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Forecasting Commercial Electricity Sales

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ABSTRACT

An important component of the New England Electric System Companies' (the 'System') total electricity sales is attributable to commercial customers. Commercial growth has recently been strong; moreover the System's peak demand is highly sensitive to commercial load. In a typical month this class represents 33 per cent of total System sales. Accurate short-run forecasts of total kWh sales are important for rate making, budgeting, fuel cause proceedings, and corporate planning. In this study we use a variety of econometric and time-series techniques to produce short-run forecasts of commercial sales for two geographical areas served by two separate retail companies.

KEY WORDS Electric utility sales Box–Jenkins State-space Econometric methods

In the first section of this study we present nine years of monthly data for commercial sales by Massachusetts Electric. (Massachusetts Electric Company and the Narragansett Electric Company are wholly owned subsidiaries of the New England Electric System, serving retail customers in Massachusetts and Rhode Island, respectively.) These data are used to construct a variety of forecasting models, including a Box–Jenkins ARIMA model, a seasonal autoregressive model, a state-space model, a model using exponential smoothing, and two econometric models. We provide a detailed discussion of the model-building process for each of these methods. In the next section we construct a set of models for Narragansett Electric. We then use our models to construct out-of-sample forecasts covering 12 months. These forecasts are compared to the actual values of the data, and the forecasting methods are ranked and compared. To preview one of our results, we find that the econometric models perform better than most of the time series models. This occurs because the econometric model is more able to predict the strong increase in sales arising from the economic expansion in late 1983 and early 1984. The exponential smoothing model is a strong competitor, and the ARIMA models perform relatively poorly. In the final section of the study we summarize our results with some concluding remarks.

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MASSACHUSETTS ELECTRICAL COMMERCIAL SALES—DATA AND MODELS

Data

Before developing the models (using FORECAST MASTER) we would like to present some plots and descriptive statistics for our data. These will show the gross features of the data that our models will have to capture. In Figure 1 we present a plot of monthly observations for Mass Electric Commercial sales from January 1975 to September 1983. The plot is very informative. The data exhibit a fairly regular seasonal pattern, with peaks occurring during the heavy winter heating and summer cooling months. There appears to be an upward secular trend in the data. The sample average of the trend and seasonal variation in the series can be determined by regressing the series on a linear trend and twelve seasonal dummies. The substantial serial correlation in the residuals suggests that the standard errors of the estimated coefficients are incorrect, but the regression does capture many of the salient features that are present in the graph. In particular, we see that the trend-adjusted series has a broad peak in January–February, followed a decline of roughly 50 GWh (gigawatt-hours) to a trough in May, an increase of 35 GWh to the August peak, followed by another decline of 30 GWh to a trough in October. The trend increase is small. The seasonally-adjusted series tends to increase by 0.44 GWh per month or 46 GWh over the 105-month sample period.

Comparing the regression results with the plot of the data, we see that the regression masks some of the important features of the data. First, the regression forces a constant trend on the data, whereas the plot suggests that the trend slowed considerably in the second half of the sample period. Next, the regression shows constant peaks in January and August, whereas the data show that the magnitude and timing of these peaks varies over the sample period. The winter peaks in 1981 and 1982 are much more pronounced than the peaks in previous years. The timing of the peaks also evolves through time. A careful look at the data shows that the winter peaks occurred in January in 1978, 1979, 1980, 1981 and 1983, and occurred in February in 1975, 1976, 1977 and 1982.

The summary statistics from the regression also include some useful information about the data.

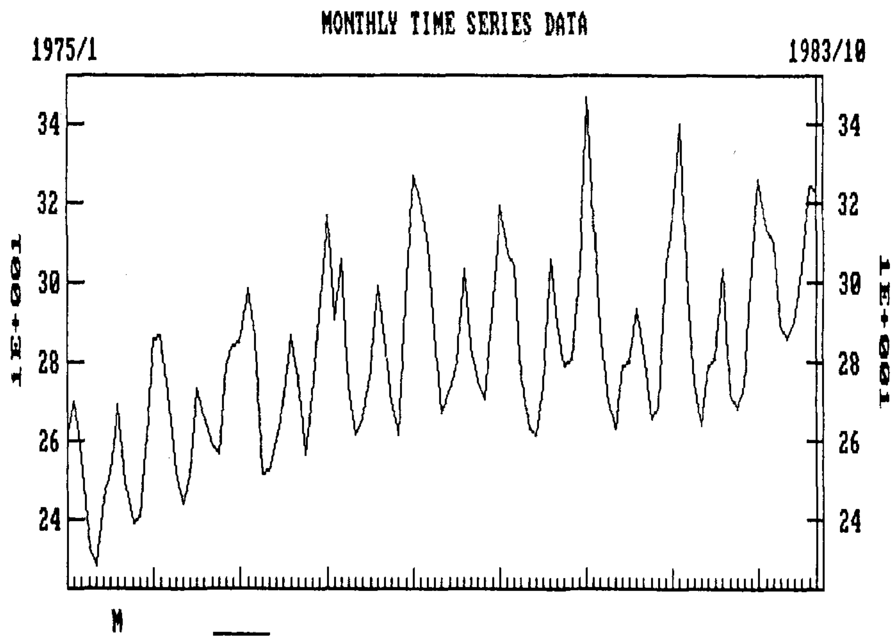

Figure 1. Mass Electric commercial sales.

The coefficient of variation (= standard deviation/mean) is 10 per cent, suggesting that the series is reasonably volatile. The standard error of the forecast—the within-sample standard deviation of the residuals—is 10.87 GWh, which can serve as a bench-mark for the other models that we will consider below. We'll now describe each of the forecasting models in turn.

Box–Jenkins model

Before estimating the Box–Jenkins model we must choose any necessary preprocessing transformations. The purpose of these transformations is to remove any trend in the data, and to make the data covariance stationary. The plot of the data does not suggest exponential growth, so we did not preprocess the data by taking logs. The preliminary analysis above suggested a trend in the data, so that we choose to difference the data. Because of the severe seasonality, we decided to use seasonal differences.

A reasonable model of this for our series might be

$$y_t - y_{t-12} = c + u_t,$$

where u_t is an error term which has a mean of zero and c is the annual trend. We will allow the error term to be serially correlated, and it is this serial correlation that the Box–Jenkins procedure will attempt to capture. To investigate the form of the serial correlation in u_t we calculated the autocorrelations in $y_t - y_{t-12}$:

Lag	1	2	3	4	5	6	7	8	9	10	11	12	13
Autocorrelation	0.25	0.10	−0.02	0.05	0.07	0.01	−0.13	−0.03	−0.08	−0.02	−0.02	−0.21	0.29

There are large autocorrelations at lags 1, 12, and 13. Unfortunately, FORECAST MASTER does not allow us to directly estimate an ARMA model which incorporates lags as large as 12 or 13. We can, however, consider a model for u_t of the form

$$(1 - \phi B^{12})u_t = (1 - \mu B^{12})e_t.$$

In this model the autoregressive coefficient ϕ picks up the significant correlation in u at lag 1, the seasonal moving average coefficient μ picks up the seasonal autocorrelation at lag 12, and the product of ϕ and μ accounts for the correlation at lag 13. To estimate this model in FORECAST MASTER, we first use the ARMA deseasonalization option. By setting the seasonal AR coefficient to 1, this procedure will seasonally difference the data, and by setting the seasonal MA coefficient to μ we incorporate a seasonal moving average of the error term. An AR(1) model can then be estimated to calculate the value of ϕ. The program does not automatically choose an optimal value of μ, but by trying a sequence of different values we can arrive at a good estimate. Below we show the estimated forecast standard error for the AR(1) model as a function of the seasonal moving average coefficient.

μ	Standard error
0.0	11.71
0.1	11.41
0.2	11.18
0.3	11.00
0.4	10.88
0.5	10.84
0.6	10.88
0.7	11.03
0.8	11.32
0.9	11.78

Table 1. Massachusetts Electric commercial sales, descriptive statistics

Variable	Coefficient	Std. Error	T-statistic	Probability
Trend	0.442874	0.035094	12.619650	1.000000
January	287.510275	4.010095	71.696619	1.000000
February	282.356291	4.025269	70.145940	1.000000
March	268.913417	4.040691	66.551347	1.000000
April	244.314989	4.056357	60.230142	1.000000
May	235.349892	4.072266	57.793345	1.000000
June	243.140351	4.088414	59.470573	1.000000
July	252.097480	4.104799	61.415302	1.000000
August	269.699049	4.121418	65.438419	1.000000
September	254.822849	4.138267	61.577192	1.000000
October	240.533042	4.253765	56.545922	1.000000
November	244.777674	4.268938	57.339245	1.000000
December	269.134801	4.284345	62.818194	1.000000

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	0.47	0.37	0.31	0.38	0.31	0.23	0.15	0.23	0.19	0.18	0.11	0.12
	0.27	0.08	0.08	0.13	0.14	0.07						

Statistic	Value	Probability
Number of observations	105	
Mean value of M	281.371428	
Standard deviation of M	23.487168	
Standard error of forecast	10.868043	
R^2 (corrected for mean)	0.810593	
$F(13,92)$	30.286666	1.000000
Adjusted R^2	0.783829	
Ljung–Box test = $\chi^2(5)$	117.703 585	1.000000
Durbin–Watson statistic	0.990208	0.999999
AIC error statistic	11.513846	
Schwartz error statistic	13.569750	

The smallest standard error is associated with $\mu = 0.5$. The entire set of results for this model are shown in Table 2.

The diagnostics shown in the table suggest that the model is reasonable, but there is still significant residual serial correlation at lag 13. As an additional check on this specification we fitted an AR(2) model to the seasonally adjusted series. The estimate of the AR(2) coefficient was small (0.07) and the various order determination criteria supported the AR(1) model. The AR(1) model is used below in our forecasting comparison.

In an attempt to adequately capture the substantial serial correlation at lag 13, we considered a seasonal autoregressive model.

Seasonal Autoregressive models

In the Box–Jenkins procedure we eliminated the trend in the data by taking 12 month differences of the data. This is a sensible thing to do when seasonal peaks and troughs appear during regular times throughout the year. When peaks and troughs can drift from month-to-month (because of the timing of severe weather for example) a modification seems to be appropriate. To motivate this modification, consider a sequence of winter peaks: when a January peak in one year is followed by

Table 2. Mass Electric commercial sales. SSI-BJ optimized Box–Jenkins forecasting

Summary of ARMA (1,0) Parameters

Seasonally differenced data
AR coefficients: 0.367
Seasonal MA coefficient: 0.50

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	0.01	0.11	−0.01	0.13	0.10	0.02	−0.12	0.01	−0.05	−0.00	−0.05	−0.09
	0.34	−0.08	−0.06	−0.03	0.03	0.02						

Statistic	Value	Probability
Number of observations	93	
Mean value of *M*	285.376344	
Standard deviation of *M*	21.432788	
Standard error of forecast	10.836979	
R^2 (corrected for mean)	0.744342	
$F(1,92)$	267.855971	1.000000
Adjusted R^2	0.741563	
Ljung–Box test $= \chi^2$ (17)	20.882856	0.768426
Durbin–Watson statistic	2.073110	0.093543
AIC error statistic	10.895082	
Schwartz error statistic	11.044445	

a January peak in the next year, a 12 month difference in the data is appropriate. However, when the January peak in one year is followed by a February peak in the next, a 13 month difference seems more appropriate. Conversely, when the peak occurs in February of one year and is followed by a January peak in the next, a 11 month difference seems appropriate. We will specify and estimate a model that incorporates this kind of behaviour.

To be precise about the behaviour, we will assume that

(1) An 11 month difference is appropriate with probability π_1
(2) A 12 month difference is appropriate with probability π_2
(3) A 13 month difference is appropriate with probability π_3 $(=1-\pi_1-\pi_2)$.

In any month chosen at random we want to take a weighted average of the differences (y_t-y_{t-11}), (y_t-y_{t-12}), and (y_t-y_{t-13}) with weights π_1, π_2, and π_3. This yields the 'differenced' series

$$[\pi_1(y_t-y_{t-11})+\pi_2(y_t-y_{t-12})+\pi_3(y_t-y_{t-13})]=c+u_t \tag{1}$$

where c is the annual trend in the data, and u_t an error term.

If we are to use the model for forecasting, we must estimate the probabilities π_1, π_2, and π_3, the constant c, and the parameters describing the serial correlation in the error u_t. To accomplish this, rearrange (1) to yield

$$y_t-y_{t-12}=c+\pi_3(y_{t-13}-y_{t-12})+\pi_1(y_{t-11}-y_{t-12})+u_t \tag{2}$$

which is just a regression model with a serially correlated error. The probabilities π_1, π_2, and π_3, can be estimated by least squares using the Autopro section in FORECAST MASTER. The results for the model, assuming that u_t follows an AR(1) process are shown in Table 3.

The residual autocorrelations, together with the basic set of diagnostics suggest that the model provides an adequate fit. The complete battery of diagnostics, however, suggested that important

Table 3. Mass Electric commercial sales, seasonal autoregressive model. Dependent variable is $M\text{–}M(-12)$

Variable	Coefficient	Std. Error	T-statistic	Probability
$M(-11)\text{–}M(-12)$	0.182378	0.061193	2.980351	0.997121
$M(-13)\text{–}M(-12)$	0.299697	0.060927	4.918941	0.999999
CONST	6.400605	2.195988	2.914681	0.996440
AUTO [−1]	0.475742	0.100799	4.719704	0.999998

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
$M\text{–}M(-12)$	−0.02	0.04	−0.07	0.08	0.19	0.01	0.01	0.01	−0.06	0.06	−0.11	−0.03
	0.20	−0.00	−0.08	−0.06	0.12	0.07						

Statistic	Value	Probability
Number of observations	91	
Mean value of $M\text{–}M(-12)$	6.204395	
Standard deviation of $M\text{–}M(12)$	13.174226	
Standard error of forecast	10.973082	
R^2 (corrected for mean)	0.329369	
$F(4, 87)$	10.6821129	1.000000
Adjusted R^2	0.298535	
Ljung–Box test $= \chi^2(14)$	14.349614	0.575997
Durbin-Watson statistic	2.103690	0.164092
AIC error statistic	11.211337	
Schwartz error statistic	11.847410	

Diagnostic test statistics

AUTO [−2] serial correlation	χ^2 (1)	0.21	$p = 0.351$
YLAG [−1] lagged variable	χ^2 (1)	3.36	$p = 0.933$
AUTO [−12] serial correlation	χ^2 (1)	0.56	$p = 0.544$
YLAG [−12] lagged variable	χ^2 (1)	6.47	$p = 0.989$
AUTO [1−−12] serial correlation	χ^2 (11)	6.16	$p = 0.137$
YLAG [1−−12] lagged variable	χ^2 (12)	15.58	$p = 0.789$
TIME TREND test	χ^2 (1)	0.45	$p = 0.498$
NONLINEARITY in x test	χ^2 (0)	0.00	$p = 0.000$
HETEROSCEDASTICITY with TIME	χ^2 (1)	1.93	$p = 0.835$
HETEROSCEDASTICITY with X	χ^2 (3)	8.22	$p = 0.958$
HETEROSCEDASTICITY with YFIT	χ^2 (1)	0.08	$p = 0.226$
ARCH [−1] process test	χ^2 (1)	1.82	$p = 0.822$
ARCH [−12] process test	χ^2 (1)	1.99	$p = 0.842$
ARCH [1−−12] process test	χ^2 (12)	13.51	$p = 0.667$
CHOW test for changing parameters	F (4, 83)	0.54	$p = 0.297$

lags were absent from the model. They suggested that $(y_{t-1} - y_{t-13})$ and $(y_{t-12} - y_{t-24})$ should be added to the model. When this was done, the coefficient on $(y_{t-13} - y_{t-12})$ became insignificant, and this variable was dropped for the model. The complete set of results are shown in Table 4.

Both of the models estimated in this section may provide good forecasts. The basic time varying seasonality model shown in Table 3 produced reasonable results. It will be used as one of our candidate forecasting models. In addition, the final model presented, passed a sequence of stringent diagnostic tests, so that it too will become one of our candidate models.

Table 4. Mass Electric commercial sales, seasonal autoregressive model. Dependent variable is M–M(–12)

Variable	Coefficient	Std. Error	T-statistic	Probability
M(–13)–M(–12)	0.165055	0.063427	2.602300	0.990740
M(–1)–M(–13)	–0.335021	0.099676	–3.361102	0.999224
M(–12)–M(–24)	–0.442983	0.096846	–4.574114	0.999995
CONST	9.841855	4.239913	2.321240	0.979726
AUTO [–1]	0.725282	0.097075	7.471355	1.000000

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M–M(–12)	0.03	–0.05	–0.18	0.13	0.19	0.07	–0.10	–0.02	0.00	–0.01	–0.03	0.01
	0.11	–0.07	–0.05	–0.01	0.11	0.08						

Statistics	Value	Probability
Number of observations	80	
Mean value of M–M(–12)	5.063749	
Standard deviation of M–M(–12)	13.016613	
Standard error of forecast	10.153888	
R^2 (corrected for mean)	0.422299	
F(5, 75)	10.965000	1.000000
Adjusted R^2	0.383786	
Ljung–Box test = χ^2 (13)	12.901868	0.544580
Durbin–Watson statistic	1.990582	0.202280
AIC error statistic	10.465535	
Schwartz error statistic	11.274300	

Diagnostic test statistics			
AUTO [–2] serial correlation	χ^2 (1)	0.22	$p = 0.359$
AUTO [–12] serial correlation	χ^2 (1)	0.36	$p = 0.453$
AUTO [1– –12] serial correlation	χ^2 (11)	6.93	$p = 0.195$
TIME TREND test	χ^2 (1)	0.04	$p = 0.163$
NONLINEARITY in x test	χ^2 (0)	0.00	$p = 0.000$
HETEROSCEDASTICITY with TIME	χ^2 (1)	1.47	$p = 0.775$
HETEROSCEDASTICITY with X	χ^2 (4)	2.62	$p = 0.377$
HETEROSCEDASTICITY with YFIT	χ^2 (1)	0.39	$p = 0.470$
ARCH [–1] process test	χ^2 (1)	4.09	$p = 0.957$
ARCH [–12] process test	χ^2 (1)	1.36	$p = 0.756$
ARCH[1– –12] process test	χ^2 (12)	12.87	$p = 0.621$
CHOW test for changing parameters	F (5, 0)	0.48	$p = 0.208$

State space model

The univariate state space model can be viewed as a special case of the general ARMA model. For example, the state space model of order 1 is an ARMA model of order (1,1) with constraints across the AR and MA coefficients. With this in mind, we expected to find that the univariate state space model would be very similar to the Box–Jenkins model. This was not the case. We used the same deseasonalization option as the Box–Jenkins model and chose a state-space model of order 1. (Recall, that the Box–Jenkins model was an AR(1).)

The estimated model, in ARMA form, was

$$ya_t = -0.45ya_{t-1} + w_t + 0.45w_{t-1}$$

Table 5. Mass Electric commercial sales. Bivariate state space model

Endogenous Variable 1: M–$M(-1)$
Endogenous Variable 2: $M(-12)$–$M(-13)$
Summary Statistics for Model with three canonical variables

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	−0.12	0.02	−0.19	−0.07	0.01	−0.13	−0.07	−0.04	−0.11	0.04	0.07	0.11
	0.31	−0.02	−0.06	−0.09	−0.01	−0.12						

Statistic	Value	Probability
Number of observations	89	
Mean value of M	285.926966	
Standard deviation of M	21.537793	
Standard error of forecast	12.360134	
R^2 (corrected for mean)	0.689373	
$F(6,83)$	30.700232	1.000000
Adjusted R^2	0.666918	
Ljung–Box test $= \chi^2$	23.859666	0.978746
Durbin–Watson statistic	2.252018	0.742638
AIC error statistic	12.768665	
Schwartz error statistic	13.885995	

where ya_t is the seasonally adjusted value of y_t and w_t is the error term. The model produced residuals with substantial serial correlation. If we rewrite the model using B, the 'Backward shift' operator, (with $Bx_t = x_{t-1}$ for any variable x_t) the reason for this serial correlation becomes clear. The model can be written as

$$(1 + 0.45B)ya_t = (1 + 0.45B)w_t.$$

Notice that both sides of the equation have the common factor $(1 + 0.45B)$. If we 'cancel' this common factor from both sides we have

$$ya_t = w_t.$$

The state space procedure models the seasonally adjusted series as white noise! But from the analysis in the Box–Jenkins model we know that ya_t has significant serial correlation. The state space model is seriously misspecified. Increasing and decreasing the order of the state space model did nothing to improve its forecastability. We abandoned this univariate framework, and considered another approach.

In this alternative state space model we did not use the de-seasonalization pre-processing. Rather, we removed the trend in the data by first differencing and included Δy_{t-12} as an additional exogenous variable in the state space model. We experimented with a variety of orders and finally chose a model of order 3. The results from this exercise are shown in Table 5.

Exponential smoothing

The exponential smoothing models are conceptually much simpler than any of the other models discussed thus far. To estimate the model we must make two choices: (1) the form of the model used —(a) level only, (b) level + trend, or (c) level + trend + seasonal; (2) the values of the smoothing parameters. The seasonality and trend presented in our data made (1c) the reasonable model choice. We let the program optimally choose the parameters of the model. The results are shown in Table 6.

Table 6. Mass Electric commercial sales. Exponential smoothing

Smoothing parameter values

Level = 0.224	Trend = 0.015	Seasonal = 0.268

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	0.11	−0.03	−0.06	0.14	0.07	−0.07	−0.17	0.00	−0.01	−0.02	−0.12	−0.07
	0.28	−0.04	0.00	0.10	0.12	0.01						

Statistic	Value	Probability
Number of observations	105	
Mean value of M	281.371428	
Standard deviation of M	23.487168	
Standard error of forecast	9.370289	
R^2 (corrected for mean)	0.843897	
F(3, 102)	183.804784	1.000000
Adjusted R^2	0.839306	
Ljung–Box test = χ^2 (15)	23.993668	0.934799
Durbin–Watson statistic	1.829158	0.740747
AIC error statistic	9.503134	
Schwartz error statistic	9.870350	

Econometric model

Construction of an econometric model is much more difficult than construction of the time series models discussed above. For those models we had to make decisions concerning pre-processing transformations, functional forms, and the number of lags to include in our specification. In the econometric model we begin by choosing a set of relevant explanatory variables, and then face the questions that arose in the time series models for each of these variables. This greatly complicates the model building process.

We used economic theory (together with common sense) to choose a set of possible explanatory variables. These can be divided into two categories. First, we chose a set of variables to explain the large seasonal variation in the series. Weather is the cause of most of this seasonal variation, and we chose two variables to capture these weather-induced effects. Our second category of variables was needed to explain secular movements in the data. Since our data represent market sales from a large number of customers, our first logical variable was the size of the market, measured by the number of commercial customers. Electricity is used in the commercial sector as a factor of production, and we can view the demand for electricity as a derived demand for the final goods and services produced by the commercial sector. We postulated that the demand for the final goods and services produced in the sector was driven by aggregate economic conditions in the region, and we included a measure of aggregate economic activity in the region to proxy for this demand. Finally, we postulated that the demand for electricity depended on its price. The exact variables that were chosen and some descriptive statistics are:

CUST = Number of Commercial Customers (in 10 thousands)
mean = 6.56 st. dev = 0.22 Coef. of Variation = 3.35%
CDD = Cooling Degree Days (65 degree base)
mean = 51.6 st. dev. = 77.4 Coef. of Variation = 150%
HDD = Heating Degree Days (65 degree base)
mean = 527.4 st dev. = 445.7 Coef. of Variation = 84.4%

UNEMP = Massachusetts unemployment rate (Seasonally adjusted)
mean = 7.2 st. dev. = 1.9 Coef. of Variation = 26.4%
P = Four month moving average of real average price charged to commercial customers
mean = 0.026 st. dev. = 0.002 Coef. of Variation = 7.69%

In addition, a dummy variable, REC, is included to capture a reclassification of customers that occurred in August 1979. The CDD and HDD variables are widely used in utility modelling for capturing the effects of weather on the sales of electricity. The UNEMP variable was chosen as a proxy for aggregate regional economic activity. The moving average of price variable requires some discussion. Economic theory suggests that demand will respond to the marginal cost of electricity, and this motivates the inclusion of price in our specification. Theory also suggests that there are important dynamic dimensions in the relationship between price and sales. With a fixed stock of capital, a firm's demand for electricity will change very little in response to a short run change in price. Sales will respond to longer run movements in price as firms invest in new capital and energy saving conservation measures. We have included a moving average of price to proxy these longer run, trend movements.

Our initial specification included the variables above. The results are shown in Table 7. They look quite reasonable. The magnitudes and signs of the coefficients seem sensible. The large residual serial correlation coefficient at lag 12 suggests that the weather variable have not completely captured the seasonality.

The regression diagnostic statistics are very informative. They suggest misspecified dynamics and possible omitted variables. They also provide important clues indicating how these problems can be cured. The significant statistics for AUTO([-12], YLAG[-12], and AUTO[1-12] suggest that the error term should be corrected for seasonal autocorrelation. The significant statistics for XLAG[-1] suggests important omitted variables. We corrected for serial correlation by including an AUTO[-12] term, and then used the specific tests for omitted variables. These tests pinpointed HDD[-1] and CDD[-1] as important excluded variables. (The omitted variable test on HDD[-1] and CDD[-1] yielded a $\chi^2(2)$ statistic of 11.52 and a p-value of 0.997). Incorporating these modifications led to the results shown in Table 8. All of the diagnostics, with the exception of HETEROSCEDASTICITY with YFIT, suggest that this is a reasonable specification. This model will be used in our forecasting comparison.

We decided to take a careful look at the heteroscedasticity problem. The diagnostic suggested that the model performed poorly for extreme values of the fitted value of the model, which arise from extreme values in the independent variables. To find out which of the independent variables was causing the problem, we regressed the squared residuals from the model on some possible explanatory variables. Since each squared residual can be viewed as a sample variance, this procedure can help us find the cause of the heteroscedasticity. The results from the regression were:

Variable	Coefficient	t-statistic
Constant	−193.2	−1.43
CUST^2	0.00	2.60
CDD	−0.49	−0.68
CDD^2	0.00	0.04
HDD	−0.25	−1.64
HDD^2	0.00	2.19

$R^2 = 0.20$

Table 7. Mass Electric commercial sales. Econometric model dependent variable is M

Variable	Coefficient	Std. Error	T-statistic	Probability
HDD	−0.039889	0.156638	−0.254657	0.201012
CDD	0.057329	0.831652	0.068934	0.054958
CUST	0.005821	0.002058	2.828086	0.995318
UNEMP	−2.365034	0.770302	−3.070269	0.997861
REC	−3.292648	3.143311	−1.047509	0.705135
CUST * HDD	0.014473	0.023925	0.604923	0.454770
P	−170.59096	567.70640	−0.300491	0.236198
CUST * CDD	0.026792	0.126430	0.211909	0.167822
CONST	−113.403514	136.570821	−0.830364	0.593667

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	0.01	−0.25	−0.00	0.03	−0.13	−0.16	−0.20	0.04	0.12	−0.03	−0.00	0.39
	0.09	−0.22	0.04	0.11	−0.11	−0.20						

Statistic	Value	Probability
Number of observations	90	
Mean value of M	285.545555	
Standard deviation of M	21.719970	
Standard error of forecast	9.282591	
R^2 (corrected for mean)	0.833768	
$F(9, 81)$	45.141156	1.000000
Adjusted R^2	0.815298	
Ljung–Box test = χ^2 (9)	45.300059	0.999999
Durbin–Watson statistic	2.043604	0.081235
AIC error statistic	9.732399	
Schwartz error statistic	11.028148	

Diagnostic test statistics

AUTO [−1] serial correlation	χ^2 (1)	0.01	$p=0.083$
YLAG [−1] lagged variable	χ^2 (1)	1.23	$p=0.733$
AUTO [−12] serial correlation	χ^2(1)	13.89	$p=0.000$
YLAG [−12] lagged variable	χ^2 (1)	11.87	$p=0.999$
AUTO [1−−12] serial correlation	χ^2 (12)	26.08	$p=0.990$
YLAG [1−−12] lagged variable	χ^2 (12)	19.51	$p=0.923$
TIME TREND test	χ^2 (1)	0.00	$p=0.038$
XLAG [−1] lagged variables	χ^2 (5)	19.94	$p=0.999$
HETEROSCEDASTICITY with TIME	χ^2 (1)	1.56	$p=0.788$
HETEROSCEDASTICITY with X	χ^2 (9)	5.85	$p=0.245$
HETEROSCEDASTICITY with YFIT	χ^2 (1)	3.57	$p=0.941$
ARCH [−1] process test	χ^2 (1)	2.90	$p=0.911$
ARCH [-12] process test	χ^2 (1)	0.55	$p=0.541$
ARCH [1−−12] process test	χ^2 (12)	8.18	$p=0.229$
CHOW test for changing parameters	$F(9, 72)$	14.55	$p=1.000$

Table 8. Mass Electric commercial sales. Econometric model. Dependent variable is M

Variable	Coefficient	Std. Error	T-statistic	Probability
HDD	0.062696	0.005203	12.051005	1.000000
CDD	0.187813	0.023320	8.053883	1.000000
CUST	0.006748	0.000963	7.007722	1.000000
UNEMP	−1.931296	0.776000	−2.488784	0.987182
REC	−3.963391	2.586696	−1.532221	0.874532
HDD (−1)	−0.007330	0.005216	−1.405401	0.840098
CDD (−1)	0.069908	0.023190	3.014588	0.997427
P	−311.99600	419.25643	−0.744173	0.543228
CONST	−174.098940	65.731042	−2.648656	0.991919
AUTO (−12)	0.309669	0.104763	2.955905	0.996883

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M	−0.04	−0.24	−0.12	−0.02	0.07	0.04	−0.12	0.03	0.04	0.07	−0.06	0.01
	0.13	−0.09	−0.05	0.11	−0.04	−0.03						

Statistic	Value	Probability
Number of observations	90	
Mean value of M	285.545555	
Standard deviation of M	21.719970	
Standard error of forecast	7.748287	
R^2 (corrected for mean)	0.885609	
F (10, 80)	61.935389	1.000000
Adjusted R^2	0.871310	
Ljung–Box test = χ^2 (8)	14.853387	0.937940
Durbin–Watson Statistic	2.129142	0.303788
AIC error statistic	8.163651	
Schwarz error statistic	9.379906	

Diagnostic test statistics

_CHDD _CCDD	χ^2 (2)	0.15	$p = 0.071$
_JAN_FEB_MAR_APR_MAY_JUN_JUL...	χ^2 (11)	11.12	$p = 0.567$
COMMON FACTOR test	χ^2 (7)	6.28	$p = 0.493$
AUTO [−1] serial correlation	χ^2 (1)	0.00	$p = 0.024$
YLAG [−1] lagged variable	χ^2 (1)	0.16	$p = 0.307$
AUTO [−24] serial correlation	χ^2 (1)	0.48	$p = 0.510$
YLAG [−12] lagged variable	χ^2 (1)	0.83	$p = 0.638$
AUTO [1−−12] serial correlation	χ^2 (11)	12.16	$p = 0.649$
YLAG [1−−12] lagged variable	χ^2 (12)	12.63	$p = 0.603$
TIME TREND test	χ^2 (1)	0.10	$p = 0.251$
XLAG[−1] lagged variables	χ^2 (5)	1.58	$p = 0.096$
NONLINEARITY in x test	χ^2 (7)	4.59	$p = 0.290$
HETEROSCEDASTICITY with TIME	χ^2 (1)	0.63	$p = 0.571$
HETEROSCEDASTICITY with X	χ^2 (9)	14.01	$p = 0.878$
HETEROSCEDASTICITY with YFIT	χ^2 (1)	9.33	$p = 0.998$
ARCH [−1] process test	χ^2 (1)	0.01	$p = 0.097$
ARCH [−12] process test	χ^2 (1)	2.98	$p = 0.916$
ARCH [1−−12] process test	χ^2 (1)	4.80	$p = 0.036$
CHOW test for changing parameter	F (10, 70)	0.55	$p = 0.144$

Table 9. Mass Electric commercial sales. Econometric model. Dependent variable is *M*/Cust

Variable	Coefficient	Std. Error	*T*-statistic	Probability
$CUST^{-1}$	−97.24075	48.631961	−1.999524	0.954448
CDD	0.026284	0.003442	7.635821	1.000000
HDD	0.007467	0.000795	9.388561	1.000000
P	−74.00429	62.789440	−1.178611	0.761447
CDD (−1)	0.011581	0.002995	3.866218	0.999889
UNEMP	−0.305025	0.114778	−2.657529	0.992129
_JAN	2.051724	0.845246	2.427368	0.984791
_FEB	0.950438	0.836853	1.135728	0.743930
_DEC	1.246292	0.694490	1.794543	0.927273
_CONST	56.402781	7.452265	7.568542	1.000000
_AUTO [−12]	0.240116	0.106035	2.264485	0.976456

Autocorrelations of lagged residual errors

Lag:	1	2	3	4	5	6	7	8	9	10	11	12
M/Cust	−0.06	−0.20	−0.06	0.02	0.02	−0.02	−0.14	0.02	0.11	0.09	−0.10	−0.02
	0.15	−0.09	−0.04	0.07	−0.04	−0.00						

Statistic	Value	Probability
Number of observations	90	
Mean value of *M*/Cust	43.627219	
Standard deviation of *M*/Cust	3.051664	
Standard error of forecast	1.172048	
R^2 (corrected for mean)	0.869065	
$F(11, 79)$	47.668626	1.000000
Adjusted R^2	0.850834	
Ljung–Box test = χ^2 (7)	13.737817	0.943954
Durbin–Watson statistic	2.170319	0.448280
AIC error statistic	1.240847	
Schwarz error statistic	1.445651	

Diagnostic test statistics

_MAR_APR_MAY_JUN_JUL_AUG_SEP...	χ^2 (8)	9.04	$p = 0.661$
AUTO [−1] serial correlation	χ^2 (1)	0.05	$p = 0.175$
YLAG [−1] lagged variable	χ^2 (1)	0.07	$p = 0.214$
AUTO [−24] serial correlation	χ^2 (1)	1.75	$p = 0.814$
YLAG [−12] lagged variable	χ^2 (1)	1.86	$p = 0.827$
TIME TREND test	χ^2 (1)	1.78	$p = 0.817$
NONLINEARITY in *x* test	χ^2 (0)	0.00	$p = 0.000$
HETEROSCEDASTICITY with TIME	χ^2 (1)	0.01	$p = 0.074$
HETEROSCEDASTICITY with *X*	χ^2 (10)	21.26	$p = 0.981$
HETEROSCEDASTICITY with YFIT	χ^2 (1)	8.59	$p = 0.997$
ARCH [−1] process test	χ^2 (1)	0.00	$p = 0.039$
ARCH [−12] process test	χ^2 (10)	1.97	$p = 0.839$
ARCH [1−−12] process test	χ^2 (12)	5.05	$p = 0.044$
CHOW test for changing parameters	$F(11, 68)$	0.60	$p = 0.168$

While the coefficients on $CUST^2$ and HDD^2 were too small to be printed out, their *t*-statistics strongly suggest that they are responsible for the heteroscedasticity.

Since the error variance seems to be proportional to the square of the number of customers, the necessary correction is to divide all of the variables in the model by the number of customers. This suggests that the original model should have been specified to explain sales per customer, rather than the total market sales. This is a reasonable alternative to the model shown above. Rather than carry out a mechanical correction for heteroscedasticity we decided to specify and estimate a model for sales per customer.

After some experimentation, we arrived at the specification in Table 9. Residual plots from a variety of specifications suggested that our models were having difficulty explaining the winter peaking months. To allow more flexibility in the specification for these months we incorporated dummy variables for December, January, and February, as well as the weather variables. The table indicates that these are useful explanatory variables. The diagnostics also indicate that we have not completely cured the heteroscedasticity problem. A variety of weighting procedures were used for weighted least squares estimation. These reduced the heteroscesdasticity. The point estimates of the regression coefficients changed very little.

NARRAGANSETT ELECTRIC—DATA AND MODELS

In Figure 2 we present a plot of the sales of electricity to commercial customers by Narragansett Electric. The basic pattern of sales seems very similar to Mass Electric's. There are a few important differences to note. First, the summer peak in sales is more pronounced; the average peak summer sales is slightly higher than the average peak winter sales over the sample period. Second, the trend in the data seems more regular; the slowing of the trend in the second half of the sample period that was present in the Massachusetts Electric data is not as dramatic. Because of the similarity in the

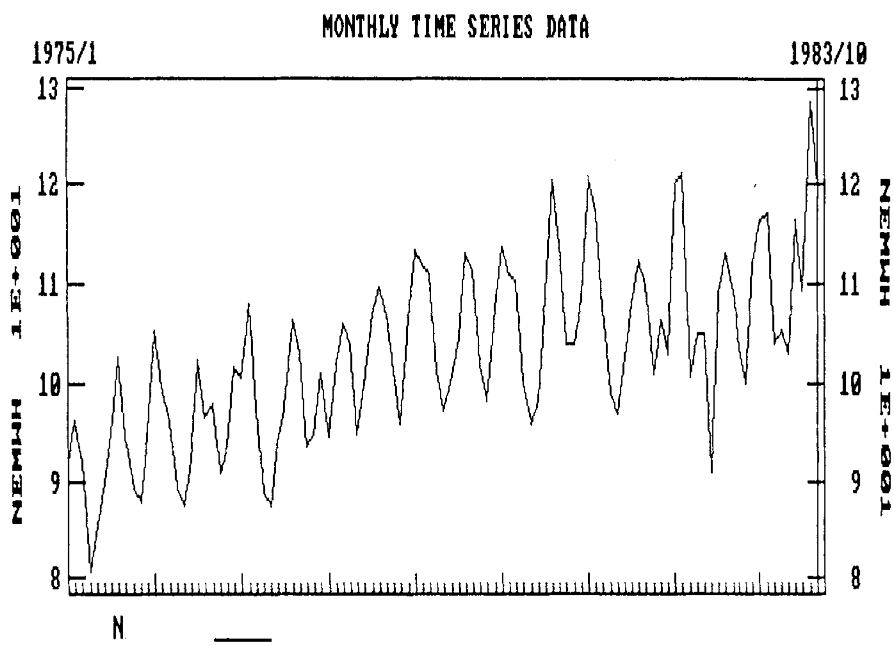

Figure 2. Narragansett Electric commercial sales.

two series there is little marginal gain in a detailed description of the model building process for Narragansett; we will just highlight the differences between the Narragansett and Massachusetts Electric models.

Box–Jenkins model

We found that an AR(1) model applied to the seasonally differenced data provided an adequate fit. The seasonal moving average coefficient was chosen by the same 'grid-search' procedure that we used for Mass Electric.

Seasonal autoregressive models

The time variation in the seasonal pattern led us to consider the same model that was estimated for Mass Electric. We regressed $(y_t - y_{t-12})$ onto a constant, $(y_{t-11} - y_{t-12})$, and $(y_{t-13} - y_{t-12})$ to estimate the probabilities discussed in the last section. An AR(1) model was used for the disturbance term.

A look at the detailed diagnostics suggested possible improvements. They showed significant correlation between the residuals and $(y_{t-1} - y_{t-13})$. This led us to consider another model that incorporated this lag and (again led by diagnostics) an AUTO[−12] term.

State space models

Experimentation with a univariate model led to the same kind of unsatisfactory results that we found with Mass Electric. We were led to a bivariate model relating the 'two' variables Δy_t and Δy_{t-12}.

Exponential smoothing

We used the same procedure as we described in the Mass Electric section.

Econometric model

We retained the basic specification that we used for Mass Electric. The relevant means and standard deviations for Narragansett and the Rhode Island area are:

Variable	Mean	St. Dev.	Coef. of Variation
CDD	62.2	96.3	155%
HDD	472.8	421.0	89.2%
CUST	2.402	0.044	1.83%
p	0.027	0.002	7.41%
UNEMP	7.40	1.92	25.9%

The diagnostics from the initial model led us to consider a specification which included seasonal dummies for the winter peaking months, the seasonal lag of the dependent variable together with a correction for seasonal autocorrelation in the disturbance. The diagnostics suggested that an additional seasonal lag of the dependent variable or of the error term may be appropriate. Because of our small sample size, we decided that the cost of this correction (12 observations) was too high. We also estimated a model using sales per customer as the dependent variable.

COMPARING FORECASTS

The models that were described in the last two sections were used to forecast commercial sales for both companies for two forecast periods. The first forecast period covers the months from October

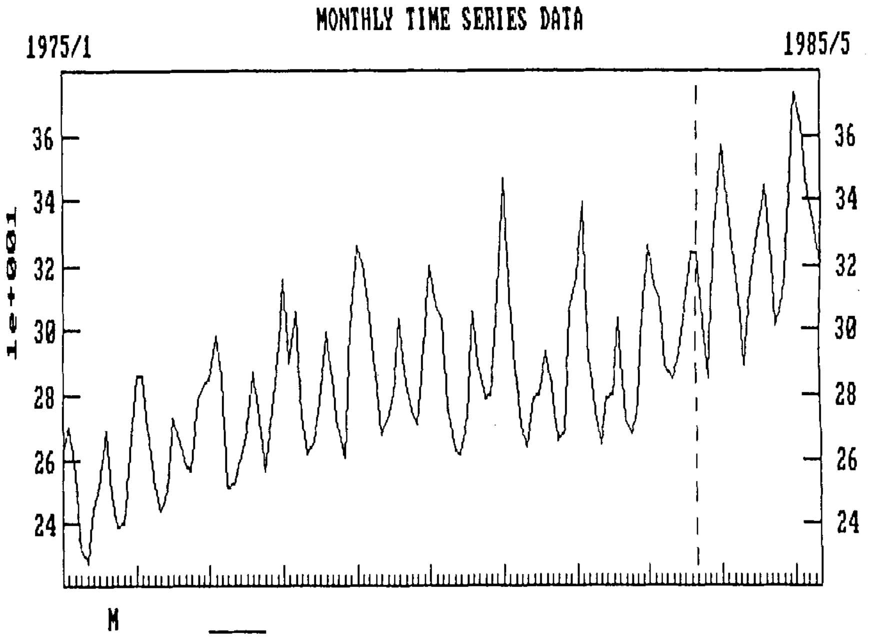

Figure 3. Massachusetts Electric commercial sales.

1983 to September 1984. Following this forecast comparison we re-estimated each of the models using data through September 1984, and then used these new models to construct forecasts from October 1984 through May 1985. Figures 3 and 4 show the sample data augmented by the values over the forecast period. The forecast period is characterized by the same general seasonal pattern as the sample period. The underlying trend is much different. This undoubtedly arises from the rapid aggregate economic expansion which occurred over the forecast period. The average annual increase for Mass Electric was 6.5 GWh over the sample period. During the forecast period the average annual increase was over three times larger. For Narragansett the annual increase during the forecast period was more than two times larger than during the sample period. This change in trend motivates our decision to carry out two forecasting experiments. The first experiment explores the performance of the methods when the series undergoes a sharp change in trend. In the second experiment, the trend in the forecast period is much like the trend in the last 12 months of the augmented sample period. We suspected that some of the methods might perform best during one of the forecast periods, while other might perform best over the other period.

For both companies we have formed forecasts using seven different models. They are:

BJ the Box-Jenkins Model
SAR1 The first Seasonal Autoregressive Model [shown in Table 3]
SAR2 The second Seasonal Autoregressive Model [shown in Table 4]
SS The bivariate State Space model
EXSM Exponential Smoothing
REG1 Econometric Model 1 [Shown in Table 8]
REG2 Econometric Model 2 [shown in Table 9]

To construct the forecasts using the econometric models, we require forecasts of the exogenous variables. Forecasts for HDD and CDD were constructed using a set of 'Normals' estimated by

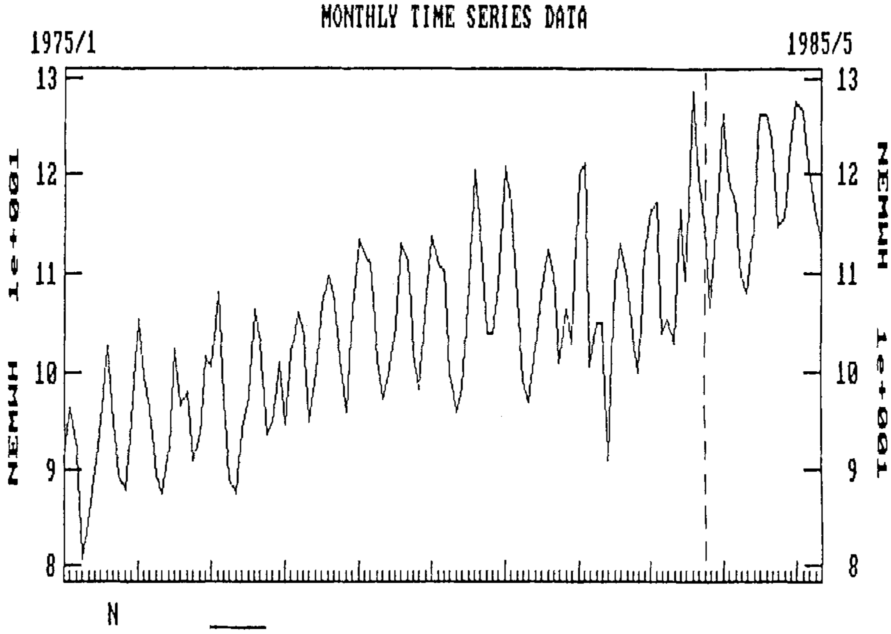

Figure 4. Narragansett Electric commercial sales.

New England Power Service. Forecasts of the unemployment rate and the number of commercial customers were constructed from ARIMA models. Price schedules are generally known 1 year in advance, and this led us to use the actual values for price.

Forecasting experiment 1—October 1983—September 1984

In Table 10 we show the actual values of the data during the forecast period together with the forecasts from the seven competing models. In Table 11 we report summary statistics for the implied forecast errors. The results are unambiguous. For both companies, the forecasts constructed from the econometric models have the lowest root mean square error. Exponential smoothing and the State Space Model also perform well. Exponential Smoothing performs relatively better for Mass Electric, and the State Space Model performs relatively better for Narragansett Electric. The Box–Jenkins and Seasonal Autoregressive Models perform poorly relative to the other methods.

A careful look at the tables show the reason for the poor performance. These models were unable to predict the increase in the trend over the forecast period. The actual average annual trend growth over the forecast period was 20.6 for Mass Electric. The annual trend increases predicted by Box–Jenkins was only 1.9. The two seasonal autoregressive models did a bit better with predicted trend increases of 7.1 and 7.7. The corresponding predicted annual average increase by the econometric models were 21.4 and 17.4, much closer to the actual trend increase. The State Space Model and the Exponential Smoothing Model predicted average annual increases of 16.6 and 16.1 respectively. Similar results were found for Narragansett.

Forecasting experiment 2—October 1984–May 1985

In Table 12 we show the actual and forecast values of the data during the second forecast period. In Table 13 we present some summary statistics comparing the methods during this forecast period.

Table 10. Forecast October 1983–September 1984

Massachusetts Electric

Obs	M	MBJ	MSAR1	MSAR2	MSS	MEXSM	MREG1	MREG2
1983.10	302.1000	290.7000	293.4000	287.7000	306.2000	293.7000	296.1000	294.7000
1983.11	285.4000	285.7000	290.9000	294.2000	300.8000	299.1000	301.7000	296.9000
1983.12	331.2000	310.4000	308.0000	317.2000	319.8000	328.5000	325.3000	323.9000
1984.01	356.3000	329.9000	324.5000	334.0000	336.5000	351.7000	341.6000	343.7000
1984.02	340.6000	324.3000	322.5000	341.8000	332.7000	344.4000	337.6000	335.7000
1984.03	322.0000	308.8000	313.1000	310.5000	319.9000	328.1000	333.4000	326.9000
1984.04	309.8000	288.4000	299.7000	299.6000	305.1000	303.0000	311.4000	306.9000
1984.05	289.5000	282.0000	292.3000	285.7000	301.9000	293.5000	303.6000	298.6000
1984.06	318.3000	289.7000	296.0000	296.0000	309.7000	301.4000	304.6000	298.9000
1984.07	329.8000	297.4000	307.7000	300.2000	321.3000	310.6000	325.8000	319.9000
1984.08	344.5000	317.2000	322.9000	323.1000	321.3000	331.6000	345.1000	339.2000
1984.09	326.2000	306.6000	323.9000	311.5000	329.9000	316.0000	339.1000	332.6000

Narragansett Electric

Obs	N	NBJ	NSAR1	NSAR2	NSS	NEXSM	NREG1	NREG2
1983.10	114.4000	107.7114	110.2000	112.0000	112.1000	109.1000	112.3000	111.6927
1983.11	106.7000	105.1158	108.1000	109.4000	108.4000	108.4000	109.3000	110.4354
1983.12	114.9000	111.1708	111.7000	112.7000	114.1000	115.5000	113.4000	111.7801
1984.01	126.2000	117.9191	118.4000	119.9000	119.6000	122.4000	122.8000	123.0910
1984.02	119.5000	118.1451	117.6000	116.4000	121.0000	122.8000	123.8000	124.6847
1984.03	117.0000	106.3722	111.2000	112.5000	114.6000	114.3000	112.8000	113.7830
1984.04	109.8000	106.8202	107.2000	105.6000	111.9000	109.5000	112.7000	113.2840
1984.05	108.1000	105.2329	108.9000	109.9000	111.6000	106.9000	110.9000	112.0470
1984.06	114.3000	109.7253	109.8000	109.1000	118.5000	110.2000	109.6000	110.5492
1984.07	126.2000	110.7498	116.4000	117.6000	118.8000	116.8000	119.5000	121.4808
1984.08	126.2000	122.2310	120.6000	119.5000	124.3000	125.1000	125.8000	127.1252
1984.09	123.9000	116.5341	120.4000	122.6000	120.1000	120.3000	122.7000	124.0077

Table 11. Forecast performance–Forecast comparison 1

Massachusetts Electric. Forecast error

Model	Mean	Std. Deviation	RMSE
Box–Jenkins	18.7	9.6	20.8
Seasonal AR Model 1	13.4	11.6	17.4
Seasonal AR Model 2	12.8	10.9	16.5
State Space	4.0	12.2	12.3
Exponential Smoothing	4.5	9.9	10.5
Econometric Model 1	−0.8	10.7	10.3
Econometric Model 2	3.1	9.4	9.5

Narragansett Electric. Forecast error

Model	Mean	Std. Deviation	RMSE
Box–Jenkins	5.8	4.1	7.0
Seaaonal AR Model 1	3.9	3.2	5.0
Seasonal AR Model 2	3.3	3.3	4.6
State Space	1.0	3.8	3.7
Exponential Smoothing	2.2	3.4	3.9
Econometric Model 1	1.0	3.5	3.5
Econometric Model 2	0.3	3.6	3.4

Table 12. Forecast October 1984–May 1985

Massachusetts Electric

Obs	M	MBJ	MSAR1	MSAR2	MSS	MEXSM	MREG1	MREG2
1984.10	301.5000	303.3041	307.1292	300.1426	316.3263	311.0609	310.7520	309.2377
1984.11	309.2000	292.9893	303.3969	294.0785	304.4595	311.6075	314.4803	311.2849
1984.12	341.3000	328.0764	329.8535	321.2147	320.3413	346.4699	344.3558	345.7982
1985.01	372.7000	350.1513	353.6873	354.4460	343.1000	371.1411	363.9013	370.0574
1985.02	362.3000	339.0791	348.8194	343.9289	342.2429	362.3548	354.3315	357.1984
1985.03	341.8000	321.4911	332.3659	330.4273	323.5561	345.2369	344.2085	342.1505
1985.04	330.6000	304.6310	317.0308	312.3412	307.8038	321.4370	328.7312	327.9313
1985.05	319.7000	291.1661	308.0478	301.9331	300.6842	308.9977	308.8794	310.2929

Narragansett Electric

Obs	N	NBJ	NSAR1	NSAR2	NSS	NEXSM	NREG1	NREG2
1984.10	114.6000	114.3035	116.5026	115.0033	116.6622	115.0993	117.5570	117.2849
1984.11	115.7000	108.4070	114.1510	113.8256	112.3966	113.1732	114.5240	115.0084
1984.12	122.7000	115.1404	117.4628	116.6131	117.2584	120.8125	122.5160	121.1474
1985.01	127.4000	123.9910	123.1353	124.0635	125.5673	128.5880	130.1374	130.1686
1985.02	126.5000	120.4455	123.7342	124.6123	125.1832	127.8661	129.9854	129.3965
1985.03	120.8000	114.1276	118.2639	117.5574	121.3533	120.3937	122.1753	122.3347
1985.04	115.8000	110.4318	114.2761	114.2343	115.6577	114.7873	120.1436	119.0926
1985.05	113.2000	108.8455	113.1768	112.9103	114.2509	112.2829	117.6480	116.0324

Table 13. Forecast performance–forecast comparison 2

Massachusetts Electric. Forecast error

Model	Mean	Std. Deviation	RMSE
Box–Jenkins	18.5	9.6	20.9
Seasonal AR model 1	9.8	7.3	12.2
Seasonal AR model 2	15.1	6.2	16.3
State space	15.1	13.9	20.5
Exponential smoothing	0.1	6.9	6.9
Econometric model 1	1.2	7.4	7.5
Econometric model 2	0.6	5.5	5.5

Narragansett Electric. Forecast error

Model	Mean	Std. Deviation	RMSE
Box–Jenkins	5.1	2.4	5.7
Seasonal AR model 1	2.0	2.3	3.0
Seasonal AR model 2	2.2	2.0	3.0
State space	1.0	2.5	2.7
Exponential smoothing	0.5	1.4	1.5
Econometric model 1	−2.2	2.1	3.0
Econometric model 2	−1.7	1.8	2.5

The ranking of the methods is broadly similar to the ranking in the first forecast period. Looking first at the results for Massachusetts Electric, we see that the exponential smoothing and the two econometric models perform far better than the competing time series models. The performance (measured by RMSE) of Box–Jenkins is roughly the same as in the first period. The seasonal autoregressive models improve slightly in terms of their RMSE. The performance of the State Space Model deteriorates substantially, and is now similar to the BJ model. The exponential smoothing and econometric models have RMSE that are approximately 40% smaller than in the first forecasting period. This is what one would expect. These methods have trends that adapt according to behaviour in the recent past (using time series models to forecast the economic variables that account for the trend in the econometric model). Since the trend in the second forecast period is similar to the trend at the end of the augmented sample period, these methods perform very well.

The forecasting results for the Narragansett Electric contain some differences. Again the exponential smoothing procedure performs very well. All of the other methods, with the exception of Box–Jenkins, perform nearly as well as one another.

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