Estimation of the Buyer's Contract Space Incorporating Learning from Experience Techniques to the Seller's Rationale in E-Commerce Context

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Abstract

Various state-of-the-art technologies are necessary to enhance the efficiency and increase the interest for e-commerce transactions. Mobile agents are one of the means that may enhance the intelligence and improve the effectiveness of systems in the e-marketplace. This paper aims to present the basic elements of the designed dynamic multilateral negotiation model and strategies that do not require a complicated rationale on behalf of the buyer agents. It focuses on the enhancement of the Seller's reasoning component by incorporating to the designed negotiation strategies a novel mechanism for the estimation of the mutually acceptable contract region by exploiting relative market data combined with knowledge acquired from previous experience. This technique is used to extend the functionality of autonomous agents, so that they reach to an agreement faster aiming to maximise their owner's utility. The framework considers both contract and decision issues, is based on real market conditions, and has been empirically evaluated.

1. Introduction

The liberalized and deregulated telecommunication market will introduce new actors, whose main role will be to constantly monitor the user demand, and in response to create, promote and provide the desired services and service features. The following are some key factors for success. First, the efficiency with which services will be developed. Second, the quality level, in relation with the corresponding cost, of new services. Third, the efficiency with which the services will be operated (controlled, maintained, administered, etc.).

The challenges outlined above have brought to the foreground several new important research areas. Some of them are: the definition of new business models, the elaboration on e-business concepts, the specification of service architectures (SAs) and the exploitation of advanced software technologies, (e.g., distributed object computing and intelligent mobile agents) [1][2][3]. The aim of this paper is, in accordance with efficient service operation objectives, to propose enhancements to the sophistication of the negotiation functionality that can be offered by e-commerce systems in open competitive communications environments. This study is based upon the notion of interacting intelligent agents which participate in trading activities on behalf of their owners, while exhibiting properties such as autonomy, reactivation, and pro-activation, in order to achieve particular objectives and accomplish their goals.

Mobile intelligent agents can act as mediators in five of the six e-commerce phases [4]: *need identification*, *product brokering*, *coalition formation*, *merchant brokering* and *negotiation*. Automated negotiation is a very broad and encompassing field. For this reason, it is important to understand the dimensions and range of options that are available. When building autonomous agents capable of sophisticated and flexible negotiation, three main areas need to be considered [5][6][7]: (i) negotiation protocol and model, (ii) negotiation issues, and (iii) negotiation strategies that the agents will employ.

In the highly competitive electronic B2C marketplace, the roles of the negotiation agents may be classified into two main categories that, in principle, are in conflict. Thus, the negotiating agents may be divided into two subsets: The Buyer Agents (BAs) and the Seller Agents (SAs), which are considered to be self-interested, aiming to maximise their owners' profit. The negotiation environment considered covers multi-issue contracts and multiparty situations, while being a highly dynamic one, in the sense that its variables, attributes and objectives may change over time. The authors exploit a multi-round negotiation mechanism, where the agents hold private information that may be revealed incrementally, only on an as-needed basis. Considering the case where SAs and/or BAs face strict deadlines, an effective negotiation strategy assisting all agents to reach to an agreement within the specified time-limits is required.

The work of this paper enhances the SA's reasoning component by incorporating to the negotiation strategies [8][9][10] designed by the authors, a novel mechanism for the estimation of the mutually acceptable contract region, hereafter called intersection region, by exploiting relative market data combined with knowledge acquired from previous experience.

The rest of the paper is structured as follows. Section 2 provides the main elements of the negotiation protocol, model and strategies designed, which constitute a dynamic, multi-party and multi-issue framework and are adequate for cases where the rationale of the BAs is limited. Section 3 elaborates on the factors that determine the duration of the negotiation procedure, while Section 4 proposes an efficient mechanism that enables SAs to estimate the acceptable contract region of the Buyers, aiming to minimize the number of the necessary negotiation rounds and reduce the negotiation costs for both parties. Finally, in Section 5, conclusions are drawn and directions for future plans are provided.

2. Basic elements of the agent negotiation problem and the designed strategies

In relative research literature, the interactions among the parties mostly follow the rules of an alternating sequential protocol in which the agents in turn make offers and counter offers (e.g., [11]). This model requires an advanced reasoning component on behalf of the BA as well as the SA. In [12], the authors consider the case where the BA does not give a counter offer (which involves incorporating to the model all BA's trade-offs between the various attributes) to the SA, but ranks the SA's offers instead. This ranking is then provided to the SA, in order to generate a better proposal. This process continues until a mutually acceptable contract is reached. This is more efficient in cases where the BA is not able to extract all user requirements and preferences in a completely quantified way, while being capable of selecting, classifying or rating the contract(s) proposed.

Once the agents have determined the set of issues over which they will negotiate, the negotiation process consists of an alternate succession of N contract proposals on behalf of the SA, and subsequent rankings of them by the BA, according to its preferences and current conditions. Thus, at each round, the SA sends to the BA N contracts (i.e., N packets consisting of n-plets of values of the n contract issues), which are subsequently evaluated by the BA, and a rank vector is returned to the SA. These steps are repeated until a contract proposed by the SA is accepted by the BA, or one of the agents terminates the negotiation. We hereafter consider the case where the negotiation process is initiated by the BA who sends to the SA an initial *Request for Proposal* (*RFP*) specifying the types and nature of the contract issues and the values of all non negotiable parameters.

The negotiation model adopted is based on the multi-issue value scoring system introduced in [13], for bilateral negotiations involving a set of quantitative variables. However this framework is incorporated into a multi-party, multi-issue, dynamic model, introducing the *decision issues* (*DIs*) concept [14]. Decision issues comprise several issues, that even though their values are not under negotiation and they are not included in the contract parameters, they affect the evaluation of the values of the contract issues (e.g., number of competitors, number of substitute or complementary products/services, the quantity of product in stock).

The agents that represent *Sellers* will be denoted by $S=\{S_1,S_2,...\}$ and the ones that represent potential *Buyers* will be denoted by $B=\{B_1,B_2,...\}$. We represent by $P^t=\{C_1^t,...,C_N^t\}$ the vector of the $N\geq 1$ contracts proposed by the Seller Agent S to the Buyer Agent B at time t, by $C_k^t=\{c_{k1}^t,...,c_{kn}^t\}$ the vector of the n contract issues values proposed by S to B at time t for the k-contract of this proposal ($k=1,...,N$), and by c_{ki}^t ($i=1,...,n$) the value of issue i proposed by S to B at time t for the k-contract of this proposal. Let now $R^t=\{r_1^t,...,r_N^t\}$ be the vector of ranking values that B assigns at time t to the previous contracts proposal made by S, and r_k^t ($k=1,...,N$) be the rank that B assigns at time t to the k-contract of this proposal.

The agent's $a\in S\cup B$ utility function for a contract $C_k=\{c_{k1},...,c_{kn}\}$ can be defined as follows: $U^a(C_k)=\sum_{i=1}^{n} w_i^a U_i^a(c_{ki},d_j^{t=t_k})$, where $U_i^a:[m_i^a,M_i^a]\rightarrow[0,1]$ is the utility that agent a assigns to a value of contract issue i in the range $[m_i^a,M_i^a]$ of its acceptable values, $\sum_{i=1}^{n} w_i^a=1$ and $d_j^{t=t_k}$, $j=1,...,m$, is the value of decision issue d_j at the time t_k, when contract C_k is proposed. Additionally, the *value constraint validity vector*: $VCV^a=[VCV_i^a]$, $i=1,...,n$, is introduced, where $VCV_i^a\in\{0,1\}$, depending on whether the value constraint for negotiating party a is met for contract issue i (i.e., $VCV_i^a=1$) or not (i.e., $VCV_i^a=0$). In case a value constraint is not met for at least one contract issue, the particular contract is rejected. The negotiation terminates either in case the agent(s) deadline is reached or in the case where a boolean variable expressing the wish of the agents to quit the negotiation is set to true. If an agreement is finally reached, then we call the negotiation successful, while in case one of the negotiating parties quits it is called unsuccessful. In any other case, we say that the negotiation thread is active.

The objective of the negotiation problem on the Seller's side is to find a contract $C_{final} = \{c_{1final}, c_{2final}, \ldots, c_{nfinal}\}$ that maximises his/her overall utility function $U^S(C_{final})$, i.e., the satisfaction stemming from the proposed contract, within the negotiation deadlines for both the BA and the SA. Nevertheless, there are constraints on the acceptable value ranges that should apply for both negotiating parties, while their individual utilities should be above a minimum acceptable threshold. The complexity of the negotiation problem is increased with regards to the number of the contract issues involved and the range of their acceptable values. In this respect, the design of computationally efficient algorithms that may provide good (near-optimal) solutions in reasonable time is required.

The general idea of the proposed negotiation strategies [8][9][10] is that all contracts $C_k^{t_l}$ ($k = 1, \ldots, n$) of a negotiation round l are generated by the same "source" contract that will be hereafter denoted as $C_0^{t_l}$. All contracts of the same round are generated so that they correspond to equal utilities for the Seller. Specifically, the core concept of the proposed SA's strategies is to propose N contracts at each negotiation round l, which yield the same utility concession quantity Θ^{t_0} with respect to the source contract $C_0^{t_l}$. That is the utility of the contracts proposed is equal to $U^S\left(C_k^{t_l}, \underline{d}^{t_0}\right) = U^S\left(C_0^{t_l}, \underline{d}^{t_0}\right) - \Theta^{t_0}$, while $U^S\left(C_k^{t_{l-1}}, \underline{d}^{t_0}\right) = U^S\left(C_0^{t_l}, \underline{d}^{t_0}\right)$, $\forall k = 1, \ldots, n$. It has been assumed that the values of all decision issues are invariable for the entire negotiation procedure.

Based on the *RFP* sent by the BA, the SA proposes an initial contract $C^{t_0} = \left\{c_1^{t_0}, \ldots, c_n^{t_0}\right\}$ to the BA at $t = t_0$, setting all contract issues at the values that maximise the Seller's utility (i.e., if $\partial\left[U^S\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i > 0$, then the SA sets $c_i^{t_0} = M_i^S$, while in case $\partial\left[U^S\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i < 0$, then the SA sets $c_i^{t_0} = m_i^S$). The utility of the initial contract C^{t_0} for the SA will be denoted by: $U^S\left(C^{t_0}, \underline{d}^{t_0}\right) = U_{\max}^{S,t_0}$, as $U_{\max}^{S,t_0}$ is the maximum utility that can be achieved for the Seller, given the values of the decision issues $\underline{d}^{t_0} = \left\{d_j^{t_0}\right\}$ at time $t = t_0$. With respect to this initial contract C^{t_0} two distinct cases may be identified. First, no *value constraint violation* exists and the Seller aims at finding a contract satisfying the Buyer's related utility constraint. Second, *value constraint violation* occurs, in which case the BA provides also its *value constraint validity vector* VCV_0^B, while the SA, as a first step, tries to acquire a contract that satisfies BA's value constraints. To this respect, until a non value constraint violating contract C^{t_l} is acquired, at each negotiation round $l > 1$ the source contract $C_0^{t_l}$ is generated on the basis of the contract $C_0^{t_{l-1}}$ by equally distributing the utility concession Θ^{t_0} amongst the contract issues, whose values are not acceptable to the BA. This process continues until a non value constraint violating contract C^{t_l} is acquired, in which case the Seller's strategy is modified in order to generate a mutually acceptable contract within reasonable time [8][9][10].

3. Factors affecting the duration of the negotiation procedure

Since the initial contract C^{t_0} is defined so that the maximum utility value $U_{\max}^{S,t_0}$ on behalf of the Seller is achieved, it is highly probable, that a potentially large number of steps (i.e., negotiation rounds) may be necessary in order to find a contract that is also acceptable for the Buyer. The number of steps required mainly depends on two factors. First, on the utility concession mechanism adopted by the Seller, which most probably would be a Boulware one [13], so as not to proceed hastily and loose an agreement with potentially better terms. Second, on the distances cL_i^m or cL_i^M that have to be covered for each contract issue i till its minimum or maximum acceptable value from the Buyer's perspective are identified respectively. Let us by $c_i \in \left[c_{i,\min}, c_{i,\max}\right]$ denote the intersection region, i.e., the mutually acceptable range, for a contract issue i. For the bounds of the intersection region it stands that: if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i > 0$, then the minimum mutually acceptable value for contract issue i is $c_{i,\min} = m_i^B$ and the maximum is $c_{i,\max} = M_i^S$, while in case $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i < 0$, then $c_{i,\min} = m_i^S$ and $c_{i,\max} = M_i^B$. As depicted in Figure 1, for the specific contract issue i considered, if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i < 0$, the distance $cL_i^M = M_i^S - M_i^B$ has to be covered for the upper bound of

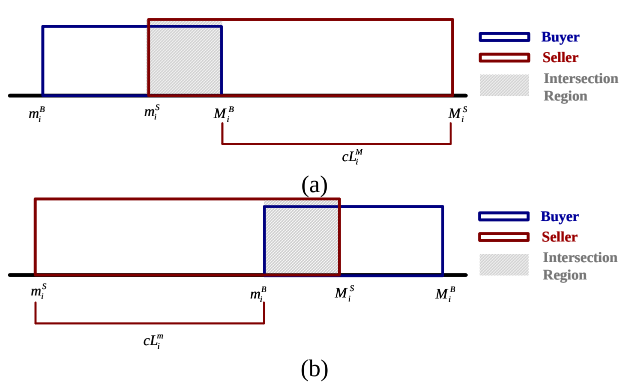

Figure 1. Definition of mutually non violating contract space (intersection region) for both cases $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i < 0$ and $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i > 0$ (depicted in (a) and (b), respectively)

the Seller, or if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$ the distance $cL_i^m = m_i^S - m_i^B$ has to be covered for the lower bound of the Seller, in order to acquire an initial mutually non violating contract, that will form a solid value constraint compliant basis for the subsequent contract proposals.

In the following section we will present a stochastic model that may help the Seller on the decision of how much to invest on establishment of a learning model that may approximate the Buyer's contract value region and of what to initially propose to the Buyer to start the negotiation procedure.

4. Enhancing SAs with learning techniques

The approach presented hereafter considers the case where the negotiation phase is initiated by the Seller that proposes an initial contract which is potentially within or at least closer to the intersection region. The goal is to omit a number of negotiation rounds that may be costly to the Seller and to the Buyer. A basic assumption at this point is that the Seller has deployed learning from experience techniques [15][16] and has exploited the knowledge acquired from previous interactions with Buyers in order to produce an estimation $\overline{L_i}$ for the potential interval lengths for each contract issue i, as close as possible to the Buyer's actual acceptable range L_i ($L_i = M_i^B - m_i^B$). Specifically, different interval lengths $\overline{L_i}$ are assumed by the Seller, which are associated with different *interval length probabilities*, $p_{il}(\overline{L_i})$ for each contract issue i, defined on the basis of relative market data as well as observed values in previous Seller-Buyers transactions. Assuming that $\overline{L_i}$ values in conjunction with $p_{il}(\overline{L_i})$ are indicative of the real situation, they may form the basis for the identification of the *intersection region*. Naturally, the Seller should apply the mechanisms for determining the intersection region, in cases it is highly likely that the information on which it will be based is accurate. For example, in environments where the Buyers do not frequently change their policies/preferences, as considered in this paper, a learning period is required for the Seller to obtain the fundamental information. Likewise, Seller updating mechanisms are required in case the Buyers will be changing their policies, in order to adapt to the changing e-market environment (e.g., emergence of new more sophisticated services, Seller updated policies). To this end, several approaches can be found in the literature, e.g., the Boltzmann exploration strategy [17]. According to the straightforward approach adopted in this paper, it can be envisaged that the Seller will employ the intersection area approximation mechanism, in case criteria, indicating that the essential (fundamental) information is not outdated, are satisfied. In the opposite case, i.e., when the information available to the Seller is likely to be outdated (inaccurate), the negotiation will evolve starting from the initial contract as specified in the contract generation mechanisms.

In the context of the proposed scheme, the *RFP* consists of a complete specification of the service (i.e., values assigned to the n contract issues). Thus, these *RFP element* values define, in essence, a point in the Buyer's non violating contract space. Therefore, the values of all contract issues comprised in *RFP* may be exploited by the Seller in order to approximate the limits of the acceptable regions $\left[m_i^B, M_i^B\right]$ of the Buyer, and thus, estimate the intersection region. At this point, the Buyer's and/or Seller's utility threshold values are not considered.

In *subsection 4.1*, a stochastic model that may help the Seller decide on how much to invest on establishing a learning mechanism is presented, while in *subsection 4.2*, the methodology followed for the approximation of the Buyer's value contract range is provided.

4.1. Stochastic model

We introduce the cost for each extra negotiation round that will be denoted by K^r. If λ_i rounds are necessary for the identification of the Seller's most favorable bound of the intersection region for contract issue i (i.e., of the lower bound $c_{i,\min} = m_i^B$, if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$, or the upper bound $c_{i,\max} = M_i^B$, in case $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i < 0$), then the overall negotiation cost for determining this bound is $\mathrm{K}_i^r = \lambda_i \cdot \mathrm{K}^r$. The Seller utility compromise that is assigned to the adjustment of contract issue i at negotiation round l is denoted by $\vartheta_i^{t_l}$ and depends on the utility concession mechanism selected by the Seller and the number of contract issues that are not within the Buyer's acceptable range in the "source" contract of this negotiation round. Thus, it stands that the contract issue i value compromise for the negotiation round l is $\Delta c_{0i}^{t_l} = \left|\vartheta_i^{t_l} \cdot \left[\frac{\partial\left[U^S\left(C_0^{t_l}, \underline{d}^{t_0}\right)\right]}{\partial c_i}\right]^{-1}\right|$, where $C_0^{t_l}$ is the source contract of negotiation round l. Therefore, if the starting negotiation point for this contract issue is $c_{0i}^{t_0}$, then the number λ_i of the necessary rounds for the identification of the Seller's most favorable bound of the intersection region for this issue is such that: $\sum_{l=0}^{\lambda_i - 1}\left[\Delta c_{0i}^{t_l}\right] \le m_i^B - c_{0i}^{t_0} \le \sum_{l=0}^{\lambda_i}\left[\Delta c_{0i}^{t_l}\right]$ if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$, or $\sum_{l=0}^{\lambda_i - 1}\left[\Delta c_{0i}^{t_l}\right] \le c_{0i}^{t_0} - M_i^B \le \sum_{l=0}^{\lambda_i}\left[\Delta c_{0i}^{t_l}\right]$ in case $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i < 0$. Assuming that quantities $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i$ and $\vartheta_i^{t_l}$ are constant for the initial λ_i rounds, then $\Delta c_{0i}^{t_l}$ is also constant and equal to $\Delta c_{0i}^{t_l} = \Delta c_{0i}^{initial}$. Thus, the following expressions stand: $\lambda_i = INT\left(\frac{m_i^B - c_{0i}^{t_0}}{\Delta c_{0i}^{initial}}\right) + 1 \cong \frac{m_i^B - c_{0i}^{t_0}}{\Delta c_{0i}^{initial}}$ when $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$ (*Case I*), or $\lambda_i = INT\left(\frac{c_{0i}^{t_0} - M_i^B}{\Delta c_{0i}^{initial}}\right) + 1 \cong \frac{c_{0i}^{t_0} - M_i^B}{\Delta c_{0i}^{initial}}$ if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i < 0$ (*Case II*). In the following analysis, we will consider that $\lambda_i = \frac{m_i^B - c_{0i}^{t_0}}{\Delta c_{0i}^{initial}}$ for *Case I* or $\lambda_i = \frac{c_{0i}^{t_0} - M_i^B}{\Delta c_{0i}^{initial}}$ for *Case II*.

What must now be defined is the probability of λ_i necessary rounds with respect to the selected starting negotiation point $c_{0i}^{t_0}$ for contract issue i. In general, it is safe to assume that the Buyers will initially propose to the Seller values for all contract issues that are close to their most favorable bound of their acceptable ranges. Thus, the Buyer will initially propose value $c_i^{RFP} = M_i^B$ if $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$ (*Case I*), or $c_i^{RFP} = m_i^B$ in case $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i < 0$ (*Case II*). The Seller's initial proposal for contract issue i could then be expressed as follows: $c_{0i}^{t_0} = c_i^{RFP} - \overline{\mu}_i - \alpha_i \cdot \overline{\sigma}_i = M_i^B - \overline{\mu}_i - \alpha_i \cdot \overline{\sigma}_i$ (*Case I*), or $c_{0i}^{t_0} = c_i^{RFP} + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i = m_i^B + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i$ (*Case II*), where $\overline{\mu}_i$ is the estimated mean value and $\overline{\sigma}_i$ the estimated standard deviation of the distribution of the Buyer acceptable range of contract issue i. Then the number λ_i of necessary rounds can be expressed as follows: $\lambda_i = \frac{m_i^B - M_i^B + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i}{\Delta c_{0i}^{initial}} = \frac{-L_i + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i}{\Delta c_{0i}^{initial}}$ for *Case I* or $\lambda_i = \frac{m_i^B + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i - M_i^B}{\Delta c_{0i}^{initial}} = \frac{-L_i + \overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i}{\Delta c_{0i}^{initial}}$ for *Case II*. Thus, for both cases it stands that $\lambda_i = \frac{\overline{\mu}_i + \alpha_i \cdot \overline{\sigma}_i - L_i}{\Delta c_{0i}^{initial}}$. We will try to define this value of α_i that results in the lowest possible cost for the Seller for the identification of the Seller's most favorable bound of the intersection region for contract issue i.

Let's assume that the learning mechanism cost for the Seller for contract issue i is equal to K_i^{lm} per deal to be reached. Naturally, the higher the certainty about the mean value μ_i and the standard deviation σ_i is, the more expensive the learning mechanism gets and the higher the cost K_i^{lm} is. As it is more difficult to determine the exact value of the standard deviation of a quantified phenomenon, than its mean value, we will assume that $K_i^{lm} = \beta_i \big/ \left|\overline{\sigma}_i - \sigma_i\right|$. The previous expression indicates that the lower the difference between the estimated standard deviation $\overline{\sigma}_i$ and its real value σ_i is, the higher the cost K_i^{lm} is by a constant known factor β_i. Thus, if the Seller decides to invest K_i^{lm} money on the establishment of a learning mechanism, he/she is aware of the fact that the expected error on the estimation of the standard deviation will be: $e_i = \left|\overline{\sigma}_i - \sigma_i\right| = \beta_i / K_i^{lm}$. We consider that the cost of identifying μ_i during the learning period is negligible and that $\overline{\mu}_i \cong \mu_i$.

Following the analysis above, the overall cost for the Seller for the identification of the intersection region for contract issue i is: $K_i = K_i^r + K_i^{lm} = \lambda_i \cdot K^r + K_i^{lm}$, where K^r is constant, while K_i^{lm} and λ_i are random variables. Therefore, for *Case I* and *Case II* it stands that $K_i = \frac{\mu_i + \alpha_i \cdot \overline{\sigma}_i - L_i}{\Delta c_{0i}^{initial}} \cdot K^r + K_i^{lm}$. What is up to the Seller to decide now, are quantities α_i and K_i^{lm}. Since $L_i \sim N(\mu_i, \sigma_i)$, it stands that $K_i \sim N\left(\frac{K^r}{\Delta c_{0i}^{initial}} \cdot \alpha_i \cdot \overline{\sigma}_i + K_i^{lm}, \frac{K^r}{\Delta c_{0i}^{initial}} \cdot \sigma_i\right)$ $\Rightarrow K_i \sim N\left(\mu_i^K, \sigma_i^K\right)$. But we have that $e_i = \left|\overline{\sigma}_i - \sigma_i\right| = \frac{\beta_i}{K_i^{lm}} \Rightarrow \sigma_i = \begin{cases} \overline{\sigma}_i + \frac{\beta_i}{K_i^{lm}}, & if \quad \sigma_i > \overline{\sigma}_i \\ \overline{\sigma}_i - \frac{\beta_i}{K_i^{lm}}, & if \quad \sigma_i < \overline{\sigma}_i \end{cases}$. Thus, it stands that: $\mu_i^K = \frac{K^r}{\Delta c_{0i}^{initial}} \cdot \alpha_i \cdot \overline{\sigma}_i + K_i^{lm}$ and $\sigma_i^K = \begin{cases} \frac{K^r}{\Delta c_{0i}^{initial}} \cdot \left(\overline{\sigma}_i + \frac{\beta_i}{K_i^{lm}}\right), & if \quad \sigma_i > \overline{\sigma}_i \\ \frac{K^r}{\Delta c_{0i}^{initial}} \cdot \left(\overline{\sigma}_i - \frac{\beta_i}{K_i^{lm}}\right), & if \quad \sigma_i < \overline{\sigma}_i \end{cases}$. From the results above, we may see that the more the Seller invests on the learning mechanism, the lower the standard deviation of the overall cost for the identification of the intersection region for contract issue i is and the higher its mean value is. This conclusion was more or less expected. However, there is also another not so obvious result that identifies $\alpha_i = 0$ as the most favorable value of quantity α_i for the Seller, so that $\mu_i^K = K_i^{lm}$. Thus, the Seller's initial "source" contract should consist of values of each contract issue i, so that: $c_{0i}^{t_0} = M_i^B - \overline{\mu}_i$ (*Case I*), or $c_{0i}^{t_0} = m_i^B + \overline{\mu}_i$ (*Case II*). The exact value of the Seller's most appropriate K_i^{lm} level can be determined by the Seller's cost policies and risk adversity. For instance, if the Seller wishes to pay up to K_i^{max} with probability P_i^{max}, then the appropriate K_i^{lm} level derives by the typical normal distribution values table [18] based on the equation: $\Phi\left(\frac{K_i^{max} - K_i^{lm}}{\sigma_i^K}\right) = P_i^{max}$, where the only unknown quantity is K_i^{lm}.

4.2. Estimation of the Buyer's contract space

In the previous subsection we have formulated a stochastic model that may help the Seller on the decision of how much to invest on the establishment of a learning mechanism. In the subsequent analysis, we will consider that the cost K_i^{lm} is constant, i.e., the Seller has two options: (i) to invest in establishing a learning mechanism and identify the values of μ_i and σ_i with a high given certainty level, or (ii) not to use any learning techniques at all. In this respect, the following approach may be adopted. The Seller for each contract issue i under negotiation specifies different regions $[\overline{m_i^B}, \overline{M_i^B}]$ associated with certain degree of uncertainty concerning the violation or not of the Buyer's acceptable region constraints. These regions are constructed as follows. Considering a single contract issue i, each specified region comprises the initial contract issue value as defined in *RFP*, while the upper and lower limit may be estimated on the basis of the pre-defined interval length $\overline{L_i}$. The Seller takes into consideration the widest region $[\overline{m_i^B}, \overline{M_i^B}]$ specified for each contract issue i, i.e., the one associated with the maximum interval length $\overline{L_i}$, which in conjunction with his own region could estimate the largest possible intersection region, forming the range of possible mutually non violating contracts. Following the previous stochastic analysis, we may assume here that the Seller selects $\overline{L_i^{\max}} = \mu_i + 3\sigma_i$ for which it stands that $P_{il}\left(\overline{L_i} \le \mu_i + 3\sigma_i\right) = 99.85\%$ Our approach considers the widest possible intersection region, since, even though it may lead to a longer negotiation phase, it would probably yield a higher utility value for the Seller. Alternatively, the Seller on the basis of specific conditions of the e-market, as well as on his/her status (e.g., time deadlines/requirements of the negotiation phase) could potentially choose to limit this initial potentially acceptable contract space (and thus, the potential maximum utility value $U_{\max}^S$ possible) in order to reach an agreement with the Buyer in a timely manner.

One possible $[\overline{m_i^B}, \overline{M_i^B}]$ region could be the one which considers that c_i^{RFP} lies in the middle, thus, may be specified in accordance with the following equations: $\overline{m_i^B} = c_i^{RFP} - \overline{L_i}/2$ & $\overline{M_i^B} = c_i^{RFP} + \overline{L_i}/2$ for both *Cases I* and *II*. Considering the case where c_i^{RFP} lies in the upper half of $\left[m_i^B, M_i^B\right]$, the aforementioned equations are modified as follows: $\overline{m_i^B} = c_i^{RFP} - 3\overline{L_i}/4$ & $\overline{M_i^B} = c_i^{RFP} + \overline{L_i}/4$.

Since c_i^{RFP} could potentially take any value in the region of $\left[m_i^B, M_i^B\right]$, each estimated region $[\overline{m_i^B}, \overline{M_i^B}]$ is associated with certain degree of uncertainty as already assumed. Our approach hereafter considers that c_i^{RFP} lies in between the upper half of the Buyer's acceptable value region $\left[m_i^B, M_i^B\right]$ for contract issue i for *Case I* and within the lower half for *Case II*. This is quite safe to assume as in each case the Buyer will initially propose a contract issue value to the Seller that is close to its preferred one. Thus, the intersection regions with respect to each contract issue i are defined in accordance with the following equations: $\overline{m_i^B} = c_i^{RFP} - \overline{L_i}/4$ & $\overline{M_i^B} = c_i^{RFP} + 3\overline{L_i}/4$. This assumption is motivated by the fact that in most cases it would lead to a good approximation of the intersection area. However, two 'problematic' cases may be identified. The first one considers the case that c_i^{RFP} lies within $\left[M_i^B - (M_i^B - m_i^B)/4, M_i^B\right]$ for *Case I* and $\left[m_i^B, m_i^B + (M_i^B - m_i^B)/4\right]$ for *Case II*. In these cases, the Seller may loose some contracts $C_k^{t_l}$ with better on his behalf terms that could potentially be accepted by the Buyer (in case the Buyer's utility with respect to the proposed contract exceed its reservation value i.e., $U^B(C_k^{t_l}) \ge U_{\min Acc}^B$). The second 'problematic' case considers the c_i^{RFP} belonging in $\left[m_i^B, m_i^B + (M_i^B - m_i^B)/4\right]$ for *Case I* and $\left[M_i^B - (M_i^B - m_i^B)/4, M_i^B\right]$ for *Case II*. In such a case, a number of negotiation rounds would be required in order to reach a mutually non value constraint violating contract. However, even then, the negotiation rounds required may be potentially reduced by employing the aforementioned technique. Nevertheless, the contract generation mechanisms considered by the authors [8][9][10] take into account the Seller's utility constraint, thus, overcoming the potential difficulty.

In Figure 2 the intersection region approximation mechanism for contract issue i with regards to the pre-defined $\overline{L_i}$ is depicted, assuming that *Case II* stands, i.e., $\partial\left[U^B\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i < 0$ and $\partial\left[U^S\left(C_k, \underline{d}^{t_0}\right)\right]/\partial c_i > 0$. Two distinct cases are illustrated. The first one considers that c_i^{RFP} lies within the lower half of $\left[m_i^B, M_i^B\right]$, while the second one assumes that c_i^{RFP} belongs to its upper half. For both cases the approximated intersection region is close to the real one, while the Seller lightens the transaction cost, since the number of negotiation rounds required in order to find a mutually non value violating contract are minimized. As illustrated in Figure 2, the c_i^{RFP} value may or may not belong to the Seller's region regarding contract issue i.

The Seller has thus identified different regions for each contract issue i under negotiation. Moving now to the core contract generation mechanism, the Seller may

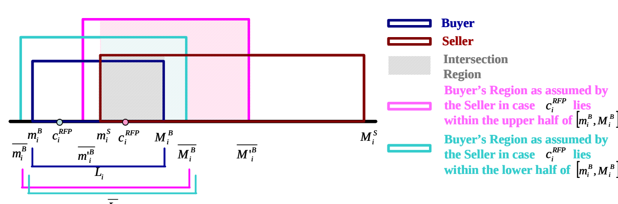

Figure 2. Buyer's private region construction and intersection region approximation

propose an initial contract on the basis of the intersection region approximation $[\overline{m_i^B}, \overline{M_i^B}]$ acquired for each contract issue i. The Seller then proposes an initial contract $C^{t_0} = \{c_1^{t_0}, ..., c_n^{t_0}\}$ to the Buyer at $t = t_0$, setting all contract issues at the values that maximise the Seller's utility considering the intersection region approximated during the previous step (i.e., if $\partial\left[U^S\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i > 0$, then the Seller sets $c_i^{t_0} = \overline{M_i^B}$, while in case $\partial\left[U^S\left(C_k, \underline{d}^{t_0}\right)\right] / \partial c_i < 0$, then the Seller sets $c_i^{t_0} = \overline{m_i^B}$).

5. Conclusions

This paper presented the basic elements of a designed multilateral, multi-issue, dynamic negotiation model and the respective negotiation strategies that are adequate for the needs of mobile intelligent agents in e-commerce environments, in case the disclosure of information is not acceptable, possible, or desired. The proposed framework considers both contract and decision issues and is based on real market conditions, while its efficiency is also due to the fact that the Buyer agent adopts a flexible and light reasoning component, which does not necessitate the explicit statement of all preferences and requirements on behalf of the Buyer in a completely quantified way. The paper mainly focused on the enhancement of the Seller's reasoning component by incorporating to the designed negotiation strategies a novel mechanism for the estimation of the mutually acceptable contract space based on monitoring the Buyer's negotiation behaviour and exploiting the appropriate market data combined with knowledge acquired from previous experience. This technique aims to extend the functionality of negotiating agents, so that the number of the necessary negotiation rounds is significantly reduced, an agreement is reached in minimal time, and the negotiation costs for both parties are minimised. Initial results indicate that the value of the proposed enhancement is quite high, in case the mutually acceptable contract space is limited. Future plans involve the adoption of various learning techniques and its extensive empirical evaluation against existent negotiation frameworks and against the optimal solution of the negotiation problem that maximises the social welfare.

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