A new mechanism for negotiations in multi-agent systems based on ARTMAP artificial neural network

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Abstract. Any rational agent involving in a multi-agent systems negotiation tries to optimize the negotiation outcome based on its interests or utility function. Negotiations in multi-agent systems are usually complex, and a lot of variables exist which affect the agents' decisions. This becomes more visible in competitive or multi-issue types of negotiations. So, the negotiator agents need an efficient mechanism to do well. The key solution to this type of problems is employing a powerful and operative learning method. An agent tries to learn information it obtains from its environment in order to make the best decisions during the negotiations. In real-world multi-agent negotiations, the main source of usable data is the negotiators' behaviors. So, a good learning approach should be able to extract the buried information in the 'negotiation history'. In this work, we used an ARTMAP artificial neural network as a powerful and efficient learning tool. The main role of this component is to predict other agents' actions/offers in the next rounds of negotiation. When an agent finds out what are the most possible offers which will be proposed, it can predict the outcomes of its decisions. In addition, a new method to apply this information and determine next moves in a negotiation is proposed. The obtained experimental results show that this method can be used effectively in real multi-agent negotiations.

Keywords: Multi-agent systems, Negotiation, Learning, ARTMAP artificial neural network

1 Introduction and Background

Negotiations in multi-agent systems (MAS) are one the challenging domains that still need more research and study in order to approach the efficiency and stability of negotiations between human beings. These negotiations become more complex when they involve multi-lateral problems and include many rational agents with different or even conflicting desires. Agents usually try to maximize their utility and minimize the negotiation duration, especially in non-cooperative domains. All of these make importance of a learning mechanism more obvious.

Agents use a learning tool to find out how to proceed the negotiation. The agents involving in different negotiations usually show a similar behavior and attitude, and some kind of pattern can usually be find in their activities. In real MAS negotiations this behavior of agents is the main usable source of information which can be used in order to learn agents' behavior and predict their next moves. MAS negotiations usually take place within sequential rounds that each agent proposes its offer/s in every round. That is why most of the existing works on MAS negotiations are based on learning methods which use the negotiation history or log [5]. Artificial neural networks (ANNs) are one of most common learning tools which the existing negotiation models already used.

In [3] an approach to modeling the negotiation process in a time-series fashion using artificial neural network is proposed. In essence, the network uses information about past offers and the current proposed offer to simulate expected counteroffers. On the basis of the model's prediction, what-if analysis of counteroffers can be done with the purpose of optimizing the current offer. The neural network has been trained using the Levenberg-Marquardt algorithm with Bayesian Regularization. AN RBF neutral network technology in multi-agent negotiations is introduced in [8]. This method establishes a bilateral-multi-issue negotiation model, and defines corresponding negotiation algorithm and utility evaluation functions. Negotiation agents learn to change their belief of the environment and other agents, using RBF neutral network, thus to determine the inference strategy in negotiation. An artificial neural network-based predictive model with application for forecasting the supplier's bid prices in supplier selection negotiation process (SSNP) is developed in [7]. By means of this model, demander can foresee the relationship between its alternative bids and corresponding supplier's next bid prices in advance. The purpose of this work is applying the model's forecast ability to provide negotiation supports or recommendations for demander in deciding the better current bid price to decrease meaningless negotiation times, reduce procurement cost, improve negotiation efficiency or shorten supplier selection lead-time in SSNP. In [9] an adaptive feed-forward ANN is used as a learning capability to model other agent negotiation strategies. Another learning based method which employs ANN is produced in [12]. The aim of this method is to implement interactions between agents and guarantees the profits of the participants for reciprocity. In the system, each agent has a learning capability implemented by an artificial neural network to generate sequential offers and can be trained by the previous offers that have been rejected by the other agent. With this negotiation model, agents can negotiate with each other over a set of different issues of a product on behalf of the real-world parties they represent. In [11], a data ratios method is proposed as the input of the neural network technique to explore the learning in automated negotiation with the negotiation decision functions (NDFs) developed in [6]. The concession tactic and weight of every issue offered by the opponent are learned from this process exactly. After learning, a trade-off mechanism is applied to achieve better negotiation result on the distance to Pareto optimal solution. An ANN and GA-assistant method which uses genetic algorithm to predict the behavior of opponents and employs MLP and RBF ANNs to refine the results is proposed in [10].

In this paper, we will introduce our method which employs ARTMAP ANN as a learning tool like the described methods. We believe that this type of ANN is the most fitting kind of ANNs that can be efficiently used in multi-agent negotiations. Firstly, in section 2, ARTMAP ANNs and their main favorable characteristics will be briefly discussed. In section 3 the proposed method will be illustrated. Section 4 discusses the experimental results. Finally, section 5 includes concluding remarks.

2 Using Neural Networks in Multi-agent negotiations

The learning mechanism that is used in MAS negotiations domains should be simple and powerful. This usually makes a trade-off between simplicity and learning ability. For example, although evolutionary based learning methods have satisfying learning ability, but they generally need considerable computing time. ANNs have both characteristics. Artificial Neural networks are among most powerful learning tools. They efficiently can be used in real-time environments. After training phase -which may last long, they can generate desired results immediately. Artificial neural networks like other pattern recognition tools, may be used in supervised or unsupervised learning based applications. In supervised domains, class type of each dataset entry is known, and a neural network tries to adapt itself to the available data. In unsupervised cases, the class types are not known.

As mentioned earlier, it is assumed that every agent involved in a negotiation has a history or archive of others' previous actions. Negotiation mechanisms usually try to maximize payoff or utility of an agent after the negotiation ends. Experiments show that agents usually repeat their behavior and use similar strategies in the same situations and show same eagerness to concede [2]. So behavior history of an agent can be used as a useful source for predicting its behavior in the future. From this point, we reach to the idea of employing Neural Networks as a prediction tool. For this purpose, as we have a kind of training set (transactions history) it seems that supervised learning types of Neural Networks are more appropriate than unsupervised ones. In addition, the agents which involve in the negotiations, do not have complete knowledge about other agents. Like the negotiations that take place in human societies, they can usually observe only what other agents offer in each round. Any additional assumption about available data may limit the generality of a negotiation mechanism. When a negotiation starts, a negotiator agent records the offers that other agents propose. As the negotiation proceeds, these records increase, and the agent's data grows. So, the artificial neural network which is used here should be able to adjusts itself to this new added data. This means that ANN must adjust itself to the new data efficiently and with minimum changes in the network. In ANNs' term, the ANN should be able to learn incrementally.

When these two main characteristics are put next to each other (effective supervised and incremental learning ability), we reach to the ARTMAP ANN. This type of ANN employs supervised learning and is able to adapt itself with the new entering data. In ARTMAP, adding new samples does not need to retrain all of the network with the enlarged training set until a new stable state is reached. Number of class nodes is not pre-determined and fixed. The fixed number of classes − which is a common property of ANNs − may result to under or over classification. In this case, there is no way to add a new class node (unless a free class node happens to be close to the new input). Any new input X has to be classified into one of existing classes (causing one to win), no matter how far away X is from the winner, and generally, no control of the degree of similarity exists. Table 1 shows several main types of ANNs. As the table shows, other type of ANNs (especially their classic versions) do not have both supervised and incremental learning ability. This makes ARTMAP one of the best candidates to be used in MAS negotiations.

Table 1: Supervised & Incremental learning support of main types of ANNs

	MLP	Recurrent Nets.	RBF	Kohonen	Art
Supervised	✓	✓	✓	×	✓
Incremental	×	×	×	✓	✓

The main problem of general ANNs is that gradually decreasing the gain parameter, usually freezes the network's weights, and consequently no flexible reaction to new data is made. ARTMAP, that is based on the theory of 'ART', could solve these issues efficiently.

Adaptive Resonance Theory (ART) is a theory developed by S. Grossberg and G. Carpenter on aspects of how the brain processes information [1]. It describes a number of Neural Network models which use supervised and unsupervised learning methods. This paper focuses on the prediction ability of ART Neural Networks. This ability is applied by negotiator agents to predict other agents' next offer/s. For more details about ARTMAP the reader is referred to [4].

3 The proposed method

In describing the proposed method, we firstly introduce the configuration of applied ANN. Fig. 1 shows the general structure of applied ANN. The existing idea here is that the ANN receives last offers which the agents proposed in the previous round of negotiation and then predicts next offer which each agent will propose. The inputs of the network are all of offers proposed by the negotiators in the previous round of negotiation plus the number of current round. The outputs of the network are the predicted offers of other negotiator agents in the next round. In this manner, in a negotiation containing 'n' agents, the number of the network's inputs is n+1, and the number of outputs is n-1(the number of other agents). The history of previous negotiations is the main source of information in real negotiation domains. Like the human negotiations, the previous offers of other negotiators and the round in which the negotiation is being performed are the most important factors that determine the offer the negotiator propose. In other words, in a same round of two negotiations which the previous offers are the same, an agent will probably propose the same offer. Our experiments show that this probability is high. As the negotiations proceed, the ANN learns more, and produces predictions that are more accurate.

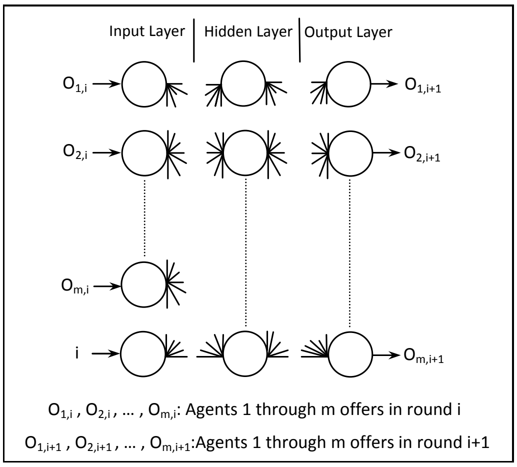

Fig. 1: Simple schema of the proposed ARTMAP ANN

Before proposing its offer in a round, a negotiator agent employs the ANN to find out the probable offers of other agents. As we discussed, "payoff" and "time" are two main factors that agents want to optimize. So, an agent uses the information that it obtains from the ANN to reach these goals.

Time effect is taken into account in MAS negotiations through different approaches. Here, we use a method which often is used in bargaining domains. In these domains a discount ratio, 'Ω', is used to represent the effect of time. This value determines the value of an offer in the next rounds, knowing its value in current round. Higher Ω value implies less importance of time for an agent. For example, if Ω is equal to 0.9 and the utility value of an arbitrary option like o_1 in the round i is 100, the utility value of this option in round $i+1$ will be 90.

Here, we illustrate our scenario for the agents to use the ANN results in order to choose their next offer. In each round, agents propose their offers. Other characteristics of negotiation domains like being single-issue or multi-issue, bilateral or multi-lateral, competitive or cooperative do not have a direct effect on our method, and the proposed method can be efficiently used in all of these domains. Every negotiation has a set of valid or admissible offers that negotiators

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1- Generate a random number (R) between 0 and 1
2- Sort the available options, and determine the option with maximum utility value \\maximal option
3- IF (R < Exploitation Probability) THEN
       \\The ARTMAP ANN is trained and its results including the agents' next offer are available
4-     Sort the options which guarantee agreement in the current round [based on the learning results], and
       determine the option having maximal utility \\rational option
5-      IF (rational option's utility > maximal option utility AND rational option's utility > agent's minimum
       utility) THEN
6-            Propose the rational option
7-     ELSE IF (Maximal option's utility > agent's minimum utility) THEN
8-            Propose the maximal option
9-     ELSE
10-           Quite the negotiation
11- ELSE
12-    Propose the maximal option \\learing is not used
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Fig. 2: Pseudo-code of the proposed method

can propose. As described in the previous paragraph an agent's first concern is to maximize its utility and after this it tries to minimize the negotiation time (because in all of MAS domains passing time is costly). Like any rational and self-interested agent, in each round the negotiator agent firstly determines the offer which maximizes its utility. We call this, 'maximal potion'. This offer usually is selected by the agent among a set of offers that the agent can propose. This may be a simple sorting process or may require complex computations. After this, the agent should take into account the 'time' measure, too. In this step, the agent checks the results of the ANN. Considering the previous offers which the agents proposed in earlier rounds in addition to the predicted offers, if the maximal option guarantees reaching agreement (and consequently, ending the negotiation) the agent will propose the maximal offer. If the maximal option does not ensure reaching agreement, the agent will check other options it can propose. If there was an option that guarantees agreement, and its utility value is greater than the utility of maximal option in the next round, the agent would propose this option. We call this option "Rational Option". Rational option is the maximal option between the options ensure reaching agreement in the current round. If proposing the maximal option ends the negotiation in the current round with an agreement, the maximal and rational option will be the same. The idea here is that the maximal option −in the best case− will be applicable in the next round (not in the current round), but the rational option although has less utility than the maximal option, but in practice the agent would gain more utility by offering the rational option. In other words, in this case the rational option becomes maximal option. Fig. 2 shows pseudo-code of the proposed method for an arbitrary agent.

To illustrate this idea, consider this example. Imagine an agent like a_1 that can choose its offer from a set of three options: o_1, o_5, o_6 in an arbitrary round, 'i'. It is assumed in this example that each agent may offer only one option in each round, and these options should be chosen from an option pool containing six options. The agreement is met when a permutation of proposed options can be found that all of six options are assigned to the agents based on their offers. The option which maximizes the agent's utility function (maximal option), is o_1 with the utility of 100. o_6 is the rational option which guarantees agreement, and its utility is greater than o_1's in the next round. Fig. 3 shows this scenario.

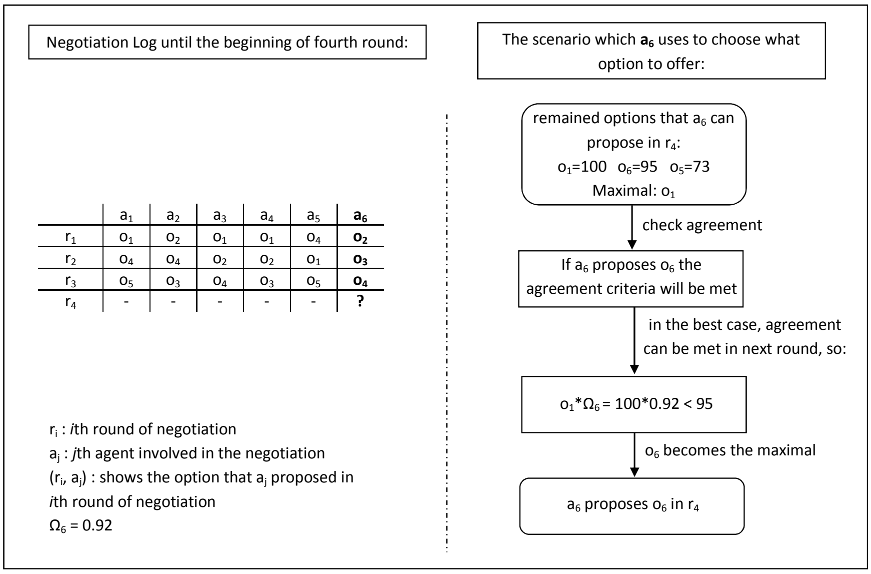


Fig. 3: Choosing the next offer using information obtained after learning

Some minute details of the proposed method are still unclear which will be illustrated here. When the negotiations starts, agents' history of previous proposed offers are empty, and consequently there is no record for the ANN to learn agents' behavior. To resolve this problem, a "exploitation probability" is assigned to each agent which indicate the probability that the agent employs the ANN's results to choose its next offer. This probability increases as the negotiation proceeds. Another issue is that each agent have a minimum utility value that indicates until when the agent is going to participant in the negotiation. An agent decide to leave the negotiation table, when it finds out that it cannot gain its minimum utility value by continuing the current negotiation.

4 Experimental Results

In this section, we illustrate several experiments which were accomplished in order to examine the proposed method. The negotiations are about a task allocation problem. There are n different tasks and n agents who want to choose the task having maximum utility. The agreement is reached when a permutation of offered options can be found that each task is assigned to one agent. Assignment of a task to an agent is possible only when that option is previously proposed by that agent. In the following experiments, the number of negotiator agents (which is equal to the number of tasks) are 20 and 100. These agents participate in 20 sequential negotiations. All of these negotiations are about the task assigning problem, but each time 20(100) tasks are randomly chosen from a pool of tasks including 40(200) different tasks. The configurations of negotiations are the same for both of methods being studied. This means that the tasks existing in each of 20 sequential negotiations are used to evaluate both of methods. Table 2 shows the configurations of the ARTMAP ANN which is used in the experiments. Number of inputs −as was shown in Fig. 1− is equal to number of negotiator agents plus the number of round in which those offers were proposed. Number of outputs is equal to the number of involved agents. In this manner, each record of an agent's history −which is used during the training phase of the ANN− includes $2n + 1$ fields: n fields for all of agents' offers in a negotiation's round, n fields for their offer in the next round, and the last remaining field for the round number. The initial values of the ANN's weights are set to 1, and each ANN is trained within 100 epochs.

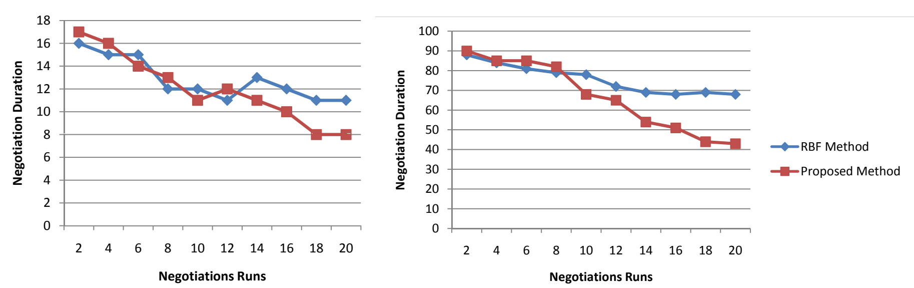
Table 2: The configurations of ARTMAP ANN used in the experiments

Inputs Num.	Outputs Num.	Net's weights	Vigilance Param.	Epochs Num.
21/101	20/100	all initially equal to 1	0.75	100

The proposed method is compared with another method which is introduced in [8]. In this work, an RBF ANN is used by the agents in order to determine their proposals in each round. The RBF ANN's settings are like the ones which are described in the original work. The applied radial basic function in the network is illustrated there, too. The inputs and outputs are the same as above.

"Negotiation time" and "Agents' utility" are two main factors that each agent wants to optimize them. Accordingly, these two measures are used in order to examine two available methods. The time (duration) of negotiation shows the number of rounds that it takes until the negotiation ends. The negotiation ends when the agreement is reached. Here, agreement is guaranteed, because the negotiators cannot propose repeated offers. Accordingly, it takes at most n rounds in order to reach agreement (after n round a permutation exists). Furthermore, the agents' utility refers to the average of the utility values that all of negotiator agents gain after the negotiation ends. A better negotiation mechanism should be able to decrease the duration of negotiation while maximizing the agents' utility. Each task has a different utility value from each agent's point of view. These utility values are randomly produced between 0 and 100.

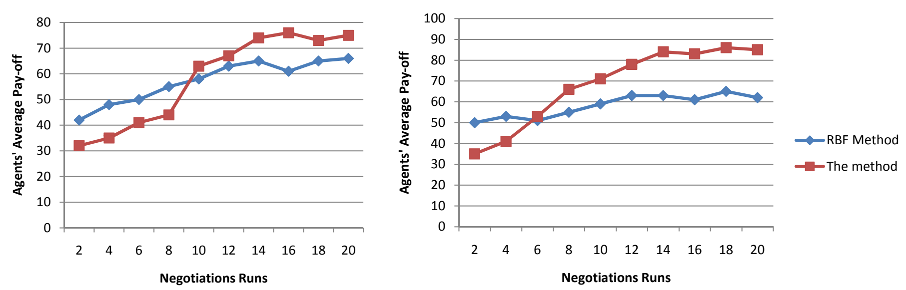
Fig. 4a shows the duration of negotiations between 20 agents. When the number of negotiations increases, both of methods were able to learn almost well.



(a) 20 agents involved in negotiations (b) 100 agents involved in negotiations

Fig. 4: Negotiation time in 20 sequential negotiations.

The proposed method's results surpass the other method after the thirteenth round. In the Fig. 4b negotiation time between 100 agents is displayed. In these experiments our method totally outperforms the RBF based method, where the second method's results approximately stays fixed after the 13th round.



(a) 20 agents involved in negotiations (b) 100 agents involved in negotiations

Fig. 5: Average agents' pay-off, in 20 sequential negotiations.

Agents' pay-off(utility) is the second measure which is studied in Fig. 5a and Fig. 5b. In these figures the average pay-off of all of agents involving in the negotiations are shown in different rounds. As the number of agents increases (from 20 to 100) our method's shows better performance. This means that the proposed method can be efficiently used in domains with many agents which makes the negotiation domain more complex.

5 Conclusion

In this work a new mechanism for negotiations in multi-agent systems is proposed. This methods relies on ARTMAP artificial neural network to learn. A negotiator agent employs this learning tool in order to determine the most possible offers which other agents will propose. Then, the agent checks the possibility of each option to end the negotiation with an agreement. Based on the utility value of each option, the agent chooses its next offer. The described characteristics of ARTMAP in the paper shows that this type of ANN which is embedded within our method is one the best candidates for our usage. Using ARTMAP allows us to implement the method in real-time applications. The proposed method was examined within several experiments and has obtained satisfactory results in its first applications.

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A short description of modifications:

The paper was reviewed in order to meet the reviewer's ideas. Several paragraphs are added to this version which are described in the following. All of manuscript's figures are modified and improved. The ARTMAP schema (Fig. 1) at the end of the second section and its related descriptions were omitted. As this information can be foundinother works on ARTMAP, and does not have an essential role in describing our method, the reader is referred to other references. This helped the manuscript to meet the maximum paper's length.

-Second Reviewer-

* Please give more justification why do you think the ARTMAP networkisespecially useful for a given task. Compare it with other approaches and kinds ofnetworks.

-The first paragraph on the second section is extended. We tried to firstly describe the reason which makes ANNs a good candidate to be used. Secondly, a new table is added to the manuscript that shows the comparison among several main types of ANNs. This comparison is based on two important characteristics of ANNs considering our domain specifications.

* Give more description of fig. 2 and extend it by addinginformation about learning results applied during the decision process.How the agents selects the negotiation options? Precise the order ofvalues of option utilities.

- A new through paragraph is addedat the beginning of the 3rd section. In this paragraph we tried to address all of requested information.

The figures of this section were revised and improved.

* Add more description to section "4 Experimental results",especially discussion of dependence between negotiation duration and agents' average pay-off.

- A new paragraph is added to this section describing "Negotiation time" and "Agents' utility", and some other descriptions.

* English is poor, it should be corrected.

-The manuscript was reviewed, in order to meet this requirement.

-Session Chair-

Also, please check your paper meets the springer formatting instructions, particularly regarding length.

NB extra pages are possible if the author pays an extra length charge.

- The manuscript is reorganized through LNCS template. It is shortened too.