Predicting partner's behaviour in agent negotiation

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ABSTRACT

We propose an improved approach for modeling behaviours of negotiation partners and predictive decision-making based on this modelling. Our prediction is based only on the history of the offers during the current negotiation. The mechanism estimates an influence of different factors contributing to partner's behaviour during negotiation and uses this information to construct a prediction about agent's future behaviour. The optimal sequence of offers is determined according to the prediction. The approach is tested in simple scenarios and the results comparing our approach to random strategy selection are illustrated.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Learning, Problem Solving

General Terms

Algorithms, Theory

Keywords

negotiation and conflict handling in agent systems

1. INTRODUCTION

Negotiation is a process of searching a space of potential agreements in order to find a solution that satisfies the preferences and requirements of all interested parties [5]. The problem of negotiation has been studied from various perspectives in many fields. These fields include: decision and game theory, management and social sciences, artificial intelligence and agent technology [9]. The essential problems of the negotiating parties are the limited or uncertain knowledge and conflicting preferences. The agent technology provides tools for solving this kind of problems. However, decision-making paradigms of the negotiation agents still need to be developed and improved. A successful agent needs to learn and adapt to complex behaviour of its negotiation partner and changing environment. An approach proposed by Faratin [4] allows for limited adaptation to partners behaviour by using so called behaviour-dependant tactics. These tactics imitate opponent's behaviour and can be mixed with other types of tactic such as time-dependant. However, it is difficult to decide which type of tactics to use and to what extent in terms of weights mixing various factors such as: time and behaviour imitation. Therefore, some approaches based on machine learning have been proposed to predict the negotiation partner's behaviour.

Most of the learning approaches supporting the negotiation such as Bayesian learning [12], Q-learning [3], case-based-reasoning [1] and evolutionary computation [11][10] focus on learning from previous negotiations. Some work [7][6] studies the negotiation scenarios by taking into account the parameters of negotiation such as: deadline and reservation value but assuming a simplified type of negotiation strategies, namely only time-dependant. The work proposing learning from current negotiation is quite rare. One of the approaches was proposed by Hou [8]. In this paper a nonlinear regression was proposed to model the negotiation opponent's behaviour based only on the previous offers. However, the approach copes only with single tactics but negotiation agent may encounter an opponent with more complex behaviour involving a mixture of different tactics.

In this paper we propose to treat the negotiation as an optimization problem because too small concessions may discourage the partner from making significant concessions and to large concession will obviously lead to a low level of utility at the end of an encounter. Our predictive decision-making mechanism allows for high adaptation to negotiation partner's behaviour based only on the history of offers in the current negotiation.

It extends the predictive decision-making mechanism described in [2]. The approach is based on difference method and is therefore computationally efficient. In the future work we will propose other prediction approach based on nonlinear multivariate regression analysis. Our extended approach allows for additional gain of efficiency compared to the previous paper [2] because instead of a brute force search of the optimal sequence of actions we propose a more efficient search based on a solution of optimization equation that reduces significantly the time of modelling.

The second section recalls an idea of estimation of different factors influencing negotiation partner's behaviour. The

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AAMAS'06, May 8–12, 2006, Hakodate, Hokkaido, Japan.

third section presents a method of constructing a prediction. In the fourth section an idea of assessing the whole sequence of offers is described. In the fifth section we describe a way of calculating values of concession. Sixth section presents the results of experiments. Conclusions and future work are presented in the 6 section.

2. THE ESTIMATION OF DEGREES OF VARIOUS FACTORS DEPENDENCY

Typically, there are two main factors that influence the negotiation agent behaviour: time and imitation. The agents behaviour depends to some extent on time and it depends to some extent on imitation. In order to be able to assess the degrees of this dependency appropriate criteria will be introduced in a form of functions mapping the sequences of previous actions of both parties in the current encounter into interval $[0, 1]$. These two criteria should state to what extent our partner responds to its time constraint and to what extent does it respond to our actions. We propose to define these criteria as necessary conditions for using pure tactics by our negotiation partner (either behaviour-dependant or time-dependant). In order to do it we have to know what is characteristic for an agent using time-dependant tactic (necessary condition) or behaviour-dependant tactic. This feature will be used as the factor dependency criterion.

2.1 Time-dependency

The time-dependant tactic may be modelled by the use of polynomial or exponential function. As mentioned before we have to determine the characteristic feature of these type of functions. The whole family of polynomial or exponential functions has a constant sign of all derivatives and this feature is treated as a necessary condition for being time-dependant. The given information is the sequence of previous offers of both parties. Based on it we want to determine the extent to which the sequence of our partner's offers is generated by a particular decision function corresponding to a pure tactic. In other words we want to determine how good the partner's behaviour fits to a particular decision function. Assuming that a decision function used to generate a sequence of offers had a constant sign of all its derivatives the differences of all orders calculated for the given sequence must also have a constant sign. This is because of a correspondence of the difference of n-th order and the n-th derivative. Having a sequence of partner offers: b_i of a length m the differences of different orders can be calculated as follows:

$$\begin{aligned}
\Delta^1 b_i &= b_{i+1} - b_i \qquad i \in \{1, 2, \dots, m-1\} \\
\Delta^2 b_i &= \Delta b_{i+1} - \Delta b_i \qquad i \in \{1, 2, \dots, m-2\} \\
\Delta^3 b_i &= \Delta^2 b_{i+1} - \Delta^2 b_i \qquad i \in \{1, 2, \dots, m-3\} \\
&\dots \\
\Delta^{m-1} b_i &= \Delta^{m-2} b_{i+1} - \Delta^{m-2} b_i \qquad i \in \{1\}
\end{aligned}$$

If all the differences for each particular order k have the same sign then the necessary condition of being time-dependant is fully satisifed:

$$\forall k \in \{1, 2, \dots, m-1\} \quad \forall i, j \in \{1, 2, \dots, m-k\} \quad sgn(\Delta^k b_i) = sgn(\Delta^k b_j)$$

In order to evaluate a degree to which time-dependency is satisfied we formulate a criterion. For the difference of each order k we introduce a subcriterion D^k. The subcriterion must be defined in such a way that it gives full level of satisfaction if all the differences are either negative or positive. If the means of the positive and negative values counterbalance each other then the criterion should give the full level of violation what corresponds to the lowest level of satisfaction. In other words the full violation means that the contributions of positive and negative values are the same. Partial degree of criterion satisfaction will be obtained if we observe a dominance of one sign over other and the higher is this dominance the higher the degree of satisfaction. Therefore, we introduce the partial degree of subcriterion satisfaction D^k of the difference of an order k as an aggregate of the means of the positive values of differences and the negative values of the differences as follows:

$$D_k = \frac{|\frac{\sigma_p^k}{m_p^k} + \frac{\sigma_n^k}{m_n^k}|}{Max\{|\frac{\sigma_p^k}{m_p^k}|, |\frac{\sigma_n^k}{m_n^k}|\}} \qquad (1)$$

where $\sigma_p^k = \sum_{\Delta_k b_i > 0} \Delta_k b_i$, $\sigma_n^k = \sum_{\Delta_k b_i < 0} \Delta_k b_i$. m_p^k and m_n^k are the amounts of the positive and negative values of $\Delta^k b_i$, respectively. If the absolute values of the averages $|\frac{\sigma_p^k}{m_p^k}|$, $|\frac{\sigma_n^k}{m_n^k}|$ are close then the value of D^k is small, what means that the criterion is highly violated. The values of all given D^k are then aggregated to the overall value of criterion satisfaction. This value is obtained by the use of weighted sum where the weights are proportional to the extent of contribution of the differences $\Delta^k b_i$:

$$D_t = \sum_{k \le m-1} w_k D_k$$

where w_k is calculated as follows:

$$w_k = \frac{Max\{|\sigma_p^k|, |\sigma_n^k|\}}{\sum_{j=1}^{m-1} Max\{|\sigma_p^j|, |\sigma_n^j|\}}$$

2.2 Behaviour-dependency

The responsiveness to partner's behaviour may be realized by behaviour-dependant tactic. We propose to use the sequence of relative first order difference as a basis for measuring the extent to which our partner is imitating our behaviour. Having the sequences of the last m concessions of our agent s_i and the sequence of the last m concessions b_i of the negotiation partner we can calculate the sequence $r_i = \frac{\Delta^1 b_i}{\Delta^1 s_i}$ describing the change of behaviour of the modelled agent in relation to the change of our agent's behaviour. We define two subcreteria allowing for the assessment of the imitative-behaviour of our negotiation partner. First subcreterion assesses how positive are the responses of the modelled agent to our offers (the values of r_i are higher then one). We aggregate all values of r_i by the use of weighted sum:

$$r = \sum_{i=1}^{m} w_i r_i$$

The weights w_i may increase with the value of index i which means that the later offers reflect better the current state of our partner's behaviour and therefore, the higher the values of indices i the more important is the quotient r_i. If the calculated value of r is greater than 1 then our negotiation partner is responding with higher concessions than ours and therefore it may be called relatively cooperative. The value of r equal to 1 means that the agent makes the same concessions as ours and can therefore be called neutral. The values of r smaller than 1 tell us that our partner is not relatively cooperative because its concessions are smaller than ours. The first subcreterion may be defined as a function $h : r \mapsto [0, 1]$ mapping the value of r into a degree of responsiveness in the following way:

$$D_1 = h(r) = Max[1, Min[0, 0.5r]]$$

The neutral value of r ($r = 1$) is assigned the value of 0.5 by function h what in terms of fuzzy logic means that the extent of condition satisfaction and dissatisfaction is the same. If the value of r is greater than 1 then the degree of subcreterion satisfaction is higher than 0.5 (more true than false) and in the opposite case ($r < 1$) the degree of satisfaction is lower than 0.5 (more false than true).

Additional subcreterion can asses the degree of relational trend in the agent's behaviour in terms of monotonicity of sequence r_i. The degree of monotinicity D_2 may be measured as a sign consistency for the differences Δr_i what can be done analogously as in previous subsection (formula 1). We calculate the average D_b of the obtained values of D_1 and D_2 and treat this value as a degree of the overall responsiveness:

$$D_b = \frac{D_1 + D_2}{2}$$

3. THE AGENT'S BEHAVIOUR PREDICTION BASED ON DIFFERENCE METHOD

As mentioned in previous sections there are two main factors contributing to the overall behaviour of negotiation agent: time and imitation. We propose to construct separate predictions of these two factors first. Then prediction can be build by mixing the time-depending and the behaviour-depending predictions together using the weights obtained in the previous section. Our prediction constitutes a function mapping a history of the previous m offers of both negotiating parties H_m and a potential offer s_{m+1} of our agent into a value of the predicted response $\hat{b}_{m+1}$ of our partner:

$$f : (H_m, s_{m+1}) \to \hat{b}_{m+1}$$

As mentioned in Introduction in the future work we will conisder other type of prediction based on the multivariate regression analysis. The two predictions, namely time-depending f_t and imitation-depending f_b that will be combined together to the overall prediction f map the history of the current encounter to the value of the predicted offer in the following way:

$$\hat{b}^t_{m+1} = f_t(H_m) \quad (2)$$

$$\hat{b}^b_{m+1} = f_b(H_m, s_{m+1}) \quad (3)$$

As stated before these mappings are combined to obtain the overall prediction as follows:

$$\begin{aligned} \hat{b}_{m+1} &= f(H_m, s_{m+1}) = \\ &= \frac{D_t}{D_t + D_b} \times \hat{b}^t_{m+1} + \frac{D_b}{D_t + D_b} \times \hat{b}^b_{m+1} \end{aligned} \quad (4)$$

The predictor f may be applied multiple l times in a recursive way. In order to reuse the predictor second time we store the time-depending prediction $\hat{H}^t_{m+1} = H^t_m \cup \{s_{m+1}, \hat{b}^t_{m+1}\}$ ($H^t_m = H_m$). We also store separately the overall prediction $\hat{H}_{m+1} = H_m \cup \{s_{m+1}, \hat{b}_{m+1}\}$. Based on this information the prediction for the second step can be obtained as follows:

$$\hat{b}^t_{m+2} = f_t(\hat{H}^t_{m+1}) \quad (5)$$

$$\hat{b}^b_{m+2} = f_b(\hat{H}_{m+1}, s_{m+2}) \quad (6)$$

where s_{m+2} is a potential offer of our agent in the next step of negotiation. The overall second step prediction is calculated as follows:

$$\begin{aligned} \hat{b}_{m+2} &= f(\hat{H}_{m+1}, s_{m+2}) = \\ &= w_t \times \hat{b}^t_{m+2} + w_b \times \hat{b}^b_{m+2} \end{aligned} \quad (7)$$

where w_t and w_b are the normalized values of D_t and D_b:

$$w_t = \frac{D_t}{D_t + D_b} \qquad w_b = \frac{D_b}{D_t + D_b}$$

As stated before we can repeat this procedure multiple l times.

3.1 Time-depending prediction

The time-dependant behaviour may be realized by the use of decision functions from the polynomial or exponential family of functions. We used this information in the previous section to determine the degree of time-dependency and in this section we want to determine a level of the particular time-dependant tactic in order to predict this type of behaviour. We propose to measure a trend in agent's behaviour in terms of a degree of concavity or convexity of the concession curve. In other words we want to determine what a kind of tactics (conceder, linear or boulware) our partner is using, and how strong is the tactic in terms of a value of the parameter β. Our time-depending prediction is based on a difference method that requires to determine the maximal order of differences that should be taken into account. In a case of linear and conceder tactics it is sufficient to consider only the first order difference because for the curve generated by the linear tactic all higher order differences are equal to zero and the curve generated by the conceder tactic is close to linear after a number of offers. The most crucial is the successful prediction of the boulware tactic because the most drastic changes of the behaviour of an agent using this kind of tactic occur when it is approaching its deadline. All the differences up to k-th order having the same sign are taken into consideration as follows:

$$sgn(\Delta^1 b_i) = sgn(\Delta^2 b_i) = \cdots = sgn(\Delta^k b_i) \neq sgn(\Delta^{k+1} b_i)$$

The more differences are consistent in a sign the stronger boulware tactic on the side of opponent agent was applied. We calculate the time-dependent prediction for the next step as follows (Figure 1):

$$\hat{b}_{m+1} = f_t(H_m) = b_m + \sum_{j=1}^{k} \Delta^j b_{m-j} \quad (8)$$

where $\hat{b}_{m+1}$ is the prediction of the $m+1$ offer and k is an index of the last difference consistent in sign. It can be proved that the difference based method is a good approximation of any function from the polynomial family of functions. The

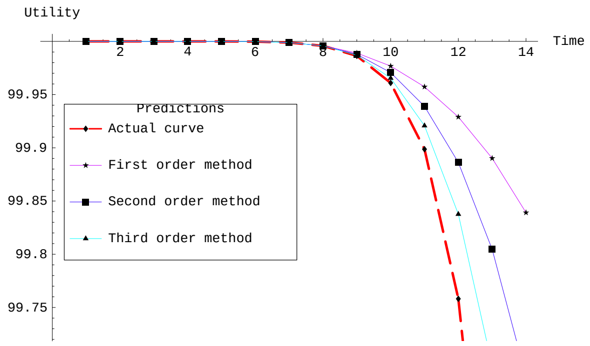

Figure 1: Examples of different order predictions for boulware tactic

recursive application of the formula (8) allows for the prediction in the next steps.

3.2 Imitation-depending prediction

The imitation-depending prediction constitutes a function that maps the history H_m of offers of the current encounter and a potential future offer s_{m+1} of our agent into the prediction about our opponent's next move $\hat{b}_{m+1}$:

$$\hat{b}_{m+1} = f_b(H_m, s_{m+1})$$

The purpose of the function f_b is to predict how the negotiation partner will respond to the potential offer s_{m+1} of our agent. In terms of control theory the history of the negotiation H_m up to an offer m describes the current state of the encounter. The variable s_{m+1} is a potential control with which we may influence partners behaviour. The updated history $\hat{H}_{m+1}$ after the step of control s_{m+1} is the next state of negotiation. In order to construct the function f_b we apply the Taylor's formula of first order as follows:

$$f_b(H_m, s_{m+1}) \quad = \quad b_m + \frac{\Delta b_{m-1}}{\Delta s_{m-1}}(s_{m+1} - s_m)$$

where the value of a relational difference $\frac{\Delta b_{m-1}}{\Delta s_{m-1}}$ is treated as an approximation of the first order derivative of the function f_b in a point s_m.

4. SEMI-STRATEGIC REASONING

The predictor described in previous sections can be regarded as a transition function that maps a state (history of previous offers) and a potential control (our potential offer) into the next state. In these terms the negotiation may be treated as a multi-stage control process and our task is to determine the sequence of optimal controls (our potential future offers) $s_{m+1}, s_{m+2}, \ldots, s_{m+l}$ knowing the sequence of our opponent's respones $\hat{b}_{m+1}, \hat{b}_{m+2}, \ldots, \hat{b}_{m+l}$. The multi-stage control process constitutes the combination of prediction with decision-making about the next offers. The mechanism described in [2] involves discretization of the space of each potential offer in each negotiation step. All possible sequences of offers in the discrete space are considered and the optimal sequence is determined. However, such an approach is a kind of brute force, and therefore is quite time consuming. We propose to determine a sequence of the optimal

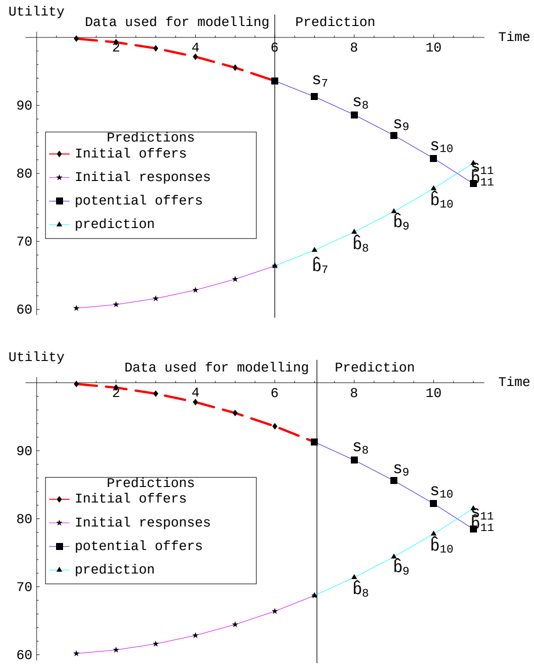

Figure 2: An example of prediction as a response to sequence of potential offers in steps 7 and 8

controls in a different way. In order to avoid the inefficiency of searching the whole space of solutions we propose to predict a small amount of k opponent's steps forward. Then we assume that we make the same average concession up to the terminal state l and determine this concession by solving optimization equation (9). In other words we want to determine the sequence of a form: $s_{m+1}, s_{m+2}, \ldots, s_{m+k}, s_{m+k} + c, s_{m+k} + 2c, \ldots, s_{m+k} + (l-k)c$. In order to determine the concession c of the second part of the sequence we solve the following optimization problem:

$$c : min\{|\hat{b}_{m+l} - (s_{m+k} + (l-k)c)|\} \qquad (9)$$

It states that we have to find a value of c for which we meet with the opponent (ia. reach an agreement) in terminal state $m + l$. After the counterpart has responded, the whole mechanism can be reused for further decision making in the next steps of negotiation.

5. CONCESSION DETERMINATION

The previous section described a way we asses a sequence of offers. Assuming that we determined the optimal sequence of concessions we have to determine the value of the next offer based on this information. It turns out that various sequences of offers may result (in terms of prediction) in similar final utility. Therefore, the decision-making process should take into account all sequences with various first concessions satisfying the optimization constraint (9). Assume we have all the optimal sequences $\{s^j\}$ with the various first

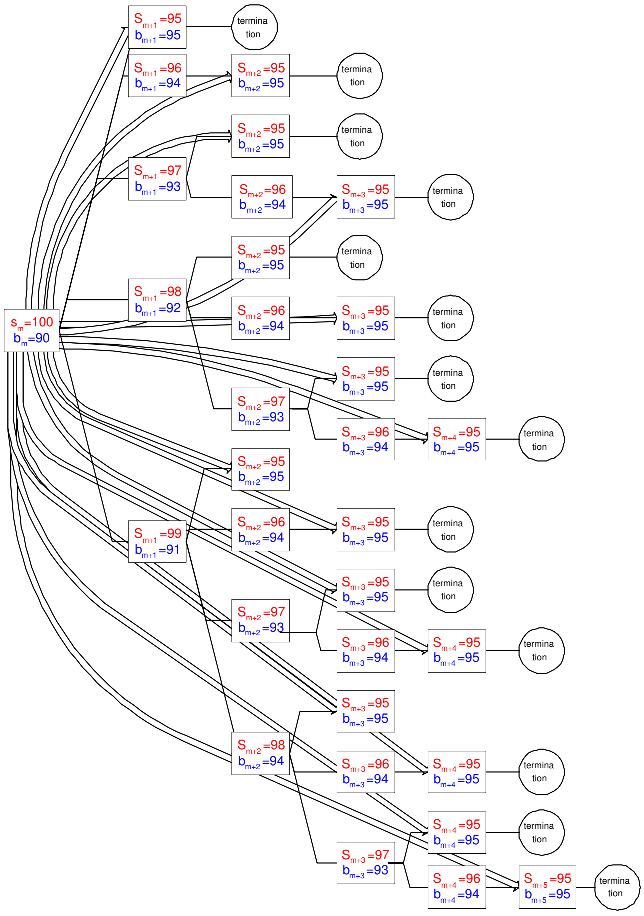

Figure 3: Simplified example of negotiation prediction. The thick arrows indicate the optimal sequences with various first concessions

concessions:

$$
\begin{array}{lcl}
s^1_{m+1} & , & s^1_{m+2}, \ldots, s^1_{m+l} \\
s^2_{m+1} & , & s^2_{m+2}, \ldots, s^2_{m+l} \\
\ldots & , & \ldots \\
s^n_{m+1} & , & s^n_{m+2}, \ldots, s^n_{m+l}
\end{array}
$$

To determine the value of a concession based on the predicted sequence we use two values: the first concession in the sequence $s^j_{m+1} - s^j_m$ and the average of all concessions in the sequence $\frac{s^j_{m+l} - s^j_m}{l}$. The less responsive an agent is the less important the first concession is. It means that in the case of time-dependant behaviour the opponent agent does not respond to our behaviour and it is not important what concession we make in what rounds. What is important is the average concession in all rounds. Therefore, the average concession should be taken into account in a case of time-dependant behaviour and the first concession should be taken into account in a case of the responsive agent. Because the extents to which the two factors influence agent's behaviour are fuzzy we have to aggregate the two types of concession taking into consideration the level of imitative behaviour and the level of time-depending behaviour. The experiments presented in the next section show that the following type of aggregation is appropriate:

$$
\begin{aligned}
offer^j \quad &= \quad s_m + sgn(s^j_{m+1} - s^j_m)(|s^j_{m+1} - s^j_m|)^{w_t} \times \\
&\times \quad sgn\left(\frac{s^j_{m+l} - s^j_m}{l}\right)\left|\frac{s^j_{m+l} - s^j_m}{l}\right|^{w_b}
\end{aligned}
$$

The offers $offer^j$ are then averaged over all the optimal sequences with the various first concessions in order to calculate the final value of an offer:

$$offer = offer^1 w_1 + offer^2 w_2 + \cdots + offer^n w_n$$

where the weights w_j are proportional to the utility that can be gained by applying j-th sequence of actions $\{s^j\}$ according to our prediction.

6. RESULTS

The enhanced mechanism has been tested in a simulated experimental negotiations with more advanced settings than in [4] (the same settings as in [2]). On a side of our negotiation agent the predictive mechanism is used and the negotiation partner uses the static strategies being a mixture of a time-dependant tactic and a behaviour-dependant tactic with various weights assigned to these two tactics. In order to make experiments feasible we choose seven time-dependant tactics and divide them into three subsets:

- Conceder: $C = \{\beta \mid \beta \in \{2, 5, 8\}\}$
- Linear: $L = \{\beta \mid \beta \in \{1\}\}$
- Boulware: $B = \{\beta \mid \beta \in \{0, 3, 0.5, 0.7\}\}$

We consider two behaviour-dependant tactics:

- Absolute Tit-For-Tat: a: $\delta \in \{1\}$ and $R(M) = 0$ (without a random factor)
- Relative Tit-For-Tat: r: $\delta \in \{1\}$

The space of weights assigned to the tactics consists of 9 values obtained through discretization. Analogously as for the set of β values we decompose the set of all weights into three subsets:

- Small: $S = \{0.1, 0.2, 0.3\}$
- Medium: $M = \{0.4, 0.5, 0.6\}$
- Large: $L = \{0.7, 0.8, 0.9\}$

The cartesian product of the sets of the time-dependant tactics, the behaviour-dependant tactics and the weights results in a set of 126 static strategies:

$$ST = (C \cup L \cup B) \times \{a, r\} \times (S \cup M \cup L)$$

The whole set of the static strategies ST is divided into 18 groups of strategies in order to illustrate the performance of our approach:

$$
\begin{aligned}
ST = (C \times \{a\} \times S) \cup (L \times \{a\} \times S) \cup (B \times \{a\} \times S) \cup \quad (10)\\
\cup (C \times \{a\} \times M) \cup (L \times \{a\} \times M) \cup (B \times \{a\} \times M) \cup \\
\cup (C \times \{a\} \times L) \cup (L \times \{a\} \times L) \cup (B \times \{a\} \times L) \cup \\
\cup (C \times \{r\} \times S) \cup (L \times \{r\} \times S) \cup (B \times \{r\} \times S) \cup \\
\cup (C \times \{r\} \times M) \cup (L \times \{r\} \times M) \cup (B \times \{r\} \times M) \cup \\
\cup (C \times \{r\} \times L) \cup (L \times \{r\} \times L) \cup (B \times \{r\} \times L)
\end{aligned}
$$

Each group will be shortly denoted using only the first letters. For example:

$$CAS = C \times \{a\} \times S$$

A simple scenario involving a buyer agent and a seller agent

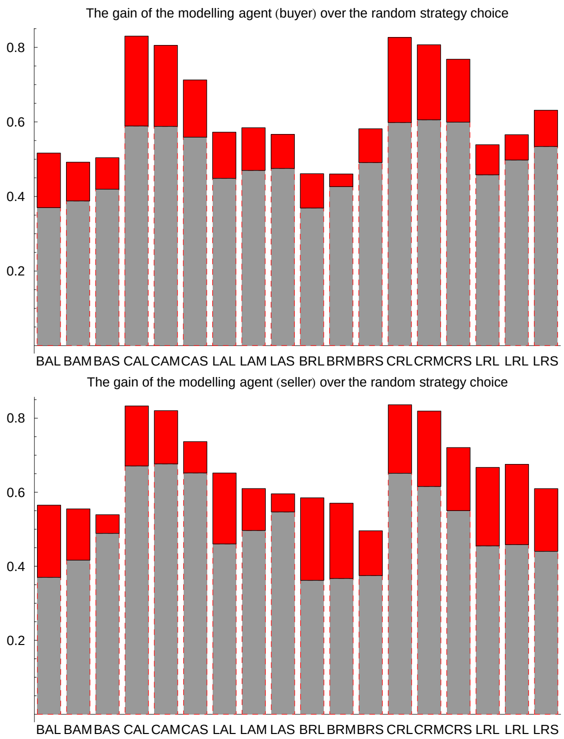

Figure 4: The performance of prediction mechanism applied for the buyer and the seller agents

is presented below. We consider following settings for the buyer: $min^b \in \{10\}$, $max^b \in \{50\}$, $k^b \in \{0\}$, and the consistent deadline for both players $t^b_{max} = 15$. The agreement ranges of both parties are assumed to be fully overlapping ($\Phi = 0$). Analogously as in [4], $max^b - min^b = max^s = min^s$ and $k^s = k^b$. $min^s = min^b + \Phi * (max^b - min^b)$, $max^s = min^s + (max^b - min^b)$. In the experiments we apply the prediction mechanism up to 9 steps forward, ie in the case of deadline $t^b_{max} = 15$ it makes prediction after the first six offers have been generated by the use of time-dependant tactic. This provides also initial data for the modelling. For the initial offers generation we use medium tough tactic ($\beta = 0.5$) with additional perturbations in order to better explore the initial responses of negotiation partner. We carry out the simulations without a communication cost and with low communication cost ($comm \in \{0.01\}$) separately (cost $\tau(t) = tanh(t * comm)$). More advanced scenarios considering different behaviour-dependant tactics and different values of communication cost will be described in further work. The performance of our enhanced modelling approach is illustrated in Figures (4) and (5). The grey parts of bars in the chart represent an average value of utility of a negotiation agent using all the strategies from particular subset of static strategies (for instance: CSA) against all the strategies from the set ST. This corresponds to playing with a random strategy from a particular subset against a random strategy selected from the whole ST according to an uni-

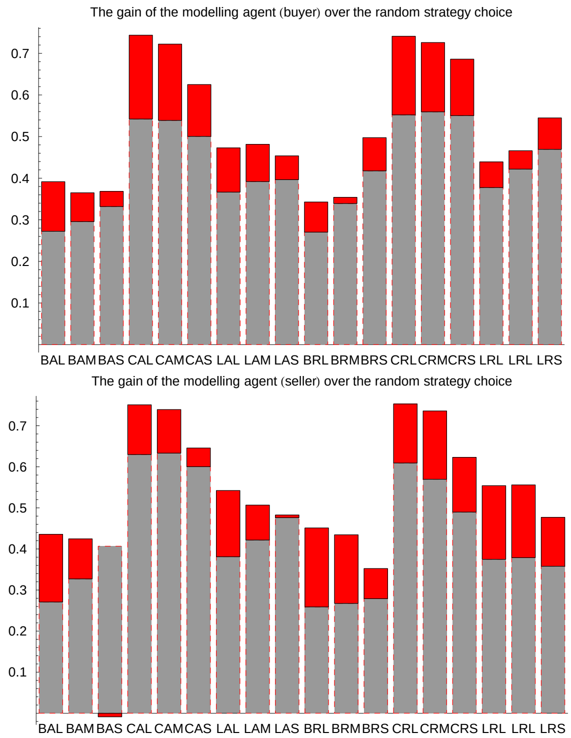

Figure 5: The performance of prediction mechanism taking into account the communication cost applied for the buyer and the seller agents

form probability distribution. The red (dark) surplus in the bar chart illustrates a gain in terms of the utility obtained by the use of our approach instead of the random static strategy choice. In cases of a gain the red (dark) surplus is above the grey part of a bar and in a case of loss it is under the grey part. The bar charts (Figure 4) clearly show that the gain of our predictive mechanism is significant, i.e. on average in comparison with the classical approach without prediction. Although, the reasoning was simplified in comparison to [2] the proposed mechanism still outperforms the random strategy choice and in terms of the gained utility the results are similar to [2]. It should be noted that in the cases of strategies with high contribution of behaviour-dependant tactics (BAS, BRS, etc.) the utility gain is smaller compared to other strategies which is caused by a specific nature of behaviour-dependant tactics. If an opponent uses the time-dependant tactic we can take advantage of it to finish negotiation earlier with a good level of utility. However, very high values of utilities are not possible because the imitation of our behaviour on the side of our partner means that roughly its concessions can not be much bigger than ours. As far as the communication cost is concerned the results are better than in [2]. The figure 5 shows that the utility gain is significant and positive in most of the cases. Another thing worth noticing is that the results are not symmetric for the buyer and for the seller because of the use of Relative Tit For Tat tactic that does not work symmetrically for both roles of an agent. The reason for it is that the value of quotient that is used in this tyoe of tactic is usually higher for the buyer than for the seller. Compared to [2] we obtained high gain in efficiency of the approach.

The simulation for the same scenario took just 20% of the time of the simulation presented in [2].

7. CONCLUSIONS AND FUTURE WORK

The paper proposes an improved approach for reasoning from the history of offers of current negotiation and decision-making based on this reasoning. The predictive mechanism allows an agent to adapt to negotiation partner's behaviour that results in better agreements. The presented results of simulated experiments show that our agent equipped with the enhanced predictive mechanism outperforms the classical approach by achieving substantial gains in terms of utility. In the future the regression analysis will be applied for partner's behaviour prediction and the approach will be tested in more complex scenarios including not consistent deadlines of negotiation parties, partial degrees of overlap of the ranges and different values of communication cost.

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