Evolution of Realistic Hybrid Auctions

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Abstract

Auctions are an important class of mechanisms for resolving multi-agent allocation problems. A genetic algorithm (GA) can be used to design auction mechanisms in order to automatically generate a desired market mechanism in an agent based E-market. One study found a new hybrid market mechanism never be found in the real-world which has very desirable market dynamics according to a measure based on Smith's coefficient of convergence. However, the auction space used in that study do not contain realistic single sided auctions. In this paper, a more realistic auction space is proposed and explored by a simple GA. The hybrid market mechanism still can be found that shows the hybrid market mechanism is not an artifact because an unfaithful auction space had been used in previous experiments.

1 Introduction

In the first generation of E-commerce, bidders are generally humans who typically browse through well defined commodities with fixed prices via the Internet (like Amazon.com). Just like the traditional marketplace, purchases are done with the prices made by sellers; buyers and sellers still have little freedom in transactions. The freedom can be increased by allowing negotiation between opposite traders, i.e., sellers and buyers. As a result, commerce will become much more dynamic and the market less frictional [9]. With the advent of agent technology, software agents can act as real-world traders in a virtual E-market. In comparison to human traders, such software agents have the advantage of being very fast, cheap and offer a tightly controlled environment in which a diverse range of experiments can be performed. Like real traders, agents representing a company or a customer are hunting for maximized *utility* which means profit for the sellers or savings for the buyers. At the same time they may have to make some sacrifices on profit to make themselves competitive in market. This kind of commerce is referred to as agent-mediated E-commerce or the second generation of E-commerce [9].

By experimenting with zero-intelligence (ZI) agents, which simply generated random prices for bids or offers, Gode and Sunder [8] presented results that appear to indicate that a random guessing strategy can exhibit human-like behavior in Continuous Double Auction (CDA) markets (see section 2). However, Cliff [2] indicated that the price convergence of ZI traders is predictable from a priori analysis of the statistics of the system, so that a more complex bargaining mechanisms or some "intelligence" is necessary. Consequently a type of agents with simple machine learning techniques was developed and referred to as zero intelligence plus (ZIP) agents (see section 3.1). Das *et al.* [7] showed that ZIP agents outperform their human counterparts in their experiments. By a series of experiments of exploring continuous auction space by ZIP agents via genetic algorithm [3, 4], Cliff discovered a hybrid auction that had never been found in the real-world but gave a more desirable market dynamics. However, in his experiments, the continuous space is not exactly the same as the real-world single sided auctions (see section 2.1 for definition of single sided auctions). Because his traders were selected randomly. In a real single sided auction, e.g., English Auction, the highest bidder wins. It is not clear that hybrid auctions would evolve more realistic auctions (see section 3.3 and 3.4). In this paper a new model of auction space which is more realistic to real-world auctions is proposed and explored by a GA.

The paper is organised as follows. Section 2 gives a short review on background economics. Section 3 starts with a brief introduction to

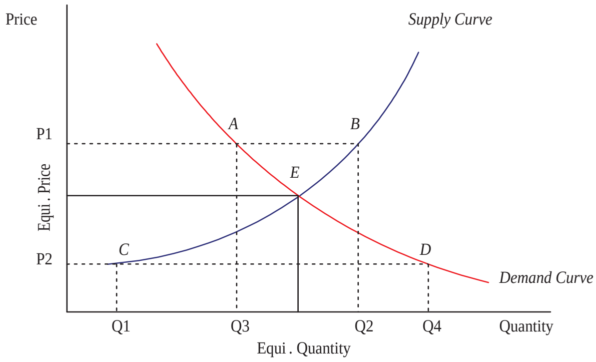

Figure 1: An illustration of supply-demand schedule, where E is the equilibrium point.

ZIP agents and propose the new auction space model. Section 4 gives the experimental results based on three supply-demand schedules. In the last section, we conclude our contributions and the significance of this research.

2 Background Economics

In every classical economic model, demand and supply always play prominent roles. Supply was used to describe the quantity of a good or service that a household or firm would like to sell at a particular price. Demand was used to describe the quantity of a good or service that a household or firm chooses to buy at a given price.

For a buyer, with increasing of quantity of the commodity, he will be inclined to bid a lower price to make a purchase, but with the less quantity of commodity, he has to increase his bid price. Because all the buyers want to make purchase, so, the demand curve slopes downward. For sellers, if the commodity is at a higher price, they will be inclined to sell as many as they can, that keeps the supply curve slope upward. The intersection of the supply curve and demand curves is called the equilibrium, and the corresponding price and quantity are called, respectively, the *equilibrium price* and the *equilibrium quantity*. Figure 1 depicts a qualitative relation of supply and demand: Equilibrium occurs at the intersection of the demand and supply curves, at point E. At any price above E, the quantity supplied will exceed the quantity demanded, the market will be in a state of excess supply. For example, at price P_1, from the demand curve, we learn that, for a particular good, consumers only need this good with quantity of Q_3, however, the producers provided the quantity of Q_2, apparently $Q_3 < Q_2$; the difference of Q_2 and Q_3 is the excess supply of the market. At any point below E, the quantity demanded will exceed the quantity supplied, the market is in excess demand. E.g. at price of P_2, consumers need Q_4 in quantity while the producers only provide Q_1 of goods. $Q_4 > Q_1$, the difference is the excess demand of the market.

In case of prices beyond the equilibrium, the market will self-correct them to the equilibrium by an "invisible hand". At an equilibrium price, consumers get precisely the quantity of the good they are willing to buy at that price, and sellers sell out the quantity they are willing to sell at that price. Neither of them has any incentive to change. In a competitive market, the price actually paid and received in the market will tend to the equilibrium price. This is called the law of supply and demand [15].

2.1 Market Mechanism

In economics and game theory, interactions of traders consist of two components: a protocol and a strategy. Protocol defines the valid behavior of traders during the interaction. It is set by the marketplace owner and should be known publicly for all the participants. Strategy is privately designed by each agent to achieve their negotiation objectives within a protocol [10]. Moreover, the effectiveness of the strategy is very much dependent on the protocol: an optimal strategy for one protocol may perform very badly for other protocols. In a marketplace, the protocol is an "auction". It is the market mechanism by which buyers and sellers interact in this marketplace. Strategy is the adaptive behavior or "intelligence" of traders such as the ZIP agents' updating rules that is discussed later.

There are many types of auctions. The following are some auctions used in this paper: English Auction (EA), sellers keep silent and buyers quote increasing bid-prices, and the buyer with highest bidding is allowed to buy; Dutch Flower Auction (DFA), buyers keep silent and sellers quote decreasing offer-prices and the seller with lowest offer is allowed to sell. EA and DFA are also called single sided auctions because either buyers or sellers are active but not both. The Continuous Double Auction (CDA), one the most popular of all auctions, allows buyers and sellers to continuously update their bids/offers at any time in the trading period. The bids/offers are quoted simultaneously and asynchronously by buyers/sellers. At any time the sellers/buyers are free to accept the quoted bids/offers [10].

2.2 Smith's Experiments

Classical economic theories always assume the number of traders in the market is infinite or very large. However, from a series of experiments performed over a six-year period starting in 1955, Smith [14] demonstrated that markets consisting of small numbers of traders could still exhibit equilibration to values predictable from classical microeconomic theory. This work helped to make a foundation for Experimental Economics[1]. In his experiments, each trader (seller or buyer) has a *private* limit price for a unit, that a seller could not sell less than and a buyer could not pay more than. Typically, different traders had different limit prices and the distribution of limit price is determined by a supply-demand schedule. In each experiment, the trading lasted for a few "days". In each day, a predefined number of transactions were given and the rights to quote were distributed to traders. Trades operated under a specific market mechanism; most of Smith' experiments used CDA. In each trade, the transaction prices were logged for studying the convergence property of the market.

In a given supply-demand schedule with n transactions, the coefficient of convergence α is introduced to measure the deviation of transaction prices from the theoretical market equilibrium price p_0 [14]. α is calculated at the end based on transaction prices p_i for $i = 1, \cdots, n$. The coefficient of convergence $\alpha = 100 \cdot \delta_0 / p_0$ where

$$\delta_0 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - p_0)^2} \qquad (1)$$

The E-market discussed in this paper as well as in [2]-[8] is based on Smith's experiment and the α measure is used to evaluate the convergence of the market.

3 Market Mechanism Design by Evolution

Market mechanism design addresses the problem of designing an auction in which the agents' interaction generates a desirable macro-scale outcome, by assuming the trading agents are self-interested. A desired market can be simply considered as the one with least transaction price variance to the equilibrium price determined by the market's supply-demand schedule. In this paper, ZIP agents [2] are used to conduct Smith's experiments discussed above.

3.1 Zero Intelligence Plus Agents

Zero intelligence plus (ZIP) agents, an augmented version of ZI agents [8] with simple machine learning technique, are fully described in [2]. In this paper, a high-level description of the parameters for ZIP traders is given for the purpose of this paper. Each ZIP trader i is given a private secret limit price, λ_i, which for a seller is the price below which it must not sell and for a buyer is the price above which it must not buy (based on Smith's experiment). Each ZIP trader i maintains a time-varying profit margin $\mu_i(t)$ and generates quote-prices $p_i(t)$ at time t according to $p_i(t) = \lambda_i(1 + \mu_i(t))$ for sellers and $p_i(t) = \lambda_i(1 - \mu_i(t))$ for buyers. Trader i is given an initial value $\mu_i(0)$ (when $t = 0$) which is subsequently adapted over time using a simple machine learning technique known as the Widrow-Hoff (W-H) rule [11] which is well used in back-propagation neural networks. The W-H rule has a "learning rate" β_i that governs the speed of convergence between trader i's quote price $p_i(t)$ and the trader's idealised target price $\tau_i(t)$ which is determined by a stochastic function of last quote price with two small random absolute perturbations: $A_i(t)$ and $R_i(t)$. $A_i(t)$ is generated uniformly from the interval $[0, C_a]$ denoted by $\mathcal{U}[0, C_a]$ for sellers and $\mathcal{U}[-C_a, 0]$ for buyers. $R_i(t)$ is generated from $\mathcal{U}[1, 1 + C_r]$ for sellers and $\mathcal{U}[1 - C_r, 1]$ for buyers. Here C_a and C_r are called system constants. To smooth over noise in the learning, there is an additional "momentum" γ_i for each trader (momentum is also used in back propagation neural networks [11]).

In the simulation of real marketplaces, we assume that each significant event (quoting, making deal or not making deal etc.) always occurs at a unique time [4]. In the CDA market described in [2, 3], at time t, an *active* ZIP trader (seller or buyer) i is chosen randomly to quote a price $p_i(t)$ to become the "current quote $q(t)$", where the active traders are ones who still have utility (goods or money) for deals. Next, all traders on the contraside (i.e. all buyers j if i is a seller, or all sellers j if i is a buyer) compare $q(t)$ to their current quote price $p_j(t)$ and if the quotes cross (i.e. if $p_j(t) \leq q(t)$ for sellers or $p_j(t) \geq q(t)$ for buyers) then the trader j is able to accept. If no traders are able to accept, the quote is regarded as "ignored". Either the current quote is accepted or ignored and the traders update their profit margins $\mu(t)$ using the W-H

1. Smith won the 2002 Nobel prize in Economics for his contributions in Experimental Economics.

rule. For example, suppose the last quote is an offer and was accepted at price q then any sellers for which their price is less than q should raise their profit margin with learning rate of β_i.

3.2 Market Mechanism Evolution in Continuous Auction Spaces

As discussed in the last section, adaptation in each ZIP trader i is governed by three real-valued parameters: learning rate β_i, momentum γ_i and initial profit margin $\mu_i(0)$. Because of the randomness and the uncertainty involved in trading, a trader's values for these parameters are assigned at initialization, using uniform distributions: for all traders, β_i is assigned a value at random from $\mathcal{U}(\beta_{min}, \beta_{min} + \beta_\Delta)$; and γ_i is assigned a value from $\mathcal{U}(\gamma_{min}, \gamma_{min} + \gamma_\Delta)$ and $\mu_i(0)$ is from $\mathcal{U}(\mu_{min}, \mu_{min} + \mu_\Delta)$. Hence, to initialise an entire ZIP trader market it is necessary to specify values for the six market-initialisation parameters β_{min},β_Δ, γ_{min}, γ_Δ, μ_{min} and μ_Δ; and also for the two system constants C_a and C_r. Clearly, any particular choice of values for these eight parameters can be represented as a vector:

$$V = [\beta_{min}, \beta_\Delta, \gamma_{min}, \gamma_\Delta, \mu_{min}, \mu_\Delta, C_a, C_r] \in \mathbf{R^8}$$

which corresponds to a single point in the 8-dimensional space of possible parameter values. A GA can be used to explore this space.

The fitness for each individual was calculated by monitoring price convergence in a series of n CDA market experiments, measured by weighting Smith's α measurement of convergence on the given supply-demand schedules. Each experiment lasted k "days" and the score of experiment number e is:

$$S(V_i, e) = \frac{1}{k} \sum_{d=1}^{k} w_d \alpha(d) \qquad (2)$$

where $\alpha(d)$ is the value of α and w_d is the weight on the day d. According to the experiments reported by Cliff [3], all experiments last for 6 days and we place a greater emphasis on the early days of trading. And the weights are set as follows: $w_1 = 1.75$, $w_2 = 1.50$, $w_3 = 1.25$ and w_4, w_5 and w_6 are all equal to 1.00. The fitness of the genotype V_i is evaluated by the mean score of n experiments:

$$F(V_i) = \frac{1}{n} \sum_{e=1}^{n} S(V_i, e) \qquad (3)$$

For the sake of computation time, n equals to 20 following [13] which reported that the average of 20 independent runs of the trading experiments are fairly stable. The Lower fitness a market has, the sooner the market approaches to the equilibrium and the smaller price variances the market has. GAs were used for optimising the parameters for ZIP agents in [3] which showed that evolved parameter settings via GAs perform significantly better than "educated guessing" in CDA and the same conclusion is also obtained in [13].

Now consider the case when we implement CDA. At time t, either a seller or a buyer will be selected to quote. Which means that sellers and buyers have a fifty-fifty chance to quote. We use Q_s to denote the probability of the event that a seller offers. Then in CDA, $Q_s = 0.5$. For English Auction $Q_s = 0$ and Dutch Flower Auction $Q_s = 1$; which means, sellers cannot quote and sellers are always able to quote, respectively. The inventive step introduced in [4] was to consider the Q_s with values of 0.0, 0.5 and 1.0 not as three distinct market mechanisms, but rather as the two endpoints and the midpoint on a continuum referred as a continuous auction space. For other values, e.g., $Q_s = 0.1$, it can be interpreted as follows: on the average, for every ten quotes, there will be only two from sellers while eight are from buyers. This also means, for a particular significant time t, the probability of a seller being the quoting trader is 0.1. The fact is, this kind of auctions is never found in human-designed markets. However, no one knows that whether this kind of *hybrid mechanisms* in which $Q_s \neq 0, 0.5$ or 1.0 are more preferable to human-designed ones. Nevertheless, there are no priori reasons that the three human-designed mechanisms (EA, DFA and CDA) should be preferable. This motivates us to use a GA to explore with additional dimension Q_s ranging from 0 to 1 giving us the following genotype based on the old one by adding a new dimension Q_s,

$$[\beta_{min}, \beta_\Delta, \gamma_{min}, \gamma_\Delta, \mu_{min}, \mu_\Delta, C_a, C_r, Q_s] \in \mathbf{R^9}$$

In the evolving market mechanism experiments, the bargaining strategy and price adapting rules for ZIP agents in the continuous auction space is not changed except for the probability of quoting described above. The evolution of market mechanisms in Cliff's model is denoted by EM-C.

3.3 A Model of Realistic Auction Space

In the previous experiments [4, 5, 6], the continuous auction space used for market mechanism evolution cannot express exactly the single sided auctions such as English Auction and Dutch Flower Auction, although the auction space in the case of $Q_s = 0.5$ is indeed a good approximation to the CDA. In CDA, by 50% chance a trader, say a seller, will be chosen to quote at the price $q(t)$. Then any buyers j with $p_j(t)$ cross $q(t)$ can accept this quote. All buyers with prices above with $q(t)$ will form a candidate price list denoted by $P(t)$. From this list, a buyer is selected randomly to accept the $q(t)$. This is indeed a good analogue to CDA. Now, consider in an extreme case of $Q_s = 0$. If a seller quotes $q(t)$, any buyers with price above with $q(t)$ have equal chances of being selected to make this transaction according to the mechanism of the old auction space. However, this is not the case in the real-world English Auction, the buyer with the highest bid is the only one allowed to make the deal, others with non-highest price have no chance to make this deal. Similarly DFA, when a buyer makes a bid, only the seller with lowest offer price can be allowed to make this deal. Since there is a lot of randomness and uncertainty involved in the experiments and the auction space used is not a faithful version to single sided auctions, a question may arise as to whether the hybrid market mechanism is an artifact of the unfaithful auction space used. To answer this, we need a more realistic model of the auction space which need to be explored by the same GA. Based on the old auction space, we propose a new model which contains true single sided auctions as well as CDA.

Suppose the last quote $q(t)$ is an offer and there are m buyers with prices above $q(t)$. We put these prices in decreasing order into a set called *sorted price list* denoted by SP, so that $SP = \{p_1, \cdots, p_m\}$ where $p_i \geq p_{i+1}$ for $i = 1, \cdots, m-1$. If last quote is a bid, we put the prices of sellers in increasing order so that $p_i \leq p_{i+1}$ for $i = 1, \cdots, m-1$. We then propose a function θ defined as follows: When the last quote is from a seller,

$$\theta = \begin{cases} 2Q_s & if \;\; Q_s < 0.5 \\ (m-1)/m & otherwise \end{cases} \tag{4}$$

and when the last quote is from a buyer,

$$\theta = \begin{cases} 2(1-Q_s) & if \;\; Q_s > 0.5 \\ (m-1)/m & otherwise \end{cases} \tag{5}$$

θ is used to construct a *restricted price list* $RP = \{p_1, \cdots, p_{m'}\}$ where

$$m' = INT(m \cdot \theta) + 1 \tag{6}$$

$INT(x)$ is a function for returning the nearest integer for x. The restricted price list (RP) is a subset of the sorted price list (SP). RP contains a number of traders with higher bid prices (for buyers) or lower offer prices (for sellers) according to Q_s. In this auction space, a trader to accept the last quote is chosen randomly from RP. By restricting the price list of potential traders, the new auction space is an exact analogue to single sided auctions as well as CDA. Auctions within this auction space model are more realistic to real-world auctions than Cliff's model. For example, when $Q_s = 0.5$, we can obtain $m' = m$ so that $RP = SP$ according to eq. 4, 5 and 6. This means, for CDA, the new auction space is the same as the old auction space. When $Q_s = 0$, we obtain $RP = \{p_1\}$ where p_1 is the highest price of a set of able buyers, and only the buyer with this price can make this transaction. This is an exact analogue to English Auction. Suppose $m = 5$ (there are 5 potential traders selected for the last quote) and the last quote is from a seller. When $Q_s = 0.1$, we obtain $\theta = 2 \times 0.1 = 0.2$ and $m' = INT(5 \times 0.2) + 1 = 2$, so that $RP = \{p_1, p_2\}$. In Cliff's model, $\{p_1, \cdots, p_5\}$ has the same possibility to be selected to make the deal. However, in the new model, because Q_s is near to English auction, the buyers with higher prices (i.e., p_1 and p_2) have more chances to be selected. The evolution of the market mechanisms in this new model is denoted by EM-Q.

4 Experimental Studies

In this section, all experimental settings are identical to Cliff's previous experiments in order to make direct comparisons. The CDA market where $Q_s = 0.5$ and markets with two types of auction spaces EM-C (section 3.2) and EM-Q (section 3.3) is explored by a simple GA based on three supply-demand schedules: M_1, M_2 and M_3 (see figure 2). Each schedule is with 11 sellers and 11 buyers. The same schedules are also used in [3].The key parameter values of the GA are given as follows: Population size is 20 and each parameter is coded with 8 bits, crossover rate is a constant with the value of 0.7 and mutation rate is 0.0015. Elitism strategy is applied which means that the fittest individual in each generation is logged. We run 600 generations in a single experiment. However, one of the drawbacks of using a GA is that it cannot be guaranteed that the solution on which the population eventually converges is a global rather than a local optimum. Thus we gain formal simplicity

Table 1: The evolved best fitness and Q_s on M_1, M_2 and M_3 after 600 generations.

S-D Schedule	**Fitness on the α Measure**			**Q_s**	
	CDA	*EM-C*	*EM-Q*	*EM-C*	*EM-Q*
$Market_1$	4.893 ± 0.122	4.591 ± 0.168	4.469 ± 0.173	0.148 ± 0.068	0.152 ± 0.081
$Market_2$	3.346 ± 0.184	2.413 ± 0.043	2.401 ± 0.066	0.086 ± 0.046	0.105 ± 0.034
$Market_3$	5.946 ± 0.209	5.725 ± 0.200	5.738 ± 0.233	0.200 ± 0.067	0.230 ± 0.100

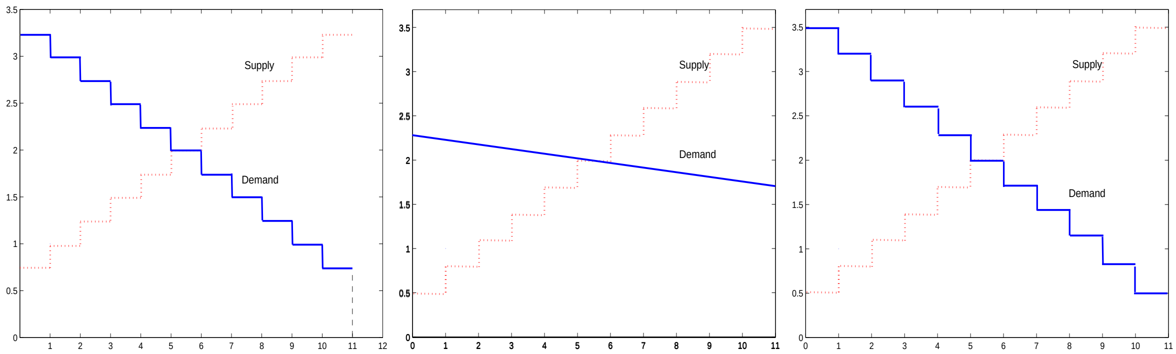

Figure 2: Supply-demand schedules: Market_1 (M_1), Market_2 (M_2) and Market_3 (M_3).

at the cost of computation. We run the entire process of evolution many times independently and reduce the effect of mutation as time goes by, to encourage convergence. The results represented here are based on 20 independent runs of the GA on the given supply-demand schedules and the average results with standard deviation through generation 600 are shown in figure 3. The results on the generation 600 are listed in table 1.

EM-C experiments replicate ones by Cliff [4], although the GA settings are different. The market mechanism parameter Q_s approaches 0.148 in M_1, 0.086 in M_2 and 0.200 in M_3. Experimental results by Cliff showed that Q_s approaching 0.086 has no significant better market performance than $Q_s = 0$ in M_2 [4]. Since there is lots of randomness involved in these experiments, the convergence is just noise (see figure 4). But on M_1 and M_3, there are new market mechanisms that are never found in real-world market. E.g., for $Q_s = 0.2$ in M_3, that means, on average, when 4 quotes come from buyers, there is only one quote from sellers. This kind of market mechanism does not exist in real-world markets. It is also interesting to see the all the three evolved market mechanisms are non-CDA.

However, previous results of Cliff [4] had found much better sets of individuals from the experiments on m_1. The possible reasons for Cliff's superior results are as follows. Because of the limitation of our computing facilities, we only ran 600 generations rather than 1000, which may not be enough for this simple GA. Second, our population size is 20 compared to 30 in previous work. The reduction of 30% is likely to reduce diversity which may constrain the search. Third, we used 8 bits per parameter. This gives 256 possible values for each locus on the genome, but the previous work used double-precision floating point numbers to represent each parameter. [5] visualizes the search space for M_1 and shows that only very few trails can locate the optimum even with a more powerful GA. Nevertheless, the results on M_2 and M_3 agree with previous results. That indicates that these differences discussed above in GA are not causing "major" differences in the results. The evolving market mechanism gives the system better fitness than CDA, which is well known for its efficiency. The hybrid mechanism is part of the nature of markets based on ZIP traders. It is independent from the optimization method we used. From table 1, we can see that the fitness are almost identical (i.e., no statistical differences were found). For Q_s values, there is a slight difference between the two auction spaces based on the given market schedules, where the Q_s value of EM-Q tends to move toward 0.5 comparing to EM-C.

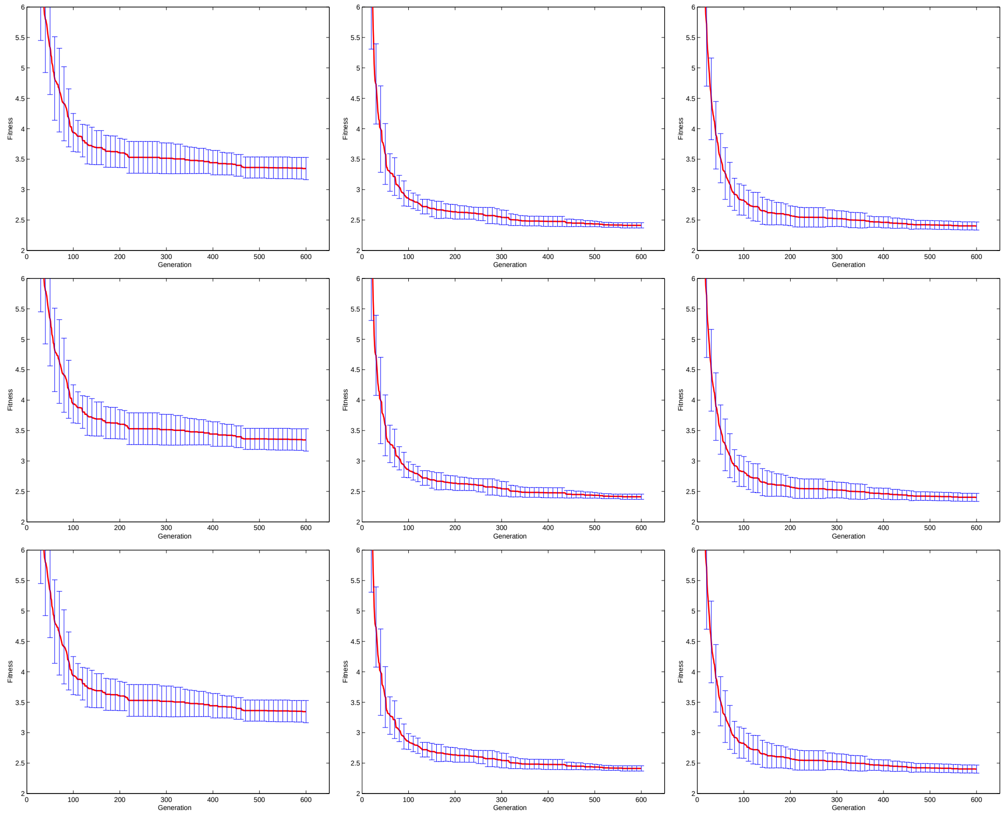

Figure 3: The mean of fitness with standard deviation in CDA (left-hand column), EM-C (middle) and EM-Q (right-hand) through 600 generations, where the upper figures are on M_1, central figures are on M_2 and lower ones are on M_3.

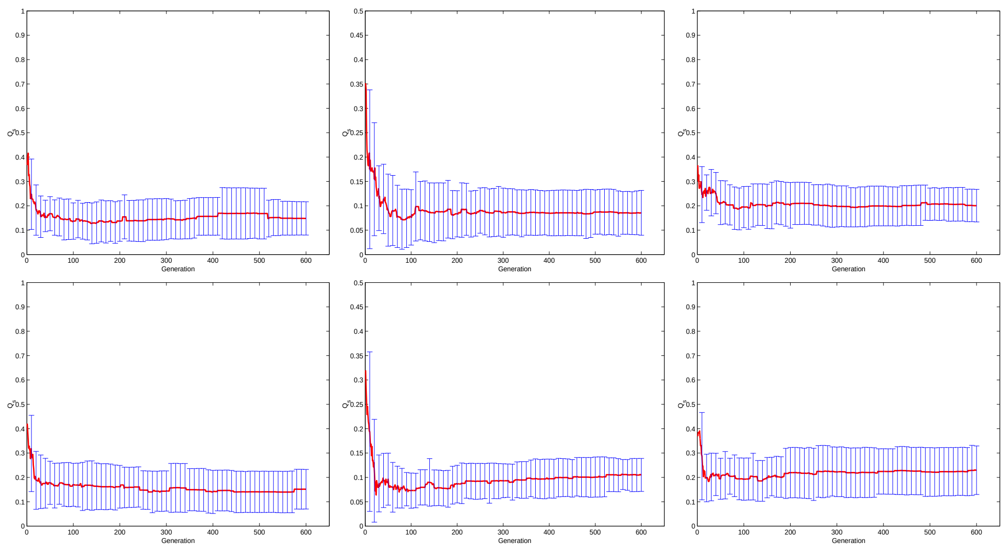

Figure 4: The evolutionary trials of Q_s in EM-C (upper figures) and EM-Q (below figures) based on M_1 (left-hand column), M_2 (central column) and M_3 (right-hand column).

5 Conclusions

The field of automated market mechanism designs for E-markets by genetic algorithm is very new. In addition to Cliff's work, Byde [1] also reports similar hybrid mechanisms with best desired market dynamics based on different experiments with sealed auctions. Our contributions are in the following two aspects. (i) The key results of the evolving market mechanism within Cliff's continuous auction space [3] are replicated with a simple GA. The results are in broad agreement with previous results indicating that differences in the GA are not causing major differences in the results. (ii) A more realistic auction space to single sided auctions is proposed. This auction space is explored by the same GA and the hybrid market mechanism with the most desired market dynamics still can be found. The market dynamics with the new auction space are almost the same as the previous auction space model and the value of Q_s in the new model tends to move toward 0.5 comparing to Cliff's model. Based on these results, we can conclude that the hybrid market mechanism is a feature of E-markets and not an artifact of the unfaithful analogy of the previous auction space model to real single sided auctions.

Finally we like to point out that this is not a trivial academic point: although the efficiency of automatically designed markets are only a few percentage points better than those designed by human, the economic consequences could be highly significant. For instance, the total value of trades on the CDA-based New York Stock Exchange (NYSE) for the year 2000 was 11060 billion US dollars [12], if only 0.1% of the liquidity could be saved by using a market employing an effcient automatically designed mechanism, there would be the value of around 10 billion US dollars [6].

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