# Day-Ahead Electricity Price Forecasting in a Grid Environment

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***Abstract*—Accurate electricity price forecasting is critical to market participants in wholesale electricity markets. Market participants rely on price forecasts to decide their bidding strategies, allocate assets, negotiate bilateral contracts, hedge risks, and plan facility investments. Market operators can also use electricity price forecasts to predict market power indexes for the purpose of monitoring participants' behaviors. Various forecasting techniques are applied to different time horizons for electricity price forecasting in locational marginal pricing (LMP) spot markets. Available correlated data also have to be selected to improve the short-term forecasting performance. In this paper, fuzzy inference system (FIS), least-squares estimation (LSE), and the combination of FIS and LSE are proposed. Based on extensive testing with various techniques, LSE provides the most accurate results, and FIS, which is also highly accurate, provides transparency and interpretability.**

***Index Terms*—Day-ahead energy market, electricity price forecasting, fuzzy inference system (FIS), grid environment, least-squares estimation (LSE), locational marginal prices (LMPs).**

## I. INTRODUCTION

ACCURATE electricity price forecasting is a key issue to both market participants and market operators in wholesale electricity markets. Market participants need to forecast short-term, mainly day-ahead, prices to maximize their profits in spot markets. They also refer to medium-term price forecasting in negotiations of bilateral contracts so that they can hedge against risks of price volatility in spot markets [1], [2]. Facility owners use long-term price trends to ensure recovery of investments in the planning of generation, transmission, or distribution [1]. Additionally, forecasted prices provide market operators with measures to predict possible exercises of market power and detect gaming behaviors leading to unreasonable prices.

The state-of-the-art techniques for electricity price forecasting are categorized into equilibrium analysis [3], simulation methods [4], econometric methods [5], time series [2], [6]–[9], intelligent systems [1], [10]–[16], and volatility analysis [10]. Time series and intelligent systems are commonly used for day-ahead price forecasting. Typical time series and intelligent system methods include auto-regressive moving average (ARMA) [7], [8], generalized auto-regressive conditional heteroskedastic (GARCH) [9], feed-forward neural networks (FFNNs) [1], [11], [13], recurrent neural networks (RNNs) [14], adaptive network-based fuzzy inference system (ANFIS) [13], [17], and support vector machine (SVM) [15], [16]. Reference [16] reports that the accuracy of SVM is similar to that of NN. The forecasting accuracy and computational complexity of most of these techniques are simulated and compared in [18]. Given the same inputs, simulations indicate that a simple intelligent system, e.g., FFNN, performs more accurately and efficiently compared to time series, e.g., ARMA and GARCH, and complex intelligent systems, e.g., RNN and ANFIS [18].

In this paper, fuzzy inference system (FIS) [19] and time series methods are proposed for day-ahead electricity price forecasting. These forecasting techniques are applied to the grid market environment that uses locational marginal pricing (LMP) [20]. The FIS is adopted due to its transparency and interpretability. least-squares estimation (LSE) is implemented to simplify the parameterization of time series [21]. Zonal/area-wide loads and day-ahead constraints are included as inputs to represent impacts of demand-side factors and congestive transmissions, respectively.

As a result of Federal Energy Regulatory Commission (FERC) orders [22], market monitoring is a key issue to market operators [20]. Price forecasting capabilities can strengthen the monitoring capability by predicting market power indexes to forecast possible exercises of market power. For example, the Lerner Index [20], [23] can be predicted as the deviation of the market price forecasts from the system marginal cost forecasts taking into account congestions in the transmission system.

This paper is organized as follows: Section II discusses the applications of electricity price forecasting; Section III describes the problem of day-ahead electricity price forecasting and investigates the selection of available input variables; Section IV proposes the methodology of FIS and time series; Section V evaluates the numerical performance of proposed forecasting techniques; finally, Section VI gives the conclusion of this paper.

## II. APPLICATIONS OF ELECTRICITY PRICE FORECASTING

Price forecasting is commonly used to assist market participants' bidding decision-making, portfolio allocation, and in-

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vestment planning. Price forecasting is also useful to market operators. They can take advantage of forecasted prices to compute various indexes and measurements for market monitoring.

### A. Applications to Market Participants

Applications of electricity price forecasting fall into three time horizons: next-day or short-term (within 6 months) bidding strategies, medium-term (6 months to 1 year) portfolio decisions and bilateral-contract negotiations, and long-term (beyond 1 year) planning.

For various time horizons, the applications of price forecasting are different. For the short-term time horizon, market participants use price forecasts to decide their bidding strategies so that they can maximize their profits in the day-ahead markets or short-term forward market [1], [2]. For the medium-term time horizon, suppliers and consumers use price forecasts to optimize the proportions of forward market and bilateral contracts in their asset allocations. Price forecasts are also references in the negotiation of bilateral contracts [1], [2]. For the long-term time horizon, facility owners use the long-term price trends to ensure recovery of investments in generation, transmission, and distribution [1].

### B. Applications to Market Operators

Because the exercise of market power can increase the volatility of electricity prices, the analysis of energy market prices plays a key role in the monitoring of participant behavior and market performance, e.g., the Lerner index [20]. Accurate price forecasts can be used to predict market monitoring indexes and measurements.

Several market power indexes are commonly used. The Herfindahl–Hirschman Index (HHI) is used to measure the concentration of market shares, the Residual Supply Index (RSI) is used to identify pivotal suppliers, and the price-cost margin index, i.e., Lerner Index, is used to calculate the markup of prices over marginal costs [20], [23].

## III. Problem Formulation

The pair of unconstrained market clearing price and unconstrained market clearing quantity is the equilibrium between aggregate demand-side offers and aggregate supply-side bids. In a spot market featuring LMP, congestion occurs when the available economical electricity cannot be delivered to all loads due to transmission limitations. When the available least-cost energy cannot be delivered to load in a transmission-constrained area, higher-cost generation units have to be dispatched to meet that load. In this situation, the price of energy in the constrained area is higher than the unconstrained market clearing price. LMP is defined as the price of lowest-cost resources available to meet the load, subject to delivery constraints of the physical network. LMP is an efficient way of pricing energy supply when transmission constraints exist [20]. Zonal pricing is a mix of LMP and unified pricing because interzonal prices are LMP whereas intrazonal prices are unified.

Locational prices in the day-ahead energy market are the main goal of day-ahead electricity price forecasting in a grid environment. Electricity prices are impacted by such various factors as transmission congestions, supply-side decision-making, and market power exercises. The selection of input variables is important in order to achieve high forecasting accuracy.

Statistical methods forecast electricity prices by modeling the correlation behaviors between prices and explanatory factors. The explanatory factors include historical prices from the financial forward market, historical loads and load forecasts from demand-side, transmission congestion from the physical grid, and capacity change and reserve requirement from supply-side.

The degree of correlation is tested using the sample auto-correlation function (ACF), sample partial auto-correlation function (PACF), and sample cross-correlation function (XCF) [17]. The significance of correlation can be investigated by P-Value normally with a confidential level of 0.05, and the degree of correlated linearity can be tested by correlation coefficients [17].

A day-ahead electricity price forecasting and monitoring system is formulated. Its inputs are correlated variables, and its outputs are specified applications. Significantly correlated variables are historical prices of same hours on previous day and the day of one week before, demand loads of local zone and area wide, and transmission constraints. These variables must be included for accurate forecasting. The temporal indexes of week day and hour are also included for possible supply-side dependency on weekday/weekend and peak/off-peak temporal patterns in bidding decisions.

## IV. Methodology

A forecasting system is proposed to realize the formulated day-ahead electricity price forecasting and monitoring system. This system integrates FIS, LSE, and market power measures as shown in Fig. 1.

The forecasting system is composed of four subsystems: FIS subsystem, LSE subsystem, FIS-LSE subsystem, and Lerner Index subsystem. One output of the forecasting system is the day-ahead price forecasts of FIS, LSE, and FIS-LSE subsystems. Another output is the price-cost markup forecast computed in the Lerner Index subsystem given marginal cost information. At the subsystem level, FIS, LSE, and FIS-LSE subsystems output zonal day-ahead LMP of current hour, respectively. The inputs of the FIS subsystem include temporal indexes, zonal day-ahead LMPs in the past, and area-wide load demands of current and previous hours. The inputs of LSE include zonal day-ahead LMPs in the past, all zonal and area-wide load demands in the system at current hour and previous hours, and constraint information of current hour. The FIS-LSE subsystem has an additional input that is the output of LSE subsystem besides the inputs of the FIS subsystem.

In the proposed method, the estimate of the forecasting system includes the heuristic forecasts of FIS, the linearly regressed forecasts of LSE, and the forecasts of FIS-LSE. LSE demonstrates the highest performance based on extensive tests. However, the linear factor structure of LSE only provides rough weights about the contributions of explanatory variables to the forecasts. On the other hand, FIS is also accurate, and it provides an explicit fuzzy rule base that explains how prices are forecasted.

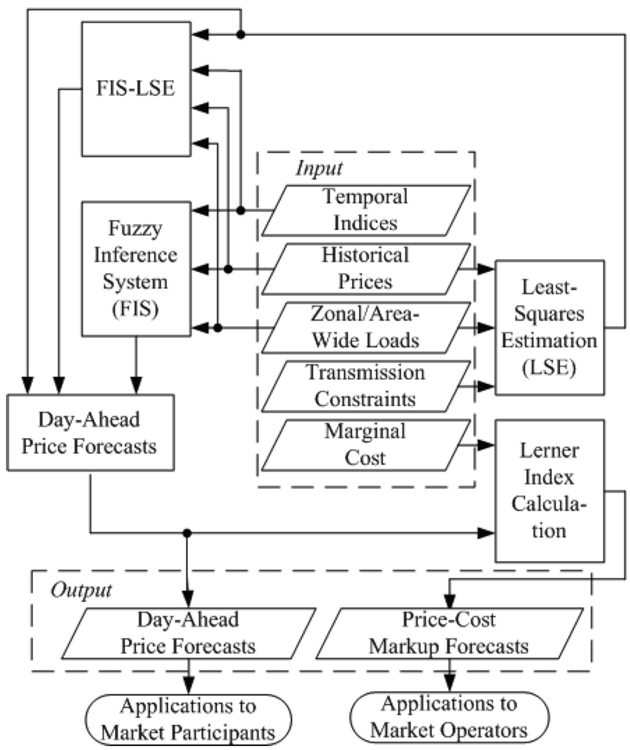


Fig. 1. Forecasting system includes FIS and LSE with application to market power measurement.

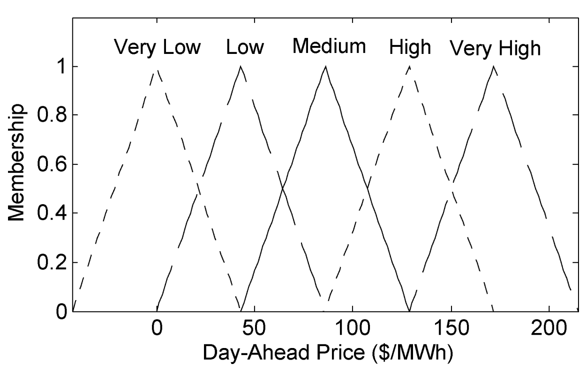


Fig. 2. Example of fuzzy membership functions.

## A. Fuzzy Inference System (FIS)

Intelligent systems are featured by adaptability and machine learning capability. In the literature, they are applied to power markets for bidding optimization, load forecasting, risk management, and price forecasting. Dilemma exists between the interpretability and accuracy for such traditional intelligence systems as artificial neural networks (ANNs) and decision tree (DT) [24]. DT provides clear interpretability, whereas ANN functions as a black box. However, the numerical performance of ANN can be superior to that of DT.

An FIS performs input-output mapping based on fuzzy logic. Fuzzy logic evaluates the intermediate states between discrete crisp states and is able to handle the concept of partial truth instead of absolute truth [19]. Fuzzy membership functions compose of fuzzy sets of input and output variables. Fig. 2 shows an example of fuzzy membership functions of day-ahead prices.

Traditional adaptive fuzzy systems include ANFIS and neuro-fuzzy systems. Both ANFIS and neuro-fuzzy methods are intended to combine the advantages of ANN and fuzzy logic. They automate the iterative learning process just as an ANN does. The difference is that ANFIS architecture has linear output functions, whereas neuro-fuzzy systems are essentially a subset of ANN applied to controls and classification techniques [24].

The effects of different market factors on prices are heuristic. The heuristics can be modeled by an FIS. FIS allows users to visualize the heuristic knowledge while at the same time providing adequate numerical performance.

An FIS implementing Wang–Mendel learning algorithm is developed for day-ahead electricity price forecasting [12], [19]. This approach is model-free and heuristic in nature. A common framework called the fuzzy rule base is constructed to combine both numerical and linguistic information. The numerical information is sampled from measurements, and the linguistic information interprets the numerical information. Another source of the linguistic information is the experience acquired from human experts. Wang–Mendel learning algorithm matches the performance of ANN. However, it passes through training samples only one time during the rule base buildup procedure. This FIS is able to bridge the gap between interpretability and accuracy by providing a verbally interpretable rule base and numerical accuracy through training [19]. Notice that FIS using Wang–Mendel learning algorithm does not require iterative training. As a result, it is more efficient than ARMA or GARCH time series techniques and ANN or neuro-fuzzy intelligent systems.

Besides numerical information, e.g., historical prices and load demands, FIS is able to include such linguistic factors as temporal indexes of week day and hour. FIS provides a transparent linguistic rule base instead of a black box. The rules may be modified manually to include expert knowledge. The rule base provides FIS the advantage of interpretability and transparency. FIS also provides flexibility in choosing predefined membership functions.

In FIS, the inputs and outputs are referred to as antecedents and consequents, respectively. The linguistic rules are statements describing logic operations among antecedents and consequents. The rule base collects the antecedent-consequent mapping of sampled entries. For those entries with same antecedents, the rule base retains the consequents with maximum product of antecedent and consequent degree of certainty (DOC) [19]. DOC is the degree by which a variable fits one or more membership functions for the considered entry. The rule base can be visualized as an array with rows of rules and columns of variables. Each generated rule is filled with membership function values of variables. Table I provides an example of linguistic rule base in a simplified FIS price forecasting. The visualization of nonlinear relation among week day index, yesterday day-ahead prices, and day-ahead price forecasts is given in Fig. 3.

The FIS algorithm can be modified for higher accuracy and efficiency. Time decay can be used to factorize the product of DOC and emphasize the priority of newly formed rules. Fuzzy memberships of midnight hours can be merged instead of separated to facilitate the generation of fuzzy rules for these hours.

TABLE I
EXAMPLE OF LINGUISTIC FUZZY RULE BASE

| Rule | Inputs | | | Output | Product of DOC |
|---|---|---|---|---|---|
| | Week Day | Yesterday DA Price | Area Load | DA Price Forecast | |
| 1 | Early | Low | Low | Very Low | 0.8171 |
| 2 | Early | Low | Medium | Low | 0.5647 |
| 3 | Early | Medium | Low | Low | 0.5481 |
| 4 | Early | Medium | Medium | Medium | 0.8819 |
| 5 | Early | Medium | High | Medium | 0.3451 |
| 6 | Middle | Low | Low | Very Low | 0.7245 |
| 7 | Middle | Low | Medium | Low | 0.5309 |
| 8 | Middle | Medium | Low | Low | 0.3926 |
| 9 | Middle | Medium | Medium | Medium | 0.8859 |
| 10 | Middle | Medium | High | Medium | 0.5033 |
| 11 | Middle | High | Medium | Medium | 0.6688 |
| 12 | Late | Low | Low | Very Low | 0.6252 |
| 13 | Late | Low | Medium | Low | 0.4601 |
| 14 | Late | Medium | Low | Low | 0.4214 |
| 15 | Late | Medium | Medium | Low | 0.7361 |
| 16 | Late | Medium | High | Medium | 0.3536 |
| 17 | Late | High | Medium | High | 0.2412 |
| 18 | Late | High | High | Medium | 0.1683 |

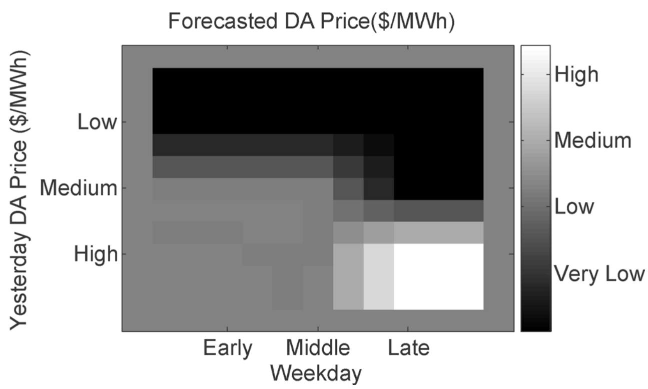


Fig. 3. Example of nonlinear relation of variables in the rule base.

Variable magnitudes and intervals can also be used to define membership functions if distribution patterns are observed. Finally, the more the membership functions are predefined, the finer each rule is. However, some finer rules may not be generated due to insufficient training data. Therefore, the selection of numbers of membership functions is a tradeoff between refining and sparseness.

Although the proposed method is heuristic, its process is systematic. The correlations between potential input variables and the output variable are calculated. Then input variables and their membership functions are initially set. These parameters are experimentally tuned by adding and/or dropping variables and changing the number and shape of membership functions. The criterion of fine tuning is the reduction of forecasting errors. As a result, different input variables and membership functions may be selected for different data sets.

### B. Least-Squares Estimation (LSE)

A stochastic time series is a sequence of random observations. This random sequence, called stochastic process, exhibits some degree of correlation from one observation to the other. This correlation structure can be used to predict future values of the process based on the past history of observations. By exploiting the correlation structure, one can decompose the time series into a deterministic component (i.e., the forecast) and a random component (i.e., the error or uncertainty associated with the forecast) [17].

One of the simplest stochastic models is auto-regressive (AR) model, which treats the disturbance as ideal white noises. AR models can be extended to ARMA, which describes the correlated disturbances of assumed white noise. ARMA models can be extended to GARCH models. GARCH computes the conditional mean and variance of a univariate time series to take into account excess kurtosis (i.e., fat tail behavior) and volatility clustering, which are two important characteristics of financial time series [17].

ARMA and GARCH models do not perform well for electricity price forecasting due to insufficiency of the structure specification. In traditional ARMA estimation, the basic assumptions on the error terms include zero mean, constant variance, and uncorrelatedness. The homoskedastic assumption of constant variance does not necessarily hold in the heteroskedastic estimation using GARCH models [9]. Indeed, the generalized heteroskedastic error specification is not strongly supported by the data applied in this paper.

A regression modeling implementing LSE is proposed to simplify the structure specification. For a linear regressive model

$$\begin{aligned} y(i) &= \varphi_1(i)\theta_1 + \varphi_2(i)\theta_2 + \cdots + \varphi_n(i)\theta_n + \varepsilon(i) \\ &= \varphi^T(i) \cdot q + \varepsilon(i) \\ \hat{y}(i) &= \varphi_1(i)\theta_1 + \varphi_2(i)\theta_2 + \cdots + \varphi_n(i)\theta_n \\ &= \varphi^T(i) \cdot q \end{aligned} \tag{1}$$

where $y(i)$ is the $i$th observed variable, $\hat{y}(i)$ is the $i$th fitted value, $\varphi(i)$ is the vector of linearly independent explanatory variables, $\varepsilon(i)$ is the residual, and $q$ is the vector of contribution factors. In the matrix format

$$Y = \hat{Y} + E = \Phi \cdot q + E \tag{2}$$

where

$$\begin{aligned} Y &= [y(1)\, y(2)\, \ldots\, y(n)]^T \\ \hat{Y} &= [\hat{y}(1)\, \hat{y}(2)\, \ldots\, \hat{y}(n)]^T \\ \Phi &= [\varphi(1)\, \varphi(2)\, \ldots\, \varphi(n)]^T . \end{aligned}$$

The objective function is to acquire the overall least-squares error

$$\begin{aligned} \min V &= \|E\|^2 = \|Y - \Phi \cdot q\|^2 \\ &= \sum_1^n \left(y(i) - \varphi^T(i) \cdot q\right)^2 . \end{aligned} \tag{3}$$

According to the theorem of LSE [21], the solution is

$$\hat{q} = (\Phi^T \Phi)^{-1} \Phi^T Y \tag{4}$$

which is the least-squares estimate of the contribution vector.

The LSE method can be interpreted in both geometric and statistical terms. In the geometric interpretation, the least-squares error $E$ is orthogonal to all linearly independent explanatory vectors. In the statistical interpretation, the least-squares estimate is unbiased and consistent [21].

In the FIS-LSE subsystem, the forecasts of LSE are fed into FIS. FIS-LSE has an additional input that is the output of LSE subsystem besides the inputs of the FIS subsystem as shown in Fig. 1. Our test results show that the output of LSE provides an accurate compensation to the FIS forecasts.

### C. Lerner Index

Concentration ratio and RSI are not bright line tests, and their relation to market power is not always clear [20]. On the other hand, the Lerner Index is a direct and clear measure of market power. It estimates the difference between the observed market price and the marginal cost.

The Lerner Index is calculated as the ratio of price to marginal cost or the percent markup over marginal cost or typically the markup as a percent of price [20], [23]

$$\beta = \frac{P - C}{P} \tag{5}$$

where Lerner Index $\beta$ is the price-cost margin, marginal cost $C$ is from the highest marginal cost unit operating, and market price $P$ is the offer of the marginal unit that sets LMP. The Lerner Index can be normalized and vary from $-1$ to 1 [20]. When the offer price is greater than marginal cost, the Lerner Index is the markup as a percent of offer price; when the offer price is lower than marginal cost, the Lerner Index is the markup as a percent of marginal cost. Notice that the Lerner Index of negative prices cannot be normalized correctly.

The calculation of Lerner Index depends on the correct determination of marginal cost. The marginal cost of an LMP market is the highest marginal cost of operating units in the market, considering transmission congestion and imports/exports. During congested periods, because identification of the highest relevant marginal cost unit is not feasible, the markup of each marginal unit is load-weighted [20]. The computation of marginal cost of one generator involves capacities, heat rates, fuel costs, variable operation and maintenance (O&M) costs, forced outage factors, and emission costs.

## V. Numerical Performance

Since the Pennsylvania-New Jersey-Maryland (PJM) market is well recognized in the U.S. and beyond, the forecasting system is tested using the data from the day-ahead energy market and system operations of PJM. The sampling period is January to December 2004 [25].

Two criteria are commonly used to evaluate the accuracy of price forecasting: root mean square error (RMSE) and mean absolute percentage error (MAPE) [2].

RMSE and MAPE are calculated, respectively, by

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - p_i)^2} \tag{6}$$

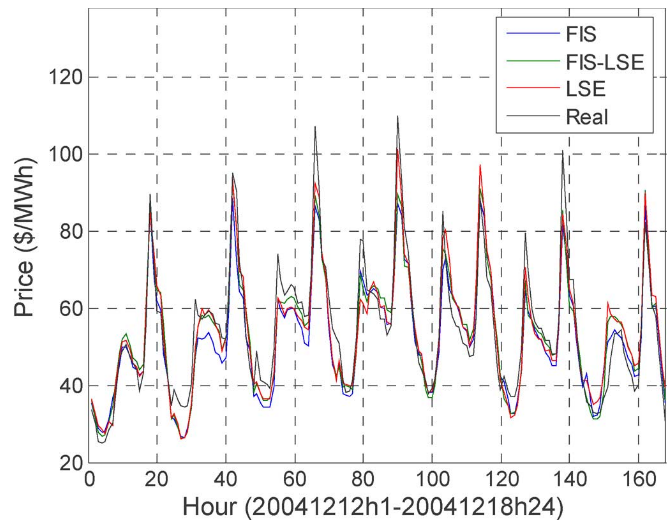


Fig. 4. Weekly example of forecasted PECO zonal LMPs in 2004 using the forecasting system.

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\frac{|\hat{p}_i - p_i|}{p_i} \tag{7}$$

where $N$ is the number of sample prices, $p_i$, $i = 1, \cdots N$ are real prices, and $\hat{p}_i$, $i = 1, \cdots N$ are price forecasts.

### A. Price Forecasting Using the Proposed System

The PJM system handles congestion through LMP [25]. For the PECO zone, the load-weighted day-ahead LMPs are tested for all 52 weeks in 2004. All the load data are measured loads in PJM because of the postponed availability of zonal demands. The simulation results are creditable given the average load forecasting error around 2% [18].

The antecedents (inputs) of the FIS include weekday index, hour index, zonal day-ahead LMPs of 24, 48, and 168 h before (yesterday, two days, and one week before, respectively), and area-wide load demands of current hour and 24 h before. The consequent (output) is the zonal day-ahead LMP of current hour. The numbers of membership functions are chosen as two for temporal antecedents, eight for remaining antecedents, and 40 for the consequent. The training set of FIS includes available entries since January 2003 until the beginning of the weekly test period.

The explanatory variables of LSE include zonal day-ahead LMPs of same hour in last two weeks, and all zonal and area-wide load demands in the system at current hour and 24 h before. The forecasted variable is the zonal day-ahead LMP of current hour. The training period is 300 days prior to the beginning of the weekly test period.

Besides above-mentioned antecedents of the FIS, the FIS-LSE has an additional antecedent that is the output of LSE. As an example, the forecasts of PECO zonal day-ahead LMPs using FIS, LSE, and FIS-LSE in the week of December 12–18, 2004 are given in Fig. 4. The weekly RMSE and MAPE of these forecasts of 52 weeks in 2004 are provided in Fig. 5.

The computation times of FIS, LSE, and FIS-LSE are compared to those of ARMA, GARCH, FFNN, and SVM in Fig. 6. The inputs and outputs of ARMA, GARCH, FFNN, and

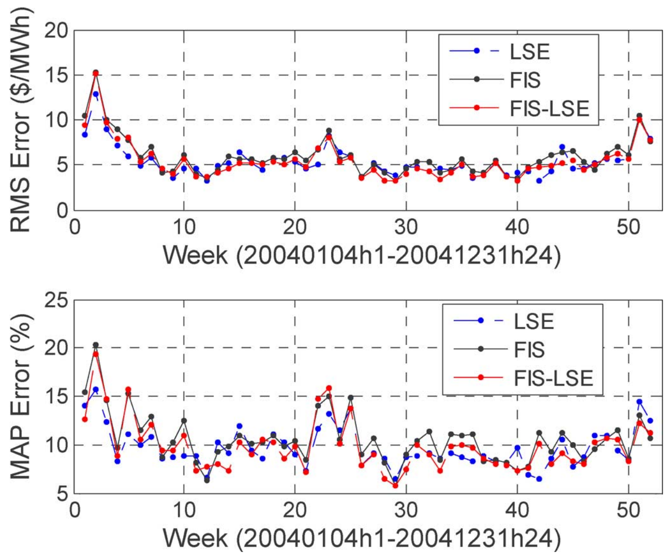


Fig. 5. Weekly RMSE and MAPE of forecasted PECO zonal LMPs in 2004 using the forecasting system.

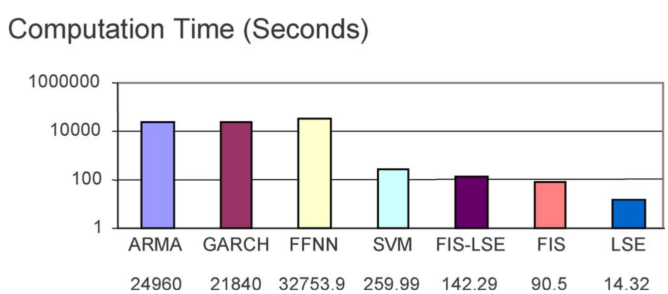


Fig. 6. Computation times of forecasted PECO zonal LMPs in 2004.

SVM are same as those of FIS except for temporal indexes. The training period of ARMA, GARCH, FFNN, and SVM is 48 days prior to the beginning of the weekly test period. The number of iterations for ARMA and GARCH is 400. The number of epochs for FFNN training is 50 000. All the simulations are performed in the MATLAB environment [17] except that SVM-Light software is implemented for SVM test [26]. It is noted that the comparison of computation times between SVM and other techniques only provides an indication because the SVM-Light software is implemented in C, whereas all other techniques are implemented in MATLAB. The hardware environment is a Dell desktop computer with Hyper-Threading CPU speed of 3.192 GHz and total physical memory of 1.024 GB.

The requirement for the computational speed is not significant for the forecasting of a single time series of electricity prices with several inputs. However, the forecasting of area-wide market power indexes requires the calculation of the price forecasts of hundreds of locations in an LMP system with dozens of inputs such as zonal loads and transmission constraints. In this situation, the requirement for the computational speed is much more significant than that of forecasting for a single location with fewer inputs. The comparison shows that FIS, LSE ,and FIS-LSE are faster than ARMA, GARCH, FFNN, and SVM.

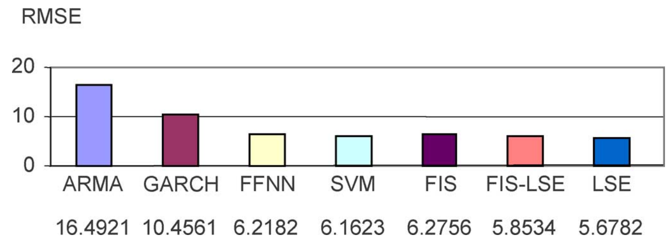


Fig. 7. Yearly RMSE of forecasted PECO zonal LMPs in 2004.

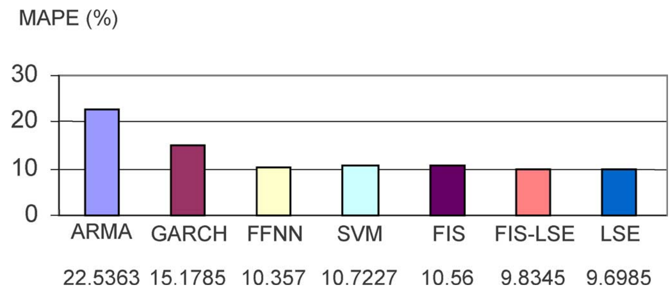


Fig. 8. Yearly MAPE of forecasted PECO zonal LMPs in 2004.

A total of 13 out of 52 weekly ARMA simulations could not regress to stationary AR polynomials due to ARMA's assumption of homoskedastic error specification. Also, three out of 52 weekly GARCH simulations could not regress to stationary AR polynomials due to GARCH's heteroskedastic error specification. GARCH's improvement over ARMA indicates that heteroskedastic error specification is more accurate for the data tested in this work.

The yearly RMSE and MAPE of FIS, LSE, and FIS-LSE are compared to those of ARMA, GARCH, FFNN, and SVM in Figs. 7 and 8, respectively. The observation is that GARCH is less accurate than all others except ARMA in terms of RMSE and MAPE. FIS, SVM, and FFNN have similar levels of accuracy, while LSE and FIS-LSE have lower forecasting errors than those of FIS, SVM, and FFNN. Regarding computational complexity, FIS, LSE, and FIS-LSE are much faster that ARMA, GARCH, and FFNN. In terms of percentage error MAPE, the forecasting accuracy of FFNN and SVM are better than that in [1] and [16]. The forecasting accuracy of ARMA and GARCH are similar to those in [2] and [9].

LSE provides the most accurate results as shown in Figs. 7 and 8. However, the linear factor structure of LSE only provides rough weights about how the explanatory variables contribute to the forecasts. On the other hand, FIS provides a high level of accuracy with explicit rules as demonstrated in Table I and Fig. 3. The forecasting system including FIS and LSE provides the advantages of high accuracy and explicit reasoning.

### *B. Improvement by Involving Neighboring Loads and Transmission Constraints*

The correlation coefficients between PECO zonal LMPs and most zonal/area-wide loads during 2003–2004 are given in Fig. 9. The observation is that LMPs are significantly correlated with local and adjacent zonal/area-wide loads. This price-load locational pattern is consistent with the LMP mechanism in

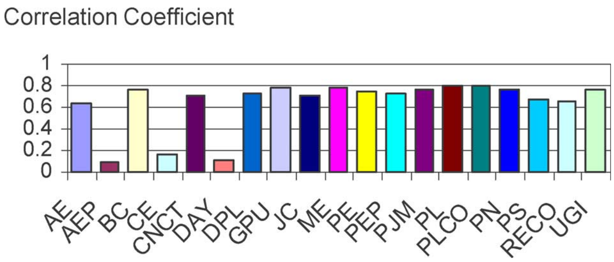


Fig. 9. Cross-correlations between PECO zonal LMPs and zonal/area-wide loads during 2003–2004.

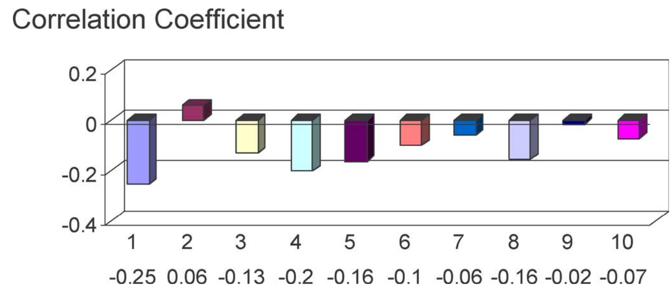


Fig. 10. Cross-correlations between PECO zonal LMPs and the shadow prices of top ten occurring day-ahead contingency events in PJM during 2003–2004.

TABLE II
TOP TEN OCCURRENCES OF DAY-AHEAD CONTINGENCY EVENTS IN PJM IN 2003–2004

| Rank | Occur-rence | Congest-ion-Event Hours | Day Ahead Contingency Event |
|---|---|---|---|
| 1 | 357 | 3139 | EAST ACTUAL |
| 2 | 245 | 1608 | CEDARGRO230 KV CED-CLIK L/O Roseland-Cedar Grove-Clifton-Athenia (B-2228) 230 |
| 3 | 237 | 1415 | CENTRAL ACTUAL |
| 4 | 222 | 2021 | BED-BLA L/O PRUNTYTOWN MT STORM LINE |
| 5 | 216 | 2273 | Cedar Interface ACTUAL |
| 6 | 216 | 1395 | LAUREL 69 KV LAU-WOO L/O CUMBERLAND AE-CHURCHTOWN 230 LINE |
| 7 | 166 | 937 | LAUREL 69 KV LAU-WOO L/O Cumberland (AE) 230/138 kV transformer |
| 8 | 156 | 1167 | SHIELDAL69 KV SHI-VIN L/O CHAMBERS-CHURCHTOWN |
| 9 | 153 | 3345 | NI to PJM PATHWAY ACTUAL |
| 10 | 151 | 1028 | SHIELDAL69 KV SHI-VIN L/O CUMBERLAND AE-CHURCHTOWN 230 LINE |

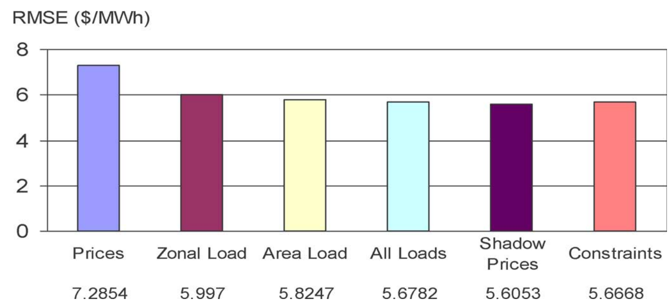


Fig. 11. Reduced yearly RMSE with eventually additional explanatory variables.

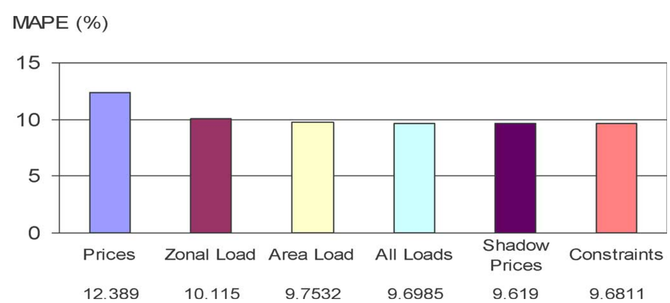


Fig. 12. Reduced yearly MAPE with eventually additional explanatory variables.

which the prices reflect transmission constraints triggered by load demand changes in neighboring zones.

The top ten occurrences of day-ahead transmission constraints during 2003–2004 are listed in Table II [25]. Here the contingency events of day-ahead constraints are identified according to monitored facilities and contingency facilities.

The impact of day-ahead constraints on LMPs is quantified by day-ahead shadow prices. The correlation coefficients between PECO zonal LMPs and the shadow prices of top ten occurrences of day-ahead transmission constraints during 2003–2004 in Table II are given in Fig. 10. The observation is that a specified LMP series is only significantly correlated with some of those transmission constraints. This indicates that the day-ahead contingency event of the most significant correlation may be different for various LMP series.

Local zonal loads (i.e., PE zonal loads), area-wide loads (i.e., PJM Mid-Atlantic area-wide loads), all available zonal/area-wide loads, shadow prices of top eight day-ahead constraints significantly correlated with PECO zonal day-ahead LMPs are eventually added to the inputs of LSE besides historical PECO zonal day-ahead LMPs. The training period is 300 days prior to the beginning of the weekly test period. For the inputs, LMPs are of the same hour in the last two weeks, loads are of the current hour and 24 h before, and constraints are of the current hour. Because the availability of shadow prices is postponed in reality, the shadow prices are approximated as the average of shadow prices of same constraints occurred at the same hour in the past. Through the involvement of more correlated variables, the improvement of forecasting performance is given in Figs. 11 and 12, respectively. Notice that the case labeled "Shadow Prices" uses actual shadow prices while the case labeled "Constraints" utilizes approximated shadow prices. It is observed that Figs. 7 and 8 provide comparisons over different forecasting techniques. On the other hand, Figs. 11 and 12 provide comparisons based on the selected predictors. The higher volatility in Figs. 7 and 8 than that in Figs. 11 and 12 indicates that the selection of techniques is more significant than the selection of predictors for the test cases.

## C. Forecasting of Lerner Index

The Western Hub is viewed as the unconstrained reference for price because it reasonably represents the unconstrained price of

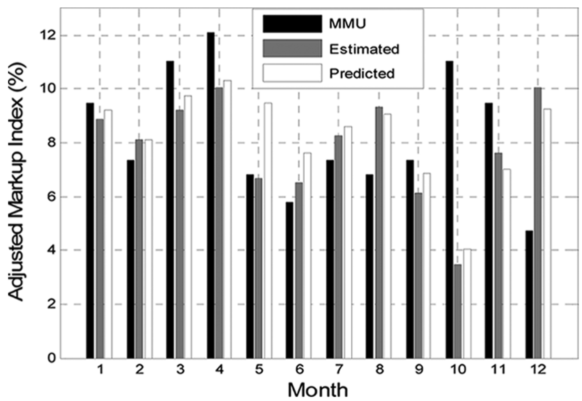


Fig. 13. Estimation and forecasting of monthly Adjusted Markup Index of PJM in 2004.

energy in the PJM Mid-Atlantic Region [20]. Given the conclusion of market monitoring unit (MMU) that there was no significant exercise of market power in 2004, and the assumption that unit owners have included a general 10% markup over actual marginal cost [20], this unconstrained reference price is assumed to be competitive and used to approximate the unconstrained marginal cost in PJM. Moreover, the markup of observed market prices over this approximated unconstrained marginal cost is a reasonable estimate to the adjusted price-cost markup index.

The advantage of fast computation of FIS and LSE is obvious if a batch of LMPs is computed at the same time for a large system like PJM. Using the PJM data of monthly day-ahead market prices during 2004, all Lerner Indexes of 253 LMPs are estimated given the approximated unconstrained marginal costs, which are 10% markup off the Western Hub day-ahead LMPs. These 253 LMPs are predicted using LSE with inputs of zonal day-ahead LMPs of the same hour in the last two weeks and all zonal and area-wide load demands in the system at the current hour and 24 h before. The training period is 300 days prior to the beginning of the weekly test period.

The estimation and forecasting of monthly Adjusted Markup Index are compared to the monthly Adjusted Markup Index from MMU in Fig. 13. Notice that the MMU results are load-weighted while the estimation and forecasting are not because the loads for most locations are not public data.

The observation is that the results of predicted average markup index are close (in the range of $\pm 2\%$) to those of MMU calculations except of those in October and December. The error in October is caused by wrongly estimated market costs because of the newly integration of AEP and DAY zones in October 2004, while the error in December is caused by wrongly estimated market costs because of the first winter peak after the integration of CE, AEP, and DAY zones. On the other hand, the predicted average markup indexes are very close (in the range of $\pm 0.4\%$) to the estimates except of that in May. The deviation of predicted markup indexes from estimates in May is caused by insufficient training data from the newly integrated CE zone. Because the predicted and estimated markup indexes are based on forecasts and actual prices, respectively, this observation verifies the accurate performance of forecasting despite changing congestion patterns caused by the continued enlarging of the PJM system [20]. The observation also suggests that both accurate marginal cost estimates and accurate locational price forecasts are necessary to the accurate forecasting of price-cost markup indexes.

## VI. Conclusions

A forecasting system including FIS, an intelligent system, and LSE, a regressive model, is proposed for the day-ahead electricity price forecasting in a grid environment. The forecasting system involves both non-numerical heuristics in the FIS and linearly correlated factors in the LSE. LSE provides the most accurate results, and FIS provides transparency and interpretability. As a result, this forecasting system has the advantages of high accuracy and explicit reasoning. It also performs more efficiently compared to NNs and ARMA and GARCH time series models. Neighboring load demands and day-ahead transmission constraints are included in the inputs to improve the forecasting accuracy because of their significant correlations with day-ahead LMPs. Besides their applications to market participants, day-ahead price forecasts are also useful to market operators' forecasting of market power indices. Our future work will focus on how to improve short-term electricity price forecasting. Improvements can be achieved by involving more significantly correlated information in the inputs, generating volatility information in the output, and extending the applications to other market power measures.

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