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Efficient agent-based negotiation by predicting opponent preferences using AHP

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Abstract: Negotiation is a process essential for a wide range of applications. The complex decision making involved in negotiation makes its automation difficult. The complexity is further increased as negotiators hide their individual preferences from each other to avoid exploitation by the opponent. Even though sharing of private preference information leads to better agreement for both sides, it is never done in the absence of trust. In this work, we learn opponent's preference information from the offers given by the opponent using Analytic Hierarchy Process (AHP). We apply our approach to the negotiation of Quality-of-Service (QoS) parameters for the establishment of Service Level Agreements (SLA) between a provider and a consumer. Experiments show that using AHP, the negotiations are faster and the agreements are on or nearer to the pareto-optimal line.

Keywords: Automated Negotiation; Opponent Modeling; Analytic Hierarchy Process; Trade-off; SLA management.

1. INTRODUCTION

In the recent years, e-commerce has seen enormous growth with more and more businesses and customers settling for trading over the Internet which in a lot of ways is convenient and faster than conventional ones. Inter-continental and cross-cultural trading are very common and hence establishment of a standard mechanism for ensuring quality of service is essential. This is done with a Service Level Agreement (SLA). But the challenge lies in fast and efficient way of establishment of SLA. Most providers today provide a verbal SLA which includes ambiguities and is flexible for the provider in many ways. To solve this problem, specifications for formal SLAs in XML format have been proposed (WSLA (Keller & Ludwig, 2003), WS-Agreement (Andrieux et al., 2007), etc.). These specifications let the provider and the consumer to negotiate before agreeing on an SLA. With increasing number of businesses opting to online service provisioning, it is becoming very time-consuming to conduct negotiation manually. Automated negotiation solves some of the problems with manual negotiation since the actual negotiation is done by software with only the requirements specified by the user. It is much faster and negotiation could be done with finer granularity when required. Intelligent negotiation agents reach optimum faster with higher payoffs for both sides (Lau, 2007).

The ultimate goal of automated negotiation is to completely replace a human negotiator with negotiating software agent. Complete automation of a negotiation

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system brings with it a range of problems most of which are hot areas of research. One of them is hidden opponent preferences. As in any human negotiation the preferences of the opponent are not always available to the user. The negotiating agents must strive to obtain the best joint outcome though best individual outcome is the objective of each agent. It is desirable that the agreement lies on or nearer to the pareto-optimal line. Pareto-optimality is reached when one negotiator cannot bargain a better offer without making the other negotiator settle for a worser offer. Opponent preference estimation provides a way for negotiators to agree on near-optimal offers faster.

Though negotiation is a universal problem applicable to broad areas, this paper discusses the problem in the context of negotiation of SLAs between a consumer and a provider in service-oriented environment. The problem of counter-offer generation in a bilateral negotiation with multiple parameters has been focused in this research work. We assume linear utility functions and none of the preferences or reserved values of one negotiating agent is known to the other. We present a simple trade-off algorithm that aims to make the offer generated by the trade-off more acceptable to the opponent. In order to reach an agreement faster and to make a trade-off more acceptable to the opponent it is necessary to learn the preferences of the opponent since this information is completely unknown or known partially.

Preference denotes the amount of importance a participant of negotiation attaches to each parameter being negotiated. When negotiators have opposite preferences, one negotiator attaches more importance to a parameter that the other negotiator attaches less importance to. It is suggested in the literature (Hindriks & Tykhonov, 2010) that it may be sufficient and more important to approximate the preference ranking of opponents although finding perfect preference values would be ideal. We propose the use of analytical hierarchy process (AHP) (Saaty, 1988) to rank the preferences of the opponent. AHP is a technique for multi-criteria decision making and it has been found suitable to be applied for preference ranking. In a multi-criteria decision making problem, the output of AHP is the relative priorities of the alternatives based on a set of criteria. The alternative with the maximum priority is generally chosen as the best alternative. But in our context, parameters that are negotiated are the alternatives and the relative priorities derived by applying AHP provides the ranks of the parameters. AHP method is simple with minimal calculations and provides straight-forward opponent ranking of parameters compared to many of the other opponent preference estimation methods in the literature. It is possible to fit in the assumptions of any opponent model into AHP in the form of additional criteria adding any number of criteria. The criteria are represented in a hierarchical manner and the AHP model also accommodates sub-criteria. Unlike other models, qualitative criteria could also be included into the AHP approach but with a drawback of human involvement making the negotiation semi-automated.

To summarize, the main contributions of this work are:

- Application of AHP for prediction of opponent rankings
- Selection of AHP criteria for accurate prediction of opponent rankings
- Validation of the proposed approach by varying several parameters

The next section overviews some of the previous works in the literature related to our work. In section 3 we give an overview of the agent-based SLA negotiation system. In section 4, we explain the overall negotiation process and we present a trade-off algorithm that aims for faster convergence. In section 5, we explain how opponent preferences are predicted using AHP and illustrate with an example. In section 6 we present the results and we conclude in section 7.

2. RELATED WORK

Automated negotiation research community has always aimed for reaching an optimal agreement with known or unknown opponent information using various approaches. Faratin, Sierra, and Jennings (2002) propose a trade-off algorithm that uses hill-climbing technique to search for offers similar to the opponent's offer. The search starts at the opponent's offered contract and proceeds by generating a set of contracts that lie closer to the iso-curve (representing the agent's aspiration level). The contract that maximizes the similarity to the opponent's last offering is selected at the end of each iteration. Another work (Cheng, Chan, & Lin, 2006) proposing search based approach uses fuzzy inference for providing trade-offs. A suitable counter-offer for an offer is selected by searching a multi-dimensional space formed by negotiable issues.

The desired values and weights are revealed to the opponents but the utility functions are kept private. Ros and Sierra (2006) propose a meta-strategy that combines concession and trade-off. Trade-off based on algorithm by Faratin et al. (2002) is done by the agents until deadlock is detected. A deadlock occurs when the proposal of an offer of an agent decreases from the previous offer. When a deadlock is detected, concession is done. Zheng (2014) proposes a negotiation approach mixing the concession and trade-off approaches to yield the benefits of both. The negotiation is for an Internet of Things environment and is based on 'game of chicken'. Vetschera, Filzmoser, and Mitterhofe (2014) present a concession based negotiation approach in which the concession in each round is variable and is determined by the user allowing more user control.

The bargaining is done in utility space and is mapped to the offers in issue space using several variants of optimization models. The trade-off algorithm proposed in this paper is simpler than any of the above approaches with only comparison of ranks for making offers more acceptable to the opponent.

Apart from these, there are other works that propose negotiation approaches to reach Pareto-optimal by predicting the preferences of the opponent. The use of Kernel Density Estimation (KDE) is proposed by Coehoorn and Jennings (2004) for estimating an opponent's preference information using history of offers given by the opponent. The kernels use probability density of weight given the value of difference between two consecutive offers to estimate the issue weights of the opponent. The tradeoff algorithm by Faratin et al. (2002) finds counter-offers most likely to be accepted by the opponent using fuzzy similarity criteria. Coehoorn and Jennings (2004) extend this algorithm by estimating the opponent's weights using KDE for calculation of similarity between two offers. Jonker, Robu, & Treur (2007) introduce component-based generic agent architecture for multi-attribute negotiation. The architecture allows the agents to share any amount of information to the opponent. A guessing heuristic predicts information not shared by the opponents using the history of the opponent's offers. The heuristic used is the difference between two consecutive bids for an attribute.

Experimental results show that both sharing preference information and guessing improves the final utilities of the opponents.

Another work that tries to learn opponent's preferences is by Hindriks and Tykhonov (2008). Bayesian learning has been employed to learn opponent model by assuming that the opponent uses a concession-based strategy. Issue priorities and preference over issue values are learnt and utility function is assumed to be linear. Noh, Ozonat, Singhal, and Yang (2011) propose modified Dynamic Weighted Majority (DWM) learning algorithm to offer multiple choices to a human negotiator in an agent-to-human negotiation. The multiple offers are generated such that they are attractive to the human opponent while the utility of the agent remains the same. Ren, Zhang, and Bai (2014) use regression analysis over history of offers to predict opponent preferences. Sim, Guo, and Shi (2009) propose BLGAN that uses a combination of Bayesian learning and genetic algorithm to generate near-optimal proposals. Bayesian learning estimates the opponent's reserve price and deadline while genetic algorithm generates optimal offers. Aydoğan and Yolum (2012) propose an opponent learning approach based on inductive learning. Most of the research that involve prediction of opponent preferences use fuzzy techniques (Cheng, Chan, & Lin, 2005; Cheng, et al., 2006; Lai, Lin, & Yu, 2010) Bayesian learning (Buffett & Spencer, 2007; Hindriks & Tykhonov, 2008; Zeng & Sycara, 1998; Zhang, Ren, & Zhang, 2015) or other probabilistic techniques (Coehoorn & Jennings, 2004; Ren, et al., 2014). The AHP approach discussed in this paper involves only simple matrix calculation and is thus light-weight compared to other approaches.

There are several works in which AHP has been used in negotiation. Huang, Liang, Lai, and Lin (2010) apply AHP for calculating weights of attributes of products negotiated. In addition to calculating issue weights, Brzostowski, Roszkowska, and Wachowicz (2012) describe methods using AHP used for scoring an offer or counter-offer. Boukredera and Hariche (2013) use AHP for deciding on the best offer that is beneficial to both the negotiators. The preferences of each negotiator are unknown to each other but are informed to a mediator who uses AHP to generate Pareto-optimal offers. To the best of our knowledge, none of these works deals with using AHP for opponent modeling. If the opponent preferences are taken to be a finite set of possible combinations, the problem becomes a decision-making problem where only one of the combinations in the set is the best set. Analytic Hierarchy Process (AHP) is a classic technique for MCDM (Multi-Criteria Decision Making) and is very much applicable to the problem of prediction of opponent preferences.

3. THE AGENT-BASED AUTOMATED SLA NEGOTIATION SYSTEM

The negotiation system is a multi-agent system with each participant being able to negotiate with one or more opponents. Each negotiator agent is an autonomous software program that negotiates on behalf of either the consumer or the provider. A negotiator agent receives proposals from opponents and accepts, rejects or generates counter proposals by giving a concession or trade-off. It also chooses the best offer from the negotiations with multiple opponents. All the counter-proposals received by a negotiator agent from one opponent are hidden from other opponents. Therefore, the negotiation system of each agent is multi-threaded with individual negotiations independent of one another. A negotiator agent could rank their opponents based on the final outcome of each negotiation. This system is particularly beneficial to a consumer who looks for the best service available among a set of providers.

While deciding whether to make a concession or a trade-off and while giving a trade-off it is useful to know the preferences of the opponent. Knowledge of preferences of opponent leads to faster negotiations with lesser number of rounds. This is because each counter proposal can be made more acceptable to the opponent if the opponent's preferences are known. We propose the application of AHP for this purpose. Each negotiator agent captures the history of earlier proposals of each opponent and applies those values to AHP to predict preferences of the opponent.

In an automated negotiation, there are various protocols that define the overall course of negotiation based on which the participants can negotiate. In alternating-offers protocol, the agents alternately make proposals. It starts with one agent making a proposal and the other agent accepts it, rejects it or makes a counter proposal. This goes on until one of the agents accepts or rejects the other's proposal or until timeout. Our negotiation system uses the alternating offers protocol which is the most suited for automated negotiations (Gatti, Di Giunta, & Marino, 2008).

The generation of a proposal is based on utility values. For calculation of utilities, the preferred and reserved values for the parameters that are negotiated need to be fixed on each side. The importance of parameters is specified by assigning weights to each parameter. We assume that the weights are normalized, that is, the sum of weights of all parameters is 1. Utility refers to the satisfaction level of a negotiator over a value. Higher the utility of a parameter value, better the negotiator is satisfied of the value. Utility of a parameter is calculated using the reserved and preferred values of the parameter. Utility normalizes the values of different parameters and it uniformly ranges from 0 to 1 independent of whether a negotiator aspires for a higher value or a lower value of the parameter. For example, a customer is better satisfied if the value of the availability parameter is higher and the cost parameter is lower. But for both these parameters a higher utility always means better satisfaction.

3.1 CALCULATION OF UTILITY

The formula used for calculation of utility of a parameter value varies depending on whether a participant aspires for a higher value of a parameter or a lower value of a parameter. Let p_{min} be the minimum and p_{max} the maximum fixed by a participant. Let p ($p_{min} \leq p \leq p_{max}$) be the parameter value for which utility is being calculated.

When the participant aspires for higher value of the parameter (p_{min} is reserved value and $p_{max}$is preferred value), utility of p is

$$u = \frac{p - p_{min}}{p_{max} - p_{min}} \tag{1}$$

When the participant aspires for lower value of the parameter (p_{min} is preferred value and $p_{max}$is reserved value), utility of p is

$$u = \frac{p_{max} - p}{p_{max} - p_{min}} \tag{2}$$

Utility is modeled as a linear increasing or decreasing function. When the participant aspires for higher value, utility is an increasing function (Eq. 1), that is, higher the value higher the utility. Otherwise, utility is a decreasing function (Eq. 2).

The total utility (Eq. 3) is calculated by assigning weights to each parameter. A higher weight denotes that the parameter is more important.

$$u_{tot} = w_1 u_1 + w_2 u_2 + w_3 \quad {}_3 + \cdots + w_n u_n \tag{3}$$

4. NEGOTIATION ALGORITHM

Our negotiation algorithm is based on the alternating offers protocol (Rubinstein, 1982). This protocol gives a fair chance to both the participants to make their proposals. Once a participant makes a proposal, the other participant calculates the utility of the proposal and decides to do one of the following: Accept the proposal, reject the proposal, generate a counter proposal by giving a concession on its own previous proposal or generate a counter proposal by doing trade-off on its own previous proposal. The primary decision making in the negotiation algorithm involves when and how to do one of the above. Concession results in the decrease of utilities of individual parameters and consequently the total utility. An agent gives concession hoping that it leads to convergence (or agreement) since a concession improves the utility of the opponent. Trade-off is done by varying individual utilities of parameters while keeping the total utility a constant. Trade-off may or may not improve the total utility of the opponent based on the weights assigned by the opponent for individual parameters.

Intuitively, concession results in faster convergence. Each time an agent gives a concession it moves towards the opponent in the utility space. But each concession lowers the utility of the conceder. Previous research (Zheng, Martin, & Brohman, 2012) has shown that trade-off is better in terms of utilities of agreements reached. Trade-off results in maximum social good. Trade-off would be most beneficial if the preferences of the negotiating parties are different. The proposed trade-off algorithm is based on this idea. The algorithm increases the utility of parameters with relatively more weightage than the opponent and decreases the utility of parameters with less weightage. This ensures that for the opponent, the lesser important utilities are decreased while the more important utilities are increased resulting in a higher total utility.

When the ranking of parameters are same on both sides, concession results in faster convergence than trade-off. The concession algorithm used in this work gives concessions that vary for different parameters. Amount of concession for each parameter is decided based on the weight of a parameter. Concession for a higher weighted parameter is lesser than a lower weighted parameter.

When an agent finds a counter proposal unsatisfactory but for some reason it is not able to make a concession or a trade-off, it replies with its own previous proposal. When the other agent receives the same proposal for three consecutive times, it rejects the proposal and terminates the negotiation. Negotiation also terminates without success when an agreement cannot be reached until time-out. We define the following terminology to represent the impact of trade-off for an opponent.

A *positive trade-off* is a trade-off given by an agent during a bilateral negotiation that results in an increase of total utility for the opponent compared to previous proposal of the agent.

A *negative trade-off* is a trade-off given by an agent that results in a decrease of total utility for the opponent compared to previous proposal of the agent.

A *zero trade-off* is a trade-off given by an agent that makes no impact on the total utility for the opponent compared to previous proposal of the agent.

4.1 TRADE-OFF ALGORITHM

The proposed trade-off approach is implemented in Algorithm 1. The algorithm is O(n) and takes proposal (P) for which trade-off needs to be given, the corresponding weights (W), parameter ranking of the agent who gives the trade-off (R_{self}), parameter ranking of the opponent (R_{opp}) and the trade-off factor as inputs. The output of the algorithm is the counter-proposal calculated after trade-off.

In algorithm 1, first the utilities of parameters are calculated (lines 1-3). Then the utilities are categorized depending on the corresponding parameter's ranking (lines 5-12). A lower number of rank means a parameter is higher ranked. Hence if self-rank number is lower than that of the opponent for a particular parameter, the parameter is ranked higher than the opponent and added to the array 'High'. Similarly utilities of lower ranked parameters and equally ranked parameters are added to the arrays 'Low' and 'Equal' respectively. The utilities in array High are increased by a factor x (lines 16-18). Then the utilities of array Low are decreased by a factor y such that the total utility (Total) remains the same (lines 22-24). 'y' is calculated as follows:

$$\begin{aligned} LowTotal_{new} &= sum(Low) - y(sum(Low)) \\ &= (1 - y)\ LowTotal_{old} \\ \Rightarrow \quad y &= 1 - (LowTot_{new}/LowTotal_{old}) \end{aligned}$$

Finally all the utilities are added to Utility new array (line 25) and the corresponding parameter values for the counter proposal are calculated (lines 26-28).

Algorithm 1: Tradeoff (P, W, R_{self}, R_{opp}, x)

Input: $P(p_1, p_2, \dots p_n)$, $W(w_1, w_2, \dots w_n)$, $R_{self}(r_1, r_2, \dots r_n)$, $R_{opp}(r_1, r_2, \dots r_n)$, x
Output: $CP(p_1, p_2, \dots p_n)$

```
for i = 1 to n
    Utility_old[i] ← calculateUtility(p_i)
end for
Total ← sum(Utility_old)
for i = 1 to n
    if R_self[i] < R_opp[i] then
        add u_i × w_i to High
    else if R_self[i] > R_opp[i] then
        add u_i × w_i to Low
    else
        add u_i × w_i to Equal
    end if
end for
LowTotal_old ← sum(Low)
EqualTotal ← sum(Equal)
for each element ∈ High
    increase element by factor x
end for
HighTotal_new ← sum(High)
LowTotal_new ← Total – HighTotal_new - EqualTotal
y ← 1 - (LowTotal_new/LowTotal_old)
for each element ∈ Low
    decrease element by factor y
end for
add High, Low, Equal to Utility_new
for i = 1 to n
    CP[i] ← calculateValue(Utility_new)
end for
```

In the next section we propose an approach to identify the importance ranking of parameters of an opponent from the counter-offers. The predicted ranking is to be applied to the trade-off algorithm.

5. LEARNING OPPONENT'S PARAMETER PREFERENCE

Attaching preference to parameters is private information and the participants in a negotiation cannot be expected to disclose that. But it is possible to estimate the opponent's order of preference of the parameters based on the offers given. We propose the use of Analytic Hierarchy Process for this purpose.

5.1 ANALYTIC HIERARCHY PROCESS

Analytic Hierarchy Process (AHP) is a process used to aid multi-criteria decision making (MCDM). The hierarchy in AHP (figure 1) consists of the goal of decision making on top, the criteria based on which the decision has to be made at the next level and the alternatives that could be chosen from at the lower-most level. The decision criteria are prioritized by pair-wise comparison using inputs from the user. These priorities serve as weights for the criteria. For each criterion, the alternatives are then pair-wise compared using user inputs. At the end of AHP, the alternatives are prioritized. AHP uses Eigen vector and Eigen value for computing the priorities. The alternative that gains the most priority is the final decision. AHP process can be used to estimate an opponent's prioritization of parameters. Here, the alternatives in the AHP hierarchy are the parameters and the goal is to prioritize the parameters.

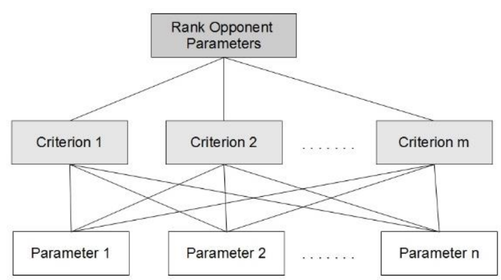

Fig. 1. AHP Hierarchy for Prediction of Opponent Preference Ranking.

5.2 IDENTIFICATION OF AHP CRITERIA FOR OPPONENT MODELING

An important part of applying AHP to predict opponent preference is the identification of right AHP criteria. It is possible to incorporate both generic and opponent-strategy-based criteria into AHP. In this section, we propose some criteria applicable to all negotiations and we also map some commonly used opponent modeling strategies to AHP criteria.

The generic criteria have been identified heuristically and they are useful in prediction of opponent preferences irrespective of the opponent's negotiation strategy. The priorities of these criteria are decided by the user based on the context of negotiation. Some of the criteria that we have identified are:

a) Difference between current offer and first offer (DCF)
b) Difference between current offer and previous offer (DCP)
c) Difference between best offer and current offer (DCB)
d) Difference between worst offer and current offer (DCW)
e) Difference between best offer and worst offer (DBW)
f) Frequency of offers above threshold (FAT)
g) Frequency of offers below threshold (FBT)
h) Best offer (BO)
i) Worst offer (WO)

If the opponent's negotiation strategy is known completely or partially, criteria specific to that strategy could be identified.

The main advantage of using AHP for prediction is it can incorporate most opponent prediction models using appropriate criteria. It is also possible to combine several models for better prediction. In (Baarslag, Hendrikx, Hindriks, & Jonker, 2012) the authors list assumptions generally made by opponent models to predict opponent preferences. Table 1 provides information on how those general assumptions could be translated to AHP criteria. It is not necessary that all the identified criteria need to be used in AHP. In fact it has been shown that opponent models that make limited assumptions perform better than models that make too many assumptions (Baarslag, Hendrikx, Hindriks, & Jonker, 2013).

Some criteria are devised based on the fact that an agent would be giving more discounts on parameters of lesser importance while being parsimonious on higher weighted parameters. Criteria (f) and (g) are based on frequency models of opponent preference prediction. If better bids are offered more frequently for a parameter it may mean that the opponent has lesser weight for that parameter. In criteria (h) and (i) best offer and worst offer are with respect to the user and not the opponent.

Since the values of criteria are in different scales across parameters, they are normalized using utility functions. The first four criteria are concerned with difference between values. The difference may be positive or negative or even zero. While constructing the AHP pair-wise comparison matrix, the ratio of differences is calculated for each comparison. So zero difference will give zero and infinity while finding ratio and hence cannot be allowed. Moreover AHP does not take negative values in the matrix. Therefore, a rescaling of the difference values is required. The rescaling is done such that the values lie in the range 1 to 10. The range has been chosen to match a conventional AHP pair-wise comparison matrix where a user usually chooses values in this range. The rescaling is done using the formula

$$A_{Norm}^{p} = 1 + \frac{(x^{p} - P_{min}) * (10 - 1)}{(P_{max} - P_{min})} \tag{4}$$

where, A_{Norm}^{p} is the rescaled value of a criterion A for a parameter p, x^{p} is the actual value of A for p, P_{min} is the minimum value of A among all parameters, P_{max} is the maximum value of the criterion among all parameters. The same normalization and rescaling apply to criteria which do not require calculation of difference as all the criteria are inter-comparable.

Table. 1. Mapping of Opponent Modeling Assumptions to AHP Criteria.

Opponent Model	AHP Criterion	Remarks
First offer is best offer (Hindriks & Tykhonov, 2008; Van Galen Last, 2012; Van Krimpen, Looije, & Hajizadeh, 2013)	First offer	Lower the first offer higher the importance for that issue
No. of times an issue value is significantly changed (Van Krimpen, et al., 2013)	No. of times DCP > threshold	The more frequently an issue value is changed the less preferred it is
Frequency model (Van Galen Last, 2012)	No. of times offer > threshold	The more frequently a value is offered the more preferred it is
Difference between two consecutive offers (Coehoorn & Jennings, 2004; Jonker, et al., 2007)	DCP	The more liberal concessions are in an issue the less important the issue is

5.3 AN ILLUSTRATION OF OPPONENT LEARNING USING AHP

Considering criteria (i) and (ii) from the list of possible criteria identified in previous section, let us see the process of AHP for determining the opponent's preference weights. Firstly, the importance of each criterion needs to be determined. This importance is given by the user by pair-wise comparison of the criteria. Then, by finding Eigenvector of the pair-wise comparison matrix the weight of each criterion is determined. Applying equal importance to all criteria is a good heuristic. But a user may alter this based on the context of negotiation. The next step in AHP is to pair-wise compare the alternatives (parameters) for each criterion. This is done by finding the value of the criterion, say, the actual difference between two consecutive offers and filling the pair-wise comparison matrix. The Eigenvectors for the pair-wise comparison matrix for each criterion is found and normalized. Finally, applying the corresponding weight for each eigenvector of the respective criterion gives the priorities of each parameter. The criteria taken are: (i) Difference between current offer and first offer (DCF) and (ii) Difference between current offer and previous offer (DCP).

Let Provider and Consumer be the two negotiators where the consumer is trying to guess the provider's preferences. Let us consider a history of 6 offers for 4 parameters. Given in tables 2(a) and 2(b) are the utilities of the counter offers of the provider calculated using max-min values of the consumer and the provider. Also given are the DCP and DCF values for each counter-offer for each parameter. The actual rankings of provider is [4,3,2,1] and for the consumer it is [1,2,3,4].

The counter-offers have been generated using the proposed algorithm. So, guessing is straightforward as the criteria of AHP exactly match with the logic of the algorithm. The correct ranking is predicted from each offer except in 4th and 6th offer on consumer's side for DCP.
The wrong prediction is due to variations in rounding off. The wrong prediction is compensated by combining with predicted rankings using DCF. If the counter-offer generation algorithm of the opponent is known, criteria may be identified accordingly for correct guessing. Even without the knowledge of the opponent's algorithm, the above identified criteria are good heuristics and mostly predict correct ranks.

The prediction of rank by consumer for offer 6 given in table 2(a) using AHP is as follows:

Applying the rescaling formula (Eq. 4) to DCP and DCF for the parameters, we get,

DCP^{A}_{Norm}: 9.5978 DCP^{B}_{Norm}: 10.0
DCP^{C}_{Norm}: 3.411 DCP^{D}_{Norm}: 1.0

DCF^{A}_{Norm}: 10.0 DCF^{B}_{Norm}: 8.865
DCF^{C}_{Norm}: 3.0248 DCF^{D}_{Norm}: 1.0

The pair-wise comparison matrix is constructed for DCP and DCF using these values. Calculating Eigen vector of each pair-wise comparison matrix we get,

$$E_{DCP} = \begin{bmatrix} 0.0696 \\ 0.0668 \\ 0.1958 \\ 0.6678 \end{bmatrix} \quad \text{(Rank: 3,4,2,1)}$$

$$E_{DCF} = \begin{bmatrix} 0.0647 \\ 0.0731 \\ 0.2142 \\ 0.6479 \end{bmatrix} \quad \text{(Rank: 4,3,2,1)}$$

Combining the weights of the criteria to the parameters,

$$=> \begin{bmatrix} 0.0672 \\ 0.07 \\ 0.205 \\ 0.6579 \end{bmatrix} \text{ is the final priority matrix (Rank: 4,3,2,1)}$$

For ranks, 1 is most important and 4 is least important. Therefore, the importance of parameters of the provider is in the order D, C, B and finally A. The criteria weights have been arbitrarily chosen as 0.5 for each criterion. But this may be changed or AHP may be applied to get criterion weights as in (Huang, et al., 2010). The predicted ranks are applied to the trade-off algorithm. When the weight rankings of both the agents are predicted to be the same, concession is given.

5.4. QUALITATIVE CRITERIA

All the criteria suggested for opponent preference prediction in section 5.2 are quantitative criteria because the concrete values of the criteria can be automatically incorporated into the pair-wise comparison matrix making the whole process fully automated. But one of the main advantages of AHP as a decision making tool is it can incorporate both qualitative and quantitative criteria simultaneously into the process. A negotiator who does not know anything about his/her opponent may benefit from using some of the quantitative criteria identified in this work. But it is possible that a negotiator has certain knowledge about the opponent from previous experience or public information. For example, in a scenario where a broker negotiates on behalf of a customer, the broker may know that the strategy for negotiation of a provider is different for different types of consumers (Eg. students, organizations, government, etc.). In that case, a broker may include "Type of consumer" as a criterion in AHP for prediction of provider's importance rankings. Thus partial quantitative or qualitative information can also be included into the process. But including qualitative criteria comes with a drawback of involving a human into the negotiation. Measurement of qualitative criteria is subjective and requires a human to construct the pair-wise comparison matrix. This makes the negotiation semi-automated. In scenarios where semi-automated negotiation is possible, qualitative criteria could be included.

Table. 2a. Utility and AHP criteria values of counter offers by provider calculated by consumer.

Offer No.	Parameter A			Parameter B			Parameter C			Parameter D			Guessed ranking (A, B, C, D)	
	Utility	DCP	DCF	Utility	DCP	DCF	Utility	DCP	DCF	Utility	DCP	DCF	DCP	DCF
1	0.25	-	-	0.25	-	-	0.16667	-	-	-0.5	-	-	-	-
2	0.325	0.075	0.075	0.30625	0.05625	0.0562	0.20833	0.041667	0.04166	-0.4625	0.0375	0.0375	4,3,2,1	4,3,2,1
3	0.3925	0.0675	0.1425	0.35828	0.05203	0.1082	0.24791	0.039583	0.08125	-0.42594	0.03656	0.07406	4,3,2,1	4,3,2,1
4	0.45077	0.058272	0.20077	0.41983	0.06155	0.1698	0.22929	-0.01862	0.06263	-0.47301	-0.04707	0.02699	3,4,2,1	4,3,2,1
5	0.50569	0.054923	0.25569	0.46334	0.04351	0.2133	0.26783	0.038535	0.10116	-0.43618	0.03682	0.06381	4,3,2,1	4,3,2,1
6	0.56301	0.057318	0.31301	0.52557	0.06222	0.2755	0.24960	-0.01822	0.08294	-0.48385	-0.04766	0.01615	3,4,2,1	4,3,2,1

Table. 2b. Utility and AHP criteria values of counter offers by consumer calculated by provider.

Offer No.	**Parameter A**			**Parameter B**			**Parameter C**			**Parameter D**			**Guessed ranking (A, B, C, D)**	
	Utility	DCP	DCF	Utility	DCP	DCF	Utility	DCP	DCF	Utility	DCP	DCF	DCP	DCF
1	0.17142	-	-	0.17857	-	-	0.25952	-	-	0.17301	-	-	-	-
2	0.14275	-0.02868	-0.02868	0.15724	-0.02132	-0.021	0.31908	0.059559	0.05955	0.21272	0.03970	0.03970	1,2,4,3	1,2,4,3
3	0.11397	-0.02878	-0.05746	0.13602	-0.02122	-0.042	0.37867	0.059593	0.11915	0.25245	0.03972	0.07943	1,2,4,3	1,2,4,3
4	0.08509	-0.02888	-0.08634	0.11490	-0.02112	-0.063	0.43830	0.059627	0.17877	0.29220	0.03975	0.11918	1,2,4,3	1,2,4,3
5	0.05611	-0.02898	-0.11531	0.09388	-0.02102	-0.084	0.49796	0.059659	0.23843	0.33197	0.03977	0.15895	1,2,4,3	1,2,4,3
6	0.02704	-0.02907	-0.14438	0.07295	-0.02093	-0.105	0.55765	0.05969	0.29812	0.37176	0.03979	0.19875	1,2,4,3	1,2,4,3

6. RESULTS AND DISCUSSION

The experiments focus on testing the efficiency and the suitability of AHP as an opponent prediction approach. The efficiency of the proposed approach is tested in terms of number of rounds of negotiation required to reach an agreement and final utilities achieved. The accuracy of prediction of AHP is measured by comparing the actual ranking and the predicted ranking using a rank correlation coefficient. We present the results in this section.

When the proposed negotiation strategy is used by an opponent, AHP using the identified criteria mostly predicts correct rankings. The effectiveness of each criterion used in AHP is measured using Kendall's tau. Kendall's tau is a measure of rank correlation. It ranges from -1 to +1 where +1 denotes same ranking and -1 denotes reverse ranking. Positive values denote more similarity while 0 denotes no correlation at all and negative values greater than -1 denote more dissimilarity. Kendall's tau is calculated between the predicted ranking and the actual ranking. Experiments were done by changing the max-min values of parameters and also varying the number of parameters. Most of the identified criteria get a positive Kendall's tau value which proves that these criteria are very effective in the estimation of opponent weight preferences (figure 2).

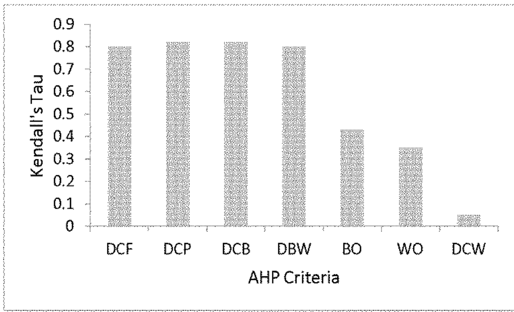

Fig. 2. Effectiveness of AHP Criteria.

For the proposed negotiation strategy, DCF and DBW are the same because current offer is always the best offer and first offer is always the worst offer. Similarly DCP and DCB are the same. All these four criteria get a high Kendall's tau which means they are very effective in predicting the opponent's rankings. BO and WO are equivalent to current offer and first offer respectively. Hence the predicting capacity of these criteria depended on how the initial proposal is fixed. DCW is irrelevant because current offer and worst offer are the same. Hence its prediction was random. Similarly FAT and FBT produced random rankings for this negotiation strategy.

The average number of rounds of negotiation required to reach an agreement using the proposed approach is less compared to other opponent learning approaches. The average number of rounds required to reach an agreement is compared for random guessing (no learning), KDE (Coehoorn & Jennings, 2004), Bayesian scalable model (Hindriks & Tykhonov, 2008) and AHP. The AHP approach requires lesser number of rounds and hence less communication load compared to other methods (figure 3).

In figure 4, we compare the utilities of proposals generated by various opponent models as a response for a counter proposal. The initial proposal is offered by agent A which is marked by a shaded diamond. For this, a counter proposal is given randomly by agent B (marked by a shaded square). The utilities of offers generated in response to this counter proposal are denoted in figure 4. In our approach and KDE (Hindriks & Tykhonov, 2008) trade-off is given hence the utility of A is the same while utility of B is improved. The offer generated by our approach lies relatively nearer to the optimal point compared to all other approaches. After many rounds of negotiation, this difference becomes significant resulting in lesser number of rounds for reaching agreement. Since trade-off approaches lead to faster negotiations, the number of rounds being lesser for AHP and KDE is justified.

The scalability of the proposed negotiation approach is also tested. Negotiations were conducted by varying the parameters from 2 to 10 with same trade-off and concession factors. The average number of additional rounds required for each additional parameter is 3. The results are compared to random approach in figure 5.

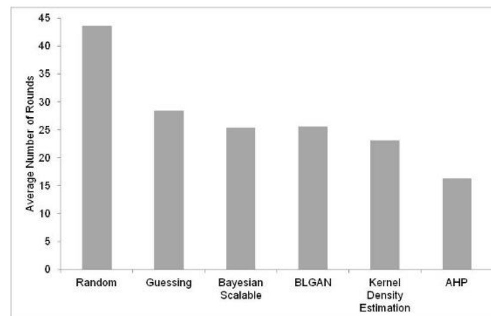

Fig. 3. Average Number of Rounds of Negotiation.

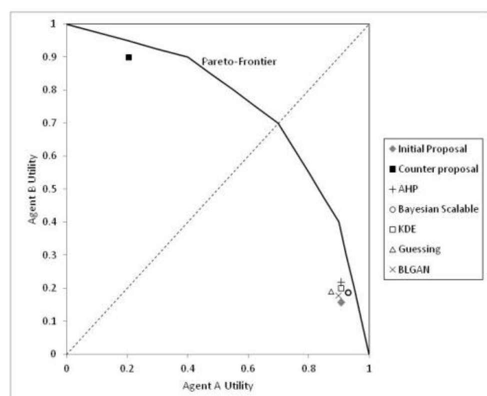

Fig. 4. Comparison of Utilities of generated proposals for different opponent models.

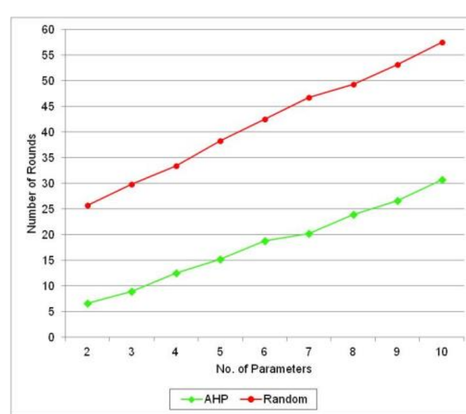

Fig. 5. Number of rounds of Negotiation varying number of parameters for AHP and random approaches.

The proposed trade-off algorithm combined with AHP prediction yields high social outcome. The joint utility (sum of utilities of the negotiators) after agreement is achieved averages to 1.297 and the difference averages to 0.02 using AHP approach. The high total and low difference indicates high joint outcome of the proposed approach. The joint utilities obtained after agreement in different approaches for different number of parameters are shown in figure 6. It can be seen that AHP performs better than the other methods in yielding high utilities for both the negotiating parties. It is to be noted that Modified DWM method (Noh, et al., 2011) and variability method (Ros & Sierra, 2006) are agent-to-human negotiations while all the other methods are agent-to-agent negotiations.

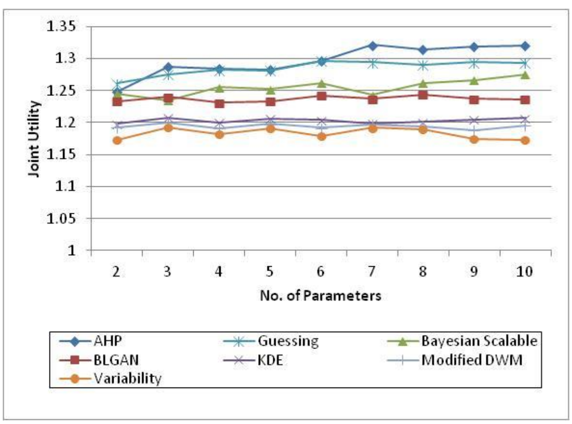

Fig. 6. Comparison of Joint-utility of agreement for various approaches.

7. CONCLUSION

While web services provisioning has become faster, negotiation of SLAs has not been taking place matching the speed of service provisioning. The best way to improve negotiation speed is to automate the process. Opponent modeling serves as a means for learning approximate preferences of the opponent which eventually leads to faster establishment of agreements. In this paper we demonstrated how AHP could be used to predict the preference ranking of an opponent in an automated negotiation. We proposed a simple trade-off algorithm that generates offers that are more acceptable to the opponent. The offers are nearer to the Pareto optimal line. Combined with AHP-based opponent preference prediction, the algorithm minimizes the number of rounds of negotiation leading to faster negotiations.

The agreements resulting in negotiations with prediction of opponent ranking by AHP are nearer to agreements resulting from known preferences. Though the trade-off algorithm is dependent on linear utilities the prediction of opponent ranking by AHP is generic and is applicable irrespective of the utility function used. The accuracy of AHP lies in the identification of right criteria for an opponent negotiation strategy. In addition to the general heuristics applicable to most negotiation strategies, any known information about an opponent negotiation strategy could be incorporated into the AHP prediction process. Moreover, qualitative information known about an opponent can be included as qualitative criteria in addition to quantitative criteria in AHP. This makes the AHP approach more flexible than other prediction approaches.

The proposed work can be extended to predict the exact issue weights of the opponent instead of only the ranking. For this, the AHP criteria for prediction need to be analyzed and applied to the process. To reduce user involvement in identifying the right AHP criteria in each negotiation, we would like to employ a technique that adjusts the weights of the criteria dynamically during negotiation. We would like to extend the trade-off algorithm by making it more generic and applicable to non-linear utility functions.

CONFLICT OF INTEREST

The autors have no conflicts of interest to declare.

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