Price Forecasting of Japan Electric Power Exchange using Time-varying AR Model

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***Abstract*—In this article, we built a state space model to analyze the price time series in Japan Electric Power Exchange(JEPX) spot market. In building the model, we aimed to achieve the following two goals that the model was able to a) forecast prices with reasonable accuracy, and b) understand the underlying market dynamics by decomposing the price time series into a reasonable set of contributing factors. To capture the time-variability of the contributing factors to price, self-AR(autoregressive) process was introduced to allow continuous change in the magnitude of influence from each explanatory variable. To estimate the model, Kalman Filter algorithm was applied for stepwise recursive estimation. After optimizing the model under the maximum likelihood method(MLM) coupled with minimum AIC(Akaike Information Criteria) conditions, the model was able to decompose the 15:00-15:30 JEPX spot electricity strip price into a couple of the most contributing factors with significant time-dependencies. Our model also yielded as good a forecasting accuracy with conventional AR econometric model estimated with ordinary least square method(OLS), with a squared error of about 1.12 [yen/kWh] per forecasting period.**

***Index Terms*—Japan Electric Power Exchange(JEPX), Day-ahead spot market, Price forecasting, Time-series decomposition, Kalman Filter algorithm**

I. INTRODUCTION

FOLLOWING the world-wide trend of liberalized electricity trade, Japan has opened its first power exchange market called Japan Electric Power Exchange(JEPX) in April 2005. Companies that participate in the market are facing the growing importance of being able to understand the market dynamics for their risk management purposes. The key interest will include the supply/demand mechanism that affects to determine the prices, as well as, with no doubt, forecasting the market prices. A number of reports on this has already been in place in preceding power exchanges overseas such as PJM in USA and Nordpool in northern Europe, obviously for the market participants' business risk management purposes. From the different light, Japan's electricity exchange, in its inception stage, is currently subject to close *ex post* monitoring by regulatory authorities and by JEPX itself, for the benign functionality and liquidity of the market. This is in part because in recent history of electricity exchange, some evidence of malicious trading conduct was unveiled associated with so-called market gaming by exercising monopolist power or playing on artificially created tie-line congestion, to manipulate prices. To model and understand power exchange markets therefore, not only the price forecast capability but also factor analysis for various contribution impacts to prices have to be taken into consideration for better understanding of the market dynamics.

In this article, we have attempted to construct a time-series JEPX price model for such goals, with use of time-varying autoregressive (AR) model estimated by the Kalman Filter algorithm.

II. LITERATURE REVIEW

The literature on electricity price analysis is vast, since price analysis is expected to reveal several market mechanism aspects that are peculiar to electricity. Topics mainly of interests to regulatory bodies and market administrators will include market power exercise, market gaming, transmission constraints, all arising from demand inelasticity and non-storability of electricity (Stoft[1]). *Ex post* market efficiency evaluation will also be of importance. Risk management, on the other hand, draws concerns of the market participants, where spot price analysis and forecast, the forward curve and term structure modeling, equilibrium price analysis, multi-agent computation, and real option approach to asset valuation, are among the key topics.

In general the electricity power price time series are observed to have both deterministic and stochastic components. Lucia and Schwartz[2], for example, discusses the deterministic component can still play a major role in determining the spot and forward price patterns by analyzing the Nordic power exchange. Nogales *et al.*[3] compares the price predictability under two modeling strategies, the AR time series and transfer function, and concludes that both have a good forecasting performance. Conventional approach by financial engineering models, namely a combination of stochastic jump-diffusion and mean-reversion processes, are exemplified by Deng[4]. Recent study explores possibility of applying regime-switching models in attempts to predict the price spike timings, such as Mari[5] and Mount *et al.*[6].

Duffie and Gray[7] proposed ARCH models for heating oil, natural gas, crude oil and electricity prices. Escribano *et al.*[8] used generalized ARCH (GARCH) models for electricity prices and ensured stationarity in volatility when price spikes are captured by separate jump-diffusion processes.

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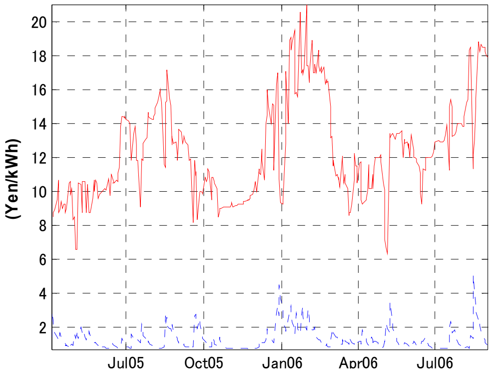

Fig. 1. Price time series(in solid line) and estimated volatility(in broken line) of the 15:00-15:30 strip from Apr 2005-Sep 2006 in JEPX spot market

Literature on Japanese power exchange is not many at the time of issuance of this article, since JEPX's operation just launched in April 2005. Goto and Yamaguchi[9] is among the few examples that applied econometric models to the JEPX data in the first operating year.

III. THE DEREGULATION AND THE MARKET ENVIRONMENT

A. Deregulation in Japan

In the recent deregulation history in Japan's electric power industry, introducing the market mechanism has started in the form of competitive bidding in the generation sector in 1995, for newly implemented generation units. On the retail level in 2000, large-scale customers greater than 20kV and 2MW were permitted to procure electricity on competitive contracts. Further, in 2004 and in 2005, the range of customers eligible has expanded to customers over 500kW and 50kW respectively. In line with this, in April 2005 the wholesale electricity exchange JEPX opened to solicit participation to power producers and procurers, in order to supplement the bilateral-basis contracts that remain the most common type of electricity deals in the country. As of November 2006, the number of participating companies in JEPX exceeds 30, although the overall trade volume remaining in less than about half a percent of the country's total electricity demand. Still, the market is expected to grow to become the county's central power exchange clearinghouse.

B. The Market

JEPX has two markets, the day-ahead Spot and the standardized Forward markets, and the Bulletin Board platform. The Spot market deals with forty-eight, 30-minute strips per day, of the next-day electricity. Due to the country's two different frequency zones, the gross buying and selling bids will be split into the eastern and western regions in case of transmission congestions at the east-west linkages. The historical record of prices and traded volumes, as well as buying and selling bid volumes, are posted on the JEPX website. In this article, we focus only on the Spot market price behavior since the Forward market still leaves much room to increase the number of deals[1], and the Bulletin Board platform does not publicize trade records, since it operates to facilitate only bilateral, hence confidential, transactions. Further details can be found at the JEPX's website[10].

To illustrate the Spot market trade records in the first one and a half years, Figure 1 shows the prices (in solid line) and the estimated time-varying volatility (in standard deviation, in dotted line) between April 2005 and September 2006, of the 15:00-15:30 spot electricity strip. It is among the typical peak-hour commodities and is one of the most actively traded. It is seen from the figure that the prices and volumes have a clear seasonal and weekly cyclic variations, that seem to be correlated with typical seasonality in electricity demand. It also appears to have a growing trend over time as an increasing number of players participate in trading, each growing assimilated in the market activities as time passes. In addition, the well-known time-dependent property (heteroskedasticity) of volatility appears existing in JEPX as well, as in other electricity exchanges overseas.

IV. MODELING THE MARKET

A. State Space Model and the Kalman Filter

In modeling the JEPX's price time series, we consider state space models[11] to take into account of various contribution factors to the prices, and time-dependent variations on the impacts from those factors. To allow time-dependency for the contributing factors, we let the coefficients to follow autoregressive(AR) processes and vary continuously over time. Then, to estimate the coefficients, we apply Kalman Filter stepwise estimation because of the heterogeneity, or the time-dependency of the coefficients. In this way, we expect to a) decompose the price time series into a set of reasonable explanatory variables, and b) allow time-dependencies to those variables and capture the time-wise variations of the contributing factors across the trade period.

On the other hand, another well-known approach will be doing the same with econometric models. In typical econometric models, the dependent variable (variable to be explained: in this case the price series) is expressed as a linear combination of contributing factors, each multiplied by parameters estimated by the ordinary least-square(OLS) method. The key assumption of OLS is stationarity, where the underlying structure does not change over time, and coefficient estimation results are the average values across the entire estimation period. Hence, when applying such econometric models one is required to do "pre-whitening" on the given time series by removing non-stationarity before working on the models.

In contrast, using state space models and Kalman Filter stepwise estimation allows us to a) incorporate time-varying properties in the coefficient of each contributing factor, and b) capture the time-dependent non-stationary trend with respect to the market growth and other influences, while decomposing

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[1] Total number of commodities that struck deals from April 2005 and September 2006 was only 42.

the price series into a linear combination of explanatory variables just like econometric models with OLS estimation.

To construct the space state model, we begin with the state vector $\boldsymbol{x}_n = (x_1, x_2, \ldots, x_{xch})^T$ (x_{ch} x 1 vector, ^{T} to represent the transposed matrix) and the observed vector y_n (herein 1x1), where n=1,2,...,T corresponding to day when the electricity gets delivered. Here, we choose the realized spot price of the 15:00-15:30 strip on day n as y_n. The State Equation and the Observation Equation are then given as: .

$$x_n = F_n x_{n-1} + GQ_n \tag{1}$$

$$y_n = Hx_n + R_n \tag{2}$$

where $\boldsymbol{F}_n$: state matrix as a function of n, $\boldsymbol{G}$: x_{ch} x q_{ch} gain matrix for state noise, $\boldsymbol{Q}_n$: q_{ch} x 1 state noise vector as a function of n, $\boldsymbol{H}$: 1 x x_{ch} observation gain matrix, and R_n: observation noise vector (herein 1 x 1) as a function of n.

In estimating $\boldsymbol{x}_n$ and its variance $\boldsymbol{S}_n$ while F_n also changes with respect to n, one can use the following Kalman Filter stepwise algorithm to recursively obtain one-step-ahead forecasts.

<Filtering>

$$\begin{aligned} K_n &= S_{n|n-1} H_n^{\,T} (H_n S_{n|n-1} H_n^{\,T} + R_n)^{-1} \\ x_{n|n} &= x_{n|n-1} + K_n (y_n - H_n x_{n|n-1}) \\ S_{n|n} &= (I - K_n H_n) S_{n|n-1} \end{aligned} \tag{3}$$

<Forecasting>

$$\begin{aligned} x_{n|n-1} &= F_n x_{n-1|n-1} \\ S_{n|n-1} &= F_n S_{n-1|n-1} F_n^{\,T} + G_n Q_n G_n^{\,T} \end{aligned} \tag{4}$$

where K_n as Kalman gain, x_n and $S_{n|n-1}$ are the next-day expected values and variance-covariance matrix estimated on day n-1, and I is the unit matrix.

B. Model Assumptions for JEPX Price Time Series

First we assume P_n to be written as the linear combination of the explanatory variables and a first-order self-AR process as:

$$P_n = c + \sum_{i=1}^{I} B_{i,n} \cdot U_{i,n} + AR^P \cdot P_{n-1} + \xi_n \tag{5}$$

where c is a constant, $B_{i,n}$ are the coefficients for the explanatory variables $U_{i,n}$ (i=1,…I), ξ_n is random, Normal noise($\sim N(0,\sigma_\xi^{\,2})$) and I is the dimension of the explanatory variables. Next, following Kitagawa and Gersch[11], in order to allow $B_{i,n}$ to change continuously over time, we assume each $B_{i,n}$ to follow a first-order self-AR process expressed as:

$$B_{i,n} = AR^B{}_i \cdot B_{i,n-1} + \nu^B{}_{i,n} \tag{6}$$

where $\nu^B{}_{i,n}$ ($\sim N(0,\sigma_{\nu i}^{\,2})$) is random Normal noise. We further assume the $AR^B{}_i$'s for all i to be equal, or $AR^B{}_1 = AR^B{}_2 = \ldots = AR^B$, for simplicity of calculation.

To illustrate an example at I=5 and $\boldsymbol{H}$=[1 0...0], (1) and (2) will be re-written as:

$$x_n = \begin{bmatrix} P_n & B_{1,n} & B_{2,n} & B_{3,n} & B_{4,n} & B_{5,n} \end{bmatrix}^T$$

$$\begin{bmatrix} P_n \\ B_{1,n} \\ B_{2,n} \\ B_{3,n} \\ B_{4,n} \\ B_{5,n} \end{bmatrix} = \begin{bmatrix} AR^P & U_{1,n} & U_{2,n} & U_{3,n} & U_{4,n} & U_{5,n} \\ 0 & AR^B & 0 & \cdot & \cdot & 0 \\ \cdot & \cdot & AR^B & \cdot & & \cdot \\ \cdot & & \cdot & AR^B & \cdot & \cdot \\ \cdot & & & \cdot & AR^B & 0 \\ 0 & \cdot & \cdot & \cdot & 0 & AR^B \end{bmatrix} \begin{bmatrix} P_{n-1} \\ B_{1,n-1} \\ B_{2,n-1} \\ B_{3,n-1} \\ B_{4,n-1} \\ B_{5,n-1} \end{bmatrix} + \begin{bmatrix} \xi_n & \nu^B{}_{1,n} & \nu^B{}_{2,n} & \nu^B{}_{3,n} & \nu^B{}_{4,n} & \nu^B{}_{5,n} \end{bmatrix}^T \tag{7}$$

$$y_n = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} x_n + w_n \tag{8}$$

where w_n is again random, Normal noise $\sim N(0,\sigma_w^{\,2})$.

C. Model Estimation and Optimization

To estimate this model, the optimal values for parameters $\boldsymbol{\theta} = \{AR^P, AR^B, \sigma_\xi, \sigma_{\nu i}, \sigma_w\}$ must be obtained. We estimate $\boldsymbol{\theta}$ by Maximum Likelihood Method (MLM). The log-likelihood (LLH) function we use will be given as:

$$LLH = -\frac{N}{2}\log 2\pi - \sum_{n=1}^{N} \log r_n - \frac{1}{2}\sum_{n=1}^{N} \frac{(P_n - Hx_{n|n-1})^2}{r_n} \tag{9}$$

where $r_n = HS_{n|n-1}H^T + \sigma_w^{\,2}$. In addition, we also check that the optimized model minimizes the Akaike Information Criteria(AIC). Using LLH, the AIC is given as:

$$AIC = -2LLH + 2(\dim(\theta)) \tag{10}$$

where $\dim(\boldsymbol{\theta})$ is the dimension of $\boldsymbol{\theta}$.

D. Benchmark Models

To assess forecasting viability in later sections, we prepare typical econometric models as benchmarks for forecasting performance. Following the conventional Box-Jenkins method[12] to build such models, we ended up obtaining the AR and ARCH models using the five explanatory variables shown in Table 1, all sourced from publicly available data. The estimation results are summarized in Table 2.

TABLE I

EXPLANATORY VARIABLES USED

Explanatory variables	Variable labels	
Buy bid volume [MWh]	$B_{1,n}$	KAI_TOUNYUU
Sell bid volume [MWh]	$B_{2,n}$	URI_TOUNYUU
Daily highest temperatures exceeding last year's average [deg]	$B_{3,n}$	MAXKAIRI_TOKYO
Daily lowest temperatures exceeding last year's average [deg]	$B_{4,n}$	MINKAIRI_TOKYO
Tokyo-area maximum electricity demand [MW]	$B_{5,n}$	SAIDAI_TOKY

TABLE II

BENCHMARK AR AND ARCH MODEL ESTIMATION RESULTS UNDER THE BOX-JENKINS METHOD

	Variable	C	YAKUTEI_RYOU	KAI_TOUNYUU	URI_TOUNYUU	MINKAIRI_TOKYO	MAXKAIRI_TOKYO^2	SAIDAI_TOKY	AR(1)	Adj.R Sq.	LLH	D.W.
AR model	Coefficient	-2.9280 **	-0.00185 *	0.0049 ***	-0.00123 ***	0.10380 **	-0.01897 ***	0.000339 ***	0.8180 ***	0.8643	-536.336	2.23
	t-Statistic	-2.0560	-1.7585	4.4936	-2.6356	2.5309	-8.5250	11.9498	26.2093			
ARCH model	Coefficient	-3.4313 ***		0.0049 ***	-0.00089 **	0.08741 ***	-0.01810 ***	0.000335 ***	0.8484 ***	0.8613	-531.645	2.31
	t-Statistic	-2.6786		5.6507	-1.9866	2.6354	-11.1066	14.9934	25.7143			
		variance const.	variance coef.									
Variance Equation	Coefficient	0.9044 ***	0.1785	Adj.R.Sq.= Adjusted R Squared, LLH = Log Likelihood, SSE = Sum of squared errors								
	z-Statistic	16.1527 ***	2.9677	D.W.=Durbin Watson Statistic								

Note: Confidence bounds 90%(*), 95%(**), 99%(***)

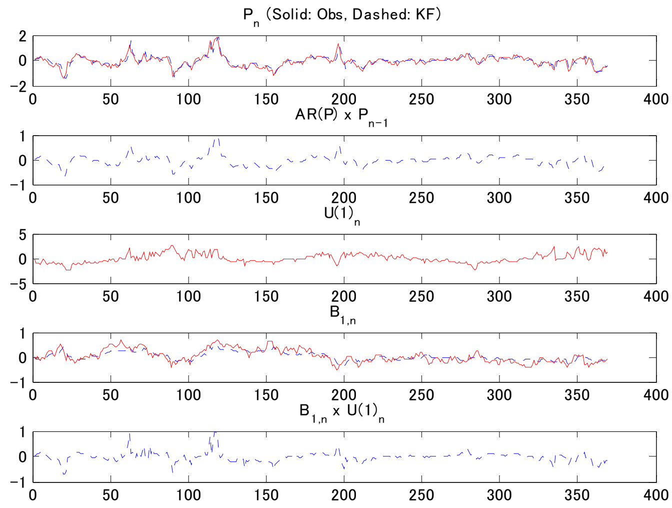

Fig. 2. Validity check result of state space model (7) and (8). From Top: Entire time series, Extracted self-AR component AR^P x P_{n-1}, Explanatory variable $U_{1,n}$, Time-varying coefficient $B_{1,n}$, and the Contribution $B_{1,n}$ x $U_{1,n}$. Solid lines represent given test data, dotted lines are the model outputs. This figure represents the result under Case II in Table 3.

E. Validation of the State Space Model

To check the validity of state space model, we fed test data to the model and saw if the model estimated as desired the time-varying coefficients of the explanatory variables, and the magnitude of the state and observation noises. The artificial test data was fed to model (7) and (8), where c = 0, I = 1, AR^B = 0.9, $P_0 = B_{1,0}$ = 0, σ_ξ and σ_w are collectively set to 0.1, and $U_{1,n}$ set to the Tokyo-area maximum electricity demand data in Table 1. The estimation result, under the LLH-maximization and AIC-minimization rules, is presented in Figure 2 and Table 3.

It is seen from Figure 2 that the model well captures the time-varying contribution $B_{1,n}$ x $U_{1,n}$ (bottom graphic in Fig. 2) by estimating the time-varying coefficient $B_{1,n}$ (graphic second from bottom). In addition, from Table 3 it is seen that parameter estimation of AR^P and σ_v provides a fair accuracy for all Cases I through III. Therefore, we concluded the state space model (7)(8) and its estimation method explained in section *C.* are acceptable. One condition to note is that the absolute value of the AR coefficient must be lower than unity to avoid divergence. The results in Table 3, though, all appears to satisfy this condition, with all $|AR^P|$'s being smaller than unity.

F. Data

Now we proceed to apply the model to the JEPX price time series.

To equalize the comparison base between the state space and the benchmark models, we employed the exact same set of the explanatory variables shown in Table 1.

The data we used is the daily JEPX Spot market price strip and the traded volume data from April 2005 to September 2006 downloaded from the JEPX website. We chose a 15:00-15:30 strip as the representative commodity since it is among the peak-hours, with typically higher prices than average. The Tokyo-area daily electricity demand in kWh are taken from the published values on the *Denki Shimbun* newspaper. The daily temperature data in Tokyo (*Otemachi* area) was taken from the historical daily log posted at the website of Japan Meteorological Agency.

TABLE III
VALIDITY CHECK (PARAMETER ESTIMATION) RESULT OF STATE SPACE MODEL

	Case I		Case II		Case III	
Parameter	true	estimated	true	estimated	true	estimated
AR^P	0.0000	-0.1750	0.5000	0.5212	0.8500	0.8443
σ_v	0.1000	0.0682	0.1000	0.1353	0.2000	0.2748

To remove the deterministic weekly cycles, we removed all weekend (Saturday and Sunday) data and left weekdays and non-weekend national holidays for analysis. Not only on weekends, typically the electricity demand is known to plummet in the following national holiday seasons: the year-end holidays, the *Obon* vacation (mid of August), and the "golden week" (late April to early May). However, we did not take away those periods this time since we wished to capture the changes around those national holiday timings too.

The data of the first 17 months (Apr. 2005-Aug. 2006) was used first to estimate the models, while the last one month (Sep. 2006) data was used as actual values to be compared with the forecasted values, for evaluation of the forecasting performance.

V. RESULTS AND DISCUSSION

A. Decomposition of Price Series into Contributing Factors

The result, provided by the optimized model under the *LLH*-maximization and *AIC*-minimization rules, is shown in Figure 3. AR^P was chosen to be 0 and AR^B 0.953 due to these rules. All left-hand-side panels are the estimated time-varying coefficients of each explanatory variable. The top right panel is the price time series, actual values in solid line and estimates in dotted line. All the other right-hand-side panels are contributions from each factor, or the time-varying coefficient (in left-hand-side) times the values of each explanatory variable. Thus, the values in those five panels add up to become those in the top right panel.

For comparison with the benchmark model, the horizontal straight lines in the left panels show the coefficient estimates by the ARCH model. These coefficient estimates are constant values, since OLS estimation gives single average values across the entire period. In contrast, one can see that, for each panel, the coefficients vary over time around the benchmark coefficient in straight lines.

Looking at all right-hand-side panels, it is also seen that the most instrumental contribution sources are essentially reduced to two: "SAIDAI TOKY" or the Tokyo-area electricity demand, and "KAI_TOUNYUU" or the buying bid volume. It is then inferred that the main determiners of the price are the electricity demand representing the market demand fundamental that is around 10 yen/kWh year round, and the buying bid volume that can further push the price up by about 5 to 10yen/kWh in, say, a cold winter. In fact, the winter in 2005 in Japan was exceptionally colder than average years, with temperature being the 30-year lowest on some days. It is seen from the KAI_TOUNYUU panel that during December '05 and March '06, its contribution has almost always been more than 5 yen/kWh-level, signifying the strong buying trend existing in the market, backed by higher-than-average demand of electricity.

One additional note will be that, it was merely for simplicity that the Tokyo-area has been chosen as the electricity demand data. So it should rather be seen as representing more general, country electricity demand. The coefficients of SAIDAI TOKY seems to be lower than the benchmark coefficient (straight line), due to relatively larger magnitude of the estimated noise variances $\sigma_w^2$and σ_v^2 than those in the OLS estimation.

B. Forecasting Performance in Comparison with Benchmark

To become a useful tool in analyzing time series, the model also has to have a good forecasting capability. Using the data from April '05 to August '06 to first estimate the model, we performed forecasting of the September '06 prices by the state space model as well as by the benchmark AR and the ARCH models. The result till September 15th (excluding weekends) is shown in Figure 4. All models are fed with actual values in September '06 of the explanatory variables, but with no previous price estimation results. In other words, none of the models makes use of the one-step-back price estimate output from itself. From this figure, one can tell that all three models do almost an equally good job of forecasting. The AR and the ARCH model results look alike since they differ mainly by the conditional heteroskedasticity term and the rest being almost the same.

To compare the forecasting accuracy on a longer time horizon, Figure 5 exhibits the cumulative sum of squared errors, averaged per forecasting period, for the three models. From this figure, one can see that till Sep. 15th, the state space model is as good as the AR model, though not beating the ARCH. For the state space model, the forecasting error almost linearly increases as the forecasting horizon becomes longer, while the AR and the ARCH models somewhat recovers after a moderate increase at the "till-20-Sep" horizon in the middle. It is inferred therefore, that at this stage, the state space model is still less robust in long-term forecast, leaving room for further tuning and improvement. The reason is thought to be the different roots on which the models do the forecast. That is, for state space models, the current recursive forecasting steps expressed as (4) makes the model to maintain the state $\boldsymbol{x}_n$ of the last period (August 31st, '06) and

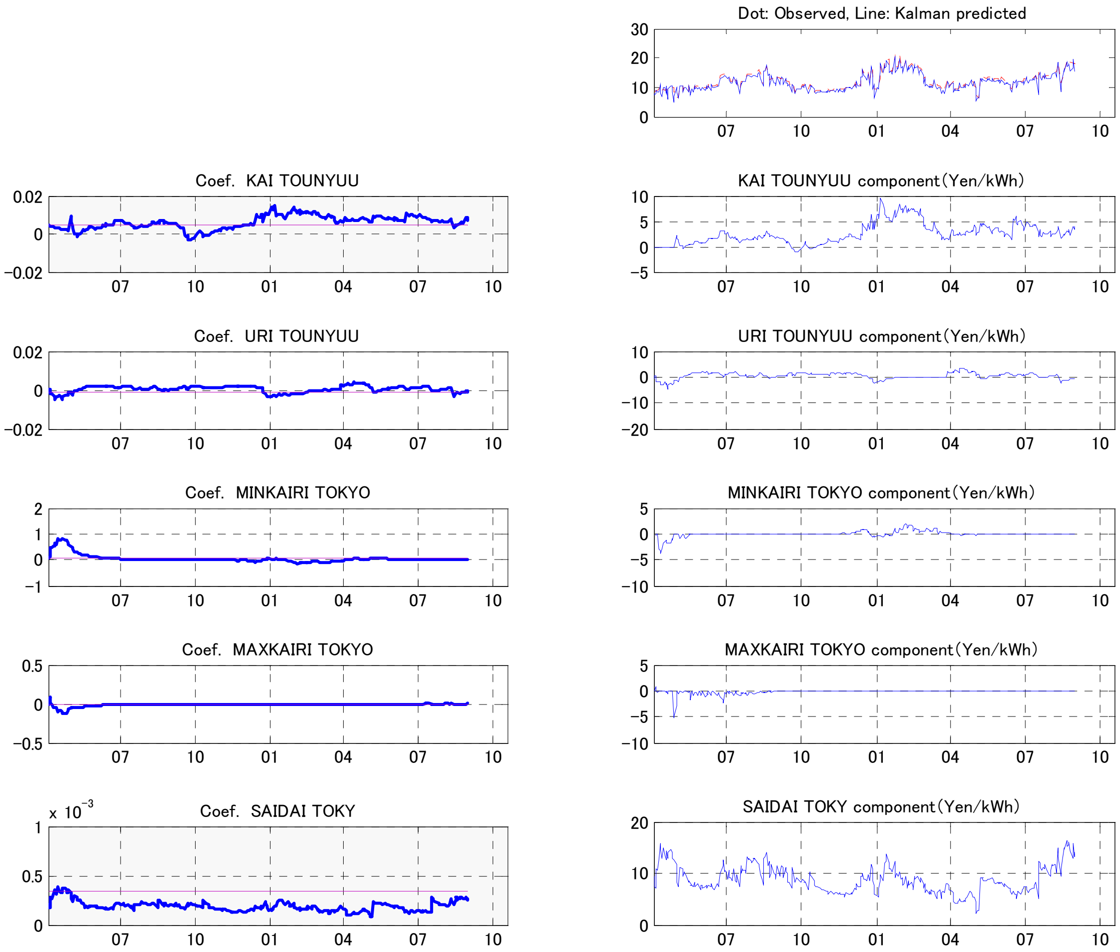

Fig. 3. Price series decomposition result, into five contributing factors, by the proposed state space model (7) and (8). Left panels are time-varying coefficients of the explanatory variables, Top right panel is the price series, the other right panels are contributions from each factor (coefficient x explanatory variables). The thin straight horizontal lines in left panels are coefficient estimates (in constant values) by the benchmark ARCH models introduced in section *D.* of Chapter IV. Herein, under the *LLH*-maximization and *AIC*-minimization rules, AR^P was set to 0 and AR^B 0.953.

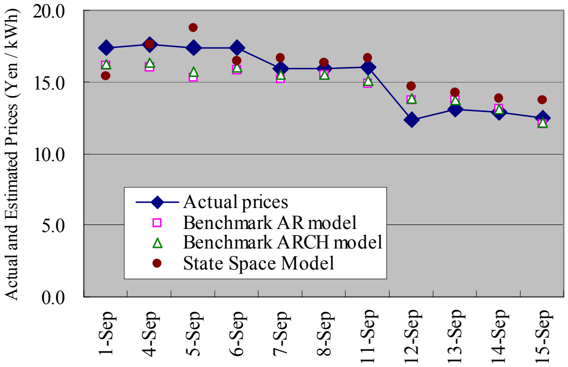

Fig. 4. State space model's forecasting result in comparison with the benchmark AR and ARCH models prepared in section *D.* of Chapter IV. Data from April '05 to August '06 was used to first determine the model, then explanatory variables' actual data was fed to all models to forecast prices in September '06.

to produce all forecast values based on that *last period* state $\boldsymbol{x}_n$, while the AR and the ARCH model forecast values are produced on the basis of the *average* structure for the entire period concerned, so, if the September '06 market structure approaches closer to the preceding average structure as the forecasting period becomes longer, the state space model will have bad odds than the AR and the ARCH models.

VI. CONCLUSIONS

Following Kitagawa and Gersch[11], we prepared a state space model that decomposes the JEPX price time series into contributing factors. In the model, the coefficients of the explanatory variables were allowed to vary over time following an self-AR process, making clear the two most significant contributions to price coming from the electricity demand and the buying bid volume, with time-dependent tendencies attributed to its magnitude of influence.

Using this state space model, we attempted a long-term forecasting. The proposed state space model yielded as good accuracy as that of the AR benchmark model, by about an average squared error of 1.25 [yen/kWh^2], which translates into 1.12 [yen/kWh], per forecast period. The forecast stability in longer horizons, however, had room for improvement, left for further refinement.

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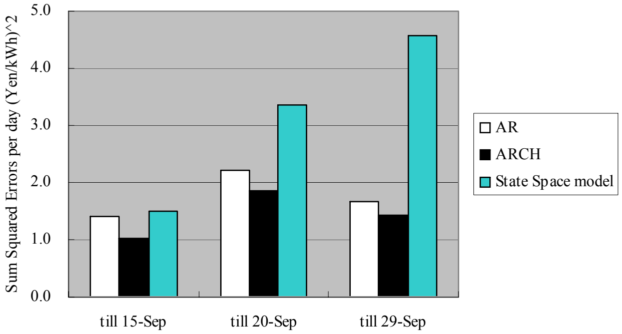

Fig. 5. Forecast accuracy comparison by cumulative sum-squared errors per forecasting period.

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