ABSTRACT
This paper applies Box-Jenkins time series analysis to the problem of modeling and forecasting monthly residential sales of electricity. Using the SAS/ETS ARIMA procedure, the identification, estimation and diagnostic checking stages are outlined and forecasts presented for an ARIMA transfer function model.

Due to the strong dependence of residential electricity usage on weather conditions, transfer functions are specified for the two input variables, heating degree days and cooling degree days. In order to account for the time varying nature of the weather parameters, the input series are preconditioned by the saturation of weather sensitive appliances. A further input, the number of residential customers, is incorporated through a user-per-customer specification of the dependent variable.

Once the final model has been selected, it is used to prepare a twelve month forecast of residential sales during the year 1983. The forecasted values are then compared with available actual data, and the resultant residuals decomposed into model error plus errors in the forecast of the input series.

INTRODUCTION
In recent years, the Box-Jenkins time-series approach has become an increasingly popular method in short-term forecasting applications. It is general enough to handle all types of series, requires a relatively small amount of data, and can be applied quickly and easily. As compared to casual type models which are driven by several explanatory variables, time series models generate predictions that are based solely on the past history of the variable to be forecast. Thus they are most useful for series that are very stable over time. However, if the time series exhibits significant variability from one sample period to the next, then the forecast variable may be highly dependent on some other variable as well as its own history. In this case, by explicitly accounting for the effect of the exogenous factor, it may be possible to reduce the total forecast error. The Box-Jenkins Transfer Function model is a time series technique which allows causal variables to impact the system, thereby providing a link between time-series models and causal models.

In this paper the Box-Jenkins Transfer Function methodology is applied to the problem of forecasting monthly kilowatt hour residential electric sales to Florida Power Corporation (FPC). A multiple input transfer function is specified to explicitly account for the effects of weather conditions on electricity consumption. Growth due to new residential customers and changes in the relationship between electricity use and weather due to increasing stocks of weather-sensitive appliances are also handled within the model framework. The results indicate that the transfer function model provides a viable alternative to the basic univariate approach. A particular advantage of the model is its ability to incorporate alternative forecasts of weather conditions as well as analyze previous forecast errors in terms of inherent model errors, and errors due to the forecast of the input variables.

DATA DEVELOPMENT
Short-term (one-month to eighteen months) sales models and forecasts are an important input to company planning processes in the area of budgeting and schedule manufacturing processes, and since kilowatt-hour sales is the primary variable affecting revenues, the sales forecast becomes the basis for revenue forecast. For fuel planning and adjustment purposes, a six-month sales forecast is used to estimate fuel requirements by type of fuel (coal, oil, etc.) and for planning fuel expenditures. Since electric rates and revenue vary by type of customer, the sales forecast is prepared for seven customer classifications: Residential, Commercial, Industrial, Sales to Public Authorities, Street and Highway Lighting, Rural Electric Authorities and Municipalities. Of these seven customer classes, the residential class is by far the largest, accounting for over forty percent of FPC's total system sales in 1983. Since the transfer function format allows for the effects of causal variables, the model may also be used as a simulation tool. With weather being the primary factor affecting monthly residential sales, it is sometimes necessary to adjust historical sales to reflect normal weather conditions. By including weather variables in the model structure, it can be used to simulate sales based on alternative weather inputs, such as actual versus normal.

One of the first steps in the forecasting process is to define the variable to be forecast and the forecast horizon. Another preliminary step is to look at the time series and identify any basic characteristics of the forecast variable such as trends or seasonality, and also note some of the factors which significantly affect the forecast variable. The objective of this study was to provide a twelve month forecast for FPC's residential electric sales during 1983. To obtain a pure forecast, only data prior to 1983 was used in building the model. The historical data base contained monthly sales for a seven year period from 1976 to 1982. The 1983 actual historical data is available and was only used as a comparison with the final forecast results for validation purposes. A graph of the residential megawatt-hour (MWH) sales data is shown in Figure 1. The notable features of this time series are the slight upward trend in the overall data and the annual seasonal pattern with dual peaks and troughs during each year that follow weather patterns. The trend and seasonal components are important characteristics of the time series that must be accounted for in the Box-Jenkins procedure. They are also useful in identifying some of the principal causal factors affecting
electricity sales. The upward trend in the data essentially represents a growth in the overall level of sales over time. This growth is mainly due to growth in the number of electric customers. As more customers enter the system, more electricity is sold. Increased usage of electricity by existing customers was also looked into as a possible cause of growth in sales, but the residential KWH use-per-customer data has remained fairly constant over the 1976-1983 sample period, implying that the average customer has not been increasing (or decreasing) his consumption of electricity. Although the Box-Jenkins procedure can pick up trends in the data quite easily, thereby eliminating the need for the customers variable, it was decided to include customers through the choice of a KWH use-per-customer specification for the dependent, or output, variable rather than total residential sales. A use-per-customer model is both theoretically and practically appealing since the residential class is a very homogeneous group that consume electricity in a similar manner and for similar reasons. In addition, the customer time series data is an extremely stable series over time and this makes it very easy to forecast using univariate Box-Jenkins techniques. The customer series exhibits an upward trend as well as a stable cyclical component that reflects the pattern of tourism and seasonal customers in the FPC service area.

With KWH use-per-customer as the output variable to be modeled, it is useful to examine this time series, compare it to the series for sales and identify any significant deviations. There is really very little difference between the historical residential use-per-customer data series and that for total sales, except for the fact that the upward trend noticeable in the sales data is completely absent in the use-per-customer data. As expected the strong seasonal component is still quite present and, as mentioned earlier, reflects the response of an average electricity customer to changing weather conditions.

In the winter, electricity consumption increases directly with the increased use of heating appliances. As the weather gets cold, people turn on their heaters. Likewise during the hot summer months, the demand for air conditioning drives up the customers' usage of electricity, while during the mild weather months, when there are very little heating or cooling requirements, electricity use is at its lowest levels. Thus, it is the demand for the use of space heating and cooling appliances which causes the seasonal nature of electricity consumption-per-customer. And it is, primarily, temperature levels that determine the need for space heating or cooling. Temperature however measures weather conditions at a single point in time, it is not a good indicator over a period of time such as a month. Therefore, two standard weather variables, heating degree days and cooling degree days serve as the basis for the calculation of the monthly weather variables. The heating degree day variable is simply defined as the difference between an average of the daily minimum and maximum temperatures and a base temperature of 65°F. The more complex cooling degree day formula considers the minimum and maximum daily temperatures separately by subtracting the base temperatures, 85° and 55° respectively, from each value.

\[
\begin{align*}
HDD_d &= 65 - \frac{\text{Min } T_d + \text{Max } T_d}{2} \quad \text{if } HDD > 0 \\
&= 0 \quad \text{if } HDD \leq 0 \\
CDD_d &= (\text{Min } T_d - 55) + (\text{Max } T_d - 85) \\
&= 0 \quad \text{if } CDD \leq 15
\end{align*}
\]

where

\[
\begin{align*}
\text{Min } T_d &= \text{minimum temp. on day } d \\
\text{Max } T_d &= \text{maximum temp. on day } d \\
\end{align*}
\]

Assuming that the 65 degree average daily temperature base point provides a close estimate of a mild weather day that does not require any heating or cooling to maintain comfortable living conditions, then the daily degree day series summed over a month, known as monthly degree days, yields a relative indication of the heating and cooling requirements for that month. The demand for heating and air conditioning arises from comfort reasons, and the monthly degree day data provides a set of weather variables that can measure relative comfort conditions over a period of time.

Because the FPC service territory is quite diverse, covering thirty-two counties in west-central and northern Florida, weather information from a single station would not provide an adequate view of weather conditions over the entire area of interest. Therefore, a weighted average of the monthly heating and cooling degree day variables were calculated based on data from three weather stations within the FPC service area. The weighting factors were derived by disaggregating the service area into three sections, each surrounding a particular weather station, and identifying the percent of total system sales within each section.

One further weighting computation was performed on the two weather variables in an attempt to capture the variable nature of the weather versus electricity use relationship. It is known that weather conditions determine the usage level of weather sensitive appliances such as heating and cooling. As the number of heating degree days increase, the demand for space heating, and consequently electricity, also increases. The problem is that the relationship between heating degree days and the consumption of electricity for heating purposes is not constant over time, but varies with the stock of heating appliances. So while the actual weather sensitivity of the system varies over time, due to increasing saturations of heating and cooling appliances, it is specified and estimated in the model as a constant parameter. As a result the
model estimate will reflect an average system weather sensitivity over the entire sample period. Given increasing saturation rates of weather sensitive appliances, this will tend to underestimate the weather sensitivity expected during the forecast period.

Annual appliance saturation surveys provide historical data on the saturation of heating and cooling appliances within the FPC service area. Monthly values were obtained through a linear interpolation of the annual data. The monthly heating and cooling degree day variables were then multiplied by the respective heating and cooling saturation rates, to obtain a set of weighted service area degree day variables to be used as inputs to the Box-Jenkins model. This aspect of the model is more of a long-term characteristic and should not significantly affect the short-term forecasting performance. The extent of its usefulness depends upon the magnitude of any changes in weather sensitive appliance stocks over the sample period.

The general model structure consists of a Box-Jenkins transfer function equation relating KWH use-per-customer to appliance weighted service area heating and cooling degree days, and a univariate model for forecasting residential customers. Total residential sales was then calculated as residential use-per-customer multiplied by the number of residential customers.

**BOX-JENKINS OVERVIEW**

The Box-Jenkins approach to time series analysis consists of three stages of model development:

1. **Identification**
2. **Estimation and Validation**
3. **Forecasting.**

In the identification stage the output variable is analyzed for the purpose of selecting, or identifying, the appropriate model structure. The first step lies in determining if the time series is stationary, since the Box-Jenkins method can only be applied to stationary series. Essentially, a time series may be considered stationary if there is no upward or downward trend component, no seasonal pattern, and no change in the variability of the series over time. Though not a precise definition, this will suffice for most practical purposes as most real data will probably be considered nonstationary for one of the reasons listed above. Although a nonstationarity series cannot be used directly for analysis, most time series can be made stationary through some type of transformation, such as differencing or taking logarithms of the original data. For example, a linear trend pattern may be removed by taking first differences, i.e., \( Z(t) = Y(t) - Y(t-1) \), and seasonal behavior can be removed through the use of seasonal differencing, \( W(t) = Y(t) - Y(t-s) \), where \( s \) represents the period of the seasonal pattern. For monthly data \( s = 12 \), while for quarterly data \( s = 4 \). If the time series exhibits a changing variability about the mean over time, a logarithmic or square root transformation will normally transform the series and result in stationarity in the variance. In practice, these three transformations should be all that is necessary to obtain a stationary time series from most nonstationary data series.

Given a stationary series, the second step in the identification process consists of determining the appropriate model specification from a general class of models known as autoregressive, moving-average models. The general autoregressive (AR) process simply states that the value of the dependent variable at time \( t \) is a linear function of \( p \) lagged values of the dependent variable plus a random error term:

\[
Y_t = \alpha + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \epsilon_t
\]

where \( \alpha, \phi_1, \ldots, \phi_p \) are parameters and \( \epsilon_t \) is a random error term.

The moving average (MA) model differs from the autoregressive in that the dependent variable at time \( t \) is assumed to be a linear function of a current error and \( q \) past error terms:

\[
Y_t = \alpha + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q}
\]

where \( \alpha, \theta_1, \ldots, \theta_q \) are parameters.

An interesting feature of the above models is that an MA process of finite order can be expressed as an infinite order AR process, and a finite order AR process can be expressed as an MA process of infinite order. This characteristic of AR and MA models is the motivating force behind the principle of parsimony in the Box-Jenkins methodology. The principle of parsimony refers to modeling a time series with the least number of parameters possible for an adequate representation of the process. With this principle in mind, it may be possible to describe time series as a mixed autoregressive moving average process involving fewer parameters than either an AR or MA process by itself. The general ARMA \((p,q)\) process has the form:

\[
Y_t = \alpha + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q}
\]

The model forms described above assume \( Y \) is a stationary time series. If in fact \( Y \) was nonstationary then the appropriate transformation to achieve stationarity would be applied to \( Y \) and the new transformed variable would be substituted for \( Y \) in the above representation. The resulting class of models for a nonstationary time series are known as autoregressive integrated moving average, or ARIMA, models. The basic tools used to identify an appropriate ARIMA model, and also nonstationarity, are plots of the estimated autocorrelation function and partial autocorrelation function. The autocorrelations essentially provide a summary of the pattern existing within the data, and their plots can reveal a good deal of information concerning the data and its characteristics. For more detail on these functions, the reader is referred to the listed references. The ARIMA model forms also provide some additional flexibility when dealing with seasonal time series in that multiplicative seasonal AR and MA parameters are allowed to enter the system as well as the regular parameters. Overall the Box-
Jenkins method is general enough to model most any time series process with a relatively simple specification.

Once the model is identified as AR, MA, or ARIMA, and the order specified, then the estimation stage of the Box-Jenkins process provides estimates of the model parameters, residuals and selected diagnostic statistics. If all the diagnostic checks prove the model to be inadequate then it can be used in the third stage of the Box-Jenkins procedure, the forecasting stage, where actual forecasts are developed based on the estimated model. For a model to be considered adequate the residual series of the fitted model must be reduced to a white noise process, i.e., no further improvement in terms of residual variance can be achieved through the addition of another parameter. If a model is judged to be inadequate then it returns to the identification stage where a new model is specified, estimated and checked. The process continues until an adequate model is formed which can be used to generate a set of forecasts. The general overview of the Box-Jenkins procedure presented up to this point has focused on modeling a single dependent, or output variable, as a function of its own history and previous errors. It can be further enhanced through the introduction of one or more independent, or input variables, into the forecasting system. This is accomplished through the use of transfer functions. A transfer function is an equation that describes the dynamic relationship between an output variable and a given input variable. The dynamic nature of the transfer function relationship lies in its ability to account for the instantaneous and lagged effects of an input variable on the output variable. This relationship can be used to improve the forecast of the output variable, as well as provide the capability of using the model for simulation analysis by plugging in alternative forecasts of the input series.

The complete transfer function model consists of a transfer function for each input variable plus a noise term which may itself be autocorrelated. Usually the output variable will not be completely determined by the input variables, hence the addition of a noise component. The development of a transfer function model follows the same identification, estimation and validation, and forecasting stages described earlier, though performed several times. Initially, a univariate model is built for each of the input variables being used. Once adequate input models are selected, a transfer function relationship is identified and estimated for each input variable. The cross correlation function is the basic tool used in identifying the transfer function parameters. The transfer function parameter estimates can be checked for significance and, if necessary, re-specified and re-estimated. After the form of the transfer functions have been determined, it remains to specify an appropriate ARIMA model for the noise component and estimate the complete transfer function - noise model. Diagnostic checks may then be performed on the full model to determine its adequacy. If the fitted model proves to be inadequate then the identification and estimation stages must be repeated for either the transfer function, the noise model or both. If however the fitted model is found to be adequate based on the diagnostic checks, then it can be used in the forecasting stage.

**MODEL RESULTS**

The modeling effort began by identifying and estimating univariate ARIMA models for the three input variables: monthly heating degree days (HDD), monthly cooling degree days (CDD), and residential customers (CUST). Both of the degree day series required only twelfth differencing transformation in order to remove the seasonal pattern that was highly visible in the monthly data. The customer series, shown in Figure 3, exhibits a strong upward trend as well as a distinct seasonal pattern. Therefore, both first differences and seasonal differences were necessary to achieve stationarity in the customer series. After identifying and estimating several possibilities, the models shown in Table 1 were selected based on diagnostic checks confirming their adequacy. For notational convenience the backshift operator $B$ will be used for expressing the ARIMA model results in a compact form. The $B$ operator is simply a lagging device applied to a time series and is useful in defining levels or degrees of differencing as follows:

$$B^k Y_t = Y_{t-k}$$

$$B^k Y_t = Y_{t-k} = Y_{t-k}$$

$$B^k Y_t = Y_t - B^k$$

With the univariate model building process completed for each of the input variables, the next step consisted of identifying and estimating the transfer functions relating residential KWH use-per-customer (UPC) to monthly heating and cooling degree days. The process began by identifying the sources of non stationarity in the use-per-customer data and creating a stationary series by applying the appropriate transformations. As presented in Figure 2, the mean of the use-per-customer data appears to remain constant over time; there is no indication of any trend component. However, a distinct seasonal pattern is present in the monthly series, implying the need for seasonal differencing of period twelve. Plots of the autocorrelation function also indicate that a stationary series can be obtained by just taking twelfth differences of the original use-per-customer time series.

The specification of the transfer functions were kept quite simple. There was no overall delay or lead time since the monthly degree day series was prepared to correspond exactly with the month over which the electricity consumption took place. The single significant cross correlation at lag zero also suggested a single overall scale factor with no lag effects of the input series or output series. Following the estimation of the transfer functions, the remaining noise process was indentified as a seasonal, twelfth order moving average model based on a plot of the residual autocorrelations and partial autocorrelations. The full transfer function - noise model was then estimated and checked. All parameters were found to be significant and the resulting residual series was essentially a white noise process; therefore, the model was considered adequate and could be used to
generate a twelve month forecast for the year 1983.

For comparison purposes a simple univariate model for the use-per-customer series was also identified and estimated. The model structure along with estimation results for both models are presented in Table 2.

**FORECAST RESULTS**

The univariate customer model was used to forecast the number of residential customers for each month in 1983. Compared with actual 1983 customers the performance of the univariate model was quite good as reflected by a mean absolute percent error of only 0.12%.

In order to forecast the residential KWH use-per-customer, it was necessary to develop a forecast for the two input variables, monthly heating and cooling degree days. During the forecast period it is assumed that normal weather conditions will take place, where normal weather is defined as a long-term, thirteen year average of heating and cooling degree days by month. This simple forecast provides a good, reasonable estimate of future weather conditions, and it also identifies a normal weather base case which can be compared against actual weather to determine the impact of non-normal weather conditions on the forecast.

Given the normal monthly degree day forecast and the estimated use-per-customer transfer function model, a forecast of residential use-per-customer was generated for each month in 1983. Finally, the total number of residential customers served on a monthly basis was calculated by multiplying the residential customer forecast times the residential KWH use-per-customer forecast. The sales forecast results are shown in Table 3 and are fairly good given the high variability in the monthly data. The mean absolute percent error (MAPE), which measure the average percent error on a monthly basis without allowing for compensating errors is 4.9%. For the total annual 1983 period the forecast is only 0.39% above actual, however, this relatively small error would be expected due to the offsetting effects of positive and negative monthly errors would over an annual period. In essence, the annual comparison of forecast bias and actual error is more a measure of forecast bias than of forecast accuracy, and should be close to zero.

One question which needs to be answered concerning the forecasting ability of the transfer function model is: How does it compare with the forecast obtained from the much simpler to implement univariate model? A comparison of the forecasts obtained from the two approaches are shown in Table 4. Surprisingly, the univariate univariate model performed about as well as the transfer function model, with the univariate model's 5.1% MAPE not that much higher than the 4.9% reported for the transfer function method. On an individual monthly basis though, the univariate forecast had four of the five largest monthly errors and this is the reason why the root mean square percent error (RMSPE) is more than a full percentage point higher for the univariate model. Still, the results do not provide strong support for implementing the transfer function model. The additional costs and time may outweigh the additional benefits.

The closeness of the univariate and transfer function forecasts however may have been a peculiarity associated with the year 1983. As another check, some out-of-sample forecasts were generated for the twelve months of 1982 from each of the models. The 1982 forecast results showed a significantly higher forecast accuracy for the transfer function model, as the MAPE and RMSPE were respectively 2.2% and 3.6% lower for the transfer function model.

For electricity sales data, the transfer function method would be expected to outperform the univariate model by its ability to separate the highly variable weather sensitive portion of demand from the non-weather sensitive component. Average weather conditions, the best forecast possible for weather, can be explicitly incorporated into the transfer function model. The univariate model however includes the high variability associated with the weather sensitive component of demand as part of the overall sales data. So while some forecast of weather conditions is implicit in the total system forecast, it will follow the general ARIMA process being used to model the sales data and may not be a good forecast of weather conditions. As a result it may place too much weight on the previous year's weather conditions. This is exactly why the 1982 forecast results were so different between the two types of models. The winter months of 1982 were extremely cold, driving electricity sales way up. As a result, the univariate model, placing quite a bit of weight on that 1981 data, greatly over-projected the winter months of 1982.

One further aspect of the transfer function model specification that should be included as a benefit, is its ability to perform simulation analysis based on alternative input forecasts, and to analyze individual components of the forecast. For example, the forecasts error may be decomposed into the following two sources of error:

1. Error in the input forecasts
2. Model error.

When analyzing the forecasting ability of the model, the total forecast error is important. However, if the factor to be analyzed is model performance then an examination of pure model error is what is needed. Model error refers to the forecasting accuracy of the model when all input variables are set to their actual values. Thus, no error is attributed to the inputs, it is all part of the model. Table 5 presents a comparison of the sales forecast results when all inputs are forecasted versus a forecast of sales that incorporates actual customers and actual weather conditions. The comparison indicates that more than half of the MAPE associated with the forecast is due to errors in the forecasts of the input variables. Had the inputs been predicted with perfect accuracy, the 4.9% MAPE would have been reduced to 2.9% and almost all of this difference is due to errors in the weather forecast.

**CONCLUSIONS**

The Box-Jenkins transfer function methodology can provide an adequate short-term forecasting...
and simulation model based on one or two primary causal variables. The additional costs of going from a univariate to a transfer function specification entails increased data requirements to account for the causal input variables, an increase in the amount of time spent identifying models for the input variables as well as the transfer function - noise process. The additional benefits of the transfer function model are that it can provide improved forecast accuracy, though the amount of improvement depends upon several factors such as the degree of correlation between the output variable and the input variable, any lead or lag time associated with the input-output relationship, and the level of forecast accuracy attainable for the input variables. The transfer function approach is especially useful for data series that have a high degree of variability rather than stability over time. Also, the transfer function specification allows the user to generate alternative forecasts of the output variable based on different input forecasts. This simulation capability may also be used for an after-the-fact forecast analysis to discover the amount of error that can be attributed to the input variable forecasts versus the actual model.

REFERENCES


TABLE 3 TRANSFER FUNCTION MODEL PERFORMANCE - 1983

<table>
<thead>
<tr>
<th>Month</th>
<th>Actual</th>
<th>Forecast</th>
<th>Error</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>6085349</td>
<td>730018</td>
<td>-1214715</td>
<td>12.9%</td>
</tr>
<tr>
<td>February</td>
<td>752760</td>
<td>529987</td>
<td>222773</td>
<td>3.0%</td>
</tr>
<tr>
<td>March</td>
<td>819975</td>
<td>728651</td>
<td>91324</td>
<td>1.1%</td>
</tr>
<tr>
<td>April</td>
<td>917466</td>
<td>826871</td>
<td>90595</td>
<td>1.0%</td>
</tr>
<tr>
<td>May</td>
<td>762765</td>
<td>758359</td>
<td>4406</td>
<td>0.6%</td>
</tr>
<tr>
<td>June</td>
<td>617980</td>
<td>609932</td>
<td>8048</td>
<td>1.3%</td>
</tr>
<tr>
<td>July</td>
<td>826483</td>
<td>796648</td>
<td>29835</td>
<td>3.6%</td>
</tr>
<tr>
<td>August</td>
<td>812714</td>
<td>726135</td>
<td>86579</td>
<td>1.1%</td>
</tr>
<tr>
<td>September</td>
<td>872700</td>
<td>857333</td>
<td>15367</td>
<td>1.8%</td>
</tr>
<tr>
<td>October</td>
<td>849714</td>
<td>849714</td>
<td>0</td>
<td>0.0%</td>
</tr>
<tr>
<td>November</td>
<td>833635</td>
<td>821997</td>
<td>11638</td>
<td>1.4%</td>
</tr>
<tr>
<td>December</td>
<td>872000</td>
<td>897112</td>
<td>-15112</td>
<td>1.7%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>10009520</td>
<td>10009520</td>
<td>-1449</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Mean Absolute Percent Error: 0.1%
Root Mean Square Percent Error: 0.1%

TABLE 4 COMPARISON OF UNIVARIATE AND TRANSFER FUNCTION MODELS

<table>
<thead>
<tr>
<th>Month</th>
<th>Univariate</th>
<th>Transfer Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>6085349</td>
<td>730018</td>
</tr>
<tr>
<td>February</td>
<td>752760</td>
<td>529987</td>
</tr>
<tr>
<td>March</td>
<td>819975</td>
<td>728651</td>
</tr>
<tr>
<td>April</td>
<td>917466</td>
<td>826871</td>
</tr>
<tr>
<td>May</td>
<td>762765</td>
<td>758359</td>
</tr>
<tr>
<td>June</td>
<td>617980</td>
<td>609932</td>
</tr>
<tr>
<td>July</td>
<td>826483</td>
<td>796648</td>
</tr>
<tr>
<td>August</td>
<td>812714</td>
<td>726135</td>
</tr>
<tr>
<td>September</td>
<td>872700</td>
<td>857333</td>
</tr>
<tr>
<td>October</td>
<td>849714</td>
<td>849714</td>
</tr>
<tr>
<td>November</td>
<td>833635</td>
<td>821997</td>
</tr>
<tr>
<td>December</td>
<td>872000</td>
<td>897112</td>
</tr>
<tr>
<td>TOTAL</td>
<td>10009520</td>
<td>10009520</td>
</tr>
</tbody>
</table>

Mean Absolute Percent Error: 0.1%
Root Mean Square Percent Error: 0.1%

TABLE 5 COMPARISON SUMMARY OF TRANSFER FUNCTION FORECASTS WITH FORECASTED INPUTS VERSUS ACTUAL INPUTS - 1983

<table>
<thead>
<tr>
<th>Month</th>
<th>MAPE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>5.18%</td>
<td>4.9%</td>
</tr>
<tr>
<td>February</td>
<td>5.71%</td>
<td>5.3%</td>
</tr>
<tr>
<td>March</td>
<td>2.4%</td>
<td>2.1%</td>
</tr>
<tr>
<td>April</td>
<td>2.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>May</td>
<td>1.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>June</td>
<td>2.4%</td>
<td>2.3%</td>
</tr>
<tr>
<td>July</td>
<td>1.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>August</td>
<td>2.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>September</td>
<td>1.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>October</td>
<td>2.4%</td>
<td>2.3%</td>
</tr>
<tr>
<td>November</td>
<td>2.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>December</td>
<td>1.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>0.6%</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

Residential Monthly Electric Sales (mWh)
1975-1982 Actual Data

Michael F. Jacob
Supervisor: Load Forecasting
Forecasting & Customer Research
Florida Power Corporation
P. O. Box 16042
St. Petersburg, Florida 33711
(813) 866-5100

49