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A Fuzzy Approach for Bidding Strategy Selection[1]

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Abstract: *The goal of this work is to explore the applicability of fuzzy logic in multi-agent systems for choosing the best bidding strategy in electronic auction. To find the multi-criterion ordering, agents use a fuzzy algorithm ARAKRI2 with direct aggregation operators MaxMin and MinAvg. The key difference between this new approach and known from the literature solution FTNA is in the lack of weighted coefficients. Despite the difference both algorithms give results that are similar. Therefore, the proposed approach can successfully solve the task for multi criteria selection of bidding strategy.*

Keywords*: Software agents, bidding strategy selection.*

1. Introduction

Multi-Agent Systems (MAS) have been successfully applied to modeling the process of decision-making in electronic commerce. On one hand, on an individual level, they allow the study of decision-making process of single agent participants. On the other hand, on collective level, they also allow the study of agents' capabilities to react to ongoing changes in the system. This paper presents empirically the problem of choosing a bidding strategy in an electronic auction on individual level. In literature various ways for finding next bids on an individual level have been described. For example, in many simultaneous English auctions for

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the same good and with large volumes of historical data, methods taken from functional analysis [7] are used for forecasting next bids. In other examples of multi-agent modeling of online auctions, agents (virtual participants) use pre-defined bidding strategies. In this case the next bid depends only on the strategy and its parameters [2, 3, 13]. There are different methods for choosing the best strategy, such as adaptive actualization of bidding strategies, genetic algorithms [14], heuristics [5], etc. G o y a l et al. [4] for the first time suggest the idea of generating the next bid via an algorithm for multi-criterion ordering using fuzzy numbers. Their algorithm with Fuzzy Techniques and Negotiable Attitude (FTNA), however, needs a huge amount of input data. For example, in a task of n alternatives and m criteria, n criteria comparison $m \times m$ matrices are needed just to estimate the criteria weight coefficients. This not only increases the algorithm complexity, but also brings subjectivity to any obtained ordering. Comparison matrices are filled-in based on expert knowledge, which in itself creates problems related to future actualization. This paper proposes an original fuzzy approach to solving the problem of choosing a strategy by direct aggregation without using weight coefficients. The fundament of the approach is the fuzzy logic capability to solve real problems in complicated dynamical and undetermined systems with variable and uncertain parameters [1]. Two varieties of algorithms for direct aggregation of fuzzy sets without weighted coefficients (*ARAKRI2*) – *MaxMin* and *MinAvg* have been implemented. The *ARAKRI2* algorithms use the aggregation operators and operations between fuzzy numbers to fuse the fuzzy numbers by all criteria corresponding to the separate alternatives [11]. The results obtained in the conducted experiments have been compared to those of *FTNA* algorithm. Conclusions have been drawn describing the pros and cons of the method. Directions of future work concern further application of *ARAKRI2* as a new module into MAS for bidding agents modeling in *MASECA* [6]. This module could extend the approach for multi-criterion decision making with “classical” algorithms of Map-Cluster [12]. It could also enhance the fuzzy solutions, coded in WindPro [11] with an alternative way for input of evaluations.

2. Defining the problem of bidding strategy selection by direct aggregation of fuzzy sets

After preliminary analysis of bidding strategies described in literature, the choice has been limited to the following ten agent bidding strategies in a Continuous Double Auction (CDA):

- snipping strategy (Snipping);
- strategy with fixed markup (L);
- three strategies with different historical prices treatments H_1, H_2, H_3;
- Zero-Intelligence Unconstrained (ZIU);
- Zero-Intelligence with budget Constraints (ZIC);
- Zero-Intelligence Plus (ZIP);
- Risk-Based strategy (RB) and
- strategy with a Genetic Algorithm (GA).

The selected strategies vary in type. One part of them are “static”, other – adaptive with regard to changes during auctions.

Three criteria have been used for strategies’ evaluation:

– time complexity;
– price prediction;
– risk attitude.

Ten comparison matrices (one matrix for each strategy) have been filled in based on experts’ opinions, according to the degree of importance of paired criteria. Evaluations vary from 1 up to 9: 1 being insignificant; 3 – more important; 5 – equally important; 7 – substantially more important; 9 – absolutely more important, and ranks 2, 4, 6, 8 represent values that are between the given ones. Filling-in the matrices has been done according to statistical data on bidding strategies’ qualities. After normalization of the evaluations, criteria weights were estimated. The weight of each criterion was given as the geometric mean of the corresponding row in the comparison matrix. If we let w be a set of weights and $w=\{w_1, w_2, ..., w_m\}$, then here we will also have $w_i \in [0, 1]$ for i =1, 2, .., m and $\sum_{i=1}^{m} w_i = 1$ (Table 1). After averaging $w=\{0.4, 0.38, 0.22\}$.

Table 1. Paired strategy comparison matrices for each strategy

Snipping	*t*	*h*	*r*	L	*t*	*h*	*r*	H_1	*t*	*h*	*R*	H_2	*t*	*h*	*r*	H_3	*t*	*h*	*r*
t	5	9	10		5	9	9		5	5	9		5	4	9		5	3	9
h	1	5	5		1	5	5		5	5	9		6	5	9		7	5	9
r	0	5	5		1	5	5		1	1	5		1	1	5		1	1	5

ZIU				ZIC				ZIP				RB				GA			
t	5	5	10		5	6	5		5	8	5		5	2	1		5	0	5
h	5	5	5		4	5	5		2	5	9		8	5	4		10	5	1
r	0	5	5		5	5	5		5	1	5		9	6	5		5	9	5

The individual matrices of strategy-criterion relationships for five bidding agents, participants in an electronic auction, have been given. Here the term “relationship” describes the preference of an agent k to choose strategy i at given criterion j. Evaluations of relationships a_{ij}^{k} (i = 1, 2, .., n; j=1, 2 , .., m; k = 1, 2, ..., l for n = 10, m = 3, l = 5) have been presented by “linguistic” terms as “very low”, “low”, “average”, “high” and “very high”. Fuzzy agents’ attitudes between strategies and criteria are filled in the relationship matrices based on historical data on deals made in the auction up to this moment. Linguistic variables are then transformed into fuzzy triangular numbers ranging from “Very Low“ = =VL= (0, 0, 0.1) to “Very High“=VH=(0.9, 1, 1) evaluations (Table 2).

The sum of matrices with individual evaluations of alternative-criterion becomes input information for filling in a summary matrix with fuzzy evaluations of strategies.

The problem is to find a descending ranking of bidding alternatives, according to algorithm *ARAKRI2*.

Table 2. Strategy-criterion relationship matrices

A^1	*t*	*h*	*r*	A^2	*t*	*h*	*r*	A^3	*t*	*h*	*r*	A^4	*t*	*h*	*r*	A^5	*t*	*h*	*r*
Snip	VH	VL	VL		ML	VL	L		ML	VL	VL		M	VL	VL		VL	VL	VL
L	VL	VL	VL		ML	VL	L		ML	VL	VL		VL	VL	VL		VL	VL	VL
H$_1$	ML	M	VL		M	VL	L		M	L	VL		L	MH	VL		L	H	VL
H$_2$	M	M	VL		M	L	L		M	L	L		L	MH	L		LM	H	VL
H$_3$	MH	M	VL		M	L	ML		M	ML	L		L	H	L		M	H	VL
ZIU	H	M	L		M	L	ML		MH	L	L		ML	MH	L		M	H	VL
ZIP	VH	VL	VL		MH	ML	ML		MH	VL	L		M	VL	VL		M	VL	VL
ZIC	H	H	VL		MH	M	ML		MH	VL	L		ML	VL	VL		ML	VL	VL
RB	L	VH	VH		MH	H	H		H	H	VH		M	VH	VH		M	VH	VH
GA	VL	VH	VH		MH	VH	VH		MH	VH	VH		MH	VH	VH		M	VH	VH

3. Solving the problem using *ARAKRI2* algorithm with *MaxMin* and *MinAvg* aggregations

The evaluations of the ten strategies on the three criteria are summarized in Table 3. As can be seen, the evaluations are trapezoidal fuzzy numbers:

$$\tilde{A}_{ij} = (a_{ij}^1, a_{ij}^2, a_{ij}^3, a_{ij}^4),\ \ a_{ij}^2 = a_{ij}^3,\ \ i = 1,\ ...,\ 10,\ \ j = 1,\ 2,\ 3.$$

To arrange the strategies in a descending order according to their evaluations, we follow the three phases – uniform, aggregation and exploitation phase [1] in the next four steps [10, 8, 9]:

Step 1. As evaluations can differ in scale and not fit into [0, 1] interval, unification and normalization of the fuzzy numbers are needed. For this purpose, a procedure which does not change the ranking of the numbers by value is applied.

Let $a_j^{\max} = \max\limits_{i=1,2,\ ,n}\{a_{ij}\},\ a_j^{\min} = \min\limits_{i=1,2,\ ,n}\{a_{ij}\},\ da = a_j^{\max} - a_j^{\min}$. Then the unified and normalized fuzzy number $\tilde{Z}_{ij} = (z_{ij}^1, z_{ij}^2, z_{ij}^3, z_{ij}^4),\ i = 1,\ ...,\ 10,\ \ j = 1,\ 2,\ 3$ is estimated by the formula:

$$\tilde{Z}_{ij} = (\tilde{A}_{ij} - a_j^{\min}) \big/ da,\ \ i = 1,\ ...,\ 10,\ \ j = 1,\ 2,\ 3.$$

Table 3. Alternative-criterion matrix

Snip	*t*			*h*			*r*		
	1.4	2.1	2.8	0.0	0.0	0.5	0.0	0.1	0.7
L	0.2	0.6	1.3	0.0	0.0	0.5	0.0	0.1	0.7
H$_1$	0.7	1.5	2.5	1.5	2.2	3.0	0.0	0.1	0.7
H$_2$	1.0	1.9	2.9	1.5	2.3	3.2	0.0	0.3	1.1
H$_3$	**1.4**	**2.3**	**3.3**	1.8	2.7	3.5	0.1	0.5	1.3
ZIU	1.9	2.9	3.8	1.5	2.3	3.2	0.1	0.6	1.5
ZIP	2.5	3.4	4.2	0.1	0.4	1.1	0.1	0.4	1.1
ZIC	1.9	2.9	3.8	1.0	1.4	2.0	0.1	0.4	1.1
RB	1.8	2.7	3.6	3.2	3.9	4.3	4.3	4.9	5.0
GA	1.8	2.6	3.5	4.5	5.0	5.0	4.5	5.0	5.0

For example, for a fuzzy number

$$\tilde{A}_{51} = (1.4,\ 2.3,\ 3.3),\quad a_1^{\max} = 4.2,\ a_1^{\min} = 0.2,\ da = 4.0\ ,$$

$$\tilde{Z}_{51} = (\tilde{A}_{51} - a_1^{\min}) / da,$$

$$z_{51}^1 = (1.4 - 0.2)/4.0 = 0.3,\ z_{51}^2 = z_{51}^3 = (2.3 - 0.2)/4.0 = 0.53,$$

$$z_{51}^4 = (3.3 - 0.2)/4.0 = 0.78,$$

i.e., $\tilde{Z}_{51} = (0.3,\ 0.53,\ 0.78)$ [7, 8, 9].

Thus, Table 4 which consists of the new evaluations was obtained.

Table 4. Normalized alternative-criterion matrix

Snip	*t*			*h*			*r*		
	0.30	0.48	0.65	0.00	0.00	0.10	0.00	0.02	0.14
L	0.00	0.10	0.28	0.00	0.00	0.10	0.00	0.02	0.14
H$_1$	0.13	0.33	0.58	0.30	0.44	0.60	0.00	0.02	0.14
H$_2$	0.20	0.43	0.68	0.30	0.46	0.64	0.00	0.06	0.22
H$_3$	**0.30**	**0.53**	**0.78**	0.36	0.54	0.70	0.02	0.10	0.26
ZIU	0.43	0.68	0.90	0.30	0.46	0.64	0.02	0.12	0.30
ZIP	0.58	0.80	1.00	0.02	0.08	0.22	0.02	0.08	0.22
ZIC	0.43	0.68	0.90	0.20	0.28	0.40	0.02	0.08	0.22
RB	0.40	0.63	0.85	0.64	0.78	0.86	0.86	0.98	1.00
GA	0.40	0.60	0.83	0.90	1.00	1.00	0.90	1.00	1.00

Step 2. If the criteria are of the same type, i.e., they all need to be maximized, the process can continue from Step 3. If some of the criteria need to be maximized and others minimized, or if all need to be minimized, then, for all criteria that need to be minimized, the complements of the fuzzy numbers to the fuzzy number (1, 1, 1, 1) are estimated, so that the criteria can be of the same type. For this purpose, the definition of difference between two fuzzy numbers is used.

$$\tilde{A} - \tilde{B} = \tilde{A} + (-1)\tilde{B}\ ,\ \text{where}\ \tilde{A} = (1,1,1,1),\ (-1)\tilde{B} = (-a_4, -a_3, -a_2, -a_1)\ .$$

Here, all three criteria are maximizing and estimating the complements of the fuzzy numbers to unit fuzzy numbers is not needed.

Step 3. The optimistic index is calculated

$$F_1(\tilde{A}) = a_1 + \frac{(a_4 - a_1) + (a_3 - a_2)}{2} \cdot \frac{1}{[(a_4 - a_3)^2 + 1]^{\frac{1}{2}}}\ . \tag{1}$$

The dual pessimist index is also found

$$F_2(\tilde{A}) = a_4 - \frac{(a_4 - a_1) + (a_3 - a_2)}{2} \cdot \frac{1}{[(a_2 - a_1)^2 + 1]^{\frac{1}{2}}}\ . \tag{2}$$

A linear combination of the previous two indices is used as the index of a fuzzy number $\tilde{A}$ (its G-index):

$$F(\tilde{A}) = kF_1(\tilde{A}) + (1-k)F_2(\tilde{A}),\quad k \in [0, 1]. \tag{3}$$

Below Table 5 is given with the G-indices of fuzzy numbers for $k = 0.5$.

Table 5. G-indices of values from Table 4

0.475	0.050	0.070
0.137	0.050	0.070
0.349	0.450	0.070
0.437	0.470	0.109
0.537	0.530	0.139
0.663	0.470	0.159
0.788	0.120	0.120
0.663	0.300	0.120
0.625	0.750	0.930
0.612	0.950	0.950

The G-index of a fuzzy number Z_{51} is

$$Z_{51} = F(\tilde{Z}_{51}) = kF_1(\tilde{Z}_{51}) + (1-k)F_2(\tilde{Z}_{51}) = 0.537 \text{ for}$$

$$\tilde{Z}_{51} = (a_1, a_2, a_3, a_4) = (0.3, 0.525, 0.525, 0.775).$$

Step 4. Fuzzy evaluations are aggregated and calculations are performed with operators without weighted coefficients.

– for the ***MaxMin*** operator which has the following mathematical model:

$$\tilde{Z}_i = \alpha \max_j \{\tilde{Z}_{ij}\} + (1-\alpha)\min_j \{\tilde{Z}_{ij}\},\ \alpha \in [0,1],\ i = 1,...,10,\ j = 1,\ 2,\ 3,$$

the calculations are for $\alpha = 0.6$. For example, for alternative a_1 from the respective row from Table 3, the maximum and minimum G-indices are found, which are the maximum and minimum fuzzy numbers from the row of evaluations of this alternative:

$$\tilde{Z}_1 = \alpha \max_j \{\tilde{Z}_{1j}\} + (1-\alpha)\min_j \{\tilde{Z}_{1j}\} = 0.6\ \tilde{Z}_{11} + 0.4\ \tilde{Z}_{12} =$$

$$= (0.6 \times 0.3 + 0.4 \times 0.0,\ 0.6 \times 0.475 + 0.4 \times 0.0, 0.6 \times 0.65 + 0.4 \times 0.1) = (0.18,\ \ 0.285,\ \ 0.43).$$

Aggregated evaluations, corresponding to the alternatives, are the fuzzy numbers $\tilde{Z}_i,\ i = 1,\ ...,\ 10,$ from Table 6.

Table 6. Aggregated evaluations of alternatives using the *MaxMin* method

Snip			**L**			**H$_1$**			**H$_2$**			**H$_3$**		
0.18	**0.285**	**0.43**	0	0.06	0.205	0.075	0.203	0.401	0.12	0.279	0.493	0.224	0.364	0.524
ZIU			**ZIP**			**ZIC**			**RB**			**GA**		
0.263	0.453	0.66	0.353	0.512	0.688	0.263	0.437	0.628	0.676	0.838	0.94	0.7	0.84	0.93

In order to rank these fuzzy numbers in a descending order, we have to estimate their G-indices, i.e., to perform the calculations from Step 3. For example, to a fuzzy number $\tilde{Z}_1 = (0.18, 0.285, 0.43)$ from (1), (2), (3) for k = 0.5, corresponds a G-index = 0.305. After substituting G-indices for the corresponding fuzzy numbers, the following ordering of alternatives has been obtained (Table 7).

Table 7. Ordering of alternatives using the *MaxMin* method

GA	RB	ZIP	ZIU	ZIC
0.815	0.809	0.52	0.461	0.445

H_3	Snip	H_1	L	H_2
0.373	**0.305**	0.273	0.102	0.036

– for the *MinAvg* operator with a membership function

$$\tilde{Z}_i = \frac{\lambda}{m}\sum_{j=1}^{m}\tilde{Z}_{ij} + (1-\lambda)\min_j\{\tilde{Z}_{ij}\},\ \lambda \in [0,1],\ i = 1,...,10,\ j = 1,2,3,\ m = 3,$$

the calculations for $\lambda = 0.6$ are:

$$\tilde{Z}_1 = \frac{0.6}{3}\sum_{j=1}^{3}\tilde{Z}_{1j} + (1-0.6)\min_j\{Z_{1j}\} = 0.2(\tilde{Z}_{11} + \tilde{Z}_{12} + \tilde{Z}_{13}) + 0.4\tilde{Z}_{12} =$$

$$= (0.06, 0.099, 0.178) + (0, 0, 0.04) = (0.06, 0.099, 0.218).$$

Aggregated fuzzy numbers $\tilde{Z}_i$, $i = 1, ..., 10$, corresponding to alternatives, are filled in Table 8.

Table 8. Aggregated evaluations of alternatives using the *MinAvg* method

Snip			L			H_1			H_2			H_3		
0.06	0.99	0.218	0	0.024	0.143	0.085	0.165	0.319	0.1	0.213	0.395	0.144	0.273	0.451
ZIU			**ZIP**			**ZIC**			**RB**			**GA**		
0.157	0.299	0.488	0.131	0.224	0.376	0.137	0.239	0.392	0.54	0.727	0.882	0.6	0.76	0.895

The ordering of alternatives, corresponding to the ordering of the G-indices of the aforementioned fuzzy numbers (Tables 9, 10).

Table 9. Ordering of alternatives, according to the *MinAvg* method

GA	RB	ZIU	H_3	ZIC
0.748	0.711	0.322	0.297	0.264

ZIP	H_2	H_1	Snip	L
0.253	0.247	0.202	0.139	0.071

Table 10. Ordering of alternatives, according to the *FTNA* method with weighted coefficients from Table 1

GA	RB	H_1	ZIU	H_3
0.450	0.406	0.319	0.266	0.232

ZIP	H_2	ZIC	Snip	L
0.204	0.198	0.198	0.159	0.055

4. Comparative analysis of experimental results

As a result of the described experiments with the *ARAKRI2* algorithm with aggregated operators *MaxMin* (Table 7) and *MinAvg* (Table 9), similar rankings have been obtained. The first places are reserved for the most adaptive strategies – GA and RB. Last in the rankings come the most “inert” strategies – L, Snip, H_1 and H_2. It is worth noting that the fact that while working with the *MinAvg* operator, one of the qualitative strategies – ZIP strategy has migrated to the second half of the ranking list and has been replaced by one of the strategies which take into account historical prices H_3. Similar peculiarity has been observed also in the ranking list generated by the FTNA algorithm. Contrary to expectations, here, too, H_1 dominates ZIC. In both cases, places are exchanged between strategies from the same groups – those with increased intelligence (ZIP and ZIC) and those taking into consideration deals’ history (H_1 and H_3).

A series of experiments has been conducted: with equal value coefficients α and γ, which change stepwise in the interval [0, 1]; with coefficients α and γ, whose sum equals 1; with a coefficient k, which varies in the interval [0, 1], with minimizing and mixed (minimizing and maximizing) criteria t, h and r. The results obtained have confirmed the applicability of the described method for solving the given problem. For example, when t was considered a minimizing criterion, first in the ranking were strategies, using a huge volume of calculations for generating bids – GA, RB, H_1, H_2, and H_3. When h was considered a minimizing criterion, first were the strategies which do not use historical prices – ZIP, ZIC, L and Snip. When r was considered minimizing – H_1, H_2, H_3 and ZIU (which are risk indifferent) were in the upper part of the ordering, while GA and RB were at its bottom. When three minimizing criteria were used, the obtained ordering was the inverted of that in Section 2.

Experiments were conducted with three different types of agent populations – risk averse, risk neutral and risk tolerant, and the first places in the ordering were taken by the increased intelligence strategy ZIP, strategies with different historical prices treatment H_1, H_2, H_3 and the “riskiest” strategies, RB and GA.

Analysis of the obtained results indicates that two algorithms – *ARAKRI2* with operators *MaxMin* and *MinAvg* and FTNA generate similar rankings of compared strategies. The main differences between FTNA and *ARAKRI2* are in their complexity in terms of memory and time. While FTNA needs more memory, *ARAKRI2* falls behind in speed, since it needs a larger volume of calculations. Among the chief advantages of *ARAKRI2* is the smaller amount of input data needed. The fact is that weighted coefficients of input data unnecessary reduces complexity in terms of memory and also alleviates subjectivity at the beginning of the algorithm.

5. Conclusion and future work

Multi-criterion decision making with direct aggregation of fuzzy evaluations can be used successfully for choosing a bidding strategy by autonomous software agents in a CDA auction. The described approach is useful in those cases when there is a time constraint on choosing a strategy, as it uses matrix calculation. Compared to other examples in literature, this approach is innovative in several aspects: it can operate without historical data and considers direct aggregation without weighted coefficients. There are limitations to the work, however. We have not explained how an agent can fulfill the attitude matrices – based on its user preferences, experts' evidence or using its own evidence.

This work will continue researching the Gamma aggregation operator which does not use weighted coefficients. This method will find application in MASECA as a specialized module, managing separate agents' behaviors during the course of an auction. Applying the described approach will increase adaptivity and effectiveness of agent-participants.

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