Multilateral Mediated Negotiation Protocols with Feedback

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Chapter 3
Multilateral Mediated Negotiation Protocols with Feedback

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Abstract When more than two participants have a conflict of interest, finding a mutual agreement may entail a time consuming process especially when the number of participants is high. Automated negotiation tools can play a key role in providing effective solutions. This paper presents two variants of feedback based multilateral negotiation protocol in which a mediator agent generates bids and negotiating agents give their feedback about those bids. We investigate different types of feedback given to the mediator. The mediator uses agents' feedback to models each agent's preferences and accordingly generates well-targeted bids over time rather than arbitrary bids. Furthermore, the paper investigates the performance of the protocols in an experimental setting. Experimental results show that the proposed protocols result in a reasonably good outcome for all agents in a relatively short time.

Keywords Multilateral negotiation • Protocols • Smart mediators

3.1 Introduction

Much attention has been paid to bilateral negotiation in which the dispute is between only two parties. However, automated multilateral negotiation in which more than two negotiating parties need to reach a joint agreement, has received relatively less attention [4], even though such negotiations are required in many circumstances. For instance, decision making process in organizations (i.e. business or governmental organizations) mostly involve more than two individuals, or in personal life a group of friends or family members need to have an agreement on a particular matter such as their holiday.

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Multilateral negotiation is more complicated than bilateral negotiation in view of the fact that the agreement needs to be reached among more than two parties means more conflicts and more interactions. An important issue is to decide on the protocol that governs the interaction between parties and determines when the final agreement will be reached. In this paper, we focus on and investigate different mediator-based protocols. In such protocols, a mediator generates and proposes bids. We investigate the feedback that agents provide in response to such mediator-generated bids. We take [6] as a starting point and propose two variants of the protocol. In that protocol, a mediator generates bids and asks negotiating parties for their approval or disapproval of the bids; finally it determines the negotiation outcome based on the votes of the parties during the negotiation. The protocol is convenient for both software and human agents since the participants just need to compare the current bid with the last accepted bid by all parties, and accordingly vote. The mediator searches the outcome spaces based on only the most recent mutually accepted bid by all parties without taking the preferences of the parties into consideration. Due to the privacy concern the negotiating parties may (possibly would) be reluctant to reveal their preferences entirely to the mediator so it is reasonable for the mediator not to ask the preferences of the parties directly. However, the mediator may try to understand preferences of the parties based on their feedback during the negotiation and accordingly revise its bids. This approach may allow the mediator to complete the negotiation earlier.

This paper presents two variants of feedback based multilateral negotiation protocol in which the mediator models the negotiating parties' preferences based on their feedback during the negotiation and generates bids by taking the utility of each negotiating party into consideration. Similar to the protocol in [6], it does not require high computational effort for the negotiating parties, so human agents may take place in the negotiation as a negotiating party. Furthermore, the mediator agent searches the outcome space based on its knowledge acquired from the feedbacks given by the negotiating parties during the negotiation. We experimentally compare the original protocol proposed in [6] with the two new variants we introduce in this paper. Experimental results show that agent benefits utility-wise.

The rest of this paper is organized as follows: Sect. 3.2 gives a brief introduction to mediated single text negotiation presented in [6]. Section 3.3 explains the proposed multilateral negotiation protocols and mediator's preference modeling approach. Section 3.4 explains our experimental setup, metrics, and results. Finally, Sect. 3.5 discusses our work.

3.2 Mediated Negotiation

According to the mediated single text negotiation protocol presented in [6], the mediator initially generates a bid randomly and asks the negotiating agents to vote for this bid. Each agent can vote to either "accept" or "reject" in accordance with its negotiation strategy. If all negotiating agents vote to accept, the bid is labeled as the most recent mutually accepted bid. In further rounds, the mediator modifies the most recent mutually accepted bid by exchanging one value with another randomly in the bid and asks negotiating agents to vote for the current bid. This process continues iteratively until a predefined number of bids are reached.

In that study, two voting strategies are defined for the agents: "Hill-climber" and "Annealer". An agent employing *hill-climber* strategy only accepts a bid if its utility is greater than the utility of the most recent mutually accepted bid. The problem with hill climber approach is if the utility of initial bid is quite high for one of the negotiating agents, that agent may not accept other bids even though those bids might be better for the majority. By contrast, the agent employing *Annealer* calculates the probability of acceptance for the current bid based on the utility difference and a virtual temperature, which gradually declines over time. There is a higher probability when the difference is small and virtual temperature is high. That is, an agent employing *Annealer* has a tendency to accept individually worse bids earlier so that the agents can find win-win bids later. Towards to the end of the negotiation, the agent has a tendency to accept only the bids whose utility is greater than the utility of the most recent mutually accepted bid. The authors also propose some other approaches to handle the exaggerator agents but those are beyond the scope of this paper since we consider that all negotiating agents are truthful in our negotiation framework.

3.3 Proposed Mediated Negotiation

Inspired from the mediated negotiation approach explained above, we present two variants of feedback based mediated multilateral protocol and a preference modeling approach for the mediator based on the feedbacks given by the negotiating agents during the negotiation. In both variants, the mediator agent tries to model the preferences of each negotiating agent by using their feedbacks about the mediator's bids. Consequently, the mediator aims to generate better bids for all of the agents by using the learnt model over time.

Basically in the proposed approach, the mediator initially generates its first bid randomly and for the further bids it modifies its *previous bid* by exchanging one value with another in the bid randomly or according to a heuristic based on the learnt preference models during the negotiation. When the negotiating agents receive a bid from the mediator, they give a feedback such as "*better*", "*worse*", and "*same*" rather than simply voting the mediator's current bid either to accept or reject. To do this, the agents compare the mediator's current bid with its previous bid and accordingly give their feedback. For example, if the current bid is better than the previous one for the agent, it says "better". Based on those feedbacks, the mediator tries to model the preferences of each negotiating party. To achieve this, the mediator only assumes that the negotiating agents give their feedback truly, preferences are total preorder, and there is no preferential interdependency among the issues. It is worth noting that the mediator does not make any other assumptions about the negotiating agents' preference representation. The agents may use a qualitative preference model to represent their preferences as well as they may represent their preferences by means of additive utility functions. Furthermore, this allows each negotiating agents to choose their preference representation freely. Unless there exist preferential interdependencies among the issues, the agents can employ different preference representations for their preferences.

In the following section, we first describe how the mediator models the preferences of each negotiating agent based on their feedbacks and then presents two variants of mediated multilateral protocol in which the mediator models the preferences and accordingly generates its bids.

3.3.1 Feedback Based Preference Modeling

As stated before, the mediator mutates its previous bid by flipping one of the issues at a time and gets feedback from the negotiating agents. This allows the mediator to have some information about each agent's preferences on that issue. To illustrate this, consider one of the agents specifies the current bid, (x_1, y_1), is better than the previous one, (x_2, y_1) where x_i and y_i denote the values of the first and second issue in the bid, say X and Y respectively. By interpreting this feedback, the mediator can deduce that the value x_1 is preferred over x_2 for the first issue by that agent. If the mediator keeps the preferential information gathered from the agent's feedback in a graphical model such as preference graph, it can extract more preferential information by using some properties such as transitivity of the preferences. That is, if we know that x_1 is preferred over x_2, and x_2 is preferred over x_3, then we can infer that x_1 is also preferred over x_3 by using the transitivity of the preference orderings.

Accordingly in the proposed approach, the mediator generates a model, M_i for each negotiating agent, A_i and updates those models after receiving feedback from the agents. M_i is a set of preference graphs, $M_i = \{PG_1, PG_2, \ldots, PGn\}$ where PG_k is the preference graph for the kth issue. The nodes of these graphs denote the values for the given issue and the edges shows the *improving flips*, changing the value of an issue with a more desired value. In other words, the direction of edges are ordered from less preferred to more preferred values. Figure 3.1 shows a sample preference graph for the issue, X whose possible values are denoted as $D(X) = \{x_1, x_2, x_3, x_4, x_5\}$. From the given preference graph, it is seen that the values x_2 and x_4 are equally preferred and those values are preferred over the values x_3 and x_5. Moreover, it can be interpreted that the value x_1 is preferred over all other values by using the transitivity of the preference ordering. According to this preference graph, x_3 and x_5 cannot be comparable since there is no path between them. By modeling the agent's preference via preference graphs, the mediator is able to extract more information from the given feedback. Transitivity can also be applied to "equally preferred" values. For instance, if the mediator knows that x_4 is preferred over x_5, it can deduce that x_2 would be preferred over x_5 since x_2 and x_4 are equally preferred. Consequently, it will be able to compare more pairs with less information.

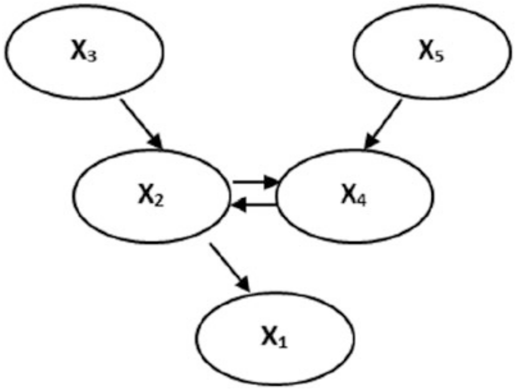

Fig. 3.1 A sample preference graph for issue X

For example, the preference graph in Fig. 3.1 can be constructed by using only four feedbacks as follows:

- Feedback 1: x_2 is better than x_3.
- Feedback 2: x_1 is better than x_2
- Feedback 3: x_4 is same with x_2.
- Feedback 4: x_5 is worse then x_4

Even though four comparisons are given, the mediator can compare nine value pairs $\{(x_3 \prec x_2), (x_3 \prec x_4), (x_3 \prec x_1), (x_5 \prec x_2), (x_5 \prec x_4), (x_4{=}x_2), (x_2 \prec x_1), (x_4 \prec x_1)\}$.

The immediate question is how the mediator uses these models to generate better bids for all the agents. As the mediator is unbiased, it would be willing to increase the social welfare. To achieve this, it would try to increase one of the social welfare metrics such as Nash product, maximizing the product of the utilities of the agents. However, it does not have quantitative measurement such as utilities. Furthermore, we might not be able to compare some value pairs in the constructed graph. This problem is similar to the problem of negotiating with CP-nets [1, 2] where the agents try to negotiate with respect to the preference graph induced from a given CP-net. In that preference graph, the nodes denote the outcomes and there are some incomparable outcomes. In those studies, the authors present some heuristics to obtain estimated utilities; consequently, the negotiating agents generate their offer and decide whether to accept the opponent's counter offer by employing those estimated utilities.

We adopt a similar approach with those studies and generate estimated utilities from the constructed graph by using a *scoring approach* similar to the *depth approach* proposed in [1, 2]. In their approach, depth of an outcome in a preference graph is estimated as the length of the longest path from the root node, so it indicates how far the outcome is from the least preferred outcome. Thus, the outcomes whose depth is higher, is preferred over that whose depth is lower. Further, if two outcomes are at the same depth, it is assumed that these outcomes are equally preferred by the user. Based on this intuition, they estimate the utility values between zero and one by applying the formula shown in Eq. (3.1).

$$U(x) = \frac{Depth(x, PG)}{Depth(PG)} \tag{3.1}$$

Since in that study the preference graph is induced from a given CP-net, there is only one root node (the least preferred outcome). Therefore, it is straightforward to estimate the depth of an outcome in the preference graph by applying graph search algorithms. However, in our case we may not know which value is the least preferred value. Therefore, we estimate a score that is similar to the concept of depth but slightly different. The main principle is that if a value x_m is more preferred over another value x_k, the score of x_m would be higher than that of x_k. If x_m is less preferred than x_k, the score of x_m would be lower. If they are equally preferred, their score would be equal.

While the mediator generates its first bid randomly, it initiates the preference graphs for each issue with respect to the first bid. Each value in the first bid is added separately to the related graph (i.e. x_i would be added to the graph belongs to X issue). To illustrate this, assume that we have two issues: X and Y, and the first bid is (x_3, y_1). The preference model would consist of two preference graphs: one for X and another for Y. The former graph would have a node associated with x_3 while the latter graph would have a node associated with y_1. The score of the first node in each preference graph is initiated as one ($x_3.SC = 1$).

As the mediator mutates its previous bid by flipping one value of the issues and requests the agents' feedbacks, it needs to update the preference models for each negotiating agent. In the case of updating a preference model, only the preference graph associated with the issue whose value has been recently changed is taken into account. Other preference graphs do not need to be updated. For instance, consider that the mediator generates its second bid by changing x_3 by x_2 and asks this bid (x_2, y_1) to the agents. Since only the value of X is changed, the agents' feedbacks reflect their preferences on that issue. If an agent gives its feedback as "better", that means that agent prefers x_2 to x_3. Therefore, only the preference graphs belonging to X issue should be updated in that case.

While updating the preference graph based on the agent's feedback, in addition to adding edges between nodes the mediator estimates or updates the score of the nodes. Algorithm 1 shows how this process is performed. In this algorithm, the previous value x_p is the value of the issue in the previous bid while the current value x_c is the value of that issue in the current bid. If x_c does not exists in the preference graph, the mediator creates a node and links it to the node associated with x_p based on the feedback and accordingly assigns a score for the x_c. If the feedback is "better" then its score will be higher than the score of x_p. In that case, we increase the score of x_p by one and assign it to the x_c. For example, the score of the x_2 would be equal to two ($= x_3.SC + 1$). If the feedback is "same", then the score of the current value would be equal to the score of the previous value. For example, in the further bid, if the mediator generates the bid by flipping x_2 by x_4 and

Algorithm 1: Pseudo-algorithm for updating the score of the nodes in the preference graph when the mediator flips the previous value x_p by the current value, x_c for a given issue and gets a $feedback$ from the agent

if x_c *not exists* **then**
  if $feedback\ is\ BETTER$ **then**
    $x_c.SC \leftarrow x_p.SC + 1$;
  if $feedback\ is\ WORSE$ **then**
    $x_c.SC \leftarrow x_p.SC - 1$;
  if $feedback\ is\ SAME$ **then**
    $x_c.SC \leftarrow x_p.SC$;
else
  if $feedback\ is\ BETTER\ and\ x_p.SC >= x_c.SC$ **then**
    foreach $x_i \in \{\ Comparable(x_c, x_i) \setminus \{x_p \bigcup AllLessPreferred(x_p)\}\ \}$ **do**
      $x_i.SC \leftarrow x_i.SC + x_p.SC - x_c.SC + 1$;
    end
  if $feedback\ is\ WORSE\ and\ x_p.SC =< x_c.SC$ **then**
    foreach $x_i \in \{\ Comparable(x_p, x_i) \setminus \{x_c \bigcup AllLessPreferred(x_c)\}\ \}$ **do**
      $x_i.SC \leftarrow x_i.SC + x_c.SC - x_p.SC + 1$;
    end
  if $feedback\ is\ SAME$ **then**
    if $x_p.SC < x_c.SC$ **then**
      foreach $x_i \in \{\ Comparable(x_p, x_i) \setminus \{x_c \bigcup AllLessPreferred(x_c)\}\ \}$ **do**
        $x_i.SC \leftarrow x_i.SC + x_c.SC - x_p.SC$;
      end
      $x_p.SC \leftarrow x_c.SC$;
    if $x_p.SC > x_c.SC$ **then**
      foreach $x_i \in \{\ Comparable(x_c, x_i) \setminus \{x_p \bigcup AllLessPreferred(x_p)\}\ \}$ **do**
        $x_i.SC \leftarrow x_i.SC + x_p.SC - x_c.SC$;
      end
end

the agent gives the feedback as "same", the score of the x_4 would be also equal to two (=$x_2.SC$). If the feedback is "worse" then the score of the current value would be equal to the score of the previous value minus one. Consider that the further bid includes x_5 and the feedback is "worse". In that case, the score of x_5 would be equal to one (=$x_4.SC$-1).

When the current value already exists in the graph, the process might be more complicated in the emergence of a *conflict*. The conflict may occur when the previous value and current value are incomparable before the feedback. In that case when the score of the previous value is higher than the score of the current value and the feedback is "better", we need to update the score of current value. If we only update the score of the current value, some inconsistencies may occur; therefore, we increase the score of all values related to the current value except the

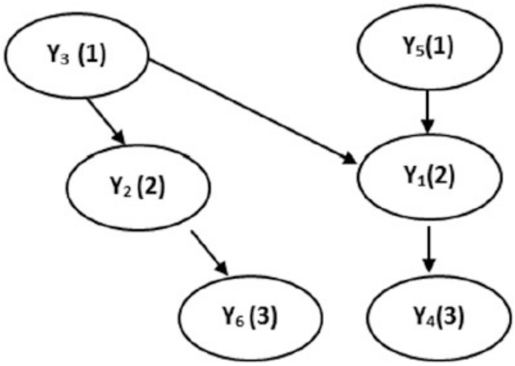

Fig. 3.2 A sample preference graph for issue Y

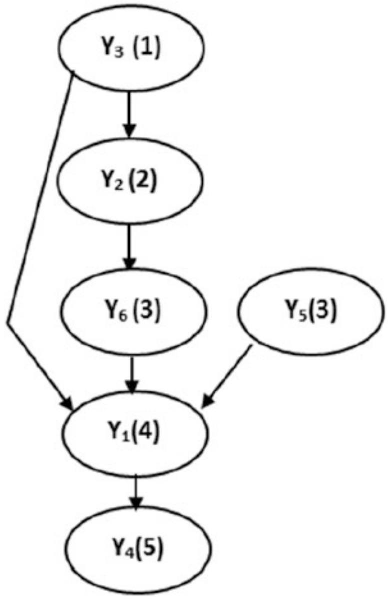

Fig. 3.3 After updating the graph in Fig. 3.2

previous value and all values less preferred than the previous value. To illustrate this, consider that we have a graph shown in Fig. 3.2. According to this graph, the values y_6 and y_1 are incomparable. When the previous value is y_6 and the current value y_1, if the feedback given by the agent is "better", we need to update the score of the y_1 and all values related to it except the nodes that are less preferred than y_6 (e.g. y_3) will be updated. These nodes to be updated are y_5, y_1 and y_4. Their score will be increased by two ($= 2 - 1 + 1$). Then, the graph will look like the graph drawn in Fig. 3.3. Similar update process will perform when the feedback is "worse" or "same", and there is a conflict between the score of the previous and current values with respect to the given feedback.

We scaled each score in a way that all scores will be greater than zero and the highest score would be one. These scaled scores correspond to the estimated utilities with respect to our heuristic approach. The mediator uses these estimated utilities to find the values giving the Nash product. To illustrate this, consider that we have three negotiating agents need to have an agreement on two issues, say W and Z whose domains are D(W)=$\{w_1, w_2, w_3\}$ and D(Z)=$\{z_1, z_2\}$. Accordingly, the mediator constructs three models consisting of two preference graphs (one for W and another for Z) for those agents after generating its first bid. During the negotiation, the mediator updates these models based on the agents' feedbacks as explained above. When the mediator decides to use its knowledge and to choose the value that increases the social welfare in terms of Nash product, it calculates the product of the estimated utilities of the agents for each value and selects the value that maximizes the product. Assume that the estimated utilities of the values for W issue are as follows:

- M_1 (for the first agent): EU(w_1) $= 1.0$; EU(w_2) $= 0.66$; EU(w_3) $= 0.33$.
- M_2 (for the second agent): EU(w_1) $= 0.5$; EU(w_2) $= 1$; EU(w_3) $= 1$.
- M_3 (for the third agent): EU(w_1) $= 0.33$; EU(w_2) $= 0.66$; EU(w_3) $= 1$.

Based on the estimated utilities above, the mediator estimates the product as P(w_1) $= 0.17$, P(w_2) $= 0.44$ and P(w_3) $= 0.33$ by multiplying EU(w_i). According to this example, the mediator chooses w_2 for W issue whose product is the maximum. As stated before, final scores should be greater than zero. It stems from the fact that when we estimate the product of those scores, the result would be zero if one of them is equal to zero.

3.3.2 Feedback Based Protocol

We present two variants of feedback based protocol for multilateral negotiation. The first protocol is called *Feedback Based Protocol* (FBP). According to this protocol, the mediator generates its first bid randomly and sends it to the negotiating agents. After each bid, each negotiating agent gives a feedback such as "better", "worse" and "same" to the mediator by comparing the current bid with the mediator's previous bid. For its further bids, the mediator mutates its previous bid by flipping one of the issues intelligently. This process continues iteratively until reaching a predefined number of bids.

In order to mutate its previous bid intelligently, the mediator needs to decide which issue will be changed and which value will be used for that issue. It can use the learnt model to generate values maximizing the product (Nash); but this may not result well at the beginning since there is no sufficient knowledge about the agents' preferences. Therefore, the mediator follows an approach like searching smartly the outcome space for a while and then using its learnt model to generate values maximizing the product.

Until reaching half of the negotiation time, it changes it previous bid by following the procedure below:

1. *Unused Values*: The mediator checks the issues whether they contain any value that has not been used in its bids yet. If there exist such issues, it randomly chooses one of them and assigns one of the unused value for that issue.
2. *Incomparable Values*: If all the issue values are used before, the mediator checks whether one of the learnt models includes some issues whose values cannot be comparable with those values in the previous bid. If there are incomparable values, the mediator will choose one of them randomly. This allows the mediator to learn more preferential information from the agents. For instance, consider that the previous offer (w_1,z_2) and according to the model for the second agent w_1 cannot be compared with w_2. If the mediator flips w_1 by w_2 and sends (w_2,z_2) to the agents as a bid for their feedback, the mediator would be able to compare these values in the next time.
3. *Random Values*: If there are not any unused and incomparable values, the mediator chooses an issue randomly whose value may improve the bid for all agents. That is, the chosen value should not be worse than the current value in the previous bid.
4. *Nash Values*: If none of the issue values cannot improve the previous bid for all agents, the mediator chooses an issue randomly and selects the value for that issue whose product of estimated utility of the agents is the maximum (Nash value) with respect to the learnt preference model.

After passing the half of the negotiation time, the mediator mostly exploits its knowledge. That is, it chooses an issue randomly and changes the issue value in the previous bid by the issue value whose product of estimated utilities of the agents is the maximum with respect to the learn models. Moreover, it can still search the outcome space as explained in the procedure above with a probability. This probability will drop by a certain amount over time and it becomes zero at the end of the negotiation. According to this probability, the mediator either searches the outcome space or exploits its knowledge about the agents' preferences. Equation (3.2) shows how we calculate the probability for search.

$$PR(Search) = \frac{TotalRound - CurrentRound - 1}{TotalRound} \tag{3.2}$$

Up to now, we explain how the mediator generates its bids and updates its preference models for the agents based on the given feedbacks by those agents. It is time to talk about how the mediator decides the final agreement. The mediator keeps and updates "*last recent better bid*" with respect to the agents' feedbacks and completes the negotiation with this bid. A bid is accepted as "last recent better bid" if none of the agents' current feedback consists of "worse". Accordingly, the mediator updates the last recently better bid after each feedback. According to this protocol, the last recent better bid will be one of recent bids that are generated mostly by choosing the values maximizing the product of estimated utilities of the agents with respect to the learnt models since the mediator has a tendency only to exploit its knowledge towards to the end of the negotiation.

3.3.3 Feedback and Voting Based Protocol

Our second protocol is called *Feedback and Voting Based Protocol* (FVBP). This protocol consists of two phases:

- *Searching and learning*: In this phase, the mediator generates its bids and models the negotiating agents' preferences based on their feedbacks in a similar way as the mediator does in *Feedback Based Protocol*. The only difference is that in this protocol the mediator does not try to generate *nash values* in this phase. It only mutates its previous offers by flipping one of the issues by using the heuristics such as unused values, incomparable values and random values that may improve the previous bid for all agents as explained in Sect. 3.3.2. Furthermore, if there is no such a value, it considers that it is time to pass the second phase and acts accordingly.
- *Voting with estimated Nash bids*: In this phase, the mediator generates estimated nash bids maximizing the product of the estimated utilities of the agents with respect to the learnt model and asks the negotiating agents to vote them either to reject or accept. Negotiating agents act according to the simple text mediated protocol explained in Sect. 3.2 and vote the mediator's current Nash bid by comparing with the *most recent accepted bid*. In our protocol, the negotiation agents adopt Hill-Climber approach to vote the bid. After proposing all estimated Nash bids, the mediator finalizes the negotiation.

It is worth noting that the mediator does not have to wait for reaching the given deadline. If it realizes there is no need for further search in the first phase, it immediately passes the second phase in which the estimated Nash bids are generated by the mediator and voted by the negotiating agents. Consequently, the mediator is able to complete negotiation earlier. Another advantage of this protocol is that the first mutually accepted bid would be chosen among the estimated Nash bids rather than a random bid. This decreases the chance of unfair negotiation outcome in the end. Notice that the first mutually accepted bid has a great influence of the negotiation outcomes in single text mediated protocol. To illustrate this, consider there are three negotiating agents and the utilities of the first mutually accepted bid for each agent are 1.0, 0.4, 0.5 respectively. Since the first agent already gets the best bid for himself, it may not have a tendency to accept the mediator's further bids (i.e. Hill Climber) even though there might exist better bids as far as all agents' preferences are concerned.

3.4 Experiments

To evaluate the proposed protocols, we have extended GENIUS [7], which is a platform for bilateral negotiation. Our extension enables more than two agents to negotiate on this platform. Consequently, we compare the performance of the

Table 3.1 Group configurations and the maximum product of utilities of the agents in each group

Group	Agents	Maximum product of utilities (Nash product)
Group-1	(A1-A2-A3)	0.76
Group-2	(A1-A4-A5)	0.61
Group-3	(A2-A4-A6)	0.50
Group-4	(A3-A5-A6)	0.64
Group-5	(A1-A7-A6)	0.78

proposed protocols with the mediated single text protocol presented in [6] with respect to the product of utilities of the agents on the agreement and negotiation duration. We first give a brief information about our experimental setup and then shows our results in the following sections.

3.4.1 Experimental Setup

In our experiments, we use the party domain from the repository of GENIUS platform. This domain consists of following six issues: *food*, *drinks*, *locations*, *invitations*, *music*, and *cleanup*. For each issue, there are three or four possible values. For example, the *music* issue has three possible values: *MP3*, *DJ* and *Band* while for *invitation* issue there are four values: *plain*, *custom-handmade*, *custom-printed* and *photo*. The total number of possible outcomes is 3,072. We asked seven students and faculty members from Delft University of Technology about their preferences on party domain. These preferences were elicited by means of additive utility functions by using GENIUS platform. For multilateral negotiation, we set up five different groups where each group consists of three individuals. Note that in our experiment, agents negotiate on behalf of the individuals. Table 3.1 shows the configuration for each group and the maximum product of utilities of the agents in each group.

– To investigate the performance of the proposed protocols, each group negotiates under four different negotiation settings. These are:

  - *Hill-Climber*: In this setting, *Mediated Single Text Negotiation Protocol* [6] is employed. Each negotiating agent in the group adopts a hill climber strategy to decide its vote (accept/reject).
  - *Annealer*: This setting also uses *Mediated Single Text Negotiation Protocol* [6] but the negotiating agents employ an Annealer strategy to decide their votes (accept/reject).
  - *Feedback*: In this setting, *Feedback Based Protocol* (Sect. 3.3.2) governs the negotiation and each negotiating agents give feedback truly with respect to their preferences.

Table 3.2 Average product of utilities of the agents over 100 negotiations when deadline is 50 rounds

Group	Hill-Climber	Annealer	Feedback	Feedback and voting[a]
Group-1	0.42	0.42	0.65	**0.71**
Group-2	0.37	0.40	**0.48**	**0.47**
Group-3	0.25	0.23	**0.30**	**0.30**
Group-4	0.53	0.46	0.62	**0.64**
Group-5	0.47	0.48	**0.56**	**0.57**
Overall:	0.41	0.40	**0.52**	**0.54**

[a] It completes the negotiation in 30 rounds on average

- *Feedback and Voting*: The last setting employs *Feedback and Voting Based Protocol* (Sect. 3.3.3). In the voting phase, the negotiating agents vote the mediator's bids by employing Hill-Climber strategy. That is, they only accepts an offer if its utility is greater than the utility of the most recent mutually accepted bid.

In our experiments, each negotiation group negotiates 100 times in each negotiating setting described above. We evaluate the protocols in term of the product of the utilities of the agents and negotiation duration. Note that to achieve a fair comparison, for the same negotiation runs, the same random seed is used in all negotiation settings (*Hill-Climber*, *Annealer*, *Feedback*, and *Feedback and Voting*).

3.4.2 Results

Table 3.2 shows the average product of the utilities of the agents over 100 negotiation when the deadline is set as 50 rounds. The results highlighted in bold are the statistically best settings. We have analyzed these negotiation results by using ANOVA (Analysis of Variance). It is seen that *Feedback and Voting Based Protocol* and *Feedback Based Protocol* outperforms *Mediated Single Text Negotiation Protocol* with Hill-Climber and Annealer settings in each group and overall with respect to the product of the utilities of the agents on the agreement. Overall, there is no statistically significant difference in the performance of *Feedback* and *Feedback and Voting*. However, the performance of *Feedback and Voting* is statistically significantly better than that of *Feedback* as far as the results for $Group - 1$ and $Group - 2$ are concerned. Furthermore, all protocols except *Feedback and Voting* complete negotiation at 50 rounds. Although *Feedback and Voting* completes negotiation earlier (30 rounds), it outperforms others on average.

When we set the deadline as 250 rounds, we obtain the results in Table 3.3. Firstly, we observe that the performance of *Mediated Single Text Negotiation Protocol* with Annealer increases drastically when the number of rounds increases while the performance of that with Hill-Climber does not change at all. As stated

Table 3.3 Average product of utilities of the agents over 100 negotiations when deadline is 250 rounds

Group	Hill Climber	Annealer	Feedback	Feedback and voting[a]
Group-1	0.42	0.61	0.65	**0.71**
Group-2	0.37	**0.52**	**0.51**	0.47
Group-3	0.25	**0.35**	0.31	0.31
Group-4	0.53	0.54	**0.64**	**0.64**
Group-5	0.47	**0.66**	0.57	0.57
Overall:	0.41	**0.54**	**0.53**	**0.54**

[a] It completes the negotiation in 30 rounds on average

Table 3.4 Average product of utilities of the agents over 100 negotiations when deadline is 500 rounds

Group	Hill Climber	Annealer	Feedback	Feedback and voting[a]
Group-1	0.42	0.66	0.66	**0.71**
Group-2	0.37	**0.55**	0.51	0.47
Group-3	0.25	**0.40**	0.31	0.31
Group-4	0.53	0.56	**0.64**	**0.64**
Group-5	0.47	**0.69**	0.57	0.57
Overall:	0.41	**0.57**	0.54	0.54

[a] It completes the negotiation in 30 rounds on average

before, the problem with Hill-Climber is when one of the agents gets a high utility in the previous rounds, it will not accept any bids whose utility is less then the previous one even though those offers might be win-win solutions for all agents. By contrast, Annealer has a tendency to accept worse bids for itself earlier so that the agents can find win-win bids later. The performance of *Feedback Based Protocol* slightly increases when it has longer negotiation duration. Further, there is no change in the performance of *Feedback and Voting Based Protocol* since it completes the negotiation in 30 rounds on average. Under 95% confidence level, it can be said that overall performance of *Annealer*, *Feedback*, and *Feedback and Voting* is not statistically significantly different from each other. That is, they perform equally better than Hill-Climber. It is worth noting that *Feedback and Voting Based Protocol* does not only result in good agreement for all parties, but also it completes the negotiation earlier.

Table 3.4 shows the product of the utilities of the agents when the deadline is set as 500 rounds. It is seen that the performance of *Annealer* slightly increases when the deadline goes up from 250 to 500. An interesting result is that overall the performance of *Mediated Single Text Negotiation Protocol* with Annealer is better than our feedback based protocols when the deadline is 500. This stems from that Annealer searches more in the outcome space and finds win-win bids. However, *Feedback and Voting Based Protocol* completes negotiation quite earlier than Annealer (30 versus 500). Furthermore, its performance is also close to the performance of the Annealer. If we both consider the performance and negotiation duration, it can be concluded that *Feedback and Voting Based Protocol* is a promising protocol that results in reasonably good agreements in a short time.

3.5 Discussion

In this paper, we have presented two variants of feedback based multilateral negotiation protocol: *Feedback Based Protocol*, and *Feedback and Voting Based Protocol*. In those protocols, a mediator agent generates bids and asks negotiating agents for their feedback about those bids. Accordingly, the mediator generates and updates a preference model for each negotiating agent by interpreting the agents' feedbacks during the negotiation. By using the learnt model, the mediator generates better bids for all agents over time.

We have compared the performance of the proposed protocols with the performance of the mediated single text negotiation protocol presented in [6] in an experimental setting in terms of both the product of utilities of the agents and negotiation duration. Our results show that *Feedback and Voting Based Protocol* does not only complete the negotiation with a reasonably good agreement for all agents but also completes negotiation early. Furthermore, when the deadline is short, *Feedback and Voting Based Protocol* and *Feedback Based Protocol* outperforms the mediated single text negotiation protocol in terms of the product of utilities of the agents on the agreements. However, when the deadline is long, the mediated single text negotiation protocol with Annealers performs slightly better than our protocols. This stems from the fact that *Feedback and Voting Based Protocol* completes negotiation quite earlier than that protocol, and the Annealer allows the protocol to search more space. When the time is crucial and it is significant to negotiate as soon as possible, it is reasonable to employ *Feedback and Voting Based Protocol*.

Chalamish and Kraus presents an automated mediator for bilateral negotiations in which agents share their preferences with the mediator [3]. In that study, the mediator monitors the negotiation and suggests possible acceptable agreements for both participants when it is necessary to speed up the negotiation. By contrast, the protocols presented in this paper supports multilateral negotiation where there are more than two negotiating agents. Also, agents do not share their preferences with the mediator because of the privacy issue; instead the mediator tries to learn their preference ordering in our study.

Hemaissia et al. propose a multilateral protocol for cooperative negotiation domains particularly crisis management systems [5]. In that study, the preferences are elicited by a multi-criteria decision aid tool, which allows the user to represent preferences involving interdependencies between issue while in our study we elicit the preferences by means of additive utility functions and assume there is no preferential interdependency between issues. According to their protocol, each agent specifies their general constraints before the negotiation so that the mediator agent can propose realistic offers that satisfy those constraints. Accordingly, the mediator generates an offer that has not been proposed before and asks other agents about their opinion. Each agent evaluates the offer and sends a feedback to the mediator. Next time, the mediator generates its offer by considering these feedbacks. The feedback involves whether the agent accepts or rejects the bid and a recommendation to improve the bid or to specify the criteria that should not be changed while in our study the feedbacks are simpler than theirs so that agents do not need any tool to generate their feedbacks. However, in that study the agents use a multi-criteria decision aid tool to evaluate offers and to generate recommendations during the negotiation.

Lopez-Carmona et al. presents a multiparty negotiation protocol taking into account the cases where no possible unanimous agreement exits. According to the proposed protocol, a mediator agent chooses an initial contract randomly and accordingly proposes a mesh, a set of contracts, from the initial contract. Each agent privately informs the mediator about their preferences on these contracts. The mediator agent aggregates the individual preferences on each contract by using the Ordered Weighted Averaging (OWA) operator and finds the preferred contract with respect to the aggregated preferences. By applying a search method, the mediator agent decides whether to continue the negotiation by generating a new mesh or complete the negotiation with the current preferred contract. While in that study the agents share their preferences on a set of bids with the mediator, in our case the agents do not need to share their preferences; instead they give a feedback about the current bid such as "it is better than the previous offer". In our study, one of the challenges is to model agent's preferences based on the given feedbacks.

As future work, we are planning to investigate the effect of the domain size and the number of negotiating agents on the performance of the protocols. Furthermore, the current preference model does not consider that each agent may have a different weight for the same issue. It would be interesting to improve the model such a way that it can handle such cases.

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