# Regional electricity planning support system
# - Electricity demand modeling with assimilation of smart electricity meter data -

Hajime Seya and Yoshiki Yamagata

National Institute for Environmental Studies, Ibaraki, Japan
email corresponding author: address seya.hajime@nies.go.jp

## Abstract

In Japan, regional- hourly- electricity demand data per each sector (residential, commercial, transport, etc) is not publicly available; hence estimating it by bottom up approach is really important not only for electricity production and distribution companies, but also urban planners. One of the conventional methods to implement this is using the intensity method. However, the problem of this approach is in that intensity value may change drastically due to the wide diffusion of new technologies such as electric vehicles or photovoltaics. Hence the present paper proposes a simple Bayesian updating method of the intensity by assimilating the information of smart meter data. Also, forecasting of the intensity is performed using several recently proposed statistical methods, and its performances are empirically compared. The results support the use of seasonal-ARIMA model, multivariate dynamic linear model, and tbats model proposed by De Livera et al. (2011).

## 1. Introduction

In Japan, we experienced rolling blackouts due to power shortages caused by the Great East Japan Earthquake (GEJE) in the year 2011. The power supply of Tokyo Electric Power Company (TEPCO) was reduced by 21GW, causing outages for 4.4 million families in eastern Japan (Okada et al. 2011). From March 14 to 29, TEPCO implemented rolling blackouts in most areas of Tokyo.

This bitter event has taught us the importance of distributed generations for diversification of risks. After the GEJE, discussions towards "resilient" city have widely occurred in Japan, accordingly the Japanese government has changed its energy policy direction toward distributed generations. As a part of such efforts, the government has issued the "Act on Purchase of Renewable Energy Sourced Electricity by Electric Utilities (Act)", which is a full-blown feed-in tariff (FiT) regime for renewable energy, became effective on 1 July 2012. It is projected that the scheme will contribute to the increase of the share of renewable energy-based electricity in Japan.

But of course, it is uncertain the success or sustainability of our FiT regime. Huenteler et al. (2012) evaluated the Japanese schema from German experience, and pointed out that the schema's "political legitimacy" is important. They noted that in Germany, the legitimacy of support for solar photovoltaic panels (PVs) is eroding, resulting in recent high-level calls to end the FiT and replace it with other, less generous policies. Hence discussing and simulating the possibility of a wide range of other schemas with looking ahead the FiT may be very important. Yamagata and Seya (2012) proposed a concept of disaster resilient electricity sharing system (DRESS) as a complement or an alternative to FiT. In this system, electricity surplus, i.e., demand minus PV-supply (generated from widely introduced PVs), is stored to the "cars not in use" in a local region. In the central part of the Tokyo metropolitan area, many cars, which are used only for weekends, are kept parking at the house during the weekdays. Hence, if we replace some of those by electric vehicles (EVs), they can be used as battery storages by vehicle to grid (V2G). In such a calculation, estimating regional- hourly electricity as accurate as possible is crucial.

One of the conventional methods for electricity demand estimation is using the intensity method, in which regional electricity demand is estimated by multiplying electricity intensity (demand per floor) by floor space in each zone. In Japan, because regional- hourly- electricity demand per each sector (residential, commercial, transport, etc) is not publicly available, studies have estimated it using the electric bill from "Family Income and Expenditure Survey" or "National Survey of Family Income and Expenditure" of Ministry of Internal Affairs and Communications. However, these data is usually available only monthly or yearly, and to the best of our knowledge, only the Japan Institute of Energy (2008) provides hourly electricity intensity (kWh/m2/h) for each of dwelling, office, hospital, hotel, store, and sport facility. But the limitation of this intensity is in that intensity's regional differences are not considered. Cleary, intensity in

Hokkaido may different from that in Okinawa. Also, intensity value may change drastically due to the future wide diffusion of EVs or PVs.

Hence the present paper first proposes a simple Bayesian updating method of the intensity by assimilating the information of measurement data. Owing to the development of smart electricity meter technologies (e.g., Matsui et al. 2012), now it is not so difficult to measure electricity in a dwelling or an office. Next, forecasting of the intensity is performed using several recently proposed statistical methods, and its performance is compared in detail.

## 2. Literature review on electricity demand modeling

Thus far numerous methods for estimating electricity demand have been proposed for different spatial scales (national, regional, etc.) and time scales (hourly, monthly, yearly, etc.). These methods are summarized in excellent review articles (e.g., Abu-El-Maged and Shinha 1982; Moghram and Rahman 1989; Alfares and Nazeerudin 2002; Kyriakides and Polycarpou 2007; Foley et al. 2010; Almeshaiei and Soltan 2011; Grandjean et al. 2012). Swan and Ugursal (2009) categorized electricity demand (load forecasting) models into top-down and bottom-up approaches. According to Grandjean et al. (2012), the latter, which is our focus, calculates energy consumption for a dwelling or a group of dwellings and extrapolate to the total housing stock. Bottom-up approach can be further categorized into statistical random models, time of use based models, and probabilistic empirical models. Because the second and third approaches require relatively detailed data such as individual end-uses of appliances (freezer, oven, washing-machine, etc.), and therefore we focus on the first–statistical random models.

Alfares and Nazeerudin (2002) classified statistical random models into the following nine categories:

- multiple regression; exponential smoothing; iterative reweighted least-squares; adaptive load forecasting; stochastic times series; ARMAX models based on genetic algorithms; fuzzy logic; neural networks and; knowledge-based expert systems.

Besides these methods, thus far many interesting statistical/computational models for energy demand estimation have been proposed, including multi-equation Bayesian regression model (Cottet and Smith 2003), Bayesian semiparametric regression (Smith 2000), ARMAX–GARCH model (Hickey et al. 2012), time varying spline (Harvey and Koopman 1993), generalized additive model (Cho et al. 2013), decomposition approach (Wang et al. 2012a), functional data analysis models (Goia et al. 2010; Vilar et al. 2012), time series with multiple seasonal patterns (Gould et al. 2008; Taylor 2010a, b), integrated nested Laplace approximation (Ruiz-Cárdenas et al. 2012), spatial autoregressive ARMA model (Ohtsuka and Kakamu 2013), moving average model considering economic shock (Lin et al. 2013), support vector regression (Hong 2009; Hong et al. 2013), multivariate meta-learning (Matijaš et al. 2013), self organization map (Yadav and Srinivasan 2011), the elliptic orbit algorithmic model (Zong-Chang 2012), echo state networks (Deihimi and Showkati 2012), non-linear fractal extrapolation (Wang et al. 2012b) among others.

Electricity demand forecasting up to 1 weak is usually termed "short-term" forecasting (STF). Kyriakides and Polycarpou (2007) discussed the importance of STF from the view point of operation of power systems, but now the STF is also important for regional electricity planning purpose. Taylor et al. (2006) compared six univariate methods for STF for lead times up to a day ahead. They found that exponential smoothing method with double seasonality performed best, and the neural network did not performed well. They discussed that the reason of the disappointing performance of neural network may be due to over-fitting or overly complex architecture, which are two common pitfalls in neural network modeling. Soares and Medeiros (2008) also compared several models, and suggested that seasonal ARIMA model and generalized long memory model of Soares and Medeiros (2006) performed well. This study attempts to compare more recent methods which are introduced below.

Javed et al. (2012) built electricity demand forecasting models using smart meter data, but their focus is on the load forecasting of each individual household, and not regional ( i.e., intensity).

## 3. Modeling electricity intensity

### 3.1. Framework

Fig.1 represents the flowchart of our regional- hourly- electricity demand estimation.

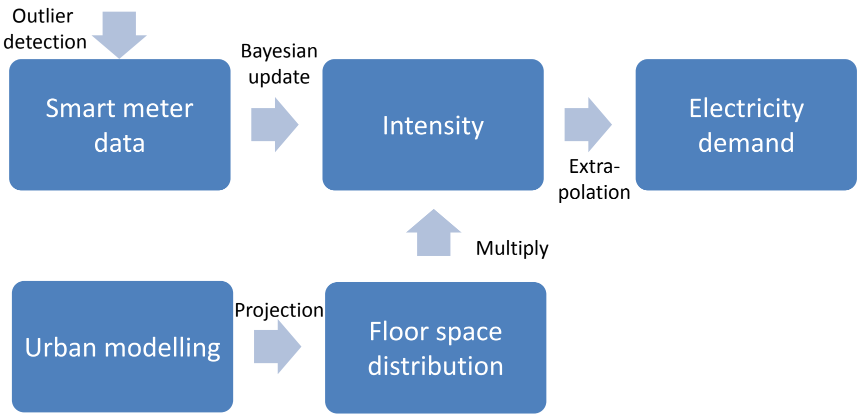


**Fig.1.** Flowchart of the regional- hourly- electricity demand estimation

Our regional- hourly- electricity demand estimation procedure consists of the following five steps.

First, regional- hourly- intensity value based on existing statistical survey, say $\tilde{x}_{h,d,m,y,i}$ is prepared, where $h$ (1, …, $H$) denotes hour; $d$ (1, …, $D$), day; $m$ (1, …, $M$), month; $y$ (1, …, $Y$), year; and $i$ (1, …, $I$), region. In Japan, we can use the above mentioned the Japan Institute of Energy's (2008) intensity.

Second, $J \times 1$ vector of smart meter data $(\dot{\boldsymbol{x}}_{h,m,y,i})'$ ( $j$-th element is given by $\dot{x}^{j}_{h,d,m,y,i}$) is prepared in order to update the existing intensity values (suppose that smart meters are installed to $J$ numbers of buildings). Smart meter data sometimes suffers from "missing" and "outliers". Missing data can easily be considered within state space framework; hence now the problem is to detect outliers (and presume it as missing). Define $Q1$: lower quartile (25%), $Q2$: upper quartile (75%), and interquartile range (IQR): $Q3$–$Q1$. Then the conventional outlier detection criterion is given as:

$$x \begin{cases} < \; Q1 - 1.5 \times (Q3 - Q1) \\ > \; Q3 + 1.5 \times (Q3 - Q1) \end{cases}. \qquad (1)$$

Here it must be noted that electricity demand typically have trend, mainly due to the temperature change. For example, if many households start to use gas fan heater in a cold day in autumn, then the demand may change significantly compared to the day before. In such case, usual observations may be regarded as outliers if based on this criterion. Hence we should test whether observations are outliers or not, for relatively short period but with sufficient number of samples, such as every one week. Also, the number 1.5 should be replaced by similar number such as 3 with sufficient consideration on ones data's characteristics[1].

Third, the intensity is updated using smart meter data. We propose a simple Bayesian updating method. Assume that exising intensity $\{\tilde{x}_{h,d,m,y,i}\}$ obeys normal distribution $N(\tilde{\mu}_{h,m,y,i}, \tilde{\sigma}^2_{h,m,y,i})$. Then using the measurement data's mean $\dot{\mu}_{h,m,y,i}$ and (unbiased) variance $\dot{\sigma}^2_{h,m,y,i}$, the posterior distribution is given as $N(\mu_{h,m,y,i}, \sigma^2_{h,m,y,i})$, where

$$\mu_h = \frac{\left(\frac{1}{\tilde{\sigma}_h^2}\right)\tilde{\mu}_h + \left(\frac{J}{\dot{\sigma}_h^2}\right)\dot{\mu}_h}{\left(\frac{1}{\tilde{\sigma}_h^2}\right) + \left(\frac{J}{\dot{\sigma}_h^2}\right)}, \tag{2}$$

$$\left(\frac{1}{\sigma_h^2}\right) = \left(\frac{1}{\tilde{\sigma}_h^2}\right) + \left(\frac{J}{\dot{\sigma}_h^2}\right). \tag{3}$$

Here, *d*, *m*, *y*, and *i* is omitted for simplicity. The inverse of variance is sometimes called "precision". In this Bayesian framework, the updated intensity is given as the average of "existing intensity" and the "average value of smart meter data" weighted by its precisions. When the number of measured data *J* is relatively large, then the weight assigned to "average value of smart meter data" becomes large, and vice ver. From the different point of view, the intensity estimated only from smart meter data is unstable when *J* is a small value, but we can stabilize it by utilizing the information of existing intensity data. Unfortunately, the prior mean and variance of existing intensity is usually not available. Hence we assume that mean value is identical to the observed value, and its standard deviation is 26.2% of the mean value (we set this value based on the electric bill from "Family Income and Expenditure Survey" of 2010). Now we have the updated intensity, $x_{h,d,m,y,i}$.

Then fourth, statistical models are applied to $x_{h,d,m,y,i}$ for obtaining the forecasted value of the Intensity. In this paper, we compare the forecasting performance of the following six models in concluding recently proposed ones:

"bats", "tbats", "lm", "am", "arima", and "multivariate".

"bats" is proposed by De livera et al. (2011), by extending the Taylor (2003)'s Holt-Winters with two seasonal components given as (*d*, *m*, *y*, and *i* is omitted for simplicity):

[1] More complicated methods are also available through e.g., "outliers" and "extremevalues" package in R.

$$
\begin{aligned}
x_h &= l_{h-1} + b_{h-1} + s_h^{(1)} + s_h^{(2)} + u_h \,, \\
l_h &= l_{h-1} + b_{h-1} + \alpha u_h \,, \\
b_h &= b_{h-1} + \beta u_h \,, \\
s_h^{(1)} &= s_{h-m_1}^{(1)} + \gamma_1 u_h \,, \\
s_h^{(2)} &= s_{h-m_2}^{(2)} + \gamma_2 u_h \,,
\end{aligned} \tag{4}
$$

where $l_h$ represents the level component; $b_h$, trend components; $s_h^{(1)}$, first seasonal component and $s_h^{(2)}$ second seasonal component; $m_1$ and $m_2$, the periods of the seasonal cycles($m_1$ = 24 and $m_2$ = 168), respectively; $u$, white-noise error. $\alpha, \beta, \gamma_1, \gamma_2$ are parameters. De livera et al. (2011) extended the work of Tayloar et al. (2003), and proposed a model which they call “bats”. “bats” considers nonlinearity in $x_h$ using box-cox transform, and also considers more than two number of seasonal terms. Moreover, error term is not restricted to white noise, but it can be ARMA($p$, $q$), where $p$ is the order of the autoregressive part, $q$ is the order of the moving-average process. “bats” is expressed as:

$$
\begin{aligned}
x_h^{(\omega)} &= \begin{cases} \dfrac{x_h^{\omega} - 1}{\omega} \,, & \omega \neq 0 \\ \ln(x_h) & \omega = 0 \end{cases} \,, \\
x_h^{(\omega)} &= l_{h-1} + \phi b_{h-1} + \sum_{k=1}^{K} s_{h-m_k}^{(k)} + u_h \,, \\
l_h &= l_{h-1} + \phi b_{h-1} + \alpha u_h \,, \\
b_h &= (1-\phi) b + \phi b_{h-1} + \beta u_h \,, \\
s_h^{(k)} &= s_{h-m_k}^{(k)} + \gamma_k u_h \,, \\
u_h &= \sum_{k=1}^{p} \varphi_k u_{h-k} + \sum_{k=1}^{q} \theta_k \varepsilon_{h-k} + \varepsilon_h \,,
\end{aligned} \tag{5}
$$

where $\varepsilon_h$ is white-noise error; $\omega, \phi\ \alpha, \beta, \gamma_k, \varphi_k, \theta_k$ are parameters. $b$ is a parameter which represents long-run trend. The introduction of this term ensures that predictions of future values of the short-run trend $b_h$ converge to the long-run trend $b$ instead of zero (De livera et al. 2011).

“tbats” replace $s_h^{(k)}$by Fourier term as:

$$
s_h^{(k)} = \sum_{j=1}^{J_k} s_{j,h}^{(k)} \,, \tag{6}
$$

$$s_{j,h}^{(k)} = s_{j,h-1}^{(k)} \cos\lambda_j^{(k)} + s_{j,h-1}^{*(k)} \sin\lambda_j^{(k)} + \gamma_1^{(k)} u_h ,$$
$$s_{j,h}^{*(k)} = -s_{j,h-1} \sin\lambda_j^{(k)} + s_{j,h-1}^{*(k)} \cos\lambda_j^{(k)} + \gamma_2^{(k)} u_h ,$$

where $\gamma_1^{(k)}$ and $\gamma_2^{(k)}$ are parameters, and $\lambda_j^{(k)} = 2\pi j / m_k$, ($m_1$ = 24 and $m_2$ = 168 in our case study). “tbats” can expresses more flexible seasonal pattern. De livera et al. (2011) empirically suggested that “tbats” surpasses “bats” in terms of forecasting performance.

“arima” is the conventional seasonal ARIMA($p$, $\delta$, $q$) ($P$, $\Delta$, $Q$)$_{[m]}$ model with covariates [temperature, squared temperature, and six calendar dummy variables], where $m$ is the seasonal frequency ($m$ = 24 in our case study). Soares and Medeiros (2008) compared several load forecasting models, and suggested the high accuracy of seasonal ARIMA model.

“multivariate” is the multivariate dynamic linear model (Holmes et al. 2012; Dordonnat et al. 2008; 2012) defined as:

$$\boldsymbol{y}_d = \boldsymbol{Z}_d \boldsymbol{x}_d + \boldsymbol{D}\boldsymbol{d}_d + \boldsymbol{v}_d ,\ \boldsymbol{v}_d \sim N(\boldsymbol{0}, \boldsymbol{R}) , \qquad (7)$$
$$\boldsymbol{x}_d = \boldsymbol{B}_d \boldsymbol{x}_{d-1} + \boldsymbol{w}_d ,\ \boldsymbol{w}_d \sim N(\boldsymbol{0}, \boldsymbol{Q}) ,$$

where $\boldsymbol{y}_d = (y_{1d}, \ldots, y_{Hd})'$ is the vector of observations, $\boldsymbol{v}_d$ is the error vector whose covariance matrix is given by $\boldsymbol{R}$, $\boldsymbol{x}_d$ is the 26×1 vector of states (including trend for each hour, time-variant coefficient for temperature and squared temperature), $\boldsymbol{Z}_d$ is the 24 × 26 matrix whose first column is given by the temperature of day $d$, the second column is given by the squared temperature of the day, and the others are given by the 24 × 24 identity matrix. $\boldsymbol{w}_d$ is the error vector whose covariance matrix is given by $\boldsymbol{Q}$. We assume that $\boldsymbol{R}$ is the diagonal matrix, and $\boldsymbol{Q}$ is the matrix whose diagonal element is given by $q_1$, and off diagonals $q_2$ (This assumption was set based on several trial and error experiments). $\boldsymbol{d}_d$ is the covariates matrix whose coefficients expressed by the matrix $\boldsymbol{D}$ are time-invariant. We assume that effects of calendar dummy variables are time-invariant.

Besides these sophisticated methods, we introduce two simple methods. “lm” is the basic multiple regression model with covariates [temperature, squared temperature, and calendar dummy variables], which is constructed for each hour ($h$ = 0, …, 23). Thus we obtain 24 adjusted $R^2$ values. “am” is the additive model. Different from “lm”, nonlinearity of the effects of temperature variables on electricity demands can be considered in this approach (see Ruppert et al. 2003 for more details).

Finally, future regional electricity demand in each sector can be estimated by multiplying the forecasted intensity by floor area in each zone. As indicated in Fig.2, urban models (e.g. Wegener 2004; Hunt et al. 2005; Iacono et al. 2008; Ueda et al. 2013) are useful for projecting future value of floor area. Yamagata and Seya (2013) noted that in urban modelling, considering the interaction of landuse (compact city with energy efficient buildings and PVs), transportation (EV and public transportation system), and energy systems (smart grid) is very important. Fig.2 represents the possible interaction between landuse, transportation and energy. Urban form will affect not only origin destination (OD) trip (transportation) distribution patterns but also energy demand and urban climate. Urban heat island effects may also affect electricity demand especially for cooling in summer season, but can be mitigated by strategic changes in land use such as re-vegetation in suburban areas (Kusaka et al. 2012).

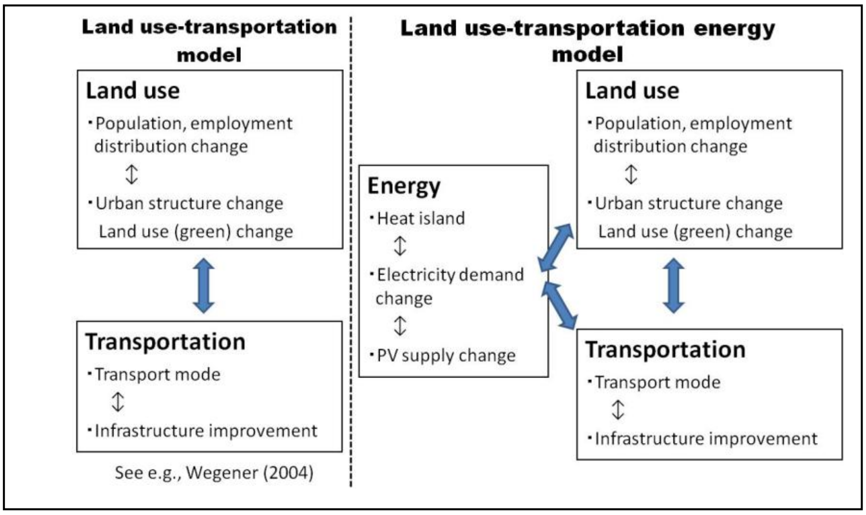


**Fig.2.** Concept of an integrated land use-transportation energy model: Possible interaction between land use-transportation and energy

Thus far many efforts have been devoted to development of urban models that consider the interaction between land use and transportation. However, there are few studies which attempt to model land use, transportation, and energy/electricity simultaneously (Chingcuanco and Miller 2012; Yamagata and Seya 2013). Hence developing regional electricity demand model itself may contribute to mainstream of urban modeling.

## 3.2. Empirical application

### *3.2.1. Data*

We have installed smart meters to four residential (detached houses), one hotel, and two buildings for town office, in Hokkaido, Japan, and have measured electricity since 2011. For the empirical illustration, we use three of four data for residential (data for the other one residential is excluded because it shows quite different consumption pattern due to the use of PVs). We use the 61 days (1464 hour) observations over two months from November 1 to December 31, 2012, and the data from January 1 to 15, 2013 (360 hour) is used for assessing forecasting accuracy. The data used here does not include any missing, and outliers (based on the above mentioned weekly IQR criterion).

### *3.2.2. Bayesian intensity updating*

Fig.3 shows the daily average of each household's measured (unit) intensity (per $m^2$; Green, blue, and red line). Also, black dashed line shows the averaged value for these three households. The intensity is rather different among the households. It is interesting to note that the movement of the green line and blue line is very similar. These movements may reflect temperature effects. The black solid line shows the existing intensity. Needless to say, daily variation in that cannot be considered in the same month.

The dotted line represents the result of Bayesian updating. Average of precision value in November is 1.49 for existing intensity, and 1.64 for samples. That for December is 1.31 for existing intensity, and 2.16 for samples. Hence relatively high weight is assigned to the smart meter data, especially for the period of the last two weeks in December, when the red line raised drastically, and the variance of samples became small.

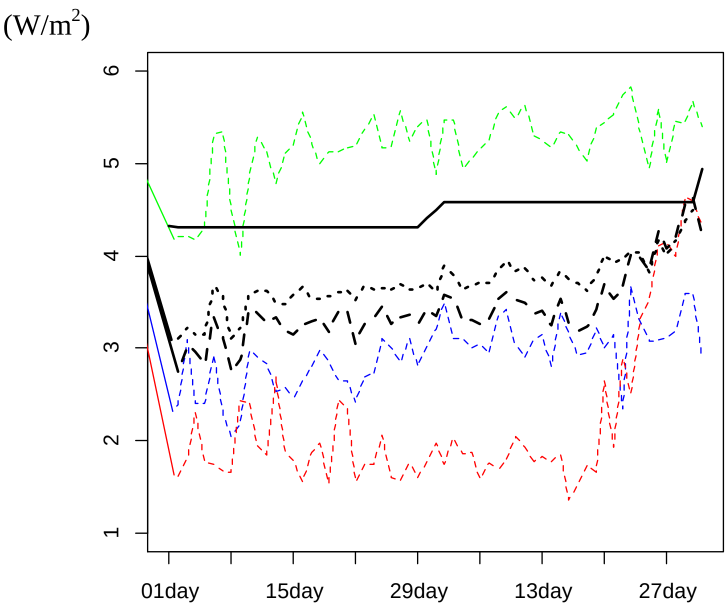


**Fig. 3.** Existing intensity and updated intensity (daily average)

Fig.4 represents the averaged intensity value for each day of week. As expected, the value is high in weekend, and therefore it is important to consider such calendar effects.

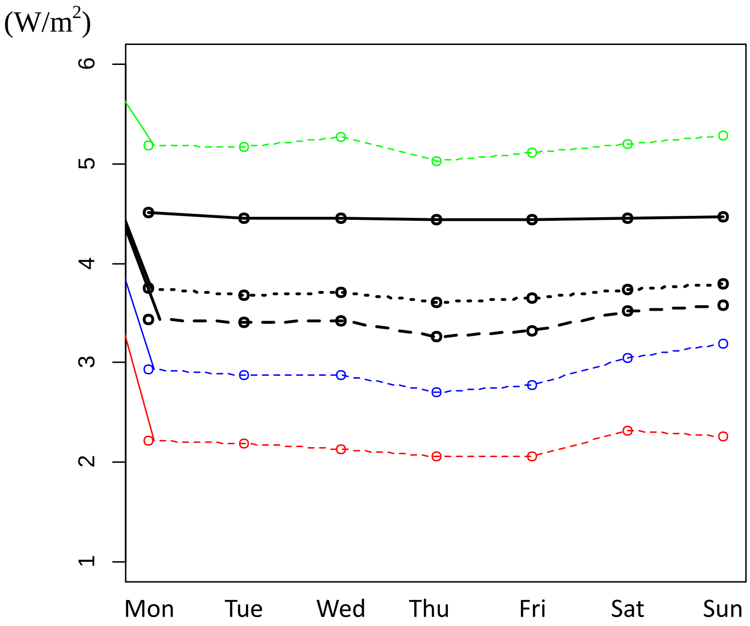


**Fig.4.** Existing intensity and updated intensity (averaged for each day of week)

#### *3.2.3. Forecasting result*

Fig. 5 represents the adjusted $R^2$ in “lm”. Although we introduced rather simple variables (temperature, squared temperature and calendar dummy variables), the fit to the observation is reasonably well. This figure suggests that the explanatory power by temperature varies hour to hour.

Fig. 6 shows the effects of temperature on electricity demand in “am” (We considered the nonlinearity only for temperature variable based on the likelihood ratio test of linearity). It is interesting to note that in the case of seven to eight o’ clock, the slope is steep, but it is not true for midnight. At zero to one o’ clock, nonlinearity of effect is implied.

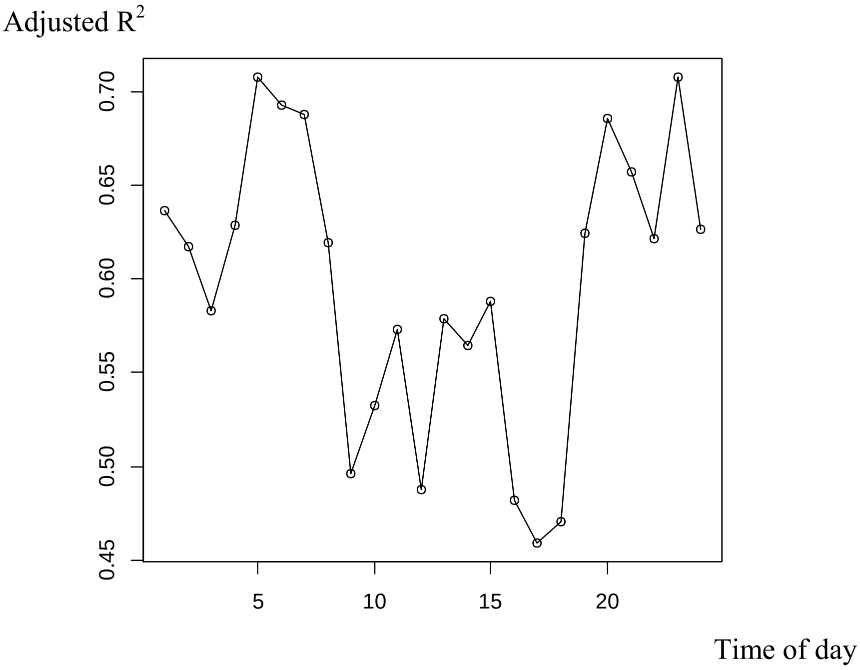


**Fig.5.** Adjusted $R^2$ in "lm"

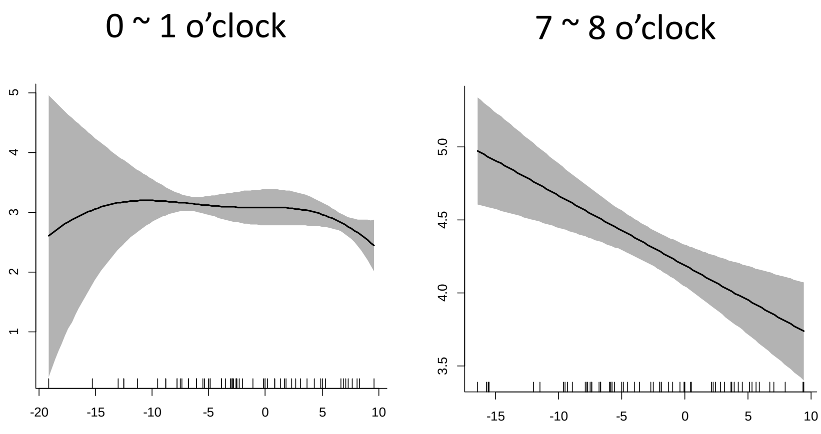


**Fig.6.** Nonlinear effects of temperature on electricity demand

Fig.7 shows the results of plotting the forecasted intensity against the actual measurement, to which Bayesian update is performed. We can find that “bats” and “arima” show similar movements, and they overestimated the high values. On the other hand, the others seem under estimated the low values. Such results bring us the interest of model averaging to reduce the model biases, although it beyond the scope of the present paper.

The parameter estimates for “bats”, “tbats”, and “arima” is shown in table 1. As for seasonal ARIMA model, ARIMA(2,1,1)(2,0,2)$_{[24]}$ is suggested based on AIC.

As the error measure of forecasting, we used the mean absolute percentage error (MAPE), which is traditionally used to measure forecasting accuracy (Taylor et al., 2006), defined as:

$$MAPE_h = \frac{1}{u} \sum_{h=H+1}^{H+u} \left| \frac{x_h - \hat{x}_h}{x_h} \right|, \; u = 1, \ldots, 360. \tag{8}$$

Fig.8 shows the result of calculating MAPE. The MAPE values are high compared to existing load forecasting studies (e.g., Taylor et al., 2006; Dordonnat et al., 2008). This is because observed temporal pattern is not stable due to the small sample size (only three measurements). Among the six models, “arima”, “multivariate”, and “tbats” performed relatively well. The high performance of seasonal ARIMA model coincident to the result of Soares and Medeiros (2008). It is interesting to note that the performance of “bats” is quite inferior to that of “tbats”.

Although “arima” and “multivariate” performed well, predicting “temperature” very accurately is another difficult task, and its prediction error may affect the result of electricity demand forecasting (e.g., Deihimi and Showkati, 2012). Hence “tbats”, which attained reasonable forecasting accuracy without covariates, seems a sounds option for regional forecasting.

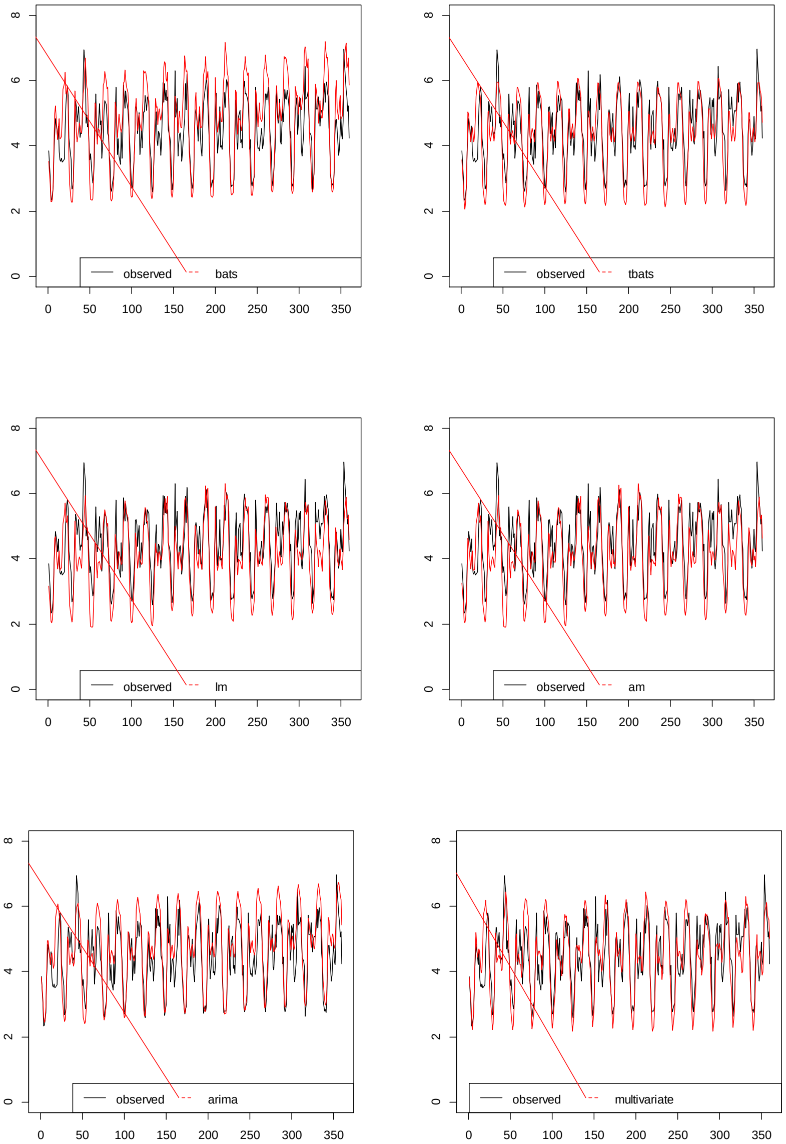


**Fig.7.** Forecasted intensity and actual measurement

**Table 1.** Parameter estimates

| Method | bats | tbats | arima |
|---|---|---|---|
| omega | 0.00267 | 0 | |
| b | 0.999 | | |
| alpha | 0.0211 | 0.0259 | |
| beta | 0.000161 | | |
| gamma1 | 0.00000780<br>0.000240 | 0.0000212<br>–0.000000533 | |
| gamma2 | | –0.0000133<br>0.0000227 | |
| AR coefficients 1 | 0.166 | –0.121 | 0.291 |
| AR coefficients 2 | –0.254 | 0.604 | 0.0793 |
| AR coefficients 3 | 0.225 | 0.478 | |
| AR coefficients 4 | | –0.227 | |
| AR coefficients 5 | | –0.0935 | |
| MA coefficients 1 | 0.170 | 0.423 | –0.985 |
| MA coefficients 2 | 0.420 | –0.365 | |
| MA coefficients 3 | | –0.479 | |
| SAR coefficients 1 | | | 0.677 |
| SAR coefficients 2 | | | 0.328 |
| SMA coefficients 1 | | | –0.508 |
| SMA coefficients 2 | | | –0.336 |
| dummy_SUN | | | 0.0364 |
| dummy_MON | | | –0.00260 |
| dummy_TUE | | | –0.0104 |
| dummy_WED | | | –0.0270 |
| dummy_THU | | | –0.0835 |
| dummy_FRI | | | –0.0443 |
| $Sigma^2$ | 0.0769 | 0.0819 | 0.117 |
| AIC | 7226.6 | 7120.4 | 1048.3 |

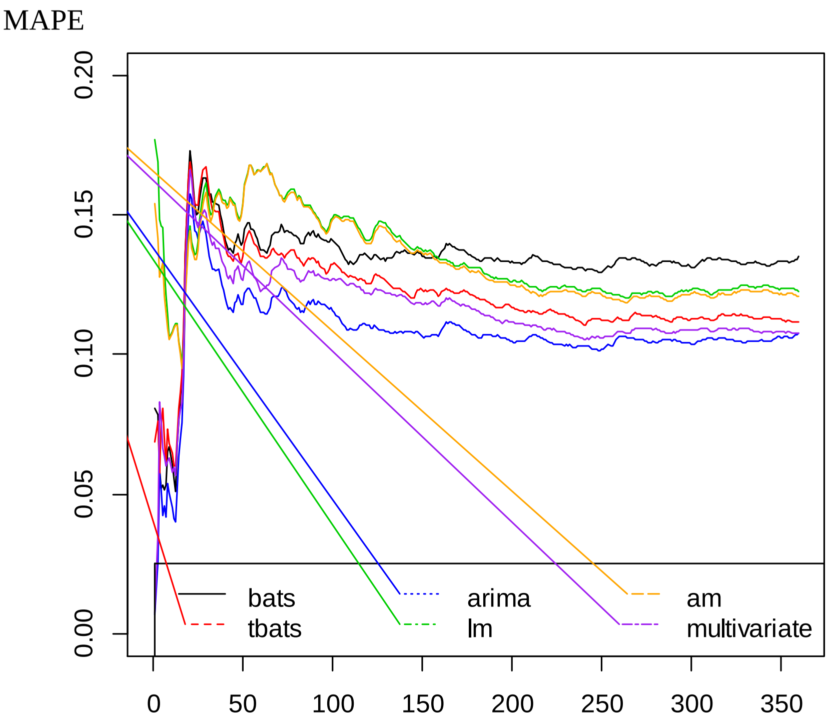


**Fig.8.** Results of calculating MAPE

## 4. Conclusions

The present paper proposed a simple Bayesian updating method of the electricity intensity by assimilating the information of smart meter data. The applicability of the method was tested with Japanese case study. Also, forecasting of the intensity was performed using several recently proposed statistical methods, and its performance was compared. The results support the use of seasonal-ARIMA model, multivariate dynamic linear model, and tbats model of De Livera et al. (2011).

In the future study, we are planning to install much large number of smart meters to various types of dwellings. Using the data, we are going to consider the differences in intensity by housing or household types.

## Acknowledgements

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