Toward an Agent-Based Computational Modeling of Bargaining Strategies in Double Auction Markets with Genetic Programming

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Abstract. Using genetic programming, this paper proposes an *agent-based computational modeling* of *double auction* (**DA**) *markets* in the sense that a DA market is modeled as an *evolving market* of *autonomous interacting traders* (*automated software agents*). The specific **DA** market on which our modeling is based is the Santa Fe **DA** market ([12], [13]), which in structure, is a *discrete-time* version of the Arizona *continuous-time* experimental **DA** market ([14], [15]).

1 Introduction

The purpose of this paper is to use genetic programming as a major tool to evolve the traders in an agent-based model of double auction (*DA*) market. With this modeling approach, we attempt to provide an analysis of bargaining strategies in DA markets from an evolutionary perspective. By saying that, the novelties of this paper, which helps distinguish this paper from early studies are two folds. First of all, to out best knowledge, the existing research on bargaining strategies in DA markets are not *agent-based models*. This research is, therefore, the first one. Secondly, while this research is not the first one to study the bargaining strategies from an evolutionary perspective, it is the first one to use genetic programming on this issue. We believe that genetic programming, as a methodological innovation to economics, may be powerful enough to enable us to get new insights on the form of effective trading strategies, and help us better understand the operation of the "invisible hand" in real-world markets. Furthermore, since the idea "*software agents*"" and "*automated programs*" should play an increasing important role at the era of *electronic commerce*, the agent-based model studied in this research can be a potential contribution to electronic commerce too. The rest of this section is written to justify the claimed novelties and significance.

2 Bargaining Strategies in DA Markets: Early Development

The *double auction* (**DA**) market has been the principal trading format for many types of commodities and financial instruments in organized markets around the

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world. The pit of the Chicago Commodities market is an example of a double auction and the New York Stock Exchange is another. In a general context, traders in these institutions face a sequence of non-trivial decision problems, such as

– how much should they bid or ask for their own *tokens*?
– how soon should they place a bid or ask?
– under what circumstance should they accept an outstanding bid or ask of some other trader?

Since [14], the experimental studies using human subjects have provided considerable empirical evidence on trading behavior of DA markets, which, to some extent, demonstrates that DA markets have remarkable efficiency properties. Nevertheless, these studies cast little light on *trading strategies* which are essentially unobservable.

Modern economic theory has attempted to explained observed trading behavior in DA markets as the rational equilibrium outcome of a well-defined game of incomplete information. The “null hypothesis” is that observed trading behavior is a realization of a Bayesian-Nash equilibrium (BNE) of this game. However, due to the inherent complexity of continuous-time games of incomplete information, it is extremely difficult to compute or even characterize these equilibria. As a result, relatively little is known theoretically about the nature of equilibrium bargaining strategies.

3 Computational Modeling of DA Markets: Zero-Intelligence “Theorem”

Recently, the computational approach, as a compliment to the analytical and the experimental ones, were also involved in the study of bargaining strategies in DA markets. Two influential early contributions in this line of research appeared in 1993. One is [7], and the other is [12]. While both addressed the nature of the bargaining strategies within the context of DA markets, the motivations behind them are quite different.

Motivated by a series of studies by Vriend Smith, [7] addressed the issue: *how much intelligence is required of an agent to achieve human-level trading performance?* Using an electronic DA market with *software agents* rather than *human subjects*, they found that the imposition of the budget constraint (that prevents zero-intelligence traders from entering into loss-making deals) is sufficient to raise the allocative efficiency of the auctions to values near 100 percent. The surprising and significant conclusion made by them is, therefore, that the traders’ motivation, intelligence, or learning have little effect on the allocative efficiency, which derives instead largely from the structure of the DA markets. Thus, they claim

> Adam Smith’s invisible hand may be more powerful than some may have thought; it can generate *aggregate rationality* not only from individual

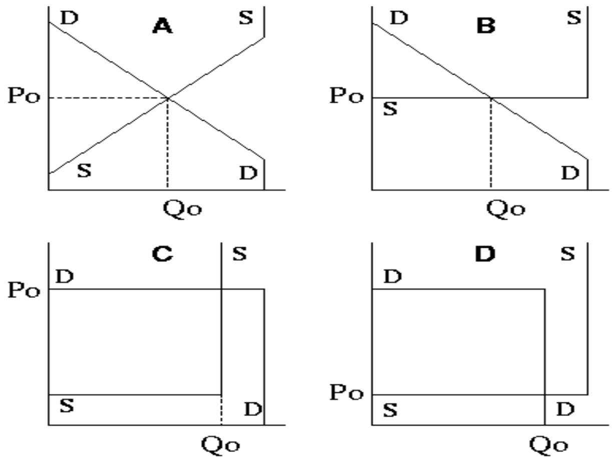

Fig. 1. Four Types of Demand and Supply Curves (Adapted from [5].)

rationality but also from *individual irrationality.*" (Ibid., p.119, Italics added.).

Furthermore,

> ... the convergence of transaction price in ZI-C markets is a consequence of the market discipline; trader's attempts to maximize their profits, or even their ability to remember or learn about events of the market, are not necessary for such convergence. (Ibid, p.131)

While it sounds appealing, Gode and Sunder's strong argument on *zero intelligence* (ZI) was demonstrated to be *incorrect* by [5]. Using an analysis of the probability functions underlying DA markets populated by Gode & Sunder's ZI traders, [5] showed that the validity of *zero-intelligence "theorem"* is largely *a matter of coincidence*. Roughly speaking, only in a market whose supply and demand curves are *mirror-symmetric*, by reflection in the line of constant price at the equilibrium value P_0, over the range of quantities from zero to Q_0 (See Figure 1-(A) above), the ZI traders can trade at the theoretical equilibrium price. In more general cases, cases shown in Figure 1-(B), (C) and (D), ZI traders can easily fail. The failing of the ZI traders indicates a need for bargaining mechanisms more complex than the simple stochastic generation of bid and offer prices.

While this line of research can be further pursued, one should notice that what actually concerns traders are their own profits from trade. There is no reason why they should behave like ZI traders simply because ZI traders might collectively generate allocative efficiency. On the contrary, they may behave "*too smart for their own interests*". Consequently, models with ZI or ZI-Plus traders are unlikely to provide a good model to the understanding of human trading strategies.

4 Computational Modeling of DA Markets: SFI DA Tournaments

Leaving *collective rationality* aside, [12]'s computational study of bargaining strategies were largely motivated by *individual rationality.* Instead of asking the *minimal intelligence* required for *collective rationality*, they asked: *is the case that sophisticated strategies make individual traders better off?* Their analysis was based on the results of computerized double auction tournaments held at Santa Fe Institute beginning in March 1990. 30 programs were submitted to these tournaments. These 30 programs were written by programmers with different background knowledge (economics, computer science, cognitive science, mathematics, ...), and hence are quite heterogeneous in various dimensions (modeling strategies, complexity, adaptability, ...). For example, in complexity, they ranged from simple *rule-of-thumb* to sophisticated adaptive/learning procedures employing some of the latest ideas from the literature on *artificial intelligence* and *cognitive science.*

After conducting an extensive series of computer tournaments involving hundreds of thousands of individual DA games, the results may sounds to one's surprise: *nearly all of the top-ranked programs were based on a fixed set of intuitive rules-of-thumb.* For example, the winning program, known as Kaplan's strategy, makes no use of the prior information about the joint distribution of token values, and relies on only a few key variables such as its privately assigned token values, the current bid and ask, its number of remaining tokens, and the time remaining in the current period. Quite similar to the classical result presented by [2] in the context of *iterated prisoner's dilemma*, i.e., to be good *a strategy must be not too clever*, [12] just reconfirmed this *simplicity principle.* In [12], the effective bargaining strategies are simple in all aspects, which can be characterized as *nonadaptive*, *non-predictive*, *non-stochastic*, and *non-optimizing.*

Therefore, while Rust et al.'s auction markets were composed of traders with *heterogeneous* strategies, their results on the *simplicity* of the effective bargaining strategies, in spirit, is very similar to what Gode and Sunder found in the markets with *homogeneous* traders. Moreover, the general conclusion that *the structure of a double auction market is largely responsible for achieve high level of allocative efficiency, regardless of the intelligence, motivation, or learning of the agents in the market* is well accepted in both lines of study. However, as the reason which we shall argue below, this conclusion with the simplicity criterion is indeed *in doubt.* For convenience, we shall call this doubtful argument *the intelligence-independent property*, which should roughly capture the essence of *zero intelligence* in [7] and "rules of thumb" in [12].

5 What is Missing? Evolution

First of all, *intelligence-independent property* is clearly not true in the context of *imitation dynamics.* For an illustration, consider Kaplan's strategy. The Kaplan

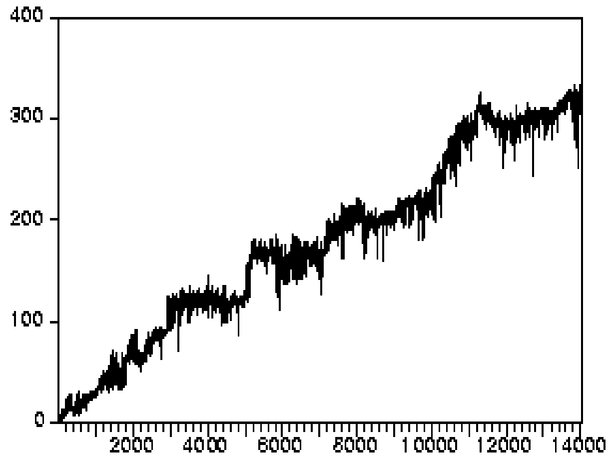

Fig. 2. Evolving Complexity of Traders' Forecasting Models (Adapted from Figure 9 in [4]).

strategy *waits in the background until the other participants have almost negotiated a trade (the bid/ask spread is small), and then jumps in and steals the deal if it is profitable.* Suppose that we allow *imitation* among traders, then we would expect growth in the relative numbers of these sorts of *background traders.* Less profitable traders should gradually exit the market due to *competitive pressure.* In the end, all traders in the market are *background traders.* However, the background traders create a negative "*information externality*" by waiting for their opponents to make the first move. If all traders do this, little information will be generated and the market would be unable to function efficiently. As a result, the "*wait in the background*" strategy would eventually be non-profitable, and hence certainly can no longer be effective. As a result, Rust et al.'s characterization of effective strategies may not able to hold in an *evolutionary* context.

In fact, the *simplicity principle* argued by [2] is recently shown to be *incorrect* by [3]. By using a larger class of strategies, they showed that the simple *Tie for Tat* strategy was beaten by a more complex strategy called *gradual* in almost all their experiments. As a conclusion, they claimed the significance of *evolution* (*adaptation*).

> Evaluation can, however, not be based only on the results of complete classes evolution, since a strategy could have a behavior well adapted to this kind of environment, and not well adapted to a completely different environment. (Ibid, p. 40)

The significance of evolution on the complexity of strategies was also shown in [4]. In their agent-based modeling of artificial stock markets, they conducted an analysis of the evolving complexity of each traders' forecasting models, and a typical result is demonstrated in Figure 2. Their results evidence that traders can evolve toward a higher degree of sophistication, while at some point in time, they can be simple as well. Therefore, it is very difficult to make much sense of the simplicity principle from a steady environment.

6 Evolving Bargaining Strategies

In literature, there are two studies which actually attempted to give an *artificial life* for bargaining strategies. One is [1], and the other is [11]. Both relied on genetic programming. Nevertheless, neither of them can be considered as a truly evolutionary model of DA markets. To see this, the market architecture of these two studies are drawn in Figure 3 and 4.

What Andrews and Prager did was to fix a trader (Seller 1 in their case) and used genetic programming to evolve the trading strategies of only that trader. In the meantime, one opponent was assigned the trading strategies "*Skeleton*", a strategy prepared by the SFI tournament. The trading strategies of the other six opponents were randomly chosen from a selection of successful Santa Fe competitors. Therefore, what Andrews and Prager did was to see whether GP can help an individual trader to evolve very competitive strategies given their opponents' strategies. However, since other opponents are not equipped with the same opportunity to adapt, this is not a really evolutionary model of DA markets.

On the other hand, [11]'s architecture can be motivated as follows. Suppose that you are an economists, and you would like to select a pair of bargaining strategies, one for all sellers, and one for all buyers. Then you are asking how to select such pair of rules so that the allocative efficiency can be maximized (as he chose the Alpha's value as the fitness function). To solve this problem, Olsson also used genetic programming. In this application, traders are not pursuing for their own interests, but try to please the economist. Moreover, they are all shared with the same strategy at any moment in time. Hence, Olsson's model, very like the model of artificial ants, is certainly not an evolutionary model of DA markets.

In sum, while both [1] and [11] did use genetic programming to "*grow*" bargaining strategies, the style by which they used GP did not define an evolutionary model of DA markets.

7 Agent-Based Modeling of DA Markets: Trading Behavior

[6] may be considered as the first *agent-based computational model* of DA markets. Based on the WebPages of agent-based computational economics:
http://www.econ.iastate.edu/tesfatsi/ace.htm,
"Agent-based computational economics (ACE) is roughly defined by its practitioners as the computational study of economies modeled as evolving systems of autonomous interacting agents.... ACE is thus a blend of concepts and tools from evolutionary economics, cognitive science, and computer science."

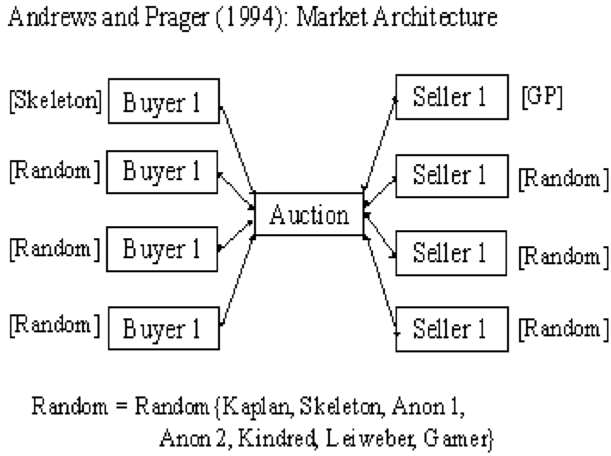

Fig. 3. The DA Market Architecture of [1]

The market architecture of [6] is depicted in Figures 5 and 6. He considered two populations of agents: 100 Buyers and 100 Sellers. Each seller has the potential to produce one unit of the commodity every period. The production costs are given by c $\in [0, 1]$ ($c = 0, 0.1$ in his experiments). The seller produces the good only if he can sell it in the same period. The buyer gain utility of $1 \geq u > c$ from consuming the good ($u = 1, 0.7$ in his cases). u and c are private information. During each period, every seller is randomly matched with a buyer and both submit a sealed bid. The buyer submits the price he is willing to pay (p_b), and the seller gives the minimum payment for which he will deliver the good (p_s). Buyers and sellers know that c and u lie in [0,1] and accordingly restrict their bids to this interval. If $p_b \geq p_s$, one unit of the good is traded at a price of

$$p_t rade = \frac{(p_b + p_s)}{2}. \tag{1}$$

Otherwise, no trade takes place. He then applied the so-called *single-population genetic algorithm* to buyers and sellers simultaneously. But, constrained by the GA, what one can observe from Dawid's model is only the evolution of bids and asks rather than the bargaining strategies by which the bids and asks are generated. Therefore, while Dawid is the first application of agent-based model to DA markets. This is really not a model suitable for the study of bargaining strategies.

8 Agent-Based Modeling of DA Markets: Trading Strategies

Given this literature development, the next step of the computational modeling of DA markets seems to be clear, and the architecture proposed in this research is briefed in Figure 7.

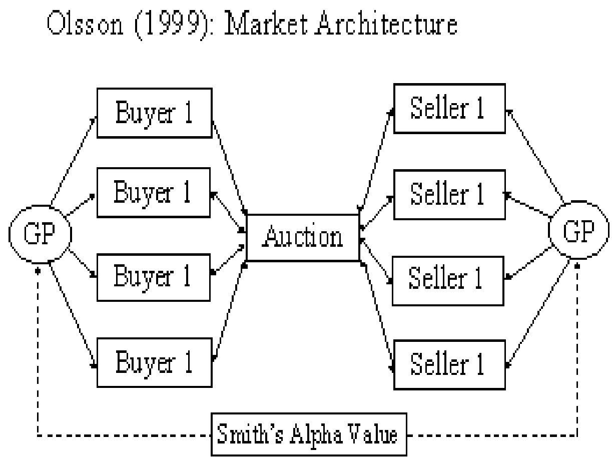

Fig. 4. The DA Market Architecture of [11]

This simple architecture shows some distinguishing features of this research. First, it is the use of *genetic programming*. But, we do not just come to say: "*Hey!. This is genetic programming. Try it! It works.*" To our understanding, genetic programming can be considered a novel micro-foundation for economics. In fact, its relevance to the study of adaptive behavior in economics can be inferred from [9]. First, he gave a notion of an agent in economics.

> In general terms, we view or model an individual as a collection of *decision rules* (*rules that dictate the action to be taken in given situations*) and *a set of preferences* used to evaluate the outcomes arising from particular *situation-action* combinations. (Ibid; p.217. Italics added.)

Second, he proceeded to describe the adaptation of the agent.

> These decision rules are continuously under review and revision; *new* decision rules are tried and test against *experience*, and rules that produce desirable outcomes supplant those that do not. (Ibid; p.217. Italics added.)

Let us read these two quotations within the context of DA markets. An individual would be treated as a trader, and a decision rule is a just a *bargaining strategy*. To be specific, we consider the three strategies studied by [12] and [13], namely, the skeleton strategy, the Ringuette strategy, and the Kaplan strategy.

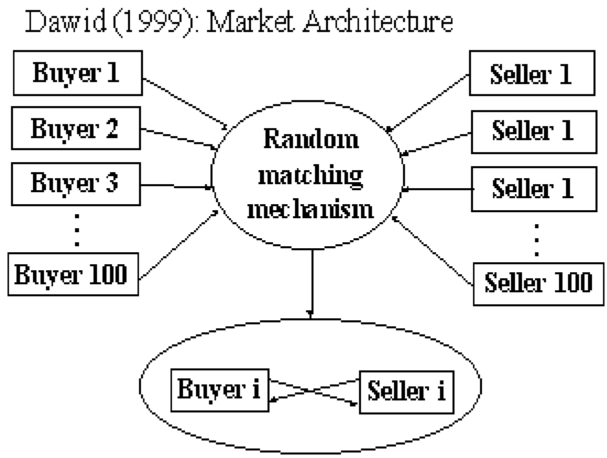

Fig. 5. The DA Market Architecture of [6]

The flowchart of there three strategies adapted from [13] is displayed in Figures 8, 9, 10.

In addition to the flow-chart representation, these three strategies can also be represented in what known as the *parse-tree* form, and are shown in Figures 11, 12, 13. In this case, what [9] meant about a *collection* of decision rules (bargaining strategies) can be concretely represented as a *collection* of *parse tress.* Then the second quotation from Lucas is about the review of these bargaining strategies (parse trees), and from this review, new bargaining strategies (parse trees) may be generated. Notice that here Lucas were not talking about just a single decision rule but a collection of decision rules. In other words, he was talking about the *evolution* of *a population of decision rules.*

Now, based on what we just described, if each decision rule can *hopefully* be written and implemented as a *computer program*, and since every computer program can be represented as a LISP parse-tree expression, then *Lucasian Adaptive Economic Agent* can be modeled as the following equivalents,

- evolving population of computer programs,
- evolving population of parse trees.

But, no matter how we may call this modeling procedure, this is exactly what *genetic programming* does, and in fact, there is no other technique known to the projector, which can accomplish this task as effective as GP. Hence, that would not be too exaggerated to claim *genetic programming as a methodological innovation to economics.*

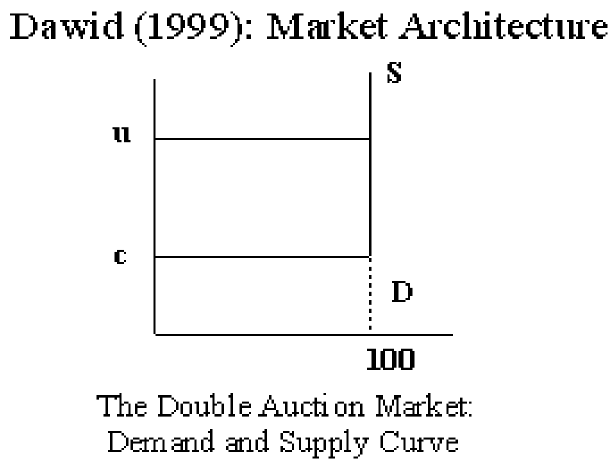

Fig. 6. The DA Market of [6]: Demand and Supply

The second distinguishing feature is not just the use of genetic programming, but the *population genetic programming*. The weakness of using simple GP in agent-based modeling has already been well pointed out in [4]. Again, there is no reason why we can assume that traders will release their bargaining strategies to others to imitate. Therefore, to not misuse GP in the agent-based computer simulation of DA markets, it is important to use population GP.

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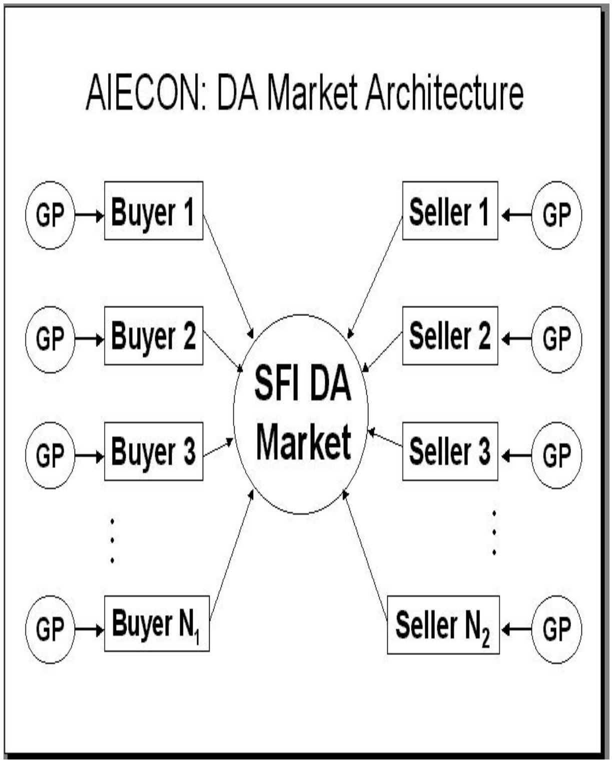

Fig. 7. The AI-ECON Agent-Based Modeling of DA Markets

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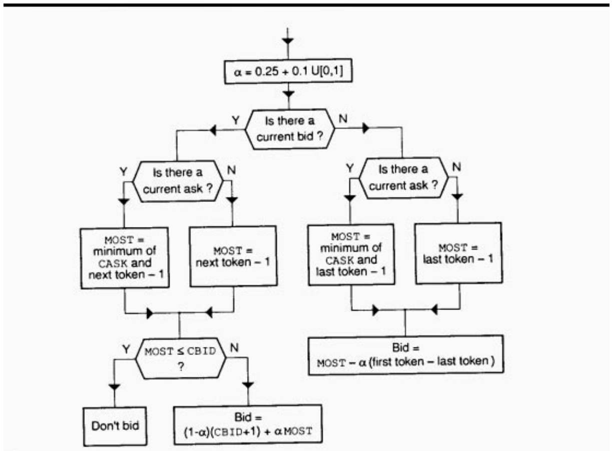

Fig. 8. The Flow Chart of the Skeleton Strategy

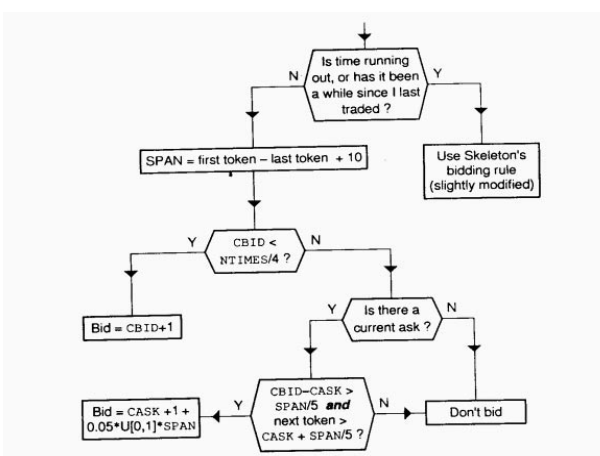

Fig. 9. The Flow Chart of the Ringuette Strategy

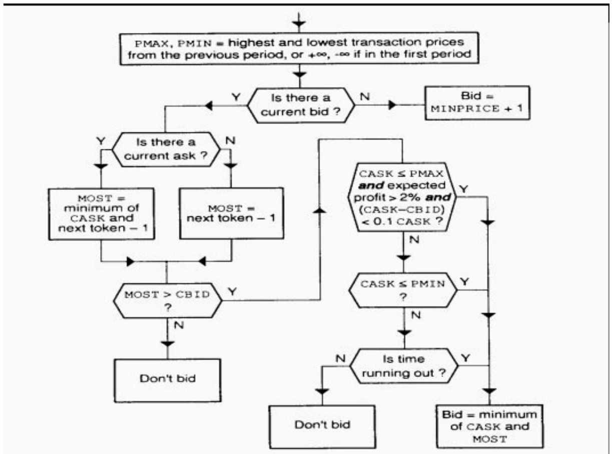

Fig. 10. The Flow Chart of the Kaplan Strategy

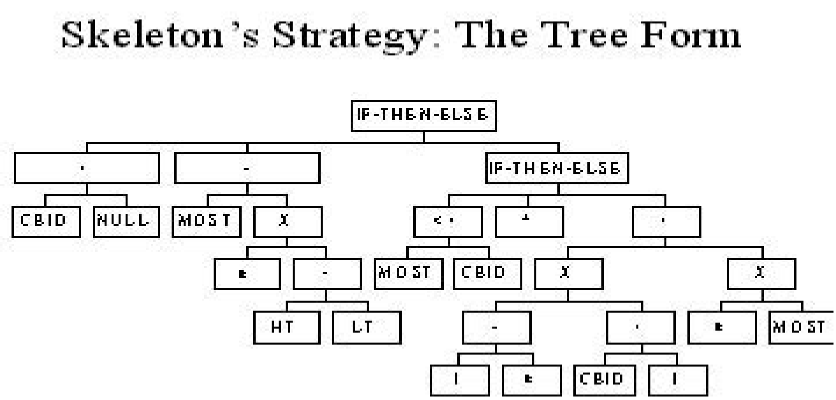

Fig. 11. The Skeleton Strategy in Parse-Tree Representation

Fig. 12. The Ringuette Strategy in Parse-Tree Representation

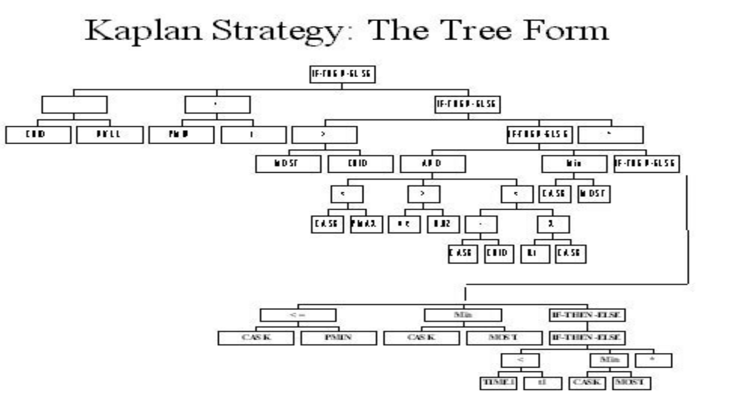

Fig. 13. The Kaplan Bargaining Strategy in Parse-Tree Representation

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