Pareto Bid Estimation for Multi-Issue Bilateral Negotiation under User Preference Uncertainty

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***Abstract*—We study the problem of how an agent that negotiates over multiple issues with an opponent can make offers given that it has incomplete information about the user it represents and the opponent it plays against. To tackle this problem, we take a multi-objective optimization stance, where the negotiating agent estimates the preferences of both user and opponent to generate bids that are (near) Pareto-optimal. However, since the negotiating agent needs to approximate the actual preferences of two parties, uncertainty is involved. To handle this uncertainty, we propose a fuzzy approach consisting of a two-phase Pareto-bid generation step where Phase-I generates the non-dominated solutions using a fuzzy multi-objective evolutionary algorithm, and Phase II ranks them to find the best bid to offer the opponent using a fuzzy multiple-criteria decision-making method. Rigorous experimentation shows that the hybrid fuzzy approach of generating the (near) Pareto-optimal bids reduces the average distance to the Pareto curve and increases the average joint or social welfare utility of the agents leading to "win-win" situations.**

***Index Terms*—Fuzzy NSGA-II, Fuzzy TOPSIS, User preference uncertainty, Fuzzy Multi-Objective Optimization problem**

I. Introduction

Automated bilateral negotiation involves two autonomous software agents, typically representing the interests of human users, seeking to reach agreement by exchanging offers over multiple issues [1]. This is not a trivial task due to (a) the uncertainty of the opponent agent's preferences (opponents keep their preferences private to avoid exploitation), and (b) the human user an agent represents (in applications with a large space of possible offers, users do not always have the means to specify complete examples on how the agent should bid). In addition, humans often impose deadlines, so agents need in limited time to create "win-win" outcomes, viz., generate bids that optimize their own utility and are more likely to be accepted by the opponent.

Generating bids that approximate "win-win" situations corresponds to a Multi-Objective Optimization (MOO) problem. In particular, one seeks to derive Pareto-optimal solutions, i.e., such that none of the agents can be made better off without making at least one agent worse off. Although previous work has explored Pareto-optimality in multi-issue negotiations [4], [7], [9], [11], there is little account of how to handle user and opponent uncertainty in the MOO problem.

When building a negotiation agent, we normally consider three phases: *pre-negotiation phase* (i.e. estimation of agent owner's preferences, preference elicitation), *negotiation phase* (i.e. offer generation, opponent modeling) and *post-negotiation phase* (i.e. assessing the optimality of offers) [3]. In this paper, we are interested in the uncertainty that arises in the first two phases. In the first phase, the uncertainty is due to the estimation of the user's preferences/utility function, while in the second phase, the uncertainty arises due to the estimation of opponent preferences/utility function. These uncertainties present a critical and sensitive obstacle because it may influence the bid search process and consequently hamper the identification of efficient solutions.

In this work we propose, to the best of our knowledge, the first bilateral negotiation model that combines MOO and uncertainty modelling with fuzzy techniques. Our approach consists of a two-phase Pareto-bid generation step during the bidding phase of multi-issue bilateral negotiation. In the first phase, a fuzzy population-based multi-objective evolutionary algorithm called fuzzy Non-dominated Sorted Genetic Algorithm - II (NSGA-II) [2] is used to create the non-dominated solutions. Then in the second phase, a fuzzy multiple criteria decision making method called Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [22] is used to rank the Pareto-optimal bid solutions and select one best bid to offer to the opponent agent.

Our work is inspired by a recently proposed negotiation model called *ANESIA* [4], which relies on the meta-heuristic optimization for estimating the user preferences in the *pre-negotiation phase*, and the combination of NSGA-II and TOPSIS to generate Pareto-optimal bids *in the negotiation phase*. However, ANESIA does not account for how uncertainty propagates from the first to the second phase before generating (near) Pareto-optimal bids. In this sense, our negotiation model can be seen as a fuzzy extension of ANESIA. To evaluate our approach with the state-of-the-art, we conducted simulation experiments in different negotiation domains and against the negotiating agents presented at the ANAC'19 competition[1] where all the agents, dealing with their owner's preference uncertainties, span a wide range of strategies and techniques.

[1] http://ii.tudelft.nl/nego/node/7

The rest of the paper is organized as follows: Section 2 reviews the various related works in multi-issue bilateral negotiation domain for generating the Pareto-optimal bids. Section 3 describes the negotiation setting with fuzzy MOO problem. Section 4 describes our 2-phase process of generating the (near) Pareto-optimal bids under incomplete preference information. In section 5, we empirically evaluate the proposed method in a range of negotiation settings and scenarios. Finally, section 6 outlines the conclusions and future directions.

II. Related work

The idea of generating a Pareto-optimal offer with perfect information was originally proposed by Raiffa in [5]. Jazayeriy et al. in [7] presented the Maximum Greedy Trade-offs algorithm to generate Pareto-optimal offers with perfect information. This was further extended in [8] to generate near Pareto-optimal offers with incomplete information of opponent's preferences, but complete preference information of the user. Sanchez-Anguix et. al. in [6] and [9] proposed a bottom-up approach to achieve a Pareto-optimal solution in a group decision making setting. By assuming incomplete preferences of the opponent only, they also provided proof that a Pareto-optimal solution in a subgroup is also Pareto-optimal in the super-group containing the sub-group.

Ehtamo et. al. in [16] considered a non-biased mediator to reach the Pareto-optimal solutions requiring that bilateral negotiation agents know their utility function and introduced a constraint proposal method, extended later to multi-party negotiations in [17]. Hara and Ito in [18] used a mediator-based negotiation approach in which a Genetic Algorithm was used over interdependent multiple issues. Instead, in our evolutionary approach we do not rely on mediation and we assume independent issues.

In [10], the prioritized fuzzy constraints were incorporated by Luo et. al. into a buyer-seller negotiation setting, and the negotiation problem was considered as a fuzzy constraint satisfaction problem. However, we deal with the fuzziness in the objective/utility functions of negotiators. The recent work of Montazeri et.al. in [11] generated Pareto solutions with the help of deep reinforcement learning for e-commerce considering only opponent's preference information. Also, a mediator was used to exclude the unreasonable (or less beneficial for buyer) offers from the feasible set of negotiation offers by the negotiation strategy. To this end, it is clear that the simultaneous consideration of uncertainties in both the user and opponent's preferences to generate (near) Pareto-optimal bid generation is still an area which needs attention.

Evolutionary approaches have been shown to be a powerful technique for MOO since they offer both flexibility in goal specification and good performance in multi-modal, non-linear search spaces [12]. The Genetic Algorithm (NSGA-II) [13] has been used previously to find multiple Pareto-optimal solutions in automated Web service negotiation for QoS components [14]. The hybridization of NSGA-II and TOPSIS has also been seen in the recent research of Bagga et. al. [4] in the multi-issue negotiation domain for generating the (near) Pareto optimal bids assuming incomplete information in the both negotiating parties. However, in this paper, we use extended-NSGA-II [2] proposed by Bahri et. al. to deal with fuzzy MOO problems to reflect the uncertainties in estimated user and opponent models which was missing in [4] and also hybridize it with fuzzy TOPSIS [15] to choose one best among a set of ranked near Pareto-optimal outcomes during negotiation. We have seen this amalgamation of extended-NSGA-II and fuzzy-TOPSIS only in a supplier selection and multi-product allocation order problem [25], so to the best of our knowledge, we are the first to explore this combination in multi-issue bilateral negotiation.

III. Fuzzy Multi-Objective Optimization (MOO) for Negotiation

In this section, we discuss our negotiation settings and provide background on fuzzy MOO to formulate the negotiation problem as a fuzzy MOO problem. We assume that our negotiation environment consists of two self-interested agents negotiating with each other over some domain D. A domain D consists of m different issues, $D = (I_1, I_2, \dots I_m)$, where each issue can take a finite set of k possible values: $I_i = (v_1^i, \dots v_k^i)$. An agent's bid ω is a mapping from each issue to a chosen value (denoted by c_i for the i-th issue), i.e. $\omega = (v_{c_1}^1, \dots v_{c_m}^m)$. The set of all possible bids or outcomes is called an outcome space and is denoted by Ω s.t. $\omega \in \Omega$. Before the agents can begin the negotiation and exchange bids, they must agree on a negotiation protocol, which determines the valid moves agents can take at any state of the negotiation [19]. Here, we consider the *alternating offers protocol* [20], with possible $Actions = \{\mathit{offer}(\omega), \mathit{accept}, \mathit{reject}\}$. Furthermore, we assume that each negotiating agent has its own private preference profile which describes how bids are offered over the other bids. This profile is given in terms of a utility function U defined as follows:

$$U(\omega) = U(v_{c_1}^1, \dots v_{c_m}^m) = \sum_{i=1}^{m} w_i \cdot e_i(v_{c_i}^i), \text{ where } \sum_{i=1}^{m} w_i = 1 \tag{1}$$

where, w_i are the normalized weights indicating the importance of each issue to the user and $e_i(v_{c_i}^i)$ is an evaluation function that maps the $v_{c_i}^i$ value of the i^{th} issue to a utility. Note that in (1), each issue is evaluated separately contributing linearly without depending on the value of other issues and hence U is referred to as the Linear Additive Utility space.

In our settings, we assume that U is unknown and our agent is given incomplete information in terms of partial preferences i.e. a randomly generated partial ordered $\preceq$ ranking over bids (w.r.t. U) s.t. $\omega_1 \preceq \omega_2 \rightarrow U(\omega_1) \leq U(\omega_2)$. Hence, during the negotiation, one of the objectives of our agent is to derive an estimate $\widehat{U}$ of the real utility function U from the given partial preferences. Our other objective is to generate the (near) Pareto-optimal solutions during the negotiation which can be defined as an MOO problem as follows:

$$max\ F(x) = (f_1(x), f_2(x))\ s.t\ \ x\ \in S \tag{2}$$

In (2), $F(x)$ is the vector of $n = 2$ objective functions to be maximized (one objective is user's estimated utility function ($\widehat{U}_u$) and another is opponent's estimated utility function ($\widehat{U}_o$)) and $x = (x_1, \ldots, x_m)$ is the vector of decision variables (i.e. a vector of all the m issues in a domain D) from the set of feasible solutions S associated with equality and inequality constraints. In a combinatorial MOP, the feasible region S becomes a discrete set of solutions, i.e. S is an outcome space Ω, which is equal to total possible bids. Besides, $F(x)$ maps the decision variables x from the decision space to the objective space by assigning a cost function $y \in Y$ that evaluates the quality or fitness of each solution as follows:

$$F : X \to Y \in \mathbb{R}^n, F(x) = y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \quad (3)$$

where $Y = F(S)$ represents the feasible points or solutions in the objective space, and $y_i = f_i(x)$ is a point of this space that represents the solution/bid quality or fitness. A solution $x^* \in X$ is considered to be an optimal (or a non-dominated) solution if $\forall x \in X, F(x)$ does not dominate $F(x^*)$, that is, $F(x) \not\prec F(x^*)^2$. Since we consider uncertainties in the objectives, the MOP with uncertain objectives can be defined as follows [2]:

$$max\ F(x, \xi) = max[f_1(x, \xi), f_2(x, \xi)]\ s.t.\ x \in X, \xi \in U_{sc} \quad (4)$$

In (4), F is the set of objective functions that may depend on uncertainty scenarios U_{sc}, x is a decision variable vector from its admissible region $X \subseteq \mathbb{R}^n$ and $\xi = (\xi_1, \xi_2, \ldots \xi_q)$ is a vector of independent uncertain variables [2]. Each $f_i(x, \xi)$ is an uncertain quantity induced by ξ. Also, the cost of evaluating $F(x, \xi)$ is represented by intervals such as a Triangular Fuzzy number (TFN). Formally, a TFN is represented with a triplet of values $A = [\underline{a}, \widehat{a}, \overline{a}]$, where $[\underline{a}, \overline{a}]$ is the interval of possible values called its support and $\widehat{a}$ denotes its modal or kernel value (the most plausible). TFN can also be deduced from transformations of other different shapes by linguistic modifiers, compositions, projections and other operations [2]. The triangular fuzzy-MOO problem of generating (near) Pareto bids in bilateral negotiation domain (i.e. two objectives: $f_1 = \widehat{U}_u$, $f_2 = \widehat{U}_o$) can be defined as:

$$max\ F(x^\tau) = (f_1(x^\tau), f_2(x^\tau))\ s.t.\ x \in X, \tau \in \mathbb{R} \quad (5)$$

In (5), $F(x^\tau)$ can be defined as a fuzzy cost function that represents the fitness of solutions/bids by assigning a triangular-valued objective vector Y_τ:

$$F : X \to Y \subseteq (\mathbb{R} \times \mathbb{R} \times \mathbb{R})^n, \quad F(x^\tau) = Y^\tau = \begin{pmatrix} y_1 = [\underline{y_1}, \widehat{y_1}, \overline{y_1}] \\ y_2 = [\underline{y_2}, \widehat{y_2}, \overline{y_2}] \end{pmatrix} \quad (6)$$

[2]An objective vector $y = (y_1, \ldots, y_n)$ Pareto-dominates another objective vector $y' = (y'_1, \ldots, y'_n)$ (denoted by $y \prec y'$) iff no component of y' is greater than the corresponding component of y and at least one component of y is strictly greater. For more details on Pareto-optimality, see [2].

IV. Solution Methods

In this section, we present the proposed two-phase solution and provide the background on the fuzzy methodologies used in this work. Our proposed work consider the state-of-the-art deep reinforcement learning based multi-issue bilateral negotiation architecture called *ANESIA* [4], which assumes incomplete information of the preferences of the user and opponent agents. In this model, the user modeling (i.e. estimation of user utility function) is done before the negotiation begins with the help of Cuckoo Search Optimization (CSO) [21], whereas opponent modeling is done with the help of distribution-based frequency model [24] during the negotiation. However, this work hasn't addressed the uncertainty aspect while generating the (near) Pareto-optimal bids in the bidding strategy while using the combination of NSGA-II and TOPSIS, which is not realistic. Therefore, we extend the *ANESIA* model by addressing the fuzzy MOO problem of generating Pareto-optimal bids in which uncertainty is expressed by means of triangular fuzzy numbers. This new approach (called *f-ANESIA*) is a two-phase process as shown in Figure 1.

A. Phase I

We address the effects of uncertainty propagation in the multi-objective setting where uncertainty is assumed to occur in the objective functions i.e. user and opponent utility functions, because of lack of information. We use an extended-NSGA-II [2], which replaces the classic Pareto dominance with the fuzzy Pareto dominance. Let Y and Y' be two triangular fuzzy solutions. Y strong dominates Y', if either y_i total dominates or partial dominates y_i' in one objective and weak[3] dominates it in another [2]. This modification allows to ensure the fitness assignment ranking in a fuzzy setting. Afterwards, a crowding-comparison procedure is applied based on a Crowding Distance (CD) that discriminates the solutions having the same rank level. Formally, the CD of a solution is the sum of its individual objectives' distances, that in turn are the differences between the solution and its closest neighbours as shown below.

$$CD(i) = \sum_{i=1 \ldots n} (f_i(i{+}1) - f_i(i{-}1)) / (f_i^{max} - f_i^{min})\ s.t.\ i \in F \quad (7)$$

where n is the number of objectives, $f_i(i+1)$ and $f_i(i-1)$ are the neighbor objective values of the i-th objective, f_i^{max} and f_i^{min} are the maximum and minimum objective values respectively in the population, and F is the i-th front to which solutions are associated. Since our objective functions are TFN vectors, the distance measure must be adapted to fuzziness. Thus, these objectives are approximated by computing their expected values before applying CD. The expected value E of a given TFN $y_i = [\underline{y_i}, \widehat{y}, \overline{y_i}]$ is calculated as follows:

$$E(y_i) = (\underline{y_i} + 2 \times \widehat{y_i} + \overline{y_i})/4 \quad (8)$$

To reflect the uncertainty in fuzzy objective values caused by the possibility of multiple utility functions as solutions,

[3]y_i partially weak dominates y'_i iff there is fuzzy overlapping or fuzzy inclusion.

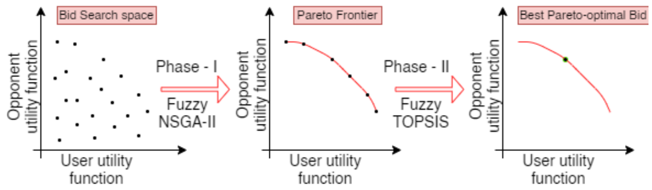

Fig. 1. Two-phase process of generating a Pareto-optimal solution during bid generation phase

we collected $K = 100$ best user models derived by CSO. Since, the fitness value for each objective function is a TFN, $\widehat{a}$ is the average utility of the K models for that bid, and the upper and lower bounds are 5-th and 95-th percentile of the k utility models respectively. Given this distribution of utility values, we derive the principles triangular sets as triangular approximation of the empirical normal approximation of the distribution. That is, let $\hat{\sigma}$ and $\hat{\mu}$ be the observed standard deviation and mean respectively, then the fuzzy-set could be: $[l, m, u]$ where $m = \hat{\mu}$, $l = \hat{\mu} - k\hat{\sigma}$ and $u = \hat{\mu} + k\hat{\sigma}$ for some $k = 1, 2, 3$ (we choose $k = 2$). The membership U of each element is given by the corresponding Gaussian probability density function value, i.e., $U(m) = 1/(\hat{\sigma}\sqrt{2\pi})$, $U(l) = U(u) = e^{-k^2/2}/(\hat{\sigma}\sqrt{2\pi})$. For the fuzzy opponent objective function, $\widehat{a}$ is the current opponent model at any time t, the upper and lower bounds are opponent models obtained at time $t \in [0.4, 0.6]$ and $t \leq 0.2$ respectively. The fuzzy NSGA-II generates a Pareto-frontier which has numerous (P) preferable optimal solutions ($P \in \Omega$). Hence, decision making approaches are essential to pick an individual solution from the Pareto Frontier.

B. Phase-II

We employ a fuzzy Multi-Criteria Decision-Making (MCDM) method called fuzzy TOPSIS [22] to pick the best optimal solution from Pareto Frontier. In our model, we have only two criteria ($m = 2$) or objectives: maximizing user utility and maximizing opponent utility (since our focus is more on "win-win" situations), based on which Ω solutions/bids/alternatives will be ordered. Our agent implements fuzzy TOPSIS with the help of vertex method to calculate the distance between two triangular fuzzy numbers $y = (y_1, \ldots, y_m)$ and $y' = (y'_1, \ldots, y'_m)$ as follows:

$$\sqrt{1/3[(y_1 - y'_1)^2 + \ldots + (y_m - y'_m)^2]} \tag{9}$$

The procedure of fuzzy TOPSIS is defined as follows:

- A fuzzy decision matrix $M = n \times m$ consisting of n alternatives and m criteria is created. Here, $n = |P|$, $m = 2$, and $m_1 = \widehat{U}(\omega_i)$ and $m_2 = \widehat{U}(\omega_i^o)$.
- Then, we normalize the fuzzy decision matrix M using (10), where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$ and x_{ij} is a value assigned to the i^{th} solution w.r.t j^{th} criteria.

$$\tilde{r}_{ij} = \left(\frac{\underline{y_1}}{c_j^*}, \frac{\widehat{y_1}}{c_j^*}, \frac{\overline{y_1}}{c_j^*} \right), and \quad c_j^* = max_i\{c_{ij}\} \tag{10}$$

- Subsequently, we create a weighted normalized decision matrix W where x_{ij} is replaced with v_{ij} and $v_{ij} = w_j \cdot r_{ij}$. In our experiments, we use the same weights which were learned in the existing $ANESIA$ model. These weights scale with negotiation time t. So, $w_1 = a \cdot t + b$ and $w_2 = 1 - (a \cdot t + b)$. Here, $a = -0.75$ and $b = 0.6$.
- Once the weighted normalized matrix is ready, the distance of each alternative from fuzzy ideal positive and negative solutions is computed.
- Finally, the ranks are ordered from high to low as per the relative closeness of each alternative to the ideal ones.

A bid solution/bid/alternative with top rank is chosen by our agent to propose to the opponent agent during this time period.

V. Experimental Results and Discussions

All the experiments have been performed using the popular GENIUS negotiation platform [26]. These experiments are designed to prove the following hypotheses:

- **Hypothesis A:** Fuzzy hybridized versions of existing negotiation strategies outperform their non-fuzzy variants in terms of U_{ind}, $Dist_p$ and U_{soc}.
- **Hypothesis B:** *f-ANESIA* outperforms the existing ANESIA agent and other winning agents from ANAC'19 competition in terms of U_{ind}, $Dist_p$ and U_{soc}.

A. Performance Metrics

We consider the same (widely adopted) metrics [23] inspired by the GENIUS simulation platform:

- R_{avg}: Average number of rounds over all successful negotiations (Ideal value: Low(1))
- $Dist_p$: Average distance to the Pareto Curve[4] (nearest bid on the frontier) (Ideal value: Low (0))
- U_{ind}: Average utility gained by an agent on successful negotiations (Ideal value: High (1.0)
- U_{soc}: Average utility gained by both negotiating agents on successful negotiations (Ideal value: High(2.0)
- $S_{\%}$: Proportion of successful negotiations (Ideal value: High (100%))
- t_{neg}: Average time on successful negotiations (Ideal value: low (1ms))

B. Experimental settings

We assume that prior to designing an agent's negotiation strategy: (a) each agent has no knowledge of the preferences and negotiating characteristics of its opponent; (b) the negotiation time is limited and there is a specific deadline (known to both negotiating parties in advance) for its termination (here, it is $60s$ normalised in $[0, 1]$), therefore the agents must consider the risk of rejecting their offer from the opponent with regard to the limited time; (c) the utility of offers might decrease over time (in negotiation scenarios with discount factor; we use the default value in GENIUS) [4]), thus, timely decision on rejecting or accepting an offer and making acceptable

[4]Pareto frontier is obtained assuming complete preference information of both the negotiating parties.

offers are of high importance for negotiators. We evaluate our approach on the same benchmark domains used in [4], i.e. Laptop ($|\Omega| = 27$), Holiday ($|\Omega| = 1024$) and Party ($|\Omega| = 3072$). For each configuration, each agent gets the chance to play both sides of the negotiation (e.g. buyer and seller in Laptop domain). We call *user profile* the specific agent's role along with its associated preferences.

C. Empirical Evaluation

1) Hypothesis A: Fuzzy hybridized versions outperform their Non-fuzzy variants: We performed the analysis of fuzzy hybrid approach of generating (near) Pareto-optimal bids by combining it with different negotiation strategies dealing with user's and opponent's preference uncertainties. We used 12 combinations of negotiations strategies involving 2 population-based user modeling approaches (Cuckoo Search CS and Genetic Algorithm GA), whereas 3 opponent-modeling approaches[5] (Bayesian model, Smith Frequency Model and a Simple/Uniform model) with and without the component of Fuzzy Hybrid approaches for the total of 6600 simulations, each in 2 different domains (Party and Holiday) with 3 different user profiles ($B = 0.2\times|\Omega|, 0.4\times|\Omega|, 0.6\times|\Omega|$). Table I shows that the the negotiation strategies involving fuzzy component (starting with $'f'-$) outperforms their non-fuzzy variants, mainly in terms of U_{ind}, $Dist_p$ and U_{soc} leading to "win-win" situations.

2) Hypothesis B: Performance of f-ANESIA outperforms ANESIA and other agents: We also tested *f-ANESIA* in a GENIUS tournament setting against opponents (winning agents) from the ANAC'19 competition[6], for a total of 1200 sessions in 3 different domains, where each agent negotiates with every other agent. Table II compares their performance in terms of U_{ind}, R_{avg}, $S_{\%}$, and t_{neg}. Figure 2 shows the increase in U_{soc} of ANESIA agent with fuzzy Pareto approach, whereas Figure 3 decrease in $Dist_{pareto}$ w.r.t original ANESIA agent. Results demonstrate that our proposed hybrid approach of generating (near) Pareto optimal bids has significantly impacted the performance of ANESIA agent. In this experiment, we chose two different user profiles and two different preference uncertainties ($B \in 10, 20$), same as in [4]. The low successful negotiation rate in Table I with high U_{ind} and high U_{soc} (in Figure 2) indicates the non-greedy behaviour of *f-ANESIA* agent, which is often seen in the agents belonging to the same institution, when they want to achieve the maximum mutual benefit instead of reaching an agreement which can be less beneficial to one of them.

VI. Conclusions

We have presented an experimental analysis of a fuzzy-NSGA-II and fuzzy-TOPSIS for the generation of (near) Pareto-optimal bids under user and opponent preference uncertainties. To the best of our knowledge, this combination is the first attempt for solving multi-objective problem of finding the Pareto-optimal outcomes in multi-issue bilateral negotiations. Extensive experiments show that the proposed hybrid approach outperforms the other agents in the analysis as well as the original non-fuzzy Pareto approach. As future work, we plan to perform experiments with concurrent bilateral negotiations over multiple issues under user preference uncertainty.

[5]Available in GENIUS

[6]*SAGA* (Genetic algorithm), *KakeSoba* (Tabu Search), and *AgentGG* (Statistical frequency modeling)

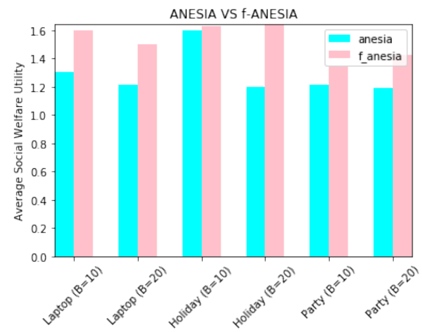

Fig. 2. Average Social Welfare Utility (↑): ANESIA Vs f-ANESIA in 3 different domains with 2 user profiles B =10, 20

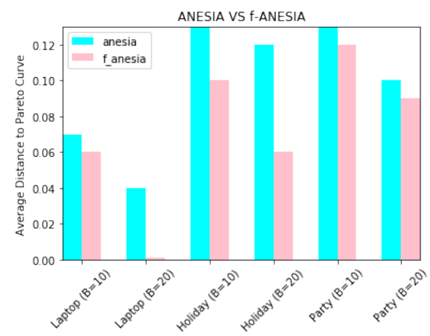

Fig. 3. Average Distance to Pareto Curve (↓): ANESIA Vs f-ANESIA in 3 different domains with 2 user profiles B =10, 20

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TABLE I

PERFORMANCE COMPARISON OF FUZZY VS NON-FUZZY NEGOTIATION STRATEGIES (BEST RESULTS IN **BOLD** ARE CHOSEN BY PAIRWISE COMPARISON OF FUZZY AND NON-FUZZY APPROACHES)

Holiday domain ($B = 0.2\Omega, B = 0.4\Omega, B = 0.6\Omega$)

Metric	f-GA-Smith	f-GA-Uniform	f-GA-Bayesian	f-CS-Smith	f-CS-Uniform	f-CS-Bayesian
$R_{avg}(\downarrow)$	(**29.18**, **24.69**, **25.34**)	(479.78, 523.15, 553.97)	(**678.20**, 676.58, 437.88)	(**166.16**, **94.28**, **61.96**)	(**111.63**, **82.84**, **79.19**)	(**916.12**, 876.43, **607.14**)
$Dist_p(\downarrow)$	(**0.16**, **0.16**, **0.10**)	(0.18, **0.16**, **0.12**)	(**0.14**, **0.14**, **0.10**)	(**0.14**, **0.14**, **0.10**)	(**0.15**, **0.13**, **0.08**)	(**0.16**,0.16,**0.11**)
$U_{soc}(\uparrow)$	(**1.59**, **1.59**, **1.67**)	(**1.58**, **1.60**, 1.64)	(**1.54**, **1.58**, **1.64**)	(**1.61**, **1.62**, **1.68**)	(**1.60**, **1.62**, **1.70**)	(**1.59**, **1.60**, **1.66**)
$U_{ind}(\uparrow)$	(**0.78**, **0.81**,0.84)	(0.76, **0.78**, **0.87**)	(**0.76**, **0.79**, **0.87**)	(**0.83**, **0.82**, **0.86**)	(**0.80**, **0.81**, **0.85**)	(0.78, 0.80, **0.85**)
Metric	GA-Smith	GA-Uniform	GA-Bayesian	CS-Smith	CS-Uniform	CS-Bayesian
$R_{avg}(\downarrow)$	(489.46, 327.08, 378.22)	(**436.53**, **344.19**, **285.96**)	(771.89, **609.39**, **400.27**)	(610.97, 530.02, 285.61)	(692.11, 888.04, 521.09)	(946.87,**834.125**,673.05)
$Dist_p(\downarrow)$	(0.18, 0.17, 0.12)	(**0.17**,0.17,0.11)	(0.18, 0.17, 0.14)	(0.16, 0.16,0.13)	(0.15, 0.14, 0.11)	(**0.16**, **0.15**, 0.12)
$U_{soc}(\uparrow)$	(1.56, 1.58, 1.65)	(1.56, 1.57, **1.66**))	(1.56, **1.58**, 1.63)	(1.59, 1.60, 1.63)	(**1.60**, 1.61, 1.66)	(**1.59**, **1.60**, 1.64)
$U_{ind}(\uparrow)$	(0.77, 0.78, **0.86**)	(**0.78**, **0.78**, 0.81)	(0.68, **0.79**, 0.80)	(0.80, 0.81, 0.82)	(**0.80**, **0.81**, **0.85**)	(**0.81**, **0.81**, 0.84)

Party domain ($B = 0.2\Omega, B = 0.4\Omega, B = 0.6\Omega$)

Metric	f-GA-Smith	f-GA-Uniform	f-GA-Bayesian	f-CS-Smith	f-CS-Uniform	f-CS-Bayesian
$R_{avg}(\downarrow)$	(**2.65**, **2.71**, **61.11**)	(926.38,2090.4,1887.62)	(**1463.56**,1709.94,1887.42)	(**2.86**, **2.71**, **2.50**)	(**2.72**, **2.64**, **3.0**)	(2408.59,1743.44,4999.87)
$Dist_p(\downarrow)$	(**0.12**, **0.13**, **0.07**)	(**0.12**, **0.11**, 0.14)	(**0.17**, **0.16**, **0.14**)	(**0.11**, 0.14, **0.08**)	(0.14, **0.08**, **0.06**)	(**0.16**, **0.11**, **0.08**)
$U_{soc}(\uparrow)$	(**1.45**, **1.46**, **1.51**)	(**1.44**, **1.34**, **1.39**)	(**1.36**, **1.37**, **1.5**)	(**1.43**, **1.45**, **1.55**)	(**1.43**, **1.52**, **1.59**)	(**1.39**, 1.39, 1.42)
$U_{ind}(\uparrow)$	(**0.67**, **0.72**, **0.78**)	(**0.74**, 0.66, **0.69**)	(**0.65**, **0.66**, **0.69**)	(0.74, **0.79**, **0.81**)	(**0.77**, **0.80**, **0.94**)	(**0.67**, **0.71**, **0.85**)
Metric	GA-Smith	GA-Uniform	GA-Bayesian	CS-Smith	CS-Uniform	CS-Bayesian
$R_{avg}(\downarrow)$	(687.0, 782.48,839.76)	(**791.81**,**798.13**,**1107.12**)	(1670.60,**1538.79**,**1766.26**)	(955.28,1308.46,2827.50)	(798.61,1069.97,2062.0)	(**1833.04**,**1626.81**,**1809.86**)
$Dist_p(\downarrow)$	(0.13,0.13, 0.10)	(0.14, 0.12, **0.12**)	(0.18,0.17,0.14)	(0.14, **0.13**,0.15)	(**0.13**, 0.13, 0.11)	(0.17,0.16,0.18)
$U_{soc}(\uparrow)$	(**1.45**, 1.45, 1.44))	(1.42, 1.33, 1.33))	(1.33, 1.30, 1.32)	(**1.43**, 1.43,1.45)	(1.42, 1.42, 1.49)	(1.35, **1.4**, **1.5**)
$U_{ind}(\uparrow)$	(0.61, 0.70, 0.75)	(0.70, **0.69**, 0.66)	(0.61,0.63,0.63)	(**0.75**, 0.73, 0.70)	(0.75, 0.74, 0.70)	(0.50,0.69,0.75)

TABLE II

PERFORMANCE COMPARISON OF F-*ANESIA* (WITH STRATEGY TEMPLATE) VS WINNING AGENTS FROM ANAC'19 (BEST RESULTS ARE IN **BOLD**)

Metric	f-ANESIA	AgentGG	KakeSoba	SAGA
		Laptop domain ($B = 10, B = 20$)		
$U_{ind}(\uparrow)$	**(0.98 ± 0.0044, 0.99 ± 0.0124)**	(0.90 ± 0.0072, 0.88 ± 0.0128)	(0.88 ± 0.0096, 0.93 ± 0.0008)	(0.83 ± 0.0078, 0.79 ± 0.0039)
$R_{avg}(\downarrow)$	**(66.46 ± 20.33, 64.85 ± 23.00)**	(2575.71 ± 5086.512, 5089.774 ± 8463.00)	(2081.211 ± 2965.04, 4991.53 ± 3578.63)	(263.99 ± 261.81, 885.83 ± 759.40)
$S_{\%}(\uparrow)$	(42.12 , 52.5)	(70.5 , 58.17)	(**79.67** ,61.33)	(77.83 , **74.83**)
$t_{neg}(\downarrow)$	**(9.56 ± 285.03, 13.91 ± 305.19)**	(21.81 ± 640.67, 40.67 ± 1730.37)	(15.17 ± 537.03, 39.16 ± 870.27)	(12.51 ± 308.611, 17.91 ± 1363.95)
		Holiday domain ($B = 10, B = 20$)		
$U_{ind}(\uparrow)$	**(0.92 ± 0.007, 0.93 ± 0.055)**	(0.87 ± 0.0036, 0.89 ± 0.021)	(0.85 ± 0.0136, 0.85 ± 0.044)	(0.76 ± 0.0291, 0.74 ± 0.0087)
$R_{avg}(\downarrow)$	**(158.73 ± 660.71 , 135.22 ± 732.85)**	(848.37 ± 313.98, 441.29 ± 546.79)	(677.70 ± 540.84, 319.63 ± 724.39)	(510.91 ± 3035.42, 466.94 ± 284.32)
$S_{\%}(\uparrow)$	(66.83, 62.17)	(68.67, 77.17)	(74.00, **82.00**)	(**74.83**, 73.00)
$t_{neg}(\downarrow)$	(26.26 ± 977.39, 23.69 ± 361.14)	(28.90± 416.10, 20.00 ± 797.25)	(26.67± 323.47, **15.52 ± 786.34**)	(**20.25 ± 1026.51**, 20.01 ± 559.35)
		Party domain ($B = 10, B = 20$)		
$U_{ind}(\uparrow)$	**(0.92 ± 0.025, 0.90 ± 0.025)**	(0.76 ± 0.044, 0.75 ± 0.039)	(0.77 ± 0.11, 0.89 ± 0.0039)	(0.55 ± 0.042, 0.54 ± 0.0471)
$R_{avg}(\downarrow)$	**(100.00 ± 673.16, 123.06 ± 523.17)**	(644.32 ± 933.16, 735.55 ± 886.89)	(669.011 ± 932.39, 781.80 ± 562.44)	(428.18 ± 972.89, 395.22 ± 835.17)
$S_{\%}(\uparrow)$	(24.83, 25.00)	(60.33, 61.83)	(60.33, 59.83)	**(70.17, 71.83)**
$t_{neg}(\downarrow)$	**(22.157 ± 714.09, 26.26 ± 308.17)**	(37.25 ± 776.29, 39.69 ± 775.12)	(41.15 ± 695.85, 43.89 ± 800.258)	(25.27 ± 812.02, 22.48 ± 817.24)

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