

## 2.1 Overview of Medical Incident Reports

With increasing social demand for the prevention of medical accidents, the Health, Labour and Welfare Ministry started the Project to Collect Medical Near-Miss/Adverse Event Information from 2001 in order to collect and analyze incident case studies and to provide information conducive to medical safety, such as measures for improvements. When the project was first started, a framework was in place in which the Pharmaceuticals and Medical Devices Agency collected incident case studies from participating medical institutions and then reported these case studies to the Health, Labour and Welfare Ministry, following which a Health, Labour and Welfare Ministry study group conducted aggregate calculations and analysis. The 1st–10th collection of incident case studies were conducted following this framework, and information based on these collected incident case studies was provided by the Health, Labour and Welfare Ministry. From 2004, the Japan Council for Quality Health Care took over the collection of incident case studies, collecting case studies from the 11th collection [4].

Osaka City University also collected 18,340 incident reports from 2007 to 2010. In the incident reports provided by Osaka City University, free composition formats are taken quite seriously compared with ones provided by other Hospitals. For instance, the average number of words in the incident reports by Osaka City University is 188 words, on the other hand, the one by the Project to Collect Medical Near-Miss/Adverse Event Information is 80 words[2]. In fact, doctors and nurses in Osaka City University have to input the reports for the free descriptions at first because of the Layout of data entry screen.

## 2.2 Data Sets

We used free composition format written in Japanese relating to medical agents from 2007 to 2011 by Osaka City University. The number of documents is 18,340. Each case study is in a free composition format, with the abstract, background, and solution being approximately 188 words long, respectively. In addition, the two classes of medicine and accident are granted to each case study. With regard to the class of treatment, there are six classes of general drug, preparation of drugs, drowsy of drugs, contraindicated drug, chemo treatment, and other drug; with regard to the class of operation, there are the nine classes of name of drug, amount of drug, regimen, amount and regimen, flow rate, drug sensitivity, diapedesis, forget to dose, and object person. With regard to the class of treatment, as all the classes of operation do not exist, there are 32 cross classes that cross calculate the class of treatment and the negligent class of operation.

When describing accidents in a free composition format, the reporter makes every effort to include every single circumstance. We can say that extracting important information from these circumstances means creating a foothold for a bottom-up type of ontological construction. Results obtained from this and links with classes granted top-down is in accordance with the future guidelines for incident analysis sought by ICPS.

## 3. METHODOLOGY OF NATURAL LANGUAGE PROCESSING AND NETWORK ANALYSIS

### 3.1 Methodologies for analyzing the incident reports

In this paper, natural language processing was first conducted on the incident reports. Keywords that emerge characteristically were then extracted for each category of “background/causes,” “details,” and “solutions,” using the tfidf method. After that, the semantic tendency of the incident report was investigated in order to create a network of words by calculating the co-occurrence information of the words using the Jaccard coefficient.

Also, we show the networks among each document which are determined by the similarities between documents based on the tfidf method. As natural language processing contains a lot of noise, there is a need to conduct preprocessing in order to obtain characteristic words that can be used in determining links.

### 3.2 Japanese language morphological analysis

In the first stage of preprocessing, we conducted morphological analysis in order to break down reports into words. Morphological analysis is a method used to delimit each word in the text where words are not delimited by spaces, such as in languages like Japanese [5]. In this research we used MeCab, one of the most common engines for conducting morphological analysis [6].

There is the possibility that words obtained using MeCab are too finely classified to conduct the analysis of links. Therefore, we connected words using the following methods and used them as new words.

We connected words using information on the parts of speech. The above-mentioned MeCab not only breaks down words but also grants major classes and minor classes relating to parts of speech. In cases where the minor class of parts of speech of certain words was a suffix and the word before it was a noun, these two words were treated as one word.

Next, we connected words based on the number of word occurrences [7]. Let us envisage a situation in which two words -hereafter called A and B- appeared consecutively. If we designate the number of word occurrences in instances where each word is considered separately as  $n(A)$ ,  $n(B)$ , then the number of word occurrences in which

- (1)
- (2)
- (3)

they appear consecutively is expressed as  $n(A \cap B)$ . In cases where  $n(A \cap B) / \min(n(A), n(B))$  exceeded the threshold value (0.1 in this research) then we treated those two words as one word.

In the documents, nominalized verbs, general nouns, and proper nouns were targeted. Focusing solely on nouns is the method generally used in extracting characteristic words. Moreover, in the case of official documents in Japanese, as many of the verbs are nominalized, a lot of information can be obtained regarding action even if using only nouns.

### 3.3 TF-IDF Method

In this research, we calculated a value called *tf-idf* from the frequency of occurrence and conducted filtering based on this values. *Tf-idf* is one of the most widely used indices in extracting characteristic words for document classes and in cases where a certain word occurs several times in a small number of documents, it is defined so as to enlarge that value[8]. *Tf-idf* is calculated as follows:

$$tf-idf(t, d) = tf(t, d) \times idf(t)$$

$$tf(t, d) = n(t) / \sum_{k \in T} n(k)$$

$$idf(t) = \log |D| / |\{d : d \in t\}|$$

Here,  $t$  is a term,  $d$  is a document,  $n(t)$  is the frequency of occurrence of term  $t$ ,  $|D|$  is the total number of documents, and is  $|\{d : d \in t\}|$  the number of documents in which word  $t$  occurs.  $T$  means the set of terms.

The *tfidf* of general words occurring in a large number of documents has a tendency to be of a low value, although words among even general words that have an abnormally high *tf* in some cases exceed the filter effect of *idf* and assume a high value.

### 3.4 Creation of Co-Occurrence Networks

The co-occurrence index is generally used as a method for finding links from the degree of similarities between words in documents. Here, the simplest co-occurrence index for finding links between the two word A and B is the number of co-occurrence  $|A \cap B|$  for two words. Here,  $|A \cap B|$  is the number of characteristic words that exist in A and B. If considered with only  $|A \cap B|$ , there are problems such as including as many characteristic words as in long texts and links with other documents being displayed as high. Consequently, a number of co-occurrence indices that improve on these points have been proposed, with representative indices including the Jaccard coefficient [9].

$$Jaccard : |A \cap B| / |A \cup B| \quad (4)$$

A link is established between the two words in the event that these indices exceed the threshold value.

## 4. PRELIMINARY ANALYSIS RESULTS

Table1: Top 10 Characteristic Word in Incident Reports (TF; Term Frequency)

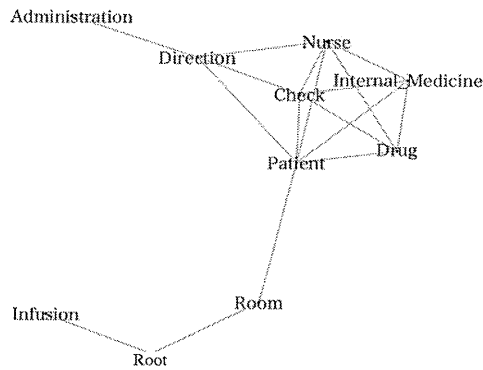
(TF)	Background	Details	Solutions
1	Patient	Report	Check
2	Check	Patient	Time
3	Drug	Check	Patient
4	Nurse	Attending Doctor	Direction
5	Direction	Monitor	Drug
6	Internal use	Duty Doctor	Explanation
7	Infusion	Doctor	Nurse
8	Pill	Direction	Thoroughness
9	Room	Nursing	Drug maker
10	Administration	Explain	Doctor

Table2: Top 10 Characteristic Word in Incident Reports (TF-IDF)

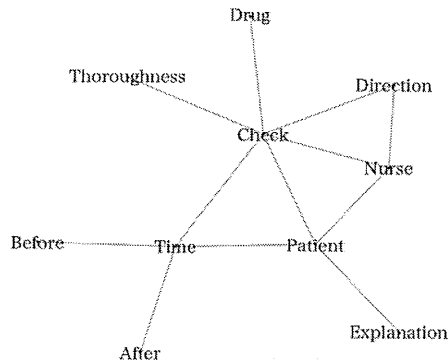
tf-idf	Background	Details	Solutions
1	Drug	Patient	Check
2	Patient	Report	Time
3	Check	Attending Doctor	Patient
4	Internal medicine	Check	Direction
5	Direction	Doctor	Drug
6	Nurse	Monitor	Explanation
7	Administration	Apologizing	Nurse
8	Infusion	Nursing	Thoroughness
9	Root	Duty Doctor	Before
10	Channel	Direction	After

The top ten characteristic words that appear in the incident report such as “background/causes,” “details,” and “solutions” with *tf* (term frequency) are shown in Table 1. The top ten characteristic words that appear in the incident report with *tf-idf* (Eq.(1)) are shown in Table 2. Under the category of “Background,” the words “Patient” “Check,” “Drug,” “Nurse,” and “Direction” rank high in Table 1. Moreover, the fact that the word “nurse” ranks high shows that there are many accidents related to nurses. Under the category of “Background,” the words “Drug” “Internal medicine,” “Infusion,” and “Channel” rank high in Table 2. Therefore, accidents related to medicines are important for analyzing the reports. Also, the words “Check,” “Direction,” and “Explanation” rank high under the category of solutions. In addition, the words related to the medical process such as “before” and “after” are high rank.

(a) Network regarding "Background/Causes"



(b) Network regarding "Details"



(c) Network regarding "Solutions"

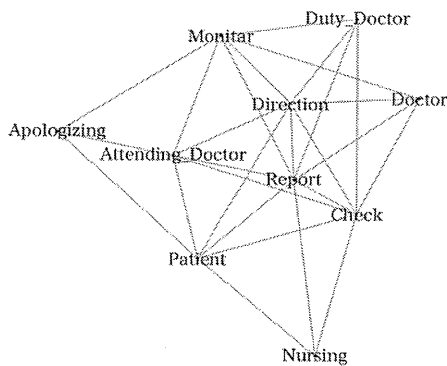


Figure 1: Co-occurrence Network of the Words in Incident Reports

One word such as "lack," "confirmation," or "drugs" alone cannot express the tendency of the accident. In this research, co-occurrence networks of words were created by connecting the words that co-occurred with each other at a high frequency. The degree of co-occurrence is calculated using the Jaccard coefficient [3] shown in Section 3.4.

Figure 1 shows the networks of characteristic words created using the accident reports related to incorrect drugs. Each node represents a word, and an edge represents the intensity of the co-occurrence between the words. First of all, in viewing the network for "background/causes" (see Figure 1 (a)) it is clear that the network is created around the word "Check," and one can see that the cause of many accidents is the fact that the "Check" on "drugs," "Patient," by "Nurse". Connecting the words that co-occur frequently allows us to understand what tends to become inadequate. In the network of "accident details" (see Figure 1 (b)) many different words appear at once, indicating the presence of diverse accident details. Viewing the network for "solutions" (see Figure 1 (c)), as with the network for "background/causes," it is created around the word "confirmation."

## 5. CONCLUSION

In this paper, the characteristic words were extracted by analyzing incident reports, and the co-occurrence networks of the characteristic words were created. As a result, the language networks with the hub of the word "check," thereby revealing that inadequate confirmations on the drug labels, instructions of a physician and patient were very significant causes of accidents. These results suggest the effectiveness of introducing the network analysis method. In the future work, we would like to focus on the medical reports for improving the notational rules for the names of drugs and dosages in incident reports. Also, we would like to analyze the differences of understanding of the incident reports between positions like doctors, nurses, pharmacists.

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## An Approach to Scalable Multi-issue Negotiation: Decomposing the Contract Space

KATSUhide FUJITA

*Department of Computer Science and Engineering, Nagoya Institute of Technology/  
Sloan School of Management, Massachusetts Institute of Technology*

TAKAYUKI ITO

*School of Techno-Business Administration, Department of Computer Science and Engineering,  
Nagoya Institute of Technology/  
Researcher, PREST, Japan Science and Technology Agency (JST).*

MARK KLEIN

*Sloan School of Management, Massachusetts Institute of Technology*

Most real-world negotiation involves multiple interdependent issues, which makes an agent's utility functions nonlinear. Traditional negotiation mechanisms, which were designed for linear utilities, do not fare well in nonlinear contexts. One of the main challenges in developing effective nonlinear negotiation protocols is scalability; they can't find a high-quality solution when there are many issues, due to computational intractability. One reasonable approach to reducing computational cost, while maintaining good quality outcomes, is to decompose the utility space into several largely independent sub-spaces. In this paper, we propose a method for decomposing a utility space based on every agent's utility space. In addition, the mediator finds the contracts in each group based on the votes from all agents, and combines the contract in each issue-group. This method allows good outcomes with greater scalability than the method without issue-grouping. We demonstrate that our protocol, based on issue-groups, has a higher optimality rate than previous efforts, and discuss the impact on the optimality of the negotiation outcomes.

*Key words:* Multi-Issue Negotiation, Interdependent Issues, Bargaining and negotiation

### 1. INTRODUCTION

Negotiation is an important aspect of daily life and represents an important topic in the field of multi-agent system research. There has been extensive work in the area of automated negotiation; that is, where automated agents negotiate with other agents in such contexts as e-commerce (Kraus (2001)), large-scale argumentation (Malone and Klein (2007)), collaborative design, and so on. Even though many contributions have been made in this area (Faratin et al. (2002)), most have dealt exclusively with simple negotiations involving one or more independent issues. Many real-world negotiations, however, are complex and involve interdependent issues. When designers work together to design a car, for example, the utility of a given carburetor is highly dependent on which engine is chosen. The key impact of such issue dependencies is that they result in agent utility functions that are nonlinear, i.e. that have multiple optima. Most existing negotiation protocols, though well-suited for linear utility functions, work poorly when applied to nonlinear problems (Klein et al. (2003)).

Recently, some studies have focused on negotiation with nonlinear utility functions. The followings are the representative studies on multi-issue negotiations for complex utility spaces. A bidding-based protocol was proposed by Ito et al. (2007). Agents generate bids by finding high regions in their own utility functions, and the mediator finds the optimum combination of submitted bids from the agents. By Fujita et al. (2008), a representative-based protocol for reducing the computational cost was proposed. In this method, the scalability of agents was improved; however, the scalability of issues was not sufficient. Robu et al.

(2005); Robu and Poutre (2006) presented the utility graph for issue interdependencies of binary-valued issues. Utility graphs are inspired by graph theory and probabilistic influence networks to derive efficient heuristics for non-mediated bilateral negotiations about multiple issues. Hindriks et al. (2006) proposed an approach based on a weighted approximation technique to simplify the utility space. It shows that existing methods for the linear utility function can work well when the nonlinear utility function is possible to be converted to approximated linear utility function. Marsa-Maestre et al. (2009) proposed an auction-based protocol for nonlinear utility spaces generated using weighted constraints, and Marsá-Maestre et al. (2010); Marsa-Maestre et al. (2009) extended this work to address highly rugged utility spaces. However, an unsolved problem is the scalability of the protocols. Our protocol focuses on the large-scale (nearly 50 issues) and interdependent multi-issue negotiations.

We propose a new protocol in which a mediator tries to reorganize a highly complex utility space into several tractable utility subspaces, in order to reduce the computational cost. First, we have to define a measure for the degree of interdependency between issues, and generate a weighted non-directed interdependency graph. Note that while others have discussed issue interdependencies in utility theory (Tamura and Nakamura (1983)), the aim of these previous works weren't to generate the efficient issue-groups. Second, we propose an efficient and scalable protocol based on the issue-groups. Agents generate the idea of issue-groups based on their utility information, and the mediator combines the idea of issue-grouping from all agents. After that, the mediator finds the contracts in each group based on the votes from all agents, and combines the contract in each group.

Actually, it is possible to gather all of the agents' interdependency graphs in one central place and then find all optimal contracts using such well-known clustering techniques as the k-means or Girvan-Newman algorithm (Girvan and Newman (2002)) in deciding the efficient issue-groups. However, most of the clustering techniques have to decide on certain parameters in employing the clustering techniques. For instance, the number of edges to be progressively removed from the graph is fixed in advance in the Girvan-Newman algorithm. There is a trade-off between the optimality rate and the failure rate in selecting the number of issue groups. In real-life negotiation, it is hard to determine the optimal parameters for central clustering in advance without enough history data. For automated agents, it is possible to recognize their issue-group idea by themselves because each agent has enough utility information for deciding on the efficient issue-groups.

Finally, we demonstrate that our protocol, based on issue-groups, has a higher optimality rate than previous efforts, and discuss the impact on the optimality of the negotiation outcomes. In addition, we analyze the clustering parts of our proposed protocol. Especially, we analyze the effectiveness between the clustering parameter and the results of issue-grouping.

The remainder of this paper is organized as follows. First, we describe a model of nonlinear multi-issue negotiation and utility functions, a measure for assessing the degree of issue interdependency, and the structure of interdependency graph based on real-life negotiation. Second, we present a technique for finding issue sub-groups, and propose a protocol that uses this information to enable more scalable negotiations. Third, we present the experimental results. Finally, we describe related works and draw conclusions.

## 2. NEGOTIATION WITH NONLINEAR UTILITY FUNCTIONS

### 2.1. Preliminaries

We consider the situation where  $N$  agents ( $a_1, \dots, a_N$ ) want to reach an agreement with a mediator who manages the negotiation from a man-in-the-middle position. There are  $M$  issues ( $i_1, \dots, i_M$ ) to be negotiated. The number of issues represents the number of dimen-

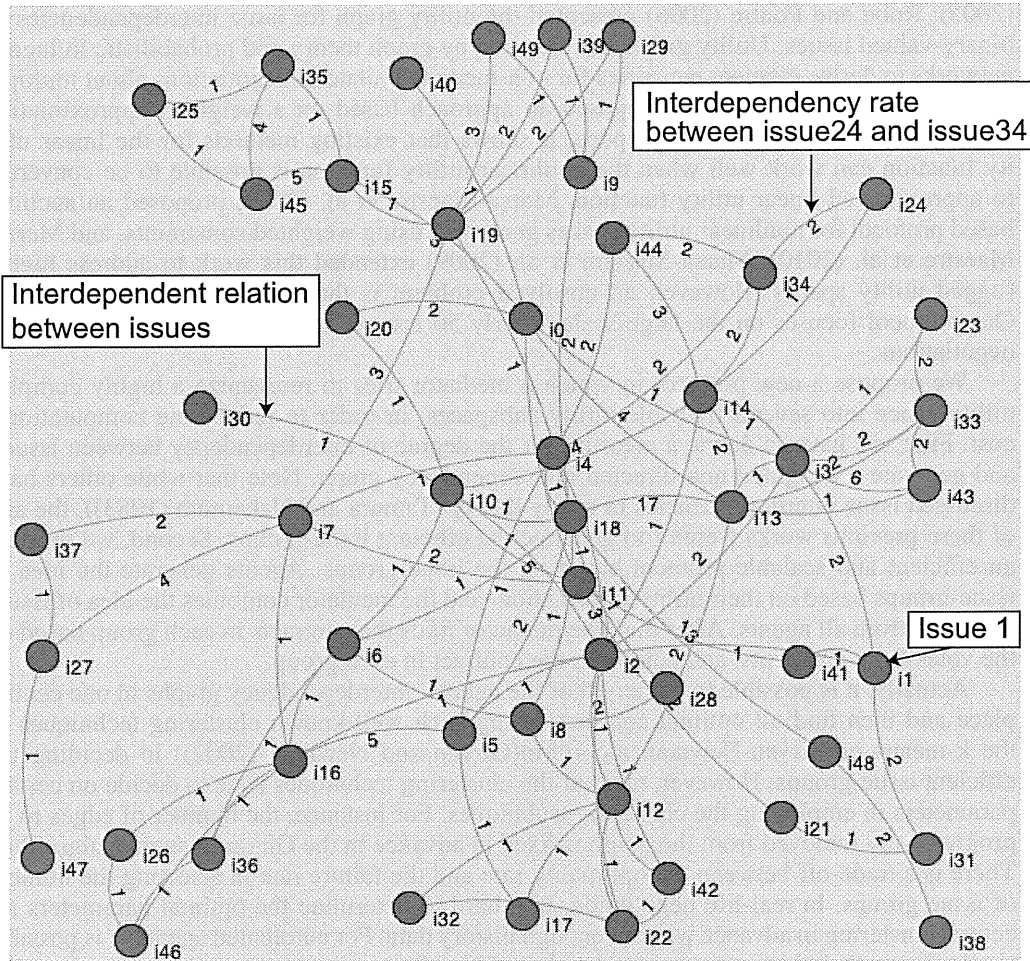


FIGURE 1. Interdependency Graph (50 issues)

sions in the utility space. The issues are shared: all agents are potentially interested in the values for all  $M$  issues. A contract is represented by a vector of values  $\vec{s} = (s_1, \dots, s_M)$ . Each issue  $s_j$  has a value drawn from the domain of integers  $[0, X]$ , i.e.,  $s_j \in \{0, 1, \dots, X\} (1 \leq j \leq M)$ .<sup>1</sup>

An agent’s utility function, in our formulation, is described in terms of constraints. There are  $l$  constraints,  $c_k \in C$ . Each constraint represents a region in the contract space with one or more dimensions and an associated utility value. In addition,  $c_k$  has value  $w_a(c_k, \vec{s})$  if and only if it is satisfied by contract  $\vec{s}$ . Function  $\delta_a(c_k, i_j)$  is a region of  $i_j$  in  $c_k$ , and  $\delta_a(c_k, i_j)$  is  $\emptyset$  if  $c_k$  doesn’t have no relationship to  $i_j$ . Every agent has its own, typically unique, set of constraints.

An agent’s utility for contract  $\vec{s}$  is defined as the sum of the utility for all the constraints it satisfies, i.e., as  $u_a(\vec{s}) = \sum_{c_k \in C, \vec{s} \in x(c_k)} w_a(c_k, \vec{s})$ , where  $x(c_k)$  is a set of possible contracts (solutions) of  $c_k$ . This expression produces a “bumpy” nonlinear utility function with high

<sup>1</sup>A discrete domain can come arbitrarily close to a ‘real’ domain by increasing its size. As a practical matter, many real-world issues that are theoretically ‘real’ numbers (delivery date, cost) are discretized during negotiations.

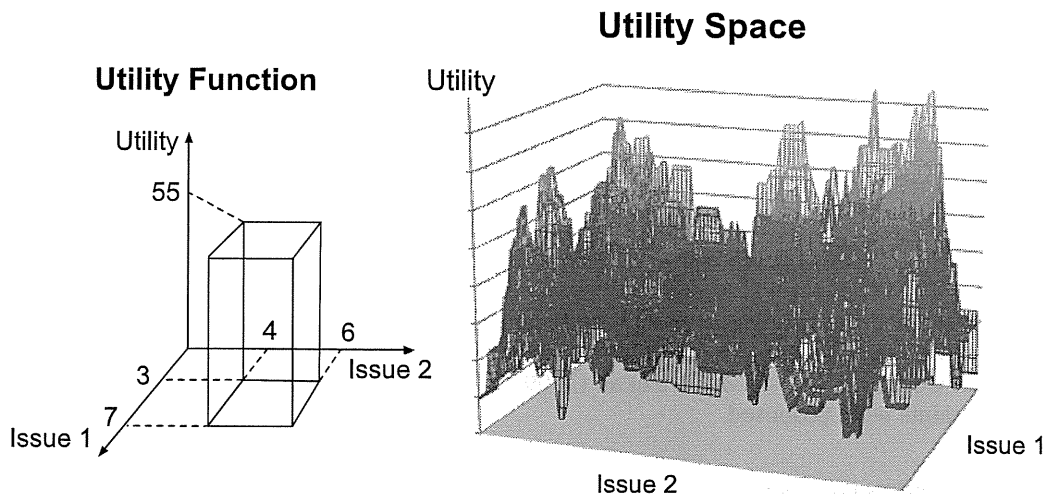


FIGURE 2. Example of a nonlinear utility space

points where many constraints are satisfied and lower regions where few or no constraints are satisfied. This represents a crucial departure from previous efforts on multi-issue negotiation, where contract utility is calculated as the weighted sum of the utilities for individual issues, producing utility functions shaped like flat hyperplanes with a single optimum.

Figure 2 shows an example of a utility space generated via a collection of binary constraints involving Issues 1 and 2. In addition, the number of terms is two. The example, which has a value of 55, holds if the value for Issue 1 is in the range [3, 7] and the value for Issue 2 is in the range [4, 6]. The utility function is highly nonlinear with many hills and valleys.

This constraint-based utility function representation allows us to capture the issue interdependencies common in real-world negotiations. The constraint in Figure 2, for example, captures the fact that a value of 4 is desirable for issue 1 if issue 2 has the value 4, 5 or 6. Note, however, that this representation is also capable of capturing linear utility functions as a special case (they can be captured as a series of unary constraints). A negotiation protocol for complex contracts can, therefore, handle linear contract negotiations.

The objective function for our protocol can be described as follows:

$$\arg \max_{\vec{s}} \sum_{a \in N} u_a(\vec{s}). \quad (1)$$

$$\arg \max_{\vec{s}} u_a(\vec{s}), \quad (a = 1, \dots, N). \quad (2)$$

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

Of course, it is theoretically possible to gather all of the individual agents' utility functions in one central place and then find all optimal contracts using such well-known nonlinear optimization techniques as simulated annealing or evolutionary algorithms. However, we do not employ such centralized methods for negotiation purposes because we assume, as is common in negotiation contexts, that agents prefer not to share their utility functions with each other in order to preserve a competitive edge.

This constraint-based utility function representation has been proposed in Ito et al. (2007). It allows us to capture the issue interdependencies common in real-world negotiations. It was

TABLE 1. Utility function for an agent: ID means the id number of every constraints.  $[a, b]$  means that the agent has a value of the utility if the value for the Issue is in the range of  $a$  and  $b$ . \* means any value

ID	Issue1	Issue2	Issue3	Issue4	Utility
1	[2, 4]	*	[4,6]	*	20
2	*	5	[3,7]	[1,6]	40
3	[3,8]	*	*	*	25
4	4	[2,7]	9	[4,5]	50

also assumed that many real-world utility functions are more complex than this, involving more than two issues as well as higher-order (e.g. trinary and quaternary) constraints. In recent work (e.g. Marsa-Maestre et al. (2009); Marsá-Maestre et al. (2010)), several types of constraints were proposed.

## 2.2. Interdependency among Issues

An issue interdependency for multi-issue negotiations is defined as follows. If there is a constraint between issue  $X$  ( $i_X$ ) and issue  $Y$  ( $i_Y$ ), then we assume  $i_X$  and  $i_Y$  are interdependent. If, for example, an agent has a binary constraint between issue 1 and issue 3, those issues are interdependent for that agent - see Table 1.

The strength of issue interdependency is measured by the *interdependency rate*. We define a measure for the interdependency between *issue*  $i_j$  and *issue*  $i_{jj}$  for agent  $a$ :

$$D_a(i_j, i_{jj}) = \#\{c_k | \delta_a(c_k, i_j) \neq \emptyset \wedge \delta_a(c_k, i_{jj}) \neq \emptyset\}.$$

This measures the number of constraints that inter-relate the two issues.

The agents capture issue interdependency information as an interdependency graph. An interdependency graph is represented as a weighted non-directed graph, in which a node represents an issue, an edge represents the interdependency between issues, and the weight of an edge represents the interdependency rate between the issues. An interdependency graph is thus formally defined as:

$$G(P, E, w) : P = \{1, 2, \dots, |I|\}(\text{finite set}), \\ E \subset \{\{x, y\} | x, y \in P\}, w : E \rightarrow R.$$

Figure 1 shows an example of an interdependency graph. The interdependency graph can have the hyper-edges because the hyper-edges are a combination of the binary-edges. For example, a trinary constraint between  $i_1, i_2$  and  $i_4$  can be represented as the combination of the binary edges between  $i_1$  and  $i_2, i_1$  and  $i_4, i_2$  and  $i_4$ .

Figure 3 shows what the interdependency graph consists of in an agent. The method of determining the interdependency between issues is as follows.

- (Step 1) Small issue-groups are generated by connecting a part of the issues randomly.
- (Step 2) The interface issues are decided randomly among issues in each issue-group. The interface issues are for connecting other small issue-groups. In small issue-groups, only the interface issues can connect to other issue-groups.
- (Step 3) Each issue-group connects to other small issue-groups. Specifically, all combinations of each issue-group are searched for, and it is decided whether connection or disconnection according to the possibility of generating connections between the small issue-groups. We call the possibility the possibility of generating connections “the possibility of connecting to other issue-groups.”

Note that in negotiations with multiple *independent* issues, we can find the optimal



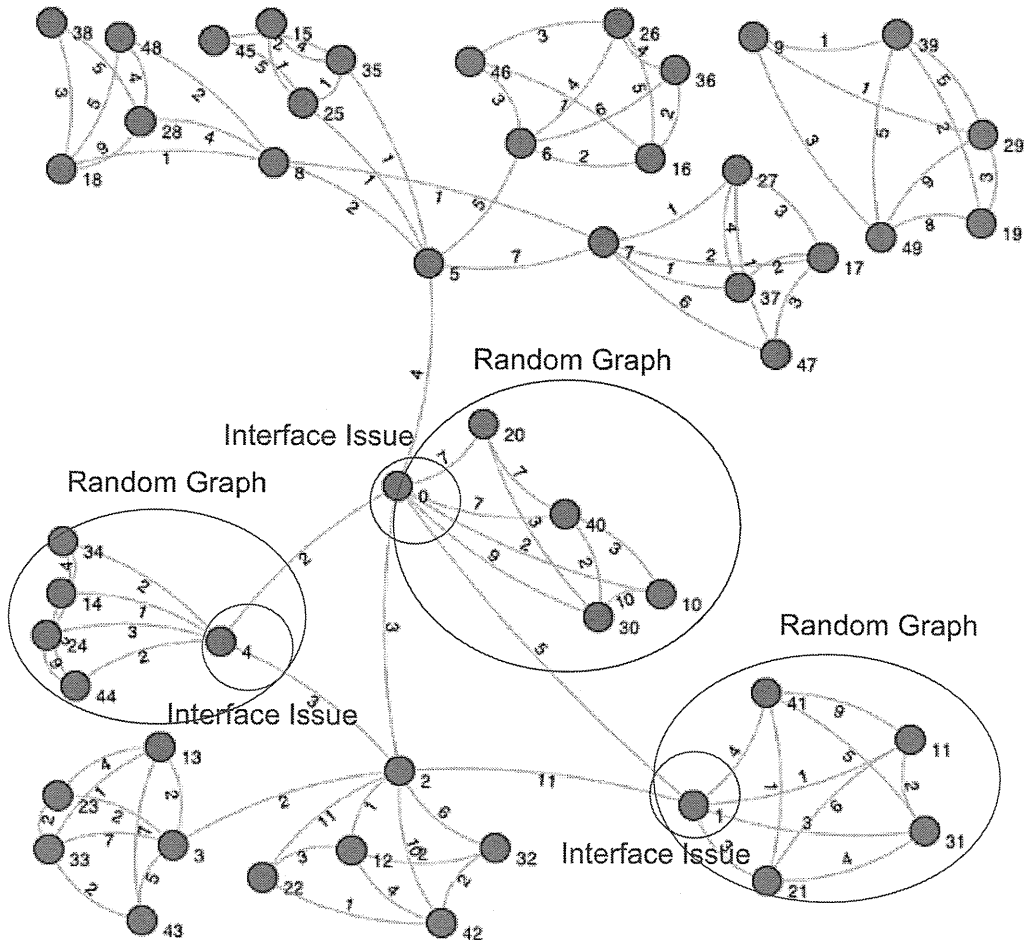


FIGURE 3. Method of determining interdependency graph

value for each issue in isolation to quickly find a globally optimal negotiation outcome. In negotiation with multiple *interdependent* issues, however, the mediator can't treat issues independently because the utility of a choice for one issue is potentially influenced by the choices made for other issues. Figure 4 shows the relationship between issue interdependency and negotiation optimality in an example with interdependent issues. In figure 4, we ran an exhaustive social welfare optimizer for each issue independently, as well as for all possible issue combinations. The number of agents is four, and the domain per issue is five. The linear utility function (independent cases) is generated by  $u_a(x) = k * x + c$  (where  $x$  is the value for that issue,  $k$  and  $c$  are constants, and  $a$  is the agent). The nonlinear function is generated by some multi-dimensional constraints. If the mediator ignores the issue interdependencies (i.e. finds optima for each issue in isolation), optimality declines rapidly as the number of issues increases. This means that the mediator must account for issue interdependencies in order to find high-quality solutions. However, if the negotiation protocol tries to do so by exhaustively considering all issue-value combinations, it quickly encounters intractable computational costs. If we have, for example, only 10 issues with 10 possible values per issue, this produces a space of  $10^{10}$  (10 billion) possible contracts, which

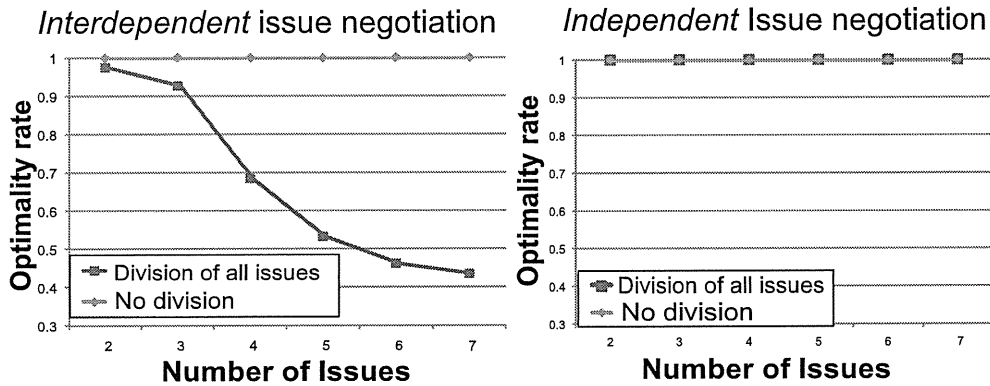


FIGURE 4. Relationship of interdependency and optimality rate with nonlinear utility function

TABLE 2. Votes and numeric values from agents

Votes	Numeric value
Accept	2
Weakly Accept	1
Weakly Reject	-1
Reject	-2

TABLE 3. Votes and utility in agents

$\frac{(\text{Utility of next situation}) - (\text{Utility of present situation})}{X_1 \sim 0 \sim X_1-1}$	Vote
$X_2 \sim -1$	Accept
$\sim X_2-1$	Weakly Accept
	Weakly Reject
	Reject

( $X_1, X_2$  are arbitrary integer numbers.)

is too large to evaluate exhaustively. Negotiation with multiple interdependent issues thus introduces a difficult tradeoff between optimality and computational cost.

### 3. NEGOTIATION PROTOCOL BASED ON ISSUE INTERDEPENDENCY

#### 3.1. Efficient Negotiation Protocol based on Issue-groups

Our proposed negotiation protocol works as follows. A mediator gathers ideas of issue-grouping from agents, identifies issue sub-groups by combining the ideas of issue-groups, and then uses that information to guide the search for a final agreement. In fact, we apply the concept of simulated annealing techniques(Klein et al. (2003)) in our negotiation protocol. By applying the concept of issue-grouping with the simulated annealing approach, we can propose a highly scalable and efficient protocol. We describe the details below.

**[Step 1: Analyzing issue interdependency]** Each agent analyzes issue interdependency in its own utility space by analyzing all constraints, and generates an interdependency graph. After that, each agent generates his/her own idea of issue-grouping using the Girvan-

Newman algorithm(Girvan and Newman (2002)), which is for computing clusters in weighted non-direct graphs based on edge betweenness. The edge betweenness shows the weighted shortest path in our protocol. Running time of this algorithm is  $O(kmn)$ , where  $k$  is the number of edges to remove,  $m$  is the total number of edges, and  $n$  is the total number of vertices.

**[Step 2: Grouping issues]** In this step, the mediator combines the ideas of issue-grouping submitted by each agent. The mediator employs the breadth-first search to generate the combined social issue-groups. If every issue-groups submitted by all agents have crossover parts, the mediator generates the union of sets of issue-groups from every agents (line 6~9 in Algorithm 1). For simple example, agent 1 submits the idea  $A_1 = \{i_1, i_2\}, \{i_3, i_4, i_5\}, \{i_0, i_6\}$  and agent 2 submits the idea  $A_2 = \{i_1, i_2, i_6\}, \{i_3, i_4\}, \{i_0\}, \{i_5\}$  when the number of issues is seven.  $\{i_1, i_2\}$  means that  $i_1$  and  $i_2$  are in a same group, and  $A_1$  is the idea of issue-groups submitted by *Agent 1*. The mediator combines  $A_1$  with  $A_2$ , and decides the issue-groups:  $A_1 \cup A_2 = \{i_0, i_1, i_2, i_6\}, \{i_3, i_4, i_5\}$ . Algorithm1 shows the details of combining the idea of issue-grouping from each agent.

---

**Algorithm 1** Combine\_IssueGroups(G)
 

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*Ag*: A set of agents, *G*: A set of issue-groups of each agent

( $G = \{G_0, G_1, \dots, G_n\}$ , a set of issue-groups from agent  $i$  is  $G_i = \{g_{i,0}, g_{i,1}, \dots, g_{i,m_i}\}$ )

```

1:  $SG := G_0, i := 1$ 
2: while  $i < |Ag|$  do
3:    $SG' := \emptyset$ 
4:   for  $s \in SG$  do
5:     for  $g_{i,j} \in G_i$  do
6:        $s' := s \cap g_{i,j}$ 
7:       if  $s' \neq \phi$  then
8:          $SG' := s \cup g_{i,j}$ 
9:       end if
10:       $SG := SG', i := i + 1$ 
11:    end for
12:  end for
13: end while

```

---

Theoretically possible to gather all the individual agents' interdependency graph into one central place and then find all optimal contracts using such well-known nonlinear optimization techniques like the k-means or Girvan-Newman algorithm, however, most of the clustering technique have to decide some parameters or the number of issue-groups previously. For instance, the number of edges to be progressively removed from the graph is fixed previously in Girvan-Newman algorithm. Also, there is a trade-off between the optimality rate and the failure rate in selecting the number of issue groups. In real life negotiation, it is hard to decide the optimal parameters previously without enough history data. In our approach, the mediator can recognize the efficient number of issue-groups because the agents in real life have some knowledge in their utility spaces. Therefore, the mediator can recognize the efficient number of issue-groups by combining the all agents' knowledge. In addition, the lack of knowledge of each agent is compensated based on a collective intelligence theory.

Algorithm 1 may not find the efficient grouping after merging because it sometimes generates giants issue-groups. However, we believe that all agents have a similar interdependent graph in real life, therefore, our algorithm can usually work well with avoiding one giant component.

In addition, Agents are at risk of making an agreement that is not optimal for themselves by dividing interdependent issues. In other words, there is the possibility of making a low utility agreement by ignoring the interdependency of some issues. However, agents can make a better agreement in this protocol because the mediator identifies the issue-groups based on the interdependency rates.

**[Step 3: Finding the Solutions]** We find the solutions based on simulated annealing techniques (Klein et al. (2003)) in order to find the optimal contract in each issue-group. The details of algorithm 2 are as follows. The mediator proposes a contract that is initially generated randomly (line 1 in Algorithm 2). Each agent then votes to accept, weakly accept, weakly reject or reject the next contract. When the mediator receives these votes, it maps them into numeric values and adds them together according to Table 2. If the sum of the numeric values from all agents is a positive value or zero, the mediator mutates the contract (by randomly flipping one of the issue values) and the process is repeated. If the sum of the numeric values from all agents is a negative value, a mutation of the most recent mutually acceptable contract is proposed instead (line 7~16 in Algorithm 2). Each agent votes based on the utility space in each issue-group. In our protocol, the agents decide based on the difference between the utility of the present situation and the utility of the next situation in each issue-group. When the agents vote, it maps the differences into accept, weakly accept, weakly reject and reject according to Table 3.

This step is based on the simulated annealing technique (Russell and Norvig (2002)). Each simulated annealing is fixed at a virtual *temperature*  $T$ , such that it will accept contracts worse than the last one accepted with the probability  $P(\text{accept}) = \min(1, e^{-\Delta U/T})$ , where  $\Delta U$  is the utility change between the contracts (line 8~15 in Algorithm 2). In other words, the higher the virtual temperature, and the smaller the utility decrement, the greater the probability that the inferior contract will be accepted.

---

**Algorithm 2** Simulated\_Annealing()

---

$\bar{Value}(N)$ : the sum of the numeric values mapped from votes to  $N$  from all agents

```

1:  $S :=$  initial solution (set randomly)
2: for  $t = 1$  to  $\infty$  do
3:    $T := \text{schedule}(t)$ 
4:   if  $T = 0$  then
5:     return  $current$ 
6:   end if
7:    $next :=$  a randomly selected successor of  $current$ 
8:   if  $next.Value \geq 0$  then
9:      $\Delta E := next.Value - current.Value$ 
10:    if  $\Delta E > 0$  then
11:       $current := next$ 
12:    else
13:       $current := next$  only with probability  $e^{\Delta E/T}$ 
14:    end if
15:  end if
16: end for

```

---

### 3.2. Incentives for Truthful Voting

Any voting scheme introduces the potential for strategic non-truthful voting by the agents, and our method is no exception. For example, one of the agents always votes truth-

fully, while the other exaggerates so that its votes are always “strong.” One might expect that this would bias negotiation outcomes to favor the exaggerator.

As we can see, even though exaggerating votes has substantial negative impact on social welfare, agents are individually incentivized to exaggerate, thus re-creating the prisoner’s dilemma game. The underlying problem is simple: exaggerating agents are able to induce the mediator to accept all the proposals that are advantageous to them, while preventing the other agents from doing the same. What we need, therefore, is an enhancement of the negotiation protocol that incentivizes truthful voting, preserving equity and maximizing social welfare.

Simply placing a limit on the number of strong votes each agent can use does not work. If the limit is too low, we effectively lose the benefit of vote weight information and get the lower social welfare values that result. If the strong vote limit is high enough to avoid this, then all an exaggerator has to do is save all of its strong votes until the end of the negotiation, at which point it can drag the mediator towards making a series of proposals that are inequitably favorable to it. The idea of the truthful voting is beyond a topic of this paper. Addressing the proof of truthful voting or concrete example of is one of the important future work in our study.

## 4. EXPERIMENTAL RESULTS

### 4.1. Setting

We conducted several experiments to evaluate our approach. We employed the common testbed data structure based on XML proposed in Fujita et al. (2009). A common testbed creating tool based on XML mainly covers the utility functions based on constraints. This paper proposed a testbed generating tool that inputs configuration data and outputs XML formatted files that represent agent utility spaces. Also, this paper defined the agent’s utility space information based on XML tags. By defining the testbed data as XMLs, users can easily read the files and change the data structure.

In each experiment, we ran 100 negotiations. The following parameters were used. The domain for the issue values was  $[0, 9]$ . The number of constraints was 10 unary constraints, 5 binary constraints, 5 trinary constraints, and so on. (a unary constraint relates to one issue, a binary constraint relates to two issues, etc). The maximum value for a constraint was  $100 \times (\text{Number of Issues})$ . Constraints that satisfy many issues have, on average, larger utility, which seems reasonable for many domains. In the meeting-scheduling domain, for example, higher order constraints concern more people than lower order constraints, so they are more important. The maximum width for a constraint was 7. The following constraints would all be valid: Issue 1 =  $[2, 6]$ , Issue 3 =  $[2, 9]$ . The number of agents is 10 in these experiments. The issues related to the constraint are decided based on the structure of interdependency graph in Section 2.2

The number of small issue-groups is ten in these experiments. Interdependency graphs are generated by the following two types based on the testbed: “1) Sparse Connection” and “2) Dense Connection.” Actually, the difference between the two types is only the possibility of connecting to other issue-groups: the possibility of “1) Sparse Connection” is 0.4, and the possibility of “2) Dense Connection” is 0.8 written in Section 2.2. Figure 5 shows the examples of interdependency graphs and the distribution between the number of issues and the sum of the weight of connections the node has to other issues in two cases. As plotted graphs in Figure 5 show, the property of “1) Sparse Connection” is closer to the scale-free distribution, in which the number of links originating from a given node exhibits a power law distribution, than that of “2) Dense connection.” In other words, the property of “2) Dense connection” is closer to the distribution of random graphs. The highest point in “2) Dense connection” is higher and more tightly-packed than that in “1) Sparse Connection.”

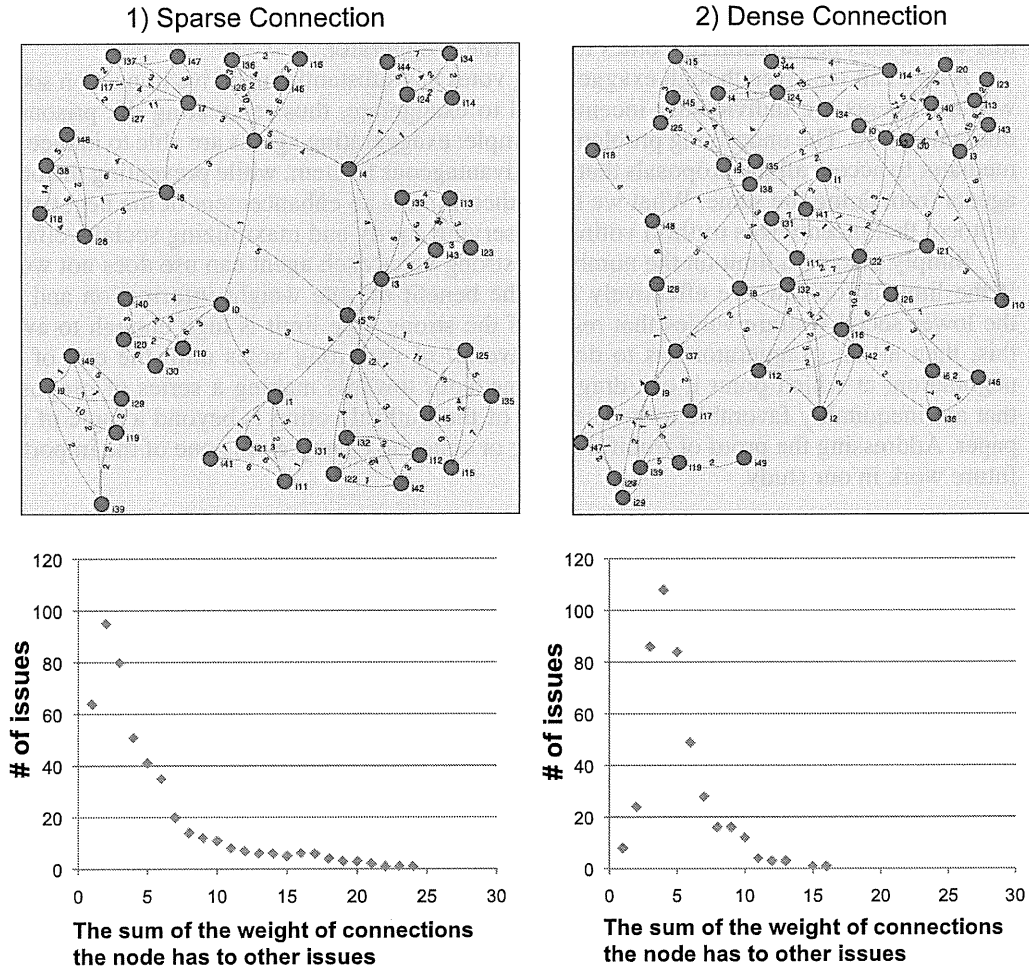


FIGURE 5. The Sparse and Dense Connection

We compare the following methods. “(A) SA based on Vote” is a method proposed in Klein et al. (2003), using a simulated annealing based on the agents’ votes without generating issue-groups. “(B) Issue-Grouping based on vote” is the issue-group protocol proposed in this paper, using a simulated annealing based on the agents’ votes we described above. “(C) Issue-Grouping with Maximizing” runs SA with several random starting points and pick the best solution for finding the social welfare utility functions with issue-grouping. The aim of employing this method is to evaluate the self-performance of issue-grouping.

The parameters for simulated annealing in (A) are as follows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 500 iterations. The initial contract for each SA run is randomly selected. The parameters for simulated annealing in each group in (B) are as follows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 50 iterations in each group. The initial contract for each SA run is randomly selected. The parameters for simulated annealing in each group in (C) are as follows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 100 iterations in each group. The initial contract for each SA run is randomly selected. The number of edges to be progressively removed from the graph (clustering parameter) for all agents is 6.

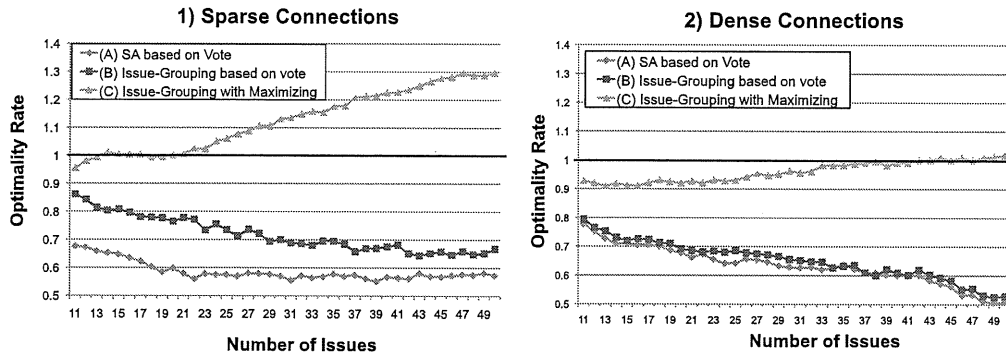


FIGURE 6. Comparison of optimality when the number of issues changes

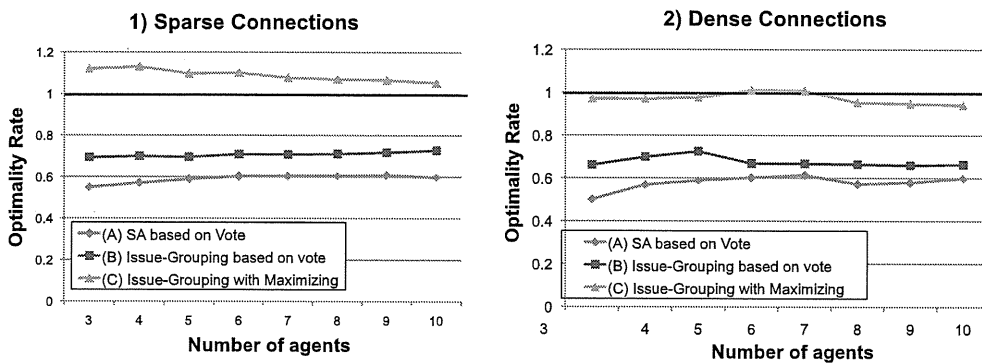


FIGURE 7. Comparison of optimality when the number of agents changes

We used simulated annealing (SA) (Russell and Norvig (2002)) gathering all the individual agents' utility functions into one central place in order to approximate the optimum social welfare for each negotiation test run. Exhaustive search was not a viable option because it becomes computationally intractable as the number of issues grows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 2,500 iterations. The initial contract for each SA run is randomly selected. The optimality value for a negotiation run, in our experiments, is defined as  $(social\ welfare\ achieved\ by\ each\ protocol) / (social\ welfare\ calculated\ by\ SA)$ .

Our code is implemented in Java 2 (1.6) and run on a core 2-duo CPU with 2.0 GB memory on Mac OS X (10.6).

#### 4.2. Experimental Results

Figure 6 and 7 compare the optimality rate in the sparse connection and dense connection cases. "(B) Issue-Grouping based on vote" proposed in this paper achieves higher optimality than "(A) SA based on vote," which means that the issue-grouping method achieves efficient and scalable negotiation. "(B) Issue-Grouping based on vote" decreases the optimality rate as the number of issues increases. The main reason is that the complexity of negotiation is higher as the number of issues becomes larger. The optimality rates of "(C) Issue-Grouping with Maximizing" is more than one when the number of issues is more than 20. This means that the method with issue-grouping can find high quality solutions than the one without

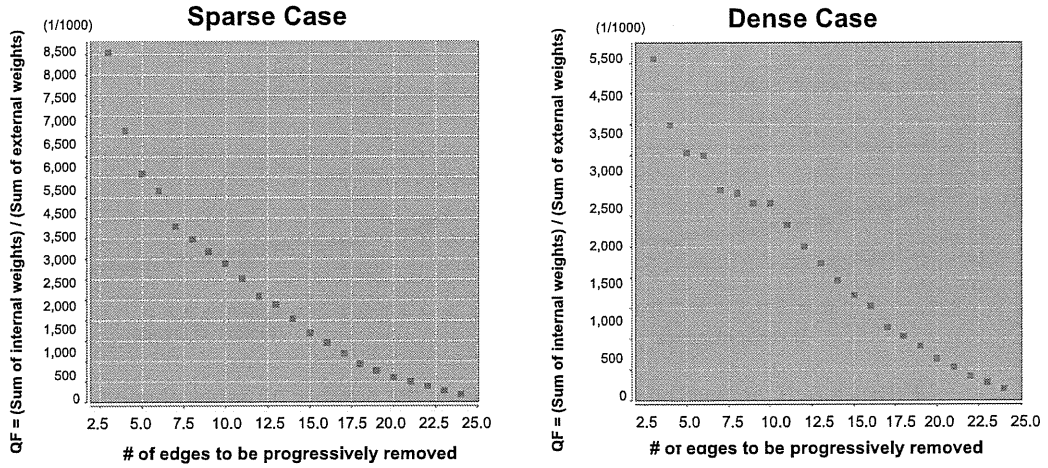


FIGURE 8. Number of edges to be progressively removed (Clustering parameter) v.s. QF

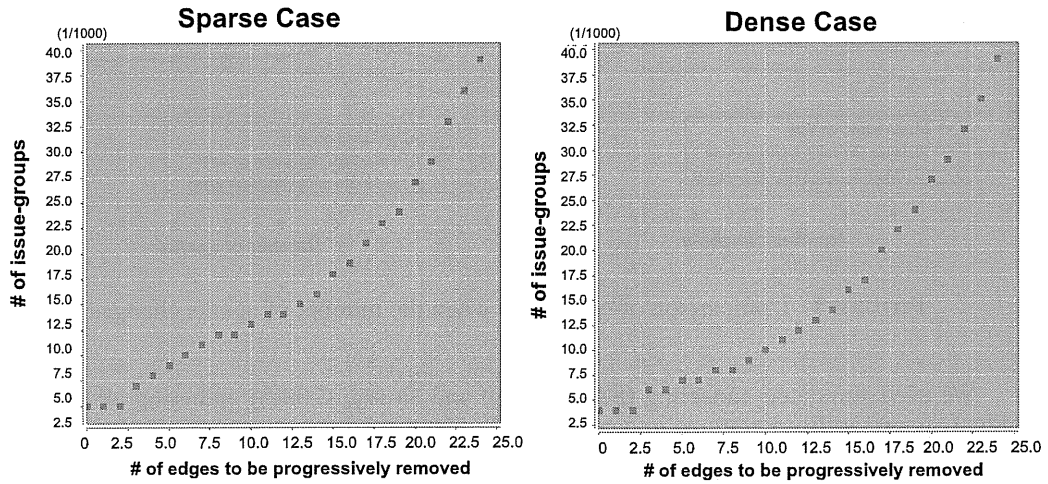


FIGURE 9. Number of edges to be progressively removed (Clustering parameter) v.s. The number of issue-groups

issue-grouping. The optimality rate is almost same when the number of agents changes as Figure 7 showing.

The optimality rates of “(B) Issue-Grouping based on vote” in “(1) Sparse Connections” are lower compared with those in the “(2) Dense Connections.” This is because the issue-grouping method proposed in this paper can achieve high optimality if the number of ignored interdependencies is low; In fact, there can be more independent issues or small interdependent issues in “(1) Sparse Connections.” In real-world negotiation, a situation like sparse connection is more common.

Figure 8 shows a scatter diagram (vertical: QF, axis: number of edges to be progressively removed) when the number of agents is 3 and 20.  $QF = (\text{Sum of internal weights of edges in each issue-group}) / (\text{Sum of external weights of edges in each issue-group})$ . The ignored weights of edges in generating issue-groups are fewer as QF increases. The axis line means the parameter of generating issue-groups in all agents. The number of issues is 500 in the



“1) sparse connection” case. The number of edges to be progressively removed is clustering parameter in the Girvan-Newman algorithm (Girvan and Newman (2002)).

As Figure 8 shows, QF becomes smaller when the number of edges to be progressively removed is larger. This is because the number of issue-groups generated by each agent is higher as the number of edges to be progressively removed becomes larger as Figure 9 showing. The rapid decrease sometimes happens as the number of edges to be progressively removed increases. These points are good parameters for decomposing the issue-groups. In real life, the utility of agents contains an adequate idea of issue-groups, and agents can determine the optimal idea of issue-groups by analyzing the utility spaces.

## 5. RELATED WORK

Even though negotiation seems to involve a straightforward distributed constraint optimization problem (Greenstadt et al. (2006); Maheswaran et al. (2005)), we have been unable to exploit existing work on high-efficiency constraint optimizers. Such solvers attempt to find the solutions that maximize the weights of the satisfied constraints, but do not account for the fact that the final solution must satisfy at least one constraint *from every agent*.

Lin and Chou (2003) explored a range of protocols based on mutation and selection on binary contracts. This paper does not describe what kind of utility function is used, nor does it present any experimental analyses, so it remains unclear whether this strategy enables sufficient exploration of utility space.

Klein et al. (2003) presented a protocol applied with near optimal results to medium-sized bilateral negotiations with binary dependencies, but was not applied to multilateral negotiations and higher order dependencies.

A bidding-based protocol was proposed by Ito et al. (2007). Agents generate bids by finding high regions in their own utility functions, and the mediator finds the optimum combination of submitted bids from the agents. However, the scalability of this protocol is limited, and the failure rate of making agreements is too high. By Fujita et al. (2008), a representative-based protocol for reducing the computational cost was proposed based on the bidding-based protocol. In this method, the scalability of agents was improved; however, the scalability of issues was not sufficient.

Marsa-Maestre et al. (2009); Marsá-Maestre et al. (2010); Marsa-Maestre et al. (2009) proposed an auction-based protocol for nonlinear utility spaces generated using weighted constraints, and proposed a set of decision mechanisms for the bidding and deal identification steps of the protocol. They proposed the use of a quality factor to balance utility and deal probability in the negotiation process. This quality factor is used to bias bid generation and deal identification, taking into account the agents' attitudes toward risk. The scalability of the number of issues is still a problem in these works.

Hindriks et al. (2006) proposed an approach based on a weighted approximation technique to simplify the utility space. The resulting approximated utility function without dependencies can be handled by negotiation algorithms that can efficiently deal with independent multiple issues, and has a polynomial time complexity. Our protocol can find an optimal agreement point if agents don't have in common the expected negotiation outcome.

Fatima et al. (2007a,b) proposed bilateral multi-issue negotiations with time constraints. This method can find approximate equilibrium in polynomial time where the utility function is nonlinear. However, this paper focused on bilateral multi-issue negotiations. Our protocol focuses on multilateral negotiations.

Zhang (2009) presents an axiomatic analysis of negotiation problems within task-oriented domains (TOD). In this paper, three classical bargaining solutions (Nash solution, Egalitarian solution, Kalai-Smorodinsky solution) coincide when they are applied to a TOD with mixed

deals but diverge if their outcomes are restricted to pure deals. However, this paper focuses on the bilateral negotiations.

Jonker et al. (2007) proposed a negotiation model called ABMP that can be characterized as cooperative one-to-one multi-criteria negotiation in which the privacy of both parties is protected as much as desired. This paper models a mechanism in which agents are able to use any amount of incomplete preference information revealed by the negotiation partner in order to improve the efficiency of the reached agreements. Moreover, this paper shows that the outcome of such a negotiation can be further improved by incorporating a “guessing” heuristic, by which an agent uses the history of the opponent’s bids to predict his preferences. This paper mainly focuses on the privacy issues of the negotiation mechanisms.

Robu et al. (2005); Robu and Poutre (2006) presented the utility graph for issue interdependencies of binary-valued issues. Utility graphs are inspired by graph theory and probabilistic influence networks to derive efficient heuristics for non-mediated bilateral negotiations about multiple issues. The idea is to decompose highly non-linear utility functions in sub-utilities of clusters of inter-related items. They show how utility graphs can be used to model an opponent’s preferences. In this approach agents need prior information about the maximal structure of the utility space to be explored. However, our approach has the advantage that outcomes can be reached without any prior information and that it is not restricted to binary-valued issues.

Shew and Larson (2008) proposed multi-issue negotiation that employs a third-party as a mediator to guide agents toward equitable solutions. This framework also employs an agenda that serves as a schedule for the ordering of issue negotiation. Agendas are very interesting because agents only need to focus on a few issues. This paper also focuses on bilateral negotiations, however, this framework can apply to the negotiations among more than two agents.

Hemaissia et al. (2007); Hemaissia-Jeannin et al. (2008) proposed a negotiation protocol for the multi-lateral multi-issue negotiation in a cooperative context. This paper uses sharp recommendations to help in accelerating the search of a consensus between the cooperative agents and in finding an optimal solution. Also, this paper shows that the protocol has the sub-game perfect equilibria and these equilibria converge to the usual maximum solution. However, this paper mainly focuses on a crisis management problem.

## 6. CONCLUSION

In this paper, we proposed a new negotiation protocol, based on grouping issues, which can find high-quality agreements in interdependent issue negotiation. In this protocol, agents generate their private issue interdependency graphs, the mediator identifies the issue-groups based on ideas of issue-groups from agents, and multiple independent negotiations proceed for each issue sub-group. We demonstrated that our proposed protocol has a higher optimality rate than the method without issue-grouping.

In future work, we will conduct additional negotiation, after the concurrent sub-contract negotiations, to try to increase the satisfaction of constraints that crossed sub-contract boundaries. In addition, the asymmetry property of issues exists in real life; for example, some agents know parts of all issues. Therefore, analysis of the asymmetry property of issues based on game theory or simulation will be important. Addressing the proof of truthful voting or concrete example of is also one of the important future work in our study written in Section 3.2. The constraints in our utility space have a utility associated to them, and it is better to generate efficient issue-groups that the interdependency rate is employed to the utility of the constraints. The detailed study of the interdependency rate is also an important future works in our protocol. Finally, we can adapt Newman’s fast partition algorithm to make it

determine the clustering coefficient dynamically, without having to pre-specify a number of clusters (something like this has already been proposed for collaborative tagging research).

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