Experimental Evaluation of a Model for Multilateral Negotiation with Fuzzy Preferences on an Agent-based Marketplace

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Abstract

This paper presents a multilateral negotiation model on an agent-based job-marketplace developed at Europe-University Viadrina Frankfurt (Oder), Germany. The negotiation model is based on many negotiation issues, a fuzzy utility scoring method and simultaneous negotiation with many negotiation partners in an environment of limited negotiation time. Although the proposed negotiation model deals with agent-based negotiation in the specific context of personnel acquisition, it can be applied with some modifications to other agent-based e-marketplaces. The negotiation model presented is evaluated with the help of some simulation experiments. The observed results provide an insight into the interrelation between negotiation tactics and time constraints on the one side and achieved utility degrees and the number of closed contracts on the other side.

Keywords: multi-agent systems, automated negotiations, fuzzy-logic, e-marketplace, simulation

1 INTRODUCTION

Agent technology for e-marketplaces is becoming increasingly important and is being used in a wide range of commercial domains. In this paper, we propose a multilateral negotiation model for agents’ negotiation with fuzzy preferences. Acquisition of personnel is a challenging application area. Offers in an electronic job-marketplace change very rapidly, so that potential employees or agencies providing manpower have to visit the marketplace very often. Agents instead can automatically search for job openings or appropriate candidates, negotiate issues of interest, and come to an agreement. Another shortcoming of present job-marketplaces is that most search criteria for appropriate jobs are crisp. However, in real-life situations an employee often cannot express his or her job preferences exactly.

In section 2, we give a brief overview of our agent-based job-marketplace, which is called FuzzyMan (Fuzzy Multi-Agent Negotiations). The underlying multilateral negotiation model with fuzzy preferences, several tactics an agent can apply to generate offers and the negotiation issues are described in section 3. In section 4, we present and discuss results from evaluating the main properties of our negotiation model with the help of some simulation experiments. Finally, in section 5, we conclude the paper and point out some future work.

2 MULTI-AGENT MARKETPLACE

The architecture of the agent-based job-marketplace as shown in Figure 1 is based on the client/server model. A mechanism for processing messages in parallel and storing them in a message queue has been implemented. An advantage of this approach is that a message can be sent to a message box without needing to know what the corresponding receiver is processing at the moment nor when the receiver will read the message. Every agent has its own ‘message box’, as indicated in Figure 1.

Initially, all users have to register when entering the marketplace to create their own agents for selling or buying on the server. Sell-agents search for adequate jobs and Buy-agents offer jobs. Every agent can uniquely be identified by its Agent-ID, which is mapped by a naming service to its current socket address. An agent created by a user contacts...
Multilateral negotiation over many issues is typical of most negotiation situations. In real life negotiation problems, constraints, preferences, etc. are usually vague (e.g. salary ‘about’ 2000 Euro, ‘quite good’ programming experience). Therefore, we consider a multilateral multi-issue negotiation model based on Fuzzy-Logic as the underlying negotiation model for our job-marketplace.

Fuzzy-Logic is based on the fuzzy set theory introduced by Zadeh (Zadeh 1965). Let \( x \) be an element of the universe \( \Omega \) and \( A \subseteq \Omega \). The crisp (non fuzzy) function \( \mu_A: \Omega \rightarrow \{0, 1\} \) denotes the membership \( x \in A \). The membership \( \mu_A \) is 1 if \( x \in A \) and 0 otherwise. Zadeh redefines the crisp function \( \mu_A: \Omega \rightarrow \{0, 1\} \) to an interval by \( \mu_A: \Omega \rightarrow [0, 1] \) measuring the degree of membership. \( \mu_A \) is a so-called fuzzy set over \( \Omega \). The closer \( \mu_A(x) \) is to 1 the more \( x \) becomes a member of \( A \).

Our negotiation model is based on multiple-issues negotiation as described in (Faratin et al. 2000, Kurbel and Loutchko 2002) rather than just a single issue like price which is found in many negotiation models. For each issue, a value \( x_j \) in a certain range \( x_j \in I_j = [\text{min}_j, \text{max}_j] \) is determined by the users of the marketplace.

Each agent has a utility function \( V_j(x[j]) = \sum_{j=1}^{n} w_j \cdot V_j(x[j]) \) to evaluate the value \( x \) of issue \( j \) in the interval of acceptable values \( [\text{min}_j, \text{max}_j] \). Utility scores are kept in the interval \( [0, 1] \). The closer the value of the utility function for a certain issue is to 1, the more satisfied an agent is with that value.

The utility over all issues is calculated by the following weighted, linear, additive value function:

\[
V = \sum w_j \cdot V_j(x[j])
\]

\( w_j \) is the relative importance that an agent assigns to...
issue \( j \). The weights are kept in the interval \([0, 1]\). The sum of weights is 1:

\[
\sum_{j} w_j = 1
\]

Imprecision refers to the difficulty of describing preferences. So to deal with imprecision we propose a scoring method based on Fuzzy-Logic and introduce the following four types of scoring functions for the evaluation of offers and counter-offers:

(i) \( V_j(x[j]) = \left( \frac{x[j] - \min_j}{\max_j - \min_j} \right)^\beta_1 \)

(ii) \( V_j(x[j]) = \left( \frac{\max_j - x[j]}{\max_j - \min_j} \right)^\beta_1 \)

(iii) \( V_j(x[j]) = \begin{cases} 
1, & x[j] = \max_j \\
1 - \left( \frac{\min_j - x[j]}{\min_j - \max_j} \right)^\beta_1, & x[j] \geq \max_j 
\end{cases} \)

(iv) \( V_j(x[j]) = \begin{cases} 
\left( \frac{x[j] - \min_j}{\max_j - \min_j} \right)^\beta_1, & \min_j \leq x[j] \leq \min_1 \\
\left( \frac{\max_j - x[j]}{\max_j - \min_j} \right)^\beta_1, & x[j] \geq \max_2 
\end{cases} \)

For simplicity, we use only one (type (iii)) and two points (type (iv)) respectively to model (convex) triangular and trapezoidal functions. To each of those one or two points we assign a unique utility degree of 1. Utility degrees between those specified points are calculated by interpolation. The utility function that constitutes the fuzzy preferences can be approximated in this way. The parameter \( \beta \) determines the convexity of the utility function.

Figure 2 shows a possible utility function of type (iv) with \( \beta = 1 \), \( \min_1 = 40 \) and \( \max_2 = 45 \). The minimal and maximal numbers of working hours are \( \{\min_j, \max_j\} = [30, 50] \). Figure 3 illustrates our approach to represent an agent’s fuzzy utility function of type (iv) in XML. A Sell-agent searching for a specific job can apply this XML representation to describe its preferences concerning the issue working hours per week (in our example an ‘average’ number of working hours per week of ‘about’ 40 to 45 hours).

In fuzzy set theory a fuzzy set is described by a membership function, which can be approximated by a...
set of points. To each point a unique degree of membership is assigned. Membership degrees between the specified points can be calculated by interpolation. For example, a fuzzy term like ‘average’ of the linguistic variable working hours per week has an attached degree of membership of 0 to 1 within the interval $[30, 50]$ (see Figure 3). For the trapezoidal function of type (iv) four discrete points are chosen to represent the term ‘average’. In our example ‘something like’ 40 to 45 hours per week is considered as ‘average’.

Table 1 summarizes the utility functions for different issues $x[j]$ applied on our e-marketplace.

### 3.2 Tactic Functions

Offers are calculated by functions called tactic functions. New values for each variable in an offer are generated by those tactic functions (Faratin et al. 2000).

An offer by agent $a$ to agent $b$ regarding issue $j$ at time $t \leq t_{\text{max}}$ can be modelled by a tactic function $\alpha_j(t)$ depending on time as follows:

$$
\alpha_j(t) = \begin{cases} 
\min_i^n + a_j^* (t) \times (\max_i^n - \min_i^n) & \text{if } V_j^* \text{ is decreasing} \\
\min_i^n + (1 - a_j^* (t)) \times (\max_i^n - \min_i^n) & \text{if } V_j^* \text{ is increasing}
\end{cases}
$$

Polynomial and exponential $\alpha_j(t)$-functions, parameterized by a value $\beta$ that determines the convexity degree, can be chosen as follows:

Polynomial: $\alpha_j(t) = k_j^* + (1 - k_j^*) \frac{\min(t, t_{\text{max}})}{t_{\text{max}}}^\beta$

Exponential: $\alpha_j(t) = \exp\left(\frac{\min(t, t_{\text{max}})}{t_{\text{max}}} \beta\right)$

$k_j^*$ is a constant that determines the value of issue $j$ to be offered in the first proposal by agent $a$. Every $\alpha_j(t)$-function must satisfy the following constraints: $\alpha_j(0) = k_j^*$, $\alpha_j(t_{\text{max}}) = 1$. $\beta$ determines the negotiation behaviour ($\beta << 1$: ‘don’t start conceding until deadline $t_{\text{max}}$ is near’, and $\beta >> 1$: ‘start with giving ground very quickly’).
### Table 1. Issues

<table>
<thead>
<tr>
<th>Issues</th>
<th>Utility function of ...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salary in EURO per hour</td>
<td>Buy-agents</td>
</tr>
<tr>
<td>Travelling in % of monthly working time</td>
<td>Type (ii)</td>
</tr>
<tr>
<td>Working time in hours per week</td>
<td>Type (ii) or Type (iv)</td>
</tr>
<tr>
<td>Extra pay in %</td>
<td>Type (iii) or Type (iv)</td>
</tr>
<tr>
<td>Work duration in EURO per month</td>
<td>Type (ii) or Type (iv)</td>
</tr>
<tr>
<td>Age of appropriate candidate in years</td>
<td>Type (ii) or Type (iv)</td>
</tr>
<tr>
<td>Job experience of appropriate candidate in years</td>
<td>Type (ii) or Type (iv)</td>
</tr>
<tr>
<td>Professional and additional skills in a specific field Fi in %</td>
<td>Type (i)</td>
</tr>
<tr>
<td>0: no additional skills</td>
<td>Crisp value (e.g. 90)</td>
</tr>
<tr>
<td>50: average skills</td>
<td>Crisp value (e.g. 6)</td>
</tr>
<tr>
<td>100: excellent skills</td>
<td>Crisp value (e.g. 30)</td>
</tr>
</tbody>
</table>

Figure 4 shows polynomial and exponential tactic functions for $\beta = 0.5$, $\min_j = 1.8$, $\max_j = 6.5$ and $k_j = 0.1$. These functions can represent our negotiation issue extra pay in %.

#### 3.3 Multilateral Negotiation Protocol

We define negotiation as the process by which a joint decision is made by two negotiation partners having contradictory demands at the beginning of their negotiation process and then move towards an agreement running through a process of concession.

Figure 5 illustrates a multilateral negotiation process with many Buy-agents ($B_1, B_2, ... B_n$) and many Sell-agents ($S_1, S_2, ... S_n$). Each agent is simultaneously negotiating with many other agents. Multilateral negotiation can be seen as a number of interdependent bilateral negotiation processes. Our proposed multilateral negotiation protocol is an extension of a formerly applied bilateral negotiation protocol, which is described in detail in (Kurbel and Loutchko 2002).

Let us first introduce the bilateral negotiation protocol. $x^a_{t,\rightarrow}b$ is the vector of values for different issues proposed by agent $a$ to agent $b$ at time $t$. The initial offer is an
The function has to be introduced for the Buy-agents. With an initial offer, given an agent which they will negotiate the negotiation thread starts. Once the agents have determined the set of issues over preferences (utility value of 1). A negotiation thread of the employees are taken into consideration. The weights of relative importance assigned are according to the level they suit for negotiation with the marketplace are ordered in a preselection process. The preselection process the issues profession, age, and ranked by the negotiation thread has its local time.

The proposed multilateral negotiation protocol consists of a set of interacting negotiation threads. Each negotiation thread has its local time.

Before the negotiation process starts all Sell-agents are ready to send in t’, then Buy-agent a accepts the best counter-offer in its message box. If in the ideal case at least one Sell-agent agrees with Buy-agent a’s initial offer Buy-agent a will make a contract with the Sell-agent, which was the first one to send its message of agreement. If more than one counter-offer is greater than the utility value of the different offers x_{t0}^a Buy-agent a is ready to send in t’, then Buy-agent a accepts the first received counter-offer in its message box, which satisfies the above condition.

The function $V_{nl}^a(y_{fix}, \omega_{nl})$ reflects the fixed preselection issues. The weights of relative importance assigned to the fixed preselection issues $y_{fix}$ of Sell-agent y are represented by a vector $\omega_{nl}$.

For a given Buy-agent b a partial order of the set of all Sell-agents is introduced according to the following rule:

A given Sell-agent y is more preferable for the Buy-agent b than another Sell-agent z (or equal) if $V_{nl}^b(y_{fix}, \omega_{nl}) \geq V_{nl}^b(z_{fix}, \omega_{nl})$.

In this case, the relation between the two Sell-agents is denoted by $y \succ z$.

Taking a particular Buy-agent, a sequence $n_1, n_2, n_3, \ldots, n_l$ of Sell-agents is determined. This sequence is sorted according to the levels those Sell-agents are suited for the negotiation with the Buy-agent: $n_1 \succ n_2 \succ n_3 \succ \ldots \succ n_l$.

Let us introduce the multilateral negotiation protocol from the point of view of a Buy-agent a negotiating simultaneously with several Sell-agents. The multilateral negotiation protocol consists of the following negotiation rules and steps, which determine the alternate succession of offers and counter-offers. Suppose that $t_{max}$ is the deadline of Buy-agent a and $n_1, n_2, n_3, \ldots, n_l$ is the sequence of the Sell-agents suitable for the negotiation with Buy-agent a and ranked by the preselection procedure $n_1 \succ n_2 \succ n_3 \succ \ldots \succ n_l$:

1. At time $t = t_0$ Buy-agent a starts negotiating when sending its initial offer $x_{t0}^a$, $k = 1, \ldots, l_i$ to each of the $l_i$ highest ranked Sell-agents $n_i, \ldots, n_{l_i}$, $l_i \leq l$ satisfying the condition: $V_{nl}^a(n_i, \omega_{nl}) = V_{nl}^b(n_i, \omega_{nl})$, $k = 1, \ldots, l_i$

2. In $t' > t = t_0$ Buy-agent a rates the received counter-offers $x_{t'}^{nl}$ in its message box using its utility function $V_{nl}^a$. If the value $V_{nl}^a$ of one of the counter-offers is greater than the utility value of the different offers $x_{t0}^a$ Buy-agent a is ready to send in $t'$, then Buy-agent a accepts the best counter-offer in its message box. If in the ideal case at least one Sell-agent agrees with Buy-agent a’s initial offer Buy-agent a will make a contract with the Sell-agent, which was the first one to send its message of agreement. If more than one counter-offer is greater than the offers Buy-agent a is ready to send and all of the counter-offers have the same utility values, Buy-agent a accepts the first received counter-offer in its message box, which satisfies the above condition.

3. To the Sell-agent, which sends the accepted counter-offer $x_{t'}^{nl}$ Buy-agent a sends a special XML message of agreement; to all other Sell-agents Buy-agent a sends a message about cancellation of the negotiation process. If the utility values $V_{nl}^a$ of the counter-offers are less than the value of Buy-agent a’s new counter-offers Buy-agent a sends these counter-offers to the $l_i$ highest ranked agents.

4. Let $I_m, I_n < l$ be the index of the Sell-agent last involved in the negotiation with Buy-agent a. At time $t = t_0$, $i = 1, \ldots, n$ Buy-agent a starts a new negotiation thread by sending its initial offer $x_{t0}^a$ to all those Sell-agents not involved before in the negotiation with Buy-agent a, which satisfy the following condition: The sum of the utility value of...
Buy-agent a's initial offer and the fixed utility value of the new potential Sell-agent is in $t_i$ for the first time greater than (or equals) the sum of the highest utility value of the counter-offers $x_{i-a}$. Buy-agent a is ready to send in $t_i$ and the fixed utility value of the Sell-agent $n_m$ last involved in the negotiation with Buy-agent a. Formally expressed:

$$V^a(x_{i-a}) + V^i_t(n_m, \omega_a) \leq V^a(x_{i-a}) + V^i_t(n, \omega_a)$$

With regard to communication cost and efficiency it is rational to start a further negotiation thread in $t = t_i$ only with those new Sell-agents, which satisfy the above condition.

5 If a message about cancellation of the negotiation process is received from one of the Sell-agents, withdraw that agent from the set $n_1, n_2, n_3, \ldots, n_l$ of Sell-agents currently participating in the negotiation.

6 At time $t = t_n, t_n \geq t_{\text{max}}$, stop the negotiation with all the Sell-agents involved in the negotiation and inform these agents by a special XML message about cancellation of the negotiation process.

Figure 6 illustrates a possible sequence of a negotiation process from a Buy-agent's point of view negotiating with two Sell-agents.

At the beginning both Sell-agents deliver their employee profiles to the mediator agent. The speech act of the corresponding FIPA-ACL/XML-message is advertise. A speech act determines which action the sender wishes to be taken in response to its message. Buy-agent A asks the mediator agent for a list of all agents (speech act recommend-all), which meet all requirements of its qualification profile.

After receiving profiles from the Buy- and Sell-agents all Sell-agents on the marketplace are ordered by the mediator in the preselection process according to the level they suit for the negotiation with a Buy-agent.

Assuming both Sell-agents $k = 1, 2$ have equal fixed utility values $V^a_{\text{fix}}(n_k, \omega_k)$ Buy-agent A starts the multilateral negotiation process with Sell-agent A and B by sending them a complete job description including the initial offer (inform).

After exchanging one offer and a counter-offer with Sell-agent B, the negotiation process ends with an agreement. Finally, the mediator is informed by Buy-agent A about the closed contract and the mediator updates its databases. Sell-agent A instead rejects the offer of Buy-agent A and asks the mediator agent within its negotiation time frame for one new job offer.
(speech act recommend-one). However, there is no job offer available in the databases at the moment, so the mediator has to refuse this request.

4 SIMULATION OF THE MULTILATERAL NEGOTIATION MODEL

4.1 Simulation Settings

The interrelation between applied negotiation tactics and limited negotiation time frames on the one side and achieved utility degrees or the number of closed contracts on the other side cannot be predicted from the theoretical negotiation model presented in Section 3 alone. There are too many interrelated factors and a too wide range of possible negotiation situations. Therefore, we evaluate the main properties of our negotiation model with the help of some simulation experiments.

Six hundred Sell-agents and 300 Buy-agents were initialized for our simulation experiments. Sell-agents were superior in number because in real-life situations there are normally also more employees searching for a specific job than job positions offered.

For the generation of offers and counter-offers polynomial tactic functions with various values of the β-parameter were applied to all negotiation issues. The values and parameters for our simulation experiments were generated automatically, because we had no real employees and employers with real data available. Since there are infinitely many potential negotiation situations in which we can evaluate our negotiation model, we had to limit the possible values of the agents’ utility functions for each issue. Therefore, we generated these values automatically based on empirical statistics. For example, to generate values for the issue working hours per week, we used an empirical statistics of the Federal Statistical Office, Germany describing the distribution of employees’ working hours per week in Germany.

The time frames for negotiation of each agent were randomly generated by integers of the interval [10, 210] in negotiation days. To shorten the actual negotiation time in the simulation experiments one negotiation day in reality corresponds to three seconds in the simulation.

Each user has to weight the relative importance of several negotiation issues in the initialization phase of its own Sell- or Buy-agents. Thus, weights of the interval [0, 1] were also generated randomly, whereas a weight of 0.5 had the highest probability (based on a normal distribution) to be randomly generated.

4.2 Experimental Results

In this section selected simulation results will be presented and interpreted. Our job-marketplace is running on a server with a Windows 2000 operating system, 40 GB hard-disc, 1 Ghz and 256 MB DDR-RAM memory.

4.2.1 Number of active agents during the negotiation period. Figure 7 shows the number of active (negotiating) Sell-agents and Buy-agents during the negotiation period. After 94% of the negotiation period no more Buy-agents are negotiating. This means, that all 300 initialized Buy-agents have closed a contract or stopped negotiation before reaching an agreement.

4.2.2 Disposable negotiation time and achieved utility degrees. In this section, we analyse the influence of the disposable time frame for negotiation on the achieved utility degrees. Figure 8 shows the results obtained for these simulation experiments. It illustrates that Sell-agents that close contracts shortly before the end of their disposable negotiation time, achieve smaller utility degrees than Sell-agents that close contracts at the beginning of their disposable negotiation time. The utility degree of Sell-agents with a contract closed 10 days before the end of the negotiation time is only 80% of a contract closed at the beginning of the negotiation process (see Figure 8).

4.2.3 Tactic functions and number of closed contracts. In this section, we examine the interrelation between

![Figure 7. Number of active agents vs. negotiation time](image-url)
applied tactic functions and the number of closed contracts. In our simulation the value for the $\beta$-parameter was generated equal distributed with $\beta = 0.25, 0.5, 1, 2$ and 4.

Figure 9 shows the percentage of closed contracts in dependence on the $\beta$-parameter value of the agents’ tactic functions. The percentage of closed contracts of Buy-agents is higher than the percentage of Sell-agents’ contracts, because in our simulation 300 Buy-agents offering a job and 600 Sell-agents searching for an adequate job were initialized. Therefore, Buy-agents have a wider choice of negotiation partners and as a consequence of that a better chance than Sell-agents to close a contract. Figure 9 shows that the $\beta$-value determines the chance to close a contract. The best chance to close a contract has a Buy-agent applying a tactic function with a $\beta$-parameter value of 4 and thus moving towards the demands of their negotiation partners early at the beginning of the negotiation process (80% of those agents closed a contract).

Figure 10 shows the percentage of closed contracts in dependence on the $\beta$-parameter values of the tactic functions the negotiation partners have applied. The most contracts were closed when both negotiation partners applied a tactic function with a $\beta$-parameter value > 1. This means, that both negotiation partners were willing to make concessions early at the beginning of their negotiation process. Only a few contracts were closed when at least one negotiation partner was not willing to make concessions or both negotiation partners have applied divergent $\beta$-parameter values for their tactic functions.

4.2.4 **Interdependence of tactic functions on utility degrees and number of closed contracts.** In this section, we analyse the interrelation between average utility degrees and the number of closed contracts on the one side and applied polynomial tactic functions with various values for the $\beta$-parameter on the other side.

Figure 11 shows that the achieved utility degrees of Buy-agents with decreasing values for the $\beta$-parameter in comparison to a $\beta$-parameter value of 8 is also decreasing. We observed also in our simulation experiments that ‘extreme’ tactical behaviour ($\beta$-value between 0.5 and 0.125) also results in a higher standard deviation. Buy-agents take obviously a ‘higher risk’ using a tactic function with a $\beta$-parameter value < 0.5 to close satisfactory contracts.

Table 2 shows the observed average utility degrees (avg. UD) in dependence on the negotiation partners’ tactic. For a better interpretation the highest and the
lowest average utility degrees are displayed in bold-faced type (see table 2). Sell-agents achieve with an average utility degree of 79% the highest utility degree when applying a tactic with a $\beta$-parameter value of 0.25 (this means, that these Sell-agents are not willing to make concessions at the beginning of the negotiation process) when Buy-agents as their negotiation partners at the same time are applying a tactic with a $\beta$-parameter value of 4 (willing to make concessions very early). Furthermore, the observed results in table 2 show that the achieved utility degrees of Sell-agents are closely correlated with the number of closed contracts.

The more contracts Sell-agents are closing when applying a specific tactic, the lower are their average achieved utility degrees. This correlation cannot be observed in the case of the Buy-agents. The main reason for this result seems to be the different numbers of initialized Sell-agents (600) and Buy-agents (300). Buy-agents have a stronger position on the marketplace than Sell-agents and therefore a better choice between several Sell-agents. As a result, they can close a great number of contracts without losing percentage in their utility degrees.

4.2.5 Efficiency Criteria. Negotiation protocols can be evaluated according to many types of efficiency criteria. Some of these criteria are symmetry, Pareto-efficiency and computational/communication-efficiency. In the following we will briefly discuss these criteria. Our multilateral negotiation protocol is symmetric in that no agent within both groups of Buy- and Sell-agents will be privileged with regard to others within these groups. However, Buy-agents and Sell-agents are treated differently. Sell-agents, which are on all Buy-agents’ sequence lists they were assigned to on a lower rank have to wait before they receive their first offers and can start the negotiation with other Buy-agents, because Buy-agents start their simultaneous negotiation processes only with the highest ranked Sell-agents. Therefore, the group of Buy-agents has a superior position on our marketplace than the group of Sell-agents. Our proposed concept is comparable to real life employment situations in that employees
(represented by Sell-agents) also have to wait before they are invited to interviews with different employers.

A negotiation outcome is said to be Pareto-efficient if there is no other outcome that will make at least one agent more satisfied without making at least one other agent less satisfied. Our proposed multilateral negotiation model is in most cases Pareto-efficient but not in all. Assuming a Buy-agent $a$ receives two offers, one from Sell-agent $b$ (under deadline pressure) and one from Sell-agent $c$ (with a longer deadline) and both offers have equal utility values for the three agents $a$, $b$, and $c$. In the proposed multilateral negotiation model Buy-agent $a$ will choose that offer, which it received first in its message box. With regard to Pareto-efficiency it would be better to choose the offer of Sell-agent $b$, which has the earlier deadline $t_{\text{max}}$, because the Sell-agent with the longer deadline has a better chance to reach an agreement before its deadline with another Buy-agent and to achieve the same or even a greater utility value. Otherwise, if agent $a$ chooses Sell-agent $b$ it is possible that agent $b$ fails due to its deadline pressure and achieves a utility value of 0.

So in this special negotiation scenario there could be an outcome that will make Buy-agent $a$ just as satisfied while making one other Sell-agent more satisfied. However, in our multilateral negotiation protocol other agents’ deadlines are private information. Therefore, we had to make a decision between Pareto-efficiency in all negotiation scenarios and privacy of information.

With regard to computational/communication-efficiency the amount of data (XML-messages) exchanged between agents applying the multilateral negotiation protocol for negotiation is on the average three times higher than on the basis of the formerly applied bilateral negotiation model. However, this is not a critical point, because whenever an agent failed it is due to its deadline and not to a communication overload or the e-marketplace server’s capacity.

5 CONCLUSION AND FUTURE WORK

The presented simulation results show that under the existing negotiation protocol efficient contracts can be realized and that the agents act logical in regard to our multilateral negotiation model. The obtained simulation results strengthen the author’s confidence to delegate negotiation tasks to the agents of the marketplace.

The main experimental results can be summarized as follows:

- The $\beta$-parameter of the applied polynomial tactic functions determines the average utility degree as well as the rate of closed contracts.
- The achieved utility degrees are lower when there is a short time frame to negotiate.
- The more contracts Sell-agents are closing when applying a specific tactic, the lower their achieved

<table>
<thead>
<tr>
<th>Tactic ($\beta$-value)</th>
<th>Avg. UD Buy-agent</th>
<th>Avg. UD Sell-agent</th>
<th>No. of contracts</th>
<th>Avg. UD/No. of contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>65</td>
<td>61</td>
<td>61</td>
<td>65</td>
</tr>
<tr>
<td>2</td>
<td>70</td>
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<tr>
<td>0.25</td>
<td>72</td>
<td>61</td>
<td>61</td>
<td>72</td>
</tr>
</tbody>
</table>

Table 2. Average utility degrees (Avg. UD) and number of closed contracts
average utility degrees, whereas a Buy-agent can close a great number of contracts without losing percentage in its utility degrees. The main reason for this result seems to be the stronger position of the Buy-agents in our simulation.

Analysing the sequence of a negotiation partner’s counter-offers it is possible that a smart agent infers the private information (e.g. applied tactic functions, deadlines, utility functions) of its negotiation partners. Methods to exploit an agent’s profile by another agent are not implemented yet in FuzzyMAN. However, we are currently implementing a Markov Decision Process [MDP] (Howard 1960) approach for anticipating other agents’ negotiation tactics from past negotiation steps. A description of our approach is given in (Teuteberg 2002). The MDP approach gives agents the ability to change their tactics over time to avoid the shortcomings of a deterministic and fixed negotiation strategy by adaptively deciding which tactic will be the best one for the next negotiation step. We are currently conducting a set of experiments in order to evaluate our MDP approach. The preliminary observed data show that agents using the MDP approach realize an average utility degree of 78%, whereas agents not using the MDP approach realize an average utility degree of only 70%.


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