A Machine Learning Approach for Mechanism Selection in Complex Negotiations

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Abstract. Automated negotiation mechanisms can be helpful in contexts where users want to reach mutually satisfactory agreements about issues of shared interest, especially for complex problems with many interdependent issues. A variety of automated negotiation mechanisms have been proposed in the literature. The effectiveness of those mechanisms, however, may depend on the characteristics of the underlying negotiation problem (e.g. on the complexity of participant's utility functions, as well as the degree of conflict between participants). While one mechanism may be a good choice for a negotiation problem, it may be a poor choice for another. In this paper, we pursue the problem of selecting the effective negotiation mechanism by (1) defining a set of scenario metrics to capture the relevant features of negotiation problems, (2) evaluating the performance of a range of negotiation mechanisms on a diverse test suite of negotiation scenarios, (3) applying machine learning techniques to identify which mechanisms work best with which scenarios, and (4) demonstrating that using these classification rules for mechanism selection enables significantly better negotiation performance than any single mechanism alone.

Keywords: Automated negotiation, Mechanism selection, Scenario Metrics

1 Introduction

Negotiation - the process of finding agreements with self-interested parties with differing preferences - is important in our society, e.g., in commerce, government, but also in science and engineering. In the past few decades, the need to handle increased volumes of transactions, more complex negotiations, and larger number of stakeholders, has driven interest in developing computer-supported

negotiation technologies, e.g. tools where software agents facilitate negotiation on behalf of their users [11,15].

The majority of negotiation research has focused on finding good negotiation mechanisms, which includes a protocol for interactions and strategies for making and accepting offers. The negotiation research community has progressed with respect to negotiation scenarios with a number of *in*dependent issues for which the overall negotiation outcome space has an order of magnitude of up to 10^5 [1,3,11,26,14,22]. Negotiation mechanisms that work well for in those negotiations tend to fare poorly when applied to significantly bigger outcome spaces [13]. For *inter*dependent issues some effective mechanisms have been proposed [13,10,21]. Still, there are open questions in the field of automated negotiation with respect to what the best mechanisms (protocols and strategies) are, when increasing the number of participants, increasing the outcome space (10^{30}) and dealing with interdependent issues (which complicates the form of the negotiation outcome space).

We argue that no single best mechanism exists for all negotiation scenarios, because of the high variability of negotiation scenarios. The variability comes from the variance in the size and form of negotiation outcome spaces, but also other aspects vary, e.g., whether there is time pressure, whether other outcome criteria hold (e.g., social welfare and fairness), and to what extent information from the other parties is available. Other complicating factors are whether or not the human stakeholders find the mechanism acceptable. For example, a layman user might object to a mechanism because it is not immediately clear that the mechanism has appropriate properties such as guaranteeing a fair outcome.

The central question pursued in this paper is how to select the best negotiation mechanism for a given problem and set of user requirements. Although this research question has been around for some time [12], to date the only work within the context of automated negotiation, has been done on selecting bidding strategies under the bilateral alternating offer protocol [8]. In comparison, this paper broadens the scope by varying over protocols, and considering *inter*dependent instead *in*dependent issues. This requires a systematic benchmarking method. There have been recent efforts to benchmark negotiation approaches in common scenarios, like the Automated Negotiation Agents Competition (ANAC) [2], but these efforts have restricted to ad-hoc domain sets and furthermore, the number of nonlinear negotiation scenarios involving interdependent issues is still limited (12 nonlinear nonlinear scenarios in ANAC 2014).

This paper addresses this challenge and proposes a machine learning approach for mechanism selection in complex negotiations. Our contribution is threefold:

- We create a framework for the characterization and generation of negotiation scenarios (Section 2) by defining a set of scenario metrics to capture the relevant features of negotiation problems (Section 2.1), and by proposing a scenario generation approach which allows us to compile a large and diverse set of negotiation scenarios for mechanism benchmarking in particular nonlinear domains (Section 2.2).

- We evaluate the performance of a range of negotiation mechanisms on our scenario test suite, demonstrating that the relative performance of the mechanisms varies from one setting to another setting (Section 4).
- We build decision trees from our experimental results to map scenario metric values to better-suited protocols, and demonstrate that using these classification rules for mechanism selection enables significantly better negotiation performance than any single mechanism alone (Section 4.2).

The rest of this paper is organized as follows. Section 2 presents a framework to define scenario metrics capturing different characteristics of a given scenario and to generate a diverse set of complex negotiation scenarios. Section 3 explains our machine learning approach for selecting the best mechanism given the negotiation problem. Section 4 provides our experimental set up and results. Finally, Section 5 summarizes our contributions, compares our work with other related approaches and discusses future work.

2 Characterization and generation of negotiation scenarios

The first step to fulfill our aim of determining how to select the best negotiation mechanisms for a given negotiation scenario with particular characteristics is to create an infrastructure which allows to systematically benchmark negotiation mechanisms in different scenarios. This infrastructure consists of the following components:

- A set of *scenario metrics* which characterize the key properties negotiation scenarios, allowing us to divide them in meaningful categories.
- A strategy for *scenario generation* which enables us to generate a variety of negotiation scenarios in a systematic way with respect to the specified scenario metrics.
- A set of *performance criteria* that will be used in benchmarking to evaluate the performance of the mechanisms. Two types of performance criteria are investigated in this study: those related to the negotiation outcome and those related to the negotiation process itself.

2.1 Scenario Metrics

A negotiation scenario is a formal description of a negotiation problem, specifying the following:

- Negotiation domain is defined by the set of issues, ND=$\{X_1, ..., X_n\}$ being negotiated over, as well as the valid values for each issues, $Dom(X_i)$=$\{x_{i_1},..., x_{i_m}\}$. A contract is an assignment of a value $x \in Dom(X_i)$ to each negotiation issue $X_i \in ND$.

– *Agent preferences* can be represented in many different ways. For our infrastructure we adopt the weighted hypercube approach [9]. According to this, a utility function is a collection of hypercube regions in the utility space, each representing a single constraint c_k. A numeric *weight* or *utility value* $u(c_k)$ is associated to each constraint. The utility for a given contract s is then calculated as the sum of the utility values for the hypercubes including that contract, as follows:

$$u(s) = \sum_{c_k \in C | Satisfy(s,c_k)} u(c_k).$$

We have generalized the representation in [9] to support "not" constraints, that is, constraints which are satisfied when the contract s is *not* contained by the hypervolume. This allows to express easily utility sinks (i.e. specific regions where utility drops) and "If-then" constraints (i.e. if X holds then Y has to hold too for the constraint to be satisfied). This way to represent preferences has the advantage of being arbitrarily expressive (i.e. given a sufficient number of constraints, we could virtually approximate any imaginable function).

Figure 1 shows a sample utility function for a two-issue negotiation problem. This utility function consists of a unary constraint $C1$ and two binary constraint $C2$ and $C3$. The corresponding utility values associated to these constraints are 5, 10 and 12 respectively. According to this example, the contract x ($issue_1$= 2; $issue_2$=3) would yield a utility value $u(x) = 15$ for the agent, since it satisfies both $C1$ and $C2$ (that is, constraints $C1$ and $C2$ overlap, creating a region of higher utility). The contract y ($issue_1 = 4$; $issue_2$=2), on the other hand, would yield a utility value $u(y) = 5$, because it only satisfies $C1$.

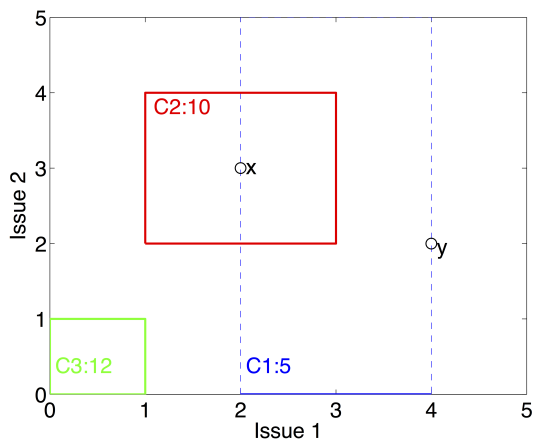

Fig. 1. Example of a utility space with two issues and three constraints

Over this definition of an scenario we use a set of metrics for characterization. Some of these metrics have been widely used in the literature. *Domain size* is measured as the number of possible contracts, and it is directly related to the difficulty to exhaustively search the contract space. *Fitness distance correlation (FDC)*, in contrast, is related to how easy is to exploit the structural properties of the utility functions to find contracts for a given utility value. In particular, it measures the correlation between the utility of a contract and its Euclidean distance, in the contract space, from the global optimum [24]. If there is a strong correlation between distance and utility, this implies a smooth utility function, where it is easy to find utility optima. If the correlation is weak, this implies a rugged utility function with many "bumps" along the way. Other researchers have also used metrics directly related to the constraint-based utility representation, such as *average number of constraints*, *average constraint size*, and *average constraint dimension* [21].

Apart from these scenario metrics from the literature, we propose a number of new ones to capture more characteristics of the negotiation problems:

- *Statistics of well-known outcome metrics.* We sample the scenario utility functions and compute the average and standard deviation for *individual utility optimality*, *social welfare optimality*, *Pareto optimality* and *fairness* (as defined in [6]). Consequently, we can account for the quality in terms of these different criteria for the expected outcomes if we used random search to find agreements, which serves as a good baseline reference.
- *Utility function cross-correlation.* We measure the correlation between utility functions for the agents in the same scenario. High cross-correlation means that agent utilities tend to have high values in the same regions, which should allow to find agreements more easily. Low cross-correlation, in contrast, would account for a more "competitive" scenario, where an agent high-gains would imply high losses for other agents.
- *Social Welfare FDC.* This metric is analogous to FDC above, but instead of being computed over individual agent utilities, we compute it over the social welfare of contracts. In this way, it gives an indication on how rugged is the social welfare landscape of the scenario, which accounts for the difficulty to find areas of high social welfare.
- *Attractor metrics.* Landscape smoothness is defined taking into account the existence of *attraction basins* towards its local optima [25]. An attraction basin towards a solution s_n is defined as the set of solutions $B(s_n)$ which have a continuous trajectory to s_n where utility never decreases. The size of the basin is given by the cardinality of the set $B(s_n)$. The larger the attraction basins in a landscape is, the smoother the landscape is. We can easily find attractors in a utility space by running hill-climber optimizers from random contracts in the space. If two contracts lead the optimizer to the same local optimum (attractor), we consider them to be in the same attraction basin. We measure both the *attractor density* of the utility landscape and the average and the standard deviation of the *attractor height*, that is, the

utility values associated with local optima. We compute these metrics for both social welfare and individual agent utilities.

– *Veto optimality.* A veto hill-climber only progresses when it can make a move which does not decrease the utility of any agent involved in the negotiation (since any agent can *veto* the move)[13]. We measure the average social welfare optimality for veto-hill climbers starting from random points. This is an indicator of how easy is to progress towards a negotiation optimum without agents making concessions in their utilities.

With all the metrics outlined above we implemented a set of 22 negotiation scenario metrics shown in Table 1. We have integrated all of those metrics into *Negowiki* [19], an online repository where members of the negotiation research community could upload their scenarios adopting the aforementioned hypercube representation and get them characterized according to the metric set. However, the existing scenario collection, although contained a representative set of scenarios used in the literature, did not cover a wide range of values for the different metrics. Therefore, a systematically created set of diverse negotiation scenarios was needed.

Table 1. Scenario Metrics

Size of contract space
Average contract utility
Average local optimum utility
Agent fitness distance correlation (FDC)
Average constraint dimension
Average number of constraints
Average of natural logarithm of volume of constraints
Density of utility function optima
Utility variance of local optima
Utility variance of random contracts
Social welfare average
Pareto average
Variance of Pareto for random contracts
Variance of social welfare for random contracts
Social welfare attractor average height
Variance of social welfare attractor heights
Social welfare fitness distance correlation FDC
Density of social welfare attractors
Average Fairness: average of all contracts
Deviation from fairness
Utility function correlation: for all contracts
Veto optimality

2.2 Scenario Generator

We developed, for this work, a scenario generator that uses a parametrized process to define a wide range of utility functions (i.e. sets of weighted hypercubes) for the agents in each negotiation scenario. Hypercubes were generated randomly within the constraints given by the following four parameters:

- *Number of issues.* The size of the contract space increases exponentially with the number of issues, making it computationally more challenging to find win-win contracts. In our experiments, we generated scenarios with 10, 30, and 50 issues, where each issue had a domain of 10 possible values (0..9).
- *Number of shared hypercubes* across the agents. If this value is 3, for example, that means that the agents in the scenario will have 3 hypercubes with the same dimensions. The similarity between agent utility functions increases when there are many shared hypercubes with equal weights, and decreases when there are many shared hypercubes with opposed weights. In our experiments, every utility function had (2 * number of issues) hypercubes all told, with either no shared hypercubes, 30% of the hypercubes shared with equal weights, or 30% of the hypercubes shared with opposed weights.
- *Dimensionality distribution* for the hypercubes in the utility functions. This specifies what fraction of the hypercubes are uni-dimensional (i.e. constrain the value of just one issue), bi-dimensional (i.e. constrain the values of two issues) and so on. In general, higher-dimensional hypercubes produce more rugged and more difficult-to-optimize utility functions. In our experiments, the scenarios included either only one and two-dimensional hypercubes (equiprobable), or one, two, three and four-dimensional hypercubes.
- *Width distribution* for the hypercubes in the utility functions. In general, narrow hypercubes create more rugged and difficult-to-optimize utility functions. In our experiments, the scenarios include either narrow hypercubes (with equiprobable widths of one, two, three or four) or wide ones (with equiprobable widths of five, six, seven or eight).

We generated 360 scenarios, consisting of 10 scenarios for each of 36 parameter combinations described above, covering a wide range in terms of the size of the contract space, the similarity of the agent's utility functions, and the ruggedness of the agent's utility functions.

2.3 Performance Criteria

In order to evaluate the performance of the negotiation mechanisms, we use the following criteria measuring the quality of the outcome from a social-welfare perspective:

- *Utilitarian Social welfare optimality*: Utilitarian social welfare is measured in terms of the sum of the agents' individual utilities [4]. Since the value of this metric may vary according to the given scenario, we normalized its value dividing it by the maximum possible social welfare value for the considered scenario.

- *Pareto optimality:* Pareto optimality of an outcome is computed by drawing a line between the zero utility point z in the scenario utility diagram and the outcome of the negotiation o, and prolonging it until it intersects the Pareto front at a point p. We define then pareto optimality for the contract as the ratio between the length of the segments $\overline{zo}$ and $\overline{zp}$.
- *Fairness:* Outcome fairness is computed as in [6], and then normalized to the maximum potential fairness in the considered scenario.

In addition to these outcome performance criteria, we define three process performance criteria:

- *Computation cost*, which accounts for the number of times the utility function is evaluated during the course of the negotiation.
- The *number of rounds* taken by each mechanism to complete the negotiation.
- The *number of messages* exchanged by agents during the negotiation.

All outcome performance criteria are computed by the *Negowiki* when experimental results are uploaded to the website. Process criteria, however, have to be manually uploaded by users, since they strongly depends on the approach implementation.

3 Mechanism Selection Approach

The proposed mechanism selection benefits from machine learning techniques such as decision trees. We take the problem of which mechanism would be the best mechanism for a given negotiation problem as a classification problem where the input features are the set of scenario metric values characterizing the given negotiation scenario and the output is the predicted best mechanism for this scenario. In the proposed approach, decision trees are chosen as the classifier method. It is easy for human users to understand the decision trees because of their simple structures. Human experts can deduce important insights by extracting decision rules from decision trees. Furthermore, decision trees have been used for similar purposes. For instance, Guerri and Milano adopt using decision trees to select the best algorithm in an algorithm portfolio in the context of combinatorial auctions[7]. Similarly, Ilany and Gal use decision trees to choose the best negotiation strategy in the context of the alternative offering protocol [8].

Figure 2 depicts the proposed mechanism selection module having the following steps:

- ***Extracting scenario metrics:*** We estimate the predefined scenario metrics from a given negotiation scenario. A negotiation scenario consists of negotiating agents' preference profiles (i.e. utility functions) where the scenario metrics capture the characteristics of the underlying scenario (e.g. the complexity of the participants' utility functions as well as the degree of the conflict between participants). As outlined in Section 2.1, for this purposes we have defined 22 scenario metrics shown in Table 1.

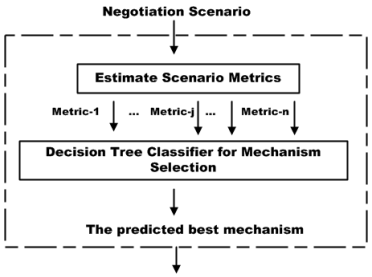

Fig. 2. Proposed Mechanism Selection Module

– ***Deciding the best candidate mechanism:*** We use the decision trees to find out the best candidate mechanism for the given negotiation. The decision trees take the scenario metrics estimated in the former step as inputs and output the best candidate mechanism.

This process requires creating the decision trees in advance. There are a variety of performance criteria for negotiation mechanisms such as fairness, social welfare, cost and so on. One mechanism may be the best mechanism according to fairness whereas another may be the best with respect to social welfare. This leads us to create separate decision trees for each performance criterion.

An important issue is how we construct the decision trees that will predict the best mechanism for the given negotiation scenario. We first generate a diverse set of negotiation scenarios and pick a set of different negotiation mechanisms. For each scenario, we test each mechanism a number of times and record their performance. For each negotiation run, we determine the best mechanism according to the chosen performance criterion. We build up the training sets by using the estimated scenario metrics as input features and the name of the best mechanism for each case as the label(i.e. class). Then, we create the decision trees whose test attributes are the scenario metrics and leaves are predicted best mechanism.

Figure 3 depicts the decision tree that has been constructed regarding to *the number of rounds* criterion. From this decision trees, we can extract some decision rules such as "If social welfare attractor density is less than 59.5 and utility function correlation is less then 0.09999, then it is recommended to use the mediated approach based on Genetic Algorithms (GA). Consequently, the decision trees will enable us to predict which mechanism we should pick for the given negotiation scenario.

4 Experiment Settings and Results

The approach we have described in the previous section is fundamentally empirical. Therefore, an extensive experiment set is needed to validate our hypotheses. In the following, we describe our experimental setting and discuss the results obtained.

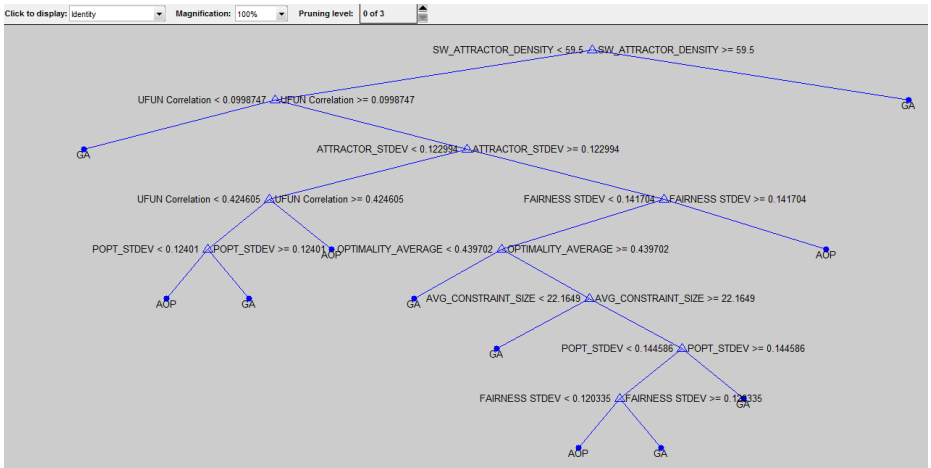

Fig. 3. The Round Decision Tree

4.1 Experiment Settings

As discussed in Section 1, the main hypotheses of our work are (1) that the relative performance of negotiation approaches (i.e. which mechanism works better) varies with the different negotiation settings and performance criteria, and (2) that we can use scenario metrics and machine learning techniques to select which mechanism is most used to handle an specific scenario. To put these hypotheses to the test, we have performed three sets of experiments:

- We have performed negotiations over all our generated scenarios using a number of relevant approaches from the literature, and measured their performance according to the criteria discussed above. This has allowed us to check whether there are clear "overall winning" approaches in these complex scenarios.
- We have used our obtained results and the aforementioned scenario metrics to train a decision tree classifier for the discrimination of the best negotiation approach for each scenario for each of the different performance indicators. We have then used this classifier for mechanism selection, showing that it significantly outperforms any mechanism alone, and also a random selection of mechanisms. This shows how the machine learning approach composed by the metrics and the decision tree is effectively able to recommend negotiation mechanisms for *known* scenarios.
- We have performed a cross-validation analysis of the decision trees to account for the *prediction* capability of the decision tree when facing *unknown* scenarios. The results show how the proposed approach effectively minimizes the performance loss when compared to the optimal performer at each negotiation.

For the negotiations, we created 36 scenario families as described in Section 2.2, varying criteria such as the number of shared constraints across agents, constraint dimensions, constraints width and domain size. For each scenario family we generated 10 instances, for a total of 360 negotiation scenarios.

For each scenario, we ran 10 negotiations with five different negotiation mechanisms taken from the literature:

- *Alternating Offers Protocol (AOP).* According to the alternating offers protocol [23], one of the agents initiates the negotiation with an offer. Other agent can respond by accepting this offer or making a counter-offer or ending negotiation without any consensus. If one of the agent accepts its opponent's offer, the negotiation ends with the agreed offer. Otherwise, this process is iteratively repeated until reaching a deadline (in our experiments, 10000 iterations). In this mechanism, the agents adopt a time-based concession strategy, as described in [5].
- *Mediated approach based on Genetic Algorithms (GA).* The mediator starts with the generation of N random contracts to propose to the agents, and iteratively each agent selects the top quarter contracts. At each iteration of the mechanism, the mediator uses the agents' selection to recombine and mutate these contracts into a new generation. This is similar to the approach used in [17].
- *A randomized single text mechanism (veto)* [13], where the mediator starts at a random contract. At each iteration, the mediator mutates the contract by altering the value of a randomly chosen issue and proposes the new contract to the agents, which will *compare* it to the previous agreement (i.e. prefer or not prefer). The mediator accepts the proposal as the current agreement if *all* agents prefer it to the previous contract.
- *A simulated annealing single text mediator (SA)*, which works as *veto*, but the mediator may accept a non-unanimously agreed contract with a finite probability depending on an annealing temperature which decreases with time. Also, agents are allowed to *strongly* or *weakly* accept or reject the current proposed contract at each iteration.
- *A pre-negotiation based mechanism (PN).* This is a mediated mechanism in which agents first agree about a suitable starting contract. In this pre-negotiation, the mediator proposes a large number of random contracts and the agents perform a runoff voting, i.e., they continue eliminating the candidates with the least votes until just one contract is left [16].

For each negotiation run, we measured computational cost, number of rounds, number of exchanged messages and quality of the outcome (i.e. social welfare optimality, pareto optimality and fairness). Then we labelled the best performing approach according to each of these six criteria and trained our decision tree classifier for each label set. We used these decision trees as mechanism selection rules and computed the results of doing the negotiations using this *mechanism selection approach (MS)*. Finally, we also tried a *random mechanism selection approach (rand)*, which basically picked randomly which mechanism to use at each negotiation, to use it as a baseline reference for comparison.

For the cross validation, we created ten disjoint validation sets comprising 10% of the scenario instances (one of each family), trained the decision trees with the remaining scenarios and tested them against the validation sets, for a total of 3240 negotiations in each training set and 360 negotiations in each validation set.

4.2 Empirical Results and Analysis

Table 2 shows the results of our experiments with the 3600 negotiation instances. For each negotiation approach, we show the "win count", that is, the number of times this approach was the best performer according to each criterion. As mentioned above, the *MS* column corresponds to our mechanism selection approach, where the decision trees are trained using the same 3600 negotiation instances (that is, for *known* scenarios), and the *Rand* column shows the results using a random mechanism selection. As seen from the results, adopting the mechanism selected by the decision trees (*MS*) outperforms sticking to any single protocol for almost all of the performance criteria. Even in the cases when there is an "overall winner", the results for our MS approach are quite close to that winner, meaning that the decision trees correctly identify the best approach to use most of the times. Furthermore, the results also support the fact that none of the mechanism is the best for all performance criteria. For instance, while alternating offers protocols with conceders (AOP) seems the best performer among the others according to the fairness criterion, MNP is the best performer with respect to the Pareto optimality criterion. Finally, it is worth noting that even when facing known scenarios we don't have a 100% guarantee of selecting the best performer (there is no cell in the table showing success in the 3600 rounds, not even in the *MS* column, where we are following the *MS* recommendation). This is due to the fact that the mechanisms used for complex negotiation scenarios have a high degree of randomness (e.g. performance of SA may highly depend on the first randomly chosen contract). We see, however that following the *MS* recommendation gives us a significant advantage over any other approach.

Table 2. "Win count" for the different approaches in the 3600 scenarios

Criterion	**AOP**	**GA**	**SA**	**Veto**	**PN**	**MS**	**Rand**
Round	109	3497	0	0	0	**3548**	730
Cost	0	1592	1576	1652	0	**2793**	952
Message	177	3425	0	0	0	**3550**	742
Swopt	141	184	104	395	3089	**3116**	839
Popt	153	261	140	572	**3261**	3152	862
Fairness	1074	674	631	655	678	**1579**	746

In the following, we show the results of the cross-validation experiments. Table 3 shows these results for the computational cost performance indicator. In this case, for each negotiation approach we show the cost differences between the best performer and the given mechanism in each of the 10 validation sets.

Therefore, low values in the table means that the approach is closer to an "omniscient" mechanism selector (i.e. one that knew beforehand what was going to happen). We can see that the average difference between the best performer and the mechanism suggested by the decision tree (*MS*) is significantly lower than the distance between the best performer and other mechanisms. It is also worth noting that no mechanisms achieves a zero difference, which means that there is no mechanism which was the best performer in all cases. This again accounts for the fact that in complex negotiation scenarios the degree of variability is much greater. It can also be seen that the different validation sets are consistent with each other. Therefore, for space limitations, we show the results for the rest of the performance indicators averaging all validation sets, as in Figure 4.

It is worth noting that there is no overall winner for all performance criteria. For example, in most of the cases GA outperforms the other mechanisms in terms of the number of rounds to complete the negotiation and number of messages sent during the negotiation while PN outperforms the others in terms of social welfare optimality and Pareto optimality. Although we have such outlier mechanisms, it is shown that the average distance between the best and the mechanism predicted by our selection method is relatively less than others except the winners for the given criterion. This result shows that the decision tree picks the winning mechanism most of the times, and supports our claim of using mechanism selection has advantage over sticking to a particular mechanism.

Table 3. The cost difference between the best performer and a given protocol in Validation Set

Set	AOP	GA	SA	Veto	PN	MS	Rand
1	1.32M	61.85	36.99	35.66	8489.78	**14.09**	297797
2	1.77M	71.95	36.02	33.68	8477.91	**10.33**	387470
3	1.56M	75.78	31.82	30.04	8488.16	**14.79**	252931
4	1.53M	62.97	40.04	38.23	8491.99	**12.36**	242828
5	1.42M	69.58	35.17	33.39	8484.14	**21.99**	231511
6	1.60M	68.08	37.27	35.91	8484.08	**19.19**	356153
7	1.60M	62.07	42.04	40.36	8490.10	**17.73**	348657
8	1.33M	65.66	41.93	40.24	8481.62	**9.59**	286569
9	1.30M	65.87	38.33	36.79	8489.18	**12.23**	271273
10	1.76M	67.40	43.68	42.01	8492.35	**18.78**	340874
Avg.:	1.52	67.12	38.33	36.63	8486.93	**15.11**	301606

5 Discussion & Conclusion

From the user perspective, it is crucial to be able to map negotiation problems to automated negotiation mechanisms, that is, finding the most appropriate approach to handle a given negotiation problem. However, research works so far have only addressed this challenge in a *per-problem* basis, focusing in specific scenarios and designing negotiation mechanisms suited for those scenarios. Although these works have been successful, the significance of their success cannot be fully assessed, because the results do not provide any insight about how the

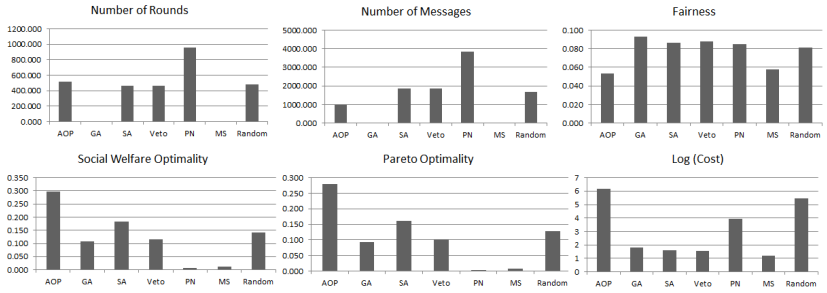

Fig. 4. Average Distances in Validation Sets

mechanisms will perform outside of the specific settings they have been tested in.

An approach to allow for consistent comparison of negotiation approaches is benchmarking. A first attempt at it was initiated in 2010, when the first automated negotiating agents competition was organized [2]. ANAC allowed to build a common negotiation repository comprising both negotiation scenarios and negotiation strategies for agents, and also provided a infrastructure, the GENIUS testbed [18], which allowed for the systematic comparison between strategies in "tournaments". Although it is promising that some researchers have recently started using ANAC repository as a benchmark in order to assess how well their approaches work [26,3], the ANAC approach has some limitations. First of all, the ANAC scenario repository consists of only scenarios where the negotiating agent preferences are represented by means of linear additive utility functions, and this scenario repository is generated in a somewhat ad-hoc manner (i.e. competitors submit new scenarios every year), so it is not aimed to provide diversity in a systematic way. Moreover, ANAC agent repository provides agent strategies to be used in a particular negotiation protocol (e.g. Rubinstein's alternating offers protocol [23]), but does not support the possibility to compare complete negotiation mechanisms involving different protocols. Finally, the tournament approach of the ANAC competition supports the "overall winner approach" assumption, which does not help to solve the problem from the user perspective, which is to be able to select which mechanism to use for a given negotiation scenario.

To meet this need, in this paper, we have established a set of scenario metrics based on our previous work in nonlinear negotiation [20], and we have generated a wide set of scenarios. We have benchmarked a selection of negotiation approaches from the literature in these settings, and analyzed the results according to performance indicators such as social welfare optimality or negotiation cost in terms of computation. Our results show that no single mechanism is a clear winner for all performance criteria, neither a single mechanism is a winner for all scenarios. The results also show that we can effectively use the aforementioned scenario metrics and a decision tree classifier to map the scenarios onto the most

suitable mechanisms to handle them. Finally, we have tested the predictive capabilities of the classification approach, showing that our classifier selects the best performing approach when facing new scenarios in more than 90% of the cases.

The experiments conducted have validated the hypothesis of this work, and open new avenues for research. We want to explore a wider variety of negotiation scenarios, increasing the number of agents involved in the negotiation and adding the effect of discount factors, for instance. We are also interested in trying different machine learning techniques, such as random forests and extreme learning machines. Finally, we would like to extend our dataset by adding more scenarios and more negotiation mechanisms from the ones available in the literature. We believe that having a large set of scenarios and mechanisms is crucial for the success of any machine-learning mechanism selection approach, and we count on the growing community of *Negowiki* users to achieve that.

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