selected.

In terms of privacy, the measurement is the range of the revealed areas. If an agent reveals one point on the grid of the utility space, he loses 1 privacy unit. If he reveals 1000 points, then he loses 1000 privacy units.

We also analyze the representative selection method in our protocol. The representative selection method remains an important research point. The selection method in which agents who reveal a larger utility area are selected as representatives is called (**RAS**), and the random selection method in which representatives are randomly selected is called (**RANDOM**). To investigate the detailed effects of RAS, we assume RANDOM is the general basis for comparison.

The following are the parameters for our experiments:

- Domain for issue values: $[0, 9]$.
- Constraints: 10 unary constraints, 5 binary constraints, 5 trinary constraints, etc. (a unary constraint relates to one issue, a binary constraint relates to two issues, and so on).
- Maximum constraint value: $100 \times (number\ of\ issues)$. Constraints that satisfy many issues have on average larger weights. This seems reasonable for many domains. To schedule meetings, for example, higher order constraints concern more people than lower order constraints, so they are more important.
- Maximum constraint width: 7. The following constraints, therefore, are all valid: issue $1 = [2, 6]$, issue $3 = [2, 9]$ and issue $7 = [1, 3]$.
- Number of samples taken during random sampling: $(number\ of\ issues) \times 200$.
- Annealing schedule for sample adjustment: initial temperature 30, 30 iterations. Note that the annealer must not run too long or too 'hot' because then each sample will tend to find the global optimum instead of the peak of the optimum nearest the sampling point.
- Threshold used by agents to select what to bid starts with 900 and decreases until 200 in the threshold adjusting mechanism. The protocol without the threshold adjusting process defines the threshold as 200. The threshold is used to excise contract points with low utility.
- Amount of threshold is decreased by $100 \times (SumAr - Ar_i)/SumAr$. $SumAr$ means the sum of all agents' revealed areas. Ar_i means agent i's revealed area.
- Limitation on number of bids per agent: $\sqrt[n]{6,400,000}$ for N agents. It was only practical to run the deal identification algorithm if it explored no more than about 6,400,000 bid combinations, which implies a limit of $\sqrt[n]{6,400,000}$ bids per agent for N agents.

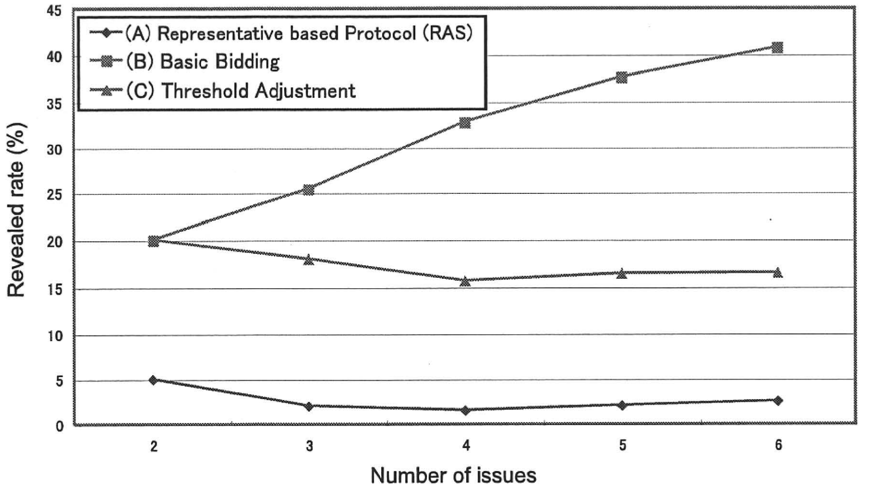

Figure 8: Revealed rate

- Number of representative agents is two in the representative based protocol.
- Number of issues is three.

In our experiments, we ran 100 negotiations in every condition. Our code was implemented in Java 2 (1.5) and run on a core 2 duo processor iMac with 1.0 GB memory on a Mac OS X 10.4 operating system.

4.2 Experimental Results

Figure 8 shows the revealed rate of three comparable protocols with three agents. (A) is the proposed protocol, which is a multi-round negotiation with the representative protocol whose selection method is RAS. (B) is the basic bidding based mechanism without threshold adjustment (explained in Section 2). (C) is the protocol with threshold adjustment.

In (B), the revealed rate increases as the number of issues increases. This means that if we do not use the threshold adjustment, agents need to reveal more of their utility space than the other protocols. On the other hand, in (A) and (C), the revealed rate decreases as the number of issues increases. When we compare (A) with (C), the revealed rate of the representative based protocol is less than basic bidding protocol with threshold adjustment for two reasons. First, the representative protocol finds solutions faster than the threshold adjustment mechanism. Second, bidding based protocol with threshold adjustment most agents need to reveal their utility space. On the other hand, only

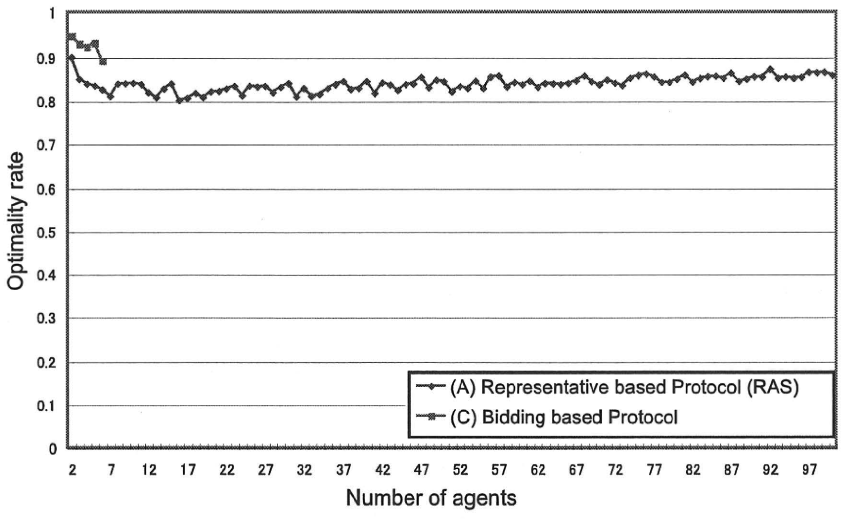

Figure 9: Scalability on number of agents

representative agents reveal their utility spaces in representative based protocol. Essentially, the representative protocol proposed in this paper drastically decreases the revealed rate compared with the other two protocols.

The next experimental results show that our negotiation protocol is sufficiently scalable on the number of agents. Figure 9 shows optimality when the number of agents ranges from 2 to 100. In this experiment, we assume agents have a shared utility area that is agreeable for them. This is because when the number of agents becomes large, finding an agreement point is quite hard using negotiation protocols and comparing optimality could be impossible. To create a common area, agents' utility spaces are randomly generated. Then a common area is randomly generated whose value is more than an agent's threshold.

The results demonstrated that optimality is more than 80% in all cases in spite of not finding solutions to 7 issues in existing work. Although high optimality came from the above common area assumption, the scalability of our new protocol is ensured by this experiment. Our proposed approach works well in single issue negotiations and multiple independent issues negotiations as well because such negotiations have lower computational complexity than multiple interdependent issues negotiations.

Figure 10 shows the failure rate for finding solutions in the three protocols. (A) is the representative based protocol and selection method RAS. (B) is the representative based protocol and selection method RANDOM. (C) is the basic bidding based mechanism without threshold adjustment explained in Section 2. Even if the number of agents increases, (A) is almost 0. On the other hand, (C) shows a drastic increase over five agents because the bid limitation starts when

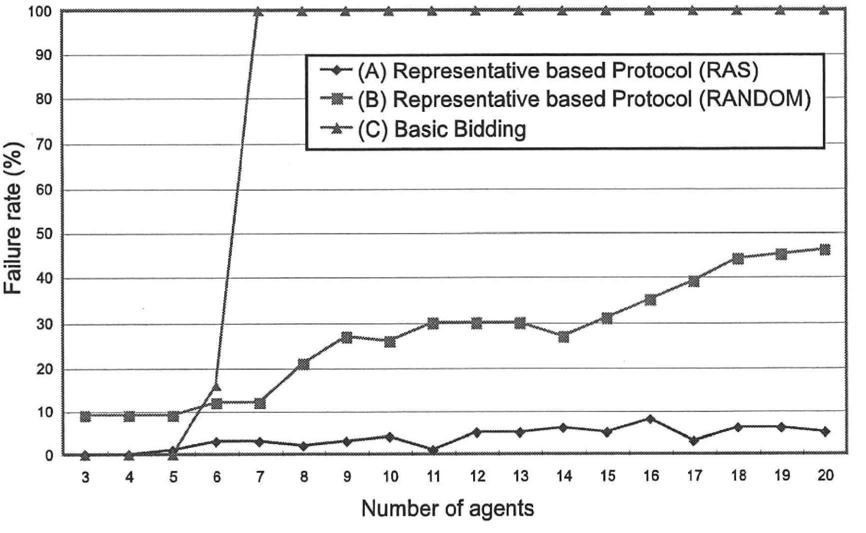

Figure 10: Failure rate

there are five agents. Also, for more than five agents, the existing mechanism fails to find solutions. Furthermore, (A) and (B) show that RAS has a lower failure rate than RANDOM. Thus, the representative protocol with selection method RAS has better failure rates.

Figure 11 compares optimality rates among "(A) Representative based Protocol (RAS)," "(B) Representative based Protocol (RANDOM)," and !H(C) Basic Bidding." Comparing (A) and (C), the difference of optimality is small, around 0.05 at most. This difference reflects that since the representative based protocol tends to find solutions at an early stage, it might miss better solutions. Furthermore, (A) and (B) show that RAS has higher optimality than RANDOM because more solutions are found in representatives with large revealed areas. Thus, the representative protocol with selection method RAS has better optimality rates

Figure 12 shows the variance of the utility value per agent. By this experiment, we can recognize the satisfactory rate of individual agents. The variance of the utility per agent is critical in bargaining theory because some experimental results suggest that fairness influences decision-making per agent ([10] etc.). (C) is better than (A) because the utility of the representatives is higher than that of the unrepresentatives in the representative protocols. However, all agents definitely satisfy the agreement points because their utility values are higher than their reservation value.

Figure 13 shows the optimality and failure rates on the number of representative agents. In this experiment, there are seven agents and three issues.

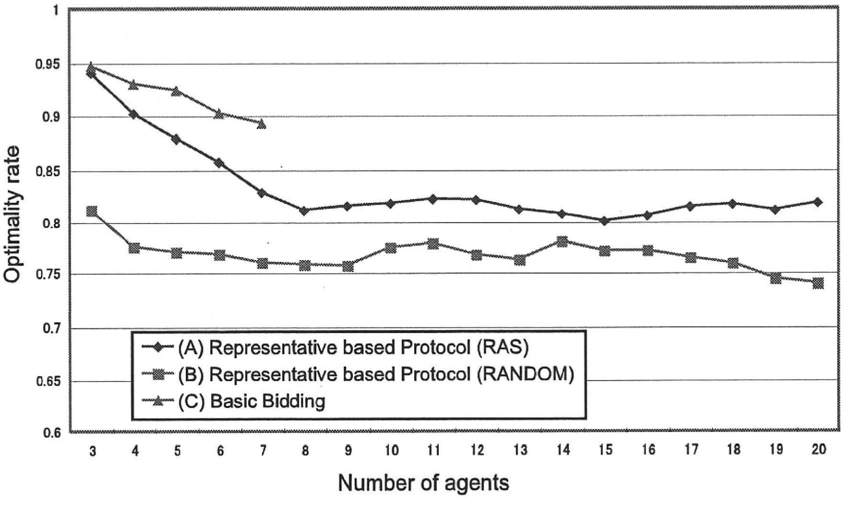

Figure 11: Comparisons of optimality

Figure 13 (A) shows that optimality increases when the number of representative agents increases. Even if agents have low utilities, they tend to be persuaded by representative agents when the number of representatives is small. Figure 13 (B) shows that the failure rate sharply increases when the number of representative agents exceeds, which is where the bid limitation starts.

5 Related Work

Most previous work on multi-issue negotiation [3, 4, 5] has addressed only linear utilities. Recently some researchers have been focusing on more complex and non-linear utilities. [11] does not describe what kind of utility function is used, nor does it present any experimental analyses. It is therefore unclear whether this strategy enables sufficient exploration of the utility space. [12] presents an approach based on constraint relaxation. However, there is no experimental analysis and this paper presents only a small toy problem with 27 contracts. [13] modeled a negotiation problem as a distributed constraint optimization problem. This paper claims the proposed algorithm is optimal, but does not discuss computational complexity and provides only a single small-scale example.

[14] presented a protocol, based on a simulated-annealing mediator, that was applied with near-optimal results to medium-sized bilateral negotiations with binary dependencies. This work is distinguished by demonstrating both scalability and high optimality values for multilateral negotiations and higher order dependencies. [15, 16] also presented a protocol for multi-issue problems for bilateral negotiations. [17, 18] presented a multi-item and multi-issue negotia-

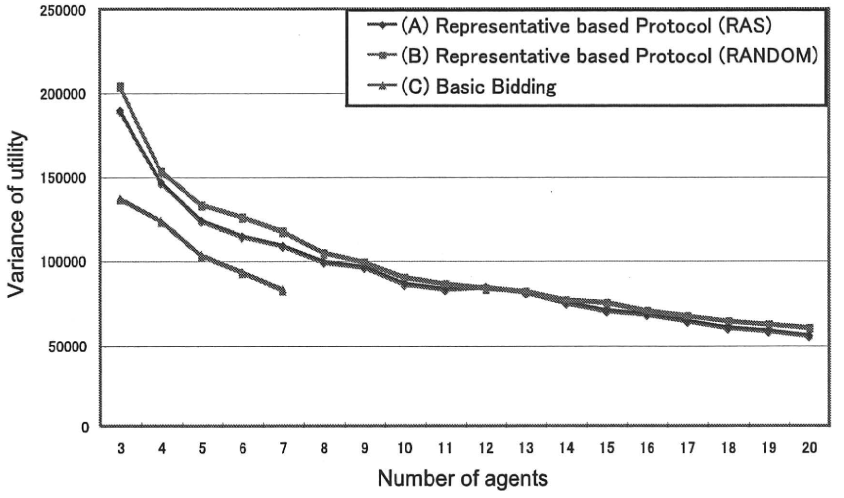

Figure 12: Comparison on variance of utility

tion protocol for bilateral negotiations in electronic commerce situations. [19] proposed bilateral multi-issue negotiations with time constraints. These studies were done from very interesting viewpoints, but focused on just bilateral trading or negotiations.

[20] proposed multi-issue negotiation that employs a third-party to act 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.

[21] proposed a checking procedure to mitigate this risk and show that by tuning this procedure's parameters, outcome deviation can be controlled. These studies reflect interesting viewpoints, but they focused on just bilateral trading or negotiations.

6 Conclusion

In this paper, we proposed a multi-round representative based protocol in very complex negotiations among software agents. The representative based protocol always reached agreements if the number of agents was large. It is important for agents to make agreements without revealing their private information during the negotiations. This proposed protocol reached an agreement while revealing as little agents' utility space as possible. The experimental results demonstrated that the representative based protocol reduced the amount of private information required for an agreement among agents, and its failure rate was almost 0. Furthermore, we compared RAS with RANDOM in the experiments. The

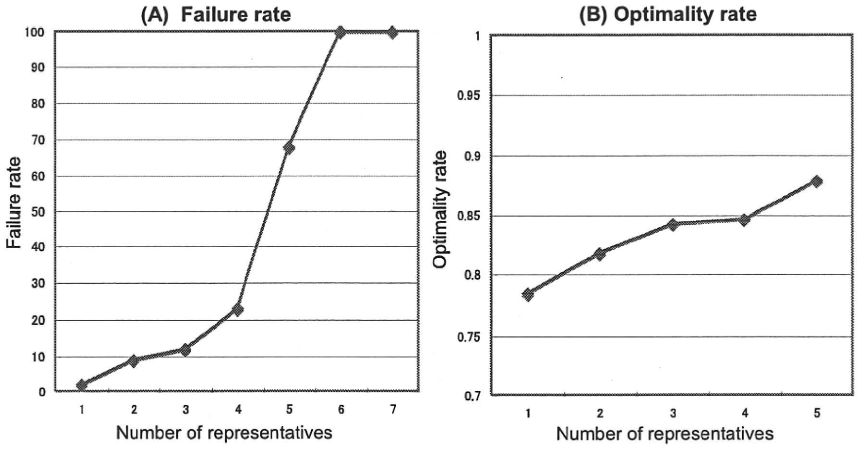

Figure 13: Optimality rate and failure rate in number of representative agents

failure rate in RAS was lower than RANDOM.

In a real parliamentary system, the representatives (in theory) have done their best to model the utility functions of the people they represent, so the solutions that satisfy the representatives are likely to be good for (the majority of) the people they represent. In the approach described in this paper, the utility functions of the representatives are purely idiosyncratic to them, so the solutions preferred by the representatives may be different from the solutions that are best for the other agents. Therefore, our approach has difficulty finding the best solution in one-shot negotiation. Changing representatives in multi-round negotiation helps support this because the possibility of selecting the best representatives in multi-round negotiation is higher than in one-shot negotiation. However, the changing mechanism proposed here is simple. Thus investigating changing mechanisms is possible future work. The effect of changing mechanisms on selecting representatives is an especially important analytic point.

Acknowledgement

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Addressing stability issues in mediated complex contract negotiations for constraint-based, non-monotonic utility spaces

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Abstract Negotiating contracts with multiple interdependent issues may yield non- monotonic, highly uncorrelated preference spaces for the participating agents. These scenarios are specially challenging because the complexity of the agents' utility functions makes traditional negotiation mechanisms not applicable. There is a number of recent research lines addressing complex negotiations in uncorrelated utility spaces. However, most of them focus on overcoming the problems imposed by the complexity of the scenario, without analyzing

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the potential consequences of the strategic behavior of the negotiating agents in the models they propose. Analyzing the dynamics of the negotiation process when agents with different strategies interact is necessary to apply these models to real, competitive environments. Specially problematic are high *price of anarchy* situations, which imply that individual rationality drives the agents towards strategies which yield low individual and social welfares. In scenarios involving highly uncorrelated utility spaces, "low social welfare" usually means that the negotiations fail, and therefore high price of anarchy situations should be avoided in the negotiation mechanisms. In our previous work, we proposed an auction-based negotiation model designed for negotiations about complex contracts when highly uncorrelated, constraint-based utility spaces are involved. This paper performs a strategy analysis of this model, revealing that the approach raises stability concerns, leading to situations with a high (or even infinite) price of anarchy. In addition, a set of techniques to solve this problem are proposed, and an experimental evaluation is performed to validate the adequacy of the proposed approaches to improve the strategic stability of the negotiation process. Finally, incentive-compatibility of the model is studied.

Keywords Automated multi-issue negotiation · Complex utility spaces · Strategy analysis

1 Introduction

Automated negotiation provides an important mechanism to reach agreements among distributed decision makers [4,42,43,71]. It has been extensively studied from the perspective of e-commerce [23,25,49,76], though it can be seen from a more general perspective as a paradigm to solve coordination and cooperation problems in complex systems [38,32], providing a mechanism for autonomous agents to reach agreements on, e.g., task allocation, resource sharing, or surplus division [15,37].

A variety of negotiation models have been proposed according to the many different parameters which may characterize a negotiation scenario [6,43]. We briefly review the key concepts about multi-attribute negotiation and the most relevant works in the field in Sect. 2.1. In the last years, there has been an increasing interest in complex negotiations [39]. Complexity of a negotiation scenario may depend on several factors, like the cardinality of the solution space, the number of negotiating agents, the number of issues under negotiation, the degree of interdependency between the issues, and structural properties of the preference landscape of the different agents, like ruggedness, modality or correlation length [80]. Specially challenging are those scenarios involving high cardinality solution spaces, since they tend to make exhaustive search in the solution space highly inefficient, and those involving highly rugged or highly uncorrelated utility spaces, since traditional negotiation approaches (mostly intended for linear or quasi-concave utility functions) cannot be applied to these scenarios. We briefly discuss utility space complexity and the techniques used to measure it in Sect. 2.2.

We can find some successful research works in the literature addressing negotiation in nonlinear utility spaces. [39] presented, as far as we are aware, the first negotiation protocol specific for complex preference spaces, based on using simulated annealing to progressively enhance an agreement between two agents. In [26], a different approach is taken, reducing the complexity of the agent's preference space by using approximations of the agents' utility functions where issue interdependency has been removed. [17] do not study the inherent complexity of agent preference spaces, but the complexity introduced in a negotiation when agent preferences change over time. We comprehensively review these and other related works in Sect. 2.3.

In our previous work [54], we proposed a mediated, auction-based protocol for nonlinear utility spaces generated using weighted constraints, such as the ones we may encounter when negotiating complex contracts with multiple, interdependent clauses [30]. We also proposed a set of decision mechanisms to generate bids at the negotiating agents and to identify feasible deals at the mediator once the bids from the negotiating agents have been received [54]. We briefly summarize the approach in Sect. 3. Experiments showed that these approaches achieve high effectiveness (measured as high optimality rates and low failure rates for the negotiations) in moderately rugged utility spaces.

In [55], we extended this work to address highly-rugged utility spaces. We proposed the use of a technique to balance utility and deal probability in the negotiation process, which we called *quality factor*. This quality factor is used to bias bid generation and deal identification taking into account the agents' attitudes (e.g. risk attitude, selfishness, willingness to cooperate). From the mechanisms we proposed to take into account quality factor in the negotiations, the most successful ones are detailed in Sect. 3.4. The experiments showed that this balance between utility and deal probability greatly improves the effectiveness of the negotiation in highly-rugged utility spaces.

However, the proposed approach draws several concerns. Though the quality factor is supposed to be able to model agents' attitudes, our previous experiments limited these attitudes to a somewhat "cooperative" environment, where all agents have the same, neutral attitude. In a real, competitive environment, we expect to have agents with different attitudes interacting. This raises the problem of agent strategic behavior, which is introduced in Sect. 4. What happens when risk averse agents interact with risk willing agents? Is there a an individually optimal strategy? If so, does this individually optimal strategy lead to satisfying solutions, or is the approach prone to situations where individual rationality lead to solutions of low social value? Furthermore, since the complexity of the utility spaces of the agents may also vary, it seems logical to think that agent strategies should vary accordingly. In this paper, we intend to address these questions in the following ways:

- We perform a strategy analysis of the auction-based protocol for constraint-based utility spaces. This analysis allows us to determine the individually optimal strategy and the socially optimal strategy for different utility space complexity levels. From the results of the analysis we conclude that the auction-based protocol, as described in [55], has stability problems, leading to situations resulting in high expected price of anarchy (Sect. 4).
- We propose a set of mechanisms intended to improve protocol stability. These approaches are based on decoupling the agent's strategies from the deal identification process, by applying different techniques on the mediator after the agents have sent their bids (Sect. 5).
- We separately study a specific stability concern, incentive compatibility, related to the possibility of agents manipulating the protocol by means of insincere revelation of information (Sect. 6).

For each contribution, an experimental evaluation has been performed to validate our hypothesis and evaluate its effect. The experimental settings are described in Sects. 4.2, 5.2, 6.2 and 6.3, along with the discussion of the results obtained. Finally, the last section summarizes our conclusions and sheds light on some future research.

2 Complex negotiation scenarios

In the last years, there has been an increasing interest in complex negotiation scenarios, where agents negotiate about multiple, interdependent issues [39]. These scenarios are specially challenging, since issue interdependency yields nonlinear utility spaces, which make classic negotiation approaches not applicable [30]. In this section we first briefly review existing research on multi-attribute negotiation and outline the key components of any negotiation model. Then we discuss the most relevant works so far on the field of agent-based complex automated negotiations. Finally, some of the issues raised by complex negotiation scenarios, which are directly relevant to our research, are described.

2.1 Multi-attribute negotiation

Multi-attribute negotiation may be seen as an interaction between two or more agents with the goal of reaching an agreement about a range of issues which usually involves solving a conflict of interests between the agents. This kind of interaction has been widely studied in different research areas, such as game theory [71], distributed artificial intelligence [13] and economics [67]. Using a notation similar to that used in [71] and [88], we can formally define a *multi-attribute negotiation domain* as a tuple

$$\langle X, D, Ag, U\rangle$$

where

- $X = \{x_i | i = 1, \ldots, n\}$ is a finite set of variables, called attributes or issues;
- $D = \{d_i | i = 1, \ldots, n\}$ is a finite set of domains, such that each domain d_i represents the feasible values of the variable x_i;
- $Ag = \{1, \ldots, m\}$ is the set of negotiating agents, also assumed finite;
- $U = \{U^j | j = 1, \ldots, m\}$, where $U^j : D \rightarrow \mathbb{R}$ represents the preference structure or utility for agent j.

Multi-attribute negotiation is seen as an important challenge for the multi-agent system research community [43], and there is a great variety of negotiation models and protocols intended to address different parts of this challenge. These models may be classified according to different criteria [6], such as their structure, the dynamics of the negotiation process, or the different constraints (e.g. deadlines, information availability...). According to the theoretical foundations of the negotiation models, we can find approaches based on game theory, heuristic approaches and argumentation-based approaches. Game theory approaches aim to find optimal solutions analytically, analyzing equilibrium conditions [59]. These models are mathematically sound and elegant, but their pratical use in some negotiation scenarios is somewhat restricted due to the assumptions usually made: unlimited computation and memory resources, perfect rationality and complete information. In *heuristic* approaches, however, these assumptions are relaxed, and participants attempt to find an "approximately-optimal" under bound rationality using heuristic search and evaluation methods [12–14,20,31,39,44,70]. In *argumentation* based negotiation, agents are given the ability to reason their positions, including a meta-information level which allows them to use promises, rewards, threats and other incentives [66].

Regardless of the theoretical approach involved, different authors agree that there are three key components in a negotiation model [16,33,41]:

- An *interaction protocol*, which defines the rules of encounter among the negotiating agents, including what kind of offer exchange is allowed and what kind of deals may be reached and how they are established.
- The *preference* sets of the different agents, which allow them to assess the different solutions in terms of gain or utility and to compare them.

- A set of *decision mechanisms* and *strategies*, which govern agents' decision making, allowing them to determine which shall be their next action for a given negotiation state.

2.1.1 Interaction protocols for negotiation

The most-widespread interaction protocol for negotiation is based on the exchange of offers and counter offers, which are expressed as an assignation of values to the different attributes. This kind of negotiation protocols are known as positional bargaining. In argumentation based negotiation, however, this exchange of offers also includes meta-information, in order to allow reasoning about the positions of the different agents. A particular protocol family for multi-lateral negotiations are *auction-based protocols*, where negotiating agents send their offers (also called *bids*) to a mediator, which then decides the winning deal [77]. Auction-based protocols allow to efficiently deal with one-to-many and many-to-many negotiations. Another important division regarding interaction protocols is between *one-shot* protocols and *iterative* protocols. In one-shot protocols, there is a single interaction step between the agents [59]. In iterative protocols, on the other hand, agents have the opportunity to refine their positions in successive protocol iterations [62].

2.1.2 Preference sets, utility functions and the use of constraints

From the decision theory perspective, preferences express the absolute or relative satisfaction for an individual about a particular choice among different options [36]. [7] classify agent preference structures in four broad families: binary, ordinal, cardinal and fuzzy preference structures. Among these families, cardinal preference structures are probably the most widely used in complex negotiations. In particular, it is usual to define agent preferences by means of utility functions.

Formally, for a given multi-attribute domain $\langle X, D, Ag, U \rangle$, the *utility function* for each agent $j \in Ag$ is defined as

$$U^j : D \rightarrow \mathbb{R},$$

assigning to each possible combination of values in X or *deal* $s = \{s_i | i = 1, \ldots, n; s_i \in d_i\}$ a real number, which represents the utility that deal s yields for agent j.

The most basic form to represent a utility function is to make an enumeration of the points in the solution space which yield a non-zero utility value. In this way, an agent's utility function may be represented as a set of pairs $\langle s, u(s) \rangle \, | u(s) \neq 0$, where $u(s)$ is the utility of the solution s for the agent. It is easy to see that, though this representation for utility functions is fully expressive, its cardinality may grow greatly with the number of issues or with the cardinality of each issue's domain. Because of that, more succinct representations for utility functions are used in most cases. Examples of such representations which are widely used in the negotiation literature are linear-additive utility functions [14] or k-additive utility functions [22].

Another widely used way to represent preferences and utility functions is the use of constraints over the values of the attributes. There is a vast variety of multi-attribute negotiation models and approaches making use of constraints in different forms, from hard constraints to soft, probabilistic or fuzzy constraints [31,47,52]. There are several reasons which favor the use of constraints in negotiation models. First, they allow for efficient methods for preference elicitation. Moreover, constraints allow to express dependencies between the possible values of the different attributes. Finally, the use of constraints for offer expression allow to limit the

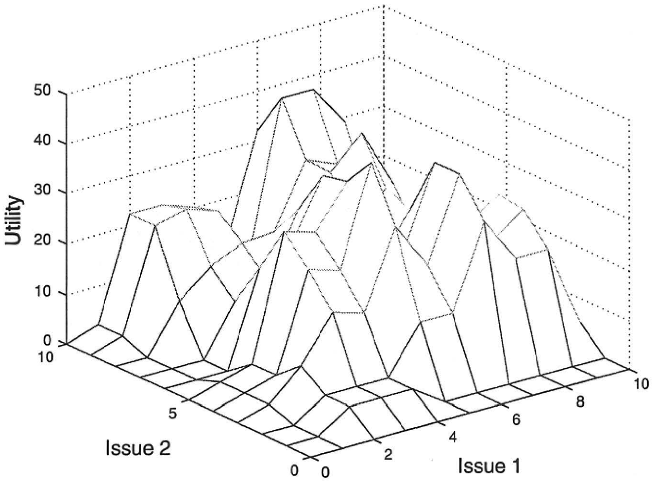

Fig. 1 Example of a nonlinear utility space defined by means of weighted constraints

region of the solution space which has to be explored in a given negotiation step. Reducing the region of the utility space under exploration according to the constraints exchanged by agents is a widely used technique in automated negotiation [48], since it makes the search for agreements a more efficient process than when using positional bargaining, specially in complex negotiation scenarios.

A particular case of constraint-based utility representation which has been used to model complex utility spaces for negotiation are *weighted constraints*. There is a utility value for each constraint, and the total utility is defined as the sum of the utilities of all satisfied constraints.

More formally, the utility space of the agents may be defined as a set of constraints $C = \{c_k | k = 1, \ldots, l\}$. Each constraint c_k has an associated utility value $u(c_k)$. If we note as $s \in x(c_k)$ the fact that a given contract $s = \{s_i | i = 1, \ldots, n\}$ is in the set of contracts that satisfy constraint c_k, an agent's utility for contract s may be defined as

$$u(s) = \sum_{c_k \in C | s \in x(c_k)} u(c_k),$$

that is, the sum of the utility values of all constraints satisfied by s. This kind of utility functions produces nonlinear utility spaces, with high points where many constraints are satisfied, and lower regions where few or no constraints are satisfied. Figure 1 shows an example of the kind of utility spaces which may be modeled using weighted constraints.

2.1.3 Agent strategies, mechanism stability and incentive-compatibility

In an automated negotiation, a strategy guides the decision making process of an agent throughout the different stages of the negotiation protocol [41]. The main challenge in an automated negotiation scenario as far as decision mechanisms are concerned is to design *rational* agents, able to choose an adequate negotiation strategy. In negotiations among selfish agents, negotiation mechanisms must be designed in a way that makes them stable, understanding stability as the impossibility (or at least difficulty) of the strategic manipulation of the mechanisms. This means that the mechanisms should motivate the agents to act in an adequate way, since if a rational, selfish agent may benefit from taking a strategy which is different to the one expected by the protocol, it will do so. This problem is closely related to the notion of *equilibrium* defined in game theory. In an equilibrium, each player of the game has adopted a strategy that they have no rational incentive to change (because it is the best alternative, given the circumstances). There are different equilibrium conditions which can be defined, like dominant strategies [40,83], Nash equilibrium [60] or Bayes-Nash equilibrium [24].

Achieving stability in a negotiation mechanism does not guarantee to reach solutions maximizing social welfare. Therefore, stability must not be used as a single criterion to evaluate decision mechanisms, and social welfare should also be considered. An specially illustrative example is the *prisoner's dilemma* [65], which describes an scenario where Nash equilibrium yields low utility values for the agents involved. A more generic concept which is becoming widely used to characterize situations where individual rationality leads agents to results which yield low social welfares is the notion of *price of anarchy*. The price of anarchy was first introduced in [63] in the context of selfish routing, as a measure of loss of social efficiency due to selfish behavior. In the context of a problem of social welfare maximization, price of anarchy can be defined as follows:

Definition 1 *Price of anarchy.* [63] The *price of anarchy (PoA)* in a given game is defined as the ratio between the social welfare of the best possible outcome of the game and the social welfare of the worst Nash equilibrium in the game:

$$PoA = \frac{\max_{s \in S} sw(s)}{\min_{s \in S_{\text{Nash}}} sw(s)},$$

where S is the set of all possible outcomes of the game, $S_{\text{Nash}} \subseteq S$ is the set of all possible outcomes induced by a Nash equilibrium in the game, and $sw(s)$ is the social welfare of a given outcome s.

Defined in this way, price of anarchy gives an indication of the potential loss in a given game when individually rational agents are confronted. In situations where PoA is high, additional mechanisms which incentivize social behavior are desirable, in order to modify the equilibrium conditions of the game and reduce this value of PoA, thus improving the stability of the protocol. Stability, however, may also come at a price. Even when worst-case equilibria can be avoided, equilibrium conditions may lead to solutions which are distant to the social optimum (generally due to the fact that stability enhancing measures favor "fair" solutions against Pareto-optimal ones). To measure this, price of stability is introduced in an analogous manner:

Definition 2 *Price of stability.* [2] The *price of stability (PoS)* in a given game is defined as the ratio between the social welfare of the best possible outcome of the game and the social welfare of the best Nash equilibrium in the game:

$$PoS = \frac{\max_{s \in S} sw(s)}{\max_{s \in S_{\text{Nash}}} sw(s)},$$

where S is the set of all possible outcomes of the game, $S_{\text{Nash}} \subseteq S$ is the set of all possible outcomes induced by a Nash equilibrium in the game, and $sw(s)$ is the social welfare of a given outcome s.

Taking this into account, when mechanisms are introduced to reduce price of anarchy in a game, their impact over price of stability should also be evaluated.

Another threat to mechanism stability is strategic revelation of information. In incomplete information scenarios [34], since the agents' beliefs about the preferences of a given agent may influence the decision mechanisms they use, an agent may use as a strategy to lie about its own preferences in order to manipulate the decision mechanisms of the rest of the agents to its own benefit. This raises an additional concern to mechanism design [83].

It would be desirable to design protocols which are not prone to be manipulated through insincere revelation of information. *Incentive-compatibility* is defined as the property of a negotiation mechanism which makes telling the truth the best strategy for any agent, assuming the rest of the agents also tell the truth.Though incentive-compatibility is usually independently studied, it is closely related to the notions of strategic equilibrium seen above. In particular, incentive-compatibility may be seen as the property of a negotiation model where, regarding the possibility of telling or not telling the truth, having all agents telling the truth is a Nash equilibrium. A more restrictive property is (*strategy-proofness*), which imposes truthful revelation of information to be a dominant strategy. This means that for any agent the best choice is to tell the truth regardless of the other agents' attitudes towards sincerity [19].

An example of an incentive-compatible protocol is the *Vickrey auction*. The Vickrey auctions are second-price, sealed, one shot auctions. In this kind of auction, that an agent i bids above its real utility value $u_i\ (s)$ is a bad strategy, since there is a chance that the second highest bid is also above that utility value, which would imply that the agent would have to pay for the product more than its value. Furthermore, as Vickrey auction is second price, bidding below the utility level $u_i\ (s)$ is also a bad strategy, since it reduces the chance to bid without any advantage, as the price the agent will have to pay for the product is not given by its bid, but by the second highest bid. Another incentive compatible mechanism is the Clarke tax method [11], where a tax is imposed to each agent once the negotiation has ended, and this tax makes each agent "pay" for the impact that its participation had over other agents' utilities, showing that, in this way, if an agent's false valuation changes the negotiation result, the utility obtained by that agent (after taxes are applied) is never higher that the utility it would have gained using truthful valuations [83].

2.2 Negotiation, optimization and complexity

Though there has been an increasing interest in complex negotiations in the last years, little efforts have been made to study complexity itself within negotiation (apart from computational complexity, which has been thoroughly studied in many scenarios). Therefore, if we want to be able to assess complexity in negotiations, we need to resort to other knowledge areas. One area where many authors have dealt with complexity characterization and measurement is optimization. In fact, negotiation scenarios and optimization problems are often closely related, since there are many similarities in the ways both problem families are defined and addressed. For example, negotiating agents are usually utility optimizers, and negotiation mechanisms are often evaluated in terms of their ability to reach Pareto-optimal solutions. In negotiation, Pareto-optimal solutions are those where payoff cannot be improved for any of the agents without decreasing the payoff for another agent. This concept of Pareto-efficiency is also sought in multi-objective optimization, trying to find solutions where no further gains can be achieved in one of the objectives without losing in another [74]. Multi-objective optimization has been widely used for negotiation support [84], and negotiation mechanisms have also been used to solve multiobjective optimization problems, usually by distributing the different objectives among negotiating agents [75]. Therefore, some of the concepts studied in multiobjective optimization may be used in negotiation, and vice versa.

In the context of a multi-attribute negotiation, complexity of a given scenario may depend at least on the number of issues, the level of interdependency between the preferences on the issues, the domain of the issues, the possibility of change over time of the negotiation context, the method used to describe preferences and the structural properties of the agent's utility spaces. In general, a large number of issues with a high interdependency and a large domain contribute to more complex preference spaces. If the negotiation context changes over time, complexity also increases. The method to describe preferences also has an influence in the complexity of the negotiation scenario. This is specially true when optimization techniques are used to find high utility regions within an agent's utility spaces, or to find deals among different agents. A constraint-based preference space, for instance, may present discontinuities which make gradient based optimizers not applicable, while differentiable utility functions contribute to a faster local optimization. Therefore, to study complexity in negotiation scenarios, we may find useful to characterize structural complexity of the agents' utility spaces, and to this end we may benefit from existing research on function characterization for optimization.

In this context, and more specifically in the field of optimization using evolutionary algorithms, structural complexity analysis plays a crucial role, since algorithm search capabilities are greatly impacted by some structural properties of the optimized function, which is usually known as *fitness landscape* in evolutionary computation.

An interesting detail about fitness landscapes is that they include the definition of a *neighborhood operator* ϕ, which expresses the probability that the search function (usually, a genetic algorithm) passes from one point in the landscape to another [27]. This operator is directly related to the search mechanism used and its parameters (e.g. simulated annealing temperature or mutation probability for genetic algorithms), which implies an important consequence: the complexity of a utility space may be different depending on the considered search algorithm and its parameters. This operator also defines the concept of *neighbor solutions* in the space, which in turn influences the definition of local optima (maxima and minima), and therefore the structural properties of a fitness landscape which are interesting regarding search complexity within the space, such as modality [28], ruggedness, smoothness and neutrality [80].

Once the properties which has an influence on the complexity of a fitness landscape or a solution space have been studied, techniques which allow to measure the complexity of a given space are needed. Most of the approaches we can find in the literature are based on the correlation between different samples of the fitness function f, like *fitness distance correlation* metrics [79] or stochastic models representing the correlation structure of the space [27]. A metric which is easy to compute in most scenarios and allows to make quantitative evaluations about the complexity of a fitness or utility landscape is *correlation length* or *correlation distance*. Correlation distance is defined as the minimum distance ψ which makes correlation fall below a given threshold (usually 0.5), which gives an idea of the distance we can move throughout the solution space while keeping a certain correlation between samples [53].

2.3 Related research on automated negotiation in complex utility spaces

Klein et al. [39] present, as far as we are aware, the first negotiation protocols specific for complex preference spaces. They propose a simulated annealing-based approach, a refined version based on a parity-maintaining annealing mediator, and an unmediated version of the negotiation protocol. Of great interest in this work are the positive results about the use of simulated annealing as a way to regulate agent decision making, along with the use of agent expressiveness to allow the mediator to improve its proposals. However, this expressiveness is somewhat limited, with only four possible valuations which allow the mediator to decide which contract to use as a parent for mutation, but not in which direction to mutate it. On the other hand, the performed experiments only consider the bilateral negotiation scenario, though authors claim that the multiparty generalization is simple. Finally, the family of negotiation protocols they propose are specific for binary issues and binary dependencies. Higher-order dependencies and continuous-valued issues, common in many real-world contexts, are known to generate more challenging utility landscapes which are not considered in their work.

Luo et al. [51] propose a fuzzy constraint based framework for multi-attribute negotiations. In this framework a buyer agent defines a set of fuzzy constraints to describe its preferences. The proposals of the buyer agent are a set of hard constraints which are extracted from the set of fuzzy constraints. The seller agent responds with an offer or with a relaxation request. The buyer then decides whether to accept or reject an offer, or to relax some constraints by priority from the lowest to highest. In Lopez-Carmona and Velasco [49], Lopez-Carmona et al. [50] an improvement to Luo's model is presented. They devise an expressive negotiation protocol where proposals include a valuation of the different constraints, and seller's responses may contain explicit relaxation requests. It means that a seller agent may suggest the specific relaxation of one or more constraints. The relaxation suggested by a seller agent is based on utility and viability criteria, which improves the negotiation process. Though these constraint-based works model discontinuous preference spaces, the operators used to compute utility and the utility spaces defined yield monotonic preference spaces, which are far from the complex preference spaces covered in our work.

Another interesting approach to solve the computational cost and complexity of negotiating interdependent issues is to simplify the negotiation space. Hindriks et al. [26] propose a weighted approximation technique to simplify the utility space. They show that for smooth utility functions the application of this technique results in an outcome that closely matches the outcome based on the original interdependent utility structure. The method is evaluated for a number of randomly generated utility spaces with interdependent issues. Experiments show that this approach can achieve reasonably good outcomes for utility spaces with simple dependencies. However, an approximation error that deviates negotiation outcomes from the optimal solutions cannot be avoided, and this error may become larger when the approximated utility functions become more complex. Authors acknowledge as a necessary future work to study which kind of functions can be approximated accurately enough using this mechanism. Another limitation of this approach is that it is necessary to estimate a region of utility space where the actual outcome is expected to be (i.e. it is assumed that the region is known a priori by the agents).

In Robu et al. [69] utility graphs are used to model issue interdependencies for 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. Authors argue that this prior information could be obtained through a history of past negotiations or the input of domain experts. 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.

There are several proposals which employ genetic algorithms to learn opponent's preferences according to the history of the counter-offers based upon stochastic approximation. In Choi et al. [9] a system based on genetic-algorithms for electronic business is proposed. In this work the utility functions are restricted to take a product combination form (i.e. utility of an outcome is the product of the utility values of the different issues). The objective function used is based on the comparison of the changes of consecutive offers. Small changes of an issue suggest that this issue is more important. For each new population, the protocol enforces that the generated candidates cannot be better than the previous offer. Unlike other negotiation models based on genetic algorithms, this proposal adapts to the environment by dynamically modifying its mutation rate. Lau et al. [45] have also reported a negotiation mechanism for non-mediated automated negotiations based on genetic algorithms. The fitness function relies on three aspects: an agent's own preference, the distance of a candidate offer to the previous opponent's offer, and time pressure. In this work agents' preferences are quantified by a linear aggregation of the issue valuations. However, non-monotonic and discontinuous preference spaces are not explored. In Chou et al. [10] a genetic algorithm is proposed which is based on a joint elitism operation and a joint fitness operation. In the joint elitism operation an agent stores the latest offers received from the opponent. The joint fitness operation combines agent's own utility function and euclidean distance to the opponent's offer. In this work two different negotiation scenarios are considered. In the first one utility is defined as the weighted sum of the different issue values (i.e. issues are independent). The second scenario defines a utility function where there is a master issue and a set of slave issues. Utility is calculated as the weighted sum of the different issue values, but the weights of the slave and master issues change according to the value of the master issue.

In Yager [87] a mediated negotiation framework for multi-agent negotiation is presented. This framework involves a mediation step in which the individual preference functions are aggregated to obtain a group preference function. The main interest is focused on the implementation of the mediation rule where they allow a linguistic description of the rule using fuzzy logic. A notable feature of their approach is the inclusion of a mechanism rewarding the agents for being open to alternatives other than simply their most preferred. The negotiation space and utility values are assumed to be arbitrary (i.e. preferences can be non-monotonic). However, the set of possible solutions is defined a priori and is fixed. Moreover, the preference function needs to be provided to the mediation step in the negotiation process, and pareto-optimality is not considered. Instead, the stopping rule is considered, which determines when the rounds of mediation stop.

Fatima et al. [18] analyze bilateral multi-issue negotiation involving nonlinear utility functions. They consider the case where issues are divisible and there are time constraints in the form of deadlines and discounts. They show that it is possible to reach Pareto-optimal agreements by negotiating all the issues together, and that finding an equilibrium is not computationally easy if the agents' utility functions are nonlinear. In order to overcome this complexity they investigate two solutions: approximating nonlinear utilities with linear ones; and using a simultaneous procedure where the issues are discussed in parallel but independently of each other. This study shows that the equilibrium can be computed in polynomial time. An important part of this work is the complexity analysis and estimated approximation error analysis performed over the proposed approximated equilibrium strategies. Heuristic approaches have generally the drawback of the lack of a solid mathematical structure which guarantees their viability, which raises the need of an exhaustive experimental evaluation. An adequate complexity analysis and establishing a bound over the approximation error contribute to give heuristic approaches part of the technical soundness they usually lack. Among the limitations of the proposal, we can point out that this work is focused on symmetric agents where the preferences are distributed identically, and the utility functions are separable in nonlinear polynomials of a single variable. This somewhat limits the complexity of the preference space.