Literature Review on Multi-attribute Negotiations

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Abstract

Automated Multi-attribute Negotiation is an important and valuable mechanism in the Navy detailing system, in order to realize efficient, distributed and "Win-Win" matching. This report provides an extensive literature review of the existing research in Multi-attribute Negotiations in the fields of Economics and Artificial Intelligence, discussing the motivation for multi-attribute negotiations, as well as some difficulties in implementation. Related to Multi-attribute Negotiations, approaches to preference elicitation and multi-criteria-decision-making are also reviewed. Based on the existing literature, we conclude that multi-attribute negotiation is an important as well as challenging research problem.

1 Introduction

Multi-attribute negotiation is a negotiation that involves multiple issues and they need to be negotiated simultaneously. Usually it is characterized by the situations in which two or even more parties[1] recognize that the differences of interest over multiple issues but also the value of cooperation exists between them and in which they want to seek a compromise agreement [1].

Multi-attribute negotiation is a useful mechanism in the Navy detailing problem, not only because commands and sailors usually have to negotiate multiple issues, for example, payment rate, projected rotation date, length of service, training and etc. [2], but also because of its advantage of possible “Win-Win” solutions for both sides. By “Win-Win” solutions we mean that in a multi-attribute negotiation because agents may have different preferences on the issues, both sides may achieve better agreement on issues that are most important for them by trading off some on those not so important. For example, commands and sailors need to negotiate the issues of payment rate, length of service, training etc., but commands may care about length of service most, then payment rate, and so on. On the other hand, sailors may care about rate most, then training, etc. Thus, through negotiating on those multiple issues they may achieve on what they care about most by conceding some on the less important issues. In contrast, single-attribute negotiation is a “Win-Lose” situation, i.e. what one party gets is the thing the other loses. Hence, we say multi-attribute negotiation is not only necessary but also valuable for the Navy detailing problem.

A multi-attribute negotiation is more complex and challenging than a single-attribute negotiation because of the following reasons:

First, in a multi-attribute negotiation the preference of an agent over multiple issues can be complex. A traditional way to deal with this is to characterize the preference with a utility function (a mathematical formula) and agents make decisions based on this utility function. However, it is not trivial for a human to construct such a utility function over

[1] In this report, we focus on the literatures dealing with two parties and multiple issues. The situations with many parties and multiple issues could be incredibly complex, because once three or more conflicting parties are involved, coalitions may form and may act in concert against the other involved parties [1].

multiple issues, especially when preference over one issue is impacted by the values of other issues; thus, preference elicitation may take a long time or sometimes be intractable.

Second, in a multi-attribute negotiation the solution space is *n*-dimensional (n>1) rather than a single dimensional line as in a single-attribute negotiation. This makes the negotiation strategy in multi-attribute negotiations complex: because the space is *n*-dimensional, every time an agent plans to concede, she needs to first decide the direction of concession. Apparently there are many choices on the concession direction she can take: to concede on issue *1*, …, *n* or different combinations of the issues. Specifically, the decision on the concession direction may also depend on the opponent's preference because conceding on the issue more important to the opponent can make the offer more acceptable. Finally, to decide how much to concede is now more complicated because the direction can impact the amount as well. So the burden of computation and reasoning for the negotiation strategy is higher in a multi-attribute negotiation than in a single-attribute negotiation.

Third, as mentioned above, in multi-attribute negotiations there exist "Win-Win" situations. For rational agents, they should not "leave extra money on the table". In other words, the ideal result for the system is to realize a *Pareto-optimal (or Pareto-efficient)* solution. A Pareto-optimal solution is one which can not be improved further without sacrificing someone's utility, i.e. if there is another solution from which one of the agents can get more than from this Pareto-optimal solution, then the other agent must get less by that other solution. We say a multi-attribute negotiation model is efficient when agents will reach a Pareto-optimal agreement in the negotiation, if there exists a zone of agreement.

The advantage and difficulties of multi-attribute negotiations have been realized for a long time. Informally, Raiffa in his literature on bargaining [1] describes multi-attribute negotiation as "It's no longer true that if one party gets more, the other necessarily has to get less: they both can get more." Furthermore, through illustration by cases, Raiffa addresses the problems of value functions, strategic misrepresentations, tradeoff and concessions, negotiation agendas, etc. on multi-attribute negotiation. More formal and theoretical research on multi-attribute negotiation first arose in the field of economics (mostly in game theory) and later in the field of AI. But s*imultaneous negotiation* on multiple issues is intractable for non-cooperative game theory. Thus, the non-cooperative game theory literature mostly addresses the challenge by decomposing the problem into *issue-by-issue negotiations*. Besides, some researchers in economics study the problem of multi-attribute negotiation from a cooperative game perspective. They propose methods on how to find out Pareto-optimal solutions by assuming agents cooperate and can solve multi-criteria-decision-making *(MCDM)* problems. In AI, research work on this problem also exists and utilizes learning and heuristic methods with the focus on building automated multi-attribute negotiation models and tractable negotiation strategies.

Thus, there are three types of research existing in economics and AI: *issue-by-issue negotiation*, *cooperative multi-attribute negotiation* and *multi-attribute negotiation with heuristics methods*. To ground our research on this problem, it is helpful to review and summarize the work of all these three types. Besides, following the main topic, we also mention some concepts and methods on preference elicitation and *MCDM* since they are important in the multi-attribute negotiation problem.

The rest of the paper is organized as follows: in Section 2, we review the literatures in economics with two subjects: non-cooperative and cooperative multi-attribute negotiation. Section 3 reviews the work in AI with different aspects of heuristic methods. Section 4 reviews two supporting techniques: preference elicitation and multi-criteria-decision-making. In Section 5, we conclude and give some discussion on the future work.

2 Multi-attribute negotiation in Economics

The study on multi-attribute negotiation in economics is mainly conducted by game theory and it can be divided into two branches: *non-cooperative* and *cooperative* multi-attribute negotiation.

2.1 Non-cooperative negotiation

The models and theorems in the former branch are concerned with the situations in which the sets of possible actions of *individual* players are the primitives [3]. Thus, the research in this branch mainly focuses on the analysis of *equilibrium* outcomes of a negotiation game. Players are in *equilibrium* if a unilateral change in strategies by any one of them would lead that player to earn less than if she remained with her current strategy [4]. The pioneering work[2] in this field is Rubinstein's alternating-offer bargaining solution [8]. Further, within different contexts, researchers studied the bargaining game with asymmetric information, incomplete information, outside options etc. [9] [10] [11] [12] [13] [14]. But most of them focus on one single issue and simultaneous negotiation with multiple issues is too complicated for non-cooperative alternating-offer game. Thus, some researchers in this field began to study the problem with issue-by-issue negotiation. They argue that the decomposition to issue-by-issue negotiation can be appropriate in some situations and that this approach is also being taken by people in real-world applications. With such an approach, there are two kinds of questions that must be addressed: first the reason to negotiate issue-by-issue, or under what contexts people will (or can) take this approach. Second, what kind of agendas can arise and the difference between them?

Before introducing the existing research in detail we first give an overview on some concepts and terminologies. Faced with multiple issues, agents need to decide two things before the negotiation: one is what kind of negotiation procedure they will take and the other is the type of agreement implementation. We call these two issues—negotiation procedure and agreement implementation: together they form a negotiation framework of multi-attribute negotiation (see Figure 1). There usually exist three types of negotiation procedures: *separate*, *simultaneous* and *sequential* [23] [28]. Separate negotiation means agents negotiate each issue separately (independently & simultaneously). We can view it as if there are *n* pairs of representatives for the two agents, and each pair of them independently negotiates one issue. Simultaneous negotiation means two agents negotiate a complete package on all issues simultaneously. The last one is that two agents negotiate issue by issue sequentially, i.e. issue-by-issue negotiation. Here, with issue-by-issue negotiation, agents also need to decide the order to negotiate each issue[3].

For agreement implementation, there can be two types: *sequential* and *simultaneous*. Sequential implementation means the agreement on each issue is implemented once it is

[2] We think we also need to mention Nash because in "Two-person Cooperative Games" [5] he solves the bargaining problem first as a non-cooperative game although it is a one-shot game.

[3] People in this field usually call the order and agreement implementation together an "agenda" of an issue-by-issue negotiation problem.

reached, while simultaneous implementation is that agreements are implemented together when all issues are settled. Usually, agreement implementation might be determined by the negotiation problem. For instance, in the Navy detailing system, the agreement can be implemented if and only if all issues are settled.

Research on issue-by-issue negotiation is mostly based on Rubinstein's bargaining model by introducing another issue (pie) into the system. By different assumptions, the two issues may have different values and be differentially preferred by the agents. Besides, the two issues can either be simultaneously available or arrived at in a sequential order.

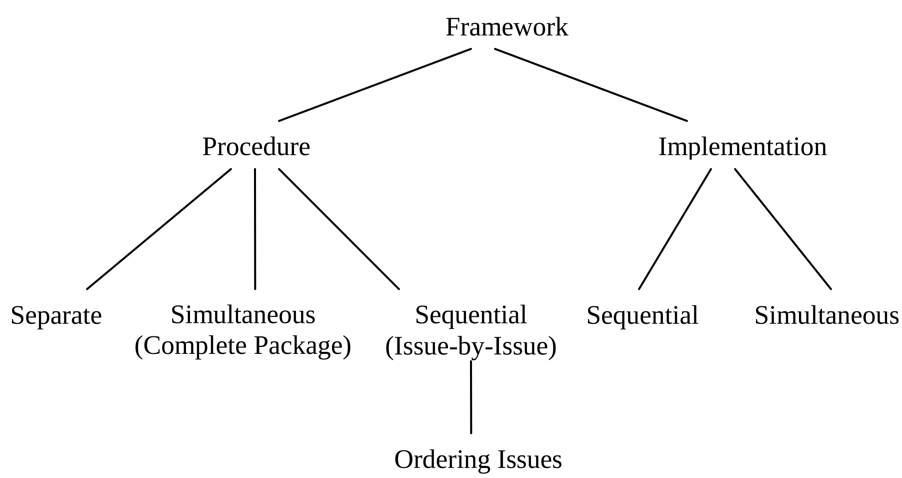

Figure 1 Negotiation framework

2.1.1 When to negotiate issue-by-issue?

The idea of negotiating issue-by-issue and some challenges it presents is illustrated by an example from the American Automobile Association [15]. They recommended that buyers should first focus on negotiating the price of the car and only discuss financing, factory rebates and the trade-in allowance once the price has been agreed upon. 'However, the thing somehow seems to be puzzling as those issues are almost perfect substitutes, i.e. all ultimately determining how much money will change hands. Why shouldn't the buyers negotiate on them simultaneously and reach an agreement right way?' One reason, as Bac and Raff say in [15], is bounded rationality, simultaneously negotiating a complete package might be too complex for individual buyers. However, this reason only provides an intuitive idea on issue-by-issue negotiation. More theoretical explanation or implication is needed. Next, we review the theoretical work in two different contexts: incomplete information and complete information.

Research with incomplete information

Signaling might be the first and only reason that researchers mention, why issue-by-issue negotiation arises under incomplete information. Bac and Raff [15] study a case with two simultaneous and identical pies where agents can either choose sequential negotiation with sequential implementation or simultaneous negotiation with simultaneous implementation. The authors show that in the context of complete information agents will take simultaneous negotiation and reach an agreement without delay. But in the context of asymmetric information (assume two players *A* and *B, A* is informed, but *B* is uncertain of *A*'s time discount, which can take one of the values: δ_H with probability π and δ_L with 1-π), the authors argue that when *B*'s time discount is in some interval (not so strong and also not so weak), the "*strong*" type of the informed agent (*A* with δ_H) may make a single offer on one pie and leave it to the opponent (*B*) to make an offer on the second pie, while a "*weak*" type of informed player (*A* with δ_L) only makes a combined offer. So if issue-by-issue negotiation arises, it is because the "*strong*" and informed agent, by a single (signaling) offer, wants to let her opponent know she is strong and make her concede.

Busch and Horstmann [17] similarly but more strictly study the signaling factor with an incomplete information model that allows for different sized pies and each kind of agreement implementation. By setting some parameter configurations, they show that issue-by-issue negotiation may arise with signaling reason and they prove under such configurations signaling does not arise if agents can only bargain a complete package. So the authors argue it is purely because some favorable endogenous agenda for issue-by-issue bargaining is available. Besides, they also show that if issue-by-issue bargaining arises agents will negotiate the "large" pie first.

However, multi-attribute negotiation under the context of incomplete information is complicated for analysis and the results are also not so intuitive. To our knowledge, there is almost no existing work.

Research with Complete Information

As mentioned above, under complete information agents will negotiate complete package if it is with simultaneous and identical pies. But when assumptions are changed, issue-by-issue negotiation could possibly arise under complete information.

In real-life, we know with sequential issues some people might like to decide all issues at once, while others prefer to decide one by one. Busch and Horstmann [18] study the difference between incomplete contract (issue-by-issue) and complete contract (simultaneous) negotiation with sequential pies on which agents have different preferences. From the equilibrium outcomes of the two procedures, we see if agents are heterogeneous, they might have conflicting favors on the two procedures, which means one prefers incomplete contract procedure but the other may prefer complete contract procedure. Further, Busch and Horstmann also show when time is costless agents will agree to negotiate complete contract, while if time is very valuable agents will take incomplete contract. With different perspective, K. Lang and R. W. Rosenthal [19] argue joint concavity of two agents' payoffs can eliminate the possibility of non-fully-bundled (issue-by-issue) equilibrium offers, but in realistic settings, the property of joint concavity usually is not true so that partial bundled offer on a subset of unsettled issues may be superior over fully-bundled offer.

Commonly people only consider the time issue in negotiation research. But the factor of breakdown also can impact a multi-attribute negotiation. We know sometimes agents insisting on some issue may lead the whole negotiation to breakdown. Chen [20] is one researcher who studied issue-by-issue negotiation with breakdown factor. Chen applies a probability setting that a negotiation on some issue breaks down if a proposal on it is rejected. However, he assumes agents' utility functions are linear additive so that one negotiation breaking down does not affect others. By comparing the equilibrium outcomes between issue-by-issue negotiation and simultaneous negotiation, Chen argues that when the probability of breakdown is low, agents prefer to negotiate a complete package because intuitively we know that the bargaining can last long enough so that agents can get to a "Win-Win" solution with inter-issue tradeoffs. However, when the breakdown probability is high, agents weakly prefer issue-by-issue negotiation. Chen also shows that if agents are sufficiently heterogeneous, issue-by-issue negotiation may also be superior over simultaneous negotiation. In and Serrano [21] assume that one negotiation breakdown can make the whole procedure fail, and agents are restricted to make an offer on only one of the remaining issues each round. They show that when the probability of breakdown goes to zero, there is a large multiplicity of equilibrium agreements and inefficiency arises. But it does not happen for simultaneous negotiation. However, if agents are not restricted to make offers on only one issue at each round (i.e. agents can make partially or fully bundled offers), the outcome turns to be Pareto-efficient [22]. Thus, their work indicates strict issue-by-issue negotiation may raise inefficiency. Inderst [23] might be the only person who compares those three different negotiation procedures in one paper. On a set of unrelated issues, Inderst argues that if the issues are mutually beneficial[4], agents will prefer to bargain simultaneously over all issues.

Besides the work above, C. J. Weinberger [24] studies the multi-attribute negotiation problem within a specific context allowing "Selective Acceptance". In such a context, the offer initially needs to be a complete package including all issues, but agents can accept or reject the whole package as well as selectively accept part of the package on some issues. But if agents accept a part on some issues, these issues can not be reopened again. The author indicates that in some situations this leads to good solutions [25] [26]. Weinberger shows "Selective Acceptance" can lead to inefficient equilibrium outcomes if some issues are indivisible or agents have opposing valuations on issues. For comparison, Weinberger shows that inefficient outcomes do not arise under the rule only to accept or reject the whole package. However, the equilibrium outcomes with "Selective Acceptance" are not dominated by the efficient outcome. It means there must be some agent who is better off by the rule of "Selective Acceptance" and will not agree on the efficient outcome.

The research results under complete information, compared to those under incomplete information, are more intuitive. However, from the results we see inefficiency may arise in issue-by-issue negotiation except when negotiation friction is big. It indicates only

[4] In this paper, Inderst assumes the maximum utility *agent 1* can get on each project (issue) *i* is characterized by a strictly decreasing, concave and continuous function on the utility of *agent 2* on issue *i*, i.e. there exists such a function $v_i(U_i)$ which maps $[U_{imin}, U_{imax}]$ to $[V_{imin}, V_{imax}]$, where U_i and V_i represent the *agent 1* and *2*'s utilities from i, and $v_i(U_i)$ represents the maximum utility *agent 1* can get if given the utility *agent 2* gets is U_i; and vice versa. Then he defines the concept of mutually beneficial as: *if there exists a realization on project i such that* $U_i>0$ *and* $v_i(U_i)>0$*, then project i is called mutually beneficial.*

when time is profitable or breakdown probability is high, agents might be better off by issue-by-issue negotiation. Especially, if agents are also sufficiently heterogeneous, issue-by-issue negotiation might be an appropriate approach.

2.1.2 What kind of agenda to take?

Negotiation agenda is important for the e-by-issue approach as it can impact the outcome [27], and normally people need to decide it before negotiation. Game-theoretical attempts to solve the agenda selection problem have provided some insights to allow people to appropriately choose the issue-by-issue approach. Tresearch can be divided into two branches with: endogenous and exogenous agendas.

Research with Endogenous agenda

In the informal literature, Raiffa [1] addressed an endogenous agenda by the negotiation case on Panama Canal, in which the Panamanian and U.S. negotiators decided to concentrate initially on those issues that would be easier to resolve, and negotiate the harder ones later. Because to first negotiate the harder ones may easily lead the negotiation to breakdown (or might be criticized by public as the harder issues are usually very sensitive). This intuition is also confirmed by the formal research. With a simplified model to divide two cakes and with sequential implementation, Flamini [29] argues that if an issue is "difficult", then agents prefer to postpone it. Here, to represent the "difficulty", Flamini uses some probability that the negotiation will break down if an offer on the issue is rejected. Besides, Flamini also shows that agents prefer to negotiate the most important issue first when they have same preferences and assuming there is no "difficult" issue. However, if different preferences arise, the situation becomes embarrassing because an agent has incentive to be the first mover to start the bargaining over her more important issue but to postpone bargaining over her rival's more important issue. One thing that can help in deciding the agenda might be to decide by games. Thus, Flamini proposes two pre-games to select agendas. One is a one-shot game, called "*soft*", in which players are assumed to choose agenda simultaneously; if the two outcomes coincide, then this is the agenda to be followed; if not, then the agents toss a coin to make the decision. The other pre-game applies "Rubinstein's bargaining game" to decide the probability with which the agenda will be agreed upon.

Agreement Implementation

People usually are not so patient to wait until all agreements are reached and then to enjoy their gains. So agreement implementation is also an important issue agents need to decide. Further, we know agreement implementation also can impact the order of negotiation on issues. If the implementation is sequential, it is usually true that people will negotiate the easier issues first; but if it is simultaneous implementation, it becomes indifferent between hard issues or easy issues if there are no other factors [1]. Busch and Horstmann [30] formally study this problem. First, they define two kinds of issues, "*easy issue*" and "*hard issue*". An "*easy*" issue is one on which the agents' time discounts are public information so that agreement will be reached without delay; a "*hard*" issue is one where there will be delay to reach agreement because of incomplete information [8] [10]. Then they show that if the implementation is sequential agents will negotiate the "*easy*" issue first, while if it is simultaneous they will settle large surplus issue first no matter whether it is "*easy*" or "*hard*". And of course agents will apply sequential implementation under issue-by-issue negotiation because by simultaneous implementation the achievements on the firstly settled issues would be depreciated when all agreements are reached.

Research with Exogenous agenda

Fershtman is one of the first people who consider the impact of agendas on issue-by-issue negotiation. Fershtman defines two different agendas with simultaneous implementation: big pie first (*agenda1*) and small pie first (*agenda2*) in [27], and he shows that when agents have identical preferences (e.g. both of them feel pie1 is the big pie and pie2 is a small one), the highest payoff under *agenda1* is higher than that under *agenda2*. Besides, Fershtman also shows under *agenda1* agents prefer to be the first mover, while under *agenda2* it doesn't matter. However, when agents have conflicting preferences, they prefer the first issue negotiated to be least important to themselves but most import to the opponent. So Fershtman argues that agenda is important for an issue-by-issue negotiation[5].

[5] We need to point out that the result here is different from that in [29]. One reason is they have different assumptions. In [29] it is assumed that the implementation is sequential, while in [27] the implementation is simultaneous.

Herrero [32], Busch and Horstmann [33] study the differences between negotiation procedures and agreement implementations by exogenous agendas. Herrero [32] points out that the equilibrium outcomes differ under these procedures in Figure 1 even when discount factors go to one. Busch and Horstmann [33] compare the results under the agendas of simultaneous bargaining with simultaneous implementation and issue-by-issue bargaining with sequential implementation. Busch and Horstmann argue that agents prefer the latter agenda if the higher value issue is negotiated first, otherwise agents will take the former agenda.

Besides, M. K. Chen characterizes an equilibrium agenda in [20], which lets agents first negotiate the most important ones among the remaining issues. In and Serrano [21] [22], and Inderst [23] also study negotiations based on exogenous agendas.

Up to now, we mentioned most of the existing work in the field of non-cooperative game theory. We see that although issue-by-issue approach is much simpler than simultaneous negotiation, it may encounter the difficulties of agenda selection and inefficiency. Besides, the implicit assumptions to take issue-by-issue negotiation are that agents' utility functions are linear or additive, and reservation price on each issue is independent. These assumptions can be found in most of the work we introduced above. However, these assumptions are usually not able to be maintained in real-life applications.

2.2 Cooperative Negotiation

Research in Cooperative game theory deals with the situations in which the sets of possible joint actions of *groups* of players are the negotiation primitives [3]. The term of "cooperative" here does not mean that players cooperate, but they are supposed to be able to discuss the situations with perfect information, agree on some rational joint plan, and the agreement is assumed to be enforceable [5]. Research on multi-attribute negotiation in this field is concerned with finding a solution when given some possible outcomes, which is required to satisfy a set of axioms such as Nash axioms. Below, we first discuss Nash solution and some other axiom work that are applicable in cooperative multi-attribute negotiation; then the methodology to find out Pareto-optimal frontier is introduced. Finally, we discuss some methods named as "fair negotiations" that are applicable in some specific situations.

2.2.1 Nash solution

The beauty of Nash solution is that it is just based on some simple axioms. The key ones among them are [5] [6]:

- *Pareto-efficient (EFF)* (Pareto-optimal): the negotiation solution should not be weakly dominated by any point in the solution space except itself, i.e. there are no other alternatives by which both agents can be better off.
- *Symmetry (SYM)*: the negotiation solution does not depend on which agent is called agent one and the only significant differences between agents are their strategy spaces and utility functions. In some situations like in [5], "symmetry" means two agents get same utility.
- *Invariance (INV)*: an order preserving linear transformation of agents' utility functions does not change the shape of solution space as well as the relative position of the solution although numerical values might be changed.
- *Independence of irrelevant alternatives (IIA)*: a restriction of an agent's strategy space (e.g. shrink) that is contained in the original one can not increase the agent's utility, and a restriction (e.g. shrink) of the solution space where the new space still contains the solution of the original game doesn't change the solution, i.e. the new game still has same solution as the original game.

Based on these axioms, Nash bargaining solution can be characterized by the payoff pair $s=(x_1,x_2)$ that maximizes the Nash product $(x_1-d_1)(x_2-d_2)$ where (d_1,d_2) is the disagreement payoff pair. Nash shows in [6] this payoff pair is the only solution that satisfies his axioms and coincides with the result of the one-shot non-cooperative negotiation game he builds[6]. Geometrical illustration of Nash solution is presented in Figure 2. Nash solution has also been generalized to asymmetric version as a payoff pair to maximize the product $(x_1-d_1)^{\alpha}\ (x_2-d_2)^{\beta}$, where α and β represent "bargaining powers" of agents [28] [34]. However, we need to point out these bargaining powers do not mean agents have unequal bargaining abilities (but unequal strategy spaces or situations, for instance, unequal

[6] We know the outcome of Rubinstein's alternating-offer bargaining also coincides with Nash bargaining solution where agents' time discounts go to one or the length of each round goes to zero. Refer to [8].

market positions) because it is already assumed in Nash's approach that two agents are sufficiently intelligent and rational, and information is perfect.

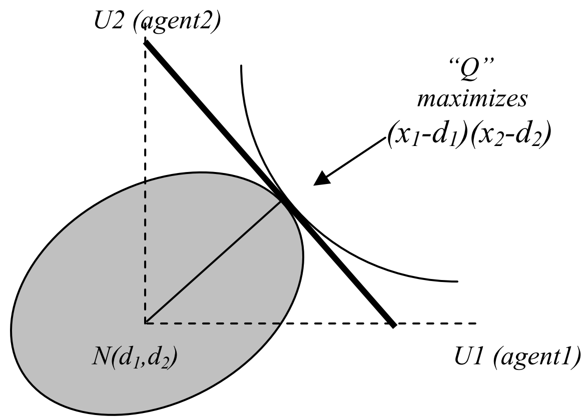

Figure 2 Nash bargaining solution

Nash's approach is also applicable even when there are multiple issues as long as the assumptions can be maintained that include: strategy space of each agent is compact convex metrizable, corresponding solution space is compact convex, information is perfect and agents are sufficiently intelligent and rational [7]. Following Nash's methodology, for two-person negotiation game on *n* issues, the first thing is to construct the mapping from strategy space (*n-dimensional*) to solution space (*2-dimensional*) (see Figure 3 and Figure 4). Here, a point on the strategy space represents a division between agents (e.g. a package offer agent1 makes to agent2), and a point on the solution space represents a pair of utilities for agents from that division. So in Figure 3 the shady region represents the feasible strategy space of the negotiation game and that in Figure 4 represents the corresponding utility distributions. Then by Nash's axioms, agents can reach an agreement on all issues based on these two regions.

From Nash's approach, we say the problem can be simplified in most of the situations where the disagreement payoff pair is fixed such that agents can not choose disagreement

[7] "Convexity" of the strategy space makes mixed strategies also included in the strategy space (see the shady region in Figure 3) and with "Compactness" (or bound) ensures solutions exist. While, for utility region, "Compactness" ensures solutions exist and "Convexity" can make the solution unique (see the shady region in Figure 4). The properties of "compactness" and "convexity" of the utility region depend on the properties of the strategy region and agents' utility functions. "Intelligent" ensures agents have reasoning and computation ability, and "rational" means the purpose of agents is to maximize their utility.

strategy as a threat, for instance, or some undetermined punishments. In other words, agents' reservation utilities are certain. Usually this assumption is reasonable for a negotiation game as Nash assumes in [5]; if there is no agreement, agents get zero utilities. (The necessity of this assumption is because the negotiation outcome is dependent on the disagreement payoff pair. If agents can choose disagreement payoff pair as a strategy, then we have to find out the whole utility region such that agents can decide the location of the disagreement payoff pair by the game.) So now to solve the negotiation problem it is not necessary to reach the whole space or even the whole frontier but the Pareto-frontier (see Figure 6) because it is assumed agents are sufficiently intelligent and rational such that the outcome is Pareto-efficient.

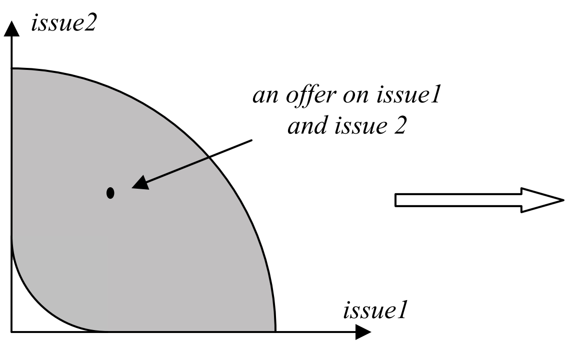

Figure 3 Strategy space

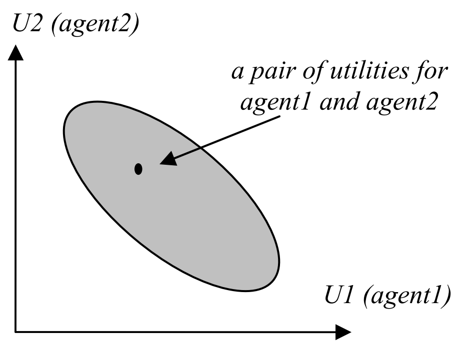

Figure 4 Solution space

2.2.2 Other bargaining solutions (by axioms)

Some researchers point out that the key axiom of "Independence of Irrelevant Alternatives" in Nash axioms lacks "monotonicity" [36] [37] [38]. Figure 7 depicts the utility regions: *Z* and *Z'* of two negotiation games. We say they have the same outcome, *x*, by Nash axioms. But *Z'* is obtained from *Z* by eliminating all the alternatives that agent1 prefers to *x*. So some researchers argue agent1 ought to not fare as well under *Z'* as she does under *Z* [38].

The Kalai-Smorodinsky bargaining solution (Axiom of "Individual Monotonicity")

Kalai and Smorodinsky [37] propose an axiom of *"Individual Monotonicity (IMON)"*: For a set *S* of individually rational and Pareto-efficient points (utility region), let $m_i(S) = \max\{s_i \mid s \in S\}$ be maximum feasible utility for each agent based on their disagreement payoff pair (d_1, d_2); then for $Z \subset S$, if $m_i(Z) = m_i(S)$ for some agent *i*, the solution for the other agent on *Z* is no better than that on *S*, $f_j(Z) \leq f_j(S)$, where *f(X)* gives the bargaining solution on region *X*. Based on *IMON*, Kalai-Smorodinsky solution then selects the maximum element in *S* on the line that joins the disagreement payoff pair (d_1, d_2) with the maximum pair $(m_1(S), m_2(S))$. Figure 8 illustrates an example of Kalai-Smorodinsky bargaining solution.

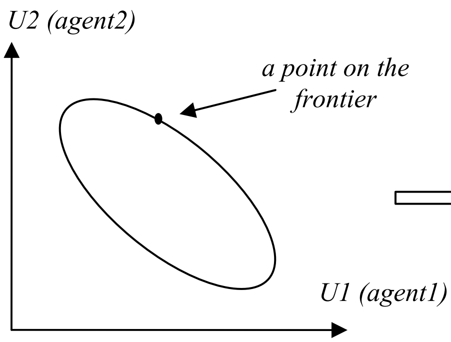

Figure 5 Frontier of the utility region

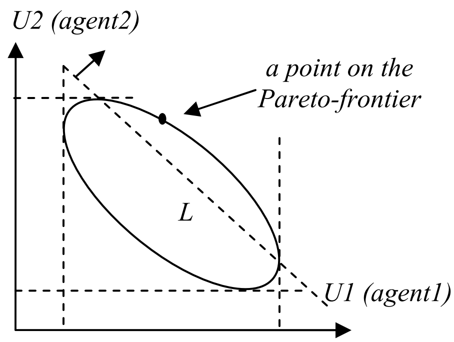

Figure 6 Pareto-frontier of the utility region (right of line L)

Kalai [39] and Myerson [40] also propose an axiom of *"Step by Step Negotiations (SSN)"*, which describes a situation where agents first negotiate an agreement on a payoff region *Z'* and then discover additional negotiation space (more utility pairs) corresponding to region *Z* that contains *Z'*; agents may reopen the negotiation and if they can not reach a mutually beneficial agreement, then implement the previous agreement.

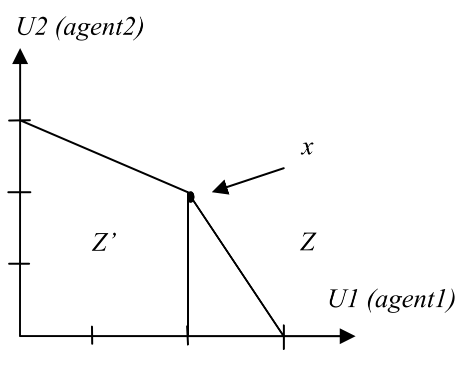

Figure 7 An example (controversy on *IIA*)

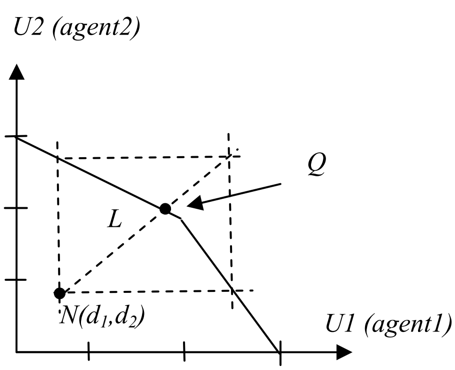

Figure 8 Kalai-Smorodinsky solution

Similarly, these solutions also can be extended to multi-attribute negotiation as Nash solution.

Axioms for Issue-by-issue negotiation

Besides the work above that focuses on simultaneous negotiation, Ponsati and Watson propose some axioms for issue-by-issue negotiation [38]. They first study an axiom of *"Issue-by-Issue Individual Monotonicity (IIM)"*, which is similar as *IMON*. Then they propose another axiom *"Simultaneous Implementation Agenda Independence (SIAI)"* which requires the solution be independent with different agendas in issue-by-issue negotiation. They show that a solution satisfies *EFF*, *SYM*, *INV*, *IIM* and *SIAI* if and only if it is the Nash solution. Ponsati and Watson also discuss some other solutions in their paper with axioms of *"Separate/Global Equivalence"*, *"Super-Additivity"*, *"Independent Implementation Agenda Independence"* and with the results of other work [41] [42] [43]. However, their work only provides some new theoretical implications of Nash solution or other solutions under issue-by-issue negotiation rather than giving some approaches to reach a solution of multi-attribute negotiation.

2.2.3 Generating Pareto-frontier

In Section 2.2.1, we said that if the Pareto-frontier can be found, then we can reach the Nash bargaining solution (or other solutions, e.g. *Kalai-Smorodinsky solution*) even when there are multiple issues. We know if agents' utility functions are known it is not hard to reach the Pareto-frontier. However, it usually can not be promised that agents both have explicit utility functions on all issues. So an approach to deal with such situations is needed.

Ehtamo, et al. [44] presents a constraint proposal method to generate Pareto-frontier of a multi-attribute negotiation. In their approach, a mediator without bias is introduced into the game and works together with agents to find out the Pareto-frontier. The procedure can be described as below:

Step 1. The mediator chooses (e.g. randomly) the first reference point in agents strategy space (see Figure 9), which is similar as that in Figure 3.

Step 2. The mediator chooses a constraint (a line or a plane) going through the reference point and announces it to agents.

Step 3. Agents choose their most preferred points under the constraint by solving their multi-criteria-decision-making (*MCDM*) problems and announce these points to mediator.

Step 4. If the two points coincide or are very close, a Pareto-efficient solution of this game is found. The mediator goes to *Step 5*. Otherwise, she goes back to *Step* 2 and adjusts the constraint by some mechanism.

Step 5. If additional Pareto-efficient solutions are to be generated, the mediator goes back to *Step 1* and chooses another reference point by some mechanism. Otherwise, the procedure is finished.

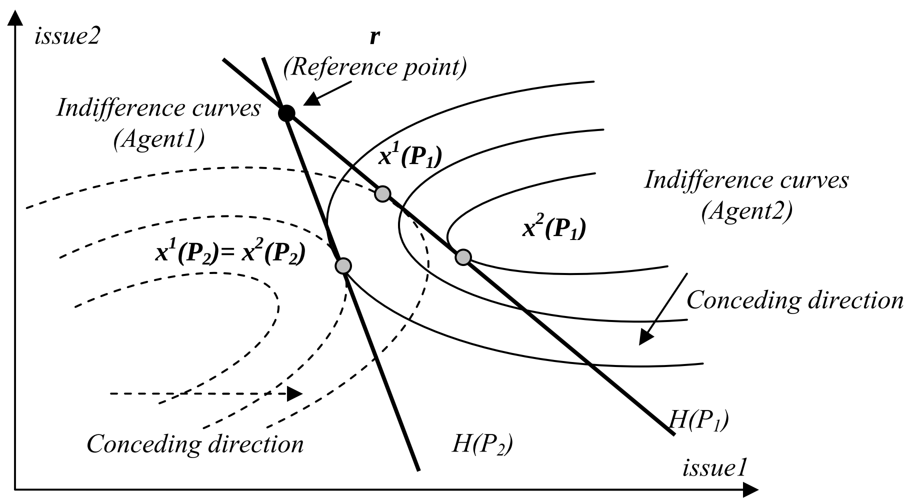

Figure 9 Constraint proposal method

Figure 9 gives a graphical illustration with a two-issue case: the dash curves are agent1's *indifference curves,* on which the points are indifferent for agent1, while solid ones are agent2's indifference curves; r is the reference point; the two solid lines are the constraints the mediator makes to agents; and the arrows are the conceding directions of agents. On the figure, we see agents reach a Pareto-efficient solution by the constraint $H(P_2)$, where $x^1(P_2)= x^2(P_2)$.

On n-dimensional decision space, the constraint going through the reference point r can be represented by its normal vector $P \in R^n$: $H(P) = \{x \mid x \in R^n, P'(x-r) = 0\}$, and we can use $d(P)\equiv x^1(P_2)- x^2(P_2)$ to represent the difference between the two feedbacks from agents. If $d(P)$ equals zero then a Pareto-efficient solution is found, otherwise the authors propose three mechanisms: fixed point iteration, Newton's iteration and quasi-Newton's iteration based on *d(P)* to generate the next constraint. Besides, the authors also provide two mechanisms (see Figure 10 and 11) in their paper to find the next reference point. The first one is based on that the global optimal solutions of the two agents are known, and the reference points are selected on the line connecting these two points. The second is an iteration mechanism: $r^{l+1} = r^l + \eta * p^*(r^l)$, where $r^{l+1}$is the next reference point, r^l is the current reference point, p^* is the constraint parameter under which a Pareto-optimal solution is found and η is the step size. So by the second mechanism the next reference point is based on the current one.

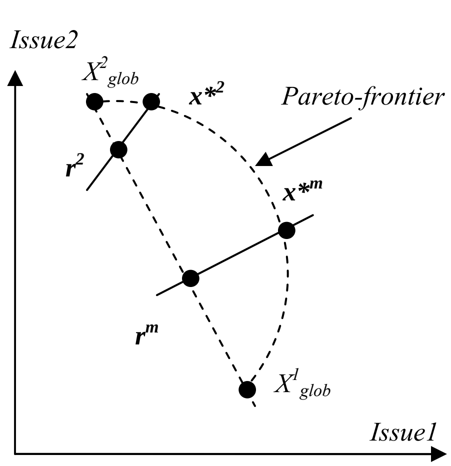

Figure 10 Mechanism 1
(Pareto-frontier)

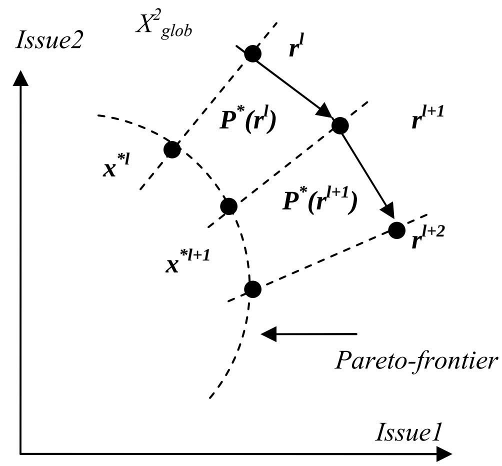

Figure 11 Mechanism 2
(Pareto-frontier)

Based on Ehtamo's idea, Heiskanen [45] studies a problem with constrained decision sets and argues that in such a situation the Pareto-efficient solution is possible on the boundary of decision set. He points out the method in [44] needs to be extended so that it also can find the boundary Pareto-efficient solutions. In the paper, Heiskanen extends it and provides heuristics for solving the mediator's problem. Moreover, Ehtamo et al and Heiskanen also study the similar problem of multiparty negotiation [46] [47].

Above, we discuss an approach with mediator that can be used to generate Pareto-frontier of a multi-attribute negotiation, and by this approach it is not necessary to elicit agents' utility functions. So it provides an alternative choice when agents' utility functions are unknown and hard to be elicited. In the following section, we introduce the idea of "Fair negotiation" that is applicable in some contexts.

2.2.4 Fair negotiation

There is also some research on multi-attribute negotiations that focuses on the concept of "fair-division" and developing division procedure from the perspective of cooperative game theory. Usually, the goal of the procedure is to fairly divide some items between two agents, and it can consist of two steps: the first step ensures an efficient outcome and the second step establishes "fairness" through a redistribution of gains.

This approach was first developed by Knaster and Steinhaus based on the idea of auctions [48]. The Knaster procedure is quite simple. In the first step, all items are assigned to the "winner" who totally values the items most, and then "fairness" is established through monetary transfers. The idea is two agents fairly share the excess. For example, in Table 1, *M* and *R* are dividing a *photo collection* and an *oil painting* that belong to both of them. *M* values two items with \$100 and \$100, while *R* values \$30 and \$10. By the idea of auction, *M* and *R* "bid" \$100 and \$20, respectively. (The "bidding" here is not a true bidding because agents need not pay when they win since the issues belong to themselves. Thus, the premise here is that agents cooperate and behave honestly.) So in the first step, *M* is the winner and gets both items. From the table we see the excess between them after the first step is \$80. By Knaster's idea each of them gets half of it, so *M* transfers \$60 (=\$100-\$40) to *R* in the second step. Thus, the procedure finishes with the outcome (\$140, \$60) for *M* and *R*.

From the result we see Knaster's procedure focuses on fairly sharing of the excess between agents, but the "*percent of estate*" of the two agents are not "fair". With such a consideration, Brams and Taylor [49] introduce another fair-division procedure named "Adjusted Winner", which implements an equitable outcome. In this procedure, each item (not all items as in Knaster's procedure) is assigned to the agent who values it most in the first step, and then some money is transferred from the temporary winner to the temporary loser in the second step such that the "*percent of estate*" between agents is the same.

Raith [48] points out the outcome of "Adjust Winner" might not be efficient. Thus Raith designs another approach named "Adjusted Knaster" based on both of them, which marries Knaster's efficient adjustment with the equitability condition of "Adjusted

Winner”. Raith also compares the outcomes of “issue-by-issue” negotiation and “package deals”, and indicates the former might not be efficient.

Table 1 The Knaster Procedure

“Fair-division”	M	R
1. Photo Collection 2. Oil Painting	100 100	30 10
Estate Value	200	40
Envy-free Share	100	20
Received Value	200	0
Excess E=80=	100	-20
Share of Excess E/2	40	40
Transfer	-60	+60
Total Value	140	60
Percent of Estate	70%	150%

3 Multi-attribute negotiation in AI

The goal of negotiation research in economics is to study the optimal mechanisms and equilibrium strategies for rational agents. However, the problem with multiple issues is so complex that rigorous modeling and analysis with Non-cooperative game theory turns to be intractable. Thus, some people study the problem with issue-by-issue negotiation and analyze when this approach is appropriate and the impact of agenda. In cooperative field, Nash and some other researchers focus on designing axioms such that the negotiation solution can be reached by these axioms. People also design methods to find out the Pareto-frontier of a negotiation problem. However, the assumptions of the research in game theory, either non-cooperative or cooperative, are strict and usually are not able to be maintained in real applications. Thus, research in the AI field has studied the negotiation problem in recent years. The goal in this field is to design appropriate models with automated and tractable negotiation mechanisms such that autonomous agents can deal with multiple issues by themselves, although the outcomes might not be optimal. In the following section, we review the research in AI with three different subjects of negotiation framework, trading-off mechanism and searching methods.

3.1 Negotiation framework

For automated negotiation, it is important to design a framework that can also be the basis of negotiation software. Fatima et al. [50] [51] [52] propose an agenda-based framework for multi-attribute negotiation. In this framework, agents can propose either combined or single offer on the remaining issues, and also they make decisions on issues independently, faced with a combined offer. For example, if there are two issues in a combined offer, say x_1 and x_2, an agent has two independent strategies S_1 and S_2, which are used to decide whether to accept x_1 and x_2. Besides, if one issue is settled, agents can not negotiate it any longer. So an implicit assumption in this framework is that the utility functions are linear additive.

Sycara [75], [77], [78] uses a case-based reasoning approach where the automated negotiating agents make offers based on similarity of the multi-attribute negotiation context (including issues, opponents, and environment) to previous negotiations. The domain is labor management negotiations. The passage o time leading up to a strike deadline is taken into consideration. This approach has been validated as realistic by domain experts. Moreover, Sycara [76] has used automatically generated persuasive argumentation as a mechanism for altering the utilities of agents, thus making them more prone to accept a proposal that otherwise they might reject.

Luo et al. develop a fuzzy constraint based framework for multi-attribute negotiation in trading environments [53]. In this framework, an agent, say the buyer, first defines a set of fuzzy constraints, and submits one of them by priority from highest to lowest to the opponent, say a seller, during each round. The seller either makes an offer based on the constraints or lets the buyer relax the constraints if a satisfactory offer is not available. The buyer then makes the decision to accept or reject an offer, or to relax some constraints by priority from lowest to highest, or to declare the failure of the negotiation. By doing so, the authors argue that the approach makes it not necessary to elicit agents' utility functions and also can realize trading-off between agents.

3.2 Trading-off mechanism

There are different ways that agents can make tradeoffs to reach a "Win-Win" solution. Faratin et al. [54] propose the use of similarity criteria based on fuzzy rules to make agents trade off. When agent makes an offer, the authors suggest, she first keeps the utility at her current level θ and selects the counter-offer from the set of

$$iso_a(\theta) = \{x \mid V^a(x) = \theta\} \tag{1}$$

to maximize the joint gain, where x is a multi-attribute offer, $V^a(\cdot)$ is utility function and $iso_a(\cdot)$ is the indifference set. The heuristic employed here is to select an offer that is most "*similar*" to the opponent's last offer by a function defined on the concept of fuzzy similarity as following:

$$trade-off_a(x, y) = \arg\max_{z \in iso_a(\theta)} \{Sim(z, y)\} \tag{2}$$

$$Sim(x, y) = \sum_j w_j Sim_j\{x_j, y_j\} \tag{3}$$

$$Sim_j\{x_j, y_j\} = \wedge_i (h_i(x_j) \leftrightarrow h_i(y_j)) \tag{4}$$

where y is the opponent's last offer, w_j is the weight on attribute j, $Sim_j\{x_j, y_j\}$ is the similarity function on attribute j, $\{h_i(\cdot)\}$ is the set of comparison criteria: $D_j \to [0,1]$ and $\leftrightarrow$ is an equivalence operator. By the experiment analysis, the authors argue that the method can help agents to squeeze out more favorable agreements and reach Pareto-optimal solution or very close.

3.3 Searching methods

Rather than the methods based on fuzzy rules [53] [54], some researchers propose some searching methods based on mathematical calculations.

Klein et al. [55] describe an approach to negotiate complex contracts with a mediator based on a random searching method. The mediator in this model makes proposals to both agents. Then agents vote it as acceptable or not. If both accept the proposal, the mediator stores it and randomly mutates it to create another proposal. If someone votes to reject, a mutation of the most recent mutually acceptable proposal is proposed instead. Repeating this procedure till there is no mutually better proposal appearing or the time limit is reached. In their paper, they define two kinds of negotiators, hill-climber and simulated annealer. Hill-climber accepts a proposal if it is better than the last mutually acceptable proposal. Simulated annealer accepts a proposal using a Monte Carlo machine which means she accepts a proposal by probability, *max(1,* $e^{-\Delta u/t}$*)*. By examples, the authors show the approach convergences and both agents applying simulate annealing can reach a more favorable agreement than both applying hill-climbing. However, if one is hill-climber and the other is simulated annealer, then hill-climber will be the winner and she can get more than that in the situation where both of them are simulated annealers. Thus, this approach might lead to a prisoner's dilemma. The paper also suggests some technique for the mediator to avoid this problem.

Tesauro and Li [56] [57] introduce a searching method based on Bayesian rules. It is assumed agents have some prior knowledge about the opponent's utility function. When they concede, agents apply depth-limited combinatorial searching based on their knowledge to find a most favorable offer. If the proposal is rejected then agents update the knowledge by Bayesian rules.

4 Supporting techniques

4.1 Preference elicitation

For most of the approaches we introduced above, either in economics or AI, it is an important issue to model an agent's preference by a utility function, i.e. preference elicitation. Research on this topic is mostly conducted in the field of decision theory.

Keeney and Raiffa [58] are the first two people who study this problem formally. They provide an eliciting procedure by assuming that utility function can be written as a linear combination of those on each attribute as equation 5:

$$v(x_1,...x_n) = \sum \lambda_i v_i(x_i) \tag{5}$$

where λ_i and $v_i(x_i)$ are the weight and utility function on attribute *i*. They create scales for each element x_i and query the agent on her behavior. The procedure can be described as follows:

Step 1: Define the value range of each element and the corresponding range of utility function as $x_i \in [x_i^0, x_i^1]$ and $v_i(x_i) \in [0,1]$.

Step 2: Obtain each $v_i(x_i)$

Step 2-1: Find the mid value point of $[x_i^0, x_i^1]$ and call it $x_i^{0.5}$, where $v_i(x_i^{0.5}) = 0.5$;

Step 2-2: Find the mid value points of $[x_i^0, x_i^{0.5}]$ and $[x_i^{0.5}, x_i^1]$;

Step 2-3: Check the consistency to make sure that $x_i^{0.5}$ is the mid value point of those above.

Do above procedure recursively till the threshold is reached.

Step 3: Find weight λ_i

Choose indifferent attribute combinations and solve the linear functions to obtain the weights λ_i. For example, if $(x_1{}^i,..., x_n{}^i) \sim (x_1{}^j,..., x_n{}^j)$, then we have equation 6:

$$\sum \lambda_i v_i(x_i{}^i) = \sum \lambda_i v_i(x_i{}^j) \tag{6}$$

By choosing sufficient number of those combinations, we can solve the function to get the value of weights. Usually, researchers can design kinds of structured question lists to obtain those mid value points. However, given even a small group of attributes, the size of outcome spaces will be quite large, so the additive independence is commonly assumed. It allows for the construction of less complicated and more manageable utility function. There are also other definitions of independence such like conditional additive independence [59].

Another traditional way to elicit preference is *Analytic Hierarchy Process (AHP)* presented by Satty [60]. In this approach, we can provide an *M*N AHP* decision matrix with *M* alternatives and *N* decision criteria as in Table 2 and let agents mark each column based on each criterion. Then by column (criteria) comparisons, we can get the weights of criteria and based on weight to get the final priority of each alternative or the value function.

Now there are also computer-aided software and websites developed to help elicit agents' preferences. Most of them are based on learning and some other AI approaches, such as constraint-based approach [61], knowledge and learning based approach [62] [63] [64], feature-oriented and needs-oriented approach [65] [66], 'Clustering, Matching and Refining' approach [67] [68], etc.

Table 2 *AHP* matrix

	Criterion					
	C_1	C_2	…			C_N
	w_1	w_2	…			w_N
Alternatives	a_{11}	a_{12}	…			a_{1N}
	…					
	a_{M1}	a_{M2}	…			a_{MN}

4.2 Multi-criteria-decision-making (MCDM)

MCDM, also called as multi-criteria or multi-objective optimization, is an important problem in many fields and has been paid lots of attentions. Here, we just briefly introduce some basic concepts and techniques dealing with *MCDM,* as there already exist lots of texts and surveys such as [69] [70] [71] [72] that introduce and summarize the research on this problem.

The goal of *MCDM* is to find solutions which need to satisfy multiple objectives. Mathematically, it can be expressed by equation 7:

$$\begin{aligned} &\min F(x) = (f_1(x), \dots f_n(x))^T \\ &s.t. x = (x_1, \dots x_m) \in S \end{aligned} \tag{7}$$

where $f_1(x), \dots f_n(x)$ are the n objective functions, $x = (x_1, \dots x_m)$ is the decision variable and S is the decision space.

"*Pareto-optimal*" is also an important concept in this problem. A solution x is said to be Pareto-optimal if there is no other solution y in S which dominates x, i.e. there is no y satisfying the following inequalities.

$$\forall i \in [1, n] : f_i(y) \le f_i(x) \quad and \quad \exists j \in [1, n] : f_j(y) < f_j(x) \tag{8}$$

The final solution of a *MCDM* problem should be selected from the set of Pareto-optimal solutions so that there does not exist any other alternative that is better in all objectives. But not all members in this set are the final solutions because agent may have different preferences on objectives. So there usually are two issues in solving a *MCDM* problem:

first is to design the optimization method and second is to design the procedure to solve a *MCDM* with the optimization method and agent's preference.

Optimization methods could be divided into derivative and non-derivative methods (see Figure 12). Now, researchers mostly focus on non-derivative methods as they are more suitable for general problems in real-world applications. Non-derivative methods do not require any derivatives of the objective function in order to calculate the optimum. Therefore, they are also known as black box methods. What's more, non-derivative methods are more likely to find global optima, and not be stuck on local optima as gradient methods might do. Some non-derivative optimization methods are listed in Figure 12.

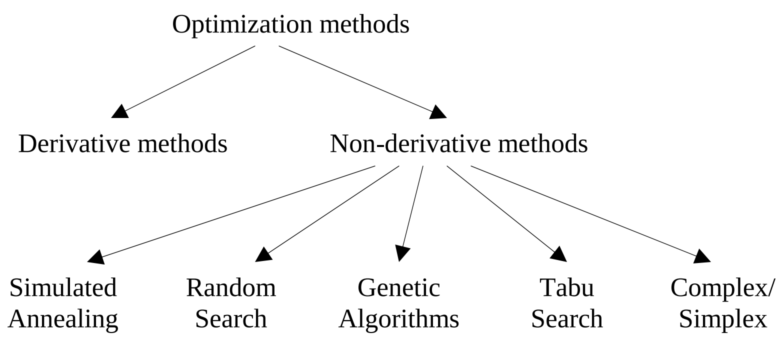

Figure 12 Optimization methods

Generally, a *MCDM* problem can be handled in four procedures depending on when to consider agent's preference: "*never*", "*prior*", "*during*" or "*posterior*" (see Figure 13). "*Never*" implies there is no preference information considered or all the objectives are identical. "*Prior*" means the procedure first aggregates multiple objectives to one single objective by agent's preference before the actual optimization process. "*During*" usually refers to interactive optimization methods, which rely on progressive information about agent's preference simultaneously as they search through the solution space. "*Posterior*" refers to the methods that enable to first search the solution space for a set of Pareto-optimal solutions and then present them to agent for decision. The advantage for this way is the first step is independent of agent's preference, however the disadvantages are that there is a large computational burden and it is hard for agent to choose one among too many alternatives. Some common methods related with each procedure are listed in Figure 13.

5 Conclusion and future work

In this report, we have surveyed the related work on multi-attribute negotiation in the fields of economics and AI. In economics, game theory is the main methodology people employ for the research on multi-attribute negotiation and generally the research can be divided into two braches: non-cooperative and cooperative. In the former branch, people mostly focus on issue-by-issue negotiation as it makes the problem much simpler and also they argue it is commonly applied in real-life situations. Researchers have studied its properties and the difference from simultaneous negotiation. Besides, they also address the problem of agenda selection. From the review we can see: in some situations where negotiation friction (time is valuable or the probability of breakdown is high) is big and agents are heterogeneous, issue-by-issue negotiation is applicable and the outcomes also can be efficient. However, inefficiency may arise in this approach since it is necessary to satisfy the premises of linear additive utility functions and independent reservation prices on each issue. In the second branch, people mainly focus on designing axioms, e.g. Nash axioms, by which the negotiation solution can be reached. This approach is applicable with multiple issues in negotiation as long as the assumptions—cooperation, perfect information and rationality can be satisfied. Besides, there also have appeared some methods to find the Pareto-frontier of a multi-attribute negotiation so that people can apply the axioms to reach the solution even where it is hard to elicit agents' utility functions or agents do not want to reveal much private information. However, the problem of the methodologies in economics is that the assumptions are usually not able to be maintained in real-life applications. In AI, the emphasis lies more on finding acceptable rather than optimal solutions by autonomous agents in real-world environments. But till now there has not appeared much research work on multi-attribute negotiation problem, although we see some ideas in the review such as fuzzy constraint-based framework, trading-off by similarity criteria and searching with Bayesian rules.

The report gives us a good knowledge on multi-attribute negotiation as well as the current research progress. Based on our understanding and analysis of the real situations, we make the following preliminary suggestions for the work that focuses on real-world applications:

First, there are two issues that are important: one is to make negotiation strategy more efficient in order to deal with multiple issues, and the second is to design a mechanism such that a (near) Pareto-optimal solution can be reached as we know "Win-Win" is the main favorable property of multi-attribute negotiations.

Second, for technical considerations we think three things are important:

- Information: Usually in real-world applications, such as for Navy detailing system, it is hard to promise the contexts are with complete information. So the future work which is for applications should focus on incomplete information. However, it is reasonable to assume agents have some prior knowledge on their opponent like that assumed in [56] [57] and our previous work on single-attribute negotiation [73].

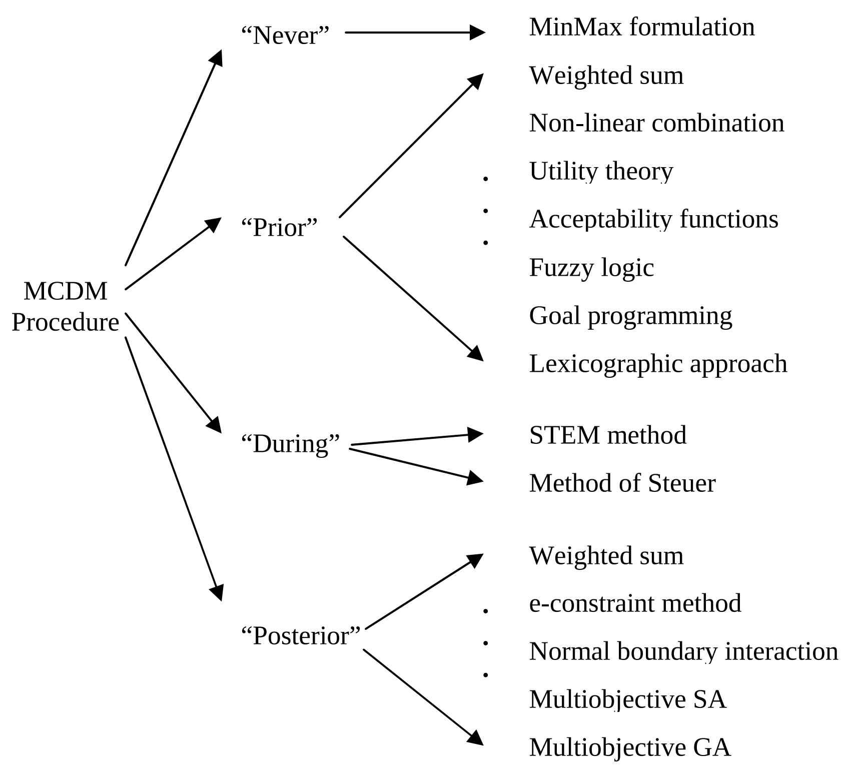

Figure 13 Method classification for MCDM

- Protocol: Alternating-offer negotiations are preferred to one-shot negotiations. One-shot negotiations limit agents' chances of adjusting the offers such that it usually requires agents have abilities to deal with complicated reasoning and computation. It is not common in real-world applications. In contrast, alternating-offer protocol is more flexible and applicable in real situations.

- Procedure and Methodology: As we introduce before, there are usually three negotiation procedures: separate, sequential and simultaneous. But for either separate or sequential negotiation procedure it is necessary to satisfy their premises. Moreover inefficiency also may arise. So if people want to take separate/sequential procedure, some supplementary work can be considered such as introducing an additional trading-off stage into the negotiation. The other choice is simultaneous negotiation procedure, but it leads to a heavy computation and reasoning burden. So for this procedure it can be considered to adopt the cooperative negotiation methodologies and introduce a mediator into the negotiation whose responsibility is to maintain the efficiency of the system [44] [45] [46] [47]. Besides, we also suggest it should consider agents' rationality such that agents can compete as well by keeping their decision rights to accept or reject an offer [55] or even to announce their preferred regions to the mediator. For agreement implementation, there are not many choices as we know it is usually determined by the negotiation problem, for example, in Navy detailing system, agreement is implemented if and only if all issues are settled.

To our knowledge, there has not been work which completely addresses these problems. Therefore, the research on resolving them will be of great challenge and significance.

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