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# An agent-based approach with collaboration among agents: Estimation of wholesale electricity price on PJM and artificial data generated by a mean reverting model

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ABSTRACT

This study examines the performance of MAIS (Multi-Agent Intelligent Simulator) equipped with various learning capabilities. In addition to the learning capabilities, the proposed MAIS incorporates collaboration among agents. The proposed MAIS is applied to estimate a dynamic change of wholesale electricity price in PJM (Pennsylvania–New Jersey–Mainland) and an artificial data set generated by a mean reverting model. Using such different types of data sets, the methodological validity of MAIS is confirmed by comparing it with other well-known alternatives in computer science. This study finds that the MAIS needs to incorporate both the mean reverting model and the collaboration behavior among agents in order to enhance its estimation capability. The MAIS discussed in this study will provide research on energy economics with a new numerical capability that can investigate a dynamic change of not only wholesale electricity price but also speculation and learning process of traders.


## 1. Introduction

An agent-based approach is a numerical method to deal with various types of system complexities in natural and social sciences. Reinforcement learning is often incorporated into software agents so that they can interact with a dynamics of environment (Abul et al., 2000, Kaya and Alhajj, 2005). The application of an agent-based approach provides us with a new type of numerical capability to understand a dynamic change of a market and adaptive behaviors of traders who participate in the market. Such applicability is confirmed in power trading. For example, the research works (e.g., Bunn and Oliveira, 2001; Jacobs, 1997 and Morikiyo and Goto, 2004) examined the dynamic change[1] of a power exchange market from the perspective of a multi-agent adaptive system. This group of research opened up a new approach for dealing with business complexity of power trading. However, the previous studies described only the development of modeling and simulation. Their agents incorporated only a single parameter to express reinforcement learning. Moreover, they are not equipped with an estimation capability to predict the market price of electricity. Consequently, the conventional use of an agent-based approach has a limit on practicality because real power trading needs multiple parameters to function reinforcement learning on bidding quantity and price.

To overcome such problems, a series of studies (Sueyoshi, 2010a,b, Sueyoshi and Tadiparthi, 2005, 2007, 2008a,b,c) investigated various types of power trading agents equipped with different learning capabilities. The software for the agent-based approach was referred to as "MAIS (Multi-Agent Intelligent Simulator)". The first research (2005) proposed a multi-agent system that incorporated learning capabilities into agents who trade wholesale electricity. The learning capabilities incorporated in the study were executed by "self-learning". The second research (2007) extended the first study by considering two groups of agents. One of the two groups incorporated multiple learning capabilities (Type I) in agents. The other group incorporated limited learning capabilities (Type II) in agents. The third research (2008a) extended the previous works (2005, 2007) further by incorporating the influence of a transmission line limit on the dynamics in a power exchange market. The study considered the power market as multiple zones connected by transmission lines. The line limit often influences the bidding decision of real traders (so, software agents in this study). The fourth research (2008b) documented the application software of MAIS. The research (2008c) applied the MAIS to investigate why California electricity crisis occurred in 2000–2001. Sueyoshi (2010a) investigated the issue further. He concluded that the price hike in the crisis occurred due to an increase in fuel prices and real demand. The change of the two market fundamentals explained 45.73% of the price increase and fluctuations during the crisis. The responsibility of energy

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[1] This study is fully aware of the fact that there are many analytical approaches to estimate a dynamic market fluctuation. For example, Goto and Tsutsui (2008) examined an impact of deregulation on technical efficiency of US electric utility firms from 1992 to 2000. Bask and Widerberg (2009) investigated a dynamic price change in the Nordic power market. Benth and Koekebakker (2008) discussed analytically electricity contracts in deregulated markets. Demers (2009) discussed a spot price of electricity from the perspective of multi-zone markets in New-England. Admits the contribution of those studies, this study needs to mention that a numerical approach may provide a new methodology by which we can investigate the price dynamics from the bidding strategy, speculation and learning of individual traders. Such a new capability originating from computer science cannot be found in the traditional research.

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utility firms was 21.41%. The policy implication regarding the California electricity crisis was different from well-known economic studies which attributed the price hike to the exercise of market power. Finally, Sueyoshi (2010b) examined strategic collaborations among traders in the California electric crisis. The study found that the learning speed of traders became slow when a large fluctuation occurred in the power exchange market. The learning speed depended upon the type of traders, their learning capabilities and the fluctuation of market fundamentals. The degree of collaboration among traders gradually reduced during the electricity crisis.

An important feature of their research efforts is that they have documented a high level of estimation capability to predict the dynamic price change of wholesale electricity. However, the previous studies, except Sueyoshi (2010b), implicitly assume that agents do not collaborate with each other in a power exchange market. Moreover, the proposed use of MAIS does not consider a mean reverting model that is widely recognized as a simulation procedure for power trading. The two issues are drawbacks of the previous studies on MAIS applied to power trading.

To overcome the drawbacks, this study examines the following three new research agendas, all of which have been never explored in the previous studies. First, to confirm how much the proposed MAIS predicts the dynamic change of electricity, we compare it with other well-known approaches in computer science. Methodological alternatives for the comparison include NN (Neural Networks), GA (Genetic Algorithm), and SVM (Support Vector Machines). In the comparative study, we measure the estimation capability of MAIS, using a real data set concerning PJM and various data sets generated by a mean reverting model. The PJM (Pennsylvania–New Jersey–Mainland) originates from the three states and now covers most of states in the north-east region of the United States. The organization is the largest US Independent System Organizer (ISO) that controls power exchange markets and a huge transmission system. The PJM is highly regarded by many individuals involved in the electric power industry. Thus, this study examines the wholesale price fluctuation of PJM by the proposed MAIS. As explored in the previous studies (e.g., Sueyoshi, 2010a,b), it is possible for us to apply the MAIS to other ISOs such as California ISO.

Second, the mean reverting model has been widely used by many studies on the estimation of wholesale electricity price (e.g., Cartea and Figueroa, 2005 and Knittel and Roberts, 2005). The previous research on agent-based approach has never used the mean reverting model for their simulation studies.

Finally, this study examines collaboration among agents and investigates how the collaboration influences the estimation result on the dynamic change of electricity price. Thus, this study provides new numerical results concerning how to design an agent-based approach from the perspective of collaboration among agents.

The remaining structure of this study is organized as follows: Section 2 describes briefly an agent-based approach for power trading. Section 3 outlines the proposed simulation study. The section also discusses methodological alternatives and empirical results on PJM. Section 4 discusses the mean reverting model and its related results. Section 5 describes how collaboration among agents influences the estimation of electricity price. Section 6 summarizes this study along with future research extensions.

## 2. Description on agent-based approach for power trading

This section returns to the previous research works (Sueyoshi and Tadiparthi, 2005; Sueyoshi and Tadiparthi, 2008a) in order to outline the proposed MAIS. An important feature of MAIS is that it consists of many different types of agents equipped with various learning capabilities. Their learning processes are characterized by adaptive learning through which agents determine their bids by interacting with an environment and other agents. The bidding strategies among agents are numerically expressed and examined by a simulation-based investigation. By incorporating a problem structure along with a simulation study, the MAIS provides us with a numerical capability to handle a large complex system where many environmental components have interactions among agents.

### *2.1. Market clearing scheme*

The research of Sueyoshi and Tadiparthi (2008a) describes the market clearing scheme incorporated in the proposed MAIS. Therefore, this study does not describe it to avoid a descriptive duplication. See Sueyoshi (2010b).

### *2.2. Agents in Type I and Type II*

The proposed MAIS considers the following two groups of adaptive agents in order to investigate the dynamics of wholesale electricity trading: (a) Type I: the first group consists of agents equipped with multiple learning capabilities. Their learning capabilities include a risk-averse utility function and a speculation capability to predict the dynamic change of electricity price over time. The group is referred to as “Type I”. (b) Type II: the second group of agents looks for a short-term gain via their limited learning capabilities. They do not incorporate any utility function and any speculation capability, as found in Type I. Thus, the second group is less informative than Type I. The group of agents is referred to as “Type II”. The research of Sueyoshi and Tadiparthi (2007) provides a detailed description on adaptive agents in Type I and Type II and their related computer algorithms. See also Sueyoshi (2010b).

### *2.3. Adaptive behavior*

In the proposed MAIS, traders are represented by software agents. Fig. 1 illustrates an adaptive learning process and its related knowledge base development, both of which are incorporated into the agents. As depicted in the figure, each agent recognizes that there is an opportunity to obtain a reward by participating in a power exchange market. He understands that the market participation is always associated with risk. Therefore, he tries to obtain a risk-hedge ability through his trading experience.

In the proposed MAIS, each market consists of many different types of agents who can accumulate knowledge from their bidding results. The agents operate in two modes: practice and real experience, as depicted in Fig. 1. During practice (at the left hand side of Fig. 1), they use non-reinforcement learning (or self-learning) where a power exchange market determines the win or lose of each practice bid. The non-reinforcement learning is separated into three processes: (a) knowledge generation, (b) knowledge accumulation and (c) knowledge creation. In the knowledge generation, each agent has to generate knowledge by itself. The purpose of “knowledge generation” process is to discover or become familiar with the market as an environment. Thus, the agent bids in the market by changing his decision parameters, using random data generation. After his bid, the value of decision parameters and his win–lose result are stored in a “knowledge accumulation” process. The accumulated knowledge is further processed by a sigmoid decision rule (for speculation on a winning probability) and an exponential utility function (for risk preference of each agent) if the agent belongs to Type I. This process is referred to as “knowledge creation.” This non-reinforcement learning is repeated until the practice period ($H$) is over. The period can be considered as a training process for each agent. The final knowledge developed at the knowledge creation process serves as a starting point for his own-bidding process of partial reinforcement learning (at the right hand side of Fig. 1).

After the practice is completed, each agent starts real trading experience. The bidding decision in the real experience period is based upon the knowledge obtained from the previous trading practice period. The real experience period follows “partial reinforcement learning” because the agent reacts according to the feedback obtained from an environment (i.e., a power trading market). The partial reinforcement learning is functionally separated into three sub-