

Why did California Electricity Crisis Occur? A Numerical Analysis Using Multi-Agent Intelligent Simulator

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Abstract—During the summer (2000), wholesale electricity prices in California were approximately 500% higher than those during the same months in 1998-1999. The price hike was unexpected by many policy makers and individuals who were involved in the electric utility industry. They have been long wondering whether the electricity deregulation policy (1996) produced benefits of competition promised to consumers. This study proposes a use of a multi-agent intelligent simulator (MAIS) to numerically examine several reasons regarding why the crisis has occurred during May 2000-January 2001. The MAIS explains the price fluctuation of wholesale electricity during the crisis with an estimation accuracy (91.15%). We also find that 40.46% of the price increase was due to an increase in marginal production cost, 17.85% to traders' greediness, 5.27% to a real demand change and 3.56% to market power. The remaining 32.86% came from other unknown components. This result indicates that the price hike has occurred due to an increase in fuel prices and real demand. The two market fundamentals explained 45.73% (= 40.46%+5.27%) of the price increase. The responsibility of energy firms was 21.41% (= 17.85%+3.56%). The numerical evidences are different from the very well-known research of Joskow and Kahn (2002), which has attributed the exercise of market power by large energy firms.

I. INTRODUCTION

During the summer (2000), wholesale prices of electricity in California were almost five times as large as the ones during the same period in 1998-1999. The price hike was unexpected by policy makers and individuals who were involved in the electric power industry. After the occurrence of the electricity crisis in California, many researchers and policy makers have been long wondering whether the deregulation policy (Energy Policy Act in 1992 and Federal Energy Regulatory Commission's Orders 888 and 889 in 1996) produces economic benefits of competition proposed to consumers. Federal and State governments investigated and reported various structural problems related to the electricity crisis in California. See, for example, reports including FERC Staff reports [1], California Independent System Operator Department of Market Analysis [2] and California Power Exchange Corporation Compliance Unit [3]. Unfortunately, all of the

governmental reports did not include any scientific evidence. Unlike previous price hikes observed in other US wholesale markets, the California experience has not been a transient phenomenon for a few days. There was a structural problem in the wholesale electricity market of California.

In the previous research, Joskow and Khan [4] explored statistically the problem of the California electricity crisis. Their research was the first effort that discussed the policy issue regarding California's electricity crisis at a level that academic individuals could accept. Their research was a real contribution on the policy issue.

The purpose of this study is to apply an intelligent simulator for the exploration of California electricity crisis. The simulator used for the application is referred to as "Multi-Agent Intelligent Simulator (MAIS)", initially developed by Sueyoshi and Tadiparthi [5-8]. This study compares numerical results obtained by the proposed MAIS and empirical results obtained by the study of Joskow and Kahn [4]. The two approaches come from different disciplines (economics/statistics vs. computer science). Hence, the comparison between the two research efforts provides important evidences regarding the California electricity crisis that have not been identified in the previous studies.

In this study, the performance of MAIS is compared with other well-known methods (e.g., neural network and genetic algorithm), using a real data set on power trading related to the California electricity crisis (from May 2000 to January 2001). After confirming the methodological validity of MAIS, we compare the numerical results obtained in this study with the empirical results obtained by [4].

The remaining structure of this article is organized as follows: The next section briefly describes a literature survey on agent-based approaches applied to power trading. Section III describes the industrial structure of US wholesale power market and the California power market during the electricity crisis. Section IV discusses a market design for power trading. Section V describes an agent-based algorithm. Section VI applies MAIS to investigate why the electricity crisis has occurred in California. Section VII summarizes this research along with future research issues.

II. LITERATURE REVIEW

Agent-based Approach: The approach was proposed as a numerical (computer-intensive) method to deal with

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various types of system complexities. Reinforcement learning was often incorporated into agents so that they could interact with a dynamic environment [9,10]. Such applications of the agent-based approach could be found in understanding various market behaviors [11]. The applicability was also found in power trading. For example, the research efforts [12-16] examined the dynamic change of a power exchange market from the perspective of a multi-agent adaptive system. Detailed discussions on historical and current issues on the agent-based approach could be found in [17]. This group of research opened up a new type of numerical approach to deal with business complexity related to power trading. However, these previous studies described only the development of agent-based modeling and simulation. Almost no research discussed the development from the perspective of machine learning and cybernetics.

Research on MAIS: To overcome the shortcoming related to the agent-based approach, Sueyoshi and Tadiparthi [5-8] explored a series of studies that investigated various types of power trading agents equipped with different learning capabilities. The software for their agent-based approach is MAIS that will be fully utilized in this study. The first research [5] proposed a multi-agent system that incorporated learning capabilities into agents for trading wholesale electricity. The learning capabilities incorporated into each trading agent were executed by “self-learning”. The second research [6] extended [5] by considering two groups of agents. One of the two groups incorporated multiple learning capabilities in agents. The other group incorporated limited learning capabilities in agents. This study uses only the first group of agents (referred to as Type I in [6]). The third research [7] extended [5,6] further by incorporating the influence of a transmission line limit on the dynamics of a power market. The study [7] considered a power market that consists of multiple zones connected by transmission lines. The fourth research [8] documented the application software (MAIS) that was theoretically developed in [5-7].

As an extension of [5-8], this study applies the software of MAIS to investigate why the California electricity crisis has occurred in 2000-2001. This type of application cannot be found in the previous research on the agent-based approach directed toward power trading.

III. US WHOLESALE ELECTRICITY MARKET

The electric power business is separated into the following four functions: (a) generation, (b) transmission, (c) distribution and (d) retailing. The main parts are generation and transmission, both of which are traded in wholesale markets of electricity. Generally speaking, two types of transactions can be found in the wholesale markets. One of the two is a bilateral (usually long-term) exchange contract between a generator(s) and a wholesaler(s). The other is a short-term, auction-based transaction. In the short-term transaction, a market operator (like California ISO)

accepts biddings from both generators and wholesalers. The operator then determines the market price and quantity of electricity. Thus, this type of wholesale market is controlled and coordinated by ISO (Independent System Operator) that opens not only a wholesale market but also a transmission market. See [18, 19] for a description on US power markets.

The wholesale market of California was functionally separated into (a) a power exchange market and (b) a transmission market. Before the electricity crisis, the exchange market was further functionally separated into (a) an Hour-Ahead (HA) market and (b) a Day-Ahead (DA) market. These markets needed to coordinate the supply capabilities so as to satisfy a constantly changing demand on electricity. Coordinated auctions with ISO were used for the two exchange markets (DA & HA). The DA trading was stopped after 31st January 2001.

IV. MARKET DESIGN FOR POWER TRADING

Assuming that a wholesale market of electricity is a single zone market, let us consider it as the market with two settlements for DA and HA, where n generators ($i = 1, \dots, n$) and k wholesalers ($j = 1, \dots, k$) participate for T periods ($t = 1, \dots, T$), as in Figure 1. The traders are adaptive agents in this study. The “ t ” indicates a specific period for real delivery of electricity.

Supply Side in DA: The i -th generator at the t -th period bids s_{it}^1 ($s_{it}^1 \leq s_{it}^m$), where s_{it}^m is the maximum amount of his power generation capacity. Here, the superscript “1” indicates DA. The bidding amount is expressed by $s_{it}^1 = \alpha_{it} s_{it}^m$, where α_{it} ($0 \leq \alpha_{it} \leq 1$) is a decision parameter to express the ratio of the bidding amount to the maximum generation capacity.

The bidding price of the generator is determined by $p_{it}^1 = MC_{it} / (1 - \beta_{it})$. Here, MC_{it} is the marginal cost of the generator and β_{it} ($0 \leq \beta_{it} < 1$) is a mark-up ratio that indicates how much the bidding price of the generator is increased from the marginal cost. The mark-up ratio reflects the pricing strategy of the generator.

Demand Side in DA: Each wholesaler predicts an electricity demand on a delivery day by using a forecasting method (e.g., moving average). Let e_{jt} be the demand estimate of the j -th wholesaler at the t -th period. Then, the wholesaler predicts a price estimate (w_{jt}^1) by using a function (F) of demand, $w_{jt}^1 = F(e_{jt})$. [See Figure 4 of [5] that depicts the demand function.] The wholesaler determines a bidding amount (d_{jt}^1) by $d_{jt}^1 = \delta_{jt} e_{jt}$. Here, δ_{jt} ($0 \leq \delta_{jt} \leq 1$) is a decision parameter to express the reduction of the bidding amount from the demand estimate.

The bidding price of the wholesaler is determined by $p_{jt}^1 = \lambda_{jt} w_{jt}^1$. Here, λ_{jt} ($0 \leq \lambda_{jt} \leq 1$) is a decision parameter to indicate the reduction of the bidding price from the price

estimate.

After all traders submit their bids on amounts and prices to ISO, the DA market determines \hat{p}_t^1 (a market clearing price for DA), \hat{s}_{it}^1 (a power request to the i -th generator in DA) and \hat{d}_{jt}^1 (a power allocation to the j -th wholesaler in DA) for the t -th period.

Supply Side in HA: The i -th generator at the t -th period bids the amount $s_{it}^0 = (s_{it}^m - \hat{s}_{it}^1)$ in the HA market, where the superscript “0” indicates HA. The bidding amount for HA is a difference between the maximum generation capacity and the real allocation from the DA market. Furthermore, the bidding price (p_{it}^0) of the generator is expressed by $p_{it}^0 = MC_{it} / (1 - \eta_{it})$, where η_{it} is the mark-up ratio of the generator ($0 \leq \eta_{it} < 1$).

Demand Side in HA: All the wholesalers must deliver the amount of electricity (r_{jt}) demanded by end-users. Therefore, they bid only their amounts, not prices, in the HA market. The j -th wholesaler at the t -th period bids an amount, $d_{jt}^0 (= r_{jt} - \hat{d}_{jt}^1)$, in the market. The HA market within ISO determines \hat{p}_t^0 (a market clearing price for HA), \hat{s}_{it}^0 (a power request to the i -th generator in HA) and \hat{d}_{jt}^0 (a power allocation for the j -th wholesaler in HA) for the t -th period.

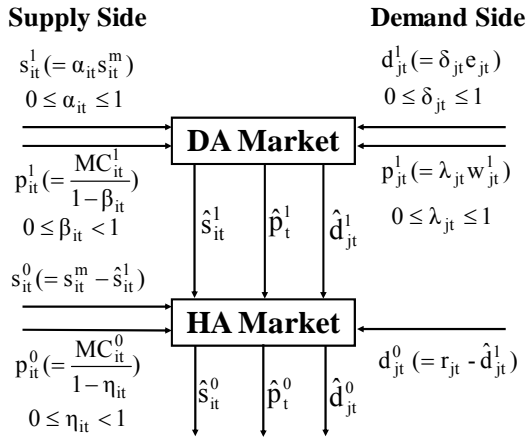


Figure 1: Two Stage Settlement System (Numerical Expression)

Auction Process for DA and HA: The difference between DA and HA is depicted in Figures 2 and 3. The two figures are obtained from [6]. Figure 2 visually describes the DA market coordination mechanism within ISO. In the proposed MAIS, the ISO reorders the bids of generators and wholesalers. The bidding pairs from the supply side (s_{it}^1 and p_{it}^1) are reordered according to the ascending order of the bidding prices. The bidding pairs from the demand side (d_{jt}^1

and p_{jt}^1) are reordered according to the descending order of the bidding prices.

In Figure 2, the ISO allocates the generation amount (s_{1t}^1) of the first generator to satisfy the demand (d_{1t}^1) of the first wholesaler. Such a power allocation is continued until an Equilibrium Point (EP) is found in the DA market. In Figure 2, EP is the equilibrium point, where the supplies from the five generators are used to satisfy the demand required by the three wholesalers. Consequently, p_{5t}^1 (the bidding price of the fifth generator) becomes the market price (\hat{p}_t^1) for DA.

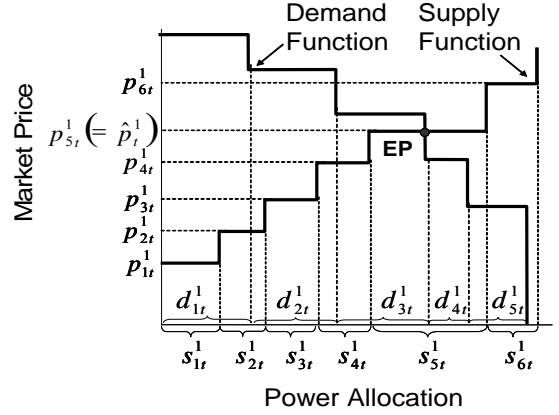


Figure 2: An Equilibrium Point in DA

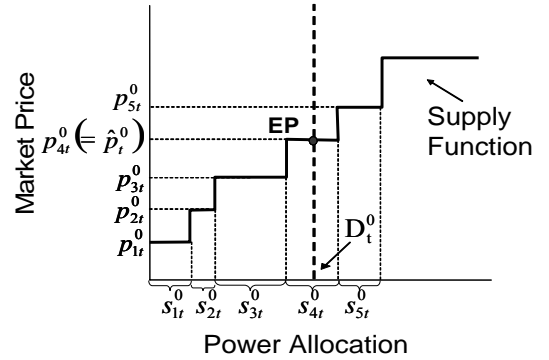


Figure 3: An Equilibrium Point in HA

Figure 3 depicts the market coordination mechanism of generators in HA where their bids are reordered according to the ascending order of the bidding prices. Meanwhile, wholesalers submit only their demands, but not bidding prices, because the demand of end users must be always satisfied. In Figure 3, the ISO accumulates the generation amounts until the total demand is satisfied. In the figure, D_t^0 is such a point at which the total demand satisfies $D_t^0 = \sum_{j=1}^k d_{jt}^0 = \sum_{j=1}^k (r_{jt} - \hat{d}_{jt}^1)$.

In Figure 3, EP is the equilibrium point where four generators are used to satisfy the total demand required by wholesalers. Consequently, p_{4t}^0 (the bidding price of the fourth generator) becomes the market price (\hat{p}_t^0) for HA.

The following comments are useful for explaining the

market mechanism of DA and HA within the MAIS: (a) In Figure 1, we need to specify information regarding $(s_{it}^m, MC_{it}, e_{jt}, w_{jt}^1, r_{jt})$. Decision parameters and mark-up ratios $(\alpha_{it}, \beta_{it}, \eta_{it}, \delta_{jt}, \lambda_{jt})$ are unknown and need to be initialized as random numbers on $[0,1]$ in the MAIS. The simulator creates various bidding strategies for generators and wholesalers by changing these magnitudes. The final power allocation between supply and demand needs to satisfy $\sum_{i=1}^n s_{it}^m \geq \sum_{i=1}^n (\hat{s}_{it}^1 + \hat{s}_{it}^0) = \sum_{j=1}^k (\hat{d}_{jt}^1 + \hat{d}_{jt}^0)$. (b) Rewards to generators and wholesalers in a single zone market are listed in [5,6] and their rewards in multiple zone markets are listed in [7,8]. (c) The previous studies [7,8] describe a market clearing scheme for multiple zone markets.

V. AGENT-BASED ALGORITHM

A. Adaptive Behavior

Figure 4, obtained from [7], illustrates the adaptive learning process of agents in the MAIS. A knowledge base development is incorporated into agents who make power trading on a computer. As depicted in the figure, each agent recognizes that there is an opportunity to obtain a reward by participating into a power market. He understands that the market participation is always associated with risk, so trying to obtain a risk-hedge ability through trading experience.

in two modes: practice and real experience. During practice, they use non-reinforcement learning where there is no feedback from the market. The non-reinforcement learning is separated into three sub-processes: (a) knowledge generation, (b) knowledge accumulation and (c) knowledge creation. Since there is no feedback from the market, the agent has to generate knowledge by himself. The purpose of the knowledge generation process is to discover or become familiar with the market as an environment. Thus, the agent bids in the markets (DA & HA) by changing decision parameters, using a random distribution. After bidding, the values of the parameters and their corresponding win-lose results are stored in the knowledge accumulation process. The accumulated knowledge is further processed by using a sigmoid decision rule (speculation on a winning probability by each agent) and an exponential utility function (risk preference of each agent). This process is knowledge creation. The non-reinforcement learning process is repeated until the practice period is over. The period can be considered as a training process for each agent.

After the practice period is completed, each agent starts real trading experience. The bidding decisions during the real experience period are based upon previous trading practice. The real experience period follows reinforcement learning because the agent reacts according to the feedback obtained from the external environment. The reinforcement learning is functionally separated into three sub-processes: (a) knowledge utilization, (b) knowledge accumulation and (c) knowledge creation. In the knowledge utilization process, each agent fully utilizes the processed information from knowledge creation process of both non-reinforcement learning (practice period) and reinforcement learning (real experience period) to create a bidding strategy. Based on the feedback, he may change the direction of decision parameters according to the algorithm for reinforcement learning. The win/lose results and the corresponding decision parameter values are stored in his knowledge base. The knowledge accumulation and knowledge creation process is similar to that of the practice period. The reinforcement learning is repeated until all iterations are completed.

B. Agents with Multiple Learning Capabilities

Agents in the MAIS incorporate multiple learning capabilities, depicted in Figure 4, that are guided by the two principles originated from large experimental psychology literature on both human and animal learning [20, 21].

“Law of Effect”: This law indicates that “choices have led to good outcomes in the past are more likely to be repeated in the future” [21, p.171]. This study considers that each agent constantly looks for an increase in an estimated winning probability. In other words, he looks for a combination of decision parameters and mark-up ratios that increases the winning probability. In the proposed MAIS, the law of effect is expressed by a sigmoid decision rule.

Sigmoid Decision Rule: The win or lose of each trade is a

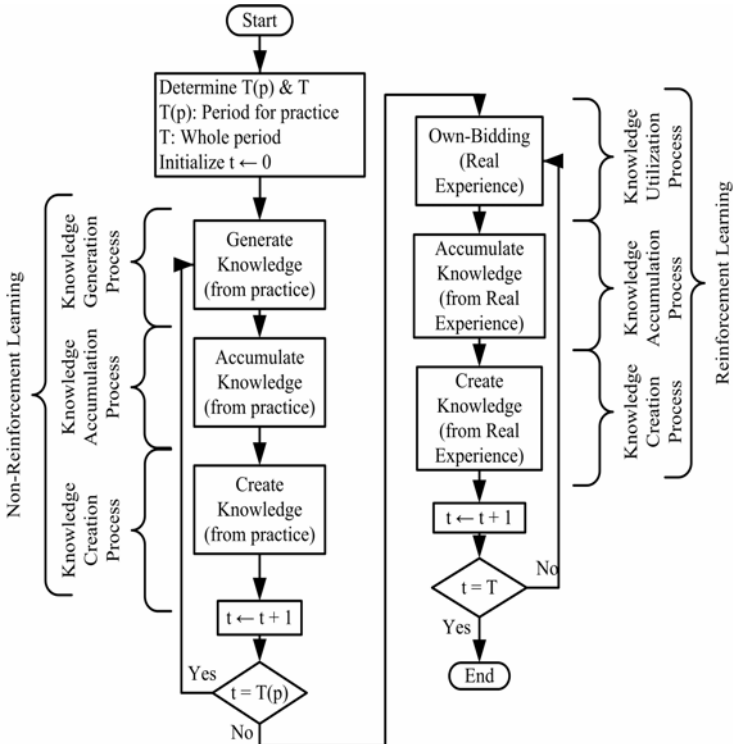


Figure 4: Adaptive Learning and Knowledge Base Development

In the simulator, each market consists of many agents who can accumulate knowledge from their bidding results to adjust their proceeding bidding strategies. They operate

binary response. To express an occurrence of the binary response, we use a sigmoid model that can predict a winning probability. Mathematically, the probability cumulative function of the sigmoid model is expressed by $F(\sigma) = \int_{-\infty}^{\sigma} e^u / (1 + e^u)^2 du = 1 / (1 + e^{-\sigma})$. The win or lose status of the i -th generator is predicted by the following linear probability model:

$$R_{it} = c_{i0} + c_{i1}\alpha_{it} + c_{i2}\beta_{it} + c_{i3}\eta_{it} + \varepsilon_t. \quad (1)$$

Here, R_{it} is a reward given to the i -th generator at the t -th period. Parameters are denoted by c_{i0} , c_{i1} , c_{i2} and c_{i3} . An observational error is listed as ε_t . These parameters are all unknown and need to be estimated by OLS (Ordinary Least Squares) regression. We use (1) to attain computational tractability. The winning probability (Prob) is estimated as follows:

$$\begin{aligned} \text{Pr ob}(W_{IN}_t) &= \text{Pr ob}(R_{it} \geq 0) \\ &= \text{Pr ob}\{\varepsilon_t \geq -(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})\} \\ &= 1 - \frac{1}{1 + \text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})} \\ &= \frac{\text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})}{1 + \text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})}. \quad (2) \end{aligned}$$

The symbol (^) indicates a parameter estimate obtained by OLS. Equation (2) suggests that the winning probability can be estimated immediately from the parameter estimates of the sigmoid model.

The reward of the j -th wholesaler at the t -th period is determined by the following linear probability model:

$$R_{jt} = c_{j0} + c_{j1}\delta_{jt} + c_{j2}\lambda_{jt} + \varepsilon_t. \quad (3)$$

Hence, the winning probability is estimated as

$$\begin{aligned} \text{Pr ob}(W_{IN}_t) &= \text{Pr ob}(R_{jt} \geq 0) \\ &= \frac{\text{EXP}(\hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt})}{1 + \text{EXP}(\hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt})}. \quad (4) \end{aligned}$$

The non-reinforcement/reinforcement learning processes, depicted in Figure 4, develop a knowledgebase within the j -th wholesaler. Using information (data) in the knowledge base, each agent obtains the three parameter estimates of the sigmoid model. Two (\hat{c}_{j1} and \hat{c}_{j2}) of the three parameter estimates are important in determining his bidding strategies. Both are associated with the two decision parameters (δ_{jt} and λ_{jt}), respectively. If a parameter estimate is positive, the wholesaler should increase his corresponding decision parameter to enhance his winning probability. Conversely, an opposite strategy is needed if the estimate is negative. Thus, the sign of each parameter estimate provides information regarding which decision parameter needs to be increased or decreased. However, the winning probability obtained from the sigmoid model does not immediately imply that he can always win in a wholesale market with the estimated probability. The probability estimate is a theoretical guess. The win or lose is determined through the market mechanism of DA and HA.

“Power Law of Practice”- Exponential Utility Function:
The law indicates that “learning curves tend to be steep

initially and then flatter” [21, p.171]. This study assumes that all agents have an exponential utility function. The exponential utility function represents a risk aversion preference on a smooth concave function. We select it among many utility functions because the utility value exists between 0 and 1.

The exponential utility function is expressed by $U(R_{jt}) = 1 - \text{EXP}(-\zeta_j R_{jt})$ on $R_{jt} \geq 0$, where ζ_j indicates a parameter to express the level of risk aversion of the j -th wholesaler.

Returning to (3), the utility value (ϕ_{jt}) regarding the reward (R_{jt}) of the j -th wholesaler at the t -th period is measured by $\phi_{jt} = 1 - \text{EXP}(-\zeta_j R_{jt})$. Hence, given ϕ_{jt} , the reward is expressed by

$$R_{jt} = -\ln(1 - \phi_{jt}) / \zeta_j = \hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt}. \quad (5)$$

Here, “ln” stands for a natural logarithm. After obtaining the parameter estimates of the sigmoid model along with a given utility value or its range, the wholesaler prepares his bidding strategy for the next ($t+1$) period. In the MAIS, his bidding strategy for the next period is specified as follows:

$$\lambda_{jt+1} \leftarrow \lambda_{jt} + \tau_{jt}\Delta_{jt}^{\lambda} \quad \text{and} \quad \delta_{jt+1} \leftarrow \delta_{jt} + \tau_{jt}\Delta_{jt}^{\delta},$$

where $\Delta_{jt}^{\lambda} = \lambda_{jt}^U - \lambda_{jt}^L$ and $\Delta_{jt}^{\delta} = \delta_{jt}^U - \delta_{jt}^L$. The prescribed quantities (λ_{jt}^U and λ_{jt}^L) indicate the upper and lower bounds on λ_{jt} , respectively. Similarly, the other prescribed quantities (δ_{jt}^U and δ_{jt}^L) indicate the upper and lower bounds on δ_{jt} , respectively. The unknown parameter (τ_{jt}) indicates the magnitude of the bidding change.

Along with the changes and given ϕ_{jt+1} , (5) becomes

$$-\ln(1 - \phi_{jt+1}) / \zeta_j = \hat{c}_{j0} + \hat{c}_{j1}(\delta_{jt} + \tau_{jt}\Delta_{jt}^{\delta}) + \hat{c}_{j2}(\lambda_{jt} + \tau_{jt}\Delta_{jt}^{\lambda}). \quad (6)$$

From (6), the magnitude is determined by

$$\tau_{jt} = -\left(\ln(1 - \phi_{jt+1}) / \zeta_j + \hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt}\right) / (\hat{c}_{j1}\Delta_{jt}^{\delta} + \hat{c}_{j2}\Delta_{jt}^{\lambda}). \quad (7)$$

Note that the description on a wholesaler’s utility function can be extended to that of a generator.

Algorithm for Bidding Strategies: Based upon the sign of parameter estimates of the sigmoid model, the j -th wholesaler has nine (= 3x3) different bidding strategies (with $t = 0$ as the start):

Step 1: Set initial bids from his knowledgebase. A forecasting method (e.g., moving average or exponential smoothing) with different time periods is used to compute the initial bids. Also, set the upper (δ_{jt}^U and λ_{jt}^U) and lower (δ_{jt}^L and λ_{jt}^L) limits.

Step 2: Use the OLS regression to obtain parameter estimates of the sigmoid model from the knowledgebase. Obtain the magnitude (τ_{jt}) from (7).

Step 3: Based upon the signs of parameter estimates, change the decision parameters according to the following conditions:

- (a) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} + \tau_{jt} \Delta_{jt}^{\lambda} \right\}$
- (b) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} \right\}$
- (c) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} - \tau_{jt} \Delta_{jt}^{\lambda} \right\}$
- (d) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} + \tau_{jt} \Delta_{jt}^{\lambda} \right\}$
- (e) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} \right\}$
- (f) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} - \tau_{jt} \Delta_{jt}^{\lambda} \right\}$
- (g) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} + \tau_{jt} \Delta_{jt}^{\lambda} \right\}$
- (h) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} \right\}$
- (i) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau_{jt} \Delta_{jt}^{\delta}, \lambda_{jt} - \tau_{jt} \Delta_{jt}^{\lambda} \right\}$

Step 4: Increment t ($t=t+1$). Compute d_{jt}^1 and p_{jt}^1 based upon

$(\delta_{jt}, \lambda_{jt})$. Then, the wholesaler submits the two bids to DA. If $t = T$, then stop. Otherwise, go to Step 5.

Step 5: If the wholesaler loses, then drop information regarding the bids from the current knowledgebase and go to Step 1. If the wholesaler wins, then go to Step 6.

Step 6: Add information regarding his bids into the current knowledgebase and go to Step 1.

Comments: (a) Even if each trader keeps the same strategy, his bidding result may be different from that of the previous bid because the wholesale markets determine the price and amount of power allocation. (b) The algorithm for a generator is the same as that of a wholesaler, as discussed above. An exception can be found in Step 3 where the algorithm for the generator needs to consider 27 ($=3 \times 3 \times 3$) bidding strategies. The algorithm for the generator needs to consider three decision parameters. This study does not discuss the algorithm here to avoid a descriptive duplication. (c) The bidding of a wholesaler for HA is only for the bidding amount of electricity because HA is a physical market, as depicted in Figures 1 and 3.

VI. CALIFORNIA ELECTRICITY MARKET (2000-2001)

The California market is divided into three zones for the purposes of pricing: NP-15 is in the north, SP-15 is in the south, and ZP-26 is in the center of the state. The central zone (ZP-26) has two transmission links, one to Northern path (NP-15) and one to Southern path (SP-15). The Northern path and Southern path are not directly connected to each other. If they need excess electricity, they have to obtain it from other states as shown in Figure 5. A data set on the California electricity market is available from the University of California Energy Institute website (www.ucei.berkeley.edu/datamine/uceidata/uceidata.zip). The data consists of all market information such as time of transaction, date of transaction, price at each zone in DA and HA markets, unconstrained price and quantity of the system, import/export quantities in each zone and prices of various auxiliary services.

Each sample represents hourly prices representing 24 hours per day. SP-15 DA and HA represent the hourly market price of southern zone of California for DA market and HA market, respectively, during the period from 1st April 1998 to 31st January 2001. NP-15 DA and HA represent the hourly market price of northern zone of California for DA and HA, respectively, during the period from 1st April 1998 to 31st January 2001. ZP-26 DA and HA represent the hourly market price of central zone of California for DA and HA, respectively, during the period from 1st February 2000 to 31st January 2001.

For all the DA markets, a maximum price of \$2499.58 was observed at 7 PM on 21st January 2001. All the HA markets had a maximum price of \$750, starting from 26th June 2000. It was observed that prices started rising steadily from the summer of 2000. The wholesale prices increased 270% and fluctuated drastically during the electricity crisis period.

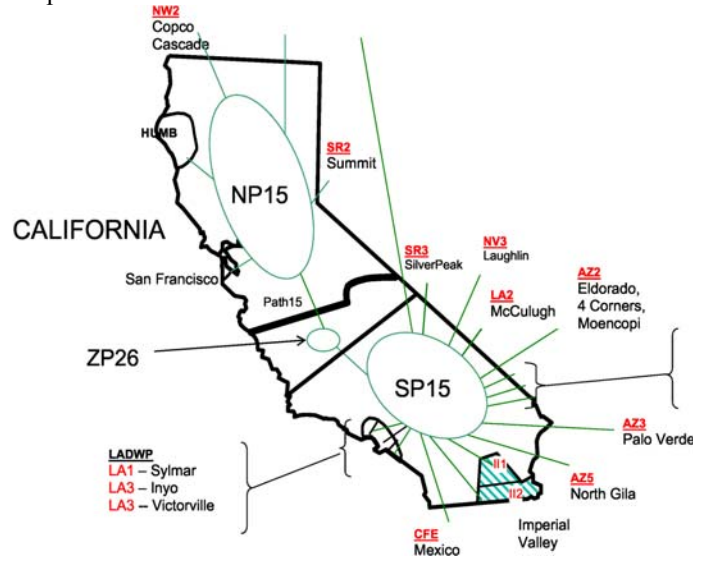


Figure 5: Three Zones in California ISO
(Source: <http://www.ucei.berkeley.edu/>)

Market Composition: Since this study cannot access the exact composition about the power market from 1998 to 2001, we use the information provided by California Energy Commission on its website for 2005, http://www.energy.ca.gov/maps/electricity_market.html. The web site provides an approximate composition of generators. Thus, this study considers 964 generators of which 343 are hydroelectric with 20% market capacity, 44 are geothermal with 3% market capacity, 373 are oil/gas with 58% market capacity, 17 are coal with 6% market capacity, 94 are wind with 4% market capacity, 80 are waste to energy with 2% market capacity, 2 are nuclear with 7% market capacity, 11 are solar with 1% market capacity. The wholesaler composition is estimated from the website: http://www.energy.ca.gov/electricity/electricity_consumption_utility.html. There are a total of 48 wholesalers. Pacific Gas and Electric has 30% of the share, San Diego Gas & Electric has 7% of the share, Southern California Edison has

31% of the share, LA Department of Water and Power has 9% of the share. Sacramento Municipal Utility District has 4% of the share, California Dept. of Water Resources has 3% of the share, and other 41 utilities have a 12% share. Self-generating agencies account for 4% of the share.

Alternate Approaches

Evaluation Criterion: This study uses estimation accuracy (%) as a criterion, which is proposed by Shahidehpour *et al.* [22].

Direct Formula (DF): As the first alternative, we employ a direct formula in which price is considered to be proportional to load [22]. The following formula is used for predicting the price:

$$\text{Price}(t) = [\text{Load}(t)/\text{Load}(t - 24)] \times \text{Price}(t - 24).$$

A period of 24 is used because the data is hourly. A spreadsheet application, like Microsoft Excel, is used to compute the DF.

Neural Network (NN): The second alternative is NN whose use for price estimation has been recommended by many researchers. We use a Normalized Gaussian Radial Basis Function Neural Networks to forecast the market price of electricity. [See, for example, neural v1.4.2 package on R 2.5.1 <http://www.r-project.org/>.] The network uses a back propagation algorithm for training the network. The input parameters used are as follows: time of day, day of week, power imports, power exports, temperature, system wide load, and previous day's price. These parameters are reported in Gao *et al* [23]. The width of each gauss function is assigned as the Euclidean distance between the two nearest training samples. [Source: Documentation of neural v1.4.2 package]. The learning rate, alpha, is assigned to 0.20. The error condition to stop is specified as 0.001, i.e. the algorithm will stop if the average error between the target vector and the predicted vector is lower than 0.001. As a preprocessing step, the data was normalized to lie in the range between -1 and 1. Each sample has been divided into three sets: training set, validation set and testing set. For SP-15 and NP-15, the first 456 days are used for training, the next 305 days are used for validation, and the next 60 days are used for testing. For ZP-26, the first 216 days are used for training, the next 148 days are used for validation, and the next 31 days are used for testing. To avoid the problem of over fitting, we conducted experiments repeatedly by varying the number of neurons in the hidden layer from 5 to 13. It is found that the number of neurons that gives the least error is 10, 10, and 7 for SP-15, NP-15, and ZP-26, respectively.

Genetic Algorithm (GA): We use "genalg" package (version 0.1.1), an R based Genetic Algorithm to run our experiments. A genetic algorithm essentially consists of three steps: initialize population, evaluate the fitness of a population, and apply genetic operators. We modeled the problem as a parameter estimation problem for a nonlinear regression model. See Pan *et al.* [24] for more information on the use of a genetic algorithm for nonlinear regression model. The DA and HA prices were modeled as unknown parameters that have to be estimated by the algorithm. The

known parameters were day-of-the-week, hour of the day, temperature, and system wide load. Each individual in the population is encoded by two binary strings. The first binary string represents the DA price. The second binary string represents the HA price. We know from the dataset that the maximum value of DA price is 2499.58. Thus, the range of DA price is [0, 2500]. Since we assume a precision of 2 digits after decimal point, the domain of DA price should have 250000 equal divisions. That is, it should be represented by a 18 bit binary string ($131072=2^{17} < 250000 < 2^{18} = 262144$). We know that the range of HA price is [0,750]. Assuming a precision of 2 digits after decimal point, the domain of HA price should have 75000 equal divisions. i.e. it should be represented by a 17 bit binary string ($65536=2^{16} < 75000 < 2^{17} = 131072$). Thus, an individual in the population is represented by a 35 (18+17) bit binary string.

The fitness value (FV) of an individual in a population is given by the following equation:

$$FV(\hat{p}_t^1, \hat{p}_t^0) = \sum \left[SWL_t - \text{Avg Load}(\text{DW}, \text{HD}, \text{Temp}, \hat{p}_t^1, \hat{p}_t^0) \right]^2$$

Here, SWL is system-wide load, DW is day of week, HD is hour of day, Temp is a temperature. We use a rank-selection strategy to choose the individuals based on the rank of the fitness function (FV) for the market prices for DA (\hat{p}_t^1) and HA (\hat{p}_t^0). The strategy is similar to the one described in Pan *et al.* (1995). For our experimental purpose, an initial population size of 50 is used. The maximum generation is 25000. The mutation chance is varied from 0.02 to 0.10. Elitism is set to 0.25. The prices for the (t+1)-th period is estimated from the previous t-th period.

Estimation Comparison

There was no data about the capacity limits of California transmission links. To determine a capacity limit on the links between zones, we calculate the difference between import and export quantities to the wholesale market. After observing the data set, a transmission limit of 11752 GWH (maximum difference) was applied on the transmission link between central zone and northern zone. The same limit was applied on the transmission link between central zone and southern zone, as well [7].

TABLE 1: ESTIMATION ACCURACY (%) OF FOUR APPROACHES

Market	Estimation Accuracy under Line Limit				
	DF	GA	NN	MAIS	
SP-15 DA	14.45	63.32	77.16	85.76	[90.54] (72.45)
SP-15 HA	16.76	62.10	76.67	86.89	[91.90] (72.93)
NP-15 DA	34.49	59.54	78.24	75.19	[81.82] (56.72)
NP-15 HA	33.19	59.67	78.11	79.32	[85.59] (61.91)
ZP-26 DA	53.12	60.12	64.19	89.71	[95.81] (87.66)
ZP-26 HA	49.18	61.74	63.95	89.12	[96.41] (86.67)
Mean	33.53	61.08	73.05	84.33	[90.35] (73.06)

a) The numbers in [] and () under MAIS indicate an average estimation accuracy before the California electricity crisis and the one during the crisis, respectively. The number listed at the left hand under MAIS is the average during the whole observed period (April 1998 to January 2001). Similarly, the numbers under DF, GA and NN indicate the average during the whole observed period. DF, GA and NN stand for Direct Formula, Genetic Algorithm and Neural Network, respectively.

Table 1 summarizes the estimation accuracy of the four approaches. The estimation accuracy of MAIS of each power market is further separated into the one before and the one during the electricity crisis. For example, SP-15 and NP-15 have the number of data points before the crisis and during the crisis that are 18312 and 6576, respectively. Meanwhile, ZP-26 has data points before and during the crisis that are 2208 and 6576, respectively. The weighted average estimation accuracy of each market is computed by [(average estimation accuracy before the crisis) x (# of observations before the crisis) + (average estimation accuracy during the crisis) x (# of observations during the crisis)] / (# of all observations before and during the crisis). The average (84.33%) for all markets is computed by the total weighted averages (= 85.76% + ... + 89.12%) divided by 6 (the number of markets).

Figure 6 visually compares the fluctuation of observed prices of electricity with the estimated prices obtained by MAIS in the NP-15 (DA) market before the crisis. Figure 7 depicts such a comparison during the crisis. Similar results are observed in all the other markets.

Finding 1: Table 1 indicates that the MAIS (average estimation accuracy = 84.33%) estimates the dynamic price fluctuation of electricity as well as the other three methods (DF: 33.53%, GA: 61.08% and NN: 73.05%). The average estimation accuracy of MAIS before the crisis is 90.35%, while the estimation accuracy during the crisis is 73.06%. It is easily observed that there is a considerable gap in estimation between the two periods. Furthermore, there is a significant difference between observed market prices and MAIS's estimates during the crisis.

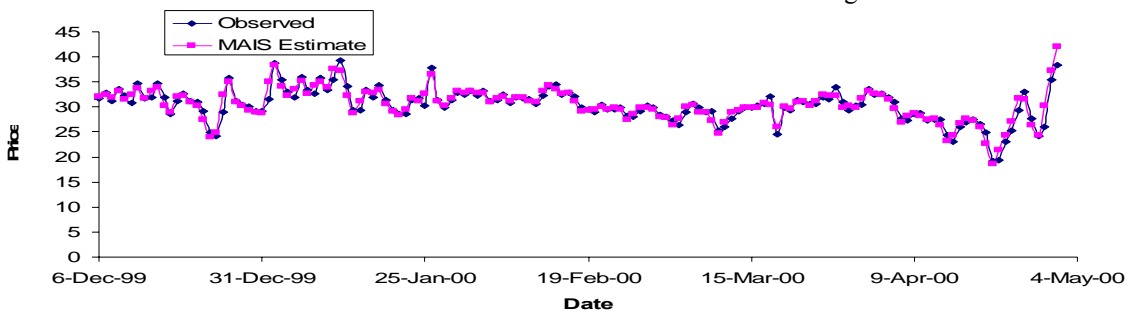


Figure 6: Observed Market Prices of NP-15 (DA) and MAIS Estimates (Before the California Electricity Crisis)

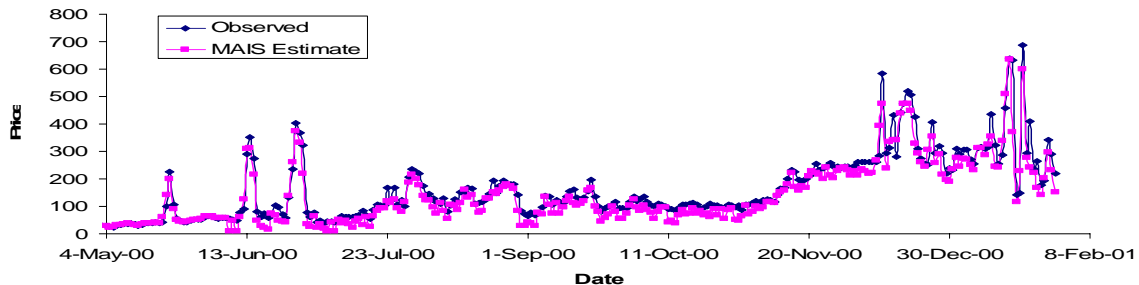


Figure 7: Observed Market Prices of NP-15 (DA) and MAIS Estimates (During the California Electricity Crisis)

Based upon such results, it is concluded that the observed high wholesale electricity prices during the crisis period cannot be explained as a natural outcome of changes in market fundamentals.

Such a difference (90.35% and 73.06%) can be visually confirmed in Figures 6 and 7. Both figures compare the price fluctuation of observed prices with that of the price estimates in the two periods (before and during the crisis). It is important to note that the price range of Figure 6 (from \$25/MWH to \$40/MWH) is much smaller than that of Figure 7 (from \$30/MWH to \$700/MWH).

Learning Speed (Convergence Rate)

Table 2 indicates that the learning speed of reinforcement learning incorporated in agents depends upon the market price changes of wholesale electricity. The proposed MAIS has five decision parameters and mark-up ratios to investigate the bidding behaviors of agents. In Table 2, for example, the decision parameter (α) of generators takes 62 iterations (on average) to converge before the crisis, whereas the decision parameter takes 119 iterations to converge during the crisis. Furthermore, the decision parameter (δ) of wholesalers needs 53 iterations (on average) to converge before the crisis, whereas the decision parameter takes 106 iterations to converge during the crisis. We observe a similar result on all the other parameters and mark-up ratios of both generator and wholesalers.

Finding 2: Table 2 indicates that the learning speeds (convergence rates) of agents depend upon the changes of market fundamentals. Hence, the average learning rate during the crisis needs more iterations than that before the crisis. In this simulation study, we find that the former is almost twice as long as the latter.

TABLE 2: LEARNING SPEED (CONVERGENCE) OF AGENTS BEFORE AND DURING THE CALIFORNIA ELECTRICITY CRISIS

		Generator			Wholesaler	
		α	β	η	δ	λ
SP-15	(Before)	69	73	54	41	63
	(During)	154	194	203	109	265
NP-15	(Before)	55	53	65	62	73
	(During)	113	129	143	146	125
ZP-26	(Before)	62	84	61	56	62
	(During)	90	103	113	63	93
AVG	(Before)	62	70	60	53	66
	(During)	119	142	153	106	161

a) The above number indicates the number of iterations used for convergence. (Before) indicates the period (December 1999-April 2000) before the electricity crisis and (During) indicates the period (April 2000-January 2001) during the electricity crisis.

Sensitivity Analysis

To identify rationales regarding why a price hike has occurred during the California electricity crisis, this study prepares six economic assertions related to market fundamentals, all of which are examined by MAIS-based sensitivity analysis.

Hypothesis 1 (Increase in Marginal Cost): An increase in the marginal cost of oil and natural gas has influenced the increase in the wholesale price during the California electricity crisis.

The first assertion is due to Joskow and Kahn [4, pp.5-7 and p.17]. They have reported that the price of natural gas has increased significantly and contributed to an increase in the marginal cost of oil/gas power plants. The sensitivity analysis examines the first hypothesis by increasing the marginal costs of 373 gas-fired generators according to the rates that are depicted in Figure 1 of [4, p.7]. The original marginal costs (observed before the crisis) used for hydroelectric, geothermal, oil/gas, coal, wind, and nuclear are \$25, \$30, \$40, \$35, \$10, and \$50, respectively. These marginal costs, except that of oil/gas, are used to examine the price fluctuation of electricity during the crisis, because a major price change has not been observed for those fuels in the crisis period.

Hypothesis 2 (Increase in Real Demand): An increase in electricity consumption has increased the wholesale price during the California electricity crisis.

The second assertion is due to an observed data set on real demand in the three zones of the California market. See also [4, p. 28] in which increased demand is considered as a factor of the price hike in the electricity crisis. The data set indicates a system wide load increase during the crisis. Hence, the sensitivity analysis increases the real demand by 20% from the original values. This increase in demand was applied only during the peak load time (from 7:00 to 21:00), because a price hike occurred during the peak load period. Any major price change was not found in the off-peak period. The 20% increase is due to the data from (www.ucei.berkeley.edu/datamine/uceidata/uceidata.zip).

According to the data source, the real demand has increased during the period from 4 May 2000 to 31 Jan 2001. For example, the load was 20,880.40 GWH (at 9:00 on 1 June 1999) and 23,694.10 GWH (at 9:00 on June 2000), respectively. This denotes an increase of 13.48% during that time. An average of all such increase in loads is 19.69%. Hence, the proposed sensitivity analysis uses 20% for increase.

Hypothesis 3 (Greed of Traders): Traders have exhibited overwhelming desire for more profit during the period of California electricity crisis. Generators were looking for less risk-averse (aggressive) bidding decisions and wholesalers were looking for more risk-averse (conservative) bidding decisions.

An important numerical capability of the proposed MAIS is that it can examine the level of trader’s greed by observing the utility function of each trader. It is observed that the wholesale market price of electricity maintained an increasing trend, but the retail price of electricity did not increase significantly during the crisis. Rather, the retail price almost remained the same under the control of regulatory agencies. The increase in market price implies that generators profited and wholesalers were bearing an economic loss from the power market. Thus, it is assumed that generators were looking for a more risk-taking behavior to make more profit. Meanwhile, the wholesalers were looking for an opposite direction. Their behaviors were avoiding risk in the power market. In our experiments, we observe a change in the parameter (ζ) that represents the level of risk aversion in the exponential utility function used in this study. For evaluating this economic assertion, the parameter range for generators is changed from (0.004, 0.065) to (0.0003, 0.0015). Similarly, the parameter range for wholesalers is changed from (0.004, 0.065) to (0.010, 0.070).

Hypothesis 4 (Electricity Withholding by Generators): Large generators withheld electricity during the period of California electricity crisis. The excise of market power contributed to the price hike during the crisis period.

The fourth hypothesis is due to Joskow and Kahn [4, pp. 19-28]. Their empirical analysis reports that some generation firms deliberately did not make their maximum supply capacities available for the California electricity market. This economic assertion is a main conclusion of their study [4]. This study reexamines their assertion. The proposed sensitivity analysis uses the mean values of output gap that are summarized in Table 7 of [4, p. 23]. In our experiments, the maximum supply of each generator is reduced to the level of (maximum supply - output gap).

Hypothesis 5 (Capacity Limit in Transmission Lines): A capacity limit in transmission lines was a source of supplier withholding. The transmission congestion occurred

during the California electricity crisis and the occurrence influenced the price hike of electricity.

Joskow and Kahn [4, p.8] reported that relatively little significant transmission congestion occurred during the crisis period. However, it is important to investigate whether the supplier withholding during the crisis was intentional by generators or was due to an occurrence of congestion in transmission lines (so, the withholding in the supply side was accidental). There is no public data available on the transmission line limits in the California transmission grid. Hence, we depend upon the data on system-wide imports and exports for both DA and HA markets. [source:www.ucei.berkeley.edu/datamine/uceidata/uceidata.zip]. To estimate a transmission limit, we calculate the average of the absolute difference between imports and exports for both DA and HA. [See [7] for the investigation.] The average is 11,752 GWH, which is chosen as the line limit for all the transmission lines. For the sensitivity analysis, the line limit is reduced by 25%. Thus, the new line limit is 8,814 GWH.

Hypothesis 6 (Combination): The price hike in the California electricity crisis was not produced by a single source (i.e., a market fundamental that is specified by each hypothesis). Rather, the problem was produced by some combination of market fundamentals.

All combinations of market fundamentals are systematically applied to a data set during the crisis and the changes in estimation accuracy are measured by the sensitivity analysis.

Identification of Initial Starting Variables: In order to examine the six hypotheses, this study needs to estimate decision parameters and mark-up ratios, using a data set before the electricity crisis. Such parameter estimates on the last convergence serve as initial starting values for the proposed sensitivity analysis. For example, using the data set before the crisis, the proposed MAIS identifies that the decision parameter (α) of the 100th generator (the total number of generators is 964) converges at 0.185103 in iteration 41. Similarly, β converges at 0.598712 in iteration 43 and η converges at 0.315906 in iteration 40. Meanwhile, the decision parameter (δ) of the 10-th wholesaler (the total number of wholesalers is 48) converges at 0.253761 in iteration 59. λ converges at 0.323862 in iteration 64.

All the parameters and mark-up ratios are used as the initial starting values to examine the behavior of the 100th generator during the electricity crisis. A similar identification process of initial starting variables related to the 100th generator can be applied to all generators and wholesalers.

Results of Sensitivity Analysis: Table 3 summarizes resulting estimation accuracies of MAIS under 32 combinations of different market fundamentals. The first row (under the number of market fundamentals is zero) indicates the estimation accuracy of MAIS. The simulator starts from the initial values on decision parameters and

markup ratios that are obtained from a data set before the California electricity crisis and then it computes the estimation accuracy, using a data set during the crisis. The estimation accuracy of MAIS is 73.06% that serves as a benchmark score for proceeding comparison. The estimation accuracy indicates how much a price fluctuation of electricity during the crisis can be explained by the market fundamentals before the crisis.

The second row indicates the result of MAIS-based sensitivity analysis that examines the first hypothesis by increasing the marginal cost of 373 gas-fired generators according to the rate depicted in [4, p.7]. The estimation accuracy increases from 73.06% to 83.96%. This implies that the increase in the marginal cost of oil/natural gas explains the price fluctuation of electricity during the California crisis at a level of 10.90% (= 83.96%-73.06%) contribution. Thus, the first hypothesis is confirmed by the MAIS-based sensitivity analysis. A similar result is identified in the second hypothesis (an increase in real demand) and the third hypothesis (traders become greedy), because these related estimation accuracies (75.40% and 80.66%) are higher than the benchmark accuracy (73.06%). Conversely, the fourth hypothesis (withholding by market power in the supply side) and the fifth hypothesis (a capacity limit on transmission lines) cannot be confirmed by the sensitivity analysis, because those estimation accuracies (72.94% and 72.60%) are lower than the benchmark score (73.06%). Thus, the estimation accuracy of 83.96(%) serves as the benchmark score under the sensitivity of a single market fundamental.

Under the MAIS-based sensitivity analysis of two market fundamentals, the combination between the first hypothesis (an increase in the marginal cost of oil/natural gas) and the third hypothesis (all traders became greedy for more profit) produces the best estimation accuracy (88.77%). This implies that the price increase and fluctuation of electricity during the crisis can be explained by the greediness of all traders at a level of 4.81% (= 88.77%-83.96%). The third hypothesis is confirmed by the sensitivity of two market fundamentals. The estimation accuracy (88.77%) becomes a benchmark score for the proceeding sensitivity analysis.

Under the MAIS-based sensitivity analysis of three market fundamentals, the combination among the previous two hypotheses and the second hypothesis (an increase in real demand) produces the best estimation accuracy (90.19%). This implies that the price increase and fluctuation of electricity during the crisis can be explained by the increase in real demand at a level of 1.42% (= 90.19%-88.77%). The second hypothesis is confirmed. The estimation accuracy (90.19%) becomes a benchmark score for the next sensitivity analysis.

Under the MAIS-based sensitivity analysis of four parameters, the combination among the previous three hypotheses and the fourth hypothesis (withholding capacity of generators) produces the best estimation accuracy (91.15%). This implies that the price increase and fluctuation of electricity during the crisis can be explained by the withholding capacity of generators at the level of

0.96% (= 91.15%-90.19%). The fourth hypothesis is confirmed by this sensitivity analysis. The estimation accuracy (91.15%) becomes a benchmark score at this stage of sensitivity analysis.

Finally, there is no increase in estimation accuracy under the five market fundamentals. This implies that a capacity limit on transmission lines do not explain the price increase and fluctuation of electricity during the crisis.

TABLE 3: ESTIMATION ACCURACY (%) OF MAIS UNDER DIFFERENT COMBINATIONS OF MARKET FUNDAMENTALS

No. of Market Fundamentals	Hypotheses (Market Fundamentals)					Estimation Accuracy (%)						
	Marginal Cost	Real Demand	Greed	Withholding Capacity	Transmission Limit	NP-15		ZP-26		SP-15		AVG
						DA	HA	DA	HA	DA	HA	
0	No Sensitivity					56.72	61.91	87.66	86.67	72.45	72.93	73.06
1	o					75.18	76.82	91.24	90.07	84.19	86.27	83.96
1		o				63.15	63.48	85.19	87.67	73.28	79.64	75.40
1			o			68.27	69.48	83.19	86.17	87.56	89.27	80.66
1				o		59.37	58.12	88.10	87.27	73.11	71.66	72.94
1					o	55.17	60.14	88.10	87.94	73.19	71.04	72.60
2				o	o	57.18	58.37	60.24	60.86	69.07	50.27	59.33
2			o		o	64.07	68.34	80.17	80.74	85.77	84.91	77.33
2			o	o		79.21	82.04	90.77	89.69	90.17	91.71	87.27
2		o			o	53.01	57.14	72.08	79.65	64.08	63.27	64.87
2		o		o		67.17	62.08	83.90	87.19	75.18	76.27	75.30
2		o	o			68.12	68.90	82.90	85.19	81.24	88.88	79.21
2	o				o	77.18	76.98	92.01	91.13	83.19	87.27	84.63
2	o			o		70.18	73.19	84.29	85.57	80.12	81.32	79.11
2	o		o			82.06	88.97	91.34	90.21	90.08	89.93	88.77
2	o	o				70.24	71.69	80.37	82.67	80.17	81.64	77.80
3			o	o	o	78.34	80.21	86.63	88.51	89.21	89.38	85.38
3		o		o	o	68.27	69.31	84.27	87.19	74.28	77.17	76.75
3		o	o		o	67.18	65.28	80.27	80.29	82.07	83.09	76.36
3		o	o	o		85.09	83.27	90.10	90.12	91.27	91.66	88.59
3	o			o	o	60.10	60.86	65.27	63.19	70.68	75.29	65.90
3	o		o		o	80.24	87.19	92.75	92.10	88.29	90.16	88.46
3	o		o	o		85.09	86.75	90.18	90.08	91.67	91.46	89.21
3	o	o			o	67.18	68.39	75.95	76.73	78.33	79.58	74.36
3	o	o		o		75.18	77.64	81.52	82.67	88.17	88.62	82.30
3	o	o	o			84.15	89.27	91.74	92.23	91.65	92.08	90.19
4		o	o	o	o	83.09	81.24	86.29	87.98	88.28	89.44	86.05
4	o		o	o	o	82.17	81.35	87.28	89.64	90.10	90.10	86.77
4	o	o		o		73.28	77.64	78.95	79.29	80.64	80.09	78.32
4	o	o	o		o	89.28	88.16	83.64	90.29	90.55	91.67	88.93
4	o	o	o	o		90.34	90.56	91.67	92.08	90.44	91.82	91.15
5	o	o	o	o	o	89.12	95.34	93.08	90.24	80.17	83.16	88.52

Finding 3: The California electricity crisis was initiated by an increase in the marginal cost of oil / natural gas. The cost increase occurred along with an increase in real demand of electricity. Under such a business circumstance, all traders became greedy for more profit. The three market fundamentals explain the price fluctuation of electricity during the crisis period at the level of 90.19% estimation accuracy. Besides the three market fundamentals, the withholding of large generators had an additional impact (at the level of 1%) to the price hike during the electricity crisis. The estimation accuracy increased to 91.15% under the four combinations. A capacity limit on transmission lines (or an occurrence of congestion) did not have any major influence on the price hike.

These results indicate that 40.46% [= (83.96%-73.06%) / (100%-73.06%)] of the price increase during the California electricity crisis was due to an increase in marginal production cost, 17.85% [= (88.77%-83.96%) / (100%-73.06%)] to traders' greediness, 5.27% [= (90.19%-88.77%) / (100%-73.06%)] to a real demand change and 3.56% [= (91.15%-90.19%) / (100%-73.06%)] to market power (withholding electricity). The remaining 32.86% came from other unknown market components and an estimation error. Consequently, the price hike during the crisis has occurred due to an increase in fuel prices and real demand at the level of 45.73% (40.46%+5.27%). The responsibility of energy firms was 21.41% (17.85%+3.56%) that was less than that of the increase of fuel price and real demand (45.73%).

Comparison with Joskow and Kahn [4]: This study compares the results obtained from the MAIS-based sensitivity analysis with the results reported in [4]. Their study is very well-known among researchers and individuals who are related to the energy industry.

First, their study mentioned in [4, p.8] that a capacity limit on transmission lines did not influence the price hike during the California electricity crisis. The proposed MAIS-based sensitivity analysis confirms the validity of their previous finding.

Second, they have concluded in [4, p.29] that “the high prices experienced in the summer of 2000 reflect the withholding of suppliers from the market by suppliers (generators or marketers).” They have added in [4, p.29] that “observed prices in California in summer 2000 were greater than benchmark competitive price level. These differences are not fully explained by higher loads, reduced levels of imports, high gas prices or by high prices for NOx (Nitrous Oxide) emissions.”

In contrast, the proposed sensitivity analysis indicates an opposite priority among those market fundamentals. That is, the California electricity crisis was initiated by an increase in the marginal cost of oil/natural gas. Such an increase occurred along with increased real demand of electricity. Under such a business circumstance, all traders became greedy for more profit. The difference between observed prices and MAIS estimates are explained at the level of 90.19% estimation accuracy. So, the three market fundamentals were main reasons of the price hike in California. As a greedy strategy of influential (usually large) generators, the withholding of generators had an additional impact (at the level of 1%, so being total 91.15% estimation accuracy) to the price hike. Thus, the empirical findings identified by the proposed MAIS-sensitivity analysis are different from their findings of [4] in which the withholding of generators (as a market power) was attributed to the price hike during the California electricity crisis.

VII. CONCLUSION AND FUTURE EXTENSIONS

MAIS was applied to examine why a price hike occurred in the California electricity crisis. In this study, the performance of MAIS was compared with other well-known methods (i.e., neural networks and genetic algorithms), using a real data set on power trading related to the California electricity crisis. The methodological comparison confirmed that MAIS performed as well as the other well-known approaches in predicting the price fluctuation of wholesale electricity.

After examining the estimation accuracy, the MAIS-based sensitivity analysis was applied to examine why a price hike occurred during the California electricity crisis. The sensitivity analysis identified that the electricity crisis was initiated by an increase in the marginal cost of oil/natural gas. The cost increase occurred along with increased demand of electricity. Under such a business circumstance, all traders became greedy for more profit. The three market fundamentals explained the price fluctuation of electricity during the crisis period at the level

of 90.19% estimation accuracy. Besides the three market fundamentals, the capacity withholding of large generators had an additional impact to the price hike during the electricity crisis. The four market fundamentals explained 91.15% of the price fluctuation during the crisis. A capacity limit on transmission lines (or an occurrence of congestion) did not have any major influence on the price hike.

As future extensions, we have the following two research agendas: First, this study compared the numerical results obtained from the MAIS sensitivity analysis with the empirical ones of Joskow and Kahn [4]. We acknowledge the existence of other research efforts such as Borenstein *et al* [25] and Wolak [26] in addition to [4]. The study [4] is a descriptive approach and is very well-known among researchers and individuals who are involved in electricity and energy policy. The research [4] is important because it provides this study with a conceptual framework regarding the California electricity crisis. We respect their study and understand their contribution on the policy issue. Therefore, this study started with the comparison between results obtained from our study and [4]. Meanwhile, both [25,26] describe analytical approaches to investigate the crisis. The comparison between this study and [25,26] needs a major restructuring of the proposed MAIS. We know that this study needs to compare our numerical results with theirs in order to make a final conclusion on the electricity crisis. The comparison between this study and [25,26] will be an important future research extension of this study.

Second, the proposed MAIS-based sensitivity analysis is a completely new approach. Previous research on agent-based approach has never explored the MAIS-based sensitivity analysis. Hence, the proposed sensitivity analysis may not be a perfectly established methodology. For example, this study uses the average of estimation accuracy as our evaluation criterion. Is there any other criterion for this type of sensitivity analysis? To answer the question, we need to explore further the methodological validity and applicability of the MAIS-based sensitivity analysis. That is an important future research task.

Finally, we hope that this study makes a contribution in machine learning and cybernetics as well as the estimation of a dynamic price fluctuation of wholesale electricity. We look forward to seeing future research extensions, as indicated in this study.

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Acknowledgement: The authors thank Dr. Vladimir Marik, an associate editor, and three anonymous referees whose constructive comments improve the quality of this research.