Chapter 13
Preliminary Estimating Method of Opponent's Preferences Using Simple Weighted Functions for Multi-lateral Closed Multi-issue Negotiations

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Abstract Multi-lateral multi-issue closed negotiation is an important class of real-life negotiations. Negotiation problems usually have constraints, such as an unknown opponent's utility in real time or time discounting. Recently, the attention in this field has shifted from bilateral to multi-lateral approaches. In multi-lateral negotiations, agents need to simultaneously estimate the utility functions of more than two agents. In this chapter, we propose an estimating method that uses simple weighted functions by counting the opponent's evaluation value for each issue. For multi-lateral negotiations, our agent considers some utility functions as the 'single' utility function by weighted-summing them. We experimentally compared the individual utility and the social welfare among some simple weighted functions. In addition, we compared the negotiation efficiency of our proposed agent with ten state-of-the-art negotiation agents that reached the final round of ANAC-2015.

Keywords Multilateral closed negotiations · Automated negotiation agent · Multi-issue negotiations

13.1 Introduction

Negotiation is a critical process in forming alliances and reaching trade agreements. Research in the field of negotiation originated in various disciplines including economics, social science, game theory, and artificial intelligence (e.g., [10, 16, 18] etc.). Automated agents, which can be used side-by-side with human negotiators who is embarking on an important negotiation task, can reduce some of the effort required by people during negotiations and assist those who are less qualified in the nego-

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tiation process. There may even be situations in which automated negotiators can replace the human negotiators [6, 22]. Another possibility is for people to use these agents as a training tool prior to actually performing the task. Thus, successfully developing an automated agent with negotiation capabilities has great advantages and implications for our field.

Motivated by the challenges of bilateral negotiations among automated agents, the automated negotiating agents competition (ANAC) was organized [1] to facilitate research in the area of automated multi-issue closed negotiation. ANAC's setup is a realistic model including time discounting, closed negotiations, alternative offering protocols, and so on. By analyzing the ANAC results, the trends of the strategies of automated negotiations and important factors for developing the competition have been shown [3]. Other effective automated negotiating agents have also been proposed through the competitions [5, 8].

Having multiple parties is a key point in achieving automated negotiation in real life. Many real-world negotiation problems assume multi-party situations because negotiations on the web are becoming more common. When an automated negotiation strategy effectively covers the bilateral negotiation, it is not always possible or desirable in multi-party negotiations. In other words, it remains an open and interesting problem to design more efficient automated negotiation strategies against a variety of negotiating opponents in multi-party situations.

In this chapter, the negotiation protocol adopts a simple extension of the bilateral alternating offers protocol that is called the Stacked Alternating Offers Protocol for Multi-lateral Negotiation (SAOP) [2]. According to it, all of the participants around the table get a turn per round; turns are taken clock-wise around the table. In addition, we propose an estimating method using simple weighted functions by counting the opponent's evaluation value of each issue. For multi-lateral negotiations, our agent considers some utility functions as the 'single' utility function by weighted-summing them. In our experiments, we compare the individual utility and the social welfare among some simple weighted functions and the negotiation efficiency of our proposed agent with ten state-of-the-art negotiation agents that reached the final round of ANAC-2015.

The remainder of the chapter is organized as follows. First, we describe related works and show the negotiation environments and the Stacked Alternating Offers Protocol for Multi-lateral Negotiation (SAOP). Next we propose a novel method for estimating opponent utility functions by weighted-summing the value of each issue. Then we demonstrate our experimental analysis and the tournament results. Finally, we present our conclusions.

13.2 Related Works

This chapter focuses on research in the area of bilateral multi-issue closed negotiation, which is an important class of real-life negotiations. In closed negotiations, opponents do not reveal their preferences. Negotiating agents that are designed using a heuristic approach require extensive evaluation, typically through simulations and empirical analysis, since it is usually impossible to predict precisely how the system and its constituent agents will behave in a wide variety of circumstances. Motivated by the challenges of bilateral negotiations between people and automated agents, the automated negotiating agents competition (ANAC) was organized in 2010 [1] to facilitate research in the area of bilateral multi-issue closed negotiation.

The following are the declared goals of the competition: (1) to encourage the design of practical negotiation agents that can proficiently negotiate against unknown opponents in a variety of circumstances; (2) to provide a benchmark for objectively evaluating different negotiation strategies; (3) to explore different learning and adaptation strategies and opponent models; (4) to collect state-of-the-art negotiating agents and negotiation scenarios and make them available to the wider research community. The competition is based on the GENIUS environment: the General Environment for Negotiation with Intelligent multi-purpose Usage Simulation [17]. By analyzing the ANAC results, the trends of ANAC strategies and important factors for developing the competition have been shown. Baarslag et al. presented an in-depth analysis and the key insights gained from ANAC 2011 [3] and analyzed different strategies using the classifications of agents with respect to their concession behavior against a set of standard benchmark strategies and empirical game theory (EGT) to investigate the robustness of the strategies. Even though most adaptive negotiation strategies are robust across different opponents, they are not necessarily the ones that win the competition. Our EGT analysis highlights the importance of considering metrics.

Chen and Weiss proposed a negotiation approach called OMAC, which learns an opponent's strategy to predict the future utilities of counter-offers by discrete wavelet decomposition and cubic smoothing splines [7]. They also presented a negotiation strategy called EMAR for such environments that rely on a combination of Empirical Mode Decomposition (EMD) and Autoregressive Moving Average (ARMA) [8]. EMAR enables a negotiating agent to acquire an opponent model and to use it for adjusting its target utility in real time on the basis of an adaptive concession-making mechanism. Hao and Leung proposed and introduced a negotiation strategy named ABiNeS for negotiations in complex environments [12]. ABiNeS adjusts the time to stop exploiting negotiating partners and also employs a reinforcement-learning approach to improve the acceptance probability of its proposals. Williams et al. proposed a novel negotiating agent based on Gaussian processes in multi-issue automated negotiation against unknown opponents [21]. Baarslag et al. focused on the acceptance dilemma; accepting the current offer may be suboptimal, since better offers might still be presented [4]. Kawaguchi et al. proposed a strategy for compromising on the estimated maximum value based on estimated maximum utility [14]. These papers made important contributions to bilateral multi-issue closed negotiation; however, they failed to deal with multi-times negotiation. Fujita [11] proposed a compromising strategy by adjusting the speed of reaching agreements using the Conflict Mode and focused on multi-time negotiations.

13.3 Negotiation Environments

13.3.1 Multi-lateral Multi-issue Closed Negotiation

The interaction among negotiating parties is regulated by a *negotiation protocol* that defines the rules of how and when proposals can be exchanged. The competition used the alternating offers protocol for bilateral negotiation [19, 20] in which the negotiating parties exchange offers in turns. The alternating offers protocol, which conforms to our criterion that advocates simple rules, has been widely studied in the literature, both in game-theoretic and heuristic settings of negotiation [9, 10, 15, 18].

The multi-player protocol is a simple extension of the bilateral alternating offers protocol, called the Stacked Alternating Offers Protocol for Multi-lateral Negotiation (SAOP) [2]. According to this protocol, all of the participants around the table get a turn per round; turns are taken clock-wise around the table.

We assume that N agents $(A_1, A_2, \ldots, A_N)$ negotiate at the same time. First A_1 starts the negotiation with an offer that is immediately observed by all the others. Whenever an offer is made, A_n in line can take the following actions:

- Make a Counter-offer (rejecting and overriding the previous offer)
- Accept the Offer
- Walk Away (ending the negotiation without any agreement)

After that, $A_{mod(n,N)+1}$ selects its next action from *Counter-offer, Accept, Walk Away*. This process is repeated in clock-wise turns until an agreement is reached or the deadline passes. To reach an agreement, all parties must accept the offer. If at the deadline no agreement has been reached, the negotiation fails.

Figure 13.1 shows an example of SAOP when the number of agents is three: (1) agent 1 makes a counter-offer; (2) agent 2 accepts agent 1's offer; and (3) agent 3

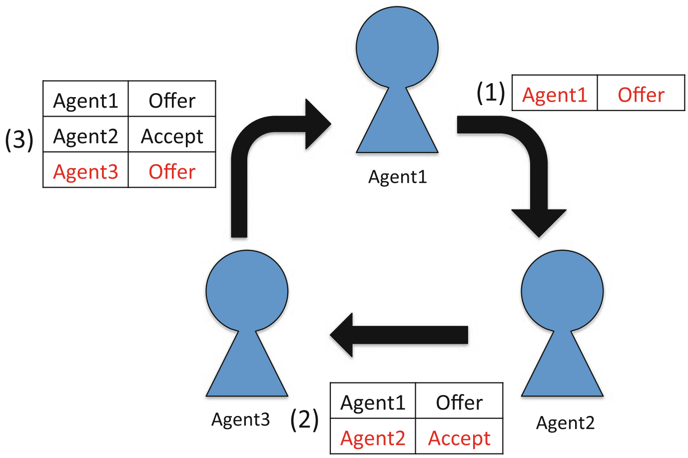

Fig. 13.1 Example of SAOP

makes a counter-offer by rejecting the last offer by agent 1. In this negotiation, the agreement failed because agent 3 selects a new counter-offer.

The parties negotiate over *issues*, each of which has an associated range of alternatives or *values*. A negotiation outcome consists of a mapping of every issue to a value, and set Ω of all possible outcomes is called the negotiation *domain*. This domain is the common knowledge shared by the negotiating parties and remains fixed during a single negotiation session. All parties have certain preferences prescribed by a *preference profile* over Ω. These preferences can be modeled by utility function U that maps possible outcome $\omega \in \Omega$ to a real-valued number in range [0, 1]. In contrast to the domain, the preference profile of the players is private information.

A negotiation lasts a predefined time in seconds (*deadline*). The time line is normalized, i.e., time $t \in [0, 1]$, where $t = 0$ represents the negotiation's start and $t = 1$ represents the deadline. Apart from a deadline, a scenario may also feature discount factors that decrease the utility of the bids under negotiation as time passes. Let d in [0, 1] be the discount factor. Let t in [0, 1] be the current normalized time, as defined by the timeline. We compute discounted utility U_D^t of outcome ω from undiscounted utility function U as follows:

$$U_D^t(\omega) = U(\omega) \cdot d^t.$$

At $t = 1$, the original utility is multiplied by the discount factor. If $d = 1$, the utility is not affected by time, and such a scenario is considered to be undiscounted.

13.3.2 Weighted-Summing Linear Utility Function

A bid is a set of chosen values $s_1 \ldots s_N$ for each of the N issues (I). Each of these values has been assigned evaluation value $eval(s_i)$ in the utility space, and each issue has also been assigned a normalized weight (w_i, $\sum_{i \in I} w_i = 1$) in the utility space. The utility is the weighted-sum of the normalized evaluation values (Fig. 13.2).

The utility function of the bid ($\mathbf{s} = (s_1, \ldots, s_N)$) is defined as Eq. (13.1):

$$U(\mathbf{v}) = \sum_{i=1}^{N} w_i \cdot eval(s_i).$$

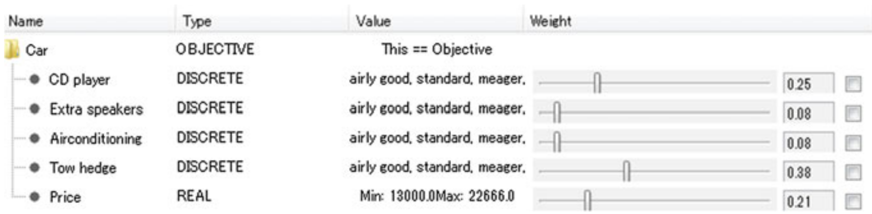

Fig. 13.2 Example of utility profiles

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13.3.3 Objective Functions of Negotiating Agents

Objective functions of negotiating agents are as follows:

- Objective Function 1 (Maximizing Individual Welfare):

$$\max_{\mathbf{s}} \; U_a(\mathbf{s})$$

- Objective Function 2 (Maximizing Social Welfare):

$$\max_{\mathbf{s}} \sum_{i=1}^{N} U_{A_i}(\mathbf{s})$$

The agent, in other words, tries to find contracts that maximize the social welfare, i.e., the total utilities for all agents. Such contracts, by definition, will also be Pareto-optimal. At the same time, each agent tries to find contracts where individual welfare exceeds the reservation value.

13.4 Negotiation Strategy with Estimating Utility Functions by Counting Values

13.4.1 Estimating Utility Functions by Counting Values

In SAOP, the bids repeatedly proposed by opponents are critical. However, it is hard to get statistical information by simply counting all of them because proposed bids are limited in one-shot negotiations. Therefore, we propose a novel method that estimates the utility functions by counting the value of the opponent's bids in multi-lateral negotiations.

In our definitions, A_N is our agent and $a(a = \{A_1, A_2, \ldots, A_{N-1}\})$ are the $N - 1$ opponents among the N-lateral negotiations. Agent a's previous bids are represented as B_a. The estimated utility function of agent a is represented as $eval'_a()$, which is defined as Eq. 13.1:

$$eval'_a(\mathbf{s_i}) = \sum_{\mathbf{s}' \in B_a} Boolean(\mathbf{s}_i, \mathbf{s}') \cdot \mathbf{w(s')}. \tag{13.1}$$

The function $Boolean(\mathbf{s}_i, \mathbf{s}')$ returns 1 when bid s' contains the s_i, and otherwise it returns 0. Function $w(\mathbf{s})$ is the weighting function that reflects the order of the proposed bids. Therefore, estimated utility function $U'_a(\mathbf{s})$ of Alternative solutions: $\mathbf{s}$ of opponent a is defined as Eq. 13.2:

$$U_a(\mathbf{s}) = \frac{u_a(\mathbf{s})}{\max_{\forall \mathbf{s}'} u_a(s')} \tag{13.2}$$

$$u_a(\mathbf{s}) = \sum_{i=1}^{N} eval'_a(s_i). \tag{13.3}$$

Using Eq. 13.2, our agent can obtain estimated utility that is normalized [0, 1] to each opponent.

In addition, we use the following three weighting functions:

- Constant Function: $w(\mathbf{s}) = 1$
- Monotonically Increasing Function: $w(\mathbf{s}) = time_a(\mathbf{s})$
- Monotonically Decreasing Function: $w(\mathbf{s}) = 1 - time_a(\mathbf{s})$.

$time_a(\mathbf{s})$ is a function that returns the normalized time when agent a proposes bid $\mathbf{s}$.

13.4.2 Strategy of Negotiating Agents Using Estimated Utility Functions

We propose an agent's strategy using the estimated utility function in Sect. 13.4.1. In multi-lateral negotiations, a novel strategy needs to determine how much our agent can compromise to each agent using the estimated utility functions. Our proposed agent employs $h_n(n = 1, 2, \ldots, N)$, which is a function for compromising to each agent$(A_1, A_2, \ldots, A_N)$, to judge subsequent bids. The evaluation function (U_{op}) of the bid $(\mathbf{s})$ that combines two opponents is defined as Eq. 13.4:

$$U_{op}(\mathbf{s}) = \sum_{n=1}^{N} h_n U_{A_n}(\mathbf{s}). \tag{13.4}$$

In this chapter, the proposed method focuses on negotiations among three agents same as the ANAC2015 rule. However, our proposed method can adopt the multi-lateral negotiations not only the negotiations among three agents. Our agent can adopt a negotiation strategy for bilateral negotiations to multi-lateral negotiations by combining the utility functions of opponents. Our agent decides its next action based on Eqs. 13.5 and 13.6:

$$target_{end} = \frac{\sum_{n=1}^{N} h_n U_{my}(arg\ max U_{A_n})}{\sum_{n=1}^{N} h_n} \tag{13.5}$$

$$target(t) = \begin{cases} (1-t^3)(1-target_{end}) + target_{end} & (d=1) \\ (1-t^d)(1-target_{end}) + target_{end} & (otherwise) \end{cases} \tag{13.6}$$

The weighting average of the estimated value proposed by the opponent in the final phase divided by h_n is calculated using Eq. 13.5. Our agent proposes a bid whose utility exceeds $target(t)$ and the highest U_{op} (Eq. 13.4). It accepts the opponent's bids when they are more than $target(t)$.

Figure 13.3 shows the changes of $target(t)$ when $target_{end} = 0.5$. Since discount factor d is small, our agent compromises soon by considering the conflicts among agents based on $target_{end}$.

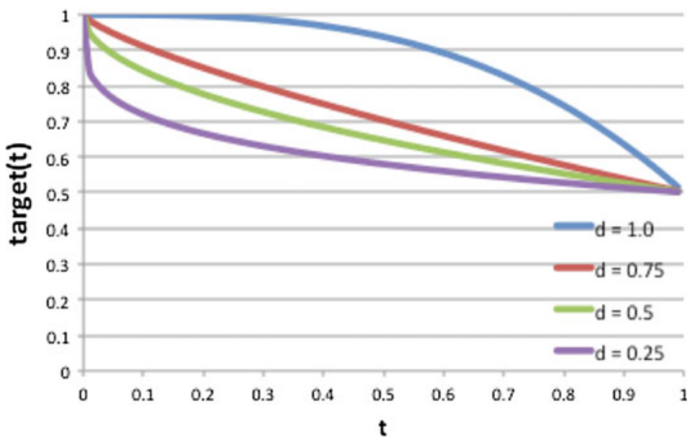

Fig. 13.3 Example of threshold of offer and accept ($target_{end} = 0.5$)

13.5 Experimental Results

Our experiments are demonstrated under the domains generated randomly. The number of values for each issue is 10. The number of issues is from 2 to 7 (Domain size is from 10^2 to 10^7). In each domain, the discount factor is set to 1.0 (without discounting) or random value (from 0.01 to 0.99), respectively. The reservation values is set to 0.

The opponents are the top five state-of-the-art agents in the individual utility and social welfare categories in ANAC2015.

- Individual Utility Category: agentBuyogV2 (Nanyang Technological University), Atlas3 (Nagoya Institute of Technology), kawaii (Nagoya Institute of Technology), ParsAgent (University of Isfahan), RandomDance (Tokyo University of Agriculture and Technology)
- Social Welfare Category: Mercury (Maastricht University), AgentX (Nagoya Institute of Technology), Atlas3 (Nagoya Institute of Technology), JonnyBlack (University of Tulsa), CUHKAgent2015 (The Chinese University of Hong Kong)

In these experiments, we compared our proposed agent with a random agent (*Random*) that doesn't estimate the opponent's utility. *Random* proposes bids over the threshold based on Eq. 13.5 whose maximum utility is the initial opponent's bid using the hill climbing algorithm. The tournament has three agents. The averages and standard deviations of the four tournaments under the ANAC2015 agents and domains are shown.

Figure 13.4 shows the individual utility (left graph) and the social welfare (right graph) using three types of $w(\mathbf{s})$ as the number of issues changes. The individual utility rate and the social welfare rate are defined as (*Utility of Three Types of* $w(\mathbf{s})$)/(Utility of Random Agent). In left graph of Fig. 13.4, the individual utility rate is higher as the domain size becomes large. Therefore, the method of estimating opponent's utility function is effective in the large sized domains. On the other hands, the social welfare rate is almost same as the domain size changes. This is because that the agents by finalists estimate the opponent's utility functions to get the higher social welfare.

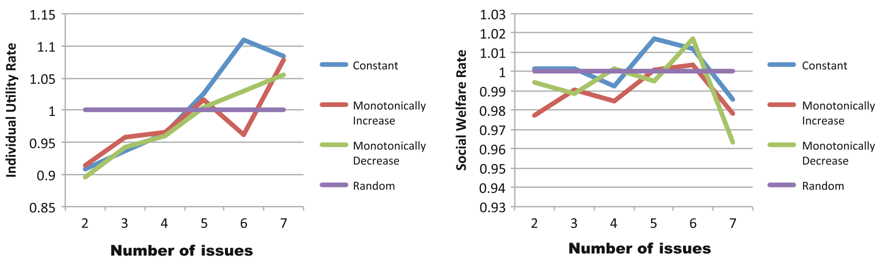

Fig. 13.4 Individual utility (*left*) and social welfare (*right*) using different $w(\mathbf{s})$

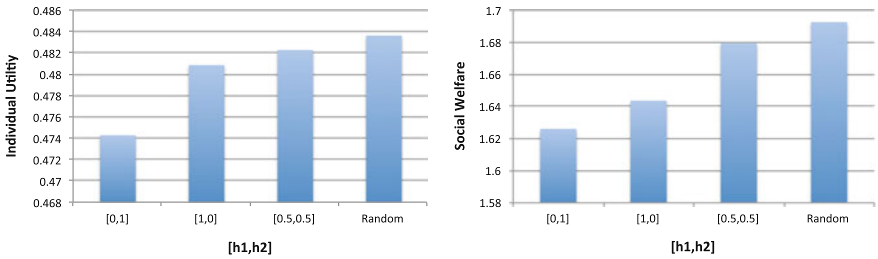

Fig. 13.5 Individual utility (*left*) and social welfare (*right*) using different h_n

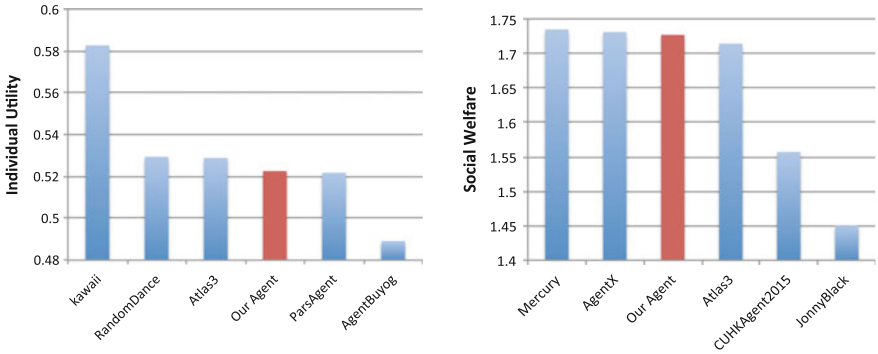

Fig. 13.6 Individual utility (*left graph*) and social welfare (*right graph*) under tournaments among ANAC2015 Agents

Figure 13.5 compares the result when the compromising function to each agent is changed. The following are the h_1 and h_2 rates: $(h_1, h_2) = (0.5, 0.5), (1, 0), (0, 1), (Random)$. The weighted function $w(\mathbf{s})$ is constant function. In individual utility and social welfare, $(h_1, h_2) = (Random)$ is the highest among all of the methods. In addition, $(h_1, h_2) = (1, 0), (0, 1)$ is lower than (0.5, 0.5) because the proposed agent compromises too much without considering another opponent's agent.

Figure 13.6 shows the individual utility (left graph) and the social welfare (right graph) under tournaments among the ANAC2015 agents. The weighting function is constant and the rate of the compromising function to each agent $(h_1, h_2) = (Random)$. Table 13.1 shows the individual utility (left table) and the social welfare (right table) only the largest domain in this experiments (Number of issues is 7, Domain size is 10^7). A rank of individual utility in the seven issues s a higher than the average in all domains. In large domain, our agent is effective despite that our agent uses the simple estimating method of opponent's utility function. However, these results aren't so high in this tournament because our proposed agent has a simple compromising strategy and constant weighting functions. In future work, we will improve our agent to get higher social welfare and individual utility.

Table 13.1 Individual utility (left table) and social welfare (right table) in issues size = 7 (Domain size = 10^7)

Agent Name	Individual Utility
kawaii	0.2047
Our Agent	0.1961
RandomDance	0.1766
Atlas3	0.1636
ParsAgent	0^a
AgentBuyog	0^a

Agent Name	Social Welfare
AgentX	0.6716
Atlas3	0.6704
Our Agent	0.6680
Mercury	0.6621
CUHKAgent2015	0^a
JonnyBlack	0^a

[a] These agents didn't work well in the large domains because the domains size of ANAC2015 is less than 2^{16}

13.6 Conclusions

This chapter focused on both multi-lateral multi-issue closed negotiations and bilateral negotiations. In multi-lateral negotiations, agents simultaneously estimated the utility functions of more than two agents. In this chapter, we proposed an estimating method using simple weighted functions by counting the opponent's evaluation value of each issue. For multi-lateral negotiations, our agent considered utility functions as a single utility function by weighted-summing them. In our experiments, we compared the individual utility and the social welfare among some simple weighted functions. We also evaluated the negotiation efficiency of our proposed agent with ten state-of-the-art negotiation agents that reached the final round of ANAC-2015.

Future works will improve the estimates of the opponent's utility in our proposed approach. To solve this problem, our approach needs to adjust the weighting functions based on opponent proposals for estimating the opponent's utility. In the experiments, we focused on the linear utility functions same as ANAC2015 rules. In the bilateral multi-issue closed negotiations, the authors proposed the method of estimating the Pareto fronts with nonlinear domains [13]. By considering these results, our approach can be improved to the nonlinear utility functions. Another important task is to judge the opponent's strategy based on modeling or a machine learning technique to further enhance our proposed method.

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