Changing Circumstances and Leveled Commitment: A Compensatory Approach to Contracting

Ilja Ponka and Nicholas R. Jennings
University of Southampton
School of Electronics and Computer Science
Southampton SO17 1BJ, United Kingdom
{imp04r, nrj}@ecs.soton.ac.uk

Abstract

In dynamic and uncertain e-commerce settings, the value of contracts can change after they have been entered into. Sometimes this can make the contract in question counter-productive to the affected parties. Given this, leveled commitment contracts, in which one agent pays the other a fee to be released from their decommitment, are widely used. However, these fees are often seen only as a deterrent of decommitment and the fact that the decommitment also affects the other party and the society in general is usually ignored. This paper investigates an alternative view, coming from law, that sees the decommitment fees as a means of compensating the victim for their loss. Moreover, we show that these compensatory policies can outperform their traditional non-compensatory counterparts in terms of total utility (the sum of all agent's utilities) in situations in which the utility of one of the parties decreases after the contract has been entered into, but before it is due to be performed.

1 Introduction

In fast-moving electronic markets, hundreds of contracts can be formed in a matter of seconds. However, in dynamic, ever-changing environments, sometimes the parties of these contracts may live to regret their choices. A better alternative may surface only seconds after agreeing to something or the circumstances may change and turn a contract from lucrative into disastrous. On the other hand, contracts (or commitments about performing a service at a later time) have been seen as an essential requirement for any type of predictable behaviour in such systems [5]. Against this background, an often used compromise is Sandholm and Lesser's [7] *leveled commitment contract*, which:

- allows unilateral decommitting for both parties at any time, but
- requires the decommitting party to pay the opponent a monetary fee (called a decommitting fee) for doing so.

This allows a party to abandon a contract that has become counter-productive to it; that is, its utility has become negative. Now, because the party must pay the penalty in order to decommit, a decommitment occurs only if the decommitment improves the decommitter's utility more than the fee to be paid reduces it. In the literature, the decommitment fee is therefore mostly seen as a deterrent of decommitment. This view, however, overlooks the effect a decommitment has on the other party (the victim) and on the society in general. In particular, the decommitment will usually decrease the utility of the victim, because he will lose the profit he was expecting and it is also possible that he has accrued some costs (preparing for its performance) before decommitment occurs. When the contract is abandoned, these costs may have been wasted. Now, if these lost profits and accrued costs outweigh the benefit the decommitter receives from decommitment, the decommitment actually decreases the sum of utilities of parties and is therefore detrimental to the welfare of the society as a whole.

In contrast, the law has traditionally taken another view, that of the victim's. In cases of non-performance, the victim (in most legal systems) is entitled to damages (there may be other remedies in some situations and in some legal systems, but we concentrate on damages here) and the aim of damages is usually to put the victim financially in the same position as if the contract had been performed appropriately [8]. That is, the damages compensate the victim for the loss that the non-performance causes. The economic efficiency of this rule has been investigated in the law and economics literature in the area of efficient breach theory [2]. The conclusion of this work is that this is the optimal policy from the society's point of view. In particular, by setting the damages (decommitment fee) equal to the damage caused by the decommitment to the other party, a breach (decommitment) occurs when and only when the benefit to the decommitter is greater than the damage to the victim. Therefore decommitment always increases the total welfare of the society.

In this paper, we will call *compensatory* any decommitment policy (a rule for setting the decommitment fees) that always tries to compensate for the loss that the decommitment causes to the opponent. Any policy that does not have this goal, is called *non-compensatory*.[1] Most of the policies used in the literature so far are non-compensatory, although many papers (e.g. [1] and [6]) have suggested using fees that increase over time. Although the reason for this is usually not explicitly stated, this type of fee can be seen as being both more compensatory and more fair than the constant fee. Also some partially compensatory policies have been suggested (e.g. [3]), but no consistent theory for doing so has been presented. We will address these shortcomings by using ideas from contract law to create novel compensatory decommitment policies and show how they (under certain circumstances) can be used to improve total utility in e-commerce settings.

However, the compensatory approach has its problems. For example, Andersson and Sandholm [1] have argued that if the victim's actual loss is not known, he has an incentive to overstate it in order to keep the contract or to make additional profit. In law, this problem is avoided by making the victim show the actual amount of loss in a court of law after the final outcome and losses are known exactly. This incurs considerable costs to the parties and is often slow. In global electronic markets of relatively low-value services, both characteristics are undesirable. We therefore suggest using the opponent's expected or average losses as a decommitment fee. These expected losses are estimated and given to all parties by the neutral marketplace. In many markets, this type of information is available or can be obtained at reasonable costs.[2] In addition, we will show that even relatively inaccurate estimates can improve the total utility over non-compensatory alternatives.

We will also show that the better the estimates are, the more they will lead to better total utilities. Since in the long run, the marketplaces that generate most welfare to their participants are likely to be the most popular, the neutral marketplace has an incentive to improve its estimates. Compensating for these losses also has a fairness aspect that many humans find appealing. In dynamic environments, all parties are occationally decommitters and sometimes victims, so the markets that treat both cases fairly may find greater acceptance among the (potential) users.

The rest of the paper is structured as follows. Section 2 introduces our model of electronic markets, in which the parties make contracts. Section 3 discusses the various decommitment policies. Section 4 details our experiments and findings. Finally, section 5 concludes.

[1]The distinction is not always clear-cut, because some non-compensatory policies can be compensatory in some circumstances. The important requirement for the compensatory policies is that they *always* try to compensate for the victim's loss.

[2]For example, in many industries the product, its preparation process and costs are well-known (e.g. printing a book). Also if all providers use similar technologies or sub-providers (e.g. teleoperators renting capacity from the same network company), it may be possible to estimate the costs.

2 The Marketplace Model

We consider a market of buyers and sellers for one service. We refer with subscript b to a single buyer (consumer) and with subscript s to a single seller (provider) in this market. We are especially interested in their utility, U_b and U_s respectively. The time t is discrete and divided into turns.

We assume that all participants expect the delivery of the service to occur at the same time $t_{delivery}$ (there are separate markets for different delivery times and other services). In the beginning ($t_0 = 0$) there are n_0 buyers and n_0 sellers in the market. This is to ensure that negotiations can start from the beginning. Over time, some buyers and sellers enter and some may exit. The numbers of entries for the parties are independent variables, but follow the same standard Poisson distribution, with the parameter $\lambda(t) = i\frac{t_{delivery}-t}{t_{delivery}}$, where i is the basic entry intensity and t is the current turn. This formulation means that entries are more probable earlier in the experiment. This is because we assume that the provision of the service takes time, t_p, and this time is different from one provider to another (selected at random). The nearer the time of performance, the fewer providers are likely to be able provide the service in time. In the experiments we discuss in this paper, we have $t_{delivery} = 1000$, $n_0 = 50$ and $i_b = 0.4$, which gives us an expected population size of 250 during an individual experimental run.

On the other hand, we assume that the provision costs money. Specifically, in order to provide the product at the delivery time, the provider s has to invest cost c_s at time $t_{c,s} (< t_{delivery})$. Each provider has a quality q_s, which is selected at random from $Uniform(0, 1)$. The cost is a function of quality and time:

$$C_s(q_s, t) = \begin{cases} 0, & \text{if } t < t_{c,s}, \\ 0.5q_s, & \text{if } t \geq t_{c,s}. \end{cases}$$

Here, we have six different settings for $t_{c,s}$:

- any: $Uniform(t_{e,s} + 1, 999)$,
- second half: $Uniform(\max(500, t_{e,s} + 1), 999)$,
- last quarter: $Uniform(\max(750, t_{e,s} + 1), 999)$,
- last 100: $Uniform(\max(900, t_{e,s} + 1), 999)$,
- turns 925-975: $Uniform(\max(925, t_{e,s} + 1), 975)$,
- turn 950: 950,

where $t_{e,s}$ is the time of entry for provider s.[3] The time $t_{c,s}$, is selected at random for each provider from the same interval. These provider characteristics are mapped into typical bilateral negotiation parameters by setting the reservation price r_s equal to the provider's preparation cost c_s and the deadline to $t_{c,s}$. This means that the provider will never accept a price that is less than its costs and that if the provider does not have a contract when it should start preparing for

[3]In the last two cases, there are no entries after turn 974 and 949 respectively.

service, it will exit the market. The provider's utility for a contract is: $U_s(p, c_s) = p - c_s$, where p is the contract price.

The consumers do not have costs, but each consumer b has a deadline $t_{x,b}$, which is selected at random from $Uniform(t_{e,b}+1, t_{delivery})$, where $t_{e,b}$ is the time consumer b entered the market. The consumer's utility for the contract is $U_b(q,p) = V_b(q) - p$, where the value function $V_b(q)$ is:

$$V_b(q) = \begin{cases} 0, & \text{if } q < q_b^{\min}, \\ v(q), & \text{if } q_b^{\min} \leq q \leq q_b^{\max}, \\ v(q_b^{\max}), & \text{if } q > q_b^{\max}, \end{cases}$$

where $v(q)$ is the consumers' common value function, $q_b^{\min}$ and $q_b^{\max}$ are consumer specific parameters of that function. Here we assume simply that $v(q) = q$. This means that each consumer has a minimum useful quality $q_b^{\min}$ and any service that does not offer at least this, is worthless ($V_b = 0$). On the other hand, the consumer also has a maximum useful quality, $q_b^{\max}$, which gives him his full utility. Any improvement above this level does not increase the value of the service to the consumer in question. The parameters $q_b^{\min}$ and $q_b^{\max}$ are selected for each consumer independently at random from $Uniform(0, 0.5)$ and $Uniform(0.5, 1.0)$ respectively. The consumer's reservation price for a given service is then equal to its value.

The buyers and sellers in the market are paired at random by the marketplace. This means that each provider will be given one consumer to negotiate with (and vice versa). The pairs then negotiate for a 100 turns on the price of the service. Both parties use simple exponential time-dependent heuristic tactics [4], in which the parameter β is selected at random. Once all negotiations finish, the parties remaining in the market are again matched at random. This process (from the random matching to the end of negotiations) is repeated 10 times.

The entries and exits can occur at any time, but the parties are only matched at turns that can be divided by 100 without a remainder (i.e. $0, 100, 200, ...$). If there is an unequal number of buyers and sellers in the market, some members of the larger population will not get an opponent and will have to wait until the next matching. The contracts are performed when the negotiations end, $t_{delivery} = 1000$.

We assume that the parties will always decommit as soon as the need arises and therefore do not engage in any type of strategic behavior about this facet of their operation. In particular, we focus on situations in which the parties always exit the market after they have found a contract and that they cannot return. Since the original contract is always beneficial to both parties ($U_s > 0$ and $U_b > 0$) they would not consider abandoning it without some external force. We therefore introduce an adverse impact that decreases the value of the contract to one of the parties after the agreement has been reached, but before the contract is due to be performed. This decrease may make the contract counter-productive to the affected party and he may want to decommit.

For the provider, the decrease means that the costs of providing the service increase by amount L_s and this will decrease its utility by the same amount. He will then need to make a decision on whether or not to decommit from the contract in this new situation. The decision is influenced by the decommitment fee f. We assume that the provider s will decommit at turn t if and only if:

$$\begin{array}{rcl} U_s(\text{contract}|L_s = l) & < & U_s(t_{decommit} = t) \\ p - c_s - l & < & -f - C(q_s, t). \end{array}$$

where $U_s(t_{decommit} = t)$ is the seller's utility, when he decommits at turn t and l is the amount the utility decreases. Here we use the following ten values $l \in \{0.1, 0.2, ..., 1.0\}$. So, the seller decommits if the decreased utility is lower than the cost it has already paid and the decommitment fee it has to pay to get out of the contract. The loss occurs at some point t_l between the time the contract was formed $t_{contract}$ and the time it was due to be performed ($t_{delivery}$).

As a performance measure, we use the sum of expected utilities of all contracts in the market. We chose the expected utilities because they give us more information than just selecting the adverse impact point at random and the sum of these because it is the simplest way to measure common good. In addition, the sum of utilities is also the measure used in law and economics literature. The expected total utility for a single contract (to which b and s are parties) is:

$$\begin{array}{l} EU_{b+s}(\text{contract}|L_s = l) \\ = \frac{1}{t_d - t_c} \sum_{t=t_{contract}}^{t_{delivery}} [D_s(l,t,P) U_{b+s}(t_{decommit} = t) + \\ \quad (1 - D_s(i,t,P)) U_{b+s}(\text{contract}|L_s = i)], \end{array}$$

where $U_{b+s}(t_{decommit} = t)$ is the total utility of the parties, when the seller decommits at time t, $U_{b+s}(contract|L_s = l)$ is the total utility if the seller stays in contract despite the losing l from his utility and P is the decommitment policy used in the market and

$$D_s(l,t,P) = \begin{cases} 1, & \text{if the seller decommits when his utility decreases by } l \text{ at turn } t \text{ given the decommitment policy } P \\ 0, & \text{otherwise} \end{cases}$$

The total utility for the case in which the contract is abandoned ($D_s = 1$) at turn t is:

$$\begin{array}{l} U_{b+s}(t_{decommit} = t) \\ = U_b(t_{decommit} = t) + U_s(t_{decommit} = t) \\ = f + (-f - C(q_s, t)) = -C(q_s, t). \end{array}$$

The seller avoids the utility decrease of the contract, because there is no contract any more, but it will have to pay the fee f. If the seller decides to perform the contract despite the utility decrease ($D_s = 0$), the total utility is:

$$\begin{array}{l} U_{b+s}(\text{contract}|L_s = l) \\ = U_b(\text{contract}) + U_s(\text{contract}|L_s = l) \\ = (V_b(q_s) - p) + (p - c_s - l) = V_b(q_s) - c_s - l. \end{array}$$

The total expected utility, EU_{market}, for each setting is then the sum of expected values of all contracts. The same logic applies to the buyer, but there are two important differences. For the buyer, the impact i decreases the value of the contract. However, because the buyer can, in many types of service, just ignore the service delivered, the value cannot be enormously negative. We therefore assume that the impacted value cannot be lower than -0.05. This small value would then come from accepting the service and disposing of the results. This means that the utility of the buyer can never go below $-0.05 - p$. We do not make a similar assumption with the seller, because the cost of producing the service can (in theory) increase without any limit (hardware failures, resource shortages, strikes, etc. can make the service very expensive to perform). The second difference is that for the buyer, always $C_b = 0$ (for the seller $C_s \geq 0$).

3 The Decommitment Policies

This section describes the decommitment policies we will examine in this paper. We first discuss the various non-compensatory policies (section 3.1), before going on to the compensatory ones (section 3.2).

3.1 Non-Compensatory Policies

Since there are an infinite number of ways to devise a non-compensatory decommitment policy, we do not try to make an exhaustive comparison. Instead, we examine some typical policies. To be more precise, we consider the following:

- *Not Allowed*: The contracts are absolutely binding and decommitment is not possible.
- *Constant*: The decommitment penalty f is constant; here we investigate cases where $f \in \{0.00, 0.25, ..., 1.00\}$.
- *Increasing*: The decommitment starts with min at t_{min} and increases linearly to max at time t_{max}. We investigate cases where $min = \{0.00, 0.25, 0.50\}$ and $max = \{0.25, 0.50, ..., 1.00, 1.50, 2.00, 2.50\}$ and $min < max$. There are three variations (all with $t_{max} = t_{delivery}$):
  - *Contract Time Only*: $t_{min} = t_0$ and $t = t_{contract}$.
  - *Decommitment Time Only*: $t_{min} = t_0$, and $t = t_{decommit}$.
  - *Both*: $t_{min} = t_{contract}$ and $t = t_{decommit}$.
- *Constant Price* [1]: The decommitment fee is a fraction of the price (p). Here we investigate cases where $f = \{0.5p, 1.0p, ..., 2.5p\}$.
- *Increasing Price*: This has the same variations as the increasing policy (contract time only and decommitment time only variations were used in [1]), but the minimum and maximum are fractions of the contract price. We investigate cases where $min = \{0, 0.25p, 0.5p\}$ and $max = \{0.5p, 1.0p, ..., 2.5p\}$ and in all case $min < max$.

In total, this means that there are 100 non-compensatory variations. Nevertheless, there is still a large number of possible policies and parameter values that we do not investigate. We have tried to choose a reasonable sized selection of the most obvious and different policies. However, we cannot claim that this selection contains the optimal non-compensatory policy for our setting. The selection should, however, give us a reasonable view on how well the various non-compensatory policies perform.

3.2 Compensatory Policies

We will discuss compensatory policies in two parts: (i) those that have access to complete information on the opponent's profits and costs (section 3.2.1) and (ii) those where this information is incomplete (section 3.2.2).

3.2.1 The Complete Information Case

In this case, we can use the decommitment policy that is optimal according to efficient breach theory:

- *Expectation Damages*: The fee is the opponent's expected profit (his utility if the contract is performed properly) plus his costs at decommitment time.

Alternatively, if the compensation does not entail compensation for the expected profit, it is possible that decommitment occurs when the increase of the decommitter's utility is lower than the expected profit that the victim loses. To investigate this, we take a decommitment policy that compensates only for the costs. This is typical in tort law and is called reliance damages:

- *Reliance Damages*: The fee is equal to the opponent's costs at decommitment time.[4]

3.2.2 The Incomplete Information Case

There are many possible ways to create a compensatory decommitment policy that works under incomplete information, but that aims to compensate for the loss the decommitment causes. Here, we introduce two of the most obvious ones: analytic compensatory and average loss.

In the analytic compensatory policy, the victim's loss is estimated analytically using available information. This approach uses estimates of the cost and value functions, the distributions for the deadlines, and so on, to analytically estimate the loss. The accuracy of these estimates can vary and we will investigate a number of possibilities.

- *Analytic Compensatory*: The fee is equal to the expected loss for the victims in similar circumstances.

In more detail, the decommitment fee for the buyer is:

$$f_b(p, q, t) = D(t)p + (1 - D(t))(p - EC(q)),$$

[4] This policy was used in [3], but it was called sunk costs.

where q is the quality, $EC(q)$ the estimated cost function and $D(t)$ a probability that the seller has paid the cost at turn t. In a similar fashion, the fee for the seller is:

$$\begin{aligned} f_s(p,q) &= EV(q) - p \\ &= [F_{mid}(q) \cdot V(q) + F_{max}(q) \cdot q_{max}(q)] - p \end{aligned}$$

where $EV(q)$ is the estimated value function, $F_{mid}(q)$ is the probability that quality q is between the buyer's minimum and maximum value, $F_{max}(q)$ is the probability that quality q is above the maximum quality, and $q_{max}(q)$ is the estimated value for $q_b^{\max}$ for the opponent b in the latter case. In case this is negative, the fee is zero.

In the other compensatory policy, average loss, we use the notion of 'normal' or typical loss. In law, the unusually large losses (even if real) are not compensated if they were not foreseeable to the other party.[5] In law, this limits the maximum for damages, but here we use it as the measure of loss. We compensate the typical loss for the opponent in the same circumstances. The circumstances are determined by information that is available to both parties, such as the turn the agreement was reached ($t_{contract}$), the decommitment turn ($t_{decommit}$), the quality of the service (q_s) and the contract price of the decommitted contract (p). As the measure of typical loss we use the average:

- *Average Loss*: The fee is equal to the average loss for the victims in similar circumstances.

Here, we investigate the variation in which the similarity of the situation is assessed by the contract price, quality, contract turn and decommitment turn, and in which each of the first three factors are divided into k categories and we have accurate information of all possible decommitment turns; that is, we have $1001k^3$ different categories. For our experiments, we establish the typical loss simply by running the market 1000 times in advance and by calculating the average losses experienced by the parties in different situations (from each contract we get the information on losses of all possible decommitment situations). In the calculation of the fee, the situation is first categorised in terms of all three factors and the similar situations are those that belong to the same categories in all three factors.

For both policies, we assume that the decommitment fees are established by the marketplace and the fee for any set of circumstances is always known by all parties. Both policies give the victim incentives to minimise his loss, because the compensation is set in advance and hence all the savings the victim can make are going to benefit him (and the society).

4 Empirical Evaluation

Having introduced the various decommitment policies, it is time to compare their performance. This section consists of three parts. First, we discuss our hypotheses (section 4.1). Second, we explain how our experiments were set up and how the analysis was conducted (section 4.2). Finally, we discuss the actual results (section 4.3).

4.1 Hypotheses

According to efficient breach theory, the *Expectation Damages* should be the optimal decommitment policy. On the other hand, if the number of decommitments is very small (nobody ever decommits) or very large (everybody always decommits), the different decommitment policies are likely to have similar results. The difference should therefore be at its clearest, when there are some but not too many decommitments. In these cases, non-compensatory policies can decommit contracts that are still beneficial or stay in contracts that no longer are. We therefore contend:

Hypothesis 1 *Under complete information, the* Expectation Damages *policy will yield at least as good an expected total utility as any of the non-compensatory alternatives and with intermediate utility losses it will be better.*

Now, the more interesting setting is the one with incomplete information. Since the total utility is maximised when the losses are always perfectly compensated, we assert that in situations in which the losses can be more accurately estimated, and therefore the decommitment fees can be set closer to the optimal ones, we should see better total utilities. To see why this is the case, we need to consider two ways that the effect the policy has on individuals can differ from the optimal policy. First, the policy may force the party to stay in a contract even if the socially optimal action would be to abandon it (adverse commitment). Second, the policy may allow the party to decommit from a contract even though it is still socially valuable (adverse decommitment). In the first case, the policy overestimates the loss and in the latter case it underestimates the loss. Both cases decrease total utility. Now, the closer the estimates are to the actual values, the fewer of these mistakes occur. The fewer mistakes, the less total utility is decreased and, hence, the higher it is.

So, when the information available to the compensatory policies improves, they are likely to get closer to the optimal decommitment fees and therefore do better. We investigate this theory first by applying it to the two compensatory policies we introduced. If we improve the information that is available to them, we expect the estimates to improve and for the reasons just described, the total utility should also improve.

Hypothesis 2 *Under incomplete cost information, the performance of the* Analytic Compensatory *policy improves when the information on the seller's deadline improves.*

In a similar manner, when *Average Loss* distinguishes between more situations, the situations that are considered sim-

[5] The actual rule is that the loss must either be directly or naturally following from the breach or the other party knew or should have known of this loss at the time of signing the contract [8]. This rule can be also seen as a special case (market-set) of liquidated damages.

ilar are likely to really be more similar (have a smaller variance) and therefore we expect the performance to improve.

Hypothesis 3 *Under incomplete cost information, the performance of the* Average Loss *policy improves when more situations are considered dissimilar.*

Now, the whole point of using the compensatory policies is that they can improve the total utility of the system. The logic is that when these policies manage to accurately compensate for the actual losses, the performance should be close to the full information case. However, they do need sufficient information of the opponent's losses to achieve this.

Hypothesis 4 *Under incomplete cost information, both the* Average Loss *and* Analytic Compensatory *policies can outperform all the non-compensatory policies.*

Speaking more generally, we believe that there is a clear relation between the accuracy of loss estimates and the performance (in the terms of total utility). To investigate this claim, we need to define a new measure for the accuracy of estimates, average compensation error, which for a single seller in a contract x is:

$$\frac{1}{1001}\sum_{t=0}^{1000} |f_s(P,t,x) - f_s^*(t,x)|,$$

where $f_s(P,t,x)$ is the decommitment fee using the policy P at time t and $f_s^*(t,x)$ is the optimal (Expectation Damages) fee for that contract at that time. An average of these averages is then calculated over all contracts. As a measure of performance, we use the average total utility over different utility loss cases. A similar calculation is performed to obtain the error for the buyer.

We are now ready to state our final hypothesis:

Hypothesis 5 *Average compensation error and the average expected total utility are inversely related. That is, lower error implies higher total utility and vice versa.*

4.2 Experimental Setup

We ran the market and saved the contracts that were formed. We use the Second Half deadline setting for the providers unless otherwise stated. We then calculated the expected total utility of each contract in 21 different settings; one setting for the situation without any adverse effects and then with 10 adverse effects on the buyers and 10 with the sellers. We ran the market with the same setup 100 times and calculated the expected value of all contracts for all 21 situations after each run (using the same contracts in different situations). We repeated the whole process for each decommitment policy we investigated.[6]

[6] In other words, the contracts that the different policies were analysing were different, but by repeating the process 100 times we get sufficient data for a statistical analysis.

4.3 Results

We will now discuss the results.

4.3.1 Expectation Damages vs. Non-Compensatory Policies

We start by investigating how well the *Expectation Damages* policy fares against the non-compensatory policies. To this end, figure 1 shows the case in which the buyer's utility decreases. Specifically the figure shows *Expectation Damages*, *Reliance Damages* and the best results any of the non-compensatory policies achieved. In other words, the best of non-compensatory plot shows the maximum result of all 100 non-compensatory policies in each data point (more than one policy has contributed to this plot).

We performed a one-tailed t-test comparing pairwisely the means of the *Expectation Damages* policy and the means of all the non-compensatory policies in turn at all of the data points.[7] As can be seen, when the buyer's utility decreases, the *Expectation Damages* policy clearly outperforms all other alternatives when the buyer's maximum utility decrease is between $0.2 - 0.7$ (at $p < 0.01$ level). This is because the other policies suffer from adverse commitments and decommitments, but the *Expectation Damages* policy makes the parties decommit optimally. With a small utility loss ($l = 0.1$), there is no statistically significant difference to the best non-compensatory policies. This is because in that case, the decommitments are rare with all the best policies and the few decommitments that do occur do not affect the total utility that much. On the other hand, all the best policies converge in the high utility loss cases ($0.9 - 1.0$), because in all of them, all contracts are abandoned.

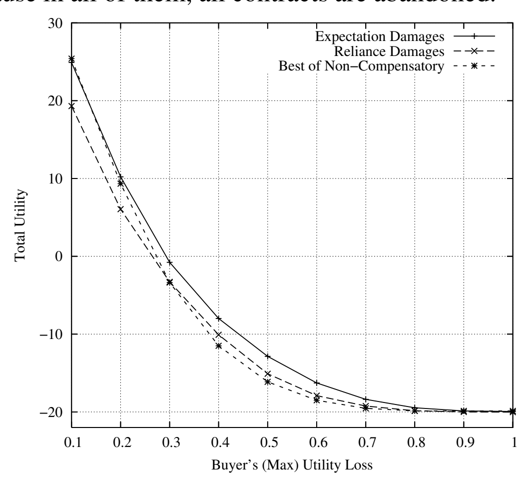

Figure 1. Compensatory vs. Non-Compensatory Policies.

The performance of the *Reliance Damages* policy is worse than that of the best non-compensatory policies when the loss is 0.1 or 0.2 (two-tailed t-test at $p < 0.001$ level), but

[7] We do this every time we compare a compensatory policy to the best of non-compensatory policies.

at intermediate levels (between $0.4 - 0.5$) it outperforms all non-compensatory policies (at $p < 0.001$ level). This is because at low loss levels it is often optimal to allow only very few if any decommitments and because *Reliance Damages* consistently underestimates the losses, it will allow some detrimental decommitments. The best non-compensatory policies are those that make it very expensive to decommit (for example *Not Allowed*). However, when the losses are bigger, these policies perform badly and other policies with less extreme fees take over. None of these policies will be able to outperform a policy that accurately compensates for the costs (*Reliance Damages*), because with $c_s = 0.5q_s$ the costs are often a significant portion of the actual losses.

The other case (in which the seller is affected) is very similar (and therefore there is no figure for that case). There are two small differences that can be explained by the different assumptions of the cases. First, the performance difference between *Expectation Damages* and the best non-compensatory policies is smaller. This is because the seller also has costs, which the *Expectation Damages* takes into account and the non-compensatory policies do not. However, the advantage of the *Expectation Damages* is maintained at the same interval ($0.2 - 0.7$ at $p < 0.01$ level). We can therefore accept hypothesis 1. The *Reliance Damages* policy does not do well here because the buyers have no costs and, therefore, it compensates nothing.

4.3.2 The Analytic Compensatory Policy

We will now investigate how the performance of the *Analytic Compensatory* policy will be affected by different levels of knowledge about the seller's deadline. We ran the experiments with the seller having the deadline selected between turns 925-975 and varied the buyer's (or the market's) knowledge of this deadline. At worst, the buyer has no reliable information of the deadline and must therefore assume that it can be at any time (after the contract has been entered into) and that all possibilities are equally likely. In the other settings, the buyer knows that the buyer's deadline is in the second half (turns 500-1000), last quarter (750-1000), last 100 (900-1000) or turns 925-975 (correct one). Here, figure 2 shows the performance in each case (Last 100 was omitted because it was statistically inseparable from the correct one and made the figure more difficult to read.) and we can see that the best compensatory policies are very close to the optimal (Expectation Damages).

From this figure, it is clear that the additional information improves the performance. All shown policies outperform the policies with less information when utility losses are between $0.3 - 0.7$ (at $p < 0.001$ level). This is what hypothesis 2 predicted, so we accept it. The figure also shows what the best of the non-compensatory policies achieve in the same setting. The *Analytic Compensatory* (Last Quarter) policy is the first one to outperfom all compensatory policies ($p < 0.001$ level with at least $0.2 - 0.4$) and policies

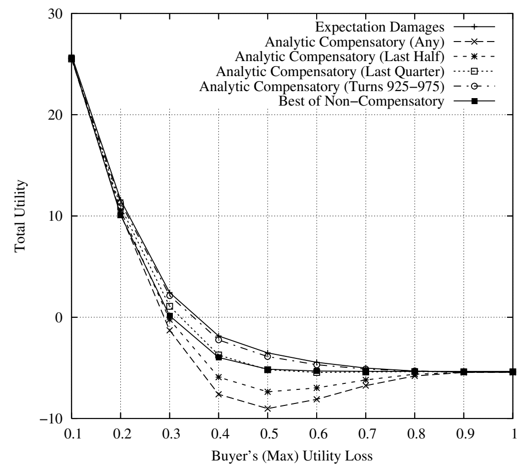

Figure 2. Analytic Compensatory Policy with Different Levels of Knowledge.

with more accurate information do this in wider number of cases. Clearly, the *Analytic Compensatory* policy can outperform all the non-compensatory policies we tried, so hypothesis 4 is accepted as far *Analytic Compensatory* policy is concerned.

4.3.3 The Average Loss Policy

We expected that our other compensatory policy would show similar improvement to those of the previous subsection, when the number of distinguished situations increases. To this end, we use the *Last 100* deadline setting. Since there were three different parameters for distinguishing situations from each other, we increase the number of different categories k on each from 1 to 10 and then 15, 20 and 25. Then some of the results are shown in figure 3. As can be seen, increasing k clearly improves the performance when k is small, but with high k there is no statistically significant improvement. This is because in our setting, most of the relevant patterns can be described with a relatively small number of distinctions. We therefore accept hypothesis 3.

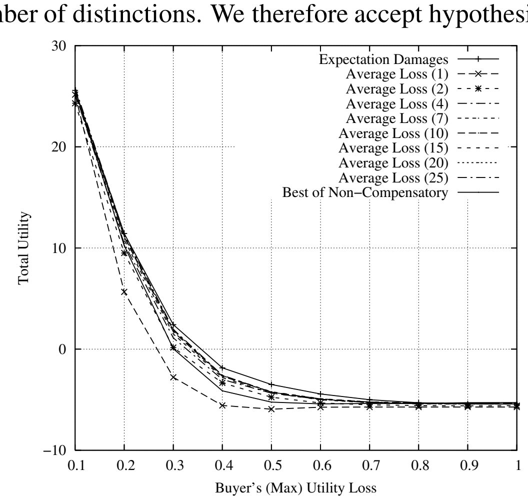

Figure 3. Average Loss and Estimator Size.

The first policy to defeat all the non-compensatory ones consistently is *Average Loss*(4).[8] It will outperform all non-compensatory policies with the losses between $0.3 - 0.6$ (at $p < 0.001$ level). Therefore we accept hypothesis 4 with *Average Loss*.

4.3.4 The Average Compensation Error

Finally, we investigate the relationship between average compensation error and the total utility. We calculated the average compensation errors and average total utility for all the policies. The preliminary results showed a clear correlation between the compensation error and performance when the fees were relatively low, but a larger variation when the fees were large (overall correlation -0.75). This is because the total average compensation error is not that good a metric if nobody ever decommits. In such cases, it hardly matters if the fee was 1 or 2.5. We can limit this effect by setting the maximum fee to be equal to the minimum one that allows nobody to ever decommit in a given contract. With this adjustment we then get figure 4, which shows a strong correlation, of -0.95, which is statistically significantly different from zero (at $p < 0.001$ level). Compensatory policies are in the bottom right corner of the graph as one might expect from the above discussion.

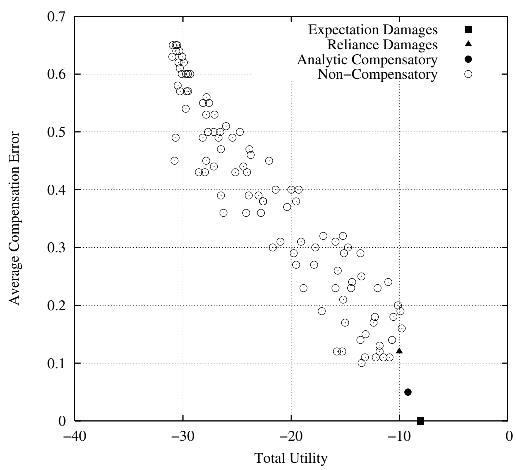

Figure 4. Average Compensation Error and Total Utility.

The seller has no similar restriction on his loss and therefore its losses can go higher and the effect described earlier is less pronounced (the correlation is -0.93 without any adjustments). Both results give a clear indication that the average total utility is inversely related to the average compensation error and therefore we accept hypothesis 5.

5 Conclusions

In this paper, we showed that compensatory decommitment policies for contracts in electronic marketplaces can improve the welfare of the society and we gave two examples of such policies that work under incomplete information. We also showed how more accurate estimates for the losses improve the performance of both our policies. Moreover, we showed that in case of changing circumstances the performance of a market under a certain decommitment policy clearly depends on how accurately a policy compensates for the actual losses.

For a designer of dynamic electronic marketplaces, the conclusions of this paper are as follows. First, decommitment policies can and do affect the performance of the marketplace. Therefore a suitable decommitment policy should be a part of the overall design of any marketplace, where the parties' preferences or circumstances can change after the contract has been entered into but before it is performed. Second, a compensatory policy is a serious contender for such policy if enough reliable information about the parties' costs, valuations, preparations times and so on is readily available and can easily be obtained.

In future work, we extend the compensatory policies to cases in which the victims try to find substitute contracts to replace the ones they lose when their opponent decommits. Another direction of future work is to consider other effects that decommitment policies may have. Specifically, the law and economics literature has identified three key decisions, in which the decommitment fees play a role: the decision of whether or not to perform a contract (performance decision, the topic of this paper), but also whether or not to rely on the upcoming performance (reliance decision) and whether or not to enter a contract in the first place (contract decision).

[8] Already Average Loss(2) defeats non-compensatory policies when the loss is 0.4 or 0.5, but it loses to some policies when the loss is 0.2.

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