An Agent-Based Commodity Trading Simulation (Demo Paper)

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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, commodity trading has lagged behind, mainly because of its complicated product categorization and logistical fulfillment considerations. These two factors greatly hinder automation efforts because whenever an event that has significant physical impact on the commodity supply chain occurs, complicated and commodity-specific reactions (might include trading, re-hedging, or even logistic adjustment, to name just a few) would be required. Due to this reason, to master even just a particular commodity market would take several years of intensive training and exposure. To facilitate better understanding on the event-centric commodity market, we built an agent-based commodity trading simulation that is driven by physical events [1]. The simulation platform serves two purposes: First, it is used as a tool that allows more effective training; second, professional trader's behaviors in face of uncertain events could be measured comprehensively for thorough analysis.

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2. THE COMMODITY MARKET

In our demonstration, 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, or live cattle. Similar to other financial market, a wide variety of derivatives are available for hedging or speculative purposes. What makes trading in commodity markets unique and challenging, despite their similarities to stock and bond markets, are the physical transactions that are behind all the financial trades in any form of commodity market. Although the volume in the financial trades (commodity derivatives) has already overtaken the physical trades, physical transactions are still critically important. This is because the balance of supply and demand and the resulting *spot prices* in the physical transactions are still the fundamental forces that are behind the commodity market, and no matter how sophisticated the used financial instruments are, all of them still need to closely reference these spot prices. Which is why trading in commodity market is challenging: physical transactions are affected by not only supply and demand of the commodity, but also all the physical elements that link together the supply and demand sides.

Although the price dynamics of commodity market have been studied extensively in the finance domain, to the best of our knowledge, none of them specifically considers physical events as the primary price driver (and thus the possibility of using sequence of events in generating desired market dynamics). This is how our event-based simulation model differs from most past models.

For simplicity, we assume that only one type of commodity future is considered and the trades are facilitated by a continuous double auction (CDA). The trading infrastructure is provided by a generic market game server, AB3D [4]. All events are revealed sequentially to both human and software agents at predetermined times. The primary attributes of an event are title, content, time to be announced, time window in which it is effective and its impacts on both buy-side and sell-side strengths. The scenario designer thus has full control over the sequence of events he would like to introduce. This allows rare but important scenarios to be simulated and experienced (e.g., the recent commodity boom and the subsequent market crash).

The price dynamics in response to the announced events are not determined by a fixed econometric model; instead, the price dynamics are generated through the interaction of a set of autonomous agents that play different roles in a commodity chain (typical such roles include producers, consumers, and speculators). This agent-based framework allows us to tap into the rich literature of “Agent-based Computational Economics” [6]. Individual agents are built with classical models and are described next.

3. AN AGENT-BASE SIMULATION

In our event-based commodity trading simulation, the price dynamics of the market is generated by the collective actions of producers and consumers in response to the sequence of events. For simplicity, we assume that producers only trade short and consumers only trade long (in other words, producers and consumers are assumed to have stable flow of productions and usages, and they adopt the simple hedge-and-forget strategy). With this assumption, an agent’s decision is reduced to the quantity and the price of the bid.

Regardless of the type of the trade, the quantity of the bid is assumed to be uniformly distributed within an agent-specific range, which corresponds to the bound on this agent’s production or usage. On the other hand, the decision on the bid price is mainly determined by agent’s individually maintained price prediction. A popular model for the commodity price is the mean-reversion process called the Ornstein-Uhlenbeck (OU) process. In this model, the commodity price prediction is generated by considering both long-term equilibrium price, which is mean-reverting, and event impacts. Both these two terms are agent-specific and highly dependent on agent’s role and private information. Considering that *perfect* prediction is usually not possible in a highly dynamic market, we assume that the submitted price will be randomly chosen within the range of the market price and the predicted price.

While “mean-reverting” producers and consumers constitute the “fundamental” part of the simulated market, the market volatility, on the other hand, is generated by the speculator agents. In our simulation, we adopt a variant of the classical *zero intelligence* (ZI) strategy [3]. In our simulation, ZI agents are allowed to take both long and short positions with equal chance, and their individual trading limits are the same as human traders. ZI agents must return to zero position at the end of the game.

The above bidding models are rigorously defined and implemented in [2].

4. VALIDATING MARKET DYNAMICS

In our simulation, completely fictitious scenarios could be generated. Unfortunately, despite the benefits brought by our approach, it also introduces challenges in simulation validations. The critical issue here is the lack of real-world data for the validation purpose and thus we will have to validate our simulation by using the simulation itself. The technique we applies here is a statistical method called *event studies*. A variant of the event study method by MacKinlay [5] is adopted and our initial study demonstrates that we could indeed generate market dynamics as hinted by the event sequence (details are provided in [2]).

5. TRADING DIAGNOSIS

The trader’s interface for our simulation is provided in Figure 1. As stated earlier, besides just building trading simulation, another important purpose of our platform is to study people’s trading behaviors in response to various events. To facilitate such analysis, whenever a trader performs certain action in our trading environment, be it reading event description or issuing trades, it will be recorded. In conjunction with this trader’s performance, we could infer what trigger’s trader’s trading decisions, and we can test whether a trader’s performance is related to any particular behavioral pattern.

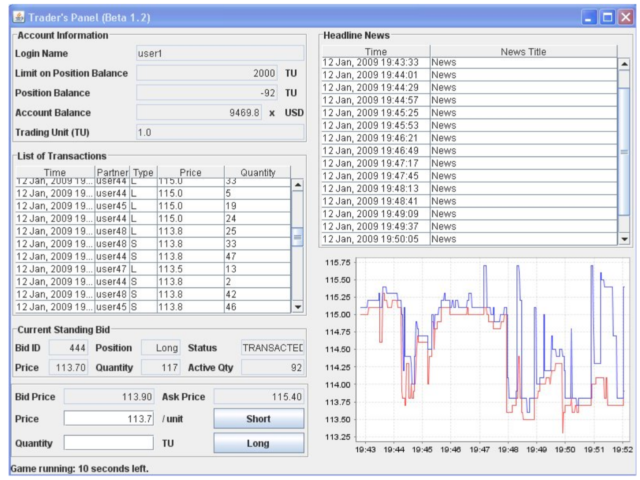

Figure 1: Human trader’s interface.

6. DEMONSTRATION DETAILS

The authors will explain how agents respond to events behind the scene. In particular, we would highlight the distinct behavior by producers, customer, and various types of speculators. We will shed light on how these individual agents could generate a rich set of price dynamics. Participants are encouraged to play the role of commodity traders, and experience some rarely seen extreme scenarios, e.g., market crash or commodity boom.

Participants will also be able to see their trading diagnoses. These reports are generated after the trading session, and could be used in reviewing one’s trading strategies.

7. REFERENCES

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