Conditional Preference Networks Support Multi-Issue Negotiations with Mediator

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Abstract. Conflicts of interest occur in various aspects of our daily life and we often come to an understanding by negotiating our way through these conflicts. This paper presents a simple interactive negotiation approach to resolve certain conflicts that involve multiple issues. The focus is on mediation to facilitate a solution based on alternating offers over a finite-time bargaining game. The mediator explores the possibilities and proposes a jointly optimal negotiation text for all the players participating in the negotiation process, based on their conditional preference networks (CP-nets). Each individual player then makes a decision to accept or reject the proposal based on their utility CP-nets. If any player rejects, the mediator offers another negotiation text and the process goes on until an agreement is achieved or some time limit is reached. Two algorithms are developed with regard to the players as well as the mediator, and a daily-life situation is investigated based on them. A historically important negotiation event has also been investigated using this model.

1 INTRODUCTION

Negotiation occurs in several areas of real-world problems: personal cases such as marriage, divorce, and parenting; business cases such as pricing between seller and buyer and sharing a market between organizations; international crisis cases like the Cuba missile crisis, the North Korean crisis, and Copenhagen climate change control. Negotiation is a process for agents to communicate and compromise in order to reach beneficial agreements. In such situations, the agents have a common interest in cooperating, but have conflicting interests over exactly how to cooperate [9].

Bargaining is a simple form of a negotiation process. It is used to establish a price to trade a fixed and defined commodity between seller and buyer. One party usually attempts to gain advantage over another to obtain the best possible agreement. Splitting a pie between two players is a simple bargaining example. In such games with many periods of offers and counteroffers, strategies are not just actions, but rather ways for choosing actions based on the actions chosen by both agents in earlier periods [20].

In competitive bargaining, the process is viewed as a competition that is to be won or lost. Positional bargaining is a negotiation strategy that involves holding on to a fixed idea, or position, of what you want and arguing for it and it alone, regardless of any underlying interests. The classic example of positional bargaining is the haggling that takes place between proprietor and customer over the price of an item. The customer has a maximum amount she will pay and the proprietor will only sell something for a price above a certain minimum amount. Each side starts with an extreme position, which in this case is a monetary value, and proceeds from there to negotiate and make concessions. Eventually a compromise may be reached. A position is usually determined by the interests of a negotiating party, and reflected in a contract that it puts forward to its counterpart.

Integrative bargaining (also called "interest-based bargaining" or "win-win bargaining") is a negotiation strategy in which parties collaborate to find a "win-win" solution to accommodate their different interests. This strategy focuses on developing mutually beneficial agreements based on the interests of the disputants. Interests include the needs, desires, concerns, and fears important to each side [19]. Integrative bargaining usually produces more satisfactory outcomes for the players involved than does positional bargaining. Positional bargaining is based on fixed, opposing positions and tends to result in a compromise or no agreement at all. Our negotiation approach focuses on integrative bargaining for achieving a satisfactory agreement for all players.

Interest-based negotiation either can get the parties to an agreement point where they can bargain or even better, to a point where they do not need to bargain at all. Interest-based negotiation typically entails two or more issues to be negotiated. It involves an agreement process that better integrates the aims and goals of all the negotiating parties through creative and collaborative problem solving.

Mediation usually consists of a negotiation process that employs a mutually agreed upon third party to settle a dispute between negotiating parties in order to find a compatible agreement to resolve disputes [10]. In negotiation, the parties agree to work with each other to resolve a dispute. In mediation, the parties agree to work with a facilitator or mediator to resolve a conflict. In many cases, international negotiations aim to achieve an agreement on various issues between multiple parties. "Camp David" is an interesting example of a negotiation that happened between Egypt and Israel in 1978, resulting in a more or less successful agreement with the help of a mediator, the United States.

In this paper, we propose a simple mediated approach for multi-issue negotiation with incomplete information based on adjusting the players' preferences. In this approach, the mediator searches for a jointly optimal negotiation text for all players in their conditional preference networks (CP-nets), using a depth-first search based algorithm. The players use utility-based CP-nets to make a decision for agreement. The purpose of the paper is to achieve a *jointly optimal preference* for all players while each player has imperfect information about his opponents. Here, a jointly optimal preference refers to all players obtaining preferences of which the utilities are not less than the average utility of the preferences.

The rest of the paper is organized as follows. In Section 2, we briefly explain preliminaries about CP-nets, which are conditional preference networks for representing and reasoning with qualitative preferences. We also discuss utility CP-nets and mediation approaches using a single negotiation text in Section 2. In Section 3, we describe the proposed negotiation approach with algorithms and illustrations. We discuss other closely related approaches to negotiation based on CP-nets and compare our approach to them in Section 4. Finally, in Section 5, we conclude the paper and mention some future directions.

2 PRELIMINARIES

We begin with background concepts of conditional preference networks (CP-nets), their induced preference graphs and the utility-based CP-nets in this section. We will also discuss a mediation approach using single negotiation text (SNT).

2.1 CP-nets and UCP-nets

Boutilier and colleagues introduced CP-nets as a graphical representation of conditional preference networks that can be used for specifying preference relations in a relatively compact, intuitive, and structured manner using conditional ceteris paribus (all other things being equal) preference statements [5, 6]. CP-nets can be used to specify different types of preference relations, such as a preference ordering over potential decision outcomes or a likelihood ordering over possible states of the world.

CP-nets are similar to Bayesian networks [17]. Both utilize directed graphs; however, the aim of CP-nets in using the graph is to capture statements of qualitative conditional preferential independence. A CP-net over variables $V = X_1, ..., X_m$ is a directed graph G over $X_1, ..., X_m$ whose nodes are annotated with conditional preference tables $CPT(X_i)$ for each $X_i \in V$. Each conditional preference table $CPT(X_i)$ associates a total order $\succ_i^u$ with each instantiation u of X_i's parents $Pa(X_i) = U$ [5].

Let $V = X_1, ..., X_m$ be a demand set of m attributes; $X_i \in V$ ($i = 1$ to m). $D(X_i)$ is the domain of X_i and is represented as $D(X_i) = x_1, .., x_n$. There are $D(X_1) \times D(X_2) \times ... \times D(X_m)$ possible alternatives (outcomes), denoted by O. Elements of O are denoted by $o, o\prime, o\prime\prime$ etc. and represented by concatenating the values of the variables [13]. For example, if $V = \{A, B, C\}$, $D(A) = \{a_1, a_2, a_3\}$, $D(B) = \{b_1, b_2\}$ and $D(C) = \{c_1, c_2, c_3\}$, then the assignment $a_2 b_2 c_1$ assigns a_1 to variable A, b_2 to B and c_1 to C.

The preference information captured by an acyclic CP-net N can be viewed as a set of logical assertions about a user's preference ordering over complete assignments to variables in the network. These statements are generally not complete, that is, they do not determine a unique preference ordering. Those orderings consistent with N can be viewed as possible models of the user's preferences, and any preference assertion that holds in all such models can be viewed as a consequence of the CP-net [6].

The set of consequences $o \succ o'$ of an acyclic CP-net constitutes a partial order over outcomes: o is preferred to o' in this ordering iff $N \models o \succ o'$. This partial order can be represented by an acyclic directed graph, referred to as the induced preference graph:

- The nodes of the induced preference graph correspond to the complete assignments to the variables of the network; and
- There is an edge from node o' to node o if and only if the assignments at o' and o differ only in the value of a single variable X, and given the values assigned by o' and o to $Pa(X)$, the value assigned by o to X is preferred to the value assigned by o' to X.

For example, consider the CP-net given in Figure 1, whose variables are A, B and C. The preference statements on variable A mean that a_1 is strictly preferred to a_2. The preferences on variable B are conditioned on variable A: If a_1 is chosen, then b_1 is preferred to b_2 and if a_2 is chosen, then b_2 is preferred to b_1. The preferences of variable C are also conditioned on the variable B. The preference graph induced by the CP-net of Figure 1 is shown in Figure 2.

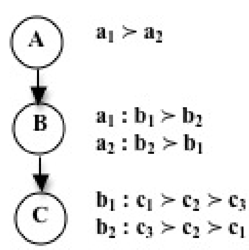

Fig. 1. CP-net, for Player 1.

The concept of Utility CP-net (UCP-net) was also introduced by Boutilier and colleagues. It extends the concept of CP-net by allowing quantification over nodes with conditional utility information. Semantically, Boutilier et al. treat the different factors $V = X_1, ..., X_m$ as *generalized additive independent* of one another for an underlying utility function u [4]; this means intuitively that the expected value of u is not affected by correlations between the variables, and implies that u can be decomposed as a sum of factors over each set of variables

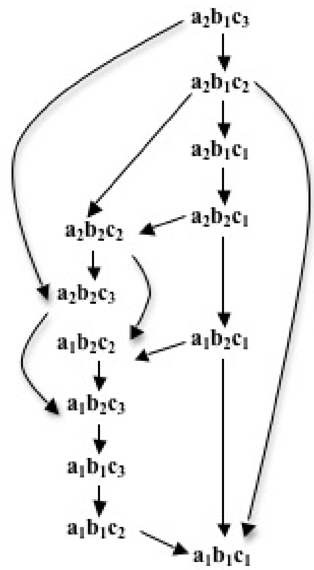

Fig. 2. Induced Preference Graph of the CP-net of Figure 1, for Player 1.

X_i [3]. For example, the CP-net in Figure 1 can be extended with utility information by including a factor (f) for each variable in the network, specifically $f_1(A), f_2(A, B)$ and $f_3(B, C)$ as shown in Figure 3. We calculate the total utility of preference strings as follows: $u(A, B, C) = f_1(A) + f_2(A, B) + f_3(B, C)$. Each of these factors is quantified by the CPT (conditional preference tables) in the network. For example, the utility of $a_1b_1c_1$ is as follows: $u(a_1, b_1, c_1) = f_1(a_1) + f_2(a_1, b_1) + f_3(b_1, c_1) = 5 + 0.6 + 0.6 = 6.2$ according to Figure 3.

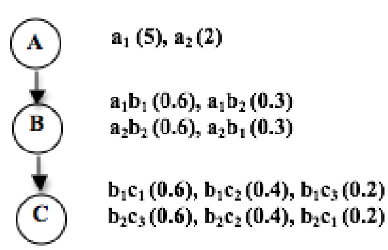

Fig. 3. UCP-net corresponding to the CP-net of Figure 1, for Player 1.

F. Rossi and colleagues presented an extension of the CP-net, called mCP-nets [21], to model the qualitative and conditional preferences of multiple agents.

They allowed the individual agents to vote to obtain mCP-nets by combining several partial CP-nets. K.R. Apt and colleagues proposed an approach for analyzing strategic games that can be used to study CP- nets [1]. They introduced a generalization of strategic games in which each player has to his disposal a strict preference relation on his set of strategies, parameterized by a joint strategy of his opponents. They showed that optimal outcomes in CP-nets are Nash equilibria of strategic games with parameterized preferences. Z. Liu and colleagues also focused on the relationship between CP-nets and strategic games [15]. They proposed a solution to resolve the optimal outcomes of CP-nets by transforming a CP-net to a game tree and using a tree algorithm to find Nash equilibria.

2.2 Mediation Using a Single Negotiation Text (SNT)

The concept of a single negotiation text (SNT) was suggested as a mediation device by Roger Fisher [10]. SNT is often employed in international negotiations, especially with multi-party negotiations [19], [11] and [8]. For example, the SNT approach was applied by the United States in mediating the Egyptian–Israeli conflict, which is known as the Camp David Negotiations (Raiffa 1982). During an SNT negotiation, a mediator first devises and proposes a deal (SNT-1) for the two protagonists to consider. The first proposal is not intended as the final agreement. It is meant to serve as an initial, single negotiating text: a version to be privately criticized by both sides and then modified in an iterative manner.

The SNT is utilized as a method of focusing the parties' attention on the same composite text [19]. The important aspect of the process is that it appears to be fair to both sides, and not divisive. Based upon the criticisms by the parties, voiced privately to the mediator only, the mediator prepares another proposal, which is not perfect, but which improves both parties' positions. Again, both parties provide suggestions on improving the proposal, and this new proposal is again criticized by the parties. This process continues until all the issues are settled and the final agreement is achieved or it is clear that no agreement is achievable. P. Korhonen and colleagues discussed the importance of the starting point of the single negotiation text [11]. They argue that, if the path taken in subsequent steps does not compensate for a biased starting point, the bias will have considerable impact on the final outcome of the negotiations.

3 THE PROPOSED APPROACH TO NEGOTIATION

In real-world negotiations, negotiators need to achieve an agreement on multiple issues with multiple players. Sometimes, a mediator is included to facilitate the negotiation process. Some negotiations fail because the parties have too many conflicts and they cannot work with each other. Therefore, a mediator may be used if the parties prefer a third party who is neutral and does not represent any party's interests. Also in situations where the parties cannot meet to negotiate directly, a mediator may be needed.

Our approach is based on a natural way to negotiate in the real world. The proposed framework consists of two types of individuals: the mediator and the players. All players and the mediator specify the issues they need to negotiate before the negotiation process starts. Each player keeps his own private information and he does not know his opponents' private information. Each player reports his partial CP-nets to the mediator. They do not directly come to know their opponents' preferences at any stage. In addition, each player defines his own utility values for each attribute and calculates his total utility for all combinations of variables, as mentioned in Section 2.1. Each player creates his own UCP-net that is used for proposing a maximum preference and for deciding to accept or reject the proposal by the mediator. The mediator seeks to propose a single negotiation text that gains optimal joint outcomes for all players by comparing players' proposed preferences based on depth-first search [13, 12, 2].

3.1 Algorithms

We have developed two algorithms. Algorithm 1 (see page 24) describes the way each of the players decides whether to accept a proposal by the mediator. Algorithm 2 (see page 25) describes the way the mediator decides which single negotiation texts to propose, given the players' CP-nets and their answers to previous proposals.

The initial input of Algorithm 1 is the utility CP-nets with the complete set of utility values and the resulting ordering (see e.g., Table 1). The initial assignments to the *Agreement* variable and the *Proposal* variable are zeros. The *Proposal* refers to a single negotiation text that combines preference variables according to the induced preference graph. The maximum utility of a player is assigned to the corresponding *maxU* variable. The threshold variable is defined to accept or reject the proposal. The threshold can change based on the nature of the negotiation problems. A player accepts the proposal if the difference between the *maxU* value and the utility value of the current proposal is less than or equal to the threshold. Otherwise, the player rejects the proposal and then he reduces and updates the *maxU* value. If the final round is reached, the player has to evaluate the previous rejected proposals. If the difference between the current *maxU* value and that corresponding to one of these proposals is less than the threshold, the player accepts this proposal. Finally, the *Agreement* variable is assigned to 1 and the player's negotiation process ends. Note that the final round is always specified, leading to the successful completion of this algorithm.

The inputs of the Algorithm 2 are N CP-nets of the N players and N proposals of the players. The algorithm omits the construction of the induced preference graphs from CP-nets. The proposal of the player is a maximum preferred string that gains the maximum utility (for instance, see Table 1). The variable *maxP* refers to the maximum acceptable probability and is assigned the value 0.9. The variable *avgP* refers to the average acceptable probability and is assigned the value 0.5. The term 'probability' is somewhat of a misnomer, because we use it to mention some value in [0, 1] without any probabilistic meaning attached to it. Such values are assigned to the vertices of the induced preference graphs that are constructed from the players' CP-nets, where the ordering of the vertices is compatible to the natural ordering of the values assigned to them.

The initial assignments to the *Agreement* variable and the *JointOptimal* variable are zeros. The value of the variable t corresponds to the number of rounds in which the single negotiation text is proposed. The constant *finalRound* can take up values depending on the context of the negotiation problems. The negotiation process repeats until the *Agreement* variable becomes equal to 1 and the number of rounds is less than the value of *finalRound*. First, a value for the *acceptableProbability* variable is searched for each player compared with the other players' proposals. The idea of this *acceptableProbability* variable is as follows. Our starting point is the bottommost string of the induced preference graph corresponding to the concerned player and we assume that the string whose edge directly points to the bottommost string gets the acceptable probability 0.9. We define probability of a string on the graph by going backward from the bottommost or maximum preferred string. We count the intermediate edges from the bottommost string to the particular string by reducing the *acceptableProbability* value by 0.1 for each edge in between. This searching process continues until the *acceptableProbability* value reaches 0.5. Otherwise, the *acceptableProbability* variable is assigned the value zero.

Moreover, the mediator marks all *acceptableProbability* values less than the threshold value (line 14, Algorithm 2, see page 25). If at least one the players rejects the proposal and the mediator has an alternative jointly optimal proposal in his previous marked list, the mediator can use the alternative as the next proposal. If there is no jointly optimal proposal among the players' proposals, the mediator tries to search for an alternative jointly optimal proposal (line 21, Algorithm 2, see page 25) that has the same *acceptableProbability* value as the players' previous proposals. The mediator searches all strings that have one backward edge from the maximum preferred string (with *acceptableProbability* value 0.9) for all players. He then searches a common string of all players. If there is no common string, the mediator continues to search all possible strings with *acceptableProbability* value 0.8. This process continues until such a common string is found with the maximum possible *acceptableProbability* value.

The proposed algorithms can provide a negotiable agreement for multiple players via the mediator. The mediator does not have a bias among the players and he can search fairly optimal preferences for all players. Although most of the players may not gain their most preferred option, they accept an outcome of which the utility value is not less than the average utility value. Even if the players are not able to realize their maximum preferences, they receive reasonably acceptable outcomes, and in some cases that is all what is needed. In such contexts, the successfully negotiable situation becomes an optimal outcome.

We consider the time complexity of the two algorithms. The basic operation of Algorithm 1 (see page 24) is searching maximum utility in the player's UCP-nets and comparing the difference with the threshold. Let the set of issues be denoted by $I = \{i_1, i_2, .., i_m\}$ and let the numbers of different preferences (that is, the number of possibilities or the cardinality of the domain) for each issue be $p_1, p_2, \ldots, p_m$, respectively. The total number of possible proposal strings is the combination of these $p_1, p_2, \ldots, p_m$ issues, and in the worst-case scenario, one needs to go through all these $p_1 * p_2 * \ldots * p_m$ possibilities, and thus a crude upper bound can be given by the $f \times\ p_1 * p_2 * \ldots * p_m$, where f is the value of *finalRound*. The computation time for constructing the induced graph grows linearly.

The basic operation in Algorithm 2 is searching the *acceptableProbability* values for all players. If n is the number of players, then the time needed for running this operation is bounded by $O(n^2)$. The basic operation runs in two loops, according to the number of rounds and the difference between the *maxP* value and the *avgP* value. Note that Algorithm 2 omits the construction of the induced preference graph from the players' CP-nets.

3.2 Case Study: Negotiation with Mediation

As an example case, let us consider three players and one mediator for three issues. In this framework, the players and mediator can be run on different computers. When starting the negotiation process, all players report their overall preference information about negotiation issues to the mediator. Then, the mediator creates induced preference graphs for all players based on their CP-nets. Let N be the set of players: $N = \{1, 2, 3\}$. We consider the three variables A, B, C as three negotiation issues. The domains of the variables are $D(A) = a_1, a_2$; $D(B) = b_1, b_2$; and $D(C) = c_1, c_2, c_3$.

This can be seen as a simple real-world negotiation between different preferences of family members. Suppose that a family including father, mother and 20 years old son decided to buy a new house. They have different preferences for the three issues:

Type of house (A): house with small garden (a_1); condo apartment (a_2);
Place near (B): market (b_1); park (b_2);
Price range (C): high (c_1); medium (c_2); low (c_3).

For example, mother (Player 1) prefers to buy a house with a small garden, situated near a market. If the house is situated near a market, she prefers a high price to a medium or a low price. If it is situated near a park, she prefers a low price to a high price. Father (Player 2) prefers a place near a park to a place near a market. If the place is near a park, he prefers a condominium apartment and if it is near a market, he prefers a house with a small garden. He prefers a high price or a low price rather than a medium price. Their son (Player 3) prefers a house with a small garden to a condo apartment. He also prefers a place situated near a park to a place near a market. If it is a house near a market or an apartment near a park, he prefers a high price to a medium or a low price. Otherwise, he prefers a low price to a medium or a high price.

Let us suppose that the real estate agent acts as a mediator and that the family members do not want to share their preferences with one another. After proposing three negotiation texts by the mediator, all family members agree to buy a new house near a park with low price. We will illustrate the details of the negotiation process in Section 3.3.

3.3 Case Study: The Negotiation Process

Assume that the CP-net and the induced preference graph given in Figure 1 and Figure 2 have been proposed by Player 1. The CP-nets and their induced graphs of Player 2 are shown in Figures 4, 5, and those for Player 3 in Figures 7, 8. All players prepare UCP-nets with their private utility values as illustrated in Figure 3, 6 and 9. Each player also calculates the total utility of strings in their UCP-nets, as shown in Table 1. They pick up one string with maximum utility outcomes in their UCP-nets and propose it to the mediator. In this example, Players 1, 2 and 3 propose a_1, b_1, c_1, a_2, b_2, c_1 and a_1, b_2, c_1 respectively. These are the bottommost strings of the induced graphs (see Figures 2, 5 and 8).

Table 1. Utility Table for Players 1, 2 and 3.

Strings	Player 1	Player 2	Player 3
$a_1b_1c_1$	6.2	3	7.2
$a_1b_1c_2$	6	2.7	7.4
$a_1b_1c_3$	5.8	2.9	7.6
$a_1b_2c_1$	5.5	5.8	8.6
$a_1b_2c_2$	5.7	5.5	8.4
$a_1b_2c_3$	5.9	5.7	8.2
$a_2b_1c_1$	2.9	2.7	4.6
$a_2b_1c_2$	2.7	2.4	4.4
$a_2b_1c_3$	2.5	2.6	4.2
$a_2b_2c_1$	2.8	6.1	4.2
$a_2b_2c_2$	3	5.8	4.4
$a_2b_2c_3$	3.2	6	4.6
Average	4.35	4.27	6.15

We now proceed to show how the algorithms work for the case study. The mediator generates a single negotiation text that we call "the proposal", by searching jointly optimal gains of all players according to Algorithm 2 (see page 25). After receiving the maximum preferred strings of all players, the mediator searches acceptable probability to the other players' strings (line 11, Algorithm 2, see page 25).

In this case study, the acceptable probability from Player 1's preferred string a_1, b_1, c_1 to Player 2's preferred string a_2, b_2, c_1 is 0.8 and to Player 3's preferred string a_1, b_2, c_1 it is 0.9 on Player 1's induced graph (see Figure 2). For Player 2, probability from his string a_2, b_2, c_1 to Player 1's proposed string a_1, b_1, c_1 is 0.8 and probability to Player 3's proposed string a_1, b_2, c_1 is 0.9 (see Figure 5). For Player 3, probability from his string a_1, b_2, c_1 to Player 1's proposed string a_1, b_1, c_1 is 0.9 and probability to Player 2's proposed string a_2, b_2, c_1 is 0.9 (see Figure 7). According to this example, a_1, b_2, c_1 is jointly optimal for all players because it obtains reachable probability 0.9 from their maximum

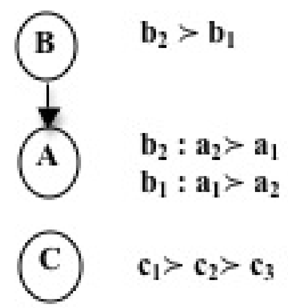

Fig. 4. CP-net for Player 2.

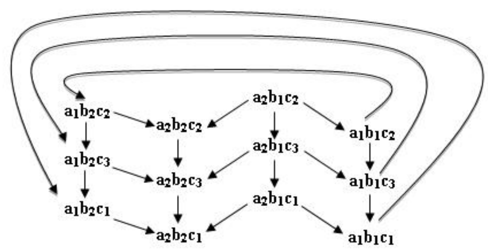

Fig. 5. Induced Preference Graph of the CP-Net of Figure 4, for Player 2.

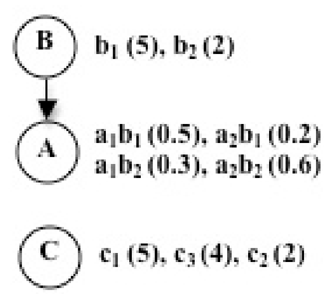

Fig. 6. UCP-net for Player 2.

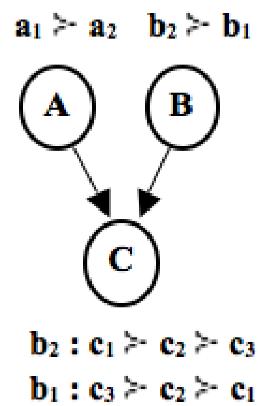

Fig. 7. CP-net for Player 3.

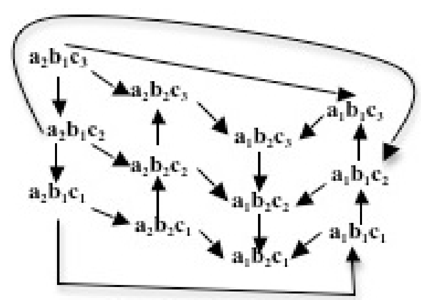

Fig. 8. Induced Preference Graph of the CP-Net of Figure 7, for Player 3.

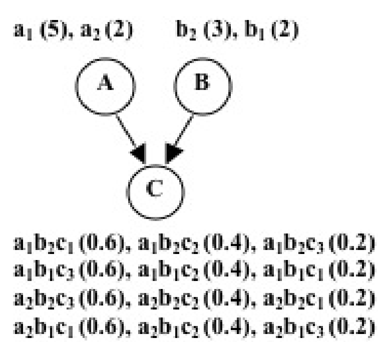

Fig. 9. UCP-net for Player 3.

preference strings. Therefore, the mediator proposes a_1, b_2, c_1 as a first jointly optimal negotiation text.

After receiving a new negotiation text from the mediator, all players check their utility outcomes (see Table 1) of the text to make a decision "accept" or "reject". Player 1 rejects the proposal a_1, b_2, c_1 because the difference between her maximum utility and the utility of the current text is greater than the threshold ($maxU - a_1, b_2, c_1 = 6.2 - 5.5 = 0.7$) according to Algorithm 1 (page 24). We assume that the starting threshold is 0.4 in Algorithm 1 (page 24). The threshold in the algorithm can be changed according to the type of utility values. Player 3 strongly accepts the current proposal because he gets his maximum utility. Player 2 also accepts because the difference between his maximum utility and the current text is less than the threshold ($maxU - a_1, b_2, c_1 = 6.1 - 5.8 = 0.3$).

The negotiation process continues until the agreement is achieved by the mediator acting according to Algorithm 2 and the players acting according to Algorithm 1. Finally, in this case, the mediator proposes $a_1b_2c_3$ as a jointly optimal negotiation text. Player 1 accepts the proposal because the difference between her maximum utility and the current text is less than the threshold ($maxU - a_1, b_2, c_3 = 6.2 - 5.9 = 0.3$). Player 2 and 3 also accept the proposal because the difference between their maximum utilities and the current text is equal to threshold ($maxU - a_1, b_2, c_3 = 6.1 - 5.7 = 0.4$ and $maxU - a_1, b_2, c_3 = 8.6 - 8.2 = 0.4$, respectively). All players achieve a jointly optimal outcome, which is greater than their average outcomes (see Table 1), although they do not achieve their maximum outcomes.

Finally, a few words on the complexity issues for this approach instantiating what we discussed in Section 3.1. It is evident that the time required for constructing the induced preference graphs depends on the number of variables and the cardinality of the variable domains. For instance, if we consider 10 issues (variable A to J) with the numbers of the domain variables being 2, 2, 3, 2, 2, 3, 2, 2, 2, 4, respectively, the total number of combinations of possible strings becomes 4608. The computation time for constructing the induced preference graphs from the CP-nets grows linearly. However, the mediator works on searching the joint optimal agreement until the average acceptable probability, 0.5 is reached, which is the worst case. Thus, it is not needed to construct the full induced graph because the algorithm processes mostly the bottom half part of the graph in many cases. Most real-world cases do not have thousands of different issues of negotiation. Therefore, the proposed approach can provide the interactive negotiation within reasonable time bounds. A detailed technical study is left for future work.

3.4 Cyclic CP-nets

In addition, our approach can achieve a negotiation outcome even when players' CP-nets are cyclic as shown in Figure 10 (a). Let us show a simple example of negotiation between two players. Player 1's preferences and induced graph are shown in Figure 10 (b) and 10 (c). Player 1's private utilities are: a_1b_1 (4), a_2b_2

(4), a_2b_1 (2) and a_1b_2 (2). Player 2's preferences and induced graph are shown in Figure 10 (d) and 10 (e). Player 2's private utilities are: a_1b_1 (3), a_2b_2 (3), a_2b_1 (3) and a_1b_2 (3). Actually, player 2's preference utilities are all the same and its induced graph is not satisfiable [5].

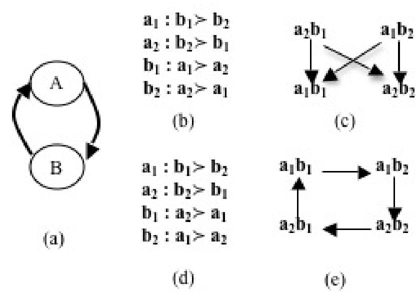

Fig. 10. Examples of cyclic CP-nets and their induced preference graphs.

In our negotiation process, Player 1 proposes a_1b_1 as her maximum preferred string and Player 2 proposes a_2b_2. When the mediator computes the acceptable probability, a_2b_2 has the same probability as a_1b_1 for Player 1 and a_1b_1 has 0.8, an acceptable probability for Player 2. If there is no backward edge from the maximum preferred string to a particular string, the two strings may have the same probability. For instance, if two strings, a_1b_1 and a_2b_2 (see Figure 10 (c)) have a backward edge from the same string (a_2b_1), then a_1b_1 and a_2b_2 have the same probability. This reasoning can easily be applied to search on the preference graphs given from the cyclic CP-nets. In our example, the mediator proposes a_2b_2 which is Player 2's proposed string. It also has the same acceptable probability as Player 1's proposed string a_1b_1. Both players accept the mediator's proposal because it meets their maximum preference utility.

3.5 Negotiating International Conflict: Camp David

Our approach can be applied to international conflict resolution as well. As a reminder, Camp David was a well-known negotiation process that happened between Egypt and Israel in 1978. The negotiation process lasted for 13 days and the United States acted as a mediator. U.S mediators had already known deeply about the preferred solutions of Egypt and Israeli and the impossibility of the countries' teams negotiating directly face to face. Therefore, they decided to use a single negotiation text (SNT). The U.S started by offering its first SNT-1 but was not trying to push this first proposal. It was meant to serve as an initial SNT; a text to be criticized by both sides, then modified, and remodified in an iterative manner. These modifications would be made by the U.S based on the recommended changes by both sides. After six rounds, a satisfactory agreement, the Camp David accord, was reached [19]. We can simulate this negotiation using the proposed approach. In Camp David, there are two players, Egypt and Israel, and four basic negotiation issues [22, 16]:

A A peace treaty and normalization of relations between Egypt and Israel;
B Demilitarization and removal of Israeli settlements from Sinai;
C The future of the West Bank and Gaza;
D A statement of principles on Israeli withdrawal from occupied territories and the right of Palestinians to self-determination.

Our considerations are meant for illustrative purposes and do not exactly fit the details of actual Egyptian and Israeli preferences. Let us consider the following as domains of the four issues A, B, C, D: $D(A) = a_1, a_2$; $D(B) = b_1, b_2$; $D(C) = c_1, c_2, c_3$; and $D(D) = d_1, d_2$, d_3. The descriptions of the alternatives are as follows:

a_1**:** Egyptian armed forces are present around Israeli sovereignty;
a_2**:** Egypt guarantees freedom of passage through the Suez Canal and nearby waterways and normal relations are established between Egypt and Israel;
b_1**:** Israeli armed forces withdraw from the Sinai;
b_2**:** Israeli armed forces are present in the Sinai;
c_1**:** Israel sovereignty exists in the West Bank and Gaza;
c_2**:** Israel withdraws from West Bank and Gaza and closes the airfields there;
c_3**:** Israel withdraws from West Bank and Gaza and the airfields there are transferred to civilian purposes only;
d_1**:** Israeli armed forces withdraw from all occupied territories and no promise for Palestinians to self-determination;
d_2**:** Israeli armed forces withdraw from all occupied territories and Palestinians gain right to self-determination;
d_3**:** Israel does not withdraw from occupied territories and keeps its military government there.

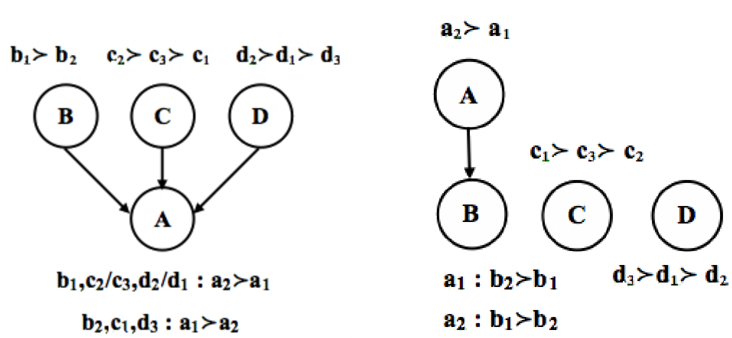

Fig. 11. CP-Nets for Player I (Israel, left) and Player E (Egypt, right).

The CP-nets for both players are shown in Figure 11. For the above preferences, there is a total of $2 \times 2 \times 3 \times 3 = 36$ possible agreements, presented in Table 2. We show all possible preference strings for both players with acceptable probabilities (see Figures 12 and 13) instead of preference graphs.

Both players also prepare their utility CP-nets (see Figure 14). Moreover, we define the total utility values of all possible strings for both players as shown in Table 2. The negotiation process continues according to Algorithm 1 (see page 24) and Algorithm 2 (see page 25). Let us sketch the main steps.

First, both players privately present their maximum preferred strings to the mediator (line 4 of Algorithm 2). Thus, Player E proposes string $a_2b_1c_2d_2$ with utility value 20, while Player I proposes string $a_2b_1c_1d_3$, also with utility value 20 (see Table 2). These proposals correspond to the bottommost strings of their induced preference graphs (lefthand columns in Figures 12 and 13).

The mediator searches the acceptable probability for both players based on their proposals according to line 11 of Algorithm 2 (see page 25). Player E's proposal $a_2b_1c_2d_2$ is calculated for acceptable probability of player I and it gets the value 0.6. Player I's proposal $a_2b_1c_1d_3$ is reached with probability 0.6 from the bottommost string of player E's graph. If there exists an acceptable probability which is equal to the maximum probability (0.9), the mediator chooses this string as a joint optimal outcome for proposing the single negotiation text (SNT). But, there is no such probability that equals 0.9. So, the mediator searches for an alternative optimal according to line 21 of Algorithm 2 (see page 25) which cannot be found in this case. This process continues for probability 0.8 (see Algorithm 2, line 15 to 30, page 25). Now the mediator finds one acceptable probability (0.8) as the alternative optimal for both players (see algorithm 2, line 21 to 23, page 25). Therefore, the mediator proposes the jointly optimal string $a_2b_1c_2d_3$ as the first SNT.

After receiving the mediator's proposal, both players check whether the proposal can be accepted or not according to line 10 and 11 of Algorithm 1 (see page 24). As we mentioned above, the threshold value can vary according to the types of the utility values. Here, we assume that the threshold (Algorithm 1, line 4, see page 24) is 3. Both players reject the proposal because the difference between the maximum utility (see Table 2) and the utility of the proposal is greater than the threshold value ($20 - 14 = 6 > 3$ and $20 - 16 = 4 > 3$).

The mediator asks for new proposals from the players. Player E proposes $a_1b_1c_2d_2$ and player I proposes $a_2b_2c_1d_3$. Then, the mediator searches for the acceptable probabilities. Once again, there exists no such acceptable probability that is equal to the maximum probability. The mediator continues the searching process to get an alternative optimal outcome and finds one with the acceptable probability 0.8.

In the second round, the mediator proposes $a_2b_1c_3d_1$ to the players. Player E accepts the proposal because the difference between his maximum utility and the utility of the proposal ($20 - 18 = 2$) is less than the threshold value (3). Player I also accepts the proposal as he gets the utility difference ($19 - 16 = 3$), which is equal to the threshold (3). Note that these utility values are greater

	probability					
bottommost	0.9	0.8	0.7	0.6	0.5	0.4
				$a_1b_2c_1d_2$	$a_1b_2c_1d_1$	$a_1b_2c_1d_3$
			$a_1b_2c_3d_2$	$a_1b_2c_3d_1$	$a_1b_2c_3d_3$	
		$a_1b_2c_2d_2$				
	$a_1b_1c_2d_2$		$a_1b_2c_2d_1$	$a_1b_2c_2d_3$		
		$a_1b_1c_3d_2$	$a_1b_1c_1d_2$	$a_1b_1c_1d_1$	$a_1b_1c_1d_3$	
			$a_1b_1c_3d_1$	$a_1b_1c_3d_3$		
$a_2b_1c_2d_2$		$a_1b_1c_2d_1$	$a_1b_1c_2d_3$			
			$a_2b_2c_1d_2$	$a_2b_2c_1d_1$	$a_2b_2c_1d_3$	
		$a_2b_2c_3d_2$				
	$a_2b_2c_2d_2$		$a_2b_2c_3d_1$	$a_2b_2c_3d_3$		
		$a_2b_2c_2d_1$	$a_2b_2c_2d_3$			
	$a_2b_1c_3d_2$	$a_2b_1c_1d_2$	$a_2b_1c_1d_1$	$a_2b_1c_1d_3$		
		$a_2b_1c_3d_1$	$a_2b_1c_3d_3$			
	$a_2b_1c_2d_1$					
		$a_2b_1c_2d_3$				

Fig. 12. All possible preference strings with acceptable probabilities for Player Egypt.

	probability					
bottommost	0.9	0.8	0.7	0.6	0.5	0.4
				$a_1b_2c_2d_3$		
			$a_1b_2c_3d_3$		$a_1b_2c_2d_1$	$a_1b_2c_2d_2$
		$a_1b_2c_1d_3$		$a_1b_2c_3d_1$		
					$a_1b_2c_3d_2$	
	$a_1b_1c_1d_3$		$a_1b_2c_1d_1$	$a_1b_2c_1d_2$		
			$a_1b_1c_2d_3$	$a_1b_1c_2d_1$	$a_1b_1c_2d_2$	
		$a_1b_1c_3d_3$				
			$a_1b_1c_3d_1$	$a_1b_1c_3d_2$		
$a_2b_1c_1d_3$		$a_1b_1c_1d_1$	$a_1b_1c_1d_2$			
			$a_2b_2c_2d_3$	$a_2b_2c_2d_1$	$a_2b_2c_2d_2$	
		$a_2b_2c_3d_3$				
	$a_2b_2c_1d_3$		$a_2b_2c_3d_1$	$a_2b_2c_3d_2$		
		$a_2b_2c_1d_1$	$a_2b_2c_1d_2$			
		$a_2b_1c_2d_3$	$a_2b_1c_2d_1$			
	$a_2b_1c_3d_3$					
		$a_2b_1c_3d_1$	$a_2b_1c_3d_2$	$a_2b_1c_2d_2$		
	$a_2b_1c_1d_1$					
		$a_2b_1c_1d_2$				

Fig. 13. All possible preference strings with acceptable probabilities for Player Israel.

Table 2. Table of utilities of all 36 possible proposals for Egypt and Israel.

Strings	Utility for Egypt	Utility for Israel
$a_1b_1c_1d_1$	12	10
$a_1b_1c_1d_2$	13	8
$a_1b_1c_1d_3$	7	12
$a_1b_1c_2d_1$	18	6
$a_1b_1c_2d_2$	19	4
$a_1b_1c_2d_3$	13	8
$a_1b_1c_3d_1$	17	8
$a_1b_1c_3d_2$	18	6
$a_1b_1c_3d_3$	13	10
$a_1b_2c_1d_1$	9	12
$a_1b_2c_1d_2$	10	10
$a_1b_2c_1d_3$	4	14
$a_1b_2c_2d_1$	15	8
$a_1b_2c_2d_2$	16	6
$a_1b_2c_2d_3$	10	10
$a_1b_2c_3d_1$	14	10
$a_1b_2c_3d_2$	15	8
$a_1b_2c_3d_3$	9	12
$a_2b_1c_1d_1$	13	18
$a_2b_1c_1d_2$	14	16
$a_2b_1c_1d_3$	8	20
$a_2b_1c_2d_1$	19	14
$a_2b_1c_2d_2$	20	12
$a_2b_1c_2d_3$	14	16
$a_2b_1c_3d_1$	18	16
$a_2b_1c_3d_2$	19	14
$a_2b_1c_3d_3$	13	18
$a_2b_2c_1d_1$	10	17
$a_2b_2c_1d_2$	11	15
$a_2b_2c_1d_3$	5	19
$a_2b_2c_2d_1$	16	13
$a_2b_2c_2d_2$	17	11
$a_2b_2c_2d_3$	10	15
$a_2b_2c_3d_1$	15	15
$a_2b_2c_3d_2$	16	13
$a_2b_2c_3d_3$	10	17
Average	13.33	12.25

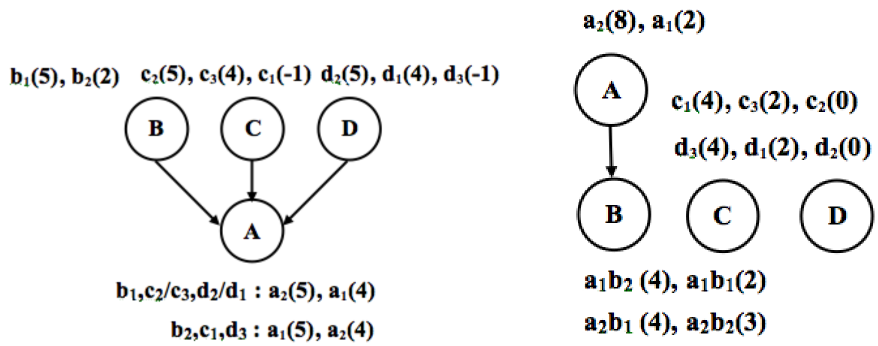

Fig. 14. UCP-net for Player E (Egypt, left) and Player I (Israel, right).

than their average utility values and they are quite close to the utility values of their maximum expected outcomes, which were 20 for both the players.

Therefore, we find that indeed, a final agreement is achieved within a limited number of rounds, and this algorithmic approach to negotiation via mediator provides a simulation of the historical Camp David Accords. Summing up, Egypt guarantees freedom of passage through the Suez Canal and nearby waterways and normal relations are established between Egypt and Israel; Israeli armed forces withdraw from the Sinai. They also withdraw from the West Bank and Gaza, and the airfields there are used for civilian purposes only. Finally, Israeli armed forces withdraw from all occupied territories. However, Israel makes no promise for Palestinians about their self-determination.

4 DISCUSSION ON RELATED WORK

This paper presents an approach for negotiation over multiple players on multiple issues with the support of a mediator. To achieve a jointly optimal agreement, the mediator offers a single negotiation text based on all players' preference graphs given from their CP-nets. Every player can decide to accept or reject the offer by checking the negotiation text's utility on his or her private UCP-nets. We proposed two algorithms for the mediator and the players. For successful negotiation between players, they often need to give up their maximum expected preferences because otherwise the negotiation process may not achieve a satisfactory agreement within a finite number of rounds. The proposed approach is appropriate for players who are willing to accept a jointly optimal choice.

M. Li and colleagues presented a protocol for negotiation in combinatorial domains [13], which can lead rational agents to reach optimal agreements under an incomplete information setting. They proposed POANCD (Protocol to reach Optimal Agreement in Negotiation over Combinatorial Domains), which has two phases. The first phase of POANCD consists of distributed formation of a negotiation tree by the participating agents, based on CP-nets of agents. After the first phase, the agents make a few initial agreements. In the second phase, the agents act cooperatively to achieve best possible agreement by exploring possible mutually beneficial alternatives. Li and colleagues also proved their approach to dominance testing in CP-nets [12]. Their approach did not have a solution on cyclic CP-nets yet in [13]. Recently, however, Li and colleagues proposed an approach called MajCP (Majority-rule-based collective decision-making with CP-nets) that can work with cyclic CP-nets as well [14].

The purpose of the proposed approach in this paper is to deal with similar situations, players do not only have preference orderings in their CP-nets, but they also have their private utility values (possibly different utilities for the same preference order). Our approach provides negotiation in an interactive way, with mediator and players as a game where the mediator proposes a single negotiation text and players can decide about agreement themselves.

K. Purrington and E. H. Durfee also proposed an algorithm to find social choices of two agents by exploiting the CP-net structure [18]. Their algorithm searches agents' outcome graphs from the top down, using the satisfaction interval associated with each tier, and it proceeds for each agent. A set of candidate outcomes is maintained for each agent. It contains all the outcomes that an agent is willing to accept. For each agent, the algorithm examines the highest tier of outcomes that are not currently in its candidate set, and for the agent(s) with the highest minimum for this next tier, adds those outcomes to the candidate set(s). If the intersection of the agents' candidate sets is non-empty, one of the outcomes in the intersection has maximin optimality. Their algorithm considers only the level of the preference graphs. Our framework provides not only the mediator's joint choice, but also the players' decisions based on their private UCP-nets.

R. Aydogan and colleagues developed a negotiation approach using heuristics for CP-nets with partial preferences [2]. They observed three negotiation strategies: depth-based, ranking-based and utility-based. They showed an example of negotiation between a producer and a consumer agent over a service. Negotiation takes place in a turn-taking fashion, where the consumer agent starts the negotiation with a particular service request. A service request can be considered as a vector of issues (discrete or continuous), which represents the service. If the producer agent does not prefer to supply this service, then the producer generates an alternative service. The consumer agent can accept this alternative service or continue negotiation to pursue a better one. This process continues until reaching a consensus or a deadline. Aydogan and Yolum focus only on one player's preferences and do not mention the other player's preferences. They do not deal with negotiation for multiple (more than two) players. The purpose of our approach is to deal with multi-player, multi-issue negotiation via a mediator.

M. Chalamish and S. Kraus presented AutoMed, an automated mediator for bilateral negotiation under time constraints, which uses a qualitative model. AutoMed produces the negotiators' preferences using Weighted CP-networks (WCP-nets). Each disputant specifies her preferences by creating her WCP-net using a graphical interface. Next, AutoMed sorts all possible agreements according to the WCP-nets and removes all non-optimal sets. During the negotiation process, AutoMed searches for an optimal offer by finding all agreements preferred to the offer made by the opponent in each list [7]. In our approach, the mediator does not use weighted or utility CP-nets but only CP-nets based on partial preferences of the players, because the players do not want to show their private utility values.

5 CONCLUSION AND FUTURE WORK

In this paper, we present a simple negotiation approach that is useful in a practical way for negotiations. The mediator offers jointly optimal negotiation texts based on CP-nets over a finite number of rounds and the rest of the players are willing to adjust their private interests at each round using UCP-nets. In this interactive framework, the mediator and the players can play on different machines by sending messages. The framework can deal with negotiation for multiple issues, and with multiple players who have different preferences even when their preference graphs are cyclic. The proposed approach provides a satisfactory agreement for all players with their optimal outcomes, which are not less than average utility. In what follows we list some future avenues for investigation.

Performance testing through experiments The algorithms provide us with certain outcomes which are acceptable to all the players (in the case studies provided in Sections 3.3 and 3.5). But to test how these algorithms work in real life scenarios, some more empirical studies are necessary. We plan to test the performance of this approach and hope to construct a more efficient search algorithm on preference graphs.

Formal investigations We have described two algorithms, Algorithm 1 and 2 for the players and the mediator, respectively. Applying these, a jointly optimal outcome could be agreed upon by all the players. The formal treatment of this approach could be a valuable contribution which would provide solid grounding for these algorithms. We would need a proof of the statement that the reached agreement found by the algorithm is indeed a jointly optimal outcome. If this is not always the case, it would also be interesting to investigate the conditions under which the reached agreement would become a jointly optimal outcome. Some conditions on the threshold value might be needed.

Moreover, the way the mediator searches for the acceptable probabilities of the players towards the outcomes is an ad hoc treatment solely focusing on the distance of an outcome from the most preferred outcome (in terms of edges in the induced graph). Several variants could be considered, introducing some other parameters, e.g. transforming the graph into some linear order. A comparative study of the different resulting algorithms could provide interesting new insights into multi-player, multi-issue negotiations.

Information, costs and incentives In this approach we have made several assumptions regarding the players and the mediator, which include the following:

- The individual partial CP-nets are known to the mediator only, whereas the UCP-nets are assumed to be private information.

– Individuals do not procure any costs while rejecting the outcomes proposed by the mediator.
– Related to the previous condition, no incentives were provided to the players that could have led them to accept non-optimal outcomes.

Changing the choices on these issues could lead to interesting further studies on obtaining agreeable outcomes through negotiation. For example, common knowledge of CP-nets and UCP-nets among the players would make the role of the mediator redundant, and it would be interesting to check the effect of the mediator for different levels of knowledge among the players. Incurring costs on individual players for possible rejections of the mediator's proposal would give a whole new dimension to Algorithm 1, the procedure which the players follow towards accepting or rejecting proposals put forward by the mediator. When the individual UCP-nets become known to other players, these may also act as incentives for their behaviors, and once again, effects of different knowledge levels in different players could be investigated.

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Algorithm 1 Negotiation Decision by Player

Input :
    UCP-nets with total utility and ordering
    $Agreement \leftarrow 0$; $maxU \leftarrow$ maximum utility
    $threshold \leftarrow x$; Proposals $\leftarrow \emptyset$
while $Agreement \neq 1$ **and** $t \leqslant finalRound$ **do**
  Search S $(U(S) = maxU)$ in UCP-net   //search maximum preferred proposal
  Send (S) to Mediator
  currentProposal $\leftarrow$ Receive(Proposal by Mediator)
  Proposals $\leftarrow$ Proposals $\cup$ currentProposal
  if $(maxU-\mathrm{U}(currentProposal)) \leqslant threshold$ **then**
    accept Proposal
    $Agreement \leftarrow 1$
  else
    reject Proposal
    Update $maxU$ //search and update the utility less than current maxU
    Send (S)
  end if
end while
if Receive(finalRound) **then**
  while $maxU > avgU$ **do**
    Update $maxU$ //search and update the utility less than current maxU
    Evaluate proposals
    if $\exists proposal : (maxU-\mathrm{U}(proposal) \leqslant threshold)$ **then**
      accept proposal;
      $Agreement \leftarrow 1$
    end if
  end while
end if

Algorithm 2 Negotiation by Mediator

```
Input:
   Player N: N = (1, 2, ..., n)
   CPN_1, CPN_2, ..., CPN_n   //Players' CP-nets
   S_1, S_2, ..., S_n   //Players' proposals
   maxP ← 0.9; avgP ← 0.5   //maximum and average acceptable probability
   Agreement ← 0; JointOptimal ← ∅; t ← 0
   threshold ← x
while Agreement ≠ 1 and t ⩽ finalRound do
  for i = 1 to n do
    for j = 1 to n do
      Search acceptableProbability (S_i, S_j : i ≠ j)
    end for
  end for
  Mark all S_i, S_j: acceptableProbability < threshold;
  while maxP > avgP do
    for i = 1 to n do
      for j = 1 to n do
        if ∃S_i : (acceptableProbability(S_i, S_j) = maxP ; i ≠ j) then
          JointOptimal ← S_i
        else
          Search alternativeOptimal(S_i) //Other proposals with same maxP
          if ∃S_l : (acceptableProbability(S_l, S_j) = maxP; l ≠ j) then
            JointOptimal ← S_l
          else
            maxP ← maxP − 0.1
          end if
        end if
      end for
    end for
  end while
  Propose JointOptimal
  if ∀ Player k ∈ N accept Proposal then
    Agreement ← 1
  else if Player k (k ∈ N) rejects S_i then
    Ask new proposal to Player k
    Update S_i (i = k)
    maxP ← 0.9
    t ← t + 1
  end if
end while
if Agreement = 0 and t = finalRound then
  Announce finalRound and Ask for evaluating all proposals to Players
end if
```