

Designing the Market Game for a Commodity Trading Simulation

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Abstract

In this paper, we propose to design a market game that (a) can be used in modeling and studying commodity trading scenarios, and (b) can be used in capturing human traders' behaviors. Specifically, we demonstrate the usefulness of this commodity trading game in a single-commodity futures trading scenario. A pilot experiment was run with a mixture of human traders and an autonomous agent that emulates the aggregated market condition, with the assumption that this autonomous agent would hint each of its action through a public announcement. We show that the information collected from this simulation can be used to extract the pattern of successful human traders. Finally, we elaborate on the potential of this market game in studying autonomous commodity trading.

1. Introduction

In recent years, the study of trading in electronic markets has received significant amount of attention, particularly in the areas of artificial intelligence and electronic commerce. With increasingly sophisticated technologies being applied in analyzing information and making decisions, fully autonomous software agents are expected to take up significant roles in many important fields. This trend is most obvious in the financial domain, where speed of reaction is highly valued and significant investments have been made in information and communication technologies.

Despite the successes of automated trading in many important classes of financial markets [5], commodity trading has lagged behind, mainly because of its complicated product categorization and logistical fulfillment considerations. To help human commodity traders in making better decisions and to enable automated commodity trading, we need better software tools.

In this paper, we propose to design a market game that is suitable for running commodity trading simulations. The goal of the designed market game is to serve as a tool

for training human traders and studying successful trading strategies, so as to lay the foundation for designing autonomous trading agents. With a classroom experiment, we demonstrate that the proposed system is indeed capable of achieving these two goals.

2. Background

2.1. Basics of the Commodity Trading Simulation

In this paper, commodity trading refers to the trading of raw or primary products that can be specified by standard contracts. Examples of such commodities include crops, oil, and live cattle. Similar to other financial market, a wide variety of derivatives are available for hedging or speculative purposes. Despite all the similarities, there are two distinguishing features of commodity market when compared to other financial markets like stock or bond. The first feature is the need to consider physical fulfillment. For example, when engaged in a commodity contract, besides just price consideration, the point of delivery, method of delivery, and date of delivery must all be carefully considered. The second feature is the seasonalities embedded in demands and supplies of many important commodities (not all). For example, the consumption of oil and the supply of agriculture products are highly seasonal, and are closely related to the weather conditions. These considerations are what make commodity trading different and challenging.

Although agent-based simulations for commodity trading (or markets that are similar to commodity markets) are not new, most related past literatures focus either on market design [7], agent-based simulations [8], or behavioral study [3]. To address our specific needs, we have to design our own simulation for studying commodity trading, with the considerations of the following criteria:

- *Realism.* The simulation should present the most challenging characteristics in a real-world commodity trading environment, namely physical fulfillment and seasonalities that are linked to various external factors.

- *Flexibility.* The simulation should be flexible enough to simulate the trading of a wide variety of commodities. These flexibilities include the ability to implement a wide range of market mechanisms, fulfillment requirements, and a rich set of external events.
- *Usability.* The organization of the user interface should be intuitive and matches real-world trading.

2.2. Market Games

A *market game* defines a collection of agents interacting with each other through market mechanisms. Analytical game-theoretic analysis usually only works on simple auction mechanisms and researchers are increasingly interested in applying empirical approaches and agent-based simulations to the study of complex mechanisms [2, 4]. When studying real-world scenarios with market games, we need a general platform that can be configured to execute various types of market mechanisms, define a wide variety of tasks, and specify agent’s strategies. In recent years, we have seen the emergence of the development of such platforms (e.g., see references in [6]). This makes empirical study of complicated market games much easier.

Despite the progress being made in the development of market game platforms, studying real-world scenarios remains challenging. In most real-world scenarios, one major challenge is to identify a collection of realistic and representative agent strategies that can be used in simulations. Develop even just one such strategy would be non-trivial, and in order to run a meaningful simulation, we need lots of them. To address this issue, researchers have turned challenging scenarios into competitions [1, 9], and through competitions, researchers can independently work to develop various agent strategies that can be used both in the competitions and later on in the simulation studies.

The success in studying complex scenarios via competitions is what motivates our research. However, the major difference of our system when compared to the past research is the deliberate involvement of human agents (compared to all autonomous agents in the previous research). We design the system this way so that we can capture the best practices from human agents. In an environment where it is difficult to design an agent strategy from scratch, the proposed system can help to extract important principles that can later be used in developing fully autonomous agents.

3. Designing and Implementing the Commodity Trading Simulation

In Section 2.1, we elaborate on what constitutes a good design for a commodity trading simulation. In this section,

we propose the actual design of the simulation.

From the previous definition, we can see that a typical commodity trading simulation constitutes a group of agents (can be autonomous or human) and a set of market mechanisms for agents to trade in. This is exactly the definition of a market game, and thus we can take advantage of existing research and development in this area. In particular, we choose to build our simulation on a generic market gaming system called **AB3D** [6].

AB3D is a flexible auction server and market game platform. With AB3D, we can describe and implement a commodity trading scenario as a market game. The scripting languages for both auction specification and market game definition allow us to easily change the commodity trading scenario without involved coding, thus we can focus on the study of the commodity trading.

For the simulation that is reported in this paper, we choose to work on a simplified scenario so as to allow a smoother learning curve for human traders. In the current simulation, we focus mainly on the impacts of external factors on commodity’s supply and demand, and neglect the physical fulfillment feature. We assume that players are trading in a commodity futures market, can assume either long or short positions at any time, and always close out their positions before the game ends (if an agent fails to close out its position, the game manager should penalize this agent and use the futures price at the end of game to close out its position). As in most real-world markets, we assume that the market mechanism used in the exchange is a continuous double auction (CDA). Also, we assume that the market can always provide contracts necessary for the player to establish long or short positions.

In the following sections, we describe in detail on how to create a commodity trading simulation on the AB3D platform.

3.1. The Setup for the Commodity Trading Game

The commodity trading game designed in this paper, as described previously, focuses on emulating the impact of external events in making trading-related decisions. More specifically, we assume that supply and demand for the futures contracts are driven by both human traders’ behaviors and aggregated market force represented by a software agent. The high-level interactions of agents and the market mechanism are illustrated in Figure 1.

There are three important components in Figure 1: the player agent that serves as the proxy for a human trader, the market agent that represents aggregated market force, and the market mechanism that brokers transactions. Each player agent is loaded with necessary user interface and underlying infrastructure for retrieving real-time market information and sending trading requests. For the market

agent, a pre-defined market scenario on the supply and demand is specified by the game designer in conjunction with associated news events that serve as hints on where the market is moving. The market game server is the central location that stores all the market-related information and executes the trades.

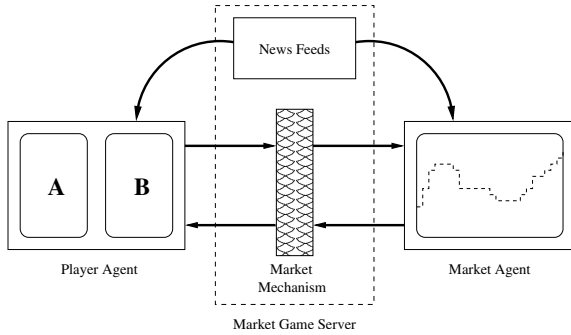


Figure 1. The setup of the trading game.

The AB3D platform provides the necessary software framework for designing trading scenarios, realizing auction designs, and providing low-level agent communications; thus we can focus on building the agents and the scenario. The design of the player agent for human traders and the market agent are described in Section 3.2 and Section 3.3 respectively.

3.2. The Design of the Player Agent

When designing the proxy agent for human traders, we focus our design on the presentation of market information, including current account snapshot, completed transactions, current standing bid, historical price evolution, and list of external events.

To simplify each player’s decision making process, we assume that he/she can have at most one standing bid containing exactly one price-quantity point, and whenever a new bid is issued by the player, it will replace the current standing bid. Therefore, the parameters that a player has to determine for each bid is just: price, quantity, and the direction (long or short).

To capture every player’s trading behaviors, important actions are recorded. In particular, whenever a player reads the detail of a news event or executes a trade, that action is attached with a timestamp and stored on the game server.

3.3. The Design of the Market Agent

In our design, human traders are trading among themselves and also with the aggregated market represented by a market agent. One important task of this market agent is to provide necessary liquidity representing underlying supply

and demand structure of the particular commodity. To emulate real-world market conditions, market agent will maintain a bid containing multiple price-quantity points, where each bid point represents the amount of long or short contract that is provided at the specific price tick. The content of this bid is regularly updated by the market agent in order to reflect the ongoing market condition.

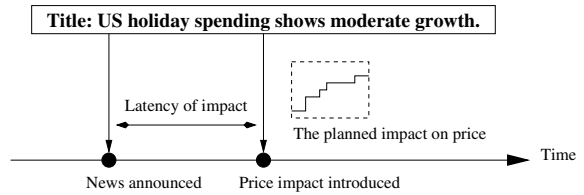


Figure 2. The definition of a typical external event (in the form of a news).

As discussed earlier, one important feature we would like to have in the simulation is time-varying market condition that can be inferred from external events. An external event is specified by the following important characteristics: (1) the title and the content that provide the context, (2) the time when the event is announced, (3) the time when the impact is introduced, and (4) the magnitude of the impact on supply or demand, represented as a function. The definition of a typical external event is illustrated in Figure 2.

4. Experiment and Analysis

To test the effectiveness of a market game in commodity trading simulation, we worked with an experienced oil trader and collaboratively generated a scenario that reasonably captured ongoing crude oil market (more precisely, the traded commodity is Western Texas Intermediate (WTI)). For the pilot experiment, the participants were drawn from students in a commodity trading class focused on crude oil trading. Prior to the simulation, these students had already been trained rigorously on the fundamentals of crude oil trading and this simulation was used as an arena for them to practice the knowledge and techniques they had learned in the class. In this section, we describe the scenario in detail and present the result and analysis on the experiment.

4.1. Experiment Setup

The crude oil trading scenario is designed to let traders trade WTI with the following setup:

- **The Players.** We assume that each player is only authorized to establish positions (either long or short) up to 2,000k barrels (bbls). Once a player has reached his

authority limit of 2,000k bbls he/she will not be able to take further positions in the same direction.

- **The Market.** At the beginning of the game, the bid and the ask prices in the market are set to \$59.90/bbl and \$60.10/bbl respectively¹. Initially, there are 200k bbls available for sell or buy at all price ticks, which is separated by 10 cents in order to exaggerate profits and losses. Subsequent announcement of the news events will alter available volumes at some prices, as indicated in Section 3.3.

The background of the oil trading scenario is set to be at the beginning of the first quarter of 2007, when the crude oil price is weak and a mix of bullish and bearish news are striking the market at the same time. The fuzzy situation involving Iran's nuclear ambition further complicates the reading on the market. This information was briefed to all participants before the game starts, and after a brief introduction and practice session, the simulation was run for about 70 minutes.

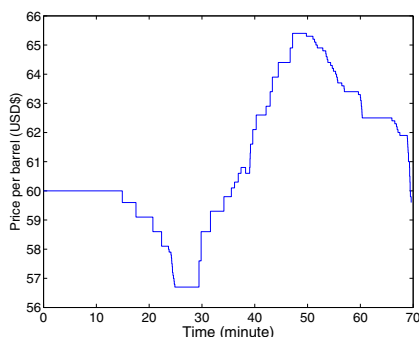


Figure 3. The price fluctuation created by market agent, when no other trading occurs.

The planned price movement can be seen in Figure 3. Notice that the movement plotted in Figure 3 is generated without any transaction from human traders. Thus it could be viewed as the underlying trend of the market that is hidden from all human players. The movement of the price is periodically hinted through the announcement of news events (to be more precise, one news event is released roughly every two minutes). The gap between a news event and its corresponding price movement (the “latency on impact” in Figure 2) is around 30 seconds.

4.2. Result and Analysis

Eleven human players participated in the simulation, where the best agent earned \$3,480k and the worse agent

¹By definition, the bid price is the highest standing buy bid, and the ask price is the lowest standing sell bid.

lost \$62,449k. Investigating what caused this difference is one of primary goals for designing the platform. In this section, we will answer this question.

As mentioned in Section 3.2, many of human players' important actions are captured by the proxy agent, thus we could base our analysis on these observations. In the post-game-analysis, we have identified three most important time series which we believe are the primary factors that determine trader's performances. These three time series are: 1) trader's position balance, b) realized market price movement, and c) planned market price movement (as plotted in Figure 3).

By plotting these three time series for the best and the worst agents, it becomes quite obvious why their performances differ so much. Figures 4 and 5 plot the best and the worst agent respectively. In both figures, the planned and the realized market price movements are plotted as thin solid line and thin dotted line respectively, with labels on the left y-axis. On the other hand, agent's position balance is plotted as the thicker line, with labels on the right y-axis.

In the following sub-sections, we illustrate and analyze the trading patterns of the best and the worst agents, and discuss their implications.

4.2.1. Analyzing Winning Agents

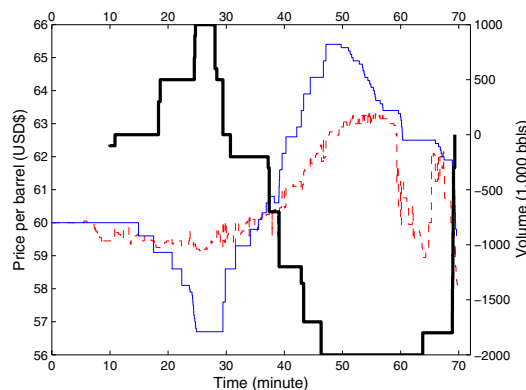


Figure 4. The agent with best performance.

Figure 4 illustrates the trading pattern of the best agent. From the chart and also from the post-game interview, it is obvious that his strategy was based on continuously updated long-term prediction on the market movement (as a result, its position balance is almost an inverse of the planned market price movement). An interesting observation is that this pattern can also be observed in other profit-earning traders, although their strategy executions are not as perfect as the one shown here. This common pattern suggests that for this simple trading scenario, a winning strategy pattern could indeed be captured by running a controlled trading experiment.

We would like to point out that since this strategy is based on the first-order price movement, if all agents adopt this strategy, any price movement will be exploited almost immediately, and thus this strategy alone will not be sufficient in emulating the dynamics of real trading². To better understand and predict what traders would do in a competitive environment, we would have to employ a game-theoretic analysis involving more than one strategy, which is beyond the concern of this paper. However, the general procedure discussed in this section can still serve as an useful guideline in discovering additional strategies.

4.2.2. Analyzing Losing Agents

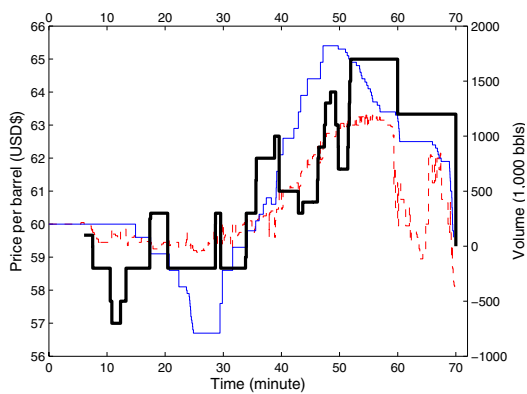


Figure 5. The agent with worst performance.

As shown in Figure 5, the worst agent followed “realized market price” instead of trading against “planned market price”, which is hinted via news events. This implies that when making trading decisions, it ignored what was hinted in the news events and just followed the market. This is a mistake that is quite common among novice traders, and as expected, it ended up “bought high and sold low”. Unlike the case of winning agents, where all of them share a common pattern, the trading patterns of the losing agents vary a lot.

4.3. Implications

From our analysis and also post-game interviews, we can get a pretty clear picture as to what constitutes a successful trading strategy. Note that the strategy identified is not what we claimed to be the major contribution. The major contribution of this experiment is to show that the market game designed for this commodity trading scenario is indeed an effective tool for identifying human trader’s strategies.

²Note that almost half of the market liquidity is provided by a pre-programmed, non-adaptive software agent, that is why this strategy could still be profitable in our experiment.

5. Conclusion and Future Work

Although this scenario appears to be trivial, beating the market and earning a profit is a non-trivial task. Trading successfully in this market involves accurate reading of the market condition, careful strategy execution, and adaptiveness to unexpected changes in market dynamics. As analyzed in the previous sections, a controlled experiment can indeed help us to isolate important factors involved in trading and identify the pattern for a winning strategy.

In our future work, we are interested in extending the current scenario so as to include physical fulfillment considerations. Such market game simulation would be quite unique and we view it as an useful tool in studying various issues involved in the commodity trading business.

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