agents' risk degrees are fixed in the three cases:

(i) $(\gamma_1, \gamma_2) = (1, 1)$, meaning that one risk seeker encounters another risk seeker;

(ii) $(\gamma_1, \gamma_2) = (1, -1)$, meaning that one risk-seeker encounters one risk averter; and

(iii) $(\gamma_1, \gamma_2) = (-1, -1)$, meaning that one risk averter encounters another risk averter.

From Figure 8(a), we can see that the average rounds to reach agreements is the lowest in the case that one risk averter encounters another risk averter in a negotiation procedure and is the highest in the case that one risk seeker encounters another risk seeker. From Figure 8(b), the number of consistent demands in agreement is the highest in the case that one risk averter encounters another risk averter in a negotiation procedure; and is the lowest when one risk seeker encounters another risk seeker. Moreover, in Figures 8(a) and 8(b), comparing the line of type “-×-” with that of type “-∗-” and comparing the line of type “-∗-” with that of type “-·-”, we can see that if a negotiating agent chooses to be a risk seeker, no matter whether his opponent is a risk seeker or a risk averter, the negotiation will take more time and the negotiating agent will get fewer demands than when he chooses to be risk averse.

In the third experiment, we also model the cases similar to the first experiment, but the average preference levels of remaining demands in each negotiating agent's outcome are different. Therefore, we carry out four cases as shown in third chart in Figure 8(c), and just draw the first negotiating agent's situation. By comparing the line of type “-·-” with that of type “-∘-” and comparing the line of type “-×-” with that of type “-∗-” type, we can see that if a negotiating agent is risk seeking, no matter whether his opponent is risk seeking or averse, his average preference levels of remaining demands is higher than that when choosing to be risk averse. That is, a risk seeker can gain more demands that he prefers than a risk averter.

Therefore, according to the above analysis, we have:

Observation 2. *A risk seeking negotiating agent can gain fewer but more preferred-demands than a risk-averse one in the fuzzy logic based model.*

This is on line with what often happens in real life. For example, in stock markets, a high income often comes with a high risk [72].

7. Benchmark with SCS

This section analyses how well our model and its solution concept (*i.e.*, DSCS) work compared with those of Zhang [34] (*i.e.*, SCS).

In the existing model, negotiating agents also do simultaneous concession; but unlike ours, their preferences do not change during the course of a negotiation and in every round all negotiating agents give up all the demands on the least preferred level. Formally, its negotiation process is defined as follows:

Definition 12. *Let $\{D_i^1, \cdots, D_i^{H_i}\}$ be the partition of D_i induced by equivalence relation $\sim$, which can be defined by preference ordering $\succcurlyeq_i$, where H_i is the height of the hierarchy. For convenience, $D_i^{>k}$ is used to stand for $\bigcup_{l>k} D_i^l$. The simultaneous concession solution's (SCS) agreement of a negotiation procedure G is given by:*

$$A_{SCS}(G) = \begin{cases} D_1^{>\mu} \bigcup \ldots \bigcup D_n^{>\mu} & \text{if } \mu < H, \\ \varnothing & \text{otherwise,} \end{cases} \tag{30}$$

where $\mu = \min\{k \mid \bigcup_{i=1}^{n} D_i^{>k}$ *is consistent*} (i.e., μ *is the minimal rounds of concessions of the procedure) and* $H = \min\{H_i \mid i \in N\}$.

In this section, we will theoretically and empirically analyse the relation between our dynamically simultaneous concession solution (DSCS) process and the static one (SCS) [34].

7.1. Theoretic Analysis

Firstly, we get some theorems about the relation between the both concepts of solutions.

Theorem 5. *For two negotiation procedures G and G′ with the same inputs,*

(i) when $A_{SCS}(G) \neq \emptyset$, $A_{DSCS}(G') \neq \emptyset$*; but*

(ii) when $A_{SCS}(G) = \emptyset$*, it is possible that* $A_{DSCS}(G') \neq \emptyset$.

Proof. (i) If $S_{SCS}(G) \neq (\emptyset, \ldots, \emptyset)$, it means that $\exists\lambda < H$ such that there is an agreement in the λ-th round by SCS, and all demands left of each negotiating agent are consistent with each other. By action function (1), only conflicting demands could be downgraded. Therefore, no matter how the dynamic preference of each negotiating agent changes, the demand set of all the negotiating agents from the first level to the $(H - \lambda)$-th level will remain consistent. This means that the negotiation procedure can reach an agreement at least in the λ-th round by DSCS.

(ii) We now consider two negotiation procedures with the same inputs. That is, the procedure contains two negotiating agents and each negotiating agent has ten demands, five of which are conflicting with those of the other negotiating agent. Moreover, a pair of conflicting demands from both the negotiating agents occurs at the top levels in both negotiating agents' dynamic demand preference hierarchies (but no restrictions on original demand preference ordering). More specifically, we can depict such a procedure as follows:

(a) N={1,2};

(b) $X_1 = \{a, b, c, d, e, f, g, h, i, j\}$ and $X_2 = \{\neg a, \neg b, c, d, e, f, g, h, \neg i, \neg j\}$;

(c) $a \succcurlyeq_1^{(1)} b \succcurlyeq_1^{(1)} c \succcurlyeq_1^{(1)} d \succcurlyeq_1^{(1)} f \succcurlyeq_1^{(1)} g \succcurlyeq_1^{(1)} h \succcurlyeq_1^{(1)} i \succcurlyeq_1^{(1)} j$;

(d) $\neg a \succcurlyeq_2^{(1)} \neg b \succcurlyeq_2^{(1)} c \succcurlyeq_2^{(1)} d \succcurlyeq_2^{(1)} f \succcurlyeq_2^{(1)} g \succcurlyeq_2^{(1)} h \succcurlyeq_2^{(1)} \neg i \succcurlyeq_2^{(1)} \neg j$; and

(e) FLS is the fuzzy system that is presented in Section 3.

Notice that in the above we just require the demands placed in the first place in the preference orderings of both negotiating agents conflict with each other, such as a and $\neg a$, but without any restriction on other demands' preference orderings. Then, in such a kind of negotiation procedures, $A_{SCS}(G) = \emptyset \bigcup \ldots \bigcup \emptyset = \emptyset$. However, by Theorem 3, $A_{DSCS}(G) \neq \emptyset$. □

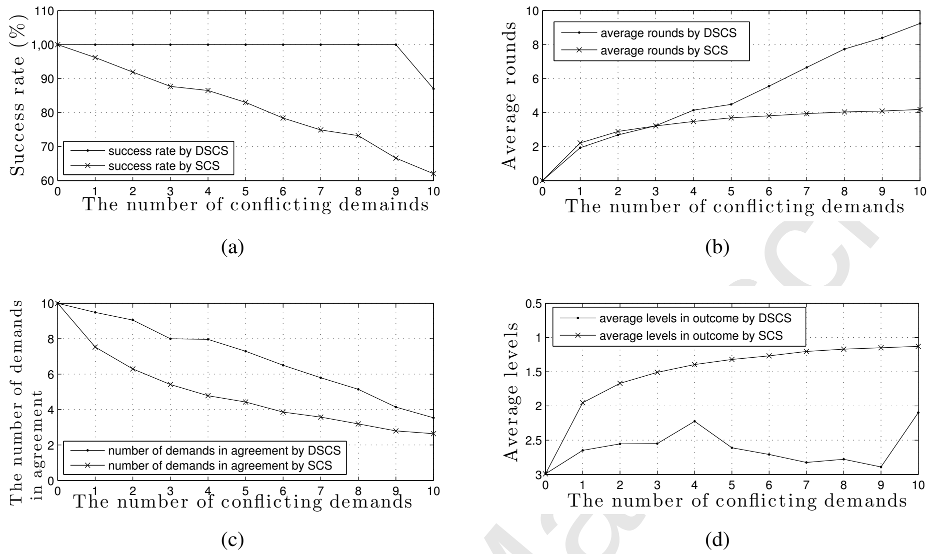

Figure 9: The success rate and the average rounds of reaching agreements, the number of demands in agreement, and the average preference levels of remaining demands in the first negotiating agent's outcome with the number of conflicting demands.

This theorem indicates that our dynamically simultaneous concession process can improve the success rate of negotiation, which is an agreeable result for all the negotiating agents. That is, if an agreement can be reached through the SCS process, it can also be reached through our DSCS process; but in some case where the SCS process cannot reach an agreement, our DSCS process is still able to reach an agreement. Therefore, in this sense our model is better than the SCS one in resolving conflicts among a set of agents.

7.2. Empirical Evaluation

We will also carry out three groups of experiments to analyse how the quality of outcomes changes with the number of conflicting demands, the number of bargainers and the number of preference levels, respectively. In addition to average rounds, the number of demands in agreement, and the average level of demands in outcome, we will introduce one more criteria to evaluate an outcome of a negotiation procedure: the success rate of negotiation. In these three experiments, we run the negotiation 1,000 times under the setting that every negotiating agent's action function is formula (1) and the fuzzy rules are those in Table 2.

In the first experiment, 10 demands are randomly put on different 5 levels for two negotiating agents and we arbitrarily label N $(\in \{0, 1, \cdots, 10\})$ of them as their conflicting demands. Figure 9 shows:

(i) The success rate of DSCS is higher than that of SCS, especially when the conflicting demands are increasing. For example, when the number of conflicting demands is 9, the success rate of our model is about 50% higher.

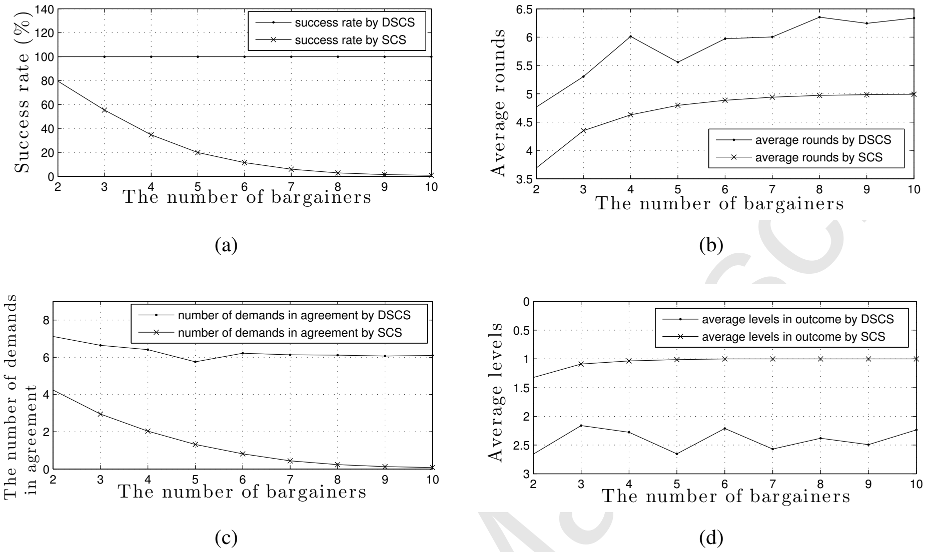

Figure 10: The success rate and the average rounds of reaching agreements, the number of demands in agreement, and the average preference levels of remaining demands in the first negotiating agent's outcome with the number of bargainers.

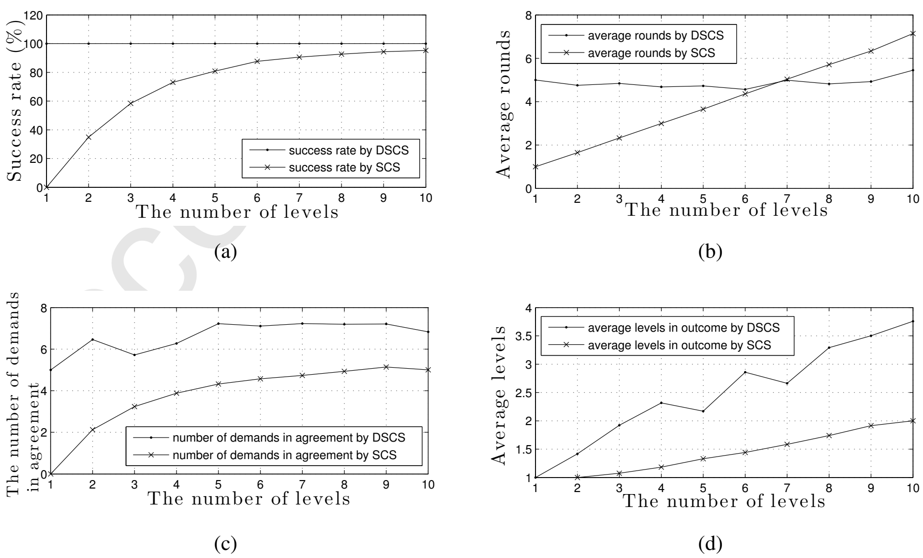

Figure 11: The success rate and the average rounds of reaching agreements, the number of demands in agreement, and the average preference levels of remaining demands in the first negotiating agent's outcome with the number of levels

(ii) In DSCS the average rounds needed to reach agreements are higher than that of SCS because by DSCS in every round there is only one demand given up for every bargainer and then there will be more negotiation rounds.

(iii) Using DSCS, the number of demands in agreement is larger.

(iv) When the number of conflicting demands increases, the average preference level in a negotiating agent's outcome using DSCS will be lower than that of using SCS.

In the second experiment, we randomly generate 10 demands on 5 preference levels for *M* negotiating agents (in-between 2 and 10) and arbitrarily select 5 of them as the conflicting demands of all the negotiating agents. The negotiation will proceed in both models. Figure 10 shows:

(i) DSCS can maintain a high success rate of negotiation even when the number of negotiating agents increases, while the success rate will obviously decrease using SCS.

(ii) Since in every round there is only one demand given up by every negotiating agent by DSCS, it needs more rounds to reach agreement when using DSCS.

(iii) More demands can be kept in the final agreement even when the negotiating agents increase using DSCS.

(iv) When the number of negotiating agents increases, the average preference level in a negotiating agent's outcome using DSCS will be lower than that of using SCS.

In the third experiment, we randomly generate 10 demands in *K* (in-between 1 and 10) preference levels for 2 negotiating agents and arbitrarily select 5 of them as the conflicting demands of all the negotiating agents. Figure 11 shows:

(i) Using DSCS can maintain a high success rate of negotiation no matter what the number of levels is, while using SCS, the success rate is low when the number of levels is low and obviously increases when the number of levels increases.

(ii) The rounds of reaching agreements by DSCS do not change as much when the number of demands levels changes, while using SCS, it increases when the number of demands levels increases.

(iii) More demands can be saved in the final agreement when the number of levels increases using DSCS.

(iv) When the number of levels increases, the average preference level in a negotiating agent's outcome using DSCS will be lower than that of using SCS.

Therefore, according to the above analysis, we have:

Observation 3. *Although the average level of agreed demands using our DSCS model is lower than that of the SCS one, since reflecting a negotiating agents' cognitive factors of risk, regret, and patience, our DSCS keeps a higher success rate and a higher efficiency, and gets more demands left in an agreement, even when the number of conflicting demands, negotiating agents or preference levels increase.*

7.3. Comparison via an example

When using SCS to solve the political negotiation problem in Section 5, the outcome is:

$$A_{SCS,1}(G) = \{\text{CJO}\},$$
$$A_{SCS,2}(G) = \{\neg\text{LR}, \text{CJO}, \neg\text{RT}\},$$

and so the agreement of two parties is:

$$A_{SCS}(G) = A_{SCS,1}(G) \bigcup A_{SCS,2}(G) = \{\neg\text{LR}, \text{CJO}, \neg\text{RT}\}.$$

By comparing (28) with (31), we can see that ours is more reasonable. In fact, the numbers of left demands of both parties and the agreement are not less than the ones using SCS. For example, through the SCS model, the negotiating agents have to give up the demands ¬FHC, BHR and IEI (which are demands consistent with both negotiating agents) as the cost of their negotiation risk attitudes. Moreover, sometimes the left demand set of a negotiating agent can strictly include the one using SCS, such as Parties 1 and 2 in this example. In addition, the agreement gained by our solution process reflects not only the negotiating agents' risk attitudes but also the other human factors in a negotiation, such as patience and regret degree.

This political example and the example in the proof of Theorem 5 in Section 7.1 reveal one serious limitation of the SCS model: their concessions always begin from the lowest level in the ranking of a demand set and the negotiating agents never change the preference, so if some conflicting demands are on the top level then the bargain will be easily broken. However, in our model, the negotiating agents' preference can be changed during the course of a negotiation, so the preferred but inconsistent demands can be moved down when the preference change degree is high enough. Thus, we can avoid an unreasonable outcome in the SCS model. To illustrate this issue more obviously, consider a simple negotiation setting with two negotiating agents whose initial preferences of the demands are as follows:

$$a \succcurlyeq_1^{(1)} b,$$
$$\neg a \succcurlyeq_2^{(1)} b.$$

Using SCS will bring a disagreement, but by using our DSCS model, before the negotiation the two negotiating agents are allowed to change the static preference structure into the following initial dynamic preference structures:

$$b \succcurlyeq_1^{(1)} a,$$
$$b \succcurlyeq_2^{(1)} \neg a.$$

Thus, the negotiating agents can reach an agreement, *i.e.*, $\{b\}$. Therefore, our negotiation process, on the one hand, can still reflect the negotiating agents' attitude of risk like SCS, as well as other psychological factors that SCS cannot reflect; on the other hand, it avoids many negotiation-broken situations that would result from using SCS.

8. Related work

In this section, we will discuss related work to show how our work advances the state-of-art in the relevant research fields. Specifically, we firstly compare our work with other fuzzy logic based negotiation models in Section 8.1. Secondly, we compare our models with some crisp logic based negotiation models in Section 8.2. Thidly, we discuss similarities and differences between our work and some consensus models in group decision making in Section 8.3. Finally, we discuss some other similar topics in Section 8.4, including opinion dynamics and dynamic preferences.

8.1. Fuzzy logic based negotiation models

In some negotiation systems, the methods of fuzzy logic have been used. In this section, we will discuss these models one by one according to the ways in which they used in negotiation and what kinds of fuzzy logic they employ.

8.1.1. Offer evaluation

In this sort of work, fuzzy rules are used for evaluating offers. For example, Kolomvatsos et al. establish a fuzzy logic based model for a buyer to decide to accept or reject a seller's offer according to the proposed price, the belief about the seller's deadline, the remaining time, the demand relevancy, and so on [73]. However, this model does not show how the negotiating agents' risk attitudes change their preferences, while ours does via a fuzzy logic system. Moreover, although they do a lot of simulation experiments to show their model's advantages over other similar models, they have done little theoretical analysis to reveal some insights into their model, as we do in this paper.

Zuo and Sun also use fuzzy logic to evaluate offers in the bilateral negotiation model [74]. Moreover, they distinguish three attitudes of negotiating agents in three concession strategies: greedy, anxious and calm. However, unlike our fuzzy logic based model, their model does not deal with risk attitudes of the negotiating agents, and their preferences on the demands are ranked by using real numbers. More importantly, in this paper we theoretically analyse: (i) the affection of parameters in our fuzzy system, (ii) the conditions under which our negotiation system can reach agreements, and (iii) the relation of our negotiation outcomes with the ones gained via the other work.

8.1.2. Offer generation

In this kind of work, fuzzy rules are used to generate offers or counter-offers during the course of a negotiation. For example, Costantino and Gravio propose a new intermediation model for analysing a possible strategic interaction in a supply chain [75]. There the output of the fuzzy inference engine is the degree to which a negotiating agent should concede. The degree is calculated by using fuzzy rules, which is similar to the way of calculating the preference change degrees in our fuzzy logic based model. However, their input parameters just include the offer in the previous round of negotiation, the current contractual power and market penetration, but ignore negotiating agents' risk attitudes. Moreover, they just do a case study, but few theoretical or experimental analyses on their negotiation model. Nevertheless, we not only theoretically reveal some critical insights into our model, but also do a lot of experiments to confirm the effectiveness of our model in terms of negotiation success rate, negotiation efficiency and agreement's quality.

Some other similar examples are as follows. Cheng et al. use fuzzy rules to represent negotiation strategies that generate offers or counter-offers during the course of a negotiation [76]. This model also employs a simple heuristic to learn the preferences of the other party, yet unlike ours their preference is not adjusted according to the progress of a negotiation. Arapoglou et al. employ fuzzy rules to reason about a buyer's next action (possibly it is an offer generation) in a negotiation [77]. This work also discusses how to generate these fuzzy rules automatically from data, whereas our work discusses how to elicit fuzzy rules from humans via psychological experiments. Carbo et al. use fuzzy rules for calculating counter-offers [78]. He et al. use fuzzy rules to determine buyers' offers (called bids) and sellers' offers (called asks) in a continuous double auction (a special kind of negotiation) [79]. Other studies on this line include [80, 81]. However, negotiating agents' preferences are not involved in these systems, and the problem of fuzzy rule acquisition is not discussed, either; but both are our concerns in this work. Yahia et al. use fuzzy rules for offer generation in negotiation for collaborative planning in manufacturing supply chains [82]. Nonetheless, unlike our work in this paper, their fuzzy rules are verbally formulated and the issue of negotiating agents' preferences are dealt with very little.

Moreover, researchers also design some adaptive negotiation strategies based on fuzzy rules. For example, in [83], for a grid resource negotiation Haberland et al. propose an adaptive negotiation strategy based on fuzzy rules for a client agent to adjust its tactics to the tendency in resource availability changes (*i.e.*, the overall direction and average speed of Grid resource dynamism) during the course of a negotiation. Although in sone sense it can be regarded as a kind of negotiating strategy that we use fuzzy rules to adjust negotiating agents' preference structure, the main difference between ours and theirs is that our adjustment is according to the changes of users' psychologic factors of risk, patience, and regret during the curse of a negotiation, while their is that of resource availability during a negotiation. In [84], Zhan et al. also propose adaptive conceding strategies for negotiating agents based on interval type-2 fuzzy logic and they use type-2 fuzzy rules to determine the change of strategies according to the remaining time and opponents cooperative degree. However, fuzzy rules there are predefined according to human intuitions, while the ones here are elicited via psychological experiments.

In addition, in some work, fuzzy rules are used to generate offers for manual negotiation. For example, Oderanti et al. develop a fuzzy logic based decision support system for human-human wage negotiation [25]. The inputs of their system are the changes in inflation and business profit, and then by using a fuzzy rule base and strategies, employers and employees can calculate the future wages. Therefore, their fuzzy logic based system is not an automated negotiation one, as ours is. Moreover, theoretically they analyse little about their decision support system, but we do and further show some advantages of our fuzzy logic based model.

8.1.3. Opponent analysis

There is a sort of work that equips a negotiating agent with fuzzy rules to analyse the relevant information about his opponent in order to take proper actions during the course of a negotiation. For example, Kolomvatsos and Hadjiefthymiades propose a fuzzy logic based model for a negotiating agent to estimate his opponent's negotiation deadline [85]. Their fuzzy rules are defined directly by human experts, while ours is by the means of psychological experiments. Since it is difficult to let human experts to define fuzzy rules directly, in order to overcome the difficulty, Kolomvatsos and Hadjiefthymiades use a clustering algorithm to automatically generate a fuzzy rule base [86]. This is actually a kind of machine learning method, which elicits the fuzzy rule from data, while ours is from humans via psychological experiments.

8.1.4. Dynamic fuzzy rules

In the existing studies above, all fuzzy rules and the membership functions of all the fuzzy variables in the rules remain unchanged during the course of a negotiation. However, some researchers argue that they should be updated during negotiation in order to adapt to dynamic negotiation information. For example, Kolomvatsos et al. develop an adaptive fuzzy logic system for the buyer side in a negotiation with a seller [87], which can update automatically by adding fuzzy rules and changing membership functions when obtaining new information during a negotiation process. In particular, in their fuzzy logic system, some new fuzzy rules will be added when the buyer's acceptance degree of a seller's offer is equal to zero. Nevertheless, according to the setting of our fuzzy rules, our fuzzy rules can cover different sets of values for input parameters and there are no cases where an output is equal to zero. As a result, our fuzzy logic system does not have the above problem. Moreover, our fuzzy rules are elicited by means of some psychological experiments, which reflect the reality better than theirs, because theirs are not via by any psychological experiment. In addition, their fuzzy logic system is used for evaluating a seller's offer and produce an acceptance degree to which the seller's offer should be accepted or rejected. However, our fuzzy logic system is used as a sort of negotiation strategy tool and its output is a preference change degree that determines which actions a negotiating agent should take to change its preference structure.

8.1.5. Fuzzy constraint

Fuzzy constraints can be viewed as a special kind of fuzzy logic and some automated negotiation systems are developed based on fuzzy constraints. For example, Luo et al. develop a fuzzy constraint-based negotiation system [2]. It actually is an instantiation of well-known principled negotiation approaches [88] (*i.e.*, negotiating based on interest, seeking alternative by trade-off, and arguing by rewarding). Therefore, the system has some nice attributes such as the capability of minimising information revelation, ensure win-win outcomes (fair for both sides), and build a long term relationship between sellers and buyers in order to generate long term profit. Nevertheless, in this work there are no discussions about how to elicit user's preferences modelled by fuzzy constraints, and the negotiating agents' preference structures remain the same during the course of a negotiation. These are its main differences from our work in this paper.

Karim and Pierluissi also build up a negotiation model based on fuzzy constraints for bilateral multi-issue negotiation [89]. The model contains two agents: (i) the information agent that stores and updates the information about the negotiation, and (ii) the negotiator agent that helps make a new price proposal according to buyer satisfaction. The fuzzy constraints are used to calculate the agent's satisfaction degree with the opponent's offer. However, there are some drawbacks in their model. For example, their fuzzy rule base for satisfaction measurement is based on their own intuitions, while our fuzzy rules are based on more reliable psychological experiments. Moreover, their simulation experimental analysis might not suffice to prove the quality of their model because it is actually a case study, whereas we do a lot of experiments, including benchmark experiments with a similar existing model (see Section 7). Another study [90] similar to that of [89] is similarly different from ours.

Hsu et al. also develop a fuzzy constraint based negotiation system to solve distributed job shop scheduling problems [91]. They model the scheduling problem as a set of fuzzy constraint satisfaction problems, interlinked by inter-agent constraints. Their system can flexibly adopt competitive, win-win, and collaborative strategies, depending on different production environments. Their experimental results show that the proposed system is flexible and effective for job scheduling problems with unforeseen disturbances. However, their work is not concerned with the acquisition of fuzzy constraints, while ours studied how to elicit fuzzy rules. This is also the difference between our work and their another similar work [92].

In [31], Zhan et al. use fuzzy constraints to represent negotiation goals and accordingly establish an offer evaluation method and a method for account-offer generation by tradeoff. There are some significant differences between our work in the paper and the one in [31]. First, negotiation issues in the previous work are in continuous domains, while the current ones are in discrete domains. Second, there are no discussions about how to acquire fuzzy constraints, here we propose a method to elicit fuzzy rules. Third, there fuzzy constraints employed to set negotiation goals, while here we use fuzzy rules to adapt the preference structure during the course of negotiation.

8.1.6. Others

Fuzzy logic approaches are also used to solve other problems in negotiation, for example: (i) to predict the negotiation strategy of the opponent [93]; (ii) to calculate, in negotiation, the need for a project according to received revenues, future business opportunities, and levels of competition [94]; and (iii) to use uninorm aggregation operators [95] to aggregate multiple pieces of evidence in automated legal argumentation [96]. However, none of them uses fuzzy logic systems to update the preference during a negotiation, as we do in this paper.

8.2. Crisp logic based negotiation models

Zhang and another Zhang propose a negotiation model based on propositional logic [97]. In their model, negotiating agents' preferences over demands in form of logic propositions are presented in total pre-orders, and an agreement is reached by all the negotiating agents' minimal simultaneous concession. Later on, Zhang proves that the solution is uniquely characterised by the five logical axioms of consistency, comprehensiveness, collective rationality, disagreement, and contraction independence [34]. Based on the work in [97, 34], Jing et al. propose a logical framework for negotiation with integrity constraints [21]. Different from the work in [34], in their paper, integrity constraints are put into account in a negotiation procedure, *i.e.*, the demand preference structure of each negotiating agent is restricted by integrity constraints. Their negotiation solution is constructed based on the hierarchies of demand structures under integrity constraints, which can also be characterised uniquely by five logical properties of consistency, non-conflictiveness, disagreement, equivalence, and contraction independence.

However, the studies [97, 34, 21] all have the following limitations, which we remove in this paper:

(i) In the models proposed in [34, 21], the concept of a solution meets the axiom of disagreement. The axiom actually says that a negotiation should reach no agreements if one of the negotiating agents has no more demands left before other negotiating agents reach an agreement. However, even if all the demands of that agent are given up, the others should be allowed to still continue the negotiation and reach an agreement together because whatever they reach has no conflict with that agent's empty demand set left. In this case, we cannot say it is unfair for that agent who got nothing left, because giving up each demand fully depends upon his/her preference and his/her strategy of adjusting preference during a negotiation. That is, it is his/her own choice and so he/she cannot complain. Moreover, in another negotiation, if one negotiating agent gets one demand in the final agreement but each of other negotiating agent gets 100 demands, then the models in [97, 34, 21] regard this as acceptable, but obviously this is almost as unfair as the former case. As a result, in this paper we just assume a solution should satisfy logical axioms of consistency, collective-rationality, and minimum-concession, but do not have to satisfy the axiom of disagreement because the axiom is not always reasonable in real life.

(ii) They all neglect the fact that a negotiating agent may need to change its preferences during the course of a negotiation because a fixed preference setting will more easily lead to a disagreement. In fact, their concessions always begin from the lowest level in the ranking of a demand set and the negotiating agents never change the preference. As a result, when some conflicting demands are on the top levels, the negotiation will be easily broken. For example, if two negotiating agents' preference structures are as follows:

$$a \succcurlyeq_1 b,$$
$$\neg a \succcurlyeq_2 b,$$

then their models get no agreements. However, our model can solve this problem by updating the demands preference according to the preference change degree that is drawn from some fuzzy rules. Therefore, in our model we can get agreement $\{b\}$ from the above example.

(iii) Their models cannot reflect how the other human factors (such as regret and patience) effect upon the outcome of a negotiation procedure, but as we argue in the introduction section it is necessary to put these human factors into the account of building up an automated negotiation. Rather, we take these factors into consideration and study how these factors influence the outcome.

(iv) In their model, when a negotiating agent makes concession, the agent has to give up all the demands on the lowest level, which is not always reasonable. For example, if a negotiating agent has 100 demands on his lowest level while another just has one, then the first one has to give up 100 demands, but the second just needs to give up one. Obviously, it is unfair for negotiators in equal positions, so that it is hard to imagine that their models will be accepted in real-life. Rather, in our model, every negotiating agent just gives up one demand in each negotiation round. Moreover, in this way our model gains not only a higher negotiation success rate but also more consistent demands in the final agreements, as our empirical analyses revealed (see Section 7.2 for details).

Vo and Li also build an axiomatic negotiation model, in which a negotiation situation is described in logic language and the preference over outcomes is ordinal [98]. Their solution satisfies the axioms of fairness, unbiasedness and unanimously efficiency (stronger than Pareto Efficiency). However, unlike our model, their model does not reflect the negotiating agents' risk attitudes and patience, which are very important factors for negotiation in real life; and their preference cannot change during a negotiation process, either. None of these problems exists in our work in this paper.

There are some automated negotiation systems in which various kinds of crisp logic have been employed. For example, Liu et al. use description logic in an automated trust negotiation [99]. In this kind of negotiation, in order to establish mutual trust between two strangers, the two need to exchange sensitive resources iteratively. The exchange processes are protected by accessing control policies, which are formalised in the description logic [99] or first order predicate logic [100]. Therefore, their crisp logic based negotiation systems is quite different from ours: they use crisp logic to express policies that control resource exchanging in a negotiation process (simply crisp logic is used to control negotiation procedures), while we use crisp logic to express the objectives (demands) being negotiated and use fuzzy logic to control negotiation procedures. Some more examples of using various kinds of crisp logic to control negotiation procedures include: defeasible logic is used to express the negotiation strategies [101]; and a BDI-like logic is proposed and used to support the agent's negotiating behavior [102]. In addition, Ragone et al. employ a kind of propositional logic as communication language among negotiating agents [90]. In our model, propositional logic is used to express negotiation objectives, fuzzy logic is used to update negotiators' preference structure of negotiation objectives, and in each round each negotiating agent gives up one demand (negotiation objective) without communication.

8.3. Consensus process

A consensus process among a group decision makers is somewhat analogous to a negotiation process. Hence, we will compare our model with those in the area of consensus process in this subsection.

8.3.1. Concept

As shown in [103], group decision making is a process in which different decision makers gather together to analyse a problem so as to obtain a solution among the alternatives. And one of the important aims of group decision making is to improve the level of consensus. Here consensus can be understood as a full and unanimous agreement, *i.e.*, every decision maker fully agrees with a collective outcome. Hence, a consensus process is required during the course of group decision making, in which the decision makers change their opinions step by step towards to a consensus. From this point of view, a consensus process can also be viewed as a special kind of negotiation process, in which the aim of negotiators is to find out a mutually acceptable level of consensus.

Even though the purpose of consensus process and negotiation process is similar in the aspect of resolving conflict among a group of different agents, the definitions of conflicts in these two processes are not exactly the same. In a consensus process, the conflict refers to the differences among individual preference structures, which reflect different opinions of different decision makers. Hence, a consensus aims to change decision-makers' individual preferences over different solution alternatives towards the collective one, and then improve the level of consensus among all the decision makers involved. However, in a negotiation process, the conflict refers to the dissatisfaction of opponents' offers. In particular, in our multi-demand negotiation model, the conflict lies in the conflicting demands, rather than preferences over demands. If one agent's proposal during a negotiation includes a demand that is conflicting with other agent's demand, then the proposal is not accepted. In other words, although the preferences over demands of different agents are different, they is also reach an agreement. Hence, the aim of our negotiation process is to find an agreement, in which there are no conflicting demands, meanwhile keeping as many demands as possible for agents.

Due to the different meanings of conflict in consensus and negotiation, their methods for conflict resolution are also different. More specifically, in a consensus process, different decision makers discuss and share their knowledge about the problem and express their opinions about the preference over different alternatives of solutions. Then a moderator agent will work out a solution and compute the level of consensus by using some measure approaches according to the information of decision makers' preferences. If the level of consensus is higher than a certain threshold, then the consensus process ends; otherwise, the moderator agent gives some feedbacks to all the decision makers and advice them to change their opinions. In a negotiation, different negotiating agents have different thresholds of the level of agreement, which are represented by the utility values or acceptability. For our multi-demand negotiation in this paper, the acceptable threshold is that there is just no conflicting demands in an offer. Hence, the negotiation ends when a negotiating agent accepts its opponent's proposal, rather than a predefined consensus level is achieved.

8.3.2. Model

Some consensus models aim to handle different kinds of preference representation structures. For example, Dong *et al.* [104] propose a framework for group decision making problems with heterogeneous preference representations: preference orderings, utility functions, additive preference relations and multiplicative preference relations. Their model also takes the effect of decision makers' psychological behaviours into consideration. Actually, they employ prospect theory [105] to reflect decision makers' psychological behaviours for reaching consensus in group decision making. Similar to their work, in this paper, we also consider the effect of humans' psychological factors in negotiation, such as the attitude towards risk, regret and patience. However, the methods for reflecting human factors are different between our model and theirs. They employ the prospect theory to reflect some psychological phenomena, such as reference dependence, diminishing sensitivity and loss aversion [105], while we use fuzzy logic rules to represent how attitude towards risk, regret and patience influence the preference over demands. In their model, decision makers involved can represent their preference structures on alternatives in the four forms, while we use total pre-order as the only form to represent the preference over an agent's demands.

There are also other kinds of preference in consensus models. For example, Wu and Chiclana [106] also propose a consensus model for group decision making problems. However, different from the hereinbefore work, they pay more attentions to the uncertainty of preference information of decision makers involved. Specifically, to deal with the situation where decision makers cannot compare different alternatives, they employ an appropriate representation of intensity of preference over alternatives, which is called intuitionistic reciprocal preference relation. In this model, decision makers employ intuitionistic fuzzy sets to represent the degree to which one alternative is preferred to the other one, and the degree to which one alternative is non-preferred to another. However, our model does not deal with this kind of uncertain preference structure, but unlike ours they do not concern dynamic preference structure. Xu *et al.* [107] propose a consensus model based on hesitant fuzzy preference relations. In their consensus process, there are two feedback mechanisms to update experts' preferences, the interactive mechanism and the automatic mechanism, which are employed in different situations where experts are willing or unwilling to offer their updated preferences. However, in our negotiation model, every negotiating agent updates its preference according to the effect of human factor, which is based on the reasoning of a fuzzy logic system. Wang and Lin [108] propose a consensus model with another preference structure, interval reciprocal preference relations. In their model, they develop ratio-based similarity measurement for interval reciprocal preference relations and an induced interval-valued cross-ratio ordered weighted geometric to aggregate interval-valued cross-ratio information. However, unlike our negotiation model, they do not consider human factors, while we take the attitudes towards risk, patience and regret into consideration during the course of negotiation.

Some studies are interested in changing the decision makers' weights when obtaining their collective preference structure. For example, Dong *et al.* [109] summarises several non-cooperative behaviours in consensus process and then propose a group decision making framework to adaptively change the decision makers' weights according to their behaviours in the previous consensus round. However, our model is different from theirs in several aspects. Firstly, normally an evaluation of one negotiator to another cannot change the opponent's negotiation power or negotiation strategies during the course of negotiation; while the values of decision makers can influence the consensus process and selection process in group decision making. Hence in their framework, they can accelerate the speed of consensus process by changing the values of decision makers; while a negotiation framework promotes the negotiation process according to negotiators' strategies. Secondly, in their model the decision makers update their preference relations during a consensus process according to a reference point, but in our model negotiators change their preference structures according to their regret degree, patience degree and risk attitudes during a negotiation.

The consensus model proposed by Dong *et al.* [110] also deal with the weights of the decision makers and attributes involved. This model supports the process of preferences-modifying, which seeks to minimise the adjustment amounts (in the sense of Manhattan distance) between the original and adjusted preferences. They also propose other two consensus models with the weights-updating function. However, our negotiation model is different in the following two aspects. (i) Our preference modifying function is based on a fuzzy logic system, but theirs is not. And (ii) in our model each demand is the same important and so is each negotiator; while in their model, different decision makers involved are important differently and so are different attributes.

There are some other models dealing with the relationship between decision makers involved. Wu *et al.* [111] proposed a novel consensus model to improve the degree of consensus among the decision makers by providing appropriate advice to the inconsistent ones. However, we aim to find mutually acceptable demand set through the negotiation dynamically simultaneous concession solution. Another difference between ours and theirs is that different negotiating agents in our model are at an equal, fair position in negotiation, whereas their work takes the different importances (weight) of decision makers into consideration. If there are social relationships between the negotiating agents, then they may elaborate together to damage the utility of other negotiators [112]. Hence, it is better for the negotiating agent to obtain similar information in a negotiation. Liu *et al.* [113] propose a trust induced recommendation mechanism for decision makers to get personalised advices only from others they trust. In their model, the consensus degree is used to indicate the degree of consistency of a decision maker in a group, rather than measuring the overall level of consensus of all decision makers' preferences. Their model can well balance the original opinion of experts and the improvement of consensus degree. However, in our model, negotiating agents do not try to balance their initial preferences and the dynamic one. As long as it is good for reaching an acceptable agreement, the negotiating agents update their preferences.

Besides various models of dealing with the trust relation among decision makers in a consensus process [113, 114, 111], there are others to improve the likelihood of implementation of recommendations for inconsistent experts. For example, Wu and Chiclana [115] propose a visual information feedback mechanism for group decision making. Based on the visualised information about consensus level before and after implementing the recommended values, the decision makers can consider to what extent they should make the recommendations. However, in our model, the negotiating agents are not allowed to see the others' preference structures; otherwise, the agents could benefit itself, which may lead to a unfair outcome of a negotiation [2].

In addition, some researchers study how to handle incomplete and dynamic information in a consensus process. For example, Dong *et al.* [116] propose a consensus model to deal with a complex and dynamic multiple attribute group decision making problem that different decision makers use individual sets of attributes to evaluate the individual alternatives, and both the individual sets of attributes and the individual sets of alternatives change dynamically in a consensus process. Moreover, in a consensus process, the model can generate adjustment recommendation for individual sets of attributes, individual sets of alternatives and individual preferences. Nevertheless, in our model, the negotiating agent can only adjust the preference ordering and give up the least preferred demand, rather changing the demands in every round of negotiation. Moreover, unlike ours they do not take the effect of any human psychological factor into consideration when changing preference like we do. Zhao *et al.* [117] propose model that can cope with incomplete, linguistic preference relations, and consider both the individual consistency and group consensus when aggregating the collective linguistic preference relation. However, our preference over demands just is a total pre-order rather than the one represented by linguistic terms.

8.4. Other relevant topics

There are also other topics relevant to this paper in the area of multi-agent system, such as opinion dynamics and dynamic preferences. We will briefly discuss them in this subsection.

8.4.1. Opinion dynamics

Opinion dynamics investigates the process of formation and evolution of certain opinions among groups of agents. This problem attracted wide attention of researchers from different fields, such as mathematics [118], statistical physics [119], multi-agent systems [120], and so on. They try to figure out what conditions (*i.e.* the rules that agents interact with each other and the ways that agents update their opinions) can lead to either a consensus or diversity in the final stage. For example, Acemoglu and Ozdaglar [121] investigate the influence of social learning when leading different opinions to consensus. Dong *et al.* [122] study the necessary and sufficient conditions under which the agents can form a consensus based on leadership. In order to put the influence of biases into account, Sobkowicz [123] proposes an opinion dynamics model based on cognitive biases. However, the study focuses of opinion dynamics and negotiation are different. In our model, negotiating agents reach a consistent agreement by making concessions to the opponents. Although different negotiating agents may still have conflicting opinions of demands (for example, one supports a policy and another opposes it), they have to concede to each other for reaching an agreement, thereby gain the important demands they desire. That is, the negotiation process is not concerned with the formation and evolution of opinions, but focuses on agents' conceding behaviours for reaching an agreement.

8.4.2. Dynamic preferences

Generally speaking, the dynamic preference refers to the process in which participants adjust their preference values according to some factors. For example, in the group decision making model of Dong *et al.* [104], some decision makers can dynamically update their preference evaluation according to the feedbacks during a consensus process. Liu [124] proposes a recommendation model to capture users' dynamic preferences by Gaussian process. Karahodza *et al.* [125] employ an improved user-based collaborative filtering algorithm to utilise the changes of users' dynamic preferences over time. In our model, a negotiating agent has two preferences over demands: one is static (used to represent agent's original demand preference) and the other is dynamic during the course of negotiation. However, the change of dynamic preferences in our model is different from the above existing models. It consists of two steps: (i) to give up the least preferred demands in dynamic preference orderings, and (ii) to adjust the sequence of demands in dynamic preference orderings.

9. Conclusion

So far, not much work on automated negotiation has dealt with multi-demand in discrete domains, although in real life this kind of negotiation problem is very common and important. Moreover, in some situations it is necessary to take human psychological characteristics into account when building an automated negotiation system. In addition, sometimes it is necessary for negotiating agents to change their preference structures during the course of a negotiation. To address these issues, this paper develops a novel model of negotiating multi-demand in discrete domains, which reflects well human psychological characteristics about risk, patience and regret. More specifically, in our model, the degrees to which a negotiating agent should change his preference structure according to the risk, patience and regret, is calculated via some fuzzy rules, which we employ psychological experiments to elicit. We also axiomatically characterise the calculation of our fuzzy rules' input parameters. Moreover, by theoretical analyses, we reveal: (i) how human psychological characteristics about risk, patience and regret change their preference structures during the course of a negotiation; and (ii) under which conditions the agreement of a bilateral negotiation can be reached. And through empirical analysis, we further figure out how attitudes towards risk influence the outcome of a negotiation; and show how our fuzzy logic based model outperforms a well-known model in terms of negotiation success rate, efficiency and quality. In addition, we also illustrate our model by solving a negotiation problem in the domain of politics.

Much more could be done in the future. For example, since psychological studies reveal human factors have a significant impact upon the result of a negotiation, we can extend our model to reflect more psychological characteristics. On the one hand, it can help improve the performance of automated negotiation; on the other hand, just as Wooldridge has argued that putting human factors into consideration can help game theory to predict human behavior better [126], it can be used to better predict human negotiation behaviours to support manual negotiation or human-computer negotiation. It is also interesting to integrate more concession strategies in continuous domains (*e.g.*, those that Pan et al. proposed [127]) into negotiation models in discrete domains. Moreover, in this paper we suppose different agents cannot collaborate with each other in private, then our simultaneous concession solution do not consider the problem of coalition among agents. However, it is significant and interesting to take coalition problem into consideration to avoid manipulation by coalitions and make a negotiation more fair to all the agents involved in a negotiation. In addition, it is worth studying under which conditions the negotiation that is impacted by various human factors will produce Pareto-outcome, and how to elicit more accurate fuzzy rules that are used in negotiation models.

Acknowledgment

This work is a significant extension of preliminary results in our conference paper [128], so firstly we should thank anonymous reviewers of the conference for their valuable comments. We also need say a big thank-you to the reviewers of this journal.

Because of their valuable comments and suggestion, this paper has been significantly improved.

This work was partly supported by MOE Project of Key Research Institute of Humanities and Social Sciences at Universities (No. 13JJD720017) China, Bairen Plan, Major Project Raising Program of Sun Yat-sen University (No. 1309089), China National Natural Science Foundation (No. 61173019), Major Projects of the Ministry of Education (No. 10JZD0006) China, China National Social Science Fund of Major Projects (13&ZD186), and Natural Science Foundation of Guangdong Province (No. 2016A030313231). Also, we should thank the Royal Academy of Engineering for the research exchanges with China award.

References

[1] N. R. Jennings, P. Faratin, A. R. Lomuscio, S. Parsons, M. J. Wooldridge, C. Sierra, Automated negotiation: Prospects, methods and challenges, Group Decision and Negotiation 10 (2) (2001) 199–215.

[2] X. Luo, N. R. Jennings, N. Shadbolt, H.-f. Leung, J. H.-m. Lee, A fuzzy constraint based model for bilateral, multi-issue negotiations in semi-competitive environments, Artificial Intelligence 148 (1) (2003) 53–102.

[3] X. Luo, C. Miao, N. R. Jennings, M. He, Z. Shen, M. Zhang, KEMNAD: A knowledge engineering methodology for negotiating agent development, Computational Intelligence 28 (1) (2012) 51–105.

[4] X. Luo, Y. Yang, H.-f. Leung, Reward and penalty functions in automated negotiation, International Journal of Intelligent Systems 31 (7) (2016) 637–672.

[5] J. F. Nash Jr, The bargaining problem, Econometrica: Journal of the Econometric Society 18 (2) (1950) 155–162.

[6] N. Anbarci, C.-j. Sun, Robustness of intermediate agreements and bargaining solutions, Games and Economic Behavior 77 (1) (2013) 367–376.

[7] A. Okada, Coalitional bargaining games with random proposers: Theory and application, Games and Economic Behavior 73 (1) (2011) 227–235.

[8] S. Lauermann, Dynamic matching and bargaining games: A general approach, The American Economic Review 103 (2) (2013) 663–689.

[9] J. Q. Jeon, C. Lee, A new measure for heated negotiation in the IPO syndicate, The North American Journal of Economics and Finance 33 (2015) 278–304.

[10] M. Fey, K. W. Ramsay, Uncertainty and incentives in crisis bargaining: Game-free analysis of international conflict, American Journal of Political Science 55 (1) (2011) 149–169.

[11] R. F. Trager, L. Vavreck, The political costs of crisis bargaining: Presidential rhetoric and the role of party, American Journal of Political Science 55 (3) (2011) 526–545.

[12] J. Zhan, M. Zhang, F. Ren, X. Luo, A negotiation-based model for policy generation, in: Proceedings of the 8th International Workshop on Agent-Based Complex Automated Negotiation, 2015, pp. 50–57.

[13] S. A. Lippman, K. F. McCardle, C. S. Tang, Using Nash bargaining to design project management contracts under cost uncertainty, International Journal of Production Economics 145 (1) (2013) 199–207.

[14] R. Kerachian, M. Fallahnia, M. R. Bazargan-Lari, A. Mansoori, H. Sedghi, A fuzzy game theoretic approach for groundwater resources management: Application of Rubinstein Bargaining Theory, Resources, Conservation and Recycling 54 (10) (2010) 673–682.

[15] S. Artinger, N. Vulkan, Y. Shem-Tov, Entrepreneurs negotiation behavior, Small Business Economics 44 (4) (2015) 737–757.

[16] R. Berger, H. Rauhut, S. Prade, D. Helbing, Bargaining over waiting time in ultimatum game experiments, Social Science Research 41 (2) (2012) 372–379.

[17] T. Chakraborty, S. Judd, M. Kearns, J. Tan, A behavioral study of bargaining in social networks, in: Proceedings of the 11th ACM Conference on Electronic Commerce, 2010, pp. 243–252.

[18] J. Mazei, J. Hüffmeier, P. A. Freund, A. F. Stuhlmacher, L. Bilke, G. Hertel, A meta-analysis on gender differences in negotiation outcomes and their moderators, Psychological bulletin 141 (1) (2015) 85–104.

[19] S. Fatima, S. Kraus, M. J. Wooldridge, Principles of Automated Negotiation, Cambridge University Press, 2014.

[20] I. Marsa-Maestre, M. Klein, C. M. Jonker, R. Aydoğan, From problems to protocols: Towards a negotiation handbook, Decision Support Systems 60 (2014) 39–54.

[21] X. Jing, D. Zhang, X. Luo, J. Zhan, A logical multidemand bargaining model with integrity constraints, International Journal of Intelligent Systems 31 (7) (2016) 673–697.

[22] T. Baarslag, M. J. Hendrikx, K. V. Hindriks, C. M. Jonker, A survey of opponent modeling techniques in automated negotiation, in: Proceedings of 2016 International Conference on Autonomous Agents and Multi-agent Systems, 2016, pp. 575–576.

[23] V. Haberland, S. Miles, M. Luck, Negotiation strategy for continuous long-term tasks in a grid environment, Autonomous Agents and Multi-Agent Systems 10 (3) (2015) 1–21.

[24] A. Rubinstein, Perfect equilibrium in a bargaining model, Econometrica: Journal of the Econometric Society 50 (1) (1982) 97–109.

[25] F. O. Oderanti, F. Li, P. De Wilde, Application of strategic fuzzy games to wage increase negotiation and decision problems, Expert Systems with Applications 39 (12) (2012) 11103–11114.

[26] A. Mori, S. Morii, T. Ito, A dependency-based automated negotiation mechanism for a hypergraph utility model, in: Proceedings of the 4th IIAI International Congress on Advanced Applied Informatics, 2015, pp. 562–567.

[27] K. M. Sim, Y. Guo, B. Shi, Blgan: Bayesian learning and genetic algorithm for supporting negotiation with incomplete information, IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 39 (1) (2009) 198–211.

[28] S.-j. Ji, C.-j. Zhang, K.-M. Sim, H.-f. Leung, A one-shot bargaining strategy for dealing with multifarious opponents, Applied Intelligence 40 (4) (2014) 557–574.

[29] B. An, N. Gatti, V. Lesser, Bilateral bargaining with one-sided uncertain reserve prices, Autonomous agents and multi-agent systems 26 (3) (2013) 420–455.

[30] A. Diamah, M. Wagner, M. van den Briel, A comparative study on vector similarity methods for offer generation in multi-attribute negotiation, in: AI 2015: Advances in Artificial Intelligence, Vol. 9457 of Lecture Notes in Computer Science, Springer, 2015, pp. 149–156.

[31] J. Zhan, X. Luo, Offer evaluation and trade-off making in automated negotiation based on intuitionistic fuzzy constraints, in: PRIMA 2016: Princiles and Practice of Multi-Agent Systems, Vol. 9862 of Lecture Notes in Computer Science, Springer, 2016, pp. 197–215.

[32] M. Cao, X. Luo, X. R. Luo, X. Dai, Automated negotiation for e-commerce decision making: A goal deliberated agent architecture for multi-strategy selection, Decision Support Systems 73 (2015) 1–14.

[33] F. C. Iklé, N. Leites, Political negotiation as a process of modifying utilities, Journal of Conflict Resolution 6 (1) (1962) 19–28.

[34] D. Zhang, A logic-based axiomatic model of bargaining, Artificial Intelligence 174 (16-17) (2010) 1307–1322.

[35] C. R. Williams, V. Robu, E. H. Gerding, N. R. Jennings, An overview of the results and insights from the third automated negotiating agents competition, in: Novel Insights in Agent-Based Complex Automated Negotiation, Vol. 535 of Studies in Computational Intelligence, Springer, 2014, pp. 151–162.

[36] J. Hao, H.-f. Leung, ABiNeS: An adaptive bilateral negotiating strategy over multiple items, in: Proceedings of the 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology, Vol. 2, 2012, pp. 95–102.

[37] J. Hao, H.-f. Leung, CUHKAgent: An adaptive negotiation strategy for bilateral negotiations over multiple items, in: Novel Insights in Agent-based Complex Automated Negotiation, Vol. 535 of Studies in Computational Intelligence, Springer, 2014, pp. 171–179.

[38] F. Ren, M. Zhang, Q. Bai, A dynamic, optimal approach for multi-issue negotiation under time constraints, in: Novel Insights in Agent-based Complex Automated Negotiation, Vol. 535 of Studies in Computational Intelligence, Springer, 2014, pp. 85–108.

[39] W. Chen, D. Zhang, M. Wu, A sequential model for reasoning about bargaining in logic programs, in: Logic Programming and Nonmonotonic Reasoning, Vol. 8148 of Lecture Notes in Computer Science, Springer, 2013, pp. 239–244.

[40] J. Ma, M. L. Goyal, Designing a successful bidding strategy using fuzzy sets and agent attitudes, in: J. Yao (Ed.), Web-based Support Systems, Advanced Information and Knowledge Processing, Springer, 2010, pp. 359–370.

[41] R. Aljaljouli, J. Abawajy, Strategies for agent-based negotiation in e-trade, Network & Traffic Engineering in Emerging Distributed Computing Applications (2012) 43–65.

[42] B. Rohrmann, Risk attitude scales: Concepts and questionnaires, Project report, University of Melbourne (2004).

[43] G. A. van Kleef, C. K. De Dreu, A. S. Manstead, Supplication and appeasement in conflict and negotiation: The interpersonal effects of disappointment, worry, guilt, and regret, Journal of Personality and Social Psychology 91 (1) (2006) 124.

[44] J. K. Murnighan, A. E. Roth, F. Schoumaker, Risk aversion in bargaining: An experimental study, Journal of Risk and Uncertainty 1 (1) (1988) 101–124.

[45] X. Luo, N. R. Jennings, N. Shadbolt, Acquiring user tradeoff strategies and preferences for negotiating agents: A default-then-adjust method, International Journal of Human-Computer Studies 64 (4) (2006) 304–321.

[46] N. B. Rothman, G. B. Northcraft, Unlocking integrative potential: Expressed emotional ambivalence and negotiation outcomes, Organizational Behavior and Human Decision Processes 126 (2015) 65–76.

[47] G. A. van Kleef, C. K. De Dreu, A. S. Manstead, The interpersonal effects of anger and happiness in negotiations, Journal of Personality and Social Psychology 86 (1) (2004) 57.

[48] H. Adam, A. Shirako, W. W. Maddux, Cultural variance in the interpersonal effects of anger in negotiations, Psychological Science 21 (6) (2010) 882–889.

[49] S. Hareli, S. David, U. Hess, The effect of the negotiator's social power as a function of the counterpart's emotional reactions in a computer mediated negotiation, Europe's Journal of Psychology 9 (4) (2013) 820–831.

[50] R. Lin, S. Kraus, J. Wilkenfeld, J. Barry, Negotiating with bounded rational agents in environments with incomplete information using an automated agent, Artificial Intelligence 172 (6-7) (2008) 823–851.

[51] R. Lin, S. Kraus, Can automated agents proficiently negotiate with humans?, Communications of ACM 53 (1) (2010) 78–88.

[52] R. Lin, Y. Gal, S. Kraus, Y. Mazliah, Training with automated agents improves people's behavior in negotiation and coordination tasks, Decision Support Systems 60 (1) (2014) 1–9.

[53] J. Mell, G. Lucas, J. Gratch, An effective conversation tactic for creating value over repeated negotiations, in: Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems, 2015, pp. 1567–1576.

[54] G. Haim, Y. K. Gal, M. Gelfand, S. Kraus, A cultural sensitive agent for human-computer negotiation, in: Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, 2012, pp. 451–458.

[55] G. Haim, Ya'akov, S. Kraus, B. An, Human-computer negotiation in three-player market settings, in: Proceedings of the 21st European Conference on Artificial Intelligence, 2014, pp. 417–422.

[56] N. Peled, Y. K. Gal, S. Kraus, An agent design for repeated negotiation and information revelation with people: Extended abstract, in: Proceedings of the 12th International Conference on Autonomous Agents and Multi-Agent Systems, 2013, pp. 1303–1304.

[57] V. J. Derlega, C. S. Cukur, J. C. Kuang, D. R. Forsyth, Interdependent construal of self and the endorsement of conflict resolution strategies in interpersonal, intergroup, and international disputes, Journal of Cross-Cultural Psychology 33 (6) (2002) 610–625.

[58] P. Carnevale, A. Ledgerwood, Identity rivalry and the group endowment effect, in: Proceedings of 18th Annual Conference on Conflict Management, 2005, pp. 1–19.

[59] F. Roberts, B. Tesman, Applied combinatorics, CRC Press, 2009, Ch. 4.2.4 Weak Orders, pp. 254–256.

[60] G. Zlotkin, J. S. Rosenschein, Mechanisms for automated negotiation in state oriented domains, Journal of Artificial Intelligence Research 5 (1) (1996) 163–238.

[61] D. G. Pruitt, Negotiation Behavior, Academic Press, 1981.

[62] H. Raiffa, The art and science of negotiation, Harvard University Press, 1982.

[63] P. Heiskanen, H. Ehtamo, R. P. Hämäläinen, Constraint proposal method for computing pareto solutions in multi-party negotiations, European Journal of Operational Research 133 (1) (2001) 44–61.

[64] T. Menzies, Evaluation issues with critical success metrics, in: Proceedings of the 11th Workshop on Knowledge Acquisition, Modeling and Management, 1998.

[65] B. Schwartz, A. Ward, J. Monterosso, S. Lyubomirsky, K. White, D. R. Lehman, Maximizing versus satisficing: Happiness is a matter of choice, Journal of Personality and Social Psychology 83 (5) (2002) 1178–1197.

[66] K. N. Kirby, N. N. Maraković, Delay-discounting probabilistic rewards: Rates decrease as amounts increase, Psychonomic Bulletin and Review 3 (1) (1996) 100–104.

[67] G. Y. Nenkov, M. Morrin, B. Schwartz, A. Ward, J. Hulland, A short form of the maximization scale: Factor structure, reliability and validity studies, Judgment and Decision Making 3 (5) (2008) 371–388.

[68] H. H. Timm, Applied Multivariate Analysis, Springer, 2007, Ch. 4.2 Multivariate Regression, pp. 186–192.

[69] L. A. Zadeh, Fuzzy sets, Information and Control 8 (3) (1965) 338–353.

[70] E. H. Mamdani, S. Assilian, An experiment in linguistic synthesis with a fuzzy logic controller, International Journal of Man-Machine Studies 7 (1) (1975) 1–13.

[71] W. Van Leekwijck, E. E. Kerre, Defuzzification: criteria and classification, Fuzzy sets and systems 108 (2) (1999) 159–178.

[72] M. Chang, M. He, A. Ekart, X. Luo, S. Zhang, Bi-directional double auction for financial market simulation, in: Proceedings of the 2013 International Conference on Autonomous Agents and Multi-Agent Systems, 2013, pp. 1313–1314.

[73] K. Kolomvatsos, C. Anagnostopoulos, S. Hadjiefthymiades, A fuzzy logic system for bargaining in information markets, ACM Transactions on Intelligent Systems and Technology 3 (2) (2012) 32:1–32:26.

[74] B. Zuo, Y. Sun, Fuzzy logic to support bilateral agent negotiation in e-commerce, in: Proceedings of 2009 International Conference on Artificial Intelligence and Computational Intelligence, Vol. 4, 2009, pp. 179–183.

[75] F. Costantino, G. D. Gravio, Multistage bilateral bargaining model with incomplete information—A fuzzy approach, International Journal of Production Economics 117 (2) (2009) 235–243.

[76] C.-b. Cheng, C.-c. H. Chan, C.-c. Lin, Buyer-supplier negotiation by fuzzy logic based agents, in: Proceedings of the 3rd International Conference on Information Technology and Applications, 2005, pp. 137–142.

[77] R. Arapoglou, K. Kolomvatsos, S. Hadjiefthymiades, Buyer agent decision process based on automatic fuzzy rules generation methods, in: Proceedings of the 2010 IEEE International Conference on Fuzzy Systems, 2010, pp. 1–8.

[78] J. Carbo, J. Molina, J. Davila, Reaching agreements through fuzzy counter-offers, in: Proceedings of the International Conference on Web Engineering, 2003, pp. 90–93.

[79] M. He, H.-f. Leung, N. R. Jennings, A fuzzy-logic based bidding strategy for autonomous agents in continuous double auctions, IEEE Transactions on Knowledge and Data Engineering 15 (6) (2003) 1345–1363.

[80] P. Kaur, M. Goyal, J. Lu, A comparison of bidding strategies for online auctions using fuzzy reasoning and negotiation decision functions, IEEE Transactions on Fuzzy Systems (2017) to appearDOI: 10.1109/TFUZZ.2016.2598297.

[81] B. Shojaiemehr, M. K. Rafsanjani, A supplier offer modification approach based on fuzzy systems for automated negotiation in e-commerce, Information Systems Frontiers (2016) 1–1.

[82] W. B. Yahia, O. Ayadi, F. Masmoudi, A fuzzy-based negotiation approach for collaborative planning in manufacturing supply chains, Journal of Intelligent Manufacturing (2015) 1–20.

[83] V. Haberland, S. Miles, M. Luck, Adjustable fuzzy inference for adaptive grid resource negotiation, in: Next Frontier in Agent-based Complex Automated Negotiation, Vol. 596 of Studies in Computational Intelligence, Springer Japan, 2015, pp. 37–57.

[84] J. Zhan, X. Luo, Adaptive conceding strategies for negotiating agents based on interval type-2 fuzzy logic, in: KSEM 2016: Knowledge Science, Engineering and Management, Vol. 9983 of Lecture Notes in Computer Science, Springer, 2016, pp. 222–235.

[85] K. Kolomvatsos, S. Hadjiefthymiades, Implicit deadline calculation for seller agent bargaining in information marketplaces, in: Proceedings of the 2nd International Conference on Complex, Intelligent and Software Intensive Systems, 2008, pp. 184–190.

[86] K. Kolomvatsos, S. Hadjiefthymiades, Automatic fuzzy rules generation for the deadline calculation of a seller agent, in: International Symposium on Autonomous Decentralized Systems, 2009, pp. 1–6.

[87] K. Kolomvatsos, D. Trivizakis, S. Hadjiefthymiades, An adaptive fuzzy logic system for automated negotiations, Fuzzy Sets and Systems 269 (2015) 135–152.

[88] R. Fisher, W. Ury, Getting to yes: Negotiating an agreement without giving in, Random House Business Books, 1981.

[89] M. S. Karim, J. Pierluissi, Fuzzy driven multi-issue agent negotiation on electronic marketplace, in: Advances in Computing and Information Technology, Springer, 2013, pp. 239–248.

[90] A. Ragone, T. D. Noia, E. D. Sciascio, F. M. Donini, Logic-based automated multi-issue bilateral negotiation in peer-to-peer e-marketplaces, Autonomous Agents and Multi-Agent Systems 16 (3) (2008) 249–270.

[91] C. Y. Hsu, B. R. Kao, V. L. Ho, K. R. Lai, Agent-based fuzzy constraint-directed negotiation mechanism for distributed job shop scheduling, Engineering Applications of Artificial Intelligence 53 (2016) 140–154.

[92] C. Y. Hsu, B. R. Kao, V. L. Ho, L. Li, K. R. Lai, An agent-based fuzzy constraint-directed negotiation model for solving supply chain planning and scheduling problems, Applied Soft Computing 48 (2016) 703–715.

[93] W.-m. Lee, C.-c. Hsu, An intelligent negotiation strategy prediction system, in: Proceedings of 2010 International Conference on Machine Learning and Cybernetics, 2010, pp. 3225–3229.

[94] M.-R. Yan, A fuzzy logic enhanced bargaining model for business pricing decision support in joint venture projects, Journal of Business Economics and Management 12 (2) (2011) 234–247.

[95] R. R. Yager, A. Rybalov, Uninorm aggregation operators, Fuzzy sets and systems 80 (1) (1996) 111–120.

[96] Q. Zhong, X. Luo, F. H. van Eemeren, F. Huang, The task model of court investigation in a multi-agent system of argumentation in court, in: Logic, Rationality, and Interaction, Vol. 8196 of Lecture Notes in Computer Science, Springer, 2013, pp. 296–310.

[97] D. Zhang, Y. Zhang, An ordinal bargaining solution with fixed-point property, Journal of Artificial Intelligence Research 33 (1) (2008) 433–464.

[98] Q. B. Vo, M. Li, From axiomatic to strategic models of bargaining with logical beliefs and goals, in: Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, Vol. 1, 2012, pp. 525–532.

[99] X. Liu, S. Tang, S. Chen, A description logic-based policy compliance checker for trust negotiation, Peer-to-Peer Networking and Applications (2015) 1–12.

[100] Z. Liao, H. Jin, D. Zou, A logic predicate based automated trust negotiation model, in: Second International Conference on Communications and Networking in China, 2007, pp. 418–422.

[101] T. Skylogiannis, G. Antoniou, N. Bassiliades, A system for automated agent negotiation with defeasible logic-based strategies–Preliminary report, in: Rules and Rule Markup Languages for the Semantic Web, Springer, 2004, pp. 205–213.

[102] M.-k. Cao, H.-l. Wang, Logic for automated negotiation in e-business, in: 2008 ISECS International Colloquium on Computing, Communication, Control, and Management, Vol. 3, 2008, pp. 201–205.

[103] F. J. Cabrerizo, F. Chiclana, R. Al-Hmouz, A. Morfeq, A. S. Balamash, E. Herrera-Viedma, Fuzzy decision making and consensus: Challenges, Journal of Intelligent & Fuzzy Systems 29 (3).

[104] Y. Dong, N. Luo, H. Liang, Consensus building in multiperson decision making with heterogeneous preference representation structures: A perspective based on prospect theory, Applied Soft Computing 35 (2015) 898–910.

[105] D. Kahneman, A. Tversky, Prospect theory: An analysis of decision under risk, Econometrica 47 (2) (1979) 263–292.

[106] J. Wu, F. Chiclana, Multiplicative consistency of intuitionistic reciprocal preference relations and its application to missing values estimation and consensus building, Knowledge-Based Systems 71 (2014) 187–200.

[107] Y. Xu, F. J. Cabrerizo, E. Herrera-Viedma, A consensus model for hesitant fuzzy preference relations and its application in water allocation management, Applied Soft Computing 58 (2017) 265284.

[108] Z. J. Wang, J. Lin, Ratio-based similarity analysis and consensus building for group decision making with interval reciprocal preference relations, Applied Soft Computing 42 (2016) 260–275.

[109] Y. Dong, H. Zhang, E. Herrera-Viedma, Integrating experts' weights generated dynamically into the consensus reaching process and its applications in managing non-cooperative behaviors, Decision Support Systems 84 (2016) 1–15.

[110] Y. Dong, J. Xiao, H. Zhang, T. Wang, Managing consensus and weights in iterative multiple-attribute group decision making, Applied Soft Computing 48 (2016) 80–90.

[111] J. Wu, F. Chiclana, H. Fujita, E. Herrera-Viedma, A visual interaction consensus model for social network group decision making with trust propagation, Knowledge-Based Systems 122 (2017) 39–50.

[112] F. Huang, X. Luo, H. F. Leung, Q. Zhong, Games played by networked players, in: IEEE/WIC/ACM International Joint Conferences on Web Intelligence, 2013, pp. 1–8.

[113] Y. Liu, C. Liang, F. Chiclana, J. Wu, A trust induced recommendation mechanism for reaching consensus in group decision making, Knowledge-Based Systems 119 (2017) 221–231.

[114] J. Wu, R. Xiong, F. Chiclana, Uninorm trust propagation and aggregation methods for group decision making in social network with four tuple information, Knowledge-Based Systems 96 (2) (2016) 29–39.

[115] J. Wu, F. Chiclana, Visual information feedback mechanism and attitudinal prioritisation method for group decision making with triangular fuzzy complementary preference relations, Information Sciences 279 (2014) 716–734.

[116] Y. Dong, H. Zhang, E. Herrera-Viedma, Consensus reaching model in the complex and dynamic magdm problem, Knowledge-Based Systems 106 (2016) 206–219.

[117] M. Zhao, X. Y. Ma, D. W. Wei, A method considering and adjusting individual consistency and group consensus for group decision making with incomplete linguistic preference relations, Applied Soft Computing 54 (2017) 322–346.

[118] M. H. Degroot, Reaching a consensus, Journal of the American Statistical Association 69 (345) (1974) 118–121.

[119] C. Castellano, S. Fortunato, V. Loreto, Statistical physics of social dynamics, Review of Modern Physics 81 (2) (2009) 591–646.

[120] S. Monica, F. Bergenti, An analytic study of opinion dynamics in multi-agent systems, Computers & Mathematics with Applications 73 (10) (2017) 2272–2284.

[121] D. Acemoglu, A. Ozdaglar, Opinion dynamics and learning in social networks, Dynamic Games and Applications 1 (1) (2011) 3–49.

[122] Y. Dong, Z. Ding, L. Martnez, F. Herrera, Managing consensus based on leadership in opinion dynamics, Information Sciences.

[123] P. Sobkowicz, Opinion dynamics model based on cognitive biases, CoRR abs/1703.01501.

[124] X. Liu, Modeling users' dynamic preference for personalized recommendation, in: International Conference on Artificial Intelligence, 2015, pp. 1785–1791.

[125] B. Karahodza, D. Donko, H. Supic, Temporal dynamics of changes in group user's preferences in recommender systems, in: International Convention on Information and Communication Technology, Electronics and Microelectronics, 2015, pp. 1262–1266.

[126] M. Wooldridge, Does game theory work?, IEEE Intelligent Systems Magazine 27 (6) (2012) 76–80.

[127] L. Pan, X. Luo, X. Meng, C. Miao, M. He, X. Guo, A two-stage win-win multiattribute negotiation model: Optimazation and then concession, Computational Intelligence 29 (4) (2013) 577–626.

[128] J. Zhan, X. Luo, C. Feng, W. Ma, A fuzzy logic based bargaining model in discrete domains: Axiom, elicitation and property, in: Proceedings of 2014 IEEE International Conference on Fuzzy Systems, 2014, pp. 424–431.

Highlights

- The concept of dynamic preference is introduced into negotiation models in discrete domains to reflect a negotiator's adaptability during the course of a negotiation, so that negotiation success rate, efficiency and quality can be increased significantly.

- A new negotiation algorithm is designed, which have many advantages over previous ones.

- A set of fuzzy logic rules are identified by lots of psychological experiments, and the rules can be used to update negotiators' preferences in each negotiation round according to their degree of regret, initial attitude to risk, and patience.

- A theoretical work has been done to show how users' psychological characteristics about regret, risk and patience influence their changing preferences during the course of a multi-demand negotiation, and under which conditions an agreement can be reached.

- Computer simulation experiments are carried out to analyse the rationale for the choice of action function in our model, the influence of input parameters in the fuzzy system, as well as the negotiation success rate, efficiency and quality of our method.

***Graphical abstract (for review)**