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Modeling Regional Electricity Load in India

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Modeling Regional Electricity Load in India

Abstract

Electricity as a product cannot generally be stored. Hence, it is required to match demand

1. Introduction

Electricity as a product cannot generally be stored. Hence, it is required to match demand and supply on a real time basis in order to avoid disturbance in grid frequency and consequently ensure quality of power supply. The agencies involved in scheduling of power in India divide a day into ninety-six time buckets- each bucket of fifteen minutes duration. The load is matched for each time bucket. However, there must be some reserve margin in the system so that local disturbances do not lead to collapse of the grid. The issue of developing an appropriate mechanism for load forecasting is important in the following ways:

(a) In order to ensure minimum disturbance in the grid frequency ‘it is relevant for electricity systems optimization to develop a scheduling algorithm for the hourly generation and transmission of electricity’([1]). Hourly load forecasts are one of the main inputs to this algorithm.

(b) The regulators in India are seriously discussing the possibility of introducing time-of-the-day pricing for bulk supply tariff. A proper understanding of intra-day load behaviour is a prerequisite for introducing such pricing system.

(c)4 The regulated bulk supply tariff in I3

[4] fitted an autoregressive moving average model (ARMA) to estimate electricity loads in California power market and obtained an acceptable out of sample forecast. The obtained residuals seemed to be independent

regulator has introduced a tariff mechanism (called, the availability based tariff) that would address the grid behaviour and at the same time would give incentive to participants for restoring grid discipline.

The heart of the availability based tariff scheduled and actual net drawals are at their respective receiving points. For calculating the net drawal schedules of beneficiaries, the transmission losses are apportioned to their drawals.

(v) The generators can however revise their schedule, which they intimate to the RLDC's by 22:00 hours.

(vi) Based on the final revised documents received by the RLDC, it draws up the final schedule by 23:00 hours and issues the schedule to both generators and beneficiaries alike. The new schedule comes into application at 00:00 hours.

The commercial mechanism of the ABT contemplates the disciplining of all three entities in the grid viz., the generator, transmitter and the beneficiaries. It accords a uniform treatment to all participants in the grid. The basic advantage in ABT is that the total tariff payable by the beneficiary to the generating station is divided into 3 components viz. 1) Capacity charge 2) Energy charge and 3) the unscheduled Interchange (UI) charges. Variation in actual generation/drawal and scheduled generation/drawal is accounted for through Unscheduled Interchange (UI) charges.

Though the UI charges are primarily intended to act as a penalty charge thus preventing the tendency of generators to over-generate in times of high frequency and the states to involve in under-drawal via the penalty mechanism, yet its very nature also provides a market pricing mechanism for the sale of power according to the intensity of demand.

All the generators irrespective of ownership would be dispatched with frequency based dispatch guidelines where at each frequency level, output of the generators are regulated by comparing their own variable cost with in our study as such data are not available to us. Such variables are expected to improve prediction of the load demand ([6]). However, for our data the linear regression models considered by us performed quite well.

For each hour h of the day we have computed the average electricity load and then computed its logarithm r_t^h on day t, where h = 1, 2, …, 24. We chose to model with the logarithm of load demands since it allows one to model weekly seasonality and national non-Sunday holiday effect through simple linear models. For fixed h, we have considered various linear regression models ([7]), to explain the mean-behavior of the series r_t^h, and tried GARCH models ([8], [9]) to capture possible heteroscedasticity of the series.

Let

…, 6, the variables are defined as follows: $D_{j,t}^{h}$ = 1 if t = day j of the week and $D_{j,t}^{h}$ = 0, otherwise. The binary variable H_t^h is defined as: H_t^h = 1 if t = a national non-Sunday holiday and H_t^h = 0, otherwise. Exploratory data analysis indicated that the regional electricity load is affected by roughly 3 seasons, namely, winter, summer and fall (Figure 2). For three seasons only two dummy variables $S_{k,t}^{h}$ are required to be included in the model. For k = 1, 2, the variable $S_{k,t}^{h}$ is defined as $S_{k,t}^{h}$ = 1 if t belongs to season k and $S_{k,t}^{h}$ = 0 otherwise.

From equations (2) and (3) we have

$$ {}_t^{h\,2} \quad V(r_t^h \mid F_{t\ 1}^h) = V(a_t^h \mid F_{t\ 1}^h) \qquad (3)$$

In model (2), the unconditional variance $V(a_t^h)$ may be constant, yet the conditional variance ${}_t^{h\,2}$ $V(a_t^h \mid F_{t\ 1}^h)$ may depend on t. Volatility models attempt to express the evolution of ${}_t^{h\,2}$, or its positive square root ${}_t^{h}$ using an exact function or a stochastic equation. The equation for ${}_t^{h}$ is called the *mean equation* for the r_t^h, and that for ${}_t^{h\,2}$ its volatility (or conditional variance) equation. A GARCH model describes the volatility evolution through a simple parametric function. A detailed discussion on GARCH models can be found in [9] and [10].

4. Results

We have used an estimation window of eleven months (January- November 2005) and each hour separately with the data specified in the previous section to find the best fit. The results are reproduced in Table 1. It is observed that AR(2) with dummies is the best fit model for all the hourly time series. The coefficient of any higher order lags proved to be insignificant. The usual diagnostics of residuals along with

Results show similar load behavior in certain clusters. For example, clusters were observed during 2300-0300 hours, 0500-0900 hours, 1400-1700 hours, and 2000-2300 hours. This load behaviour makes sense. For example, during early hours of the day, most of the load arises from continuous process industry and residences. This load remains same throughout the week.

The findings of the paper may have profound

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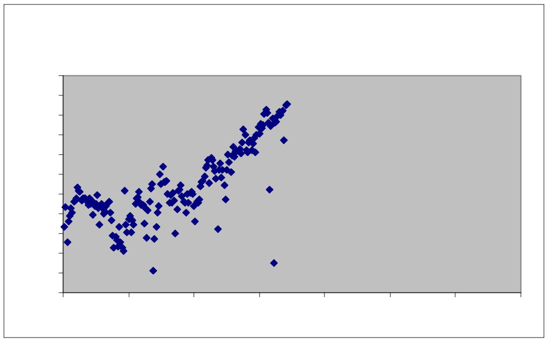

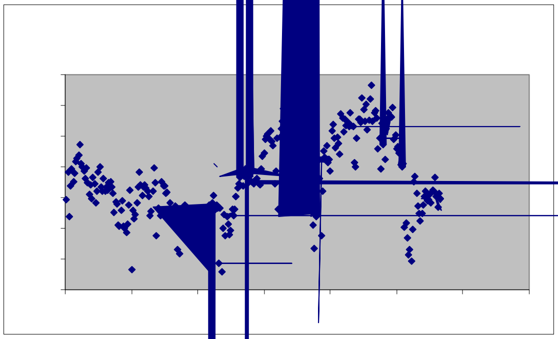

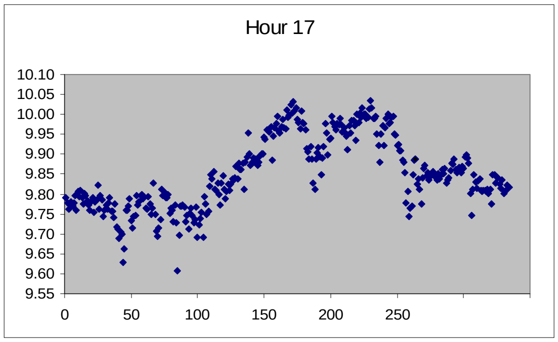
Hour 17
10.10
10.05
10.00
9.95
9.90
9.85
9.80
9.75
9.70
9.65
9.60
9.55
0
50
100
150
200
250

Table 2: MAPE for the month of December 2005 for our best fitted models, as summarized in Table 1, for each hourly log-load data

	MAPE calculated over all 31 days of December 2005											
Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
MAPE	**0.14%**	**0.15%**	**0.16%**	**0.18%**	**0.18%**	**0.18%**	**0.21%**	0.41%	0.48%	0.35%	0.31%	0.28%
Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
MAPE	0.23%	**0.20%**	**0.19%**	**0.18%**	**0.18%**	**0.17%**	**0.17%**	**0.16%**	**0.14%**	**0.13%**	**0.14%**	**0.16%**
	MAPE calculated over 27 days of December 2005, excluding 22-25 December											
Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**