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Review

A review on soft computing techniques in automated negotiation

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Automated negotiation offers new capability for buyers and sellers to efficiently trade goods and services in online markets. In high-dimensional real world negotiations, many agents may communicate with each other over multi-issue products. In this paper, we review soft-computing techniques used in e-negotiation. Although implementation of real world negotiations is very hard but using soft computing techniques can lead us to a suitable approximation in automated negotiation. Using a combination of soft computing techniques can decrease the complexity of high-dimensional negotiation.

Key words: Electronic marketplace, automated negotiation, soft computing, complexity.

INTRODUCTION

Interest in building electronic market places on the web has been increasing rapidly. In fact easier access to the required information at the right time and in the most suitable form by the customers makes the Web as the focal point of attentions and research. But this significant media, the Web, is not utilized to satisfy the customers and providers needs because of the products and contracts complexity. Consequently, automated negotiations have received more attention as their key form of interaction between providers and customers (Matos et al., 1998).

The main goal of bilateral negotiation (bargaining) is to find a joint agreement. Although, bargaining problem is an old problem in the field of game theory and Economics, nowadays, this problem is an interesting area of research in information technology as automated negotiation.

Negotiation is the process by which a group of agents communicate with one another to try to reach agreement on some matter of common interest (Lomuscio et al., 2003). One of the main benefits of negotiation in e-individual customer preferences, and it supports buyer decisions in settings which require agreements over complex contracts. Automating the negotiation process through the use of intelligent agents which negotiate on behalf of their owners, enables electronic merchants to go beyond price competition by providing flexible contracts, tailored to the needs of the individual buyers. In addition, online markets are more efficient than their physical-world counterparts thus lowering transaction costs for both merchants and consumers. For example, low transaction cost is one reason why Amazon[1] and eBay[2], as e-marketplaces, can offer a greater selection and lower prices than its physical-world competitors.

Soft Computing refers to a collection of computational techniques in computer science, artificial intelligence and machine learning, which attempt to study, model, and analyze very complex phenomena: those for which more conventional methods have not yielded low cost, analytic, and complete solutions. Complex systems arising in commerce, the humanities, management sciences, and similar fields often remained intractable to conventional mathematical and analytical methods.

Although, no polynomial-time algorithm has yet been discovered for complex problems, but no one has proven

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[1] http://www.amazon.com/
[2] http://www.ebay.com/

that no polynomial-time algorithm can exist for them. Usually, we can't find the exact solution for complex systems in a short time, therefore most of the researchers looking for proper approximation for their problems or reducing the complexity of the system.

Using soft computing in intelligent software agent is one of most effective approaches to automate negotiation between e-commerce parties. There are many attempts to make automated negotiation closer to real world negotiation by using soft computing. The aim of this paper is to present the area of using intelligent agents in automated negotiation and reviewing artificial intelligent (AI) techniques used in recent researches that can reveal the problems associated with e-negotiation.

AUTOMATED NEGOTIATION ROADMAP

The term-automated negotiation encompasses techniques and mechanism that are used to deliver a value-added trading experience in electronic market places. This value is usually attained by using soft computing techniques to improve the efficiency of decision making. Two basic components are important when designing an automatic negotiation system: the negotiation protocol and the negotiation strategies (Lomuscio et al., 2003). The former specifies the "rules of encounter" between the negotiation participants. That is, the protocol defines the circumstances under which the interaction between the agents takes place: what deals can be made and what sequences of offers are allowed. An agent's negotiation strategy is the specification of the sequence of actions (usually offers or responses) the agent plans to make during the negotiation. There are many strategies that are compatible with a particular protocol, each of which may produce a different outcome. A negotiation mechanism consists of a negotiation protocol together with the negotiation strategies for the agents involved. There are some properties that are generally considered desirable for a negotiation mechanism (Lomuscio et al., 2003) such as: computational efficiency, communication efficiency, individual rationality, distribution of computation and Pareto efficiency.

An outcome is Pareto efficient if there is no other outcome that improves the lot of one agent without making another agent worse off. All other things being equal, Pareto efficient solutions are preferred over those that are not (Lomuscio et al., 2003). This review concentrates on computational complexity.

Real world negotiation has many features which makes it complicated to be automated. For example, following features can show the complexity of negotiation:

1. Number of issues for generating a new offer and for analyzing counter-offers (for example, price, quantity, delivery time, quality).
2. Number of agents involving in negotiation (it can be one-to-one, one-to-many or many-to-many).
3. Number of possible strategies to make a new offer.
4. Finding opponent's preferences to make offers which can accelerate reaching to total agreement.
5. Utility function for each negotiation parties (it can be non-linear and hard to be predicted by the agents).
6. Tradeoffs between negotiation issues.

A high-dimensional negotiation can be considered as a multi-agent system for trading multi-issue goods with tradeoffs between them; where we need a decision making through strategies space to maximize utility function of negotiation parties.

In multi-issues negotiation, the search space is very huge and finding an agreement is time consuming. Satisfying all negotiation parties is one of the Nondeterministic Polynomial-time hard (NP-hard) problems (Parkes et al., 1999). It means that the time of negotiation will grow exponentially by a little increasing of the negotiation's dimension. In other words, finding exact solution for NP-hard problems needs a lot of time. So, approximation techniques are useful in automated negotiation. There have been several attempts to find a proper approximation for automated negotiation where soft computing techniques are appropriate to use.

Argumentation-based negotiation (ABN) is another approach to find an agreement in possible offer search space. ABN uses logic-based inferring mechanism to find agreement which is more similar to real world negotiation.

SOFT COMPUTING IN E-NEGOTIATION

Soft computing is defined by Zadeh (1965) as follows: "Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty and partial truth. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost. At this juncture, the principal constituents of soft computing (SC) are fuzzy logic (FL), neural network theory (NN) and probabilistic reasoning (PR), with the latter subsuming belief networks, genetic algorithms, chaos theory and parts of learning theory. What is important to note is that SC is not a mixture of FL, NN and PR. Rather; it is a partnership in which each of the partners contributes a distinct methodology for addressing problems in its domain. In this perspective, the principal contributions of FL, NN and PR are complementary rather than competitive"[3].

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[3]Soft Computing Home Page URL: <http://www.soft-computing.de/def.html>

Table 1. General attributes of soft computing techniques.

Variable	Fuzzy system	Neural network	Genetic algorithm	Probabilistic reasoning
Learning ability	None	Very good	Good	Good
Fault tolerance	Good	Very good	Good	Good
Type of inference	Approximation	Approximation	Approximation	Approximation
Using expert's knowledge	Very good	None	None	Good

In this paper we will review four soft computing techniques: Fuzzy system, neural network, genetic algorithm and probabilistic reasoning.

Table 1 summarizes general attributes of these techniques (Gorzatczany, 2002). Although synergy of these techniques can yield a powerful system, but most of the researches in automated negotiation have used them alone.

Fuzzy system

The theory of fuzzy sets and fuzzy logic were formulated by Zadeh (1965). This theory was introduced as a means for representing, manipulating, and utilizing data and information that possess non-statistical uncertainty (Gorzatczany, 2002). Fuzzy logic provides inference mechanism capabilities that enable approximation reasoning and model human reasoning capabilities to be applied to knowledge-based systems. The theory of fuzzy sets provides a mathematical apparatus to capture and handle the uncertainty and vagueness inherently associated with human cognitive processes, such as perception, thinking, reasoning and decision making.

In automated negotiation, agents negotiate on behalf of their owner. For this to be effective, agents must be able to adequately represent their owner's interest, preferences, and prejudices in the given domain such that they can negotiate faithfully on their behalf.

Luo et al. (2003) used fuzzy constraints to acquire user's preferences. They showed that fuzzy constrains can be applied in e-negotiation, because: User's preferences are often expressed by constraints on the various negotiation issues (for example, price and time).

1 Users often have tradeoffs among various negotiation issues, and these can be modeled by fuzzy constraints.

2 Usually, there is an ordering over preferences constraints (for example, delivery time may be more important than the price for a user).

Finding tradeoffs among issues can help to reduce negotiation complexity. Although, Luo et al. (2003) showed that, fuzzy constraints can cover tradeoffs among issues, but their implemented interface needed a lot of interaction with user to find user interest before starting negotiation.

Kowalczyk (2002) presented a prototype of fuzzy e-negotiation agent for autonomous multi-issue negotiation in e-commerce. Negotiation in his work has been considered as a form of distributed decision-making in the presence of limited common knowledge and imprecise/soft constraints, and modeled as a distributed fuzzy constraint satisfaction problem. In general, he has shown that fuzzy constraint-based reasoning allow agents to find a consensus that maximizes the agent's utility and the level of its fuzzy constraint satisfaction subject to its acceptability by other agents.

A similar work to Luo et al. (2003) and Kowalczyk (2002) has been done by López-Carmona and Velasco (2006), where fuzzy constraints are used. In their work, a buyer agent attends to the seller's requirements in order to select the alternative from the set of trade-off proposals that is likely to benefit both agents. Typically, this has been done employing an estimation of the similarity between an offer and the set of feasible counter-offers. The problem related to their work is that they assumed that the potential offers are related among agents, and this is not always the case.

He et al. (2003) applied the fuzzy logic to negotiation strategy. In their work, a fuzzy logic strategy uses heuristic fuzzy rules and a fuzzy reasoning mechanism to decide what bids or asks to place. They then extended this strategy so that the agent could adapt its bidding behavior to its prevailing market context.

Although these researches showed that applying the fuzzy logic can improve the e-negotiation process, but we believe that synergy of fuzzy logic and neural network will provide a better tools for automated e-negotiation.

Neural network

A neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases, an NN is an adaptive system that changes its structure based on external or internal information that flows through the network.

In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

Papaioannou et al. (2006) presented a single-issue bilateral negotiation framework designed for self-interested autonomous agents that act in e-commerce environments. It focused on the design and evaluation of a negotiation strategy that exploits an efficient learning technique in order to increase the possibility of successful negotiations. This technique has been employed by client agents and is based on the training of a feed-forward back-propagation neural network with a single output linear neuron and three hidden layer's neurons. Their proposed negotiation strategy couples this learning technique with a fair relative tit-for-tat imitative tactic, and attempts to estimate the Provider's subsequent price offer upon the expiration of the Client's deadline. The obtained results indicate that in case the acceptable price intervals of the negotiators are identical, the proposed approach always succeeds in reaching to an agreement. Although, Papaioannou et al. (2006) showed that NN can reduce the cases of unsuccessful negotiations and maximize the client's utility, but in contrast with the real world negotiation, they just examined NN in low-dimensional negotiation.

Zhang et al. (2004) described a hybrid negotiation strategy mechanism using a strategy pool framework that allows negotiation agents to communicate more flexible and robust in an automated negotiation system. They address two problems in automated negotiation. First, agents are not as flexible and adaptive to different negotiation environments as desired. Negotiation environment is a set of pre-defined negotiation features which are not negotiable in negotiations. This means that an agent may work well under one set of negotiation features, but perform worse in others. Second, a fixed strategy or a static group of strategies may become known by competing agents as a result of negotiation processes, after which those agents can potentially exploit this knowledge in future negotiations. To solve these problems they used the strategy pool framework to support: a) dynamically assigning an appropriate negotiation strategy to a negotiation agent according to the current negotiation environment and b) creating new negotiation rules by learning from past negotiations. The learning forms used for the framework were feed forward back propagation (FFBP) neural networks and multidimensional inter-transaction association rules mining.

Moreover, Papaioannou et al. (2006) tried to compare the performance of multi-layer perceptron (MLP) and radial basis function (RBF) neural networks employed in single issue bilateral negotiating. Proposed negotiation strategies couple with the neural network learning techniques used to estimate the Provider's subsequent price offer upon the expiration of the Client's deadline. They found that RBF neural networks can work faster than MLP neural network for learning.

These studies show that neural network has been used either in single-issue negotiation or in bilateral negotiation. But in high-dimensional real world negotiations, many agents may communicate with each other over multi-issue products. This means that using just neural network is not efficient to reduce the complexity of high-dimensional e-negotiation. Neuro-Fuzzy (NF) is a synergy of neural network and fuzzy logic. As a future work, we propose using of NF in high-dimensional e-negotiation.

Genetic algorithm

A genetic algorithm (GA) is a search technique used in computing to find true or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (Sumathi et al., 2008).

Genetic algorithms are implemented as a computer simulation in which a population (called chromosomes) of candidate solutions (called individuals) evolves toward better solutions for optimization problems. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. A general form of GA can be like this:

1. Choose initial population
2. Evaluate the fitness of each individual in the population
3. Repeat
a. Select best-ranking individuals to reproduce
b. Breed new generation through crossover and mutation (genetic operations) and give birth to offspring
c. Evaluate the individual fitness of the offspring
d. Replace worst ranked part of population with
e. offspring
4. Until <terminating condition>

Oliver (1996) reinforced the idea that computational science in general, and evolutionary algorithms in particular, provide a rich tool for the study of bargaining and negotiation. He showed that agents can learn strategies by using GA to effectively participate in business negotiations.

Matos et al. (1998) presented an empirical evaluation of a range of negotiation strategies and tactics in a number of different types of environment. They take an evolutionary approach encoding negotiation parameters as genes in a GA. The aim of the evaluation was to assess the operational benefits and drawbacks of a number of negotiation strategies. To this end, they have presented a number of concrete results about the relative merits of particular tactics and strategies.

Like two previous works, Tu et al. (2000) used genetic algorithm to implement strategies for automated negotiations. In their work, genetic algorithms evolve FSMs (Finite State Machines). Each of these FSMs represents a negotiation strategy that competes against other strategies and is modified over time according to the outcome of this competition by using GA principles. They showed that their results can be at least as good as Oliver's work (Oliver, 1996).

The problem related to GA in high-dimensional negotiation is that, it needs a lot of time to generate all population and find the optimum answer.

Probabilistic reasoning

Bayesian learning is most prominent probabilistic approach in e-negotiation. A Bayesian network (or a belief network) is a probabilistic graphical model that represents a set of variables and their probabilistic dependencies. Formally, Bayesian networks are directed acyclic graphs whose nodes represent variables, and whose arcs encode the conditional dependencies between the variables. Nodes can represent any kind of variable; it can be a measured parameter, a latent variable or a hypothesis.

Zeng and Sycara (1989) proposed a sequential decision making model of negotiation, called Bazaar. It provides an adaptive, multi-issue negotiation model capable of exhibiting a rich set of negotiation behaviours. Within the proposed negotiation framework, they modeled learning as a Bayesian belief update process to learn opponent's strategy.

Saha and Sen (2005) presented a novel Bayesian network based argumentation and decision making framework that allows agents to utilize models of the other agents. The agents will generate effective arguments to influence the other agent's belief and produce more profit. The Bayes nets allow capturing the complex interrelationships between domain issues and their influence on the opponent's decisions.

However, a significant drawback of Bayesian learning is that the agent has to have a priori knowledge about the probability distribution of the likely outcome of the negotiation (Coehoorn and Jennings, 2004). This is difficult to provide because of the private nature of the information needed to compute this. Coehoorn and Jennings (2004) explored the use of kernel density estimation to find opponent's preferences in multi-issue bilateral negotiation. The kernel density estimation is a way of estimating the probability density function of a random variable. As an illustration, given some data about a sample of a population, the kernel density estimation makes it possible to extrapolate the data to the entire population. They couch their work in the context of making negotiation trade-offs and show how their approach can make the negotiation outcome more efficient for both participants.

However, it is shown that probabilistic reasoning can be useful in e-negotiation but its abilities to find opponent's preferences and negotiation trade-offs are almost the same as fuzzy logic.

ARGUMENTATION-BASED NEGOTIATION

Argumentation-based negotiation (ABN) allows agents to argue and justify their desires and intentions during the negotiation process (Meyer et al., 2004; Rahwan et al., 2003; Sycara, 1989). An agent may persuade the opponent to change its belief state by proposing threats, rewards and promises via iterative exchange of offers (Parsons et al., 1998; Ramchurn et al., 2007). That is, similar to strategic approaches, in ABN, agents should be able to alternate offers and dialogues. Moreover, they should be equipped by a communication language that facilitates uttering different locutions needed for logic-based argumentation (LBA).

ABN enables richer form of negotiation than what have previously been possible in axiomatic or strategic approaches, due to its similarity to real world negotiation. But ABN is a young area of research compared to the axiomatic and strategic approaches. Recent studies on ABN highly concentrate on designing a conceptual framework that support argumentation (Amgoud et al., 2007; Parsons et al., 1998; Ragone et al., 2008; Rahwan et al., 2003).

So far there is no standard framework for ABN. There is still a need for more work on developing a mechanism for argument evaluation and generation that support agents' intentions by satisfying their preferences and fulfilling social norms.

Having a communication language that supports ABN's requirements can be helpful. In multi-agent systems, two major agent communication languages (ACL) have received serious attention, namely the KQML[4] (Mayfield et al., 1996) and the FIPA ACL (FIPA00003, 2000). But, they have limited locutions (for example, FIPA ACL has 22 locutions) and fail to capture all utterances needed in an ABN. For example, there are no locutions in FIPA ACL expressing the desire to enter or leave a negotiation interaction, or to request an argument for a claim. In other words, ABN needs more locutions (like threaten, reward, promise, and so on) to substantiate argument and rational behavior in MAS (Ramchurn et al., 2003; Sierra et al., 1998).

A successful ABN should be equipped by a mechanism that supports logic and dialogues to integrate argumentation into a belief-desire-intention (BDI) agent

[4] Knowledge Query and Manipulation Language

(Parsons et al., 1998; Rahwan et al., 2003).

During the last decade, researchers have tried different approaches to substantiate the ABN, such as Logic-based argumentation (LBA) (Ragone et al., 2008; Skylogiannis et al., 2007; Zhang and Zhang, 2006) and dialogue games (Amgoud et al., 2000; Mcburney et al., 2003; Sadri et al., 2001). Little research has studied the argumentation with incomplete information. Ragone et al. (2007) applied the description logics in the multi-issue negotiation with incomplete information. Although, their proposed solution support non-linear utility, agents do not have trade-offs capability, and therefore, there is no guarantee to settle a Pareto-efficient solution in limited time. Finding a Pareto-optimal offer with incomplete information is still an interesting area of research.

CONCLUSION

In this paper, a review on some prominent researches in e-negotiation is presented where soft computing techniques is used to reduce the complexity of negotiation and to make it closer to real world negotiation.

Fuzzy Logic (FL), Neural networks (NN), Genetic algorithm (GA) and Probabilistic reasoning (PR) have different abilities which can be applied in different parts of negotiation. These techniques can be merged to facilitate searching in the offer space. Using a combination of soft computing techniques in high-dimensional negotiation where many agents communicate with each other over multi-issue products may also reduce the complexity of negotiation. For example, adding the GA to the NF may utilize the negotiation to find the best strategy for each agent.

Abbreviations: LBA, Logic-based argumentation; **BDI,** belief-desire-intention; **ACL,** agent communication languages; **LBA,** logic-based argumentation; **ABN,** argumentation-based negotiation; **FSMs,** Finite State Machines; **MLP,** multi-layer perceptron; **RBF,** radial basis function; **FFBP,** feed forward back propagation; **NN,** neural network.

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