Strategy Analysis for Competitive Bilateral Multi-Issue Negotiation

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Abstract: In most existing negotiation models, each agent aims only to maximize its own utility, regardless of the utility of the opponent. However, in reality, there are many negotiations in which the goal is to maximize the relative difference between one's own utility and that of the opponent, which can be regarded as a kind of zero-sum game. The objective of this study is to present a model of competitive bilateral multi-issue negotiation and to analyze strategies for negotiations of this type. The strategy we propose is that the agent makes predictions both about the opponent's preference and how the opponent is currently predicting its own preference. Based on these predictions, the offer that the opponent is most likely to accept is proposed. To demonstrate the usefulness of this strategy, we conducted experiments in which agents with several strategies, including ours, negotiated with one another. The results demonstrated that our proposed strategy had the highest average utility and winning rate regardless of the error rate of the preference prediction.

1 INTRODUCTION

Automated negotiation is a process in which an autonomous agent interacts with another agent (or human) to form an agreement that is desirable for both parties. Several studies have been conducted on automated negotiations over a period of decades, interacting with fields such as artificial intelligence and e-commerce. (A comprehensive survey of research in this area is provided by (Baarslag et al., 2016) and (Kiruthika et al., 2020).)

Various negotiation models have been proposed regarding the number of agents and incomplete information. However, in most of these, each agent's objective is only to maximize its own utility, regardless of the utility of its opponent. Therefore, the objective of all agents in a negotiation is to achieve a Pareto-optimal outcome. However, in the real world, many negotiations exist in which agents are required not only to increase their own utilities, but also to maximize the difference between their own utilities and those of their opponents. Typical examples of this include various tradings such as foreign exchange transactions, and negotiations between parties in competitive relationships, as modeled in some board games such as CATAN (CATAN GmbH, nd). The negotiation of this type requires more skillful tactics that have not been considered in existing negotiation models.

The objective of this study is to provide a model of bilateral multi-issue competitive negotiation, and to propose a strategy for negotiations of this type. Competitive negotiation is a special type of negotiation in which the relative difference between the utilities obtained by an agent and its opponent is evaluated as the actual utility. In this sense, this problem is a kind of zero-sum game. Another difference between conventional negotiations and competitive ones is that, in the former, the utility obtained as a result of an agreement is known in advance, whereas in competitive negotiation, the actual utility is not known in advance because it depends in part on the opponent's utility.

Generally, in negotiations, agents make decisions such as the choice of the contents of offers and whether to agree to the opponent's offer, while making predictions regarding the opponent's preferences. In this study, we focused on decision-making strategies rather than the prediction technique. Specifically, our proposed strategy comprises two tactics. The first tactic applies to setting a target value (i.e., the minimum acceptable relative utility) for an agent, based on the prediction of the opponent's preference as well as the prediction of how the opponent will predict the agent's own preference. The second tactic is used when choosing the content of the offer to which the opponent is most likely to agree.

We evaluated the effectiveness of our strategy by conducting bilateral negotiations on three competitive issues. The experimental results showed that the pro-

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The remainder of this paper is organized as follows. Section 2 presents related work. Section 3 describes the model of competitive negotiation. Section 4 introduces strategies for competitive negotiation. Section 5 presents experimental results. Finally, Section 6 concludes the paper and presents plans for future work.

2 RELATED WORK

A representative early study on the automated negotiation was conducted by Faratin et al. (Faratin et al., 1998). This study disseminated a technique for searching for an agreement point by concessions and described the basic idea of strategic negotiation. Fatima et al. (Fatima et al., 2006) analyzed negotiation strategies and equilibrium in bilateral negotiations, where in which there is a negotiation deadline and the opponent's preferences are unknown. Jennings et al. (Jennings et al., 2001) classified the existing negotiation strategies by approaches, and studies (Cao et al., 2015; Zheng et al., 2014) proposed negotiation approaches that combine multiple strategies and dynamically change an agent's behavior according to that of the opponent.

Our study and those described above focus on bilateral negotiations, but there have also been studies on negotiations involving more than two agents. For example, (Aydoğan et al., 2014) investigated the strategies and protocols in such negotiations. There are also studies, such as (Mansour and Kowalczyk, 2015; An et al., 2011) regarding situations in which single-issue negotiations between two agents to obtain multiple resources are performed in parallel in e-commerce.

The negotiation problem targeted by the above studies aims at maximizing each agent's own utility through negotiation. Conversely, our study focuses on the competitive negotiation problem that aims to maximize the difference between one's own utility and the opponent's utility, which has not been thoroughly investigated.

There is a study (Keizer et al., 2017) targeting negotiation in CATAN, which is a specific example of competitive negotiations. Although that study did not present a negotiation model, it implemented negotiation strategies by a rule-based technique and machine learning.

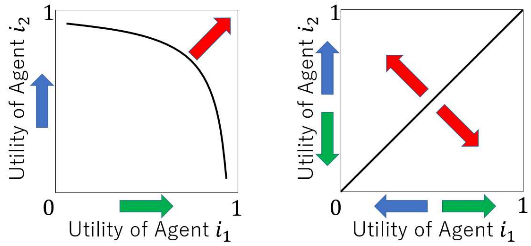

Figure 1: Utility spaces of non-competitive (left) and competitive (right) bilateral negotiation.

3 COMPETITIVE BILATERAL NEGOTIATION MODEL

In this section, we define competitive bilateral multi-issue negotiation model. In addition, we show that this negotiation with perfect information always leads to an agreement in which the utility for both agents are zero.

3.1 Basic Concept

As explained earlier, the objective of a rational agent in conventional bilateral negotiations is to reach an agreement that maximizes its own utility regardless of that of the opponent. Conversely, the objective of the agent in the competitive bilateral negotiation proposed in this study is to maximize the difference in utility between itself and the opponent. In this sense, this negotiation can be regarded as a zero-sum game. Therefore, even if high utility is obtained as a result of negotiation, it is undesirable to bring high utility to the opponent as well. Rather, it is desirable that the difference in utility relative to the other party is larger, even if one's own utility is lower.

Figure 1 illustrates the difference between non-competitive (left) and competitive (right) negotiations. Here, the utility spaces of agents i_1 and i_2 in each negotiation are shown, and the green and blue arrows represent the vector of utility aimed at by i_1 and i_2, respectively. In non-competitive negotiations, the combined vector of both agents is indicated by a red arrow. This means that the goal of the agents is to reach agreement on the Pareto frontier represented by the curved line. On the contrary, in competitive negotiations, each agent aims both to maximize its own utility and minimize that of the opponent. Therefore, the combined vectors of each agent are opposite to each other as indicated by the red arrows. This implies that each agent aims to reach an agreement on its own side of the diagonal line that indicates a relative utility of zero for both agents.

3.2 Formal Model

The formal model of negotiation is defined as a tuple of the following components: a set of negotiation agents, negotiation domain (often called the outcome space), negotiation protocol, and preference profiles. (The paper (Baarslag et al., 2016) presents a survey that provides more details.)

Let I be the set of negotiation agents. Because this study deals only with bilateral negotiations, we fix $I = \{i_1, i_2\}$. We also use the notation $-i$ to indicate the opponent of agent $i \in I$. The negotiation domain, or often called the outcome space (denoted by O) represents the set of all possible negotiation outcomes. The negotiation protocol determines the rules of negotiation, such as the order of offers and the conditions of agreement. The preference profile is a binary relation over the negotiation domain for each agent, that determines which of any two outcomes is more preferable. Here, we follow the game-theoretic convention and define the relation by a utility function $U^i : O \rightarrow \mathbb{R}$ (for $i \in I$). However, in competitive negotiations, the goal is to maximize the difference in utilities between the two agents. Therefore, in addition to the usual utility function, we introduce $RU^i : O \rightarrow \mathbb{R}$, which represents the relative utility. The formal definitions of these components are given below.

3.2.1 Negotiation Domain

The negotiation domain O is represented as a product of one or more sets (called issues) of possible outcomes. The set of indices for the issues is represented by $J = \{1, \ldots, j\}$, where j is the number of issues. The set of outcomes for each issue is represented by O_k ($k \in J$), and thus O is defined to be $O_1 \times \cdots \times O_j$.

3.2.2 Negotiation Protocol

As with many previous studies on bilateral negotiations, we follow the alternating-offers protocol (Rubinstein, 1982), in which agents take turns making suggestions while searching for a mutually acceptable outcome. More specifically, an agent with turn proposes one of the elements of the negotiation domain as the content of offer. The other agent who received the proposal selects one of the following three actions.

Accept: Agree to the proposal. Both agents obtain utility based on the agreed outcome.

Offer (Counter-offer): Reject the proposal and make a new offer to the other party.

EndNegotiation: Reject the proposal and end the negotiation. Both agents receive a utility of zero.

Times (steps) in the progress of negotiation are represented by discrete values $t = 1, 2, \ldots \in T$. Negotiations may have a time limit (denoted by $t_{\max}$) and, if no agreement is reached within it, both agents gain a utility value of zero.

3.2.3 Preference Profile

The utility of agent $i \in I$ for outcome $o \in O$ is defined by the following equation:

$$U^i(o) = \Sigma_{k=1}^{j} w_k^i V_k^i(o_k),$$

where w_k^i denotes the weight assigned to agent i for issue k, satisfying $\Sigma_{k=1}^{j} w_k^i = 1$. $V_k^i : O_k \rightarrow \mathbb{R}$ is the evaluation function for issue k for agent i. According to convention, in this study, the range of utility is defined as $[0, 1] \subseteq \mathbb{R}$.

3.2.4 Relative Utility Function

A relative utility function $RU^i : O \rightarrow \mathbb{R}$ is introduced to represent the difference between the utility of the two parties in a competitive negotiation. This is defined as

$$RU^i(o) = U^i(o) - U^{-i}(o).$$

3.3 Analysis of Perfect Information Case

In competitive negotiations, if the agents' preference profiles are common knowledge, the utility for both agents will be always zero. We demonstrate this fact in game theory.

Here, we assume that the negotiation has a time limit $t_{\max}$ and that the utility function of the agents is common knowledge. First, let i be the agent having a turn at time $t_{\max}$ and consider the optimal action of i at this time. At $t_{\max}$, i can choose only *Accept* or *EndNegotiation*, and if offer o made by $-i$ at $t_{\max} - 1$ satisfies $RU^i(o) > RU^{-i}(o)$, i can obtain a positive relative utility by choosing *Accept*. Otherwise (i.e., $RU^i(o) \leq RU^{-i}(o)$), and i obtains relative utility zero by choosing *EndNegotiation*. Thus, at $t_{\max} - 1$, $-i$ should offer o' with $U^i(o') \leq U^{-i}(o')$, which results in a final relative utility of zero for both agents. Using the same argument in the reverse direction, we find that at any time $t < t_{\max}$, both agents make offers with positive relative utility, leading to the same result.

4 NEGOTIATION STRATEGIES

This section presents some possible strategies for competitive negotiations, the effectiveness of which is analyzed empirically in the next section.

4.1 Tactics

In general, negotiation comprises two decisions: choosing an outcome from the negotiation domain as one's own offer and deciding whether to accept the opponent's offer. To decide what to offer, a plausible approach is to set a target value (i.e., the minimum acceptable relative utility) in advance, and make an offer that exceeds this target. Furthermore, there are two possible ways to select an outcome to offer: one is to select an outcome randomly that exceeds the target value, and the other is to select an outcome that the opponent is more likely to accept. To decide whether to accept an offer, a plausible approach is to set a target value in advance, and agree to the opponent's offer if it exceeds the target value. Here, these two target values may generally differ and may vary with time.

Below, we discuss possible tactics for each of these decisions.

4.1.1 Tactics to Decide Target Value for Offer

Algorithm 1: Evaluation of TRU with prediction-dependent tactic.

Update $U^{-i}_{est(i)}$ and $U^{i}_{est(i)}$
for all $o \in O$ **do**
  if $RU^i(o) = TRU^i_t$ **then**
    if $U^{-i}_{est(i)}(o) - U^{i}_{est(i)}(o) > U^{-i}_{est(i)}(o_{t-2}) - U^{i}_{est(i)}(o_{t-2})$ **then**
      $O^i_t.add(o)$
    end if
  end if
end for
if $O^i_t \neq \emptyset$ **then**
  $TRU^i_t = TRU^i_t$
else
  $TRU^i_t = TRU^i_t - c$
end if

There are two main approaches to determine the target relative utility for an agent's offer. The first fixes the value through negotiation (called fixed-value tactic) and the second allows it to vary over time. The latter can be classified further into two types: the time-dependent tactic, in which the target value is determined depending only on time, and the prediction-dependent tactic, in which the target value is determined depending both on time and on predictions about preferences.

The definitions of these three tactics are given below, where TRU^i is used to denote the target value of agent i.

Fixed-Value Tactic: This tactic always sets the target value to any value greater than zero.

Time-Dependent Tactic: The target value of agent i in this tactic is defined as follows:

$$TRU^i_t = \min{}^i + (1 - \alpha^i(t)) \times (\max{}^i - \min{}^i).$$

This tactic is based on the idea of (Faratin et al., 1998). Here, $\min^i$ (called the reservation value) and $\max^i$ denote the minimum and maximum relative utilities that agent i desires in negotiation regardless of time, respectively.

The function $\alpha^i : T \to \mathbb{R}$ is called a time-dependent function, and satisfies both $\alpha^i(0) = \kappa^i$ and $\alpha^i(t^i_{\max}) = 1$ (where κ^i is a constant). Various time-dependent tactics can be defined according to the definition of this function. Some well-known ways of defining this function include polynomials and exponential functions. In this study, the following polynomial function is used:

$$\alpha^i(t) = \kappa^i + (1 - \kappa^i) \times (\min(t, t^i_{\max})/t^i_{\max})^{1/\beta}.$$

This function changes the speed of concession depending on the value of β. When $\beta = 1$, yielding progresses at a constant rate (linear); when $\beta > 1$, yielding progresses early; and when $\beta < 1$, few concessions are made while time t is small, whereas concessions are suddenly made near $t^i_{\max}$.

Prediction-Dependent Tactic: This is introduced in this study for competitive negotiation. This tactic makes the following types of predictions:

- Prediction of the opponent's preference.
- Prediction about how the opponent will predict one's own preference.

Based on these predictions, the target value is set taking into consideration whether the offer will be accepted by the opponent and the current time.

The detailed algorithm to determine the target value is as follows. Let $U^{-i}_{est(i)}$ be the preference function of $-i$ predicted by agent i, and let $U^{i}_{est(i)}$ be the prediction of $U^{i}_{est(-i)}$ by agent i.

The algorithm for the target value TRU^i_t at time t for agent i is described in Algorithm 1. Here, o_{t-2} denotes the previous offer by agent i, O^i_t denotes the set of candidates of offers(i.e., the set of possible offers expected to yield a relative utility that matches the target value TRU for agent i at time t), and c denotes the amount of change in the target value when agent i concedes.

As shown in Algorithm 1 below, this tactic does not change the target value if there is an offer that the opponent is more likely to agree with that has the same target value as the previous offer. Otherwise, the target value is decreased.

Table 1: Strategies for competitive bilateral negotiation.

Strategy name	Target value for offer	Offer choice	Target value for agreement
PMT	Prediction-dependent	Mislead	Time-dependent
TRT	Time-dependent	Random offer	Time-dependent
PMF	Prediction-dependent	Mislead	Fixed
TRF	Time-dependent	Random offer	Fixed
FMF	Fixed	Mislead	Fixed
FRF	Fixed	Random offer	Fixed

4.1.2 Tactics for Offer Choice

There are two main approaches to choose an offer. The first, called the random offer tactic, chooses an offer randomly from the set of offers that might bring a relative utility above the target value. The second approach, called mislead tactics, is proposed in this study for competitive negotiation. This uses the prediction of the opponent's preference as well as the prediction of how the opponent will predict one's own preference. Based on these predictions, the offer to be selected is the one that the opponent is most likely to accept from among the possible outcomes exceeding the current target value. The formal definition of this tactic is as follows: Let O_t^i be the set of candidates for the target value of agent i at time t. Offer o_t at time t by mislead tactics is then expressed as follows:

$$o_t = arg\max_{o \in O_t^i}(U_{est(i)}^{-i}(o) - U_{est(i)}^{i}(o)).$$

4.1.3 Tactics for Determining Agreement

Tactics on agreement can be divided into two categories, depending on whether the target value is fixed or variable. In both cases, agreement is chosen when the predetermined target value is exceeded. Similar to the target value used to determine the offer, tactics can be time-dependent or prediction-dependent. Only the simple time-dependent tactic is analyzed in this study.

4.2 Negotiation Strategies

Negotiation strategies are realized by combining the tactics described above. Therefore there are 12 strategies, consisting of three tactics to determine the target value for the offer, two to choose the content of the offer, and two to determine the target value as the criterion for agreement. Of particular interest are the six strategies shown in Table 1.

5 EXPERIMENTS

In order to evaluate the usefulness of the proposed negotiation strategy, we conducted experiments in which the strategies defined in Section 4 were negotiated with each other.

5.1 Parameter Settings

5.1.1 Negotiation Domain

The negotiation domain used in the experiments consisted of three issues, each with ten options. The negotiation domain therefore consisted of a set of 1,000 outcomes.

5.1.2 Negotiation Strategies

For the experiments, we developed negotiation agents for each of the six strategies defined in the previous section, whose parameter settings were presented below.

For the time-dependent tactic, the values of the four parameters are as follows.

- min $= 0.05$.
- max $= 1.0$.
- $\kappa = 0.1$.
- $\beta = 1.0$.

For the prediction-dependent tactic, the parameter c for concession is set to 0.05. However, if this tactic makes a concession resulting in $TRU \leq 0$, to prevent the agent from making an offer that would hurt itself, the value of TRU was updated to 0.05 and chose an offer satisfying $RU > 0$. In the experiment, the offers based on the random-offer tactic and mislead tactic were selected within the range of 0.02 round the value of TRU. This is because the agent may not find an offer that yields utility exactly equal to TRU. Thus, the agent set the value of TRU at time t to $RU(o_{t-2})$ (where o_{t-2} denotes the previous offer), and decided whether to make concession by Algorithm 1.

5.1.3 Preferences

The preferences defined by the weights and utility functions for i_1 and i_2 were set as follows, respectively. Here, the same utility functions were used for all issues.

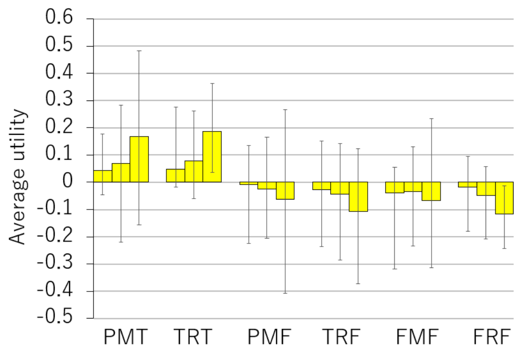

Figure 2: Average utility for each strategy when the cosine similarities of predictions were 0.99, 0.95, and 0.9.

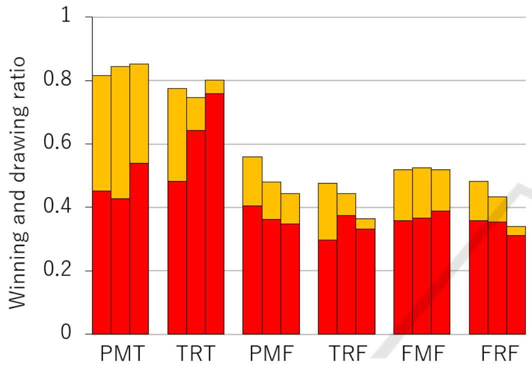

Figure 3: Win rate (denoted by red) and draw rate (denoted by orange) for each strategy when the cosine similarities of predictions were 0.99, 0.95, and 0.9.

- $w^{i_1} = (0.2, 0.3, 0.5)$.
- $V^{i_1} = (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0)$.
- $w^{i_2} = (0.5, 0.3, 0.2)$.
- $V^{i_2} = (1.0, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1)$.

Each agent i was not informed about the exact preferences of its opponent. Instead, it was initially informed of its own and its opponent's preferences with a certain range of error, which mimicked the predicted value $U^{-i}_{est(i)}$ and $U^{i}_{est(i)}$. Specifically, for each of the weights of the agents' preferences and the evaluation functions, we gave predictions with errors such that the cosine similarity is $0.99, 0.95$ and 0.9. Here, since the difference between the preferences of it's own and the opponent can be large or small depending on the predicted values, in the experiment all of the cases were evaluated.

5.2 Experimental Results

Under the settings described in the previous section, the results of round-robin matches with six negotiation strategies are shown below.

Figure 2 shows the average utility obtained by each strategy. Here, the horizontal axis represents the results of each strategy, and the three graphs show the results when the cosine similarities of the preference predictions are 0.99, 0.95, and 0.90, respectively, from the left. The vertical axis shows average utilities with their maximum and minimum values.

Figure 3 shows the sum of the win and draw rates for each strategy. Here, the horizontal axis represents the results of each strategy, and the three graphs show the results when the preference predictions have cosine similarities of 0.99, 0.95, and 0.90, respectively, from the left. The vertical red and orange graphs represent win and draw rates, respectively.

As shown in Figure 2, PMT and TRT strategies were found to be superior to the other strategies, with a positive average utility regardless of the error rate of prediction. Specifically, when the cosine similarity of the preference predictions was 0.99, the average utilities of PMT and TRT strategies were about 0.043 and 0.049, respectively. Also, when the cosine similarity was 0.9, the average utilities of these two strategies were about 0.168 and 0.187, respectively. On the other hand, the average utilities of the other four strategies always had negative average utility.

From the above results, it can be seen that the utility of both PMT and TRT strategies increases as the difference in expectations increases. A possible reason for this is that both the PMT and TRT strategies have time-dependent target values for agreement. The larger the prediction error, the greater the probability of making a wrong decision about one's relative gain for a proposal, and the greater the probability of a larger error in the value of that relative gain. While other strategies choose to agree when their relative gains are large (relative utilities greater than 0), the PMT and TRT strategies have stricter criteria for agreement, so they are less likely to agree to an agreement that will actually be to their detriment. As a result, the larger the forecast error, the higher the relative utility of the PMT and TRT strategies, suggesting that having a time-dependent agreement target value is important for competitive negotiation.

Figure 3 shows that PMT strategy had a lower win rate than TRT strategy, but the sum of the draw rate and the win rate was always the highest for the PMT strategy. For example, when the cosine similarity of preference predictions was 0.99, the win rates of PMT and TRT strategies were about 0.452 and 0.482, respectively. The draw rates for these strategies were about 0.365 and 0.293 respectively. Thus, the sum of the win and draw rates for PMT and TRT were about 0.816 and 0.775, respectively, with 4.2 percentage point higher win or draw rate for the PMT strategy.

Examples of the negotiation process for PMT and

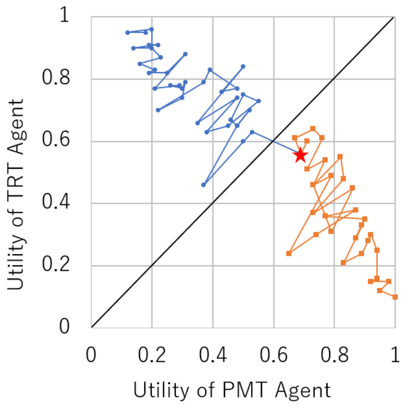

Figure 4: The negotiation process in which PMT won over TRT by the largest utility margin.

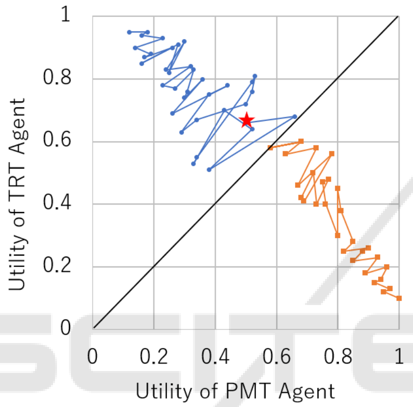

Figure 5: The negotiation process in which PMT lost to TRT by the largest utility margin.

TRT strategies are shown in Figures 4 and 5. Here, the orange and blue plots indicate the history of the offers by PMT and TRT agents, respectively, and the red star indicates the agreed outcome. Figures 4 and 5 both show the results when the Cosine similarity of the preference prediction was 0.99.

Figure 4 shows the negotiation process when PMT wins TRT by the largest margin of utility. In Figure 4, neither agent agreed with the other's offer and continued to make offers that were profitable for them, but in the end, TRT made a mistake and made an offer that was more profitable for PMT. As a result, the utility of PMT became positive.

Figure 5 shows the negotiation process when PMT lost by the largest margin of utility to TRT. In Figure 5, both agents made offers that were advantageous to them until the end. However, in the end, PMT mispredicted the utility of the offer received from TRT and chose to agree, resulting in a negative utility for PMT.

In competitive negotiations, winning is important, but not losing is also important. PMT strategy is also an excellent strategy in terms of stability. Based on the above results, the PMT strategy is considered to be the optimal negotiation strategy in competitive negotiations.

6 CONCLUSIONS AND FUTURE WORK

In this study, we proposed a model of competitive bilateral multi-issue negotiation, in which an agent's utility and that of the opponent are evaluated relative to each other and the actual utility can be regarded as a zero-sum game. We also proposed a strategy for the negotiations of this type, in which the basic idea is to choose the offer that the opponent is most likely to accept, based on the prediction of the opponent's preference and the prediction of one's own preference from the opponent's perspective.

To demonstrate the effectiveness of the proposed strategy, we conducted experiments in which agents with various strategies negotiate competitive three-issue bilateral negotiations. The results show that the proposed strategy achieves the highest utility and winning rate, regardless of the prediction error rate. We also showed that time-dependent target value for agreement is important for gaining relative utility in competitive negotiations.

In future work, we will develop a prediction method required in our negotiation setting, based on some existing methods such as those using Bayesian estimation (Lin et al., 2006) or heuristics (Jonker and Robu, 2004). We are also interested in applying our strategy to the development of agents that play board games involving competitive negotiation.

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