Leveled Commitment Contracts with Myopic and Strategic Agents

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Abstract

In automated negotiation systems consisting of self-interested agents, contracts have traditionally been binding, *i.e.*, impossible to breach. Such contracts do not allow the agents to efficiently deal with future events. This deficiency can be tackled by using a *leveled commitment contracting protocol* which allows the agents to decommit from contracts by paying a monetary penalty to the contracting partner. The efficiency of such protocols depends heavily on how the penalties are decided. In this paper, different leveled commitment protocols and their parameterizations are experimentally compared in sequences of multiple contracts. In the different experiments, the agents are of different types: self-interested or social welfare maximizing, and they can carry out game-theoretic lookahead or be myopic. Several meeting technologies, ways of setting the contract price, and ways of setting and increasing the penalties are compared.

Surprisingly, self-interested myopic agents reach a higher social welfare quicker than cooperative myopic agents when decommitment penalties are low. The social welfare in settings with agents that perform lookahead does not vary as much with the decommitment penalty as the social welfare in settings that consist of myopic agents. In all of the settings, the best way to set the decommitment penalties is to choose low penalties, but ones that are greater than zero. This indicates that leveled commitment contracting protocols outperform both full commitment protocols and commitment free protocols.[1]

JEL: L140, D830, C780, C630

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[1] An early version of this paper appeared at the National Conference on Artificial Intelligence (AAAI) [Andersson and Sandholm, 1998b].

1 Introduction

Systems which include automated negotiation are starting to play an increasingly important role in our society. One reason is the technology push of a growing standardized global communication infrastructure—*e.g.*, IP, WWW, Java, HTML, XML, and KQML—over which separately designed agents belonging to different organizations can interact in an open environment in real-time, and safely carry out transactions [Sandholm, 1997, Choi et al., 1997]. Another form of technology push comes from advances in automated negotiation technology itself (see *e.g.* [Sandholm, 1996, Sandholm and Vulkan, 1999, Sandholm et al., 1999a, Sandholm and Lesser, 1997, Sandholm, 1993, Rosenschein and Zlotkin, 1994, Kraus, 1993]). The second reason for increased importance of automated negotiation is strong application pull for computer support for contracting, especially at the operative decision making level. For example, we are witnessing the advent of small transaction commerce on the Internet for purchasing goods, services, information, communication bandwidth, *etc.* [Choi et al., 1997]. Automated negotiation is also proliferating into business-to-business commerce, for example in electricity markets [Ygge and Akkermans, 1996, Sandholm and Ygge, 1997] and transportation exchanges [Sandholm, 1993]. Furthermore, there is an industrial trend toward virtual enterprises: dynamic alliances of small, agile enterprises which together can take advantage of economies of scale when available—e.g. by being able to respond to larger and more diverse orders than they could individually—but do not suffer from diseconomies of scale.

Multiagent technology facilitates the automated formation of such dynamic alliances on a per order basis by automated contracting. Such automation can save labor time of human negotiators, but in addition, other savings are possible because computational agents are often more effective at finding beneficial contracts and contract combinations than humans are in strategically and combinatorially complex settings.

Contracts in automated negotiation systems consisting of self-interested agents have traditionally been binding, *i.e.*, impossible to breach. Such contracts do not allow the agents to act efficiently upon future events because contracts might become unfavorable to one or both of the agents after the contracting. If the agents were allowed to breach contracts, they could accommodate changes in the environment more efficiently and the social welfare (sum of the agents' payoffs) would improve. In the case of self-interested agents, there is a need to compensate the party who is the victim of a decommitment. On the other hand, in systems with cooperative agents, decommitting from contracts without reprisals can be accepted, even after the other party has partly completed the task of the contract [Sen and Durfee, 1994, Sen and Durfee, 1998, Smith, 1980], since each agent wants to maximize the sum of all agents' profit.

Contingency contracts have been proposed as an instrument for increasing the economic efficiency of contracts between self-interested agents in settings of incomplete information about future events [Raiffa, 1982]. In these contracts the obligations of the contract are made conditional on future events. Contingency contracts can increase the payoff of both parties, so contracts not possible with full commitment protocols may become beneficial for both parties. However, it may be impossible to anticipate and enumerate all future events. Monitoring all events after the contract is made can also be impractical. If some events are observable by only one of the parties, another problem arises: one party can have an incentive to lie about the events in order to be better off himself.

Recently, *leveled commitment contracts* were proposed as an alternative instrument for increasing the economic efficiency of contracts between self-interested agents in settings of incomplete information about future events [Sandholm and Lesser, 2000, Sandholm and Lesser, 1995]. In a leveled commitment contract, each agent can decommit from the contract by simply paying a decommitment penalty to the other contract party. The decommitment penalties are decided at the time of contracting and the penalties do not need to be the same for the contract parties. It was shown through game-theoretic analysis that this leveled commitment feature increases the Pareto efficiency of contracts and can make contracts individually rational to both parties even in cases where full commitment contracts cannot. Furthermore, leveled commitment contracts can never be worse than full commitment contracts because they can emulate the latter by setting sufficiently high penalties. In another paper, algorithms were presented for computing the decommitting equilibria given a contract, as well as algorithms for optimizing the contract itself (price and penalties) [Sandholm et al., 1999b]. In a further paper, it was shown that certain sequential and simultaneous decommitting protocols surprisingly lead to the same sum of the agents' payoffs if the contract is optimized for each of the protocols separately [Sandholm and Zhou, 2000]. All of these analyses have focused on a single contract only. This paper focuses on sequences of leveled commitment contracts.

Leveled commitment contracts enable profitable construction of composite contracts from basic contracts [Andersson and Sandholm, 1998a]. As an example setting, we have shown that in task allocation, contracts of a single task at a time usually lead to only local optima, and that this problem can be addressed by cluster contracts (where multiple tasks are negotiated over atomically), swap contracts (where tasks are swapped between agents), and multiagent contracts (where a contract has more than two parties) [Sandholm, 1998, Sandholm, 1996, Andersson and Sandholm, 1999]. Leveled commitment contracts allow any of these composite contracts to be constructed from a sequence of basic contracts. This may avoid the need for these more complex combinatorial contract types. For example, say that the only profitable contract is one where agent A gives task t_1 to agent B, and agent C gives task t_2 to agent A. Now A can make the unprofitable contract with B in anticipation of the contract with C which will make the combination profitable. Then, if C does not agree to the contract with A, agent A can decommit from the contract that it made with B.

With leveled commitment protocols there is no need for an agent to conduct a feasibility check before contracting. If it turns out that the agent cannot fulfill the contract obligations, *e.g.*, due to lack of resources, the agent can decommit. Similarly, the agent does not need to perform a complete computation of the marginal cost of taking on the contract obligations before accepting the contract. Instead, the agent can complete the computation after contracting. If the contract turns out to be unbeneficial, the agent can decommit. This allows the agent to act faster and with less constraints in the contracting process than if it always had to perform a feasibility check and a thorough marginal cost calculation before contracting. The system also becomes more efficient computationally if only one agent (the one that takes on the task) conducts a thorough marginal cost calculation, than if all the agents that bid for the task would carry out such a calculation.

The concept of breaching contracts in the real world has been analyzed in the economics of law (see *e.g.* [Posner, 1977]). The main ideas are that the party that breaches must compensate the victim for lost profit and that the penalties for breaching should be set so that the social welfare is maximized.

Strategic thinking behind contracting and one-sided decommitment among self-interested agents has also been studied via modeling the setting as a Markov-process [Park et al., 1996]. In that work it was assumed that the agents expect none of their bids to be accepted, which makes the approach inconsistent with noncooperative equilibrium analysis of game theory.

Diamond and Maskin (1979) have studied systems in which both agents can decommit from a contract by paying a decommitment penalty to the other party of the contract. Those penalties can be set in different ways: they can be compensatory or privately decided (*i.e.* liquidated; not necessarily decided by the parties of the contract – maybe imposed by a court) in the contract. The compensatory decommitment penalties are favored because of efficiency, *i.e.*, they provide, whenever possible, an increasing mutual welfare between the agents that enter a new contract. However, the social welfare may decrease because of the inefficiency arising from the contract that is breached. Another argument for the compensatory penalties is that they are exactly the penalties that two rational parties would agree on for privately decided penalties. One reason for having over-compensating penalties is that one agent can make himself more trustworthy and the expected utility of the other agent will increase enough to make the contract possible [Posner, 1977]. Hence, over-compensating penalties can increase the space of possible contracts. However, it would limit the space of possible decommitments.

Leveled commitment contracts can also be useful in auctions of multiple goods where a bidder's valuation for a combination does not equal the sum of the bidder's valuations of the individual goods. If the bidder does not receive a complete bundle that she desires, she could decommit—for a predetermined penalty—from the items of the partial bundle that she did get. Similarly, one could allow the auctioneer to take back an item from a winning bidder for predetermined penalty (the idea being that some other bidder may now bid higher given what items he has decommitted from and what items the auctioneer has taken back from him). In the Federal Communications Commission's bandwidth auction the bidders were allowed to retract their bids [McAfee and McMillan, 1996, Cramton, 1997, Plott, 1997, Ledyard et al., 1997]. In case of a retraction, the item was opened for reauction. If the new winning price was lower than the old one, the bidder that retracted the bid had to pay the difference. This guarantees that retractions do not decrease the auctioneer's payoff. However, unlike our leveled commitment contracts, this mechanism exposes the retracting bidder to considerable risk because she does not know the penalty when decommitting. Also unlike our leveled commitment contracts, that mechanism only allows one party of the contract (bidder) to decommit. The auctioneer cannot take back items.

1.1 Setting the decommitment penalties

In leveled commitment contracts, the penalties could be chosen freely by the agents, in which case each agent would try to optimize the penalties in its favor. The negotiation will be more complex if the agents can decide the penalties themselves compared to when they are set by the protocol because there would be more variables to agree on in order for all parties to accept a contract. If the penalties are set by the protocol, the negotiation becomes easier, but the result may not be optimal (*e.g.,* fixed penalties do not guarantee that it is is profitable for the agents to decommit in all situations where a decommitment is mutually profitable for the agents involved in the contract).

Another method is to relate the decommitment penalty to the price of the contract. This could be done by choosing the penalty as a percentage (or a more complex function) of the price. Another way is to make the penalties compensate the victim of the breach for its lost profit. Because the victim would have an incentive to lie about the expected profit, a mechanism for calculating the lost profit would be necessary. The state of both agents might have changed since the contract was made, so the expected lost profit at contracting time and breaching time may differ. In the extreme, the lost profit for the victim can be negative at breaching time, that is, also the victim of the breach benefits from being freed from the contract obligations.

A breach close to the execution deadline of the contract or late in a negotiation is likely to be more costly for the victim since it can be hard to find someone else to contract with within a short amount of time. In order to prevent such occurrences, the decommitment penalties can be increased over time.

This paper studies leveled commitment contracting protocols in order to conclude which mechanism should be used for setting the decommitment penalties among qualitatively different agents. Several environments are studied, and in each of them, 16 protocols with many parameterizations are tested. The next section presents the experimental setup. Section 3 introduces the different types of agents of this study. Section 4 presents the different leveled commitment contracting protocols of the study. The results are presented in Section 5. Section 6 offers conclusions, and Section 7 lays out avenues for future research.

2 Experimental setup

To investigate the performance of different mechanisms of setting the decommitment penalties, the agents are divided into two subsets: *contractors* and *contractees*. The contractors have one task each and a cost associated with the task. A contractor considers contracting out its task to a contractee that could handle the task at a lower cost than the contractor. The contractees do not have any tasks initially. They have resources to handle a maximum of one task each at a cost. The cost of handling the task depends on the contractee and the task. The fallback position of a contractor is the cost of handling the task it has at the start of the negotiation. The fallback values of the contractees are zero (they have no tasks or pending expenses at the beginning of the negotiation).

In our experiments, there were two contractors and two contractees. These numbers were kept small so that we were able to allow a reasonable number of meeting (contracting) rounds in the game without precluding the possibility for an agent to exactly solve the game. If larger numbers of agents would have been allowed with these numbers of rounds, it would have become computationally intractable to solve the game by lookahead in the game tree. In such games one cannot (due to computational complexity) determine how a rational agent would act.

Initially each agent was randomly assigned a cost for handling each task. The contractors' costs were drawn uniformly in the interval $[100, 200]$ and the contractees' in the interval $[0, 100]$. The experiment was executed for 100 randomly generated problem instances with 5 negotiation rounds in each. The number of negotiation rounds was assumed to be common knowledge. In each round, one chosen contractor gets a chance to make a contract with one chosen contractee. The contractors never negotiate with each other. Neither do the contractees.

To compare the different protocols, the *ratio bound* was used: social welfare of the solution obtained by a given protocol divided by the optimal social welfare. The mean ratio bounds (over the 100 problem instances) were calculated for all the different leveled commitment protocols and agent types. In other words, each protocol was tested with each agent type on each problem instance. In addition to the means, the 95% confidence intervals were computed from which the results could be statistically analyzed. These confidence intervals are also shown in each graph.

In the experiments with a random meeting technology, we did not rely on a randomization device to establish the outcome of a given protocol and agent type on a given problem instance since that would have introduced unnecessary variance into the results. Instead, all possible outcomes were enumerated and the true expected value of the ratio bound was computed.

3 Types of agents in this study

Four types of agents are included in the study. In each experiment, agents of the same type were matched against each other. All of the agents are assumed to be risk neutral. There are two dimensions along which the agent types differ: the amount of *lookahead* the agent performs before it accepts or rejects a proposed contract, and how *self-interested* the agent is.

3.1 Agents with and without lookahead

The agents of this study either perform full lookahead or none at all. An agent that does full lookahead solves the current subgame of the game tree by looking ahead all the way to the leaves of the tree. The agent agrees to the contract if and only if the expected payoff of agreeing is greater than rejecting, *i.e.*, such an agent acts strategically exactly as game theory prescribes. The myopic agents that perform no lookahead only consider the immediate payoff of the contract under negotiation. Such an agent agrees to the contract if the contract increases the agent's immediate payoff.

3.2 Individually rational and cooperative agents

The agents can be *self-interested* (*SI*). Such an agent only agrees to a contract if it increases the agent's own payoff (expected or immediate, depending on whether the agent performs lookahead or not). Alternatively, an agent can be an explicit social welfare maximizer (*SWF-maximizer*), *i.e.,* a *cooperative agent.* Such agents consider the summed payoffs of all agents in the system when deciding to accept or reject a contract. That is, a SWF-maximizer can agree to a contract even if that makes the agent worse off as long as the social welfare in the system increases.

Our motivation of studying these two agent types was the following. In cooperative distributed problem solving (see, *e.g.,* [Durfee et al., 1989]), the systems designer is in control of the interaction mechanism (rules of the game) and each agent's strategy. In such settings, the system designer would design the agents to be SWF-maximizers. On the other hand, in multiagent systems—used, for example, for electronic commerce—the system designer can only design the interaction mechanism while each agent is designed by and represents a different self-interested real-world party such as a company or an individual in the negotiation. In such settings, it is reasonable to assume that the agents will be self-interested. We study how much welfare loss self-interest causes in different settings, and as show that, surprisingly, in certain settings self-interested agents lead to higher social welfare than SWF-maximizing agents.

4 Types of leveled commitment protocols

In this section we define leveled commitment contracts, and present the different leveled commitment contracting protocols of the experiment. The leveled commitment contracts of this study are defined as follows:

Definition. 1 *A* leveled commitment contract *is a tuple* $\langle \mathcal{C}, , \rangle$*, where* $\mathcal{C}$ *is the underlying full commitment contract and* , *is the set of decommitment penalties. Let* $A_{\mathcal{C}}$ *be the set of agents involved in the contract* $\mathcal{C}$*. Then* , *will consist of one decommitment penalty for each pair of agents in* $A_{\mathcal{C}}$*, so* $|,| = \frac{|A_{\mathcal{C}}|^2-|A_{\mathcal{C}}|}{2}$.

This definition has the nice feature of separating the leveled commitment framework from the obligations of the contract, called the underlying contract $\mathcal{C}$. This means that the leveled commitment protocol can be applied to any type of full commitment contract. If an agent wants to decommit from the underlying contract, it has to pay the decommitment penalties stated in , to all agents involved in the contract. In the most common case where there are two agents involved in a contract, this means paying a penalty to the other contract party. In the experiments of this paper, each contract occurs between two parties only.

The concept of leveled commitment is not specific to task allocation problems, although the experiments of this paper focus on task allocation. All the leveled commitment protocols in this study have as their underlying contract, $\mathcal{C}$, a contract that transfers one task from one agent to another (with sidepayments as will be discussed).

The following subsections introduce the different leveled commitment contracting protocols tested in this study. They differ based on how the decommitting penalties are set, how the contract price is determined, and what is the order in which agents meet each other to explore the possibility of a contract.

4.1 Ways of setting the decommitting penalties

Four different mechanisms of deciding the decommitment penalties are studied: *fixed*; *percentage* of contract price; increasing and decided at the time of *contracting*; and increasing and decided at the time of *breaching*.

4.1.1 Decommitment penalties as a fixed value (FIX-protocol)

In the FIX-protocol, all contracts have the same fixed decommitment penalty. It is decided prior to the start of the negotiation and it stays constant throughout the negotiation. Experiments with six different values of the fixed decommitment penalty were conducted. Table 1 summarizes the different values.

FIX-protocol	PER-protocol	CON-protocol BRE-protocol
0	0.1	0.25
5	0.25	0.5
10	0.4	0.75
15	0.5	1.0
30	0.75	2.0
50	1.0	4.0

Table 1: Parameterizations in the study of leveled commitment protocols in different environments. (Note that 10% is written as 0.1 in the tables for the PER-, CON-, and BRE-protocols.)

4.1.2 Decommitment penalties as a percentage of the contract price (PER-protocol)

In the PER-protocol, the decommitment penalty is a percentage of the price of the contract. The same percentage is used for all contracts throughout the negotiation. The particular percentages that are used in the experiments are presented in Table 1. The experiments suggested that it does not make sense to explore penalties that exceed the contract price in this case.

4.1.3 Decommitment penalties decided at the time of contracting (CON-protocol)

In the CON-protocol, the decommitment penalty of each contract is fixed at contracting time. However, the later the contracting time, the higher the penalty. Specifically, the penalty is increased linearly with contracting time. It starts from zero and goes to a percentage of the contract price.[2] Table 1 presents the percentages for setting the highest penalty. As the table shows, in some of the experiments we allowed the later penalties to exceed the contract price significantly.

4.1.4 Decommitment penalties decided at the time of breaching (BRE-protocol)

In the BRE-protocol, the decommitment penalty of each contract is fixed at the time of breach. The later the breaching time, the higher the penalty. Specifically, the penalty is increased linearly over time, starting from zero. A contract that is breached on the last round of the game has the highest penalty. This highest penalty is a percentage of the contract price. Table 1 shows the specific percentages used in the experiments. Again, in some of the experiments we allowed the later penalties to exceed the contract price significantly.

4.2 Methods of computing the contract price

The price of a contract that is under consideration is set so that the profits of the two agents of that contract are equal. However, the profits can be calculated in two different ways:

[2] Since a contract that is made on the last round of the game cannot be breached because the game ends, the highest penalty is applied to the contract that is made at the second to last round of the game (if an agreement is made at that round). A contract made in that round can be breached on the last round.

- **"Fallback protocols":** Each agent's profit is computed as the agent's payoff under the contract under consideration minus the agent's fallback payoff. The current payoffs from existing contracts do not factor into this calculation. Neither do the decommitment penalties that the agents may need to pay to undo an existing contract.

- **"Current protocols":** Each agent's profit is computed as the agent's payoff under the contract under consideration minus the agent's payoff under its current contract (this is the agent's fallback payoff if the agent is not under contract) minus the decommitment penalty that the agent has to pay.

4.3 Sequencing of contracts: the meeting technology

The order in which the agents meet for negotiation is either **deterministic** or **random**. In the deterministic model, the order is decided prior to negotiation (contractor 1 meets contractee 1, contractor 1 meets contractee 2, ..., contractor 2 meets contractee 1, ...). In the random model, in each round of the game, one contractor and one contractee are randomly picked to negotiate with each other. In either case, the negotiation protocol is sequential, that is, only two agents—one contractor and one contractee—negotiate in each round.

If the agents are individually rational, a contract is accepted if the payoffs (immediate or with lookahead) after the contract will be greater for both the contractor and the contractee compared to the payoffs before a potential acceptance of the contract. If one of the agents is indifferent, that is, the contract does not increase its payoff, the other agent decides whether or not to make the contract. If both the agents are indifferent, the contract is rejected.

4.4 Summary of the dimensions varied in this study

Before presenting our results, let us summarize the different agent design dimensions and protocol design dimensions that were varied in this study:

1. Agents conducted **lookahead** or were **myopic**.

2. Agents were **self-interested (SI)** or **social welfare maximizing (SWF)**.

3. The decommitment penalty was **fixed**, a **percentage** of contract price, **increasing based on contract time**, or **increasing based on decommit time**.

4. The contract price was determined either based on the original **fallback** positions of the two agents that are considering a contract, or based on the **current** situations of those two agents.

5. The meeting technology was either **deterministic** or **random**.

5 Results

The results are presented in the following order. First, the agent types are compared, then the methods of sequencing the contracts, and then the different ways of deciding on a contract price. Finally, the best protocols for each agent type are discussed.

5.1 Comparison of agent types

Overall, agents that performed lookahead reached a higher social welfare than myopic agents. By definition, the social welfare maximizers that conduct full lookahead always reach the best solution that is reachable given the sequence of the contracts. Under the deterministic meeting technology, these agents always reached the global optimum (Figures 1 and 2).

Comparing the myopic agents (self-interested and social welfare maximizing) using deterministic meetings, the self-interested agents surprisingly outperformed the social welfare maximizers (recall that the evaluation criterion is social welfare) in the region of low decommitment penalties (Figures 3 and 4). They did that for all eight deterministic protocols. Without lookahead, not even social welfare maximizing agents will reach the global optimum in a limited number of negotiation rounds in general. The reason why self-interested agents lead to higher average social welfare than social welfare maximizing agents is that it is often advantageous for the social welfare in the long run to conduct a decommit that is myopically social welfare decreasing. When this type of breach occurs among self-interested agents, the breacher gains immediately by definition, and the other party of the contract suffers a loss that exceeds the breacher's gain, but is freed to look for good deals in later negotiation rounds (with no need to pay a decommitting penalty to accept such a new contract). For some instances, if the negotiation contained more rounds, the social welfare maximizing agents reached the same social welfare as the self-interested ones.

In several cases the myopic agents performed almost as well as the agents with full

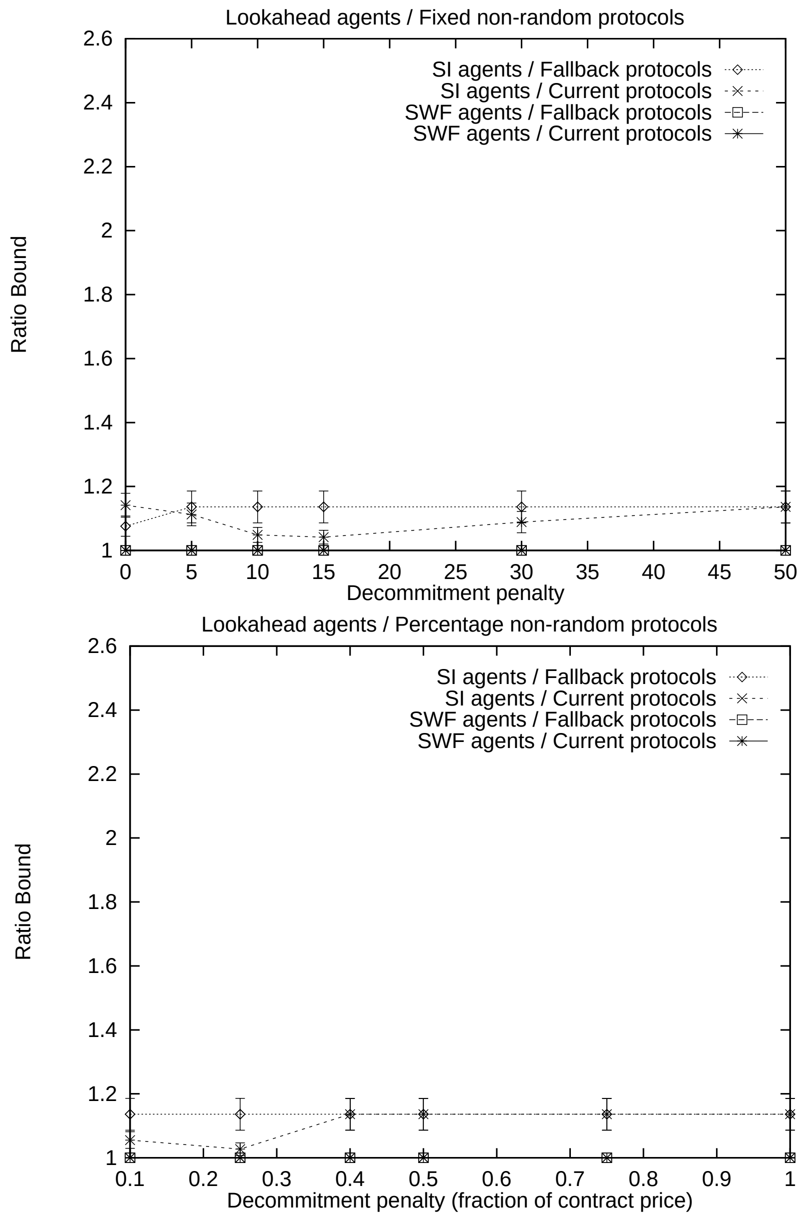

Figure 1: *Agents that perform lookahead; deterministic meetings.*

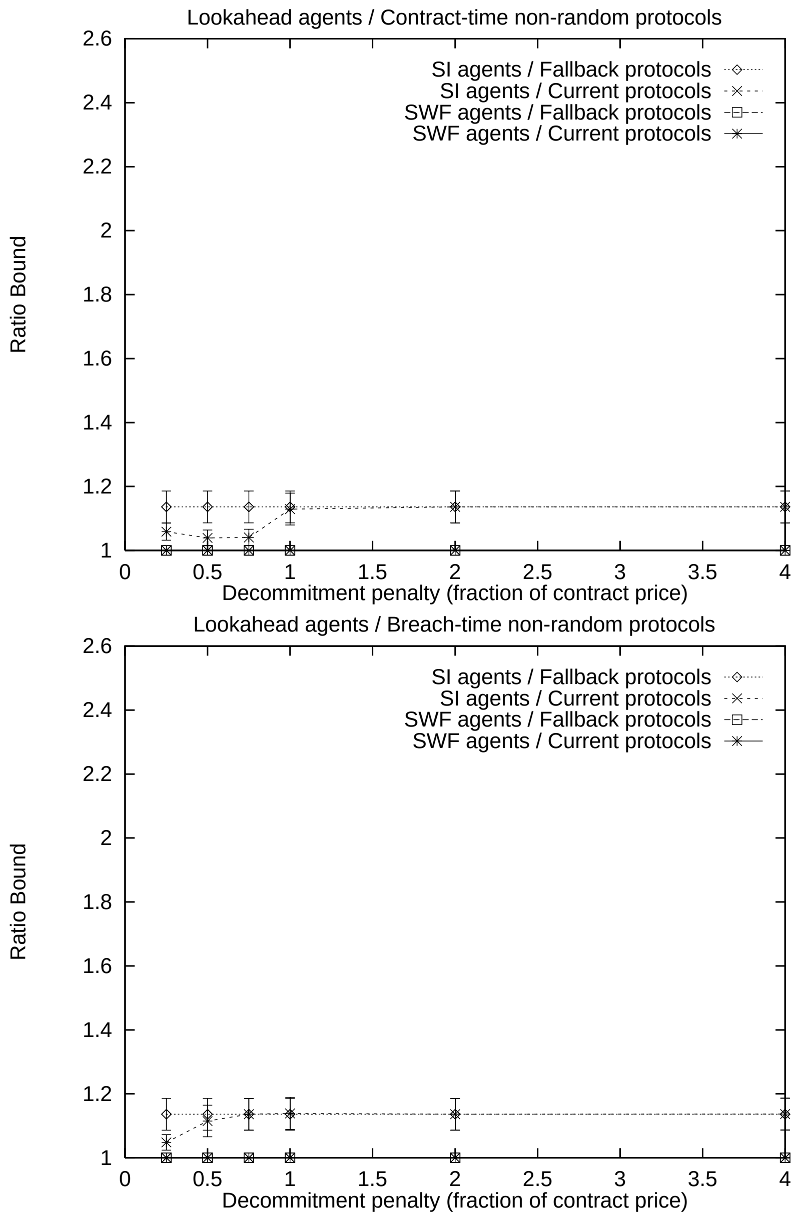

Figure 2: *Agents that perform lookahead; deterministic meetings.*

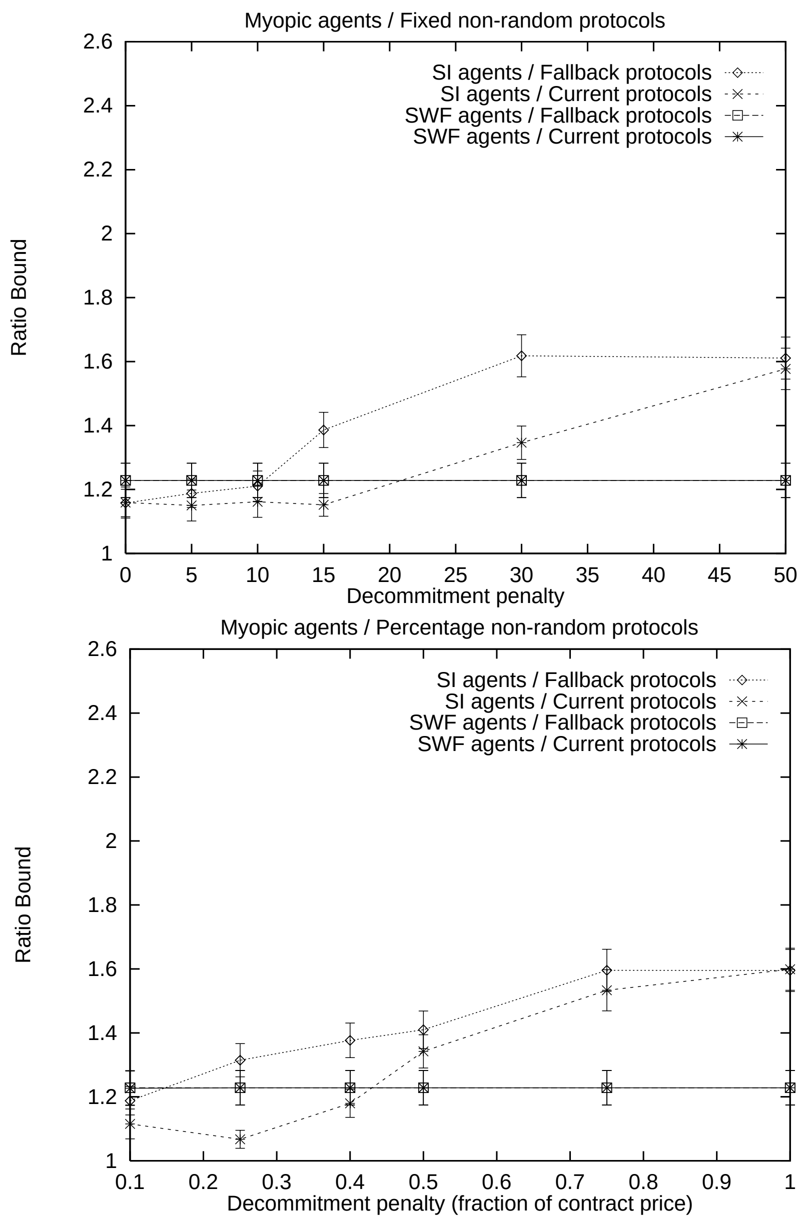

Figure 3: *Myopic agents; deterministic meetings.*

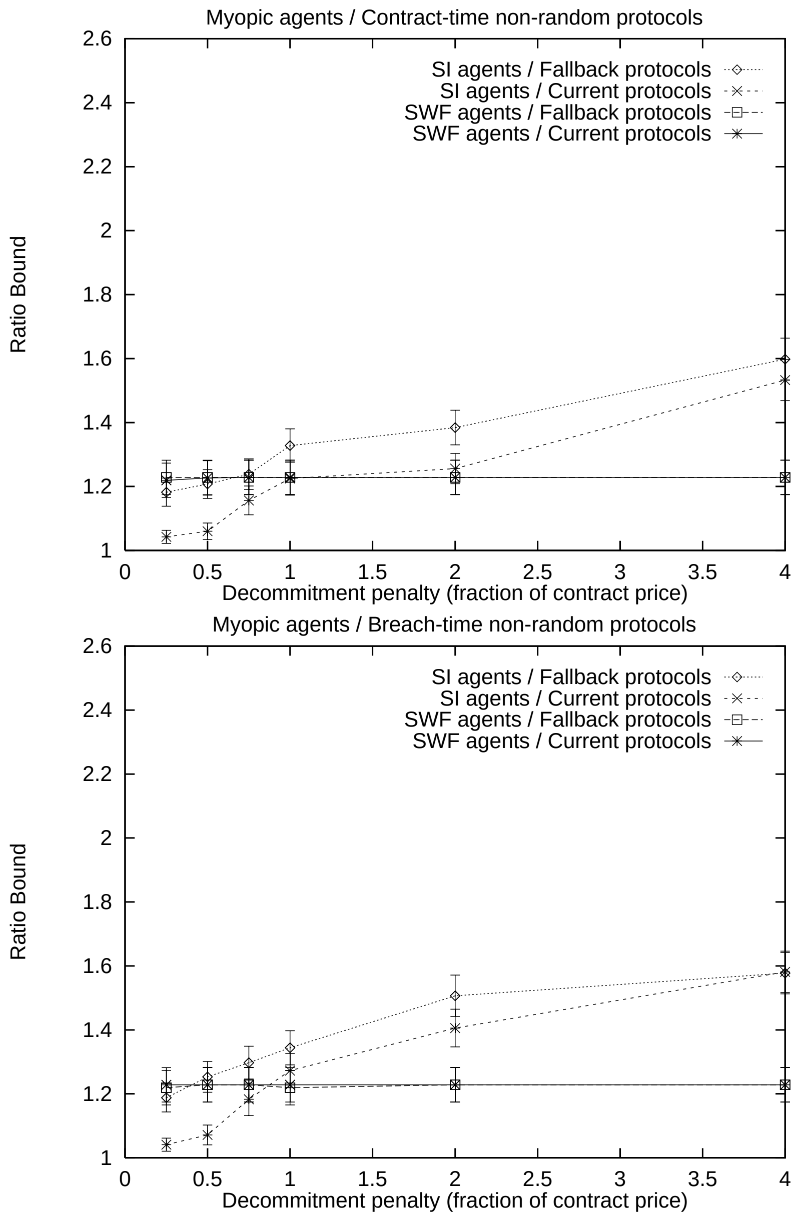

Figure 4: *Myopic agents; deterministic meetings.*

lookahead (Figures 1-8). There is a clear trade-off between reaching the globally optimal solution, and computation cost. In these experiments, with small problem sizes, the agents do not gain much by performing a full lookahead compared to myopic agents with well set decommitment penalties. It is considerably more complex to perform a full lookahead than no lookahead, and for large problem instances a full lookahead is not possible at all due to intractability. On the other hand, the decommitment penalties do not have to be chosen so carefully if the agents perform a full lookahead. That is because the agents can evaluate the future events and act upon that knowledge up front, reducing the risk in a commitment.

5.2 Comparison of contract sequencing methods

Comparing the deterministic and random meeting technologies, the deterministic method always yielded a lower (better) ratio bound (Figures 1-8). That can be explained by the fact that the best possible ratio bound that is achievable with the random method is greater than one. That is because the ratio bound is averaged over all possible outcomes, including those that never can reach the optimum. The extreme example is when the same contractor and contractee meet each other in every round of the negotiation. In such cases, the other agents do not get to participate in the reallocation process at all, leading to suboptimal social welfare.

The best achievable result with the random method was always reached by the social welfare maximizers that conduct full lookahead. For the meeting sequences where the random protocol could theoretically perform well (*i.e.*, where all the agents participated in the negotiation), it did indeed perform well.

5.3 Comparison of methods for computing the contract price

Of the two methods of computing the contract price, the method that computes the profit from the original static fallbacks was never better than the method that computes the profits from the current situation which includes penalties—if the optimal method and parameterization for setting the decommitment penalties for each agent type and meeting technology was used (Table 2).

For other penalty setting methods and parameterizations, the best method of setting the price varied. With a deterministic meeting technology, the method that considers the current

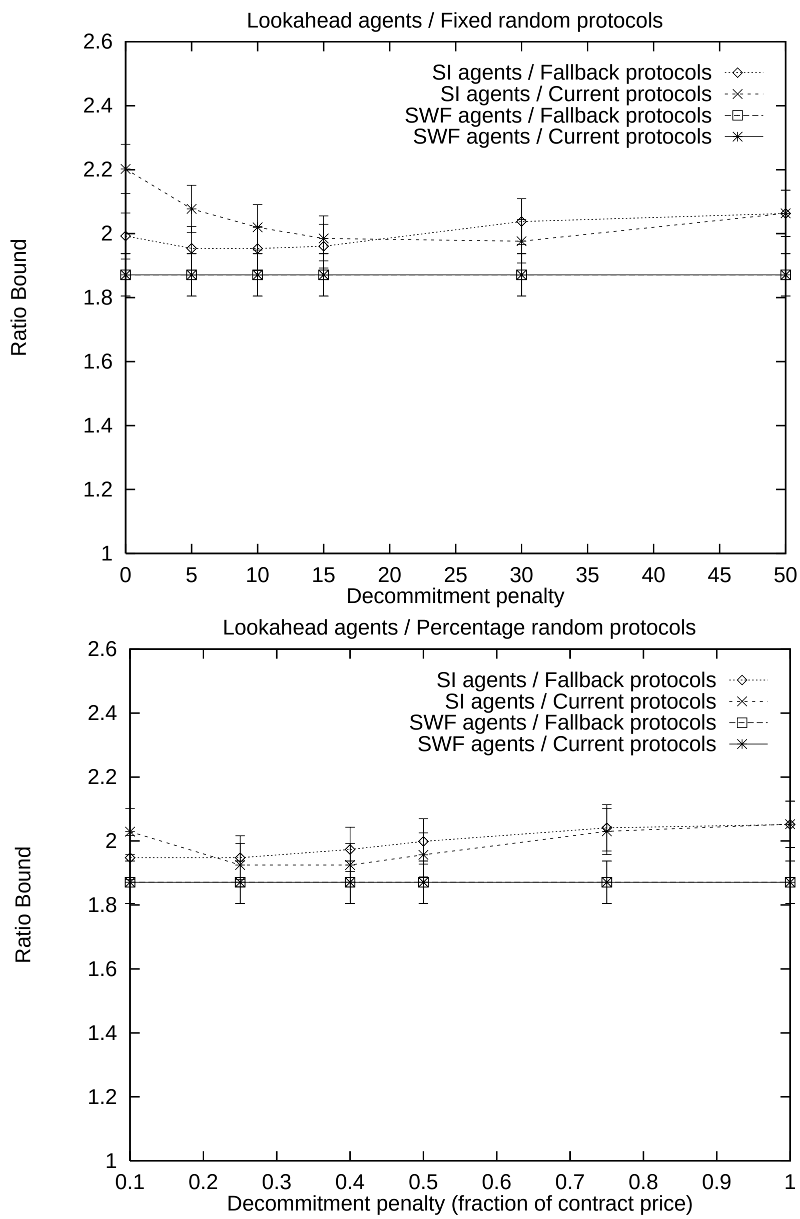

Figure 5: *Agents that perform lookahead; random meetings.*

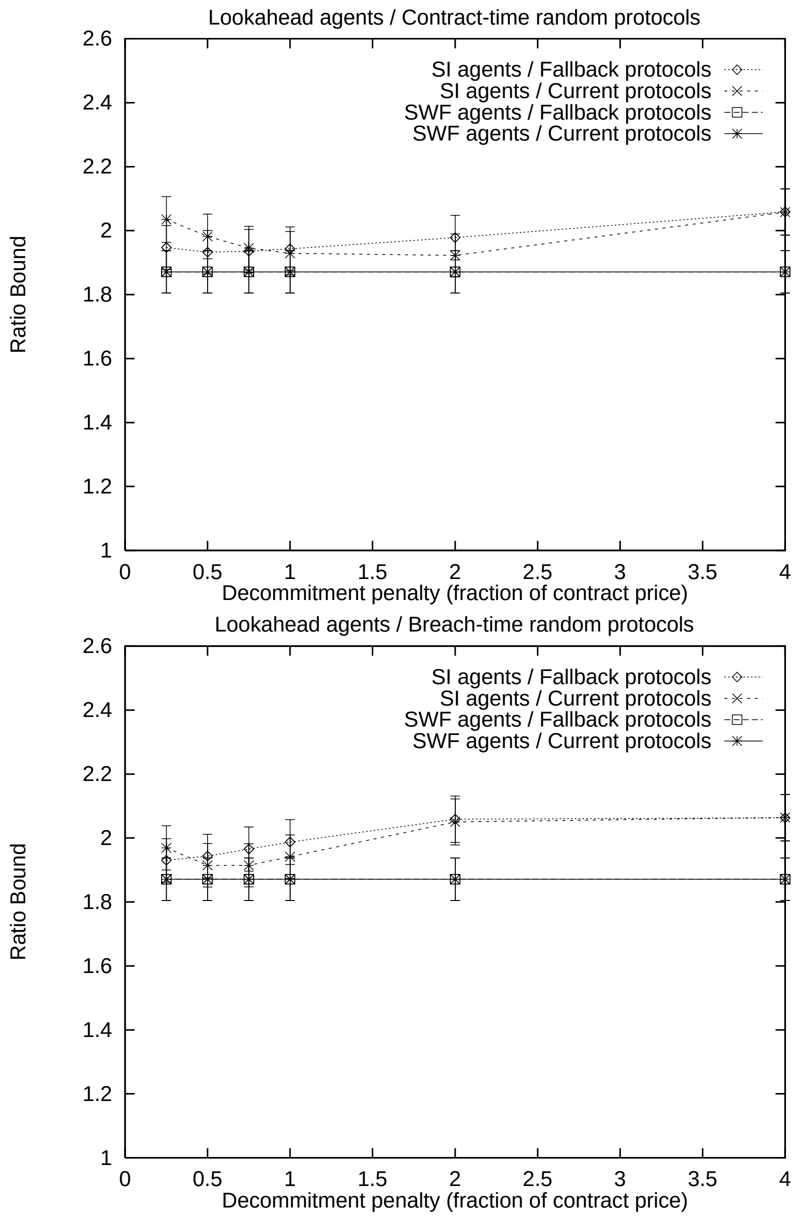

Figure 6: *Agents that perform lookahead; random meetings.*

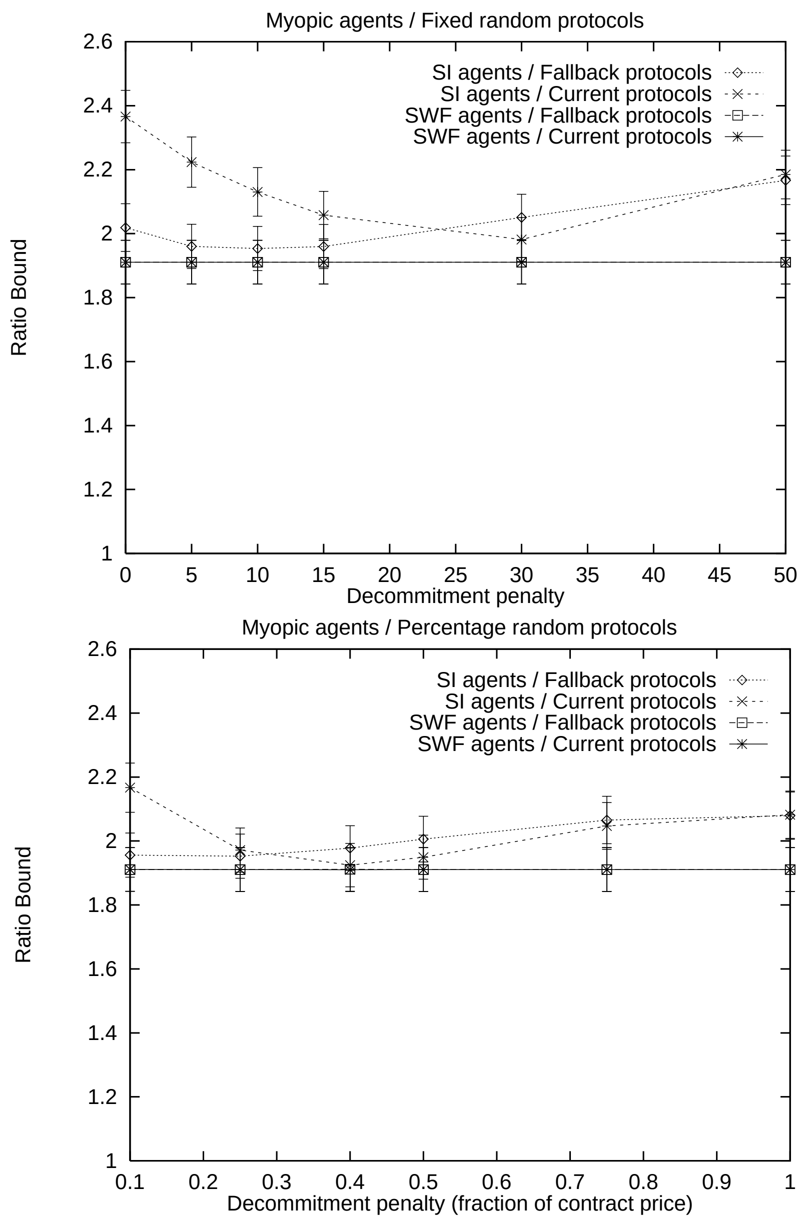

Figure 7: *Myopic agents; random meetings.*

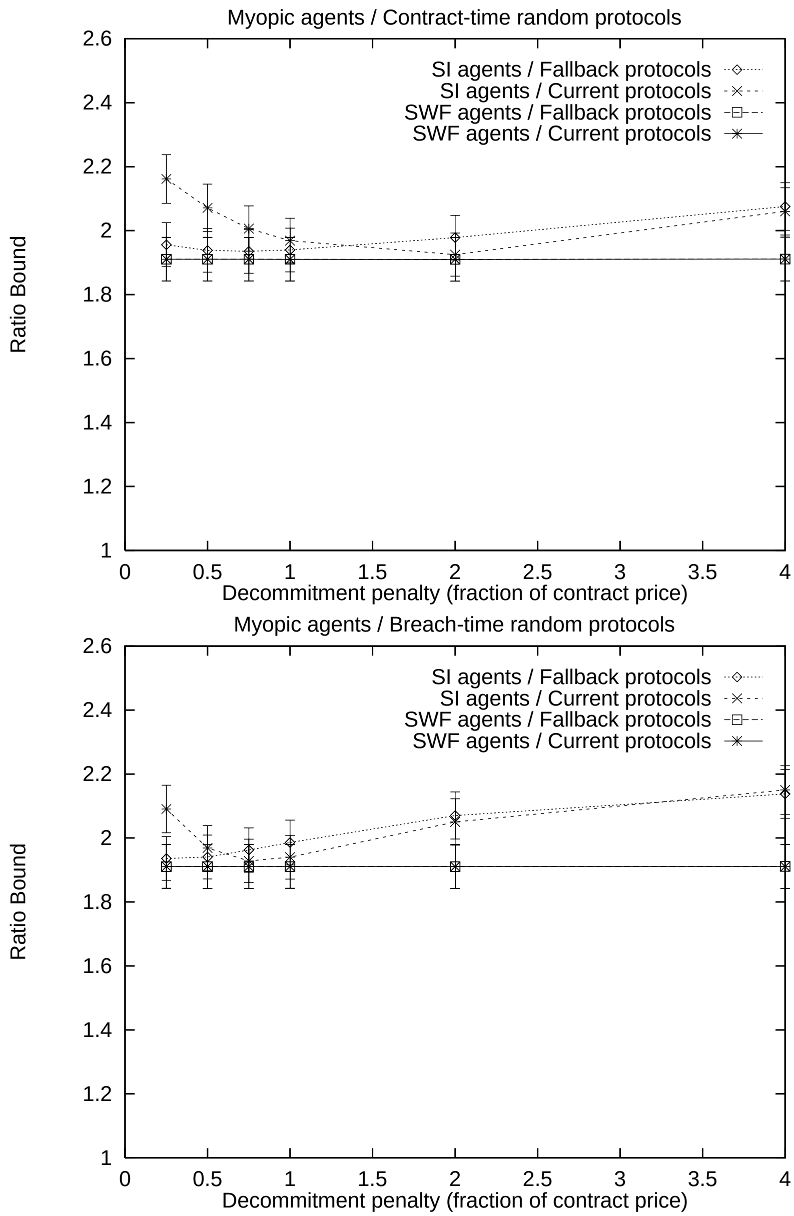

Figure 8: *Myopic agents; random meetings.*

profit performed better for low penalties (however, for zero penalties, the method based on static fallbacks performed better) (Figures 1-4). With a random meeting technology, the method based on static fallbacks performed better for low penalties, but the method that considers current profit was better in the middle range of penalties (Figures 5-8). For the high range, they were roughly equally good.

5.4 Comparison of methods and parameterizations of setting the decommitment penalty

Table 2 summarizes which method of setting the penalties was best for different agent types under different meeting technologies. For all the protocols, the optimal choice of parameters was to use a low decommitment penalty (or a low percentage of the contract price) which was still greater than zero. Neither zero penalties nor high penalties performed well.

One interesting phenomenon is that for the protocols where the penalties increase over time, especially if they increase as a function of the contract time, it can be beneficial to have them increase to significantly more than the contract price if the agents are myopic and self-interested. For example, in Figure 8 top, the final penalty that led to the best average social welfare was twice the contract price. A similar phenomenon can be observed in Figure 6 top. One explanation for this phenomenon is that average social welfare decreases if these self-interested agents breach close to the end of the game because that can leave the old contract partner with no contract at all.

Another interesting point is that for every meeting technology, agent type, price determination mechanisms, and penalty setting mechanism, the average social welfare has only one local optimum (in the parameter of how hefty the decommitment penalty should be). This is clear in each one of the figures. This suggests that it might be relatively easy to learn the optimal parameter value for setting the penalties using adaptation.

6 Conclusions

In automated negotiation systems with self-interested agents, it has traditionally not been possible to breach contracts. Because of that, the agents have been lacking the ability to act efficiently in a dynamic environment since they cannot accommodate future events efficiently. Contingency contracts have been suggested to solve this problem but in many

	Random meetings	
	Lookahead	**Myopic**
Self- interested	Increasing penalty based on breach time Price based on current deals Mean ratio bound = 1.92	Penalty as percentage of contract price Price based on current deals Mean ratio bound = 1.93
Social welfare maximizing	All Mean ratio bound = 1.87	Increasing penalty based on contract time Price based on current deals Mean ratio bound = 1.90

	Deterministic meetings	
	Lookahead	**Myopic**
Self- interested	Penalty as percentage of contract price Price based on current deals Mean ratio bound = 1.04	Increasing penalty based on breach time Price based on current deals Mean ratio bound = 1.04
Social welfare maximizing	All Mean ratio bound = 1.00	Increasing penalty based on contract time or Increasing penalty based on breach time Price based on current deals Mean ratio bound = 1.23

Table 2: Summary of the optimal choice of leveled commitment contracts for different meeting technologies and agent types. In this comparison, the best parameterization for each protocol was used. A mean ratio bound of 1 means that the social welfare maximizing solution is found every time. A mean ratio bound of 2 would mean that on average, half of the available welfare is captured.

environments they are not practical as was discussed. Another alternative is to renegotiate, but that incurs extra negotiation overhead and requires all parties of the contract to accept the new contract. Recently we introduced leveled commitment contracts as an alternative, more practical, instrument for capitalizing on the gains that uncertain future events provide [Sandholm and Lesser, 2000, Sandholm and Lesser, 1995]. In such a contract, agents can decommit from a contract by paying a penalty to the other contract party(ies). It was shown through game-theoretic analysis of strategic decommitting games that this leveled commitment feature increases the Pareto efficiency of contracts and can make contracts individually rational to both parties even in cases where full commitment contracts cannot [Sandholm and Lesser, 2000].

The efficiency of leveled commitment protocols depends on how the contract price and the decommitment penalties are set. Previously we analyzed isolated leveled commitment contracts, proving interesting results using game-theoretic equilibrium analysis [Sandholm and Lesser, 2000, Sandholm and Zhou, 2000]. We also developed algorithms for computing the optimal decommitting strategies given a contract, and algorithms for optimizing the contract itself (price and penalties) [Sandholm et al., 1999b]. Using these algorithms we offer a service for optimizing leveled commitment contracts on the web at `http://ecommerce.cs.wustl.edu/contracts.html`. However, that theoretical work has focused on optimizing a contract in isolation.

In this paper we studied sequences of multiple leveled commitment contracts. Again, the efficiency of the protocols depends on how the decommitment penalties are decided. We studied several different methods of setting them. If it would be possible for the agents to choose the penalties freely, they would try to optimize the penalties in their favor. As a result, the negotiation would be more complex: there would be more variables to agree on in order for both (all) parties of the contract to accept. On the other hand, if the penalties are set by the protocol, complexity would be eliminated from that negotiation. For example, the penalties could be fixed at a certain level by the protocol, but this may lead to suboptimal results. Another method is to relate the decommitment penalty to the price of the contract. The penalty can be either a percentage or a more complex function of the contract price. Another approach is to choose the penalties so that they compensate the victim of the breach for its lost profit. In that case, the agent would have an incentive to lie about the expected profit, so a non-manipulable mechanism for calculating the lost profit would be necessary.

A breach close to the execution deadline of the contract, or late in a negotiation, is likely to be more costly to the victim of the breach since it could be hard to find someone to contract with in a short amount of time. In order to discourage such occurrences, the decommitment penalties can be increased over time.

Methods for setting the penalties were compared while holding the parameters for each method at the best observed level. Fixed penalties were never best. Penalties set as a percentage of the contract price, increasing with contract time, and increasing with decommitting time all had selective superiority depending on the meeting technology and agent type.

As expected, deterministic meeting technologies (sequences of pairing the agents for negotiation) were better than random ones. Of the two methods of computing the contract price, the method that computes the profit from the current situation, including penalties, was better than the method that computes the profits from the static initial fallback positions—if the optimal parameterization for each protocol was used. For other parameterizations, the best method of setting the price varied. The method that considers the current profit performed well for low penalties with the deterministic protocol. The method based on fallback positions performed well under low penalties with the random meeting technology, while the other method performed better for penalties in the mid-range. For the high range, the methods were roughly equally good.

Surprisingly, self-interested myopic agents reached a higher social welfare quicker than cooperative myopic agents when decommitment penalties were low. The social welfare in the settings with agents that performed lookahead did not vary as much with the decommitment penalty as the social welfare in settings that consisted of myopic agents. For a short range of values of the decommitment penalty, the myopic agents performed almost as well as the agents that looked ahead.

In all of the settings that we studied, the best way to set the decommitment penalties was to choose relatively low penalties. However, allowing decommitting for free was not optimal. Neither were high penalties. This is a further justification for leveled commitment contracts. The best protocol was to have low decommitment penalties and a low rate of increase of the penalties. This verified our intuitions about setting decommitting penalties.

Another interesting point is that for every meeting technology, agent type, price determination mechanisms, and penalty setting mechanism, the average social welfare has only one local optimum (in the parameter of how hefty the decommitment penalty should be). This suggests that it might be relatively easy to learn the optimal parameter value for setting the penalties using adaptation.

7 Future research

While in this paper we paired agents of the same type against each other, in the future we plan to experiment with heterogeneous populations of agents (some that are myopic and some that conduct full lookahead, as well as some that are self-interested and some that are social welfare maximizing). We are also planning to increase the spectrum of lookahead to allow for partial lookahead. Also from a theoretical perspective it would be extremely important to develop normative ways of controlling partial lookahead in game trees. This is because in many practical sequential games it is intractable to compute a rational strategy due to the intractability of a full lookahead in the game tree. Yet it is unfounded to simply assume myopic behavior: by partial lookahead a self-interested agent could manipulate a mechanism that is designed under that assumption. It would be desirable to design an agent that searches the game tree optimally given its limited computational capabilities (this might involve different levels of lookahead on different branches of the tree). Clearly this would have far reaching repercussions on the design of interaction mechanisms.

Yet another important part of our future work will be to come up with better ways of deciding the contract price and decommitment penalties. In this paper they were imposed by the protocol, but alternatively the agents could be allowed to choose them. We have already developed algorithms for setting the price and penalties optimally according to a game-theoretic analysis in the context of a single contract, but in settings with multiple sequential contracts this remains challenging. We also strive to develop bargaining protocols that lead the agents to choose contract prices and decommitment penalties that are efficient for the contract parties, the systems as a whole, or both whenever possible.

Even among mechanisms where the penalties are imposed by the protocol, significant future research remains. For example, would it be beneficial to set the penalty as a percentage of the benefits of a contract instead of as a percentage of the contract price?

Answers to these questions would advance the state of the art in automated negotiation, but could also lead to useful prescriptions for non-automated negotiation and contract law.

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