Using Neural Network and Genetic Algorithm for Business Negotiation with Maximum Joint Gain in E-Commerce

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Abstract
Combination of new information technologies with decision analysis tools provides us great opportunities for improving the efficiency and effectiveness of decision-making and negotiation. Emerging Internet related technologies and, in particular, the World Wide Web and E-Commerce provide yet another opportunity for radical change and improvement in the support and practice of negotiations. In this paper we report our research about using a comprehensive method for achieving an acceptable joint gain in a two party negotiations for negotiation support systems like INSPIRE. In our approach we use artificial neural networks and genetic algorithms for stages of negotiation in order to suggest a suitable compromise for two parts of negotiation that makes their total utility maximized. Applying the proposed model for an example, the results are compared with INSPIRE which is a known negotiation support system.

1. Introduction
Growth of Internet and World Wide Web technology has provided a suitable background for widespread use of electronic commerce tools. Negotiation is one of the most important parts of human capabilities especially in business. It is like a bridge between two major parts of a business: recognition and execution. There is a great need for more powerful infrastructures for negotiation support in digital economy and globalization of economic age. These infrastructures should support different cultures and languages and should be flexible and friendly to use for people.

The aim of this paper is presenting a method based on Artificial Neural Network (ANN) and Genetic Algorithms (GA) for two party negotiations. First we review electronic commerce and the importance of negotiation in the process of business and effect of E-Commerce on negotiation. Then we briefly study the stages of negotiation from literature and INSPIRE system for supporting web-based negotiations. In other sections we briefly discuss ANN and GA and their implications for our main purpose. We describe preparation phase of negotiation with our approach over two issues: Price and Guarantee. Then we outline our proposed model for conduct phase in order to improve understanding of negotiators about their utilities. The method is presented for attaining an acceptable compromise for negotiation in post-settlement phase and offering it to negotiators using GA. We designed a Visual C++ program for our simulation.

2. Electronic Commerce and Negotiation
Electronic commerce is a common name for a variety of software tools and systems that offer services such as search for information, transaction management, authentication and authorization, payment on-line, accounting and reporting, document handling and so on [1,2,3]. These systems provide basic infrastructure for Internet-based commercial activities.

The availability of E-commerce tools allows individual and organizational customers to search for suppliers anywhere and make deals electronically. It is necessary to address two interrelated issues, arising from
this trend that significantly complicate the life of an Internet shopper [4].

Companies aggressively try to attract customers; in conjunction with the expansion of the markets, this sharply increases the number of companies a customer may have to deal with for his success.

- Business decision making and negotiations (conducted both by individuals and organizations) become increasingly complex as access to markets becomes faster and wider, and the amount of interaction shoots up almost uncontrollably.

Negotiations between buyers and sellers, both institutional and individual, involve several activities grouped in the value chain [4,5]. The activities are parallel and involve in both the buyer and seller. During negotiation, the buyer and the seller interact and exchange information. Negotiation may concern only the price (this is typical to auctions), or a wider range of product attributes, product options, including guarantee, delivery time, payment schedules, and service terms. Negotiation is often the first moment when the buyer and the seller interact. The result of this activity is an agreement followed by order placement. It is an important aspect of negotiation that it may establish a relationship between the buyer and the seller that leads to a continuing business [4].

According to negotiation literatures [6,7,8,9], there are three phases for every negotiation as follows:

1. Preparation
2. Conduct of negotiation
3. Post-settlement

During the preparation phase each part individually performs activities like indicating the main issues and options, the possible offers (packages) and criteria. This phase also involves specification of preferences in order to construction of the user’s utility functions.

Negotiators at conduct of negotiation phase exchange offers and messages. The utility of each package is calculated according to information in preparation phase. Each part of negotiation can change his preferences at any time in this phase. At the end of this phase a compromise can be achieved or they can cancel negotiation.

If efficient compromise is not achieved during conduct of negotiation, post-settlement can be started. At this stage negotiators search for another compromises that improve their utilities. Potential compromises should be on contract curves [7]. Therefore another negotiation can be continued like previous phase on these potential settlements, but at this stage the preferences cannot be changed. Packages’ offering is based on information have previously acquired from users in order to constructing utility functions and changing preferences lead to change contract curve and potential efficient compromises.

3. Theoretical Aspect of Negotiation in INSPIRE

INSPIRE is a Web-based negotiation support system. It contains a facility for specification of preferences and assessment of offers, an internal messaging system, graphical displays of the negotiation's progress, and other capabilities. Currently the technique for construction of utility functions in INSPIRE is based on conjoint analysis, in which the utility of a given package is determined from the user's preference orderings over a set of factorial designed alternatives (packages) [11,12]. A hybrid (composition as well as decomposition) approach is used and it comprises three steps as follow [6]:

i. The user evaluates the relative importance of the issues to be negotiated. The rating assigned to each issue is viewed as a component of the total utility of a package. The utility component of each issue is assumed to be independent of the other issues, i.e., any possible interactions are assumed to be insignificant. Therefore the utility components are simply added together to form the total utility function and this is called composition.

ii. The user evaluates the relative importance of each issue's options. The rating of each option constitutes the utility component of an issue when that particular option is the one that's present in a package.

iii. The user makes a comparative evaluation of several complete packages selected by INSPIRE, viewing each package as a whole. This is the decompositional step. The total utility is decomposed into constituent option utilities using an additive model:

\[ \text{Rating (P)} = \text{constant} + \sum_i \sum_j x_{ij} \mu_{ij} + \text{error} \]

Where rating (P) is the total utility of a package and \( u_{ij} \) is the utility associated with issue \( i \) and option \( j \), and \( x_{ij} \) is a binary variable indicating whether the given option is present in the package.

There are a large number of packages that could be presented, and we need some way of selectively presenting just a few packages for the user to rate, yet obtain reliable utility values. This is a problem in the design of fractional factorial experiments. One of the most compacts and effect design problems is the orthogonal design, in which the packages are chosen such that the \( x \) matrix is orthogonal. INSPIRE uses the information obtained in the issue and option ratings steps to select the set of packages presented to the user for the package-rating step. Given the ratings for these orthogonal packages, the weights \( u_{ij} \) are computed that minimize the error terms using linear regression.
4. Description of Proposed Approach

The main purpose of our approach is to present an accepted compromise for two parts of negotiation. We use Artificial Neural Network to learn utilities in the preparation and conduct phases of negotiation and Genetic Algorithm to propose negotiators an offer that maximizes their total utilities in the post-settlement phase.

4.1. Conduct Phase

In the conduct phase, two parties exchange offers and counter offers and messages. In the proposed method, counter offer utilities are calculated via Artificial Neural Network (ANN). Two ANN models are applied for buyer and seller separately.

Artificial Neural Network is a method for calculation and processing, different from conventional method of using computer and program instructions. Many times we have several input data with their specific outputs without any known functional shape. Using ANN we can interpolate or extrapolate a block box function over that data. Then we can produce output for other data different from the training set. As the training set become larger the training will be better and approximation will be closer to reality. Simply each ANN comprises individual neurons. Each neuron has several inputs and only one output with several branches. On each connection between neurons there is a weight coefficient. Output from a neuron multiplies with this weight as an input to subsequent neuron. Each neuron has two internal functions: Additive Function and Transfer Function. Additive function calculates the weighted sum of inputs. Transfer function is a non-linear function act on additive function and makes final neuron output. Networked neurons can calculate all arithmetical operations. Training, returns to this fact that the weights can be updated by mechanism like back-propagation [14].

We can construct a continuous space for utilities instead of piecewise linear approximation in current methods used in INSPIRE. In conduct of negotiation phase like INSPIRE our method calculate utilities for each offer but if a utility doesn’t satisfy preferences of a negotiator, user can modify the utility of this package. This package as a new member is added to training set of neural network and training restart to update the weights of ANN and constructing new utility function for negotiator. Then it is a dynamic way to take dynamism of preferences of negotiator into account.

If the value of this calculation is not acceptable for a party, user changes the rating and adds this new package to the training set of neural network. ANN is trained with this new data set. Then new offer can be presented according to new understanding of utilities constructed.

Figure 1 shows the ANN model for proposed method. In this method the ANN model reads output files for utilities and retrieve weight, bias and normalization parameters values and re-builds utilities. In this stage the ANN model constructs joint utility and draws them for more understanding. P1 and p2 are initial offers. Operation terminates when negotiators accept an offers or they cancel negotiation

In the proposed ANN models, the number of input nodes equals the number of issues (e.g. price, guarantee and etc.). Each ANN model has just one output node showing the utility of offering package. The number of nodes in hidden layer is considered two times to input nodes. The back-propagation mechanism and sigmoid function are used to train the ANN’s (under supervision) and as transfer function respectively.

![Figure 1. Re-building utilities in conduct phase](image)

4.2. Post-Settlement Phase

In post-settlement phase, if two parts of negotiation reach inefficient compromise in conduct phase, we use Genetic Algorithm (GA) to propose them an offer that maximizes their total utilities.

GA is an evolutionary and heuristic method useful for solving many NP-complete problems. GA is a heuristic search method that usually finds solution in feasible space. GA is based on two natural facts in evolution theory: Mutation and Crossover. Simply the set of chromosomes as a vector of inputs and their related outputs are produced as an initial population. Then mutation and crossover are used for expanding the population. According to natural selection, the best top members of population are selected for next generation and other members are rejected. This process is repeatedly done for new generation to improve the population. Initial population determination and selection of chromosomes for crossover or mutation is random. The size of population is fixed. Mutation action decreases the probability of settling down local optima. The bigger probability of mutation is the less probability for local optima problem and the more for oscillation. GA approaches have various forms.

We define joint utility as an average of two utility functions. Although other joint utilities can be defined,
this definition seems logical because of its simple structure. Other types of joint utility function can be also defined. The proposed GA model is applying the dynamic mutation and linear crossover [14]. The linear crossover is defined as follows:

\[ v'_i = \lambda v_i + (1 - \lambda) v_{i+1}, \quad v''_i = \lambda v_i + (1 - \lambda) v_{i-1}, \quad 0 < \lambda < 1 \]

Where \( v_i \) and \( v_2 \) are two chromosomes selected as parents in crossover, \( v'_1 \) and \( v'_2 \) are two offspring resulted by crossover respectively and \( \lambda \) is a parameter between 0 and 1.

The dynamic mutation, also called non-uniform mutation, defines as follows:

\[ x'_k = x_k + \Delta(t, x_k^u - x_k) \quad \text{Increasing mutation} \]
\[ x'_k = x_k - \Delta(t, x_k - x_k^l) \quad \text{Decreasing mutation} \]

Where \( x_k \) is the \( k^{th} \) element of parent \( x \), selected for mutation and \( x'_k \) is the \( k^{th} \) element in the new parent after mutation. The function \( \Delta(t, y) \) returns a value in the range \([0, y]\) such that the value of \( \Delta(t, y) \) approaches 0 as \( t \) increases (\( t \) is the generation number). This property causes the operator to search the space uniformly initially (when \( t \) is small) and very locally at later stages. The function \( \Delta(t, y) \) is given as follows:

\[ \Delta(t, y) = y r(t) \left( \frac{T}{t} \right)^b \]

Where \( r \) is a random number from \([0, 1]\), \( T \) is the maximal generation number, and \( b \) is a parameter determining the degree of non-uniformity. The roulette wheel mechanism is used for selection procedure. The flowchart of proposed GA is drawn in figure 2.

5. An Illustration Example

We designed a Visual C++ program for application of proposed approach. In this example two parties negotiate for selling a commodity with two issues, \textit{i.e.}, price and guarantee. The negotiation is leaded in three phases as mentioned already.

5.1. Conduct Phase

As mentioned the negotiation is established with two issues: Price and Guarantee. We assume the range \((\$300000, \$3200000)\) for Price and \((0 \text{ month}, 2 \text{ year})\) for Guarantee. Also we assume salient options for these two issues listed in table 1.

<table>
<thead>
<tr>
<th>Guarantee (Month)</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$300,000</td>
</tr>
<tr>
<td>6</td>
<td>$310,000</td>
</tr>
<tr>
<td>12</td>
<td>$320,000</td>
</tr>
</tbody>
</table>

Therefore 12 different combinations as offers can be constructed for these issues. We request rating for these 12 combinations both from buyer and seller. In our method it is not necessary for training all these combinations because there is a mechanism for updating that strengthens the training process. Therefore we construct initial utility functions for them. We used three-layer neural network with six nodes. For most application this simple structure is suitable for training. Transfer function is sigmoid that is very common in ANN. We consider output as utility function, ranged from zero to one. The learning rule is Back Propagation. It is a good idea to normalize input data. Therefore the value of data not only remains the same but also becomes more concentrated around a specific area. These formulas can be used for such normalization.

\[ \text{Pr}_{\text{ice}} = \frac{\text{price} - \mu_{\text{price}}}{\sigma_{\text{price}}} \quad \text{Guarantee}_{\text{guarantee}} = \frac{\text{Guarantee} - \mu_{\text{guarantee}}}{\sigma_{\text{guarantee}}} \]

Where \( \mu \) and \( \sigma \) are the mean and standard deviation of input data respectively. Next we enter training set input data and their desired output for buyer to begin training. When total error reaches an acceptable level, we can stop training. Such a process can be done for seller as well. Two binary files containing weights, biases and normalization values are produced as outputs of this step of simulation.

5.2. Post-Settlement Phase

We use these binary files as inputs to re-evaluate utility functions and calculating joint utility. The proposed approach maximizes this joint utility using Genetic Algorithm. In fact the GA model generates different combinations (chromosomes) and which are evaluated applying the ANN models (for buyer and seller). The characteristics of GA model is as follows:

- Mutation probability = 0.1, Crossover probability = 0.3
- Population size = 10, Max iteration = 1000
- Low Price = $300,000, High Price = $320,000
- Low Guarantee = 0 month, High Guarantee = 24 month
After 1000 iteration, the best solution is achieved in 841st iteration with rounded price equal $311,839 and 9 months guarantee and joint utility equals 0.65 (Fig. 3).

The results show an improvement compared to INSPIRE. INSPIRE solution for this example is illustrated in figure 4 with package offer ($320000, 24 month). INSPIRE compares the boundary values (discrete points) and selects the final solution. As illustrated in fig. 3, joint utility evaluation of ($320000, 24 month) is about 0.59 and is less than the offer of our system.

6. Conclusion

At this paper we tried to show a method based on ANN and GA for dealing with two party negotiations. It can be used in a web-based negotiation support system like INSPIRE. We used two different sub-systems for such a simulation using VC++ that works with each other: Artificial Neural Network and Genetic Algorithms. ANN outputs were used for attaining and improvements in utilities of negotiators at preparation and conduct phases. The GA model was used for offering an acceptable compromise for two parts of negotiation. The results show an improvement compared to INSPIRE. While INSPIRE is restricted on the boundary values, proposed method suggests more flexibility. This flexibility is based on ANN capability on estimating a non-linear function and power of GA for effective searches.

Although these methods intuitively seem slow, but in our simulation, we attain relatively acceptable results in relatively acceptable time. It is usable, for more off-line international negotiations in worldwide web and calculation time overhead seems to be acceptable. Further researches are necessary through implemented web-based systems or virtual simulations.

References