Design and Implementation of Intelligent Negotiating Agents in E-Commerce Based on a Combined Strategy Using Genetic Algorithms as well as Fuzzy Fairness Function

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ABSTRACT- **In order to be successful in multi-agent electronic negotiating environments, intelligent agents should be capable of adapting their negotiation strategies and tactics so that they can achieve an agreement with optimized profit. In this paper, some findings are going to be shown in which negotiating intelligent agents in electronic commerce start negotiating using a simplified standard protocol in conjunction with a combined negotiation. Taking advantage of a new developed evolutionary algorithm, agents configure their negotiation strategies somehow they can get more profit. They can use fuzzy fairness function to behavior with fairness or without fairness.**

Index Terms - **Next generation E-Commerce, intelligent agents, e-negotiating, Genetic algorithm, fuzzy logic**

I. INTRODUCTION

Negotiation plays an important role in multi-agent systems. Intelligent agents negotiate with each other in order to synchronize their activities so that they can achieve a mutual agreement about division of resources. Intelligent agents should be capable of mimicking a wide variety of different behaviors by changing their parameters. An intelligent agent with a bounded limit of time should behave different from an intelligent agent without a bounded limit of time in order to achieve an agreement. Moreover, intelligent agents should also be able to show flexible behaviors in actual environments. Experimental studies show that heuristic methods used in modeling, most of the time seem to be more suitable [1]. In this paper based on standard protocols and tactics [2], an extended model of negotiation is introduced which is based on strategies and tactics used for defining the intelligent agent's behavior [3 , 4 , 5].

II. NEGOTIATION MODEL

Multi-dimensional negotiation model is based on a set of abilities and multi-subjective negotiation. During the negotiation values of the subjects are bounded between a minimum and a maximum value (i.e. xj∈Dj = [minj, maxj]). Each intelligent agent (a) has a grade function as Vja: Dja →[0,1] which shows the grade of subject j for intelligent agent a in acceptable range Dja. For the reason of simplicity, profits are considered in the range [0, 1] which either increase or decrease monotonously. One of the profit functions given in [6, 7] is:

$$V_j^a(x_j)=\begin{cases}\dfrac{\max_j^a - x_j}{\max_j^a - \min_j^a} & if \quad increasing \\ \dfrac{x_j-\min_j^a}{\max_j^a - \min_j^a} & if \quad decreasing\end{cases}$$

If the value of a specific subject during the negotiation was increasing, the first function is used in order to calculate the profit of j-th subject. Otherwise the second function is used. The total of all profits of proposal x for intelligent agents is calculated using the equation below:

$$V^a(x)=\sum_{1\le j\le n} W_j^a \times V_j^a(x_j) \quad , \quad \sum_{1\le j\le n} W_j^a = 1$$

Where W_j^a represents the importance of subject j for the intelligent agent a and n is the number of negotiation subjects. Intelligent agents use the output value of the above function in order to evaluate received proposal and also for their decision-making. Suppose xta →b represents arrow of proposed values from agent a to agent b at the time t and xta →b[j] is the value of the subject j. In negotiation between

intelligent agents a and b at the time tn, xtna ↔b represents an n-length limited series like xt1a→b, xt1a←b, xt2a→b, ... where:
For all i ; ti+1>ti
For all j and i=1, 3, 5, … ; xia→b[j] ∈Dja, xib→a[j] ∈Djb. Considering the negotiation process, the last element of these series is either 'accept' or 'reject' claiming the acceptance or rejection of the negotiation from both parties respectively.
Proposal and mutual proposal are produced by linear combination of a set of functions called tactics. Tactics set the value of any specific subject of negotiation based on individual criteria such as: remaining time, remaining resources or the other party's behavior. If numerous criteria were important in calculating value of a subject, various tactics can be combined, which is the main idea of combined negotiation model. In this case, each tactic will be assigned a weight regarding its importance.

III. TIME DEPENDENT TACTICS

Time dependent tactics model the fact that when intelligent agent gets closer to its deadline it should concede some grades rapidly [8]. All tactics in this group use minimum or maximum value of subject at the time of tamax. The distinguishing characteristic of these tactics is the shape of their curve for conceding grades. Using a time dependent function (αja), the proposal of intelligent agent a to intelligent agent b for the subject j in time t ≤ tamax is modeled. One of the functions used in electronic negotiations is the following [9]:

$$x^{t}_{a\to b}[j] = \begin{cases} \min^{a}_{j} + \alpha^{a}_{j}(t) \times (\max^{a}_{j} - \min^{a}_{j}) & if\ V^{a}_{j} \quad decrea\sin g \\ \min^{a}_{j} + (1-\alpha^{a}_{j}(t)) \times (\max^{a}_{j} - \min^{a}_{j}) & if\ V^{a}_{j} \quad increa\sin g \end{cases}$$

A wide range of functions can be defined by changing the evaluation approach for αja(t). For eaxample, following exponential function can be used:

$$\alpha^{a}_{j}(t) = \left(\frac{\min(t, t^{a}_{\max})}{t^{a}_{\max}}\right)^{\frac{1}{\beta_j}}$$

where parameter βj ∈R+ represents the convergence rate of the curve.
This expression represents an unlimited number of possible tactics for each value of βj. Anyway, in order to understand their behavior more deeply, these functions are divided into two categories [5], each of which represents different set of behaviors. Boulware behavior (giving the grade doesn't start until the deadline is close enough) with β<<1 and conceder behavior (fairly and quickly) with β>>1. One of the reasons for this type of behavior is that the other party of negotiation would be encouraged for staying in the negotiation in order to get an agreement quickly. Time dependent model is used in most of the e-negotiating agents like Kasbah (MIT University), because they are similar to human negotiation behavior.

IV. RESOURCE DEPENDENT TACTICS

In these types of tactics proposals are produced based on how much resources are used:

$$\alpha^{a}_{j}(t) = e^{-\frac{\mu^{a}_{j}}{|x^{t}_{a\leftrightarrow b}|}}$$

This relationship includes time μja(the time which seems rational for agent a to spend on negotiation about each subject j) and also the number of messages (messages passed during negotiation).

V. BEHAVIOR DEPENDENT TACTICS

This type of tactics is based on the other party's behavior. These tactics vary in degree of mimicking the other party's behavior. Three categories of these tactics are explained below. By default, if duration of negotiation doesn't permit usage of one tactic (i.e. t<2δ), then intelligent agent would choose boulware tactic with β=2 (as Alxelrod R.(1984) [5] has suggested).

- **Relative Tit-For-Tat (Relative-TFT)**

As the name suggests this tactic, value of new proposal is calculated (when δ=1) based on the grade values of other party's proposal in two recent offers (δj≥ 1).

$$x^{t_{n+1}}_{a\to b}[j] = \min(\max(\frac{x^{t_{n-2\delta_j}}_{b\to a}[j]}{x^{t_{n-2\delta_j+2}}_{b\to a}[j]} x^{t_{n-1}}_{a\to b}[j], \min^{a}_{j}), \max^{a}_{j})$$

- **Random Absolute Tit-For-Tat (Random-TFT)**

It's similar to Relative-TFT except that behavior is mimicked using the absolute values of expressions:

$$x^{t_{n+1}}_{a\to b}[j] = \min(\max(x^{t_{n-1}}_{a\to b}[j] +$$
$$(x^{t_{n-2\delta_j}}_{b\to a}[j] - x^{t_{n-2\delta_j+2}}_{b\to a}[j]) + (-1)^{s_j} R(M_j), \min^{a}_{j}), \max^{a}_{j})$$

If Vja was increasing or decreasing, value of sj will be either 1 or 0, respectively. The R(Mj) function generates a random integer within the range [0, Mj] uniformly.

- **Averaged Tit-For-Tat (Average-TFT)**

It considers change ratio in a window sized (λj ≥ 1) for calculating the value of predefined subject:

$$x^{t_{n+1}}_{a\to b}[j] = \min(\max(\frac{x^{t_{n-2\lambda_j}}_{b\to a}[j]}{x^{t_n}_{b\to a}[j]} x^{t_{n-1}}_{a\to b}[j], \min^{a}_{j}), \max^{a}_{j})$$

VI. COMBINED NEGOTIATION MODEL

When intelligent agent a receives a proposal from intelligent agent b, this proposal will become the last element of current negotiation. If a assumes that proposal is not satisfactory, it would produce another proposal in return. In producing such a counter-proposal, intelligent agent a might use any combination of (six previously discussed) various weighted tactics for each subject of negotiation and thereby, it may have mimetic and time dependent behaviors in addition to resource dependant behavior. That's why each intelligent agent assigns a special weight to each behavior for each subject regarding to importance of each tactic for achievement to the maximum profit received by both parties. In a negotiation between intelligent agent a and b at time tn, xtna↔b in the range D=D=D1*D2*...*DP and last(xtna↔b)= xtna→b and a limited set of m tactics (in this case m=6) exists Ta={ τi|τi:MSa →D}i∈[1,m] where MSa is the set of all possible parameter values for intelligent agent a. Weighted counter-proposal, xtn+1a→b is a linear combination of assumed tactics using weight matrix, i.e. based on different tactics, value of each subject is evaluated by its grade conceding rate and then m different proposals based on m different tactics are produced and combined together using the weight matrix and so the main proposal is produced. The given explanation can be shown mathematically as:

$$\gamma_{a\to b} = \begin{pmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1m} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ \gamma_{p1} & \gamma_{p2} & \cdots & \gamma_{pm} \end{pmatrix}$$

hence: $x^{t_{n+1}}_{a\to b} = (\gamma_{a\to b} \otimes T^a(MS_a))$

Where Ta(MSa) is a matrix which involves calculated values of negotiation subjects based on previously discussed tactics using MSa. General form of this matrix will be:

$$T^a(MS_a) = \begin{pmatrix} x^{t_{n+1}}_{a\to b}[1]_1 & x^{t_{n+1}}_{a\to b}[1]_2 & \cdots & x^{t_{n+1}}_{a\to b}[1]_m \\ x^{t_{n+1}}_{a\to b}[2]_1 & x^{t_{n+1}}_{a\to b}[2]_2 & \cdots & x^{t_{n+1}}_{a\to b}[2]_m \\ \vdots & \vdots & \cdots & \vdots \\ x^{t_{n+1}}_{a\to b}[p]_1 & x^{t_{n+1}}_{a\to b}[p]_2 & \cdots & x^{t_{n+1}}_{a\to b}[p]_m \end{pmatrix}$$

In the above matrix $x^{t_{n+1}}_{a\to b}[i]_j$ indicates the value of i-th subject based on the j-th tactic (τj). The operation ⊗ is defined as:

$$x^{t_{n+1}}_{a\to b}[j] = \sum_{1\le i\le m} x^{t_{n+1}}_{a\to b}[j] \times \gamma_{jm}$$

VII. IMPLEMENTED NEGOTIATION PROTOCOL

During negotiation process, negotiation protocol indicates the type of sending and receiving proposals, periodically. The negotiation protocol forms the main part of the communication and control module. Table 1 contains a list of commands related to negotiation. These are a subset of commands defined in ACL (Agent Communication Language). Due to simplicity of this system, only commands shown in the table are required:

Table 1. Protocol commands

Propose	sending the proposal
Accept	accepting a specific proposal
Terminate	termination of the current negotiation process
Reject	rejection of the current proposal
Acknowledge	acknowledgement of receiving a message
Modify	correction of the last sent proposal
CFP	call for first proposal

In the figure below the used protocol in the suggested intelligent agents is depicted that is implemented in the control and communicative module.

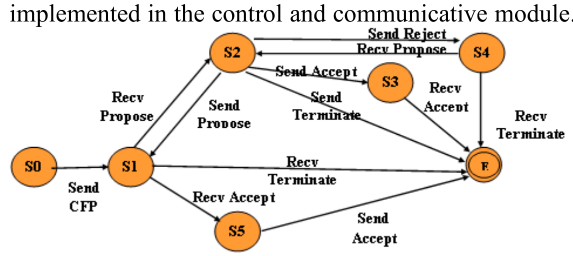

Figure 1.Suggested negotiation protocol for intelligent agent negotiator [1]

In automata,s0 to s5 shows different aspect of an negotiator intelligent agent during the process of negotiation. E is the final state that reflect agreement or not.

The function that has the role of negotiation interpreter in deduction unit is [5]:

$$I^a(t_{n+1}, x^{t_n}_{b\to a}) = \begin{cases} reject & if \quad t_{n+1} > t^a_{\max} \\ accept & if \quad V(x^{t_n}_{b\to a}) > V(x^{t_{n+1}}_{a\to b}) \\ x^{t_{n+1}}_{a\to b} & \quad otherwise \end{cases}$$

VIII. HOW TO ESTIMATE NEGOTIATION STRATEGIES AND COMBINED TACTIC PARAMETERS

The EA algorithm depicted in figure 2 is used for generating and evaluating intelligent agent negotiation strategies.[9]

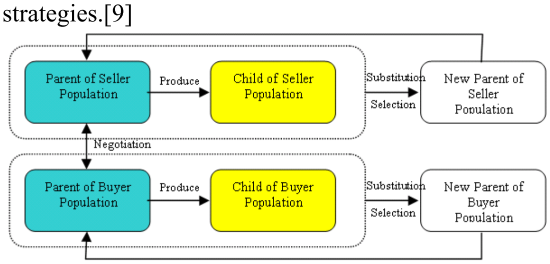

Figure 2. Evolutionary Algorithm (EA) flowchart[9]

For finding strategies that work optimally for different aspects of negotiation, an initial population of intelligent agents with different strategies is generated and then using EA an agent with high fitness is found.

IX. CODING INTELLIGENT AGENT STRATEGIES AS GENE

Each intelligent agent, i. e. each chromosomes, is represented as a two dimensional array. Each element of this array refers to a gene representing one parameter of intelligent agent combined strategy negotiation.

- tamax: a real number that shows the maximum time for negotiation by intelligent agent

- Genes related to subject

For each subject, there are some genes with the following values and concept which should be determined by the user and never change during the execution of evolutionary algorithm.

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Dja=[minja,maxja] : acceptable distance for each subject

Type-Vja: represents the type of profit function which can be ascending or descending

W: represents the importance of each subject

- Genes related to tactic

Time dependent: a real value (βj) that if much smaller than 1, has a profit keeper behavior, otherwise, it has a profit grant behavior. For each of two time dependent behaviors, a different gene has been assigned (0≤βboulware≤1 ,1≤βconceder≤40)

Resource dependent: µja is an integer representing the discussed rational time in order to negotiate for subject j, µja≤Tmax

imitating tactics

Relative-TFT: δj is an integer representing the number of previous steps (1≤δrelative≤Tmax/2)

RANDOM-TFT: δJ is an integer representing the number of preceding paces. Mj is the maximum value that the agent can change its imitating behaviour (1≤δrandom≤Tmax/2)

AVERAGED-TFT: λj is an integer representing the size of window which average is calculated based on it. (1≤λaverage≤minja)

- Genes related to strategy: γij represents importance of tactic j for subject i.

Tmax																
Min1	Max1	W1	Type-V1	βboulware1	βconceder1	µresource1	δrelative1	δrandom1	M1	λaverage1	γ11	γ12	γ13	γ14	γ15	γ16
Min2	Max2	W2	Type-V2	βboulware 2	βconceder 2	µresource 2	δrelative2	δrandom2	M2	λaverage2	γ21	γ22	γ23	γ24	γ25	γ26
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Minp	Maxp	Wp	Type-Vp	βboulware p	βconceder p	µresource p	δrelativep	δrandomp	Mp	λaveragep	γp1	γp2	γp3	γp4	γp5	γp6

Figure 3.chromosome coding matrix which uses the combination of all 6 types of tactics[2]

The first row in figure 3 shows the maximum required time for negotiation (Tmax) and the first subject's combined tactic parameters is included in second row. The first four columns in the left hand side of the matrix do not change during execution of negotiation. These five types of constant genes are used just in generation of other genes and also during calculation of chromosome fitness value.

X. CALCULATION OF INTELLIGENT AGENT FITNESS WITH DIFFERENT STRATEGIES

Fitness value of intelligent agent shows that how better it acts in comparison with other agents in the same population. According to the following evolutionary concepts, fitness value also determines the intelligent agent surviving chance. In order to calculate intelligent agent fitness, a tournament selection in a round robin manner is done in a way that each buyer negotiates with all of the sellers. Determination of a profit assigning to an agent is a time consuming task and algorithm complexity (O(n2)) increases according to population size. Fitness function used, introduced by Fratin [5], compares profit related to deal with profit related to Nash point equilibrium (point in which buyers and sellers' fitness values are equal):

$$f(x_c^{t_n}) = \begin{cases} V^c(x_c^{t_{deal}}) - V^c(x_c^N) & if \quad Last(X_c^{t_n}) = accept \\ -V^c(x_c^N) & otherwise \end{cases}$$

Where xctdeal is the last proposal in agent negotiation and xcN is the deal corresponding to Nash definition.

XI. RESULTS OF CONDUCTED EXPERIMENTS

All evolutionary system settings are listed in Table 2. For the seller agent price value is between 110$ and 160$ and the direction of changes is descending and the delivery time value is between 8 and 12 days. For the buyer agent the price value is between 100$ and 150$ and time value is between 10 and 15 days. During 25 different executions, the algorithm averagely has finished by the 18th generation. In a sample execution

Table 2. Negotiation system parameters

Evolutionary algorithm parameters	Population size	20
	Number of generations	100
	Crossover probability(Pc)	0.5
	Mutation probability (Pm)	0.02
	Tournament size (K)	2
	Number of elites	2
Negotiation parameters	Number of negotiation subjects	(time and price of delivery)2
	Buyer weight vector	(0.3,0.7)
	Seller weight vector	(0.7,0.3)
	Maximum time	50

the following result has been accomplished and further investigation shows that the results of other 24 executions were approximately the same.

Figure 4 shows that the status of average profit changes during the first 19 generations. The weights of buyer and sender agents are symmetrical and thereby, convergence happens relatively in small number of generations.

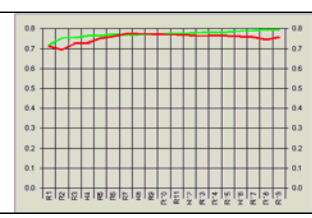

Figure 4. Average profit for buyer and seller agent(red=Buyer, green=Seller)

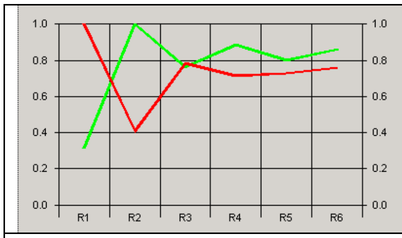

Figure 5. Changes in profits for buyer and seller agents

In figure 4, horizontal and vertical axes denote generation number and average profit, respectively. Value of average profit for the buyer and seller agents in the last generation are 0.79126 and 0.7598, respectively, which indicates mutual profit for both parties. Figure 5 depicts the best profit for buyer and seller agents. In this graph the horizontal axis shows the round number and vertical axis shows the profit of buyer and seller agents with the best fitness. As we can see in figure 5, using calculated strategies of Table 4 (without fairness columns) has yielded in profit of 0.86126 for seller and 0.78120 for buyer agent.

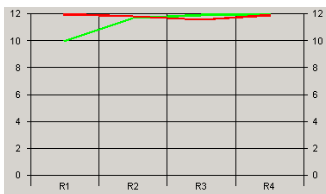

Figure 6. Changes in delivery time during successive rounds

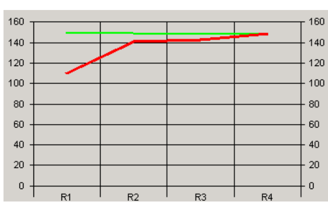

Figure 7. Changes in price during successive rounds

Table 3. The exchanged proposals between buyer and seller agents for coming to an agreement

Buyer suggestions	Seller suggestions
(110.000000, 12.000000)	(150.000000, 10.000000)
(141.049176, 11.830099)	(149.117589, 11.714375)
(142.532732, 11.567738)	(148.427439, 11.945387)Accepted

XII. DEVELOPING THE MODEL USING FAIRNESS PARAMETER

Intelligent agent model has been extended using fairness parameter and the effect of fairness rule has been depicted. The model represented in [11] to simulate human negotiation can be used for fairness modeling in electronic negotiation. Considering such a model in negotiator agent's deductive unit, the function (checkfairness) representing the fairness model has been implemented. This is a function of gained profit in the negotiation and is named fairness function which is a 3-segment linear function as shown in figure 8. In this extended model, fairness rule is controlled in all successive rounds of negotiation which makes decision about potential agreements. That is if profit of received proposal were greater than profit of generated proposal, fairness rule is checked. So the function $I^a(t_{n+1}, x^{t_n}_{b\to a})$ changes as in figure 8.

$$I^a(t_{n+1}, x^{t_n}_{b\to a}) = \begin{cases} reject & if \quad t_{n+1} > t^a_{\max} \\ checkfairness & if \quad V(x^{t_n}_{b\to a}) > V(x^{t_{n+1}}_{a\to b}) \\ x^{t_{n+1}}_{a\to b} & otherwise \end{cases}$$

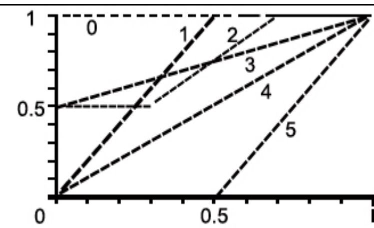

Figure 8. Negotiation function equation and fairness function graph (probability of acceptance vs. profit)[11]

According to the conducted experiments (with the same assumption and values in the previous section) it is possible to see the fairness rule effects in the conducted negotiation. In these experiments by changing the fairness rule, the operation of negotiator intelligence agents profit in each population is observable.

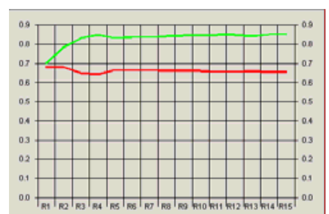

Figure 9. Average profits of buyer and seller during 100 generations using fairness function 4

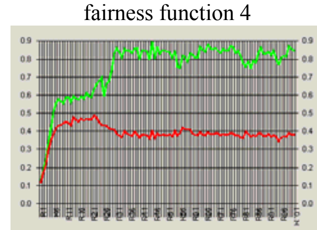

Figure 10. Average profits of buyer and seller during 100 generations using fairness function 5

The figures below is depicting the buyer and seller intelligent agent's profits changes and value of delivery time and price during negotiation with parameters derived from evolutionary algorithm after 100 generation.

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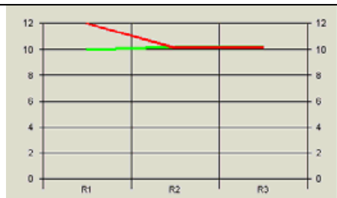

Figure 11. Delivery time values (fairness function 5)

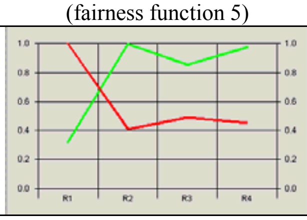

Figure 12. Profit (fairness function 5)

Table 4. Comparison of Buyer and seller agent parameters with and without of fairness function

Parameters	Seller agent strategies			
	Delivery Time		Price	
	With Fairness	Without Fairness	With Fairness	Without Fairness
βboulware	0.543517	0.874269	0.536061	0.54054
βconceder	9.074021	34.310974	37.440962	32.695497
μresource	16	8	12	7
δrelative	4	16	2	22
δrandom	5	5	7	8
M	3.521842	0.308737	47.684649	36.255109
λaverage	15	3	11	2
γ1	0.243298	0.54967	0.14943	0.240987
γ2	0.720855	0.027595	0.641624	0.690239
γ3	0.032677	0.39148	0.02875	0.011843
γ4	0.002807	0.002006	0.134988	0.034176
γ5	0.000142	0.013967	0.015127	0.020094
γ6	0.00022	0.015282	0.030081	0.002661
Parameters	Buyer agent strategies			
	Delivery Time		Price	
	With Fairness	Without Fairness	With Fairness	Without Fairness
βboulware	0.952742	0.457096	0.66037	0.54825
βconceder	32.461339	8.237193	21.411889	1.404535
μresource	45	48	25	24
δrelative	23	9	24	9
δrandom	21	8	6	13
M	0.458763	3.680573	46.183839	41.172996
λaverage	15	22	12	22
γ1	0.983481	0.111602	0.957056	0.801457
γ2	0.007723	0.435354	0.003264	0.039563
γ3	0.001126	0.211816	0.020272	0.102206
γ4	0.007249	0.189875	0.002905	0.025733
γ5	0.000381	0.043798	0.013286	0.020631
γ6	4e-005	0.007556	0.003217	0.010411

XIII. CONCLUSION

Nowadays, considering the increasing number of internet users and different goods and services providers in the internet, the first generation E-commerce sites don't satisfy the customers' needs. So, distributed artificial intelligence is used for developing the second generation of E-commerce sites in two countries Japan and America limitedly .As mentioned ,a new generations of E-commerce sites are represented which uses learning techniques helping users for making better and more secure deals which can be used by electronic corps removing the drawbacks exist in the current E-commerce.

In the combined model described in the last section, it tried using considerable models which each own several cons and pros, create a combined model that contain the maximum number of optimal parameters .this combined model by using the parameters of 6 different tactics that has been depicted ,and an developed evolutionary algorithm which has been used for the first time, and also by using a fairness model ,chooses the best possible parameters from a big environment and modeling an optimal negotiation

That the result of the conducted tests reflects its ability in comparison with the model pointed in [3].this model can be used easily in the real negotiations.

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