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SHORT-TERM ENERGY FORECASTING USING TIME SERIES TECHNIQUES: CHILE, A CASE STUDY

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Contents

Executive Summary

This study evaluates the use of seven time series methods to predict twelve monthly values of five Chilean energy variables *ex post* one year forward. The forecast errors of the best of these seven methods are compared to the errors of two naive forecasting models, a structural model, and a composite forecast model. The purpose of this exercise is to show Latin American energy forecasters the potential usefulness of time series methods as short-term energy forecasting vehicles.

A naive forecasting model turned in the best predictive performance, a clear report that the complexity of a forecasting method does not provide any protection against predictive error. ARIMA models were also successful forecast vehicles.

The study emphasizes the importance of analyzing the raw data on a variable before forecasting it and of approaching the forecasting exercise with caution, on the one hand, and with methodological rigor and a respect for the managerial requirements of a forecast, on the other. While the study stresses the attractiveness of the economic and financial gains from better forecasting, it also underscores the difficulty of achieving them.

The study supports the conclusion that, in spite of the difficulties to be faced, a forecaster can make headway against predictive error. It demonstrates the use of many techniques that are available for this purpose in the time series category. The study also constitutes a clear warning to forecasters who would act as if there is some technique or mechanical way of turning in an accurate forecast: in fact, there is no such easy victory over the powerful forces always working to generate forecast error.

PREFACE

One of the interesting aspects of the energy crisis was the atrocious record of forecasting that accompanied it. During most of the seventies, billions of dollars were invested in energy projects based on wildly erroneous forecast of oil and other energy prices. The results of these poor energy forecasts have been tragic, especially in Latin America. The debt crisis is, in part, one result of this widespread bumbling in energy forecasting.

The present work should be read with this failure in mind. It is a case study exercise in short-term energy forecasting using time series techniques. This is a difficult and technically complex area, but one capable of generating big gains in forecast accuracy at low cost. It is, therefore, of interest to energy managers.

This study will be followed by another which will compare time series models with structural and mixed econometric models as energy forecast vehicles over different time horizons. Together, these studies are seen by ECLAC as a contribution to improved energy forecasting in Latin America.

The study is presented in simple language which, despite the technical difficulty of the subject matter, hopefully will make for easy reading. To achieve this, mathematical treatment has been kept to a minimum. Emphasis is on straightforward exposition of the basic concepts of time series forecasting and on their use in specific cases.

Exposition posed a problem. Although the study is addressed to energy forecasters in Latin America, the degree of technical preparation of individuals in this group obviously varies widely. Additionally, the methodological scope of this study is broad. It includes seven distinct time series forecast methods, ranging in complexity from the mathematically simple technique of, say, classical decomposition to methods using sophisticated mathematical routines: for example, Harrison's harmonic smoothing employs Fourier analysis, and the ARIMA method uses the maximum likelihood method for calculating parameter values.

The problem posed for exposition, therefore, is in what degree of detail should each of these seven time series methods be explained in the text. Full explanation of each method would mean writing a textbook. This option was rejected as unrealistic. At the other extreme, the complete absence of explanation would mean that many readers, inexperienced in statistical methods, would be unable to follow even the thread of the forecasting argument developed in the study.

An option was chosen between these two extremes, and it will undoubtedly be a frustrating one for many readers. It was decided to give a thumbnail sketch of each method, referring the reader to two texts which explain, in lucid detail, each of the seven methods used in the study [1, 2]. The second book cited is also the guide for using the Sibyl-Runner time series program [3]. A glossary is included at the end of the study.

Even the interested reader without a statistical background should understand the essentials of the overall approach to time series forecasting laid out here. However, if he wants to employ any of these methods in his own work, there is no alternative to the study of the materials discussed in the two basic references, at a minimum. In this regard, this analysis is intended to bring time series forecasting methods to the greater awareness of energy forecasters in Latin America, not of producing trained forecasters.

INTRODUCTION

Objective

This study is directed to energy forecasters in Latin America, a group under continuous pressure to forecast a host of variables over diverse time spans, typically with inadequate statistical information. The objective of the study is to help these forecasters improve their short-term energy predictions through increased familiarity with time series forecast methods.

The study is an exercise in the application of time series methods to short-term energy forecasting, that is, for periods up to a year. Five Chilean energy variables are selected for forecasting: the apparent consumption of household kerosene, diesel oil, and low octane (81-grade) motorgasoline; and gross electricity production and peak electric power demand in Chile's interconnected power system.

From the many time series forecast methods potentially available, seven are selected as candidate predictive vehicles for each one of the five Chilean energy variables. These seven methods are: exponential and harmonic smoothing; classical and Census decomposition; time series multiple regression; and two univariate autoregressive/moving average (ARIMA) techniques: sequential generalized adaptive filtering and the Box-Jenkins method.

For each of the five Chilean energy variables, one of these seven time series methods is used to generate an *ex post* forecast for 1983. Then, the accuracy of each of these five forecasts is compared with the accuracy of two naive models and with a one-equation structural regression model. A composite forecast approach is also discussed.

While this study presents five *ex post* forecasts, this is not its objective. There is no profit to be made in forecasting the value of energy variables for past periods. The five forecasts are developed strictly for a didactive purpose, that is, for making more intelligible to the reader the various tasks involved in time series forecasting.

Computational Support

Two computer programs were used in the study: the Sibyl-Runner time series forecast program for personal computers and the SAS time series program [3,4]. The Sibyl-Runner program set the limit on the maximum number of monthly observations that could be handled: 144. In the case of one variable, the apparent consumption of diesel oil, only 84 consecutive observations were available. However, for each of the five energy variables, the number of observations used is sufficient to support the statistical generalizations tabled in the study.

The SAS program was used to generate the ARIMA models evaluated in the experimentation. Sibyl-Runner was used to generate the forecasts based on the smoothing, decomposition, time series multiple regression, and sequential generalized adaptive filtering models. Special programs were also written to deal with particular statistical problems.

An IBM 4341 was used to process the SAS program. An IBM PC/XT was used to process the Sybil-Runner program and a Digital PDP-11 was used to process the other, specially written, programs.

Organization

The study is developed around three key questions:

First, why should any effort at all be spent on applying sophisticated time series or any other formal methods for predicting the five energy variables under study? Why not use a technically naive and low-cost forecast routine for this purpose, say, for example, predicting the value of a variable in one period as a function of its value in the immediately prior period?

Second, why not use a little less naive predictive model, such as taking last period's seasonally adjusted value as the predictor of this period's seasonally adjusted value and deseasonalizing the latter to derive the forecast value? In other words, wouldn't it be better to limit the investment in improving forecast accuracy just to making a seasonal forecast, stopping short of investing in more complex and costly forecast methods?

Third, what is the best forecast that one could reasonably hope for in the case of each of the five energy variables? And, is the increase in the accuracy of that 'optimum' forecast, over that of a naive model, worth the effort of making it? In other words, is the apparently best forecast possible really worth making?

The study is organized in the following way. Chapter I provides a brief description of the three classes of forecasting models: time series, structural, and mixed models. The statistical characteristics of the five Chilean energy time series used in this study are identified. The implications of these characteristics for choosing a time series forecast model for each of them are discussed. The three questions raised above about forecast accuracy are treated initially at this point. The scope for improving forecast accuracy is assessed for each variable.

Chapter II begins with a brief description of time series forecast methods in general. The essentials of each of the seven candidate time series methods used in this study are then described.

Chapter III presents the experimentation. It begins with a statement of the statistical screening criteria used to evaluate the numerous candidate forecast equations generated in the experimentation. The results of the experimentation are presented.

Five forecast equations are selected, and used to make twelve monthly *ex post* forecasts for 1983. The accuracy of each of these forecasts is compared with the accuracy of forecasts made using two naive models and a simple structural equation. A composite forecast approach is evaluated. The predictive accuracy of these time series forecasts methods is compared with that of an optimum forecast model.

Chapter IV returns to the three questions initially posed about forecast accuracy, but with the results of the experimentation now in hand.

The study ends with a summary of its key conclusions.

Choice of Chilean Energy Data

Initially, data were collected on a diversity of energy variables for several countries in the region. For three reasons, it was decided to use the Chilean energy variables as the basis of the study:

first, the Chilean data were available in sufficient quantity to support the research; second, the Chilean data are apparently of high reliability; and, third, if they were to arise, questions about the data for Chile could be resolved relatively easily since all the research would be undertaken in Santiago, Chile.

The selection of Chilean data means, of course, that the empirical findings of the study will be Chile-specific. Nevertheless, the techniques used in the study are generally applicable to all energy forecasters. The usefulness of this study is really rooted in this latter point.

CHAPTER I

FORECASTS: APPROACHES AND ACCURACY

A. Forecast Approaches

1. The Array

Techniques for predicting economic and business variables fall into one of two groups: qualitative or quantitative.

Qualitative techniques depart from expert opinion, processed in more or less quantitative ways, to arrive at a forecast. Qualitative forecasting techniques use either exploratory methods, such as the S-curve, which argue from past trends and the present situation to the future value of some variable; or normative methods, such as the Delphi method and scenario development, which work backward from some concept of an assumed future value of a variable to the implications for the value of that variable today. Obviously, these two methods have quantitative aspects. However, at root, they are subjective and, hence, qualitative.

Quantitative forecast models are either naive or formal. The naive model employs a simple arithmetic rule for forecasting. An example of a naive forecast routing is using today's actual value as the predictor of tomorrow's value. Naive forecast models do not employ formal, probabilistic reasoning. They table 'point', not stochastically bounded, forecasts and, so, are widely criticized. In general, naive quantitative methods are declining in popularity among forecasters because they are often outperformed by formal, quantitative predictive routines, especially those incorporating stochastic processes.

Formal forecast methods use rigorous statistical concepts and procedures for generating and evaluating a predictive model. They incorporate stochastic processes, and so, for planning purposes, their forecasts are more useful than the point forecasts of naive models.

There are three types of formal, quantitative predictive models: first, the structural (or casual) model, as exemplified in the one-equation and multiple equation regression models; second, time series models, which include smoothing, decomposition, time series multiple regression, and ARIMA models; and third, mixed models, such as the multivariate ARIMA models, which combine the structural and time series approaches to forecasting. This study focuses on the use of time series models for short-term forecasting of energy variables.

2. Structural Models

Some comments are in order at this point on structural, time series, and mixed models. The structural model departs from a theory of the basic causes producing change in the variable to be forecast, the dependent variable. For example, growth in motorgasoline consumption might be taken as a function of several independent, or casual, variables, such as the stock of automobiles, the relative price of motorgasoline, and real family income. A single equation could be used to specify the causal forces at work. Economists often forecast demand using such single equations, preferring simplicity at the cost of reduced forecast accuracy. More defensible in this case, however, would be an elaborate model of the forces promoting motorgasoline consumption, owing to the complexity of the underlying causal processes and the inability of a one-equation model to deal adequately with them.

Whichever the approach, however, the dependent and independent variables are scaled and fitted to a function selected by the forecaster. If the causal specification is perfect, the data are error-free, and the fitting method without bias, then the difference between any observation and its value on the fitted trend line will be a residual error that reports the impact of random, or stochastic, processes. In this case, the forecast error has been reduced to the minimum level as given by the random process, or chance. That error is unavoidable. It is not forecastable.

In generating the structural forecast equation, only past values of the dependent and independent variables are required. The equation is potentially useful for policy evaluation and decision-making in general. However, to forecast using that equation, the forecaster must predict the value of each independent variable once for each forecast period. So, using a structural model to predict places the burden of the forecaster's ignorance on the independent variables. He must predict each of those variables to forecast.

For example, the forecaster could use the same one-equation structural model referred to earlier with four independent variables. To predict motorgasoline consumption using this equation, he would have to predict the value of those four independent variables, one prediction for each of the four variables and once for each forecast period. So, a forecaster might reject a structural model in this case as his forecast tool on the grounds that he is not confident of his ability to predict the values of these independent variables. He might prefer to predict motorgasoline consumption head-on or to find another forecast method that did not force him to predict a string of independent variables. Time series models offer precisely this option.

The structural regression model is often used for policy analysis. For example, if the central government is considering a tax on electric power consumption, a structural model could be used to estimate the probable impacts of the tax on real output, employment, domestic savings, investment, and the distribution of income. In this case, forecasting is not the purpose of the model. An elaborate econometric model containing many equations would be specified, and a fitting method would be selected to determine each of the parameters of the structural policy model. In this case, the purpose is to facilitate policy analysis and decision-making. The structural model can, in fact, be a powerful forecasting device when the prior, theoretical knowledge bearing on economic causation is strong, and, of course, when the required data are available and trustworthy and the fitting method is sound. By way of comparison, a time series model would be inapplicable for assessing these kinds of complex economic impacts.

3. Time Series Models

Time series models are constructed for forecasting, not policy analysis. The only variable used in this case is the variable to be forecasted. There are no causal variables in the time series approach to forecasting.

In time series methods, only the target variable and time are involved. The time series model has no explicit logical content beyond its mathematics. Therefore, it is inapplicable for exercises in economic or business policy evaluation. The time series model is oriented exclusively to forecasting. It is completely mechanical. Its greatest failing is that it provides no insight whatsoever as to why the forecast values might emerge. In the time series approach, the whole system generating changes in the target variable is treated as a black box. In the structural model, the way in which the dependent and the independent variables interact is treated as the black box.

Both the time series and the structural approaches to forecasting are threatened by improper specification of a model and by the use of an incorrect fitting technique. Both approaches are weakened by inaccurate data and by the invalidation of the assumption underlying all mechanically generated forecasts: that past patterns of change in the data will repeat during the forecast period.

The structural model suffers from two defects that time series models avoid. First, it is difficult to specify a structural model well in theoretical terms and to have that model remain well specified over time. In a sense, time series implicitly capture in their trend, cycle, and seasonal components many of the forces explicitly specified in the form of the causal economic variables in the structural model. Second, structural models often pose severe data problems, since every variable specified must be scaled and all variables included in the structural model must be scaled for the same period. The resulting information requirement is often prohibitive.

Time series models do not suffer as seriously as structural models do on these two counts. With the possible exceptions of the Box-Jenkins and generalized adaptive filtering methods, model specification is not a serious problem in time series forecasting, and, even in these two cases, as will be discussed shortly, the problem of specification is one related to statistical theory, not economic theory. When the prior knowledge required to specify a structural model is absent, time series models become all the more attractive for short-term forecasting. Data requirements are often less restrictive with time series models than with causal models. From both points of view, time series models are potentially attractive forecasting tools, particularly for Latin American energy forecasters working on short-run forecasting problems with data are often very limited in quantity and of questionable worth. These two advantages are won at a cost, however, since time series models are limited to forecasting applications and they are inapplicable for policy evaluation.

4. Mixed Models

Mixed models combine the causal and time series approaches to forecasting. Two kinds of mixed models are in widespread use today: MARMA models and joint causal/ARIMA regression models.1/

Multivariate autoregressive/moving average (MARMA) models combine the causal and time series approaches to forecasting by using aspects of both the univariate time series and multiple regression techniques. The idea of MARMA models is to specify quantitatively the relationship between a dependent variable and one or more causally related and negatively lagged independent variables. Changes in these independent variables will precede, or lead, changes in the dependent variable. Once these variables and their lead relationships have been determined, they can be used to forecast changes in the dependent variable. For example, changes in the price of motorgasoline and in real family income in immediately prior periods could be used to predict the volume of motorgasoline consumption in the current period. Or, changes in the money supply in prior periods, operating via total real output in the present period, might be used to predict change in an energy variable in the current period. By choosing independent variables that lead changes in the dependent variable, the forecaster using a MARMA model avoids the need to predict the value of independent variables to derive his forecast. He already knows the past values of these independent variables. To predict, he merely needs to insert them into his MARMA model. This makes MARMA models widely attractive as candidate forecast vehicles.

The MARMA approach is a class of predictive routines that includes bivariate and multivariate MARMA models, intervention analysis, and Kalman filters. Generally speaking, MARMA models are of recent origin, technically complex, and costly to use. Moreover, they are not necessarily superior to either the simpler and less costly time series models or to structural models.

Joint causal/ARIMA models combine aspects of the structural and time series approaches to forecasting. In this mixed approach, a dependent variable, say, motorgasoline consumption, is first taken as a function of certain independent variables, say, the stock of automobiles and the relative price of motorgasoline. In this stage of model specification, it is known that other important variables, such as real family income, for example, are being omitted from the specification. For this reason, it is also known that the residual values of the equation corresponding to this stage in the approach will include a systematic error. Nevertheless, the equation is generated, and its residuals are calculated. Then, the critical assumption is made that these residuals are generated by a specific ARIMA process. Given the ARIMA model generating these residuals, the final forecast equation is constructed. It contains the structural component, with its independent variables, the ARIMA component, and the now normally distributed residuals, free of all pattern.

MARMA models and joint casual/ARIMA models will not be examined in this forecast exercise. Here, the focus is on the use of univariate time series techniques for forecasting.

B. Forecast Accuracy

1. The Five Time Series: Basic Patterns

The original monthly values of the five Chilean energy variables are presented and plotted in Exhibit 1. Appendix A presents the data in tabular form. The natural logarithms of these values are plotted in Exhibit 2. The five variables are: the apparent consumption of household kerosene, 81-grade motorgasoline, 2/ and diesel oil; and gross electricity generation and peak electricity demand in Chile's interconnected grid system.

A comparison of the pattern of change in these five variables is revealing. There is no evidence of a business cycle impact in any of them. However, seasonality is strongly evident in each, although its degree varies widely. The two electric power variables show a steadily repeating pattern of seasonal change of twelve month periodicity with a positive, relatively mild and steady trend. The diesel oil series is marked by a repeating and disordered pattern of twelve-month seasonality and by a mild and positive trend. The kerosene time series has a strong seasonal pattern and a weak negative trend. The 81-grade motorgasoline variable shows a progressive disintegration, with a fading seasonal component and a negative trend.

Exhibit 2 shows how the five variables have fluctuated in percentage terms over their sample periods. In the case of the two electric power variables, percentage changes appear stronger in more recent periods while they appear stronger in earlier periods in the case of the three refined oil products. Thus, a pattern of inequality of variance, or heteroskedasticity is suggested. The importance of heteroskedasticity and the need to test for its presence in forecast equations will be discussed later.

The data presented in Exhibits 1 and 2 are monthly observations. Exhibit 3 presents the annual values of each of the five time series. Summing has removed seasonality and, so, much of the volatility from each time series. The two electric power series show a clear and steady upward trend while the trends in the three refined oil product variables are more complex and less consistent over time.

There are not any extreme, or outlier, observations in any of the five time series. This is statistically important since the presence of extreme values complicates the technical task of parameter estimation.

All in all, the statistical diversity of these five Chilean energy variables makes them interesting as a set of cases for forecasting work.

2. Components of Change

What are the factors that have promoted change in the five energy variables over their sample periods, and how strongly have each of these factors operated? The figures in Exhibit 4 show the result of decomposing each time series into its seasonal, trend, cycle, and residual components using Sibyl-Runner's CENSUS time series decomposition routine. These data underscore the dominance of seasonality and the residual component in promoting change in each of the five Chilean energy variables during their sample periods. The data also report the virtual absence of the trend and cycle components as promoters of change in these five variables during that period. In the case of kerosene and the two electric power series, seasonality was the major component of change. In the case of the two road transport fuels, motorgasoline and diesel oil, seasonality was strong while trend and cycle were relatively weak with the residual component being, by far, the dominant source of change. In fact, in all five cases, the shares of the residual and seasonal components' contribution to change were very high.

What lies behind the high share of the residual in each of these five energy variables? What is its significance for forecasting?

The residual measures the contribution to change in each variable over its sample period that is not captured empirically in the estimations of the contributions of the seasonal, trend, and cycle components. Thus, it picks up the error in the empirical measurement of the seasonal, trend, and cycle factors. Additionally, the residual picks up random errors, the effect of errors in data reporting, and the net impact of all factors not contained in the trend, cycle, and seasonal measurements.

Of these several factors, the error made in estimating the seasonal component is probably small. Estimating a seasonal component is a simple and generally reliable undertaking. Significant errors are more likely when estimating trend and the cycle components. In the decomposition routine used to derive the residual values, the trend was taken as a simple linear function ($y=a+bx$). Obviously, this assumption is simplistic and generates some error. Undoubtedly, the cycle component also contains error. It was derived by subtracting the estimated trend values from the smoothed series. This smoothed series was presumed to contain only trend and cycle values when, in fact, this is not the case. There is considerable error in these estimates of the trend and cycle components.

Data errors probably make a minor contribution to residual error in all five energy variables. This is another way of saying that the original data on the five time series are probably fairly accurate, but it not possible to confirm this. Also, it is unlikely that random errors explain these large residuals. It is inconceivable that the explanation for the large residuals in all five energy variables lies in the random error, for if this were true in the case of diesel oil (72%) and motorgasoline (61%), for example, it would imply that an outlandish process would be generating consumer demand for these fuels.

These comments suggest the obvious: in order to explain the high share of the residual in all five energy variables, it is necessary to introduce economic reasoning, not just time series considerations. Total real output in the Chilean economy increased by only 0.8% on the average during 1971-1982. 3/ This is a pivotal point since increases in the volume of production are a prime force behind increases in energy consumption. The other two factors at work here were, on the one hand, the sharp rise in real domestic energy prices that occurred in Chile during the sample period owing to increased world energy prices; and, on the other hand, the falling domestic fuel subsidies that were being recorded during the sample period as a result of profound changes in economic policy favoring free market practices in general and in energy markets in particular. These three factors levelled the trend component and compressed the cycle component over the sample period, increasing the share of the residual to high levels. In this vein, the two fuels with the highest residual components, diesel oil (72%) and motorgasoline (61%), not only had small trend and cycle components but also little seasonal volatility (Exhibit 4).

The implication of this analysis is clear. Time series forecasting of each of these five variables requires that the trend and cycle components continue to be of the minor consequence over the forecast period that they were over the sample period. If either the trend or the cycle component is expected to change markedly over the forecast period, then using a forecast equation based on earlier data will generate highly erroneous forecasts. This is an important consideration for forecasting each of these five energy variables.

3. <u>Scope for Improved Accuracy</u>

What accuracy might one expect in predicting these five energy variables? How much improvement in forecast accuracy is possible beyond the level that is easily achieved using a naive model? How much effort should one spend to acquire that improvement in forecast accuracy?

Exhibit 5 presents data that are helpful in approaching these questions. Column 1 shows the mean absolute monthly percentage change in each variable over its observation period. These data report the degree of volatility in these variables. NF 1 and NF 2 are naive forecasting models. Each uses last month's value to predict this month's value. The difference is that NF 1 uses the original data to do this while NF 2 uses a deseasonalized series. More specifically, in NF 2 a deseasonalized series for each variable is first calculated by smoothing the original data. Smoothing eliminates seasonality and randomness, leaving, in theory, only the trend and cycle components. This deseasonalized series is used to derive a normalized seasonal index. That index is used to deseasonalize the original data. These deseasonalized values are used to predict the deseasonalized forecast values. Finally, the deseasonalized values are seasonalized and compared with actual values to derive the average error of the NF 2 method.

The figures in columns 2 and 3 of Exhibit 4 are the mean absolute monthly percentage errors (MAPE) of NF 1 and NF 2. In the Exhibit, OF means the optimum forecast, or the error of what will be taken to be a commendable forecast effort. It serves as a referent for the best forecast realistically possible. OF is measured as the MAPE of the residual component of the CENSUS time series method as calculated by the Sibyl-Runner program. It is taken as a proxy for the error that is unavoidable and, therefore, it is used as the measure of the floor to forecast error. Using the MAPE of the residual error in this way implies, of course, that the decomposition technique generating that residual error is an accurate estimator of the known past. This is obviously not the case, so there is undoubtedly some error involved in its use in this way. Arithmetically, of course, a specific forecast could have a MAPE below the OF of the predicted variable. The interpretation of this event would be that the forecast was even better than the reference level for a good forecast. In short, while the conceptual basis of the OF measure, as treated here, is theoretically weak, hopefully it will be practically useful as an empirical gauge of what is a good forecast.

If an NF 1 model were used to forecast each variable, one would expect the average forecast error reported in column 2 (Exhibit 4). In this approach, yesterday's value is used to predict today's. Using NF 1 as a forecast vehicle is a minimum effort exercise, low cost, rapid, and easy, but weak from the point of view of statistical theory. It generates a point forecast, which is bound to be wrong in the specific case. While the lack of a stochastic component severely limits the usefulness of NF 1 as a predictive vehicle, it can be profitably employed, nevertheless, as a referent for gauging the degree of improvement in forecast accuracy achieved by other statistically more rigorous forecast techniques over and above the level achieved by this naive predictive routine. This will be its purpose in this study.

As just explained, NF 2 links a seasonal forecast to the predictive mechanics of NF 1. Thus, NF 2 reduces forecast error below that of NF 1 by making a seasonal forecast, but nothing more.

The gains from making a seasonal forecast can be substantial, even when tied to the predictive mechanics of such a simple technique as NF 1. As shown in Exhibit 5, just by making a seasonal forecast, predictive error was reduced by 72% and 60% with the two electric power series and by 64% with kerosene during their sample periods. These big gains in forecast accuracy stem from the fact that, as the data in Exhibit 5 show, the contribution of seasonality to changes in these three variables is high. By way of comparison, making a seasonal forecast reduces forecast error by 43% and 37% for diesel oil and motorgasoline, fuels the demands for which, while highly seasonal, were less so than in the cases of kerosene and the two electricity variables. For all five fuels, however, the error reduction from making a seasonal forecast is obviously worth securing, given the low cost and ease of making one.

How much more improvement in forecast accuracy is available beyond the levels shown for NF 2 in column 3 of Exhibit 5? The figures in column 4 suggest an answer. They are the MAPE of the residual errors for each of the five energy variables. As discussed earlier, the residual reports the forecast error that, it is being assumed here, will unavoidably confront the forecaster, on the average, over his forecast horizon.

A comparison of the figures in columns 2 and 4 reveals the potential improvement in forecast accuracy by switching from NF 1 method to a formal forecast method. The potential gain is impressive in the case of the 30 percentage point MAPE reduction for kerosene. The gain is in the 4-5 percentage point range for the other four energy variables.

In shifting from NF 2 to a formal predictive model (columns 3-4, Exhibit 5), the gains are less, but still attractive. They are less because NF 2 has already secured a big share of the total potential error reduction just by making a seasonal forecast. The gains remaining are still attractive, however, since the residual errors (column 5) are relatively high even after NF 2's seasonal forecast has been made; that is, potential forecast error is still high enough for a prudent investor in an energy company to consider risking resources to reduce it further by good forecasting.

By way of summary:

First, NF 1 is a weak forecast vehicle, not only conceptually and statistically, but also in terms of the forecast accuracy it promises. The method generates high forecast error. In the case of all five energy variables, the MAPE of a forecast using NF 1 is close to the average rate of change in the series itself. Thus, NF 1 has little forecast power.

Second, a seasonal forecast reduces MAPE sharply. In fact, shifting from NF 1 to NF 2 achieves a high fraction of the total improvement possible in forecast accuracy. This is because seasonality is an important determinant of change in each variable. Nevertheless, forecast error might be reduced further by switching from NF 2 to a formal predictive method, such as a formal time series technique.

Third, forecast error is directly related to both the volatility of the series and the share of the residual. Thus, as one would expect, higher volatility in a time series implies higher minimum forecast error, and the higher the forecaster's ignorance about what drives a variable, the greater is his error in predicting it. Using the MAPE as a measure of the minimum possible forecast error, one would expect the lowest forecast errors to be with the two electric power series and diesel oil, higher with gasoline, and the highest with kerosene.

Fourth, a formal quantitative forecast technique that incorporates a seasonal forecast routine might deliver not only accurate forecasts but relatively more useful ones as well. By using stochastic processes, a formal forecast method makes it possible to assess the variability inherent in the forecast, an advantage not available with naive forecast routines. In fact, one might well prefer a formal forecast method over a possibly more accurate informal method just to have this advantage. For planning purposes, it is highly valuable.

4. The Goal of Improved Forecast Accuracy

The previous discussion focused on forecast error. The objective of forecasting was taken to be maximum predictive accuracy for given levels of cost, timeliness, and technical difficulty. That objective was relevant in evaluating two naive forecast methods and for assessing the desirability of shifting from a naive to a formal forecast method.

However, is it always worth the effort to improve forecast accuracy? Is, say, another one percentage point gain in forecast accuracy always a worthwhile target? At what point does the quest for improvement in forecast accuracy become meaningless or contra-productive?

These questions focus the forecast effort. In energy companies, the uses of the short-term sales forecast are like those of any other manufacturing enterprise. With regard to production, it is the foundation for many actions: purchasing materials and transport services in spot and term markets, ordering equipment, scheduling production, anticipating spare parts and maintenance requirements, contracting sales force, and inventory planning. In terms of financial considerations, the short-term sales forecast is critical in managing short-term assets and liabilities: anticipating accounts receivable and payable, financing planned inventory changes, planning for short-term bank financing, or for placing surplus cash at loan. The key use of short-term forecasts is to help assure that product demand can, in fact, be satisfied from planned facilities and inventories.

A poor short-term sales forecast will have many consequences for an energy company, but certainly one of them will be unanticipated changes in its inventory. The cost of over-forecasting sales in the short-run is to make unnecessary investments in inventory and expenses for its maintenance that could have been used more profitably elsewhere. Under-forecasting sales means unanticipated inventory reduction and, possibly, lost sales.

The gains to the private energy company from better short-term forecasting depends on a host of factors including the previously prevailing record of average error in the company's forecasting efforts and the scale of the investment required to improve forecast accuracy. A company with a highly accurate forecasting record stands to gain less from an increment in better forecasting than one with an historically poor record of forecast accuracy. In this context, it is important to note that the time series techniques being reviewed in this study all involve small investments, and each potentially can deliver big gains in forecast accuracy.

What can one say about the economic value of reducing forecast error? For illustrative purposes, what would be the economic value, say, of reducing oil inventories in the Chilean economy by just one percent?

The Chilean economy consumed about 1,500 million gallons of refined oil products in 1986. Oil inventories were held in three forms in support of that consumption: in crude oil, both in-transit on the sea and stored in oil tanks on land, and in the form of semi-refined and refined oil products. Assume that, on average, the Chilean oil industry targets for an oil inventory, in all three forms, an amount equal to three months consumption of refined oil products: one-third in the form of crude oil at sea, one-third crude oil on land, and one-third in semi-refined and refined oil products. 4/

The cost of this inventory is the sum of out-of-pocket expenses of generating and maintaining it plus the interest lost on the capital locked up in it. Taking crude oil (CIF, Chilean refinery) at, say, US$17/barrel, or US$.40/gal., of refined product, this would mean a weighted average lock-up roughly US$.50 per gallon of inventory. 5/ This estimate of US$.50 per gallon implies an investment in oil inventory nationally of about US$188 million at that level of sales (1.5 bn. gals x 3/12 mos x US$.50/gal). If better sales forecasting could reduce average national oil inventory levels by one percent, this would mean an average reduction in oil inventory nationally of about US$1.9 million (US$188 million x .01). If sustained, the economy would record a similar saving each year, changing in proportion to sales.

It is impossible to make a detailed estimate of the costs of achieving this level of improved forecast accuracy for refined oil product consumption in the Chilean economy and for specific companies in it. In order to make some headway, however, assume that none of these companies had previously invested in computer facilities for energy forecasting; that, in effect, naive forecasting methods are being used with relatively low accuracy (this is surely not the case, and it is assumed here for illustrative purposes only). Assume further that, for the economy as a whole, twenty oil forecasting units would each require one microcomputer which, together with the required software, would cost US$20,000 each to equip, excluding taxes. Assume that this investment cost of US$400,000 (20xUS$20,000) is repeated ten years later. Also, assume that each of these twenty forecast units would include a skilled forecaster, two assistants, and a secretary, the cost of which, including all associated marginal costs, would run about US$25,000 per team, or US$500,000 (20xUS$25,000) in total. Double this estimate of US$500,000 to cover overhead and all other costs. Then, the cost of the forecast exercise nationally would be about US$1 million per year, excluding taxes.

Now, given this profile of expected costs and the estimated annual savings from improved forecasting nationally of US$1.9 million, the internal economic rate of return on the forecasting investment would be about 200%; and, using a 20% discount rate, the present value of savings over costs would be about US$4 million over a twenty year project life. These savings can be invested in a wide variety of projects. Compare the scale of these savings to the investment required for a basic rural hospital in Chile today, say, about US$100,000-$200,000; or to the annual cost of a rural teacher, about US$2,000-$3,000; or to the investment required to produce a basic urban low-cost house with infrastructure in Santiago, say, in the range of US$6,000. Clearly, the social gains from better energy forecasting are potentially very attractive.

For the private corporation, the gains while less, would still be high. To the figures above, add 15% for import duties on the two-time investment in imported computer equipment (excluding IVA which, while a real expense, is quickly recovered). Assume a three-year write-off on the computer investment and an average corporate profit tax rate of 20%. For the twenty companies assumed to be investing to achieve the one-percent reduction in oil inventories, the internal rate of return on their collective investment would be about 150%, and the net present value of savings over costs would be about $3 million. The payback period on the original investment would be about three weeks. Recall that this gain is captured by realizing a sustained reduction in the permanent component of oil inventories by better short-term sales forecasting. This one percent reduction in average inventory levels implies an improvement in accuracy in short-term oil forecasting nationally of only one-quarter of one percent (.01x.25) of sales. Obviously, managers of energy companies can set goals higher than this modest one, used here for strictly illustrative purposes. In any event, the prospectively high yields, both economically and financially, on investments in improved energy forecasting are powerful forces working to promote them.

Consulting the figures in Exhibit 3 on motorgasoline, kerosene, and diesel oil, which, typically account for about one-half of Chile's refined oil consumption, the room for forecast improvement (Exhibit 5, column 6) using formal predictive techniques is indeed substantial. Clearly, improved forecasting is potentially a lucrative field for investment for the economy's energy companies. While investments in improved forecasting methods is an attractive idea to contemplate, this study will also show that the gains of improved energy forecasting are, in fact, not easily achieved.

C. Summary

Forecasts using naive models are generated easily, rapidly, and at low cost. They may be accurate. Increasingly they are being abandoned for the formal forecast models [1]. Whatever their accuracy in a specific case, however, naive forecast models lack the statistical rigor of the formal forecasting models: time series, structural models, and mixed models. The accuracy of the naive forecast model does provide a useful bench-mark for gauging the accuracy of formal forecast methods and, then, for assessing the advisability of investing in these more sophisticated forecast techniques.

The gains in forecast accuracy from making a seasonal forecast alone are significant for every one of the five Chilean energy variables under study. In each case, the seasonal forecast will probably capture a large share of the full potential for improvement in forecast accuracy. Formal forecast methods might improve forecast accuracy even further, above and beyond the level easily attainable by using informal predictive routines. Formal predictive routines are also desirable for planning purposes because of their stochastic properties.

The savings from improved energy forecasting can be substantial. The costs of achieving them using time series techniques are typically low, making the investment in improved forecast accuracy an interesting prospect for individual energy companies and for the economy as a whole.

CHAPTER II
Time Series Forecast Methods

1. Introduction

This chapter has two purposes: first, to indicate the principal features of the key time series forecast techniques in use today; and, second, to explain the basic mechanics of the seven methods that will be used in this study as candidates for predicting each of the five Chilean energy variables.

2. Stationarity and Seasonality

There are four classes of time series forecast methods: smoothing, decomposition, time series multiple regression, and ARIMA methods. Each one, in turn, includes a number of variant routines, so that the full range of time series forecast vehicles is indeed substantial.

Many of these time series techniques cannot deal adequately with two characteristics evident in almost all energy time series: seasonality and trend. Thus, from the set of time series forecasting techniques potentially available, it is necessary to reject as candidate forecast methods those that cannot manage either a trend or a seasonality component, or both. This reduces considerably the number of potentially usable time series forecast routines.

An example will help explain this point. The mean is a time series forecast vehicle in the smoothing category. However, the mean will not be a good predictor of a variable with a trend or a seasonality component. It will perform well as a time series forecast method only if the observations on the variable are stationary and randomly distributed; that is, only if the observations track out randomly along the variable's time axis. Using the mean as a predictor of a series with a trend will generate a systematic forecast error, either positive or negative, depending on the trend. The error will also gyrate with changes in the seasonal component. This pattern of error would be the result of having used a forecast model the requirements of which are not satisfied by the data. Therefore, those time series predictive routines that cannot manage either a trend or a seasonal component, or both, must be rejected as candidate predictors of the five Chilean energy variables under study.

3. Smoothing Methods

There are many smoothing methods. Simple smoothing methods generate forecasts by adding a percentage of previous forecasts errors to a percentage of previous forecast values. Exponential smoothing methods are different. They assign exponentially decreasing weights not to past forecast errors but, rather, to past forecast values. Both approaches, however, require stationary and non-seasonal data to be effective forecast routines.

Simple averages and moving averages, single exponential smoothing, and adaptive-response rate single exponential smoothing are smoothing methods that cannot handle either a trend or a seasonality component. These methods require stationary data to be accurate predictors. So, they are not viable forecast candidates for present purposes [1,2].

Other smoothing methods can manage a linear trend but not a seasonal component and, so, they also are not defensible forecast routines for present purposes. These methods include linear moving averages, linear exponential smoothing, Brown's one-parameter adaptive method, Brown' one-parameter linear exponential smoothing method, Chow's adaptive control method, and the Box-Jenkins three parameter smoothing method [1,2].

Winter's linear and seasonal exponential smoothing method and Harrison's harmonic smoothing method are smoothing routines that can manage data containing both a trend and a seasonality component. They are, therefore, valid forecast vehicles for each of the five energy variables under consideration [1,2].

Winter's linear and seasonal exponential smoothing method smoothes, or weights, past observations in an exponentially decreasing manner [1,2]. It uses three equations for describing past data and a fourth equation for forecasting. The first three equations require the solution of three parameter values: the alpha parameter, which smoothes for randomness; the beta parameter, which smoothes for seasonality; and the gamma parameter, which smoothes for trend. In effect, these three parameters cover the three parts of the pattern that are being treated in Winter's method: the stationary, linear, and seasonal parts. Given the value of these three parameters, the fourth equation is used to forecast. The Sybil-Runner program solves for the values of the alpha, beta, and gamma parameters using a trial and error method that minimizes the mean square error of the forecast equation. It also generates a forecast.

Harrison's harmonic smoothing method rests on the assumption that a time series is a multiplicative combination of trend, cycle, seasonal, and random terms [1,2]. The method first removes the trend-cycle term and derives a rough seasonal index. Then, Fourier analysis is used to smooth the estimated seasonal and trend-cycle terms. Extreme observations are removed. A refined seasonal index is generated. This index is used for forecasting in conjunction with the estimated value of the trend-cycle component. The Sibyl-Runner program generates a forecast equation using Harrison's harmonic smoothing method and then forecasts using that equation.

4. Decomposition Methods

Decomposition methods decompose the time series into its fundamental components: trend, cycle, seasonality, and randomness. The first three components comprise the pattern. Each is identified and then forecasted. These three individually forecasted components are summed to derive the overall forecast. It is impossible to forecast the random component, approximated period by period as the difference between the original data and the sum of the fitted, or estimated, trend, cycle, and seasonal components. In decomposition, any errors in the data or made in estimating the seasonal, cyclical, and trend components will turn up in the residual component.

There are two major decomposition techniques in use today: the ratio-to-moving average, or classical, decomposition method and the Census method [1,2]. Both techniques usually are employed in a multiplicative model, so that a change in any one of the three components impacts the target variable through the other two factors, which also will be changing.

The classical and the Census techniques are arithmetically similar in construction. The Census technique has evolved over time and is now highly sophisticated in its procedures and outputs. The classical decomposition method is simpler. However, both methods are ad hoc and pragmatic, and they are both widely criticized for their lack of theoretical rigor. Both the classical and Census methods will be used as candidate predictors of the five Chilean energy variables. Sibyl-Runner provides the software for forecasting using these two decomposition methods.

5. Time-Series Multiple Regression

The time series multiple regression model is another approach to forecasting in the time series category. Basically, this approach assumes that time (i.e., a time-trend variable) and seasonality (i.e., the month of the year) are the two factors that produce change in the dependent variable. The difference between the time series multiple regression model and the one-equation structural multiple regression equation is that the former inputs a time trend variable and seasonal observations (coded in dummy form), while the later inputs causal variables [1,2]. Time series multiple regression can manage a series with both trend and seasonality. The Sibyl-Runner time series program will be used for forecasting with this method.

6. ARIMA Models

This set of time series techniques includes the Box-Jenkins autoregressive/moving average method and generalized adaptive filtering (GAF) [1,2,5,6]. The power of ARIMA models derives from the mathematically proven assertion that any discrete time series can be expressed either as an autoregressive, moving average, or combined autoregressive/moving average model. So, forecasters try to find the ARIMA process that is generating a given time series, and, once found, they model that process to predict with it. Until recently, the complex mathematics of ARIMA models restricted their use. Now, the computer has eliminated this obstacle.

In the Box-Jenkins and GAF models, the forecast is generated as a function of either past values (X_i) of a time series, an AR process; or, as a function of past forecast errors (e_i) generated in prior predictions of that series, an MA process; or, as a function of both past values and past forecast errors, a joint ARIMA process. The Box-Jenkins and the GAF methods require stationary data. The expression for the general Box-Jenkins ARIMA (p, d, q) model operating on a stationary time series without a constant term is:

$$X_t=[\phi_1 X_{t-1}+\phi_2 X_{t-2}+\ldots+\phi_p X_{t-p}+e_t] - [\theta_1 e_{t-1}-\theta_2 e_{t-2}-\ldots-\theta_q e_{t-q}].$$

The first bracketed expression is the general Box Jenkins AR(p) model, and the second is the general Box-Jenkins MA(q) model. Both expressions together constitute the general Box-Jenkins ARIMA (p,d,q,) model. The term (X_t) indicates the original time series which is assumed to be stationary. The (e_i)-terms are the residual errors, calculated as the difference between an actual time-series value (X_i) and its corresponding value ($\hat{X}_i$) generated by fitting an AR(p) process to the data.

The general form of the GAF model is:

$$X_t=[\phi_{1t} X_{t-1}+\phi_{2t} X_{t-2}+\ldots+\phi_{pt} X_{t-p}+e_t]-[\theta_{1t} e_{t-1}-\theta_{2t} e_{t-2}-\ldots-\theta_{qt} e_{t-q}].$$

A comparison of the general form for the Box-Jenkins model and the generalized adaptive filtering model reveals the basic difference between them. In the Box-Jenkins approach, the parameters ϕ_i and θ_i are solved simultaneously using all the data. In the generalized adaptive filtering approach, the parameters ϕ_{it} and θ_{it} are solved using an iterative technique, a new set of parameter values emerging with each fresh observation. Hence, a subscript ($_t$) accompanies each parameter expression in the generalized adaptive filtering model, which is not so the case with the Box-Jenkins method because, in this case, the solution is simultaneous using all observations.

In both the Box-Jenkins and the generalized adaptive filtering methods, there is no a priori commitment to a parameter weighting scheme as in the case with smoothing techniques, for example. This imparts a flexibility to ARIMA models that is absent from other time series methods. For example, in moving average forecast models, past values of a time series that are included in the average are all weighted equally in a fixed way; in exponential smoothing, past values of a time series are weighted in an exponentially decreasing and fixed manner; and in a naive model, the last observation is given all the weight, with prior observations being ignored completely. In these three cases, a rigid scheme for generating parameter weights is strictly maintained, regardless of any changes in the pattern of the data. Approaches that assign parameter weights so inflexibly are typically not as accurate in their forecasting results as those that, like ARIMA models, assign parameter weights flexibly and in response to emerging patterns in the data. This flexibility is a clearly an important advantage in forecasting with ARIMA models.

In the Box-Jenkins approach, the forecaster must specify the order (p) of the AR(p) process, the order (q) of the MA(q) process, and the order (d) of the differencing of the data required to achieve stationarity. Given this information, the ARIMA model is written:

ARIMA (p,d,q).

Additionally, if the data are seasonal, as in the case with each of the five energy variables under study, a separate seasonal model must be specified when using the Box-Jenkins ARIMA method. Hence, the full specification of the Box Jenkins ARIMA model in this case is:

ARIMA (p,d,q) (P,D,Q).

where (P),(D),and (Q) indicate the parameters of the seasonal model. In the Box-Jenkins approach, the seasonal and non-seasonal components of the model are related multiplicatively.

In the Box-Jenkins methodology, there is a specific technique for identifying the orders (p),(q), and (d) and their seasonal counterparts. This process of identification requires the study of the autocorrelation and partial autocorrelation coefficients of the original data. Personal judgement is important in this exercise because the theoretical rules used to choose an ARIMA model are developed in terms of expected values of these coefficients while only the actual values of these coefficients are available and these contain randomness. Hence, it is possible that two trained forecasters could choose different ARIMA models after studying the same patterns of autocorrelation and partial autocorrelation coefficients. The subjectivity inherent in the choice of an ARIMA model is its main weakness.

Once identified, the parameters of an ARIMA (p,d,q) (P,D,Q) model are calculated using a non-linear algorithm that minimizes the mean square error of the forecast equation. Algorithms used for this purpose include maximum likelihood, least-squares, and the Marquandt algorithm of constrained optimization. The method used in this study is the maximum likelihood method as executed by the SAS time-series program.

Adaptive filtering may be applied to an AR(p) or MA(q) process. Generalized adaptive filtering is the term used when referring to the use of an adaptive filtering approach with an ARMA (p,q) model. The identification task for these models can be executed on the basis of a study of the autocorrelation and partial autocorrelation coefficients (as in the Box-Jenkins method), or by using a short-cut approach that reduces the identification task to fairly mechanical steps. Generalized adaptive filtering requires stationary data, and it can manage seasonal data. As a method, it has the advantages of simplicity and automatic self-adaptation to the data. It requires few data points, and there are few constraints involved in its operation.

The Sibyl-Runner program is used in this study for applying the adaptive filtering seasonal model to the five Chilean energy variables. The specific variant of the generalized adaptive filtering model that is used in the Sibyl-Runner program is called the sequential ARIMA seasonal model. In this method, stationary data inputs are required. The number of parameters is initially set equal to the length of seasonality of the forecast variable (i. e., twelve, in all five cases). If this approach fails, the number of parameters is then set equal to the time lag of the absolutely highest autocorrelation coefficient of the forecast variable. Parameter values are determined using the iterative method of steepest descent wherein the algorithm minimizes the mean square error of the forecast equation. In executing this method, a filter is used to regulate the conversion of old parameter values into new ones.

CHAPTER III

STATISTICAL SCREENING CONCEPTS, EXPERIMENTATION, AND THE FIVE FORECASTS

A. Screening Concepts

1. Introduction

This chapter begins with a statement of the statistical criteria used to screen candidate forecast equations. Following this, the results of the experimentation are summarized. Five forecast equations are selected and discussed.

2. Statistical Screening Criteria

The objective of the statistical experimentation is to select a sound forecast equation for each of the five Chilean energy variables.

The following statistical criteria are used to screen each candidate forecast equation, all tests being made at the 95% confidence level: 6/

a) The t-tests should indicate that the coefficients of the forecast equation are statistically significant [1].

b) The F-test should indicate significance of the equation, and its R^2 should be reasonably high [1].

c) The forecast equation should be free of heteroskedasticity and autocorrelation; multicollinearity should not be a problem [1].

d) For Box-Jenkins models, the specification of the forecast equation should be consistent with the pattern of its autocorrelation and partial autocorrelation coefficients [1,2]. The ARIMA (p,d,q)(P,D,Q) model should have parameters that are constrained by the bounds of stationarity and invariability of these models 7/ [5,6]. Also, the Box-Jenkins equation should pass an overfitting test [9].

e) The residuals of a forecast equation should be normally distributed and relatively small [1].

f) The candidate equation should have acceptable forecast power. For judging this, four measures are used: Theil's U-coefficient

[1,7], the Janus coefficient [8], a second fit test [9], and the degree of success of the equation in predicting turning points and sign changes over its sample period [7].

g) A forecasting model should be parsimonious and simple; that is it should have few parameters, each of a low power.

3. Heteroskedasticity

Heteroskedasticity means inequality of variance. Variance is the sum of the squared differences between each observation and the mean of a time series divided by the number of observations in the series less one (an adjustment for degrees of freedom); as such, variance is a quantitative measure of dispersion in a time series about its mean.

Heteroskedasticity is often found in business and economic time series. A heteroskedastic structure in an equation's residuals suggests that either the wrong function or the wrong variables, or both, have been selected. It should be removed from an equation prior to using it for forecasting because it implies biased parameter values and, probably, inaccurate forecasts. In this study, the original observations are transformed into logarithms, reciprocals, or power functions whenever a heteroskedastic structure is detected in an equation's residuals. Experimentation is then continued using these transformed values.

A perfect test for the presence of heteroskedasticity does not exist. Given the seriousness of its threat to forecast accuracy, this study employs seven tests for its presence. 8/ If a candidate forecast equation passes all seven tests at a 95% confidence level, it is very likely free of heteroskedasticity. Failure on one or more of these tests invokes the need for judgement as to the acceptability of the forecast equation in the light of all of its statistical characteristics.

4. Autocorrelation

Autocorrelation means that the residuals of an equation are correlated. If the residuals of a forecast equation are autocorrelated, this implies either that the wrong function or the wrong variables have been selected or that there are strong trends in the independent variables [1,8,14,15]. As was the case with heteroskedasticity, autocorrelation is also a violation of one of the conditions that must hold for the use of time series and regression techniques. An autocorrelated equation will probably generate poor forecasts because its parameters are biased. In theory, the systematic error can be removed from the residuals using a technique such as the Cochrane-Orcutt correction. In this study, the decision was made to reject an autocorrelated equation and to search for a defensible one without it.

Two tests are conducted for autocorrelation, neither of which is perfect: the Box-Pierce (Q) test of residuals [1] and the Durbin-Watson (d) test [1,8,14,15].

5. Multicollinearity

Multicollinearity exists when changes in one of an equation's independent variables are too closely related to changes in another, resulting in biased parameter estimates [1,8]. In such cases, one of the correlated variables might well be dropped from the equation. Forecasting using an equation containing multicollinearity will probably generate high forecast error due to biased parameter values. The presence of multicollinearity is suggested when the correlation coefficient between two independent variables of an equation is higher than that equation's multiple correlation coefficient. The equations based on two of the seven time series methods used in this study will be evaluated for multicollinearity: time series multiple regression and the Box-Jenkins ARIMA method.

6. Distribution and Scale of Residuals

It would be indefensible to use a candidate equation as a predictor if its residuals were not normally distributed because that would mean that a systematic error process was at work generating those residuals. That systematic process should be removed and included in a respecified forecast equation which should have normally distributed residuals. Forecasting with an equation containing a systematic error will probably generate high error because its parameters are biased.

Tests for skewness and kurtosis are conducted to evaluate for the normality of the distribution of the residuals of each candidate equation [8, 16]. Kurtosis refers to the degree of peakedness in a distribution, and skewness refers to the degree of symmetry in it, both measured relative to the normal distribution. Pronounced departure from the pattern of a normal distribution on either, or both, grounds suggests that a systematic force is at work which is not specified in the forecast equation. In theory, this force should be captured explicitly in a respecified equation. In addition to tests for skewness and kurtosis, a variety of error statistics are provided on the scale of error of the fit of each forecast equation to the sample data. Each has its characteristic strengths and weaknesses. [1,2]. Finally, the autocorrelation function of residuals is inspected for the presence of unacceptable patterns.

7. <u>Overfitting</u>

A test for overfitting is conducted on a candidate forecast equation generated using the Box-Jenkins method [9]. The purpose of this test is to assess whether that equation is properly identified.

In the overfitting test, the Box-Jenkins equation under evaluation is refitted first with a (p) and then with a (q) value one degree higher than that used in the candidate equation and then with a (P) and a (Q) value similarly higher. Thus, with Box-Jenkins models, four refitting exercises are executed: one for the orders of p, P, q, and Q, respectively. A significance test is performed on the slope coefficients on each of these four refitted equations. If all of the slope coefficients on any of the four refitted equations tests significantly different from zero, at a 95% confidence level, then the acceptability of the candidate ARIMA forecast equation under evaluation is questionable.

8. <u>Apparent Forecast Power</u>

Four criteria are employed to judge an equation's apparent forecast power. The first test is the Theil U-coefficient [1,6]. This coefficient is defined as the square root of the ratio of the mean square error of the predicted change to the mean squared error of the actual change. For an acceptable forecast equation, the value of Theil's U-coefficient should be less than unity.

A Theil coefficient less than unity means that the equation having that coefficient is a better predictor than a naive forecasting model. A Theil U-coefficient equal to unity means that the equation will probably forecast just as accurately as the naive forecasting model. A Theil U-coefficient above unity means that the naive model will probably be a better predictor than the equation under review.

The second criteria of apparent forecast power is provided by the second fit test [7.9]. In this test, the actual values of the variables are regressed on the forecast values and a constant generated by the candidate equation. If the constant and slope of this linear equation test insignificantly different than zero and one, respectively, at the 95% confidence level, then the equation is taken as an attractive predictor, the idea being that actual and predicted values were closely related over the sample period and, hopefully, they will continue to be so over the forecast period as well.

Accuracy in predicting turning points and sign changes over the sample period is a third criterion for asessing an equation's apparent forecast power [7]. An equation that predicted these well during its sample period is preferable to one that did not.

Finally, the Janus coefficient is used for judging prospective forecast power [8]. This coefficient is defined as the ratio of the average squared error made in predictions outside the sample range to predictions made inside it. Since the five ex post forecasts tabled in this exercise are for 1983, the Janus coefficient was calculated for 1982 using an equation with the same specification as the candidate equation but fitted to the sample data for 1971-1981 (for diesel oil: 1976-1981). Thus, if there were no changes in 1982 in the conditions underlying the candidate forecast equation, the Janus coefficient would have a value of unity. The greater the departure from unity, the greater the change in the underlying conditions of the equation in 1982 vis-a-vis prior years and, hence, the more risky it might be to use the candidate equation as an ex post forecast vehicle for 1983.

B. The Results of the Experimentation

Discussed below are the results of the statistical experimentation for each of the five Chilean energy variables. Exhibit 6 summarizes the principal statistical characteristics of each of the five models finally selected for forecasting.

1. Diesel Oil

The 84 monthly observations on the apparent consumption of diesel oil in Chile were processed using the seven time series methods. Of the many equations generated, only three merited intensive evaluation: ARIMA (012)(111); ARIMA (111)(011); and ARIMA (011)(011).

Equations based on the two exponential smoothing models, the two decomposition models, and the time series multiple regression model were rejected for autocorrelated residuals and heteroskedasticity. The equation based on the time series multiple regression model was also rejected for multicollinearity and for insignificant t-values on several of its slope coefficients. The generalized adaptive filtering model was rejected for heteroskedasticity.

A close study of the autocorrelation and partial autocorrelation coefficients of the three candidate ARIMA models led to the rejection of ARIMA (012)(011) and ARIMA (111)(011).

The parameters of ARIMA (011)(011) are significant. The model's specification is consistent with the pattern of its autocorrelation and partial autocorrelation coefficients. The values of the equation's parameters meet the stability and invertibility conditions for ARIMA models. This model passed its overfitting test.

The data in Exhibit 6 show the principal statistics for ARIMA (011)(011). Its R^2 is 1.0 (rounded), adjusted for degrees of freedom and for the absence of a constant. The equation's F-value is significant. The model is apparently free of autocorrelation. Multicollinearity is not a problem. The equation's residual errors are small and appear normally distributed. There is no problem with either kurtosis or skewness. The Thiel U-statistic (0.71) of this equation means that it was a better predictor than the naive forecast model, NF2, over the sample period. The equation's Janus coefficient

(1.27) reports relative stability in the underlying conditions of the model in 1982 vis-a-vis 1976-1981, suggesting that it might not be too risky to use it as a predictive vehicle for 1983. The model passed its second fit test. ARIMA (011)(011) performed acceptably well in predicting both turning points (40%) and sign changes (36%). The model is both parsimonious and simple: that is, it has few parameters (i.e., two) and each parameter is of low power (i.e., first power in both cases).

ARIMA (011)(011) is selected as the time series forecast equation for diesel oil. The only reservation in using this forecast model is its failure on three of the seven tests for heteroskedasticity. Appendices C1-C4 presents the plots of the autocorrelation function, the partial autocorrelation function, the residuals, and the autocorrelation function of the residuals of ARIMA (011)(011).

2. Household Kerosene

The original values of household kerosene were fitted using the seven time series methods. Not one of the resulting equations was statistically defensible. Each equation tested positively for heteroskedasticity and/or autocorrelation, and each equation contained at least one other major statistical flaw.

The values of the original observations were transformed into natural logarithms. These were fitted using the same seven time series models. Two equations survived statistically: ARIMA (110)(011) and ARIMA (011)(011). Close study of the autocorrelation and partial autocorrelation coefficients of ARIMA (110)(011) led to its rejection.

ARIMA (011)(011) was selected as the forecast equation. The patterns of its autocorrelation and partial autocorrelation coefficients are consistent with its specification. Parameter values are acceptable. The model is both parsimonious and simple. It passed its overfitting and F-tests. Its slope coefficients are statistically significant. The R^2 (adjusted) of this equation is 1.0 (rounded). The equation appears free of autocorrelation. However, it failed two of the seven tests for heteroskedasticity. Multicollinearity is not a problem. The model's aggregate error statistics are low. While skewness is not a problem, kurtosis is. The model's Theil coefficient (.47) is attractive, but its Janus coefficient (1.59) suggests underlying instability in the series in 1982. The model predicted turning points and sign changes well during its sample period: 46% accuracy in both cases..

ARIMA (011)(011) is chosen as the predictor for household kerosene consumption, despite its failure on the second fit test, its weakness in regard to kurtosis and heteroskedasticity, and the threat to forecast accuracy suggested by the value of its Janus coefficient in 1982. Appendices DI-D4 presents the various plots for this forecast model.

3. Motorgasoline

The 144 original values of this variable were fitted to the seven time series models. Each of the resulting equations was rejected for heteroskedasticity and autocorrelation and, in some cases, for other statistical failures.

In view of these results, the natural logarithms of the original data were fitted to the same seven models. Again, each of the seven resulting equations had to be rejected.

Experimentation was then undertaken using a series of transformations of the original data to deal with the problem of heteroskedasticity. Of the many equations generated using these transformations, only two survived: ARIMA (210)(011) and ARIMA (011)(011), data in both cases being scaled in the reciprocals of the original values.

Detailed study of the autocorrelation and partial autocorrelation coefficients of these two surviving models led to the rejection of ARIMA (011)(011) and to the acceptance of ARIMA (210)(011).

The statistical features of ARIMA (210)(011) are shown in Exhibit 6. This model is parsimonious and simple. Its parameters pass their respective t-tests, and they satisfy the stability and invertibility conditions. The equation appears free of autocorrelation and heteroskedasticity. Multicollinearity is not a problem. The equation's R^2 (corrected) is high (.98). It passed its F-test and overfitting test. Its Theil U-coefficient (0.82) suggests that it is a better predictor than the NF 2 model. It predicted turning points reasonably well (30%) and sign changes very well (71%) during its sample period. Kurtosis is a problem, but skewness is not. Residuals are small.

ARIMA (210)(011) is a statistically acceptable equation. The only drawbacks to its use as a forecasting equation are: first, its failure on the second fit test; second, the problem with kurtosis; third, its failure on one of the seven tests for heteroskedasticity and, fourth, the very high value of the equation's Janus coefficient (23.9). This pronounced instability in this series in 1982 implies that it might generate a poor forecast in 1983. Despite its shortcomings, ARIMA (210)(011) is selected as the predictor for 81' motorgasoline consumption. The plots for this model are given in Appendices EI-E4.

4. Gross Electricity Generation

When the 144 original values of this variable were fitted using each of the seven time series methods, every equation showed serious statistical flaws. As a result, the original observations were scaled in natural logarithms, and these values were fitted to the same functions. When this was done, only one equation was statistically attractive: ARIMA (210)(011).

The order of ARIMA (210)(011) is consistent with the pattern of its autocorrelation and partial autocorrelation coefficients. The equation's parameter values satisfy both the stability and invertibility conditions for ARIMA models. This ARIMA model is both parsimonious and simple.

As shown in Exhibit 6, ARIMA (210)(011) is a statistically strong equation. The equation's R^2 is 1.0 (rounded), after adjustment for degrees of freedom and for the equation's lack of a constant. This model passed its overfitting test. The t-values for each of its slope coefficients and the equation's F-test value are all significant. There is no problem with either autocorrelation or multicollinearity. The equation's residuals are small and without skewness. There is, however, a problem with kurtosis. The equation's U-coefficient (.40) and its 'second fit' test suggest attractive forecast power. The model did very well in predicting turning point (64%) and sign changes (60%).

ARIMA (210)(011) has one big weakness. As shown in Exhibit 6, it failed four of the seven tests for heteroskedasticity. In view of its generally excellent statistical properties, however, ARIMA (210)(011) will be used as the predictor for gross electricity production in 1983. The risk on heteroskedasticity is simply judged to be worth taking. Appendices F1-F4 present the various plots on this variable.

5. Peak Electricity Demand

The 144 original values of this time series were fitted using the seven time series models. Every one of the resulting equations was rejected either for autocorrelation, heteroskedasticity, or some other serious statistical inadequacy.

The exercise was repeated using the natural logarithms of the original values. Three ARIMA models emerged as potential forecast equations: ARIMA (011)(111), ARIMA (011)(011), and ARIMA (011)(110), all three scaled in natural logarithms.

The parameters of ARIMA (011)(111) did not satisfy the stability and invertibility conditions for ARIMA models, and one of its MA parameters failed its t-test. So, this model was rejected. The non-seasonal MA parameter of ARIMA (011)(011) failed its t-test, and it was rejected. ARIMA (011)(110) was retained for more intensive screening.

ARIMA (011)(110) is a reasonably strong model. Its parameter values are significant. Its R^2 (corrected) is 1.0 (rounded), and its F-value is significant. It passed its overfitting test. There is no problem with multicollinearity and apparently none with autocorrelation. The model passed four of its seven tests for heteroskedasticity. Residuals are small and free of skewness. Kurtosis, however, is a problem. Apparent forecasting power is high, judging from the values of this model's Theil coefficient (.38). The model predicted turning points and sign changes well (38% and 67%, respectively), and it passed its second fit test.

The only two reservations in accepting ARIMA (011)(110) is that it failed three of its seven tests for heteroskedasticity and its

Janus coefficient is very high (4.98). Appendices G1-G4 presents the values of this model's autocorrelation and partial autocorrelation functions, its residuals, and the autocorrelation function of its residuals.

C. <u>The Five Forecast Equation</u>

A time series forecasting equation has been selected for each of the five Chilean energy variables. Seven time series methods were considered as forecast vehicles in each case. The surviving time series prediction method was an ARIMA model in all five cases.

Each of the five ARIMA models chosen as forecast equations passed many rigorous statistical screening criteria. There were failures on some criteria. Generally speaking, however, the five surviving equations are good to excellent in quality.

Several features of these five ARIMA models should be underscored. First, each model is both parsimonious and simple, making it attractive as a forecast vehicle from a methodological point of view.

Second, all five equations have statistical defects, but in varying degree. Each one failed at least one of the seven tests conducted for heteroskedasticity, and three equations failed three or more of these tests. Four equations have kurtosis in their residuals. However, these failures should be read in the context of the overall statistical strength of these five forecast equations.

Third, the failure on the heteroskedasticity criterion of all five Box-Jenkins equations prompted a review of their individual defensibility statistically with that of the smoothing, decomposition, time series multiple regression and GAF models generated earlier in the research and rejected. This review led to the conclusion that, with the exception of the GAF models, each of the five Box-Jenkins models was a statistically superior predictive vehicle; but that the five Box-Jenkins models and their counterpart GAF models were both basically defensible in all five cases. The evidence for this conclusion is presented in Exhibit 14. The data show that each of the Box-Jenkins and GAF models presented in the Exhibit failed at least two of the seven tests conducted for heteroskedasticity. Although each of these equations is attractive on other statistical grounds, the problem of heteroskedasticity constitutes a serious flaw in all of them. In short, the problem of heteroskedasticity proved intractable, rendering suspect for forecast purposes every ARIMA model that emerged from the experimentation. In choosing between these two ARIMA models, the rest of this study will be based on the use of the five Box-Jenkins models owing to the fact that they have highly valuable stochastic properties which the GAF models lack. Aside from the problem with heteroskedasticity, it should be underscored that, generally speaking, both the Box-Jenkins and the GAF ARIMA models are attractive predictors, a fact which reflects, in large part, the close similarity of the underlying methodology of these two ARIMA forecast methods.

D. The Five Forecasts

Exhibit 7-13 presents the results of the 1983 *ex post* forecast for each variable using the five Box-Jenkins ARIMA models. Four features of these forecast results are noteworthy. First, every one of the sixty actual values for 1983 fell within the 95% confidence limits of the standard error of each equation's respective forecast. Second, these error limits are all relatively narrow. Third, four out of five of these forecasts had relatively low errors, their MAPE's falling in the range of 0.8-6.6% (Exhibit 7). The exception here was the motorgasoline forecast which had a comparatively high MAPE: 10.9%. Fourth, the scale of forecast error of all five variables was related fairly closely to the degree of volatility in their series during their sample periods (Exhibit 10), once again underscoring the importance of studying a time series closely before forecasting it.

Given the high quality of the five Box-Jenkins equations, these relatively good forecast results are attributable, in significant degree, to the fact that the three factors that shaped the course of these five energy variables during their sample period remained more or less in operation during 1983: Chile's total real output continued to grow sluggishly in 1983 (0.7%) as it did, on the average, during 1972-1983 (0.8%); and the cycle component of each variable remained weak and the seasonal component continued strong in 1983.

All in all, an energy planner who had used these five Box-Jenkins ARIMA models to forecast 1983 monthly values would not have been surprised as the actual values emerged in the market. He would have done a reasonable good forecasting job in all five cases in 1983.

E. The ARIMA Models and Other Forecast Models

Would it have been better to have avoided making the incremental investment required to predict with the Box-Jenkins ARIMA method over and above that required to predict with the other, technically simpler, forecast routines that were used? What would have been the change in predictive accuracy if a logical, or structural, model had been used instead of the Box-Jenkins ARIMA time series models? In this same vein, what would have been the change in predictive accuracy if, say, a completely unsophisticated predictive model, like NF 1, had been used to forecast each of these five Chilean energy variables instead of the five ARIMA models?

Five structural equations were generated, one for each of the five Chilean energy variables. The data underlying these five equations are presented in Appendix B. The statistical characteristics of the equations are summarized in Exhibit 15. The data in this Exhibit show that each of these equations is statistically defensible. Each has a simple causal content, although lacking in economic sophistication. In this regard, many other structural equations were tested, but each failed on one or more statistical and/or theoretical grounds. These five one-equation structural equations were used to generate ex post forecasts of the five Chilean energy variables.

Exhibit 16 presents the error statistics for predictions of the five Chilean energy variables using NF 1, NF 2, the five one-equation structural models, and the five ARIMA models. The errors of the OF are shown for each variable. Errors are also presented for a composite forecast model, an approach which will be discussed in the following section.

A comparison of the results of these predictive approaches is instructive. The first point to note is that NF 2 predicted all five variables more accurately than NF 1. The superior performance of NF 2 is due to the simple fact that it made a seasonal forecast while NF 1 did not, and all five variables have marked seasonality.

The second point to note is that NF 2 was a better predictor than the structural model in all five cases.

Third, NF 2 was more accurate than the ARIMA method in predicting three out of the five variables.

Fourth, the ARIMA method generated more accurate forecasts than the structural model in three out of five cases. So, there is no basis in these results for asserting that the more costly and more complex Box-Jenkins ARIMA method is clearly a superior forecast vehicle to either the technically simple multiple regression technique, or, in fact, to naive models.

Fifth, with the exception of the kerosene forecast, the average error (MAPE) of the NF 2 forecasts were relatively low: they fell within a 3-5% range. Sixth, the MAPE of all five forecasts using NF 2 were far above the MAPE of the OF, the optimum or best attainable forecast. Mathematical sophistication failed to bring forecast error down close to minimum attainable levels.

Finally, the ARIMA models did bring down average forecast error to these minimum levels in two out of five cases (kerosene and electrical generation), a fact which points to the potential strength of the ARIMA forecasting approach.

Why did NF 2 perform relatively well as a predictor? What are the implications of its success?

The reasons for the relative success of NF 2 are straightforward. Each of the five Chilean energy variables had strong seasonality, a big residual, and weak trend and cycle components. Since the residual isn't predictable, forecast accuracy, in every case, turned basically on the accuracy of its seasonal forecast. Given its predictive mechanics, NF 2 can compete well in such cases. ARIMA models can also do well under such circumstances, but structural models are at a disadvantage.

There are two basic implications of NF 2's comparative success in forecasting. First, it shows that there is no relation between the mathematical sophistication of a forecast method and its predictive accuracy. NF 2 is a simple predictive routine. Yet, it turned in a far better forecast performance than the more complex structural and ARIMA models. From a managerial point of view, this suggests that, while the gains from more accurate energy forecasting may be impressive, so are the difficulties of capturing them. Second, the superior results of NF 2 underscore the critical importance of studying a time series closely before choosing a forecast method. There were clear signs in the data for all five variables that a simple method such as NF 2 might, in fact, be a superior vehicle. In fact, it was. Second, NF 2's relative success shows that there is no relation between the mathematical sophistication of forecast method and its predictive accuracy. NF 2 is a simple predictive routine. Yet, it turned in a far better forecast performance than the more complex structural and ARIMA models. From managerial point of view, this suggests that, while the gains from more accurate energy forecasting may be impressive, so are the difficulties of capturing them. Third, the predictive success of NF 2 in 1983 should not be taken as an indicator of its success in future periods.

Summing up: the unsophisticated and low-cost NF 2 method predicted more accurately than the other candidate forecast methods. A forecaster would have done well using this simple routine to predict the twelve monthly values of each of these five Chilean energy variables in 1983. His forecast would have been reasonably accurate, low cost, and rapid. But, all five NF 2 forecasts had average errors far higher than an optimum, or best attainable, forecast. Managers of energy forecast groups in Latin America, where budgets are tight and reliable data are scarce, should reflect on these results.

F. A Composite Forecast Approach

The superior predictive performance of NF 2 was for one year, 1983. These results are anecdotal. They have only an illustrative value, nothing more. Forecasts for other years would have different outcomes. What the forecaster needs to know, but never will, *a priori*, is what is the predictive method that will have the most accurate results on the average over the time periods that he must forecast. In this lies the attractiveness of the stochastically conditioned forecast because it responds to the idea that a prediction of fact must be couched in probabilistic terms to be meaningful.

Viewed in this context, an alternative and potentially attractive approach to short-run energy forecasting is suggested: weight, in some objective way, the forecast values for each of several methods, each of which has a feature worth capturing, and generate a composite forecast.

For example, NF 2 was superior to NF 1 because it made a seasonal forecast while NF 1 did not. NF 2 is really an extreme case of a moving average in which only one observation, the last one, is included in the average. A moving average, such as NF 2, performs best either when there is a systematic pattern and little randomness in the data or when the forecaster expects an abrupt turning point. While each of the five variables show a systematic pattern and frequent turning points, they have high, not low, randomness, as evidenced by their high residual values (Exhibit 4).

High randomness argues for the inclusion of an ARIMA model in a composite forecast routine. The ARIMA approach focuses on the separation of the pattern from the random process with a purpose of using the pattern for forecasting. Each of the five ARIMA models that survived was statistically strong, suggesting that it probably identified the pattern fairly well. Also, in straining out randomness, the ARIMA model uses all past information available on the variable. NF 2 does not strain out randomness. ARIMA models tend to be fairly good seasonal predictors. In short, there are good reasons for including the ARIMA model in the construction of a composite forecast vehicle, given the inclusion of NF 2.

ARIMA models and NF 2 lack an associative, or causal, content. Also, after a relatively few forecast periods, predictions generated by an ARIMA model gravitate toward the mean of the stationary series. This is not the case with the one-equation structural models used in this study, which have a simple, although economically strained, causal content. The structural equation would take account of such causal forces and, to this extent, might also be helpful in predicting turning points. On the other hand, the structural model is a weak seasonal predictor. The decision was made to construct a composite forecast model using NF 2, ARIMA, and the one-equation structural model.

Exhibit 16 shows the results of predicting the 1983 values of the five Chilean energy variables with the composite method. The error of the OF is also shown to give an idea of the accuracy of a good forecasting effort. The errors of the composite forecasts are least-squares weighted, so they fall within the error limits of the component forecast method. In effect, the composite forecast approach lets the forecaster hedge his bet against uncertainty by employing the advantages of each component method while simultaneously retaining the advantage of having a stochastic prediction routine for his planning needs.

Exhibit 16 shows that the composite forecast method was reasonably accurate with the two electric power series and diesel oil. These three variables evolved more or less normally in 1983. On the other hand, the composite forecast method generated high forecast error with motorgasoline and kerosene, both of which experienced unusually strong change in 1983 (Appendix B). In both cases, the high error of the structural model explains the high forecast error of the composite model. In general, the errors of the composite forecasts were higher than those of the optimum forecasts, reflecting the fact that the component forecast models fared poorly against the OF, the two exceptions being the ARIMA forecasts of kerosene and electricity generation. The results suggest that if a forecaster expects unusual change in a variable, he might better forecast it using a single technique, such as NF 2 or an ARIMA model. However, if he expects a regular pattern of evolution in the variable over the forecast horizon, the composite method does let him combine the advantages of several methods and hedge his bet against any one of them being wrong.

G. <u>Summary</u>

Seven time series forecast methods were reviewed for use in predicting five Chilean energy variables. Stringent statistical screening criteria were employed. In all five cases, the result was the same: an ARIMA forecast equations was selected. Additionally, in each case a GAF model was highly competitive and might well have been selected as the forecast equation instead of the Box-Jenkins model actually selected. Each Box-Jenkins model was both parsimonious and simple. Each has its characteristic weaknesses. On the whole the five Box-Jenkins ARIMA models are statistically strong.

The five ARIMA equations were used to forecast, ex post, the twelve monthly values of 1983. In all sixty cases, the actual values for 1983 fell within the consistently narrow 95% confidence limits of the respective equation's standard error of the forecast.

The forecast accuracy of these five ARIMA models was compared with that of a one-equation structural model and two naive models, NF 1 and NF 2. The results were that NF 2 outperformed the ARIMA model four out of five times, and it forecasted more accurately than the structural model and NF 1 in all five cases.

These results show that the technically simple, low-cost, and rapid forecast method of NF 2 turned in the best forecast record. Methodological complexity provided no protection against forecast error in 1983. On the other hand, as just noted, the five ARIMA models also turned in good forecast results. Given its stochastic character, an ARIMA model is a highly competitive forecast vehicle for short-term forecasting on a continuous basis. While NF 2 and the ARIMA models turned in reasonably good forecast results, both methods were far less accurate than an optimum forecast. There were two exceptions: the ARIMA model turned in a forecast on a par with an optimum forecast in the cases of kerosene and electricity generation.

Finally, an ex post forecast for 1983 was made with a composite method. This method combines the desirable properties of its component methods and, under certain circumstances, it might offer the forecaster protection against uncertainty while retaining the advantages of a stochastic method. Given the weighting scheme of the composite forecast method, the pattern of its predictive errors will fall within the limits of the errors of its component methods.

CHAPTER IV

Summary and Conclusions

This study began with three questions. The first two questions asked why any effort should be made at statistical sophistication in energy forecasting work. The study has shown that the small investment required to move from NF 1 to NF 2 was well rewarded. In fact, NF 2 turned out to be the most accurate predictive routine of those reviewed. Little investment was required to use it, and it gave the most accurate forecast results for 1983.

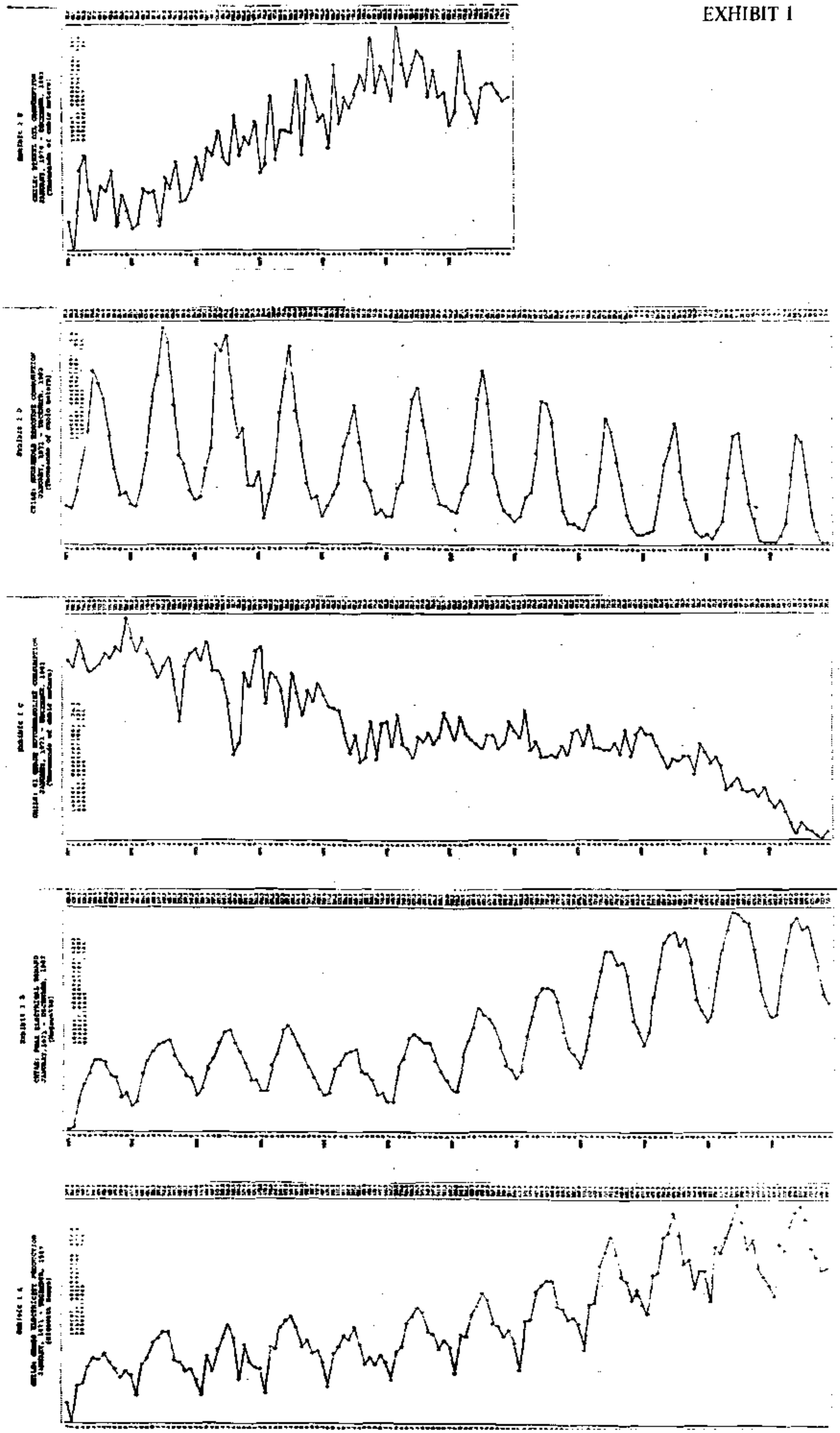
The third question asked if it would have been worthwhile to invest in more sophisticated forecast technology, having already achieved the predictive accuracy of NF 2. That method delivered the best forecast results in 1983 with four out of five variables. So, an investment in any of the other time series method reviewed in this study would have been wasted in forecasting those four variables in that year.

However, the study argued that it would be misguided to assume that NF 2's predictive success in one year, 1983, should be extrapolated into the future. The research demonstrated that Box-Jenkins (and GAF) models were also solid forecasting vehicles in 1983, and that they were preferable to NF 2 model for repeated forecast exercises because of their superior statistical strength, on the one hand, and, in the case of Box-Jenkins but not GAF models, because of the stochastic properties of the forecasts that they generate, on the other.

Several fundamental points should be drawn from this case study. First, before forecasting, study the data well. Second, avoid complexity. Third, do not underestimate the difficulty of achieving increased forecast accuracy on a sustained basis over and above levels that simple methods might readily deliver. It is all well and good to know that big savings are available in the abstract from improved forecast accuracy. It is quite another matter to achieve that increased accuracy. Forecast error is a formidable enemy and costly mistakes lie ahead for those who act as if an increment in mathematical complexity of forecast technology will always reduce it.

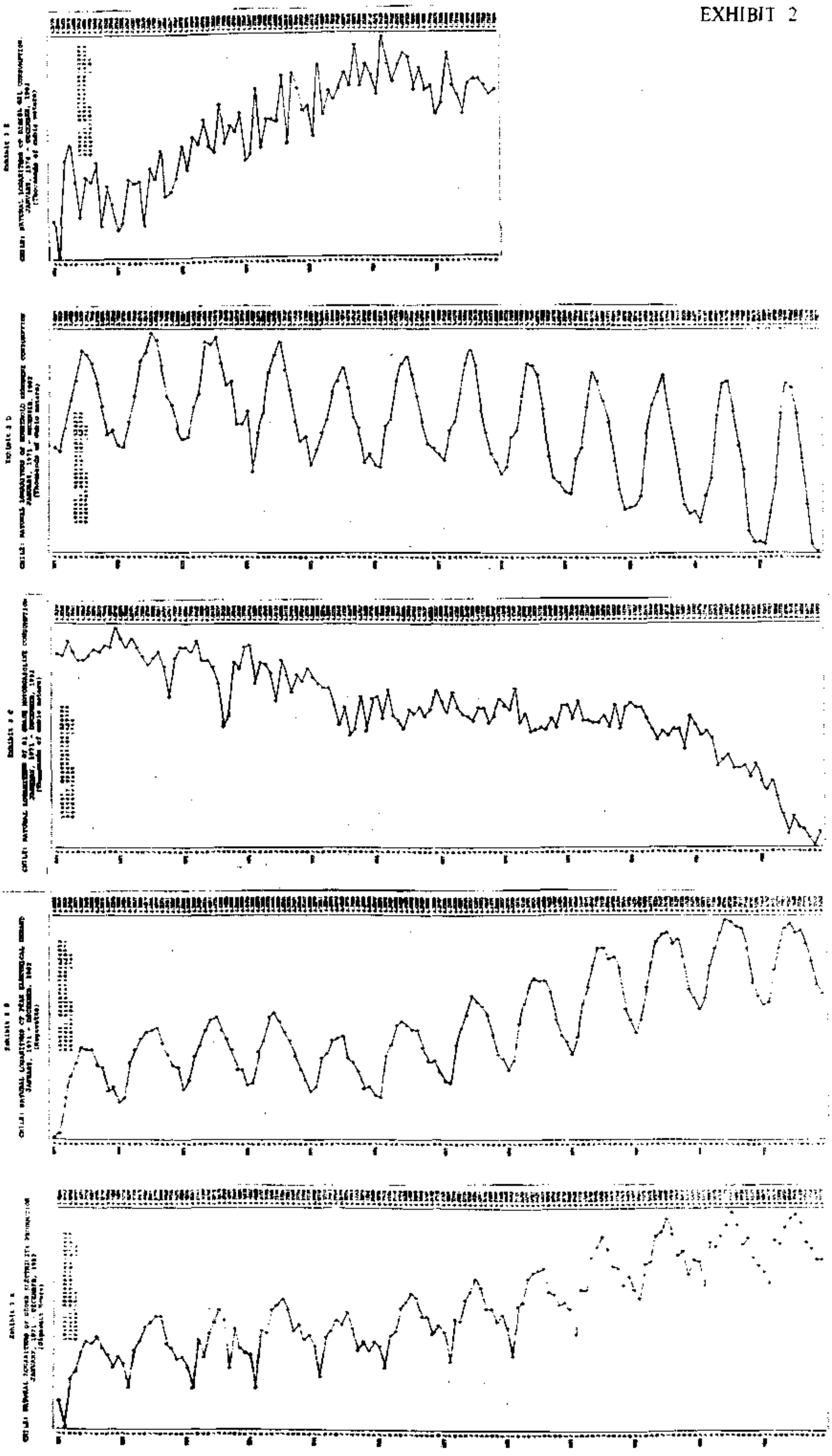
Fourth, apply rigorous criteria when screening candidate forecasting equations. It is much easier to generate a bad equation than to find a good one. NF 2 might have predicted best in 1983, but, as just noted, this does not mean that it would do so in the future on a continuous basis. For this purpose, statistically strong, stochastic models such as the five Box-Jenkins ARIMA models developed in the study are attractive predictors. Finally, these models, by their probabilistic nature, are more useful devices for planning in an energy company than the simple point forecasts generated by naive and other time series models. Nevertheless, a shortcoming of ARIMA models in some energy companies might be their mathematical complexity. Experience has suggested that managers should feel comfortable with the predictive routines employed in their organizations if their forecast efforts are to be successful in the broad sense [1]. In this regard, the study points to the importance of managing the forecast effort well in an overall administrative sense, rather than conceiving of it simply as the mechanical processing of quantitative methods by technicians.

EXHIBIT 1



Source: Appendices A(1) - A(5).

EXHIBIT 2



Source: Appendices A(1) - A(5).

EXHIBIT 3

CHILE: 1971-1983
ANNUAL VALUES OF THE MONTHLY
DATA PRESENTED IN EXHIBIT 1
(in units as indicated)

Year	Household Kerosene (Thsd. cubic meters)	81-grade Motorgasoline (Thsd. cubic meters)	Diesel Oil (Thsd. cubic meters)	Electricity Production (mm.kwh/yr)	Peak Electricity Demand (000KW) a/
1971	517	1412	n.a.	5471	583
1972	617	1363	n.a.	5918	626
1973	621	1266	n.a.	5914	651
1974	517	1226	n.a.	6262	657
1975	399	1012	n.a.	6052	606
1976	456	982	1015	6443	639
1977	444	983	1021	6741	700
1978	395	939	1217	7133	740
1979	322	942	1300	7789	822
1980	294	899	1429	8377	864
1981	266	754	1503	8745	903
1982	243	526	1414	8759	892
1983	191	382	1486	9359	953

Source: Calculated from the original monthly data for each of the five variables presented in Exhibit 1.

a/ The figures in this column report the highest monthly peak electricity demand recorded during the indicated year.

n.a.: Not available.

Exhibit 4

CHILE: JANUARY, 1971-DECEMBER, 1982
MEAN ABSOLUTE PERCENTAGE CHANGE OF FIVE
ENERGY VARIABLES: TOTALS AND COMPONENTS
(In % as indicated)

	Household Kerosene:		Diesel Oil a/:		81-grade Motorgasoline:		Peak Electricity Demand:		Gross Electricity Production:	
	Avg. Percentage: Change	Contrib.	Avg. Percentage: Change	Contrib.	Avg. Percentage: Change	Contrib.	Avg. Percentage: Change	Contrib.	Avg. Percentage: Change	Contrib.
Total	28.7	100	8.8	100	7.6	100	4.5	100	5.8	100
Trend-cycle	1.4	5	0.7	7	0.9	11	0.5	10	0.5	8
Trend	0.7	-	0.6	-	0.6	-	0.3	-	0.4	-
Cycle	1.3	-	0.6	-	0.8	-	0.4	-	0.3	-
Seasonality	17.2	56	2.0	21	2.3	27	2.9	59	3.9	62
Residual	11.9	39	6.7	72	5.2	61	1.5	31	1.9	30

Sources and Notes: The figures in this Exhibit were generated by the Census decomposition routine of the Sibyl-Runner times series program. For each variable, the figures in the left-hand column report the average monthly absolute rate of change over the period indicated. The figures in the right-hand column under each variable are the average absolute monthly contributions of each component to the total absolute monthly rate of change, each summed over the period indicated. A dash means less than 0.1 rounded.

a/ January, 1976 to December, 1982

EXHIBIT 5

CHILE: 1971-1982
FIVE ENERGY VARIABLES, HISTORICAL ACCURACY
OF VARIOUS TIME SERIES FORECAST TECHNIQUES
(In percentages, as indicated)

Variable	Original Data: Mean Absolute Monthly % Change 1971-1972	Mean Absolute Percentage Error (MAPE) for 1971-1982 using:			Improvement Potential of Forecast:	
	(1)	NF1 (2)	NF2 (3)	OF (4)	(2-4) (5)	(3-4) (6)
Household Kerosene Consumption	28.7	37.6	13.4	7.7	29.9	5.6
Diesel Oil Consumption a/	8.8	5.6	3.2	1.4	4.2	1.8
81-grade Motor-Gasoline Consumption	7.6	7.6	4.8	2.3	5.3	2.5
Gross Electricity Generation	5.8	4.5	1.8	1.0	3.5	0.8
Peak Electricity Demand	4.5	4.6	1.3	0.6	4.0	0.7

Sources and Notes:

The figures in Col. (1) are from Exhibit 4. The figures in Cols. (2), (3) and (4) were calculated using the Sibyl component of the Sibyl-Runner time series program. In calculating the figures in Col. (4), Sibyl uses the Census decomposition method. (NF1) means Naive Forecast Model (1), which uses last period's actual observation to forecast this period's value. (NF2) means Naive Forecast Model (2), which uses last period's seasonally adjusted value to predict this period's seasonally adjusted value. The latter is then converted to a seasonally unadjusted value using the seasonal index generated by Census. (OF) means the "Optimum Forecast" and the figures in column (4) report the (MAPE) of the forecast, which is the MAPE of its residual errors, isolated using the CENSUS decomposition method. As used here, MAPE reports the error imposed by the residual, which includes the effect of randomness. The MAPE is the sum of the absolute percentage errors (between actual and forecast for a given period) divided by the number of errors.

a/ January, 1976 to December, 1982.

EXHIBIT 6

CHILE: SELECTED STATISTICS FOR FIVE BOX-JENKINS FORECAST EQUATION OVER THEIR RESPECTIVE SAMPLE PERIODS

Concept:	Apparent Consumption of: Diesel Oil	Household Kerosene	81°-grade Motorgasoline	Electricity: Generation	Peak Demand
A. Data and Equation:					
Sample Period	1/76-12/82	1/71-12/82	1/71-12/82	1/71-12/82	1/71-12/82
Box-Jenkins Model	(011)(011)	(011)(011)	(210)(011)	(210)(011)	(011)(110)
Scaling of Variables	Originals	Loge	Reciprocals	Loge	Originals
No. Observations	84	144	144	144	144
No. Residuals	71	131	131	131	131
No. Parameters	2	2	3	3	2
Q-Data (lag=24)	51.7*	145.7*	85.1&*	71.7*	59.2*
R^2	1.0	1.0	.97	1.0	1.0
R^2 (Corrected)	1.0	1.0	.93	1.0	1.0
F	-5740	-30550	874	-34833	-30346
ARI/LAG 1			-.41(-4.93)	-.33(4-17)	
ARI/LAG 2			-.27(-3.23)	-.26(-3.22)	
MAI/LAG 1	.69(7.85)	.61(8.77)			.18(2.10)
MAI/LAG 2					
ARI/LAG 12					-.37(-4.21)
MAI/LAG 12	.46(3.73)	.51(5.55)	.76(7.03)	.89(6.44)	
Overfitting test	Pass	Pass	Pass	Pass	Pass
B. Autocorrelation:					
Durbin-Watson	2.31	1.70	2.08	1.86	1.96
Q-Residuals (df)	20.8(22)	48.0(22)	23.9(21)	21.8(21)	16.0(22)
Q-Residuals (df)	33.6(68)	82.8(128)	56.9(127)	61.2(127)	59.0(128)

Exhibit 6 (continued)

Concept:	Apparent Consumption of: Diesel Oil	Household Kerosene	81°-grade Motorgasoline	Electricity Generation	Peak Demand
C. Multicollinearity:					
R	1.0	1.0	.98	1.0	1.0
Correlation Matrix:					
MA(1) - MAI(12)	.05	-.14			
ARI(12) - MAI(1)					.17
ARI(2) - MAI(12)			.15		
ARI(12) - MAI(12)				-.02	
ARI(2) - MAI(12)			.08	-.05	
ARI(2) - ARI(1)			.33	.27	
D. Heteroskedasticity:					
Goldfeld-Quandt:					
50/50	0.73	0.26	1.15	0.09	6.40*
37.5/25/37.5	0.76	0.20	1.16	.05	5.00*
F-test	2.11	1.13*	1.53	2.29	0-.64
Bartlett	2.08	0.11	1.25	4.73*	1.40
Cochran	0.68*	0.53	0.60	0.70*	0.61
Hartley	2.11*	1.13	1.53	2.29*	1.56
Spearman's R	0.91*	0.95*	0.96*	0.95*	0.95*

Exhibit 6 (continued)

Concept:	Apparent Consumption of: Diesel Oil	Household Kerosene	81°-grade Motorgasoline	Electricity Generation	Peak Demand
E. Normality & Scale of Errors:					
Kurtosis	-1.72	4.25*	16.46*	17.27*	5.18*
Skewness	-0.01	-0.27	1.61	-0.14	-1.06
Max. Error	19.4	-0.6	-	0.1	-57.7
Quadratic Measures:					
MSE	63.6	-	-	-	206.1
RMSE	8.0	0.2	-	-	14.4
RMSPE	7.6	5.3	8.2	0.5	2.2
SSE	4516	3.4	-	0.1	26,995
SDE	8.0	0.2	-	-	14.4
Linear Measures:					
MAPE	6.2	3.9	5.5	0.4	1.7
ME	-0.1	-	-	-	-0.7
MPE	-0.2	-0.7	0.7	-0.1	-0.1
MAD	6.6	0.1	-	-	11.4
SE	1.0	-	-	-	1.3
F. Forecast Power:					
Theil Coefficient	0.71	0.47	0.82	0.40	0.38
Janus Coefficient	1.27	1.59	23.88*	a/	4.98*
Second Fit Test	Pass	Fail	Fail	Pass	Pass
% Correctly Predicted:					
Turning Points	40	46	30	64	38
Signs	36	46	71	60	67

Exhibit 6 (continued)

Concept:	Apparent Consumption of: Diesel Oil	Household Kerosene	81°-grade Motorgasoline	Electricity Generation	Peak Demand
G. Predictive Accuracy Over Sample Period of:					
N1	5.6	44.2	5.7	4.0	5.7
N2	3.3	25.3	5.3	2.5	2.6
SM	3.6	112.2	42.5	6.4	3.6
BJ	5.0	6.6	10.9	0.8	3.9
Memo: OF	1.4	7.7	2.3	1.0	0.6

Source: SAS and CEPAL programs using data as indicated below.

Notes:

A. Data and Equation:
The scaling of variables was either in original values (Appendices A (1-5)), in the natural logarithms of these values (Exhibit 2), or in the reciprocals of the original values, these latter two transformations being introduced to deal with the problem of heteroskedasticity. The Q-statistic is the Box-Pierce (chi-squared) statistic for gauging the degree of pattern (or randomness) in a series. It is shown here for a calculation based on 24 lags to gauge the degree of pattern in the original data; also, it is shown for all the lags [5,6]. The value of R^2 (corrected) includes an adjustment, first, for degrees of freedom and, second, for the fact that there is no constant term in any of the five Box-Jenkins forecast models presented here. When R^2 is adjusted for the absence of a constant, its value can rise above 1.0 and the value of the respective equation's F-statistic can be negative [9], results which occurred in four out of the five cases shown here. When it occurred, R^2 (corrected) is reported as 1.0, and the negative F-value is shown directly. The slope coefficients are the parameters of the model. For each, its t-value is shown in parenthesis alongside the coefficient. ARI/LAG 1 and ARI/LAG 12 mean the first AR term in the non-seasonal (lag1) and seasonal (lag 12) components of the model, respectively. AR2/Lag1 means the second AR term in the non-seasonal (lag1) part of the model. MA means the moving average term. The overfitting test is described in the text and in [9]. "Pass" and "Fail" mean that the model either passed or failed the indicated test.

B. Autocorrelation:
The Durbin-Watson test is the "d" test for first-order serial autocorrelation [1,8,14]. The Q-test noted here is the Box Pierce (chi-squared) test of residuals for each of the two sample sizes (N) shown [1]. Comparison of this Q-statistic with the one in (A) above provides a comment on the degree to which the underlying pattern has been wrung from the original data. The absence of an asterik in all three cases means that the model passed its test for the absence of autocorrelation at the 95% confidence level.

Exhibit 6 (conclusion)

C. Multicollinearity:
R is the square root of R^2 (corrected) shown above. The correlation matrix shows the R value for each set of two independent variables as indicated.

D. Heteroskedasticity:
Seven tests are conducted for the presence of heteroskedasticity [1,2,8,10,11,12,13]. An asterik indicates the presence of heteroskedasticity at the 95% confidence level.

E. Normality and Scale of Errors:
Tests are conducted for kurtosis and skewness in the distribution of residuals at the 95% confidence level [10,16]. Failure of either of these two tests is indicated by an asterisk. Maximum error means the highest single residual error; MSE: the mean square error; RMSE: the root mean square error; RMSPE: the root mean square percentage error; SSE: the sum of squared errors; SDE: the standard deviation of error; MAPE: the mean percentage error; MAD: the mean absolute deviation; SE: the standard error of estimate. These various error measurements are discussed in [1] and [2].

F. Forecast Power:
Theil's coefficient is discussed in [1], the Janus coefficient in [8], and the second fit test in [9]. "% correctly predicted" refers to the fraction of times that the forecast model correctly predicted turning points and the sign of change in the time series over its sample period.

G. Predictive Accuracy Over Sample Period:
Shown here for each variable over its sample period is the mean absolute percentage error (MAPE) of four forecast routines: N1, N2, the structural model (SM), and the Box-Jenkins model (BJ). Also shown is the error of the optimum forecast, OF, over the variable's sample period. As explained in the text, OF is the MAPE of the residuals generated by the Census decomposition technique. The MAPE of the four forecasting routines and OF are those shown in Exhibits 4-6. When the MAPE of a forecast technique is below that of OF, it means that the average error of the former was below the average of the residual errors generated by the CENSUS decomposition technique, the reference level for a very good forecasting job.

A blank space means that the concept is irrelevant. A dash means that the value of the statistic is less than the reporting unit after rounding. As noted, an asterisk means failure of the test statistic at the 95% confidence level. Pass and fail are used in the obvious sense with respect to the results of two tests that have multiple features; a failure on any one of these multiple tests is reported as "fail" for the test as a whole.

a/ This test statistic could not be calculated due to the emergence of a Jacobian singular, terminating the maximum likelihood estimation of parameter values of this ARIMA model by the SAS program. Without these parameter values, the Janus coefficient could not be calculated for this model.

EXHIBIT 7

CHILE: 1983
SELECTED ERROR MEASUREMENTS OF A 1983 EX POST FORECAST OF FIVE ENERGY VARIABLES USING THE FIVE SURVIVING BOX-JENKINS FORECAST EQUATIONS
(In percentages)

	Apparent Consumption of:				
Error Measurement	Household Kerosene	81-grade Motor-Gasoline	Diesel Oil	Electric Power Generation	Peak Electricity Demand
RMSPE	10.5	12.0	6.0	0.9	4.3
MAPE	6.6	10.9	5.0	0.8	3.9
MPE	-2.6	10.3	5.0	0.8	2.1

Source: CEPAL computer printouts.

Notes: RMSP is the root mean square percentage error, the square root of the average percentage error squared. MAPE is the mean absolute percentage error, the average of the absolute percentage errors. MPE is the mean percentage error, the average of the percentage errors.

EXHIBIT 8

CHILE: 1983
VALUES OF AN EX POST FORECAST FOR 1983 OF THE APPARENT CONSUMPTION OF DIESEL OIL USING BOX-JENKINS MODEL (011)(011) WITH INPUT VALUES SCALED IN ORIGINAL FORM

1983	Forecast Value	Forecast Range: Lower 95%	Upper 95%	Memo: Standard Error
JAN	110.0	94.6	125.5	7.9
FEB	108.9	92.7	125.1	8.3
MAR	131.0	114.1	147.9	8.6
APR	117.1	99.5	134.7	9.0
MAY	115.2	96.9	133.4	9.3
JUN	112.4	93.5	131.2	9.6
JUL	120.5	101.0	139.9	9.9
AUG	122.9	102.9	143.0	10.2
SEP	117.4	96.8	138.6	10.5
OCT	121.2	100.0	142.4	10.8
NOV	115.3	93.6	137.1	11.7
DEC	117.2	94.9	139.4	11.4

Source: SAS printout.

EXHIBIT 9

CHILE: 1983

Values of An *Ex Post* Forecast for 1983 of Gross Electricity Generation Using Box-Jenkins Model (210)(011) with Input Values Scaled in Natural Logarithms of Original Observations

1983	Forecast Value	Forecast Range: Lower 95%	Upper 95%	Memo: Standard Error
JAN	6.5013	6.4476	6.5550	0.0274
FEB	6.4196	6.3549	6.4842	0.0330
MAR	6.5831	6.5127	6.6534	0.0359
APR	6.5813	6.5026	6.6599	0.0401
MAY	6.6626	6.5766	6.7486	0.0439
JUN	6.6886	6.5965	6.7807	0.0470
JUL	6.7223	6.6242	6.8204	0.0501
AUG	6.6908	6.5870	6.7946	0.0530
SEP	6.6044	6.4953	6.7136	0.0557
OCT	6.6167	6.5025	6.7310	0.0583
NOV	6.5586	6.4395	6.6777	0.0608
DEC	6.5793	6.4555	6.7031	0.0632

Source: SAS printout.

EXHIBIT 10

CHILE: 1983
VALUES OF AN EX POST FORECAST FOR 1983 OF PEAK ELECTRICAL DEMAND USING BOX JENKINS MODEL (011)(110) WITH INPUT VALUES SCALED IN ORIGINAL VALUES

		Forecast Range:		
1983	Forecast Value	Lower 95%	Upper 95%	Memo: Standard Error
JAN	679	651	707	14.4
FEB	692	655	728	18.6
MAR	775	732	818	22.0
APR	828	779	877	25.0
MAY	880	826	935	27.6
JUN	903	842	960	30.0
JUL	885	822	948	32.2
AUG	883	815	950	343
SEP	857	786	929	36.3
OCT	806	731	880	38.1
NOV	732	654	811	39.9
DEC	708	627	790	41.6

Source: SAS printout.

EXHIBIT 11

CHILE: 1983
VALUES OF AN EX POST FORECAST FOR 1983 OF THE APPARENT CONSUMPTION OF MOTORGASOLINE (81^{O}) USING A BOX JENKINS MODEL (210)(011) WITH INPUT VALUES SCALED IN THE RECIPROCALS OF THE ORIGINAL OBSERVATIONS

1983	Forecast Value	Forecast Range: Lower 95%	Upper 95%	Memo: Standard Error
JAN	0.0261	0.0242	0.0280	0.0010
FEB	0.0270	0.0248	0.0292	0.0011
MAR	0.0261	0.0237	0.0285	0.0012
APR	0.0273	0.0246	0.0300	0.0014
MAY	0.0286	0.0256	0.0315	0.0015
JUN	0.0296	0.0265	0.0327	0.0016
JUL	0.0286	0.0253	0.0319	0.0017
AUG	0.0293	0.0258	0.0328	0.0018
SEP	0.0294	0.0257	0.0331	0.0019
OCT	0.0294	0.0255	0.0332	0.0020
NOV	0.0304	0.0263	0.0344	0.0021
DEC	0.0285	0.0243	0.0327	0.0021

Source: SAS printout.

EXHIBIT 12

CHILE: 1983
VALUES OF AN *EX POST* FORECAST FOR 1983 OF THE APPARENT CONSUMPTION OF HOUSEHOLD KEROSENE USING A BOX JENKINS MODEL (011)(011) WITH INPUT VALUES SCALED IN THE NATURAL LOGARITHMS OF THE ORIGINAL OBSERVATIONS

1983	Forecast Value	Forecast Range: Lower 95%	Upper 95%	Memo: Standard Error
JAN	1.7285	1.4129	2.0440	0.1610
FEB	1.6818	1.3436	2.0201	0.1726
MAR	2.0363	1.6768	2.3959	0.1834
APR	2.4472	2.0675	2.8268	0.1937
MAY	3.1765	2.7778	3.5752	0.2034
JUN	3.5493	3.1324	3.9663	0.2127
JUL	3.5509	3.1166	3.9853	0.2216
AUG	3.2083	2.7572	3.6594	0.2302
SEP	2.7070	2.2397	3.1742	0.2384
OCT	2.2136	1.7307	2.6965	0.2464
NOV	1.6673	1.1692	2.1653	0.2541
DEC	1.5460	1.0333	2.0587	0.2616

Source: SAS printout.

Exhibit 13

CHILE: FIVE ENERGY VARIABLES
COMPARISON OF THE AVERAGE FORECAST ERRORS OVER
THE SAMPLE PERIODS AND THE AVERAGE ERRORS OF THE TWELVE
MONTHLY FORECASTS FOR 1983
(In percentage error as indicated)

Variable:	Forecast Error (MAPE): Sample Period 1971-1982:	Forecast Error (MAPE): Average Monthly for 1983:
Apparent Consumption of:		
Household Kerosene	28.7	6.6
Diesel Oil a/	8.8	5.0
81-grade Motorgasoline	7.6	10.9
Electricity:		
Generation	5.8	0.8
Peak Demand	4.5	3.9

Memo: Spearman's Rank Correlation Coefficient:- 0.60 -

a/ January, 1976-December, 1982.

Sources and Notes: Exhibit 4, row(1), for sample period data. Exhibit 7 for 1983 average monthly forecast data. MAPE is the mean absolute percentage error, the sum of the absolute percentage errors (between actual and forecast for a given period) divided by the number of such errors.

Exhibit 14

CHILE: SELECTED STATISTICS FOR SIXTEEN CANDIDATE
FORECAST EQUATIONS FOR FIVE ENERGY VARIABLES

	Diesel Oil:		
	GAF(1)	GAF(2)	Box-Jenkins
A. Data and Equation:			
Sample Period	1/76-12/82	1/76-12/82	1/76-12/82
Model	-	-	(011)(011)
Scaling of variables	Originals	Log.Nat.	Originals
Nº Observations	84	84	84
Nº Residuals	60	60	71
Nº Parameters	12	12	2
Q-Data (lag=24)	179.5*	90.2*	51.7*
B. Autocorrelation:			
Durbin-Watson	1.88	1.94	2.31
Q-Residuals (df)	21.4(47)	23.3(47)	20.8(22)
C. Heteroskedasticity			
Goldfeld-Quandt			
50/50	.57	.32	0.73
37.5/25/37.5	.35	.22	0.76
F-test	1.22*	1.63*	2.11
Bartlet	.12	.75	2.08
Cochran	.55	.62	0.68*
Hartley	1.22	1.63	2.11*
Spearman's R	.90*	.91*	0.91*
D. Forecast Power:			
Theil's Coefficient	.62	.65	0.71
Janus Coefficient	2.28	1.21	1.27
Second Fit Test	Fail	Fail	Pass
% Correctly Predicted:			
Turning Points	53	51	40
Signs	13	13	36

Exhibit 14 (continued)

	Household Kerosene:		
	GAF(1)	GAF(2)	Box-Jenkins
A. Data and Equation:			
Sample Period	1/71-12/82	1/71-12/82	1/71-12/82
Model	-	-	(011)(011)
Scaling of variables	Originals	Log.Nat.	Log.Nat.
Nº Observations	144	144	144
Nº Residuals	120	120	131
Nº Parameters	12	12	2
Q-Data (lag=24)	96.9*	68.2*	145.7*
B. Autocorrelation:			
Durbin-Watson	1.75	2.10	1.70
Q-Residuals (df)	37.86(107)	50.76(107)	48.0(22)
C. Heteroskedasticity			
Goldfeld-Quandt			
50/50	30.68*	11.04*	0.26
37.5/25/37.5	68.14*	.26	0.20
F-test	5.47	2.94	1.13*
Bartlet	16.77*	7.18*	0.11
Cochran	.85*	.75*	0.53
Hartley	5.47*	2.94*	1.13
Spearman's R	.95*	.95*	0.95*
D. Forecast Power:			
Theil's Coefficient	.51	.55	0.47
Janus Coefficient	.49	1.71	1.59
Second Fit Test	Pass	Pass	Fail
% Correctly Predicted:			
Turning Points	32	16	46
Signs	78	77	46

Exhibit 14 (continued)

	81°Motorgasoline			
	GAF(1)	GAF(2)	GAF(3)	Box- Jenkins
A. Data and Equation:				
Sample Period	1/71-12/82	1/71-12/82	1/71-12/82	1/71-12/82
Model	-	-	-	(210)(011)
Scaling of variables	Originals	Log.Nat.	Reciprocals	Reciprocals
N° Observations	144	144	144	144
N° Residuals	120	120	120	133
N° Parameters	12	12	12	3
Q-Data (lag=24)	142.6*	156.0*	155.1*	85.1*
B. Autocorrelation:				
Durbin-Watson	1.83	2.01	.74	2.08
Q-Residuals (df)	37.09(107)	43.40(107)	47.68(107)	23.9(21)
C. Heteroskedasticity				
Goldfeld-Quandt				
50/50	.99	1.63*	1.44	1.15
37.5/25/37.5	1.00	1.63	1.49	1.16
F-test	5.88	3.47	1.75	1.53
Bartlet	18.08*	9.42*	1.99	1.25
Cochran	.85*	.78	.64	0.60
Hartley	5.88*	3.47	1.75	1.53
Spearman's R	.95*	.95*	0.95*	0.96*
D. Forecast Power:				
Theil's Coefficient	.85	.86	.90	0.82
Janus Coefficient	.22	.56	11.27	23.88*
Second Fit Test	Fail	Fail	Fail	Fail
% Correctly Predicted:				
Turning Points	39	37	65	30
Signs	37	42	49	71

Exhibit 14 (continued)

	Electricity Generation		
	GAF(1)	GAF(2)	Box-Jenkins
A. Data and Equation:			
Sample Period	1/71-12/82	1/71-12/82	1/71-12/82
Model	-	-	(210)(011)
Scaling of variables	Originals	Log.Nat.	Log.Nat.
Nº Observations	144	144	144
Nº Residuals	120	120	131
Nº Parameters	12	12	3
Q-Data (lag=24)	548.1*	543.9*	71.7*
B. Autocorrelation:			
Durbin-Watson	1.75	1.91	1.86
Q-Residuals (df)	52.87(107)	75.64(107)	21.8(21)
C. Heteroskedasticity			
Goldfeld-Quandt			
50/50	1.19	.14	0.09
37.5/25/37.5	1.08	.10	0.05
F-test	.99*	2.17	2.29
Bartlet	.36	3.79	4.73*
Cochran	.50	.68*	0.70*
Hartley	1.01	2.17*	2.29*
Spearman's R	.95*	.96*	0.95*
D. Forecast Power:			
Theil's Coefficient	.41	.46	0.40
Janus Coefficient	4.21	3.89	a/
Second Fit Test	Pass	Pass	Pass
% Correctly Predicted:			
Turning Points	53	49	64
Signs	67	66	80

Exhibit 14 (continued)

	Electricity Peak Demand		
	GAF(1)	GAF(2)	Box-Jenkins
A. Data and Equation:			
Sample Period	1/71-12/82	1/71-12/82	1/71-12/82
Model	-	-	(011)(110)
Scaling of variables	Originals	Log.Nat.	Originals
Nº Observations	144	144	144
Nº Residuals	120	120	131
Nº Parameters	12	12	2
Q-Date (lag=24)	194.5*	194.4*	59.2*
B. Autocorrelation:			
Durbin-Watson	1.93	2.11	1.96
Q-Residuals (df)	41.35(107)	48.87(107)	16.0(22)
C. Heteroskedasticity			
Goldfeld-Quandt			
50/50	1.80*	.81	6.40*
37.5/25/37.5	2.16*	.40	5.00*
F-test	.77*	1.33*	0.64
Bartlet	.44	.52	1.40
Cochran	.57	.57	0.61
Hartley	1.30	1.33	1.56
Spearman's R	.95*	.96*	0.95*
D. Forecast Power:			
Theil's Coefficient	.42	.46	0.38
Janus Coefficient	5.63	8.53	4.98*
Second Fit Test	Pass	Pass	Pass
% Correctly Predicted:			
Turning Points	48	41	38
Signs	82	77	67

Exhibit 14 (conclusion)

Sources: Exhibit 6 and CEPAL printouts using the Sibyl-Runner time series program and specially written programs.

Notes: All the data shown for the five ARIMA models presented here are taken from Exhibit 6. The footnotes to that Exhibit are generally relevant to this one. Since the sequential generalized adaptive filtering seasonal model has parameter values calculated by using an iterative technique, classical tests of confidence do not apply. This is the reason for the omission of many test statistics in this Exhibit that are presented in Exhibit 6.

GAF(1),GAF(2), and GAF(3) refer to the three GAF models based on the use of the original data used on the logarithms and reciprocal transformations of the raw data, respectively. An asterisk means that this test statistic failed the indicated test of confidence at the 95% confidence level. A dash means 'not applicable'. BJ/ARIMA means the Box-Jenkins/integrated autoregressive moving average model. GAF means the sequential generalized adaptive filtering seasonal model.

It was not possible to calculate an F-statistic for the Janus coefficients of the various GAF models presented in this Exhibit because the number of degrees of freedom in the numerator of that statistic was insufficient in every case.

a/ This test statistic could not be calculated due to the emergence of a Jacobian singular, terminating the maximum likelihood estimation of parameter values of this ARIMA model by the SAS program. Without these parameter values, the Janus coefficient could not be calculated for this model.

EXHIBIT 15

CHILE: 1983

STATISTICAL CHARACTERISTICS OF FIVE REGRESSION EQUATIONS FOR PREDICTING
EX POST THE 1983 MONTHLY VALUES OF FIVE CHILEAN ENERGY VARIABLES

Dependent Variable:	Constant	Le(STK)	Time	1983 Predicted Values	F	SSE	R/R2	DW
Le (81-grade Motorgasoline)	1.67	0.56 (3.4)	-0.09 (-10.5)	542	67.6	0.08	0.97/0.94	1.82
		Le(Y/P)	(Time)					
Le (Diesel Oil)	0.13	0.04 (3,1)	0.60 (2.2)	1440	33.7	0.05	0.96/0.93	1.74
		(RPKer)						
Household Kerosene	616.3	-2.65 (4.71)		320	22.2	75.1	0.83/0.69	1.82
		(Y)	(Time)					
Electricity Generation	2488.8	3.08 (6.7)	254.1 (17.4)	8773	399.3	137.1	0.99/0.99	1.37
		(ELGEN)	(Y/P)					
Peak Power Demand	-65.5	0.095	0.001	907	375.6	14.1	0.99/0.99	1.95

Source: CEPAL printouts.

Notes: (LE) means the 'natural log of'. (STK): the stock of 81-grade motorgasoline-consuming vehicles, for which stock of motorcycles and motonetas served as a proxy. (Time): a time trend variable. (Y/P): Chile's real gross domestic product per capita (in US$ 1980). (RPKer): the index of real household kerosene prices; (Y): Chile's real gross domestic product (in US$ 1980). (ELGEN): the time series on Chile's gross electricity generation. Parameter fitting was executed using either $(y = a + bx)$ or $(y = ax^b)$, with n=12 (1971-1982) in all five cases. t-values are shown in parentheses under their coefficients. Each equation was derived using the ordinary least squares regression technique.
DW refers to the Durbin-Watson test statistic for first-order serial correlation.
These five equations were used to generate the 1983 annual values of each variable. In turn, these values were translated into the respective twelve monthly values of 1983 using the seasonal index of the classical decomposition method.

Exhibit 16

CHILE: 1983
ERRORS OF THE 1983 EX POST FORECASTS OF THE FIVE CHILEAN ENERGY VARIABLES USING FOUR DIFFERENT PREDICTIVE ROUTINES
(In percentages)

Variable and Forecast Method:	Forecast Error (%):		
Peak Demand			
N1	5.7	7.4	0.1
N2	2.6	3.5	0.3
BJ	3.9	4.3	2.1
SM	3.6	4.2	0.5
CM	2.6	3.1	0.6
OF	0.6	-	-
Electricity Generation			
N1	4.0	6.2	0.8
N2	2.5	3.0	1.0
BJ	0.8	0.9	0.8
SM	6.4	6.7	6.4
CM	3.5	4.0	3.5
OF	1.0	-	-
Diesel Oil			
N1	5.6	7.6	0.5
N2	3.3	3.9	0.7
BJ	5.0	6.0	5.0
SM	3.6	4.1	3.0
CM	4.7	5.7	4.7
OF	1.4	-	-
Motorgasoline			
N1	5.7	8.0	-2.3
N2	5.3	6.7	-2.2
BJ	10.9	12.0	-10.3
SM	42.5	43.2	-42.5
CM	17.6	18.6	-17.6
OF	2.3	-	-

Exhibit 16 (continued)

Variable and Forecast Method:	Forecast Error (%):		
Household Kerosene			
N1	44.2	76.4	-16.9
N2	25.3	44.8	-6.9
BJ	6.6	10.5	-2.6
SM	112.2	129.9	-112.2
CM	29.5	46.9	-26.0
OF	7.7	-	-

Sources and Notes: CEPAL computer printouts. MAPE: the mean absolute percentage error; RMSPE: the root mean square percentage error; MPE: the mean percentage error. N1 and N2 refer to naive models 1 and 2 as defined in the text and in Exhibit 5. BJ means the Box-Jenkins model shown in Exhibit 6. SM means the structural model shown in Exhibit 15. CM means the composite forecast model as discussed in the text. OF is the MAPE of the optimum forecast as defined in Exhibit 5; by definition, there is no RMSPE or MPE measures for this concept.

APPENDIX A(1)

CHILE: 1965-1984
MONTHLY VALUES OF PEAK ELECTRICITY DEMAND
IN CHILE'S INTERCONNECTED POWER SYSTEM
(in Megawatt Hours/Hour)

YEAR	MONTHS											
	J	F	M	A	M	J	J	A	S	O	N	D
1965	329.7	348.3	366.3	378.9	408.4	408.5	415.3	406.0	404.8	390.9	369.3	367.5
1966	346.1	356.9	385.0	402.3	417.5	430.8	434.7	443.1	422.2	405.6	395.2	389.9
1967	365.1	367.6	394.1	418.0	455.2	468.9	476.9	408.1	464.3	432.1	422.3	409.2
1968	395.3	400.6	440.6	462.1	475.9	485.6	465.7	452.1	444.5	426.2	402.4	391.6
1969	378.1	395.9	418.8	430.8	488.6	500.8	502.6	488.4	466.1	460.6	454.5	419.9
1970	402.0	405.4	457.3	487.7	520.9	548.3	532.9	518.2	496.4	481.2	441.2	440.8
1971	429.8	436.5	494.5	530.0	556.8	582.9	581.9	579.8	550.2	545.2	504.3	510.8
1972	486.3	494.4	554.9	581.3	600.8	617.2	619.7	625.9	591.7	573.3	549.7	545.5
1973	509.3	523.7	567.3	587.8	621.5	645.1	650.5	621.0	603.4	578.7	542.1	541.2
1974	516.5	517.5	574.5	599.3	647.8	657.3	638.4	616.8	600.2	567.2	544.4	522.5
1975	506.0	511.8	564.2	573.9	596.3	602.7	605.7	561.8	553.5	540.5	507.6	512.9
1976	495.8	493.9	568.6	588.8	629.9	639.3	630.5	622.3	619.3	584.5	560.1	540.0
1977	522.3	518.3	590.9	624.1	655.0	699.5	683.2	675.9	656.2	612.6	572.5	562.6
1978	544.7	560.8	636.6	679.7	720.0	739.7	737.6	735.3	710.7	645.8	612.8	599.8
1979	570.1	607.7	676.2	721.8	776.4	821.7	821.7	793.9	797.9	767.3	668.3	643.9
1980	614.5	643.8	719.1	781.9	839.7	857.8	864.3	833.7	847.5	799.0	716.5	692.8
1981	670.4	691.4	776.9	823.4	868.6	903.2	899.0	887.3	881.1	824.4	732.9	699.9
1982	676.2	683.8	766.1	822.8	879.2	892.0	868.6	871.8	835.6	786.7	723.9	705.3
1983	659.6	663.9	770.6	840.3	924.5	952.6	953.3	931.3	895.7	781.6	758.7	739.6
1984	713.4	745.0	830.5	897.0	969.1	991.0	1015	978.1	894.1	-	-	-

Source: CHILECTRA, "Informe Estadístico Anual".

Note: The data are for peak demand recorded within Chile's interconnected grid system.

APPENDIX A(2)

CHILE: 1965-1983
MONTHLY GROSS ELECTRICITY PRODUCTION
IN CHILE'S INTERCONNECTED POWER SYSTEM
(Gigawatt Hours)

YEAR	MONTHS											
	J	F	M	A	M	J	J	A	S	O	N	D
1965	265.1	242.4	282.5	281.7	314.6	314.5	336.5	314.9	311.1	305.4	295.9	294.3
1966	276.1	251.3	308.2	308.4	338.3	358.9	367.1	363.2	330.4	329.4	316.6	322.4
1967	312.2	280.5	324.0	325.2	361.8	382.3	401.3	390.5	354.0	353.1	331.3	331.0
1968	322.6	299.2	344.8	350.3	355.1	370.7	393.3	374.6	343.7	362.2	324.1	330.6
1969	323.7	288.1	345.7	341.9	381.1	392.9	420.3	407.8	376.0	388.0	359.5	366.9
1970	353.1	316.8	368.3	369.9	404.1	430.9	443.3	434.9	390.3	409.3	391.4	398.2
1971	397.0	357.6	432.5	440.5	475.0	496.3	491.8	505.5	483.5	473.2	450.6	467.8
1972	457.4	416.7	480.1	494.6	526.3	535.2	548.4	549.2	491.1	483.7	465.1	470.4
1973	449.6	416.8	498.9	466.7	513.4	535.8	563.8	538.4	450.3	521.6	483.3	474.9
1974	472.8	418.3	516.6	513.4	560.4	572.8	584.2	561.5	516.2	532.7	502.5	510.5
1975	487.3	435.8	504.3	517.5	541.1	529.5	559.5	522.4	481.8	496.3	478.4	497.7
1976	486.5	447.7	509.3	518.6	566.3	580.3	601.9	591.4	548.3	547.2	513.8	531.3
1977	519.7	459.8	545.5	540.4	588.3	605.4	635.2	619.0	567.4	566.0	540.5	553.9
1978	526.5	473.2	572.5	579.9	637.6	654.3	661.3	663.0	606.0	600.3	575.9	582.7
1979	567.0	515.1	612.3	612.9	694.4	721.1	753.6	718.2	669.0	662.1	619.4	644.2
1980	611.9	592.3	673.7	680.3	754.3	764.5	804.5	757.6	696.1	709.9	646.6	685.2
1981	682.8	621.2	734.0	721.8	754.0	781.9	821.2	787.3	728.7	749.2	690.7	671.7
1982	652.2	626.9	740.3	727.8	778.4	804.8	817.9	791.0	731.9	714.1	685.0	689.1
1983	680.4	645.9	771.7	764.9	840.1	855.0	855.7	863.0	797.4	769.8	755.4	759.4

Source: CHILECTRA, "Informe Estadístico Anual".

Note: The data are for production in Chile's interconnected grid system.

APPENDIX A(3)

CHILE: 1970-1984

APPARENT MONTHLY CONSUMPTION OF

HOUSEHOLD KEROSENE

(in thousands of cubic meters)

YEAR	MONTHS											
	J	F	M	A	M	J	J	A	S	O	N	D
1970	20.5	18.9	23.8	30.1	44.8	64.4	69.7	57.6	36.3	32.6	23.5	23.8
1971	21.3	20.6	28.0	40.4	52.5	77.0	72.2	66.0	50.3	36.6	25.6	26.7
1972	22.5	21.7	30.2	43.0	66.8	75.5	95.8	89.2	63.3	42.5	38.6	27.9
1973	24.1	25.2	37.1	44.4	87.8	85.2	91.3	65.8	48.9	52.7	29.3	29.3
1974	34.5	16.0	26.1	33.9	58.9	73.8	87.0	60.6	46.4	30.7	23.8	25.0
1975	17.3	21.1	26.1	30.8	45.6	51.3	62.5	47.8	31.7	27.5	17.8	19.6
1976	17.1	16.9	28.4	30.9	52.3	65.6	70.3	56.6	42.8	30.6	22.6	21.4
1977	19.7	18.4	27.1	30.5	44.1	65.6	77.0	63.7	35.1	26.3	19.9	17.5
1978	15.3	16.5	25.0	27.2	42.7	64.5	63.7	56.1	36.0	19.4	14.4	13.8
1979	12.3	11.9	18.6	21.6	36.5	57.5	52.4	39.8	30.5	18.1	12.7	9.8
1980	9.9	10.3	11.6	26.0	38.2	45.6	56.1	35.8	24.5	16.3	10.2	9.1
1981	9.4	8.2	11.6	14.7	33.0	49.9	51.5	35.1	22.4	16.1	7.4	6.4
1982	6.3	6.1	9.1	14.6	34.0	50.5	47.4	34.2	18.8	10.3	6.2	5.6
1983	5.4	4.3	7.8	9.7	24.7	40.4	37.1	26.8	18.8	5.5	5.3	5.2
1984	5.1	5.1	4.8	6.8	8.6	-	-	-	-	-	-	-

Source: ENAP, "Estadísticas de Petróleo y Derivados".

APPENDIX A(4)

CHILE: 1976-1984

APPARENT MONTHLY CONSUMPTION OF

DIESEL OIL

(in thousands of cubic meters)

YEAR	MONTHS											
	J	F	M	A	M	J	J	A	S	O	N	D
1976	76.8	68.1	93.9	98.8	87.2	77.9	89.0	87.1	93.6	75.9	86.0	81.1
1977	74.7	76.4	88.1	86.8	87.3	75.7	91.5	88.2	96.4	83.3	84.5	88.2
1978	97.8	90.9	101.1	99.1	106.8	98.1	96.2	112.2	98.5	104.6	102.7	109.4
1979	93.1	95.6	118.1	97.6	106.8	107.1	106.1	123.5	98.8	124.8	118.5	109.9
1980	112.0	100.9	128.7	108.7	117.4	113.9	118.4	124.8	119.6	137.1	119.3	128.1
1981	123.3	115.9	140.4	128.2	121.1	128.6	133.0	131.0	117.9	126.4	117.7	119.1
1982	108.5	112.4	132.9	119.0	115.7	108.6	120.3	122.1	121.8	118.9	116.3	117.7
1983	110.5	109.4	135.5	121.9	124.0	122.1	125.4	123.6	126.1	134.5	123.5	129.1
1984	123.8	128.6	145.0	132.3	131.7	-	-	-	-	-	-	-

Source: ENAP, "Estadísticas de Petróleo y Derivados".

APPENDIX A(5)

CHILE: 1970-1984

APPARENT MONTHLY CONSUMPTION OF

81-GRADE MOTORGASOLINE

(in thousands of cubic meters)

YEAR	MONTHS											
	J	F	M	A	M	J	J	A	S	O	N	D
1970	114.6	108.4	112.3	113.5	104.2	106.1	106.9	107.5	102.5	114.3	107.2	121.5
1971	114.8	112.8	124.2	116.7	110.6	110.9	113.2	117.7	115.9	120.9	119.4	133.2
1972	125.2	118.9	125.2	118.6	113.7	107.5	112.2	116.7	106.4	88.1	112.1	118.5
1973	120.0	115.6	123.3	110.1	110.3	106.1	95.9	73.7	78.6	109.5	104.0	119.1
1974	121.2	95.9	109.0	107.2	101.9	86.6	109.8	100.6	91.1	101.3	96.6	104.9
1975	99.3	95.2	93.5	92.8	83.7	74.9	82.3	70.3	72.9	88.1	71.4	87.5
1976	88.3	77.5	91.4	78.3	76.3	72.7	81.4	79.8	83.2	78.6	81.7	92.5
1977	86.4	80.8	90.4	83.3	79.9	78.4	76.6	82.7	82.4	76.0	78.2	87.7
1978	83.8	81.5	93.4	75.3	79.8	72.1	72.5	73.8	72.6	77.4	73.7	83.5
1979	84.0	77.5	86.0	76.4	76.3	75.2	75.2	78.5	73.8	83.8	72.9	82.4
1980	85.3	82.3	82.4	77.8	73.0	68.1	71.7	70.2	72.9	72.4	64.6	78.7
1981	74.5	69.6	72.2	68.7	58.5	60.3	62.4	57.8	57.4	58.3	54.8	59.3
1982	53.3	50.7	53.4	48.7	43.7	38.7	43.0	40.5	40.0	37.9	36.2	39.6
1983	36.6	35.7	39.9	33.3	31.0	31.1	28.4	28.5	28.4	28.8	28.9	31.1
1984	31.5	30.0	31.2	28.4	26.6	-	-	-	-	-	-	-

Source: ENAP, "Estadísticas de Petróleo y Derivados".

APPENDIX B

CHILE: 1960-1983
ANNUAL VALUES OF FIVE CHILEAN ENERGY VARIABLES
(in units as indicated)

Year	Apparent Consumption of: Household Kerosene a/ (Thsd. cubic meters)	81-grade Motorgasoline b/ (Thsd. cubic meters)	Diesel Oil c/ (Thsd. cubic meters)	Electric Power Generation d/ (mn kwh/yr)	Peak Power Demand e/ (000 KW)
1960	258	675	286 est.	2342	307
1961	269	749	272 est.	2552	329
1962	277	804	328 est.	2804	330
1963	291	819	352 est.	3164	388
1964	297	862	380 est.	3400	416
1965	314	898	401 est.	3559	415
1966	334	959	493 est.	3870	443
1967	361	1048	733 est.	4147	477
1968	358	1145	1008 est.	4171	486
1969	408	1250	1168 est.	4362	503
1970	446	1319	1168 est.	4711	533
1971	517	1412	1128 est.	5471	583
1972	617	1363	1030 est.	5918	626
1973	621	1266	927 est.	5914	651
1974	517	1226	980 est.	6262	657
1975	399	1012	1148 est.	6052	606
1976	456	982	1015	6443	639
1977	444	983	1021	6741	700
1978	395	939	1217	7133	740
1979	322	942	1300	7789	822
1980	294	899	1429	8377	864
1981	266	754	1503	8745	903
1982	243	526	1414	8759	892
1983	191	382	1486	9359	953

Notes: "est." means 'estimated'.

Sources: a/ 1971-1983: Exhibit 1.
1960-1970: Comisión Nacional de Energía, Balance de Energía, 1960-1978, Chile, pp. 186-187.

b/ 1970-1983: Exhibit 1.
1960-1969: Comisión Nacioal de Energía, Balance de Energía, 1960-1978, Chile, pp. 184-185.

c/ 1976-1983: Exhibit 1.
1960-1975: Comisión Nacional de Energía, Balance de Energía, 1960-1978, Chile, pp. 182-183.

d/ 1965-1983: Exhibit 1.
1960-1964: CEPAL energy data bank based on official sources.

e/ 1965-1983: Exhibit 1.
1960-1964: Endesa, Producción y Consumo de Energía Eléctrica, Chile, 1964.

APPENDIX C(1)

CHILE : 1976-1982 autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
0	1.00000		********************
1	-0.53413	***********	
2	0.00577		
3	0.07518		**
4	0.03397		*
5	0.01941		
6	-0.12036	**	
7	0.11324		**
8	0.01169		
9	-0.12400	**	
10	0.04376		*
11	0.14004		***
12	-0.19981	****	
13	-0.01668		
14	0.11884		**
15	0.02964		*
16	-0.25211	*****	
17	0.26307		*****
18	-0.10899	**	
19	0.04993		*
20	-0.11215	**	
21	0.06874		*
22	0.11694		**
23	-0.14916	***	
24	-0.03564	*	

APPENDIX C(2)

CHILE : 1976-1982 partial autocorrelation coefficient for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
1	-0.53413	***********	
2	-0.39109	********	
3	-0.21379	****	
4	-0.02579	*	
5	0.13453		***
6	-0.00505		
7	0.03461		*
8	0.08505		**
9	-0.07458	*	
10	-0.12833	***	
11	0.10472		**
12	-0.05942	*	
13	-0.20908	****	
14	-0.10748	**	
15	0.06363		*
16	-0.22627	*****	
17	0.07990		**
18	0.01568		
19	0.07218		*
20	-0.02043		
21	-0.05466	*	
22	0.03091		*
23	0.10599		**
24	-0.11892	**	

APPENDIX C(3)

CHILE : 1976-1982 partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
1	-0.17494	***	
2	0.04233		*
3	0.12306		**
4	0.13431		***
5	0.19953		****
6	-0.12491	**	
7	0.02784		*
8	-0.00611		
9	-0.08193	**	
10	0.01024		
11	-0.03624	*	
12	0.03300		*
13	-0.07099	*	
14	0.03857		*
15	-0.05745	*	
16	-0.11632	**	
17	0.17036		***
18	0.03566		*
19	-0.04836	*	
20	-0.02576	*	
21	0.04673		*
22	0.04829		*
23	0.01696		
24	-0.12741	***	

APPENDIX C(4)

CHILE : 1976-1982 autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
0	1.00000		********************
1	-0.17494	***	
2	0.07164		*
3	0.09967		**
4	0.09376		**
5	0.16139		***
6	-0.15382	***	
7	0.12754		***
8	0.00766		
9	-0.05643	*	
10	0.04479		*
11	-0.07069	*	
12	0.07930		**
13	-0.11915	**	
14	0.05151		*
15	-0.05263	*	
16	-0.11887	**	
17	0.19421		****
18	-0.08597	**	
19	-0.01799		
20	-0.03642	*	
21	0.06684		*
22	0.08741		**
23	-0.09378	**	
24	-0.04715	*	

Source : CEPAL, using SAS's ARIMA computer program.
Note : "." marks two standard errors.
CORR. = CORRELATION

APPENDIX D(1)

CHILE : 1971-1982 autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.00000	|********************
1	-0.46107	*********|
2	-0.10447	**|
3	0.29652	|******
4	-0.29476	******|
5	0.02576	|*
6	0.01208	|
7	-0.02312	|
8	0.24606	|*****
9	-0.25483	*****|
10	0.08024	|**
11	0.24205	|*****
12	-0.53256	***********|
13	0.27960	|******
14	0.11546	|**
15	-0.16947	***|
16	0.09591	|**
17	-0.00699	|
18	-0.01936	|
19	-0.04374	*|
20	-0.04015	*|
21	0.08058	|**
22	-0.02162	|
23	-0.02832	*|
24	0.10460	|**

APPENDIX D(2)

CHILE : 1971-1982 partial autocorrelation coefficient for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.46107	*********|
2	-0.40267	********|
3	0.06562	|*
4	-0.17995	****|
5	-0.18147	****|
6	-0.28739	****|
7	-0.16996	******|
8	0.22888	***|
9	-0.02812	|*****
10	-0.06629	*|
11	0.22794	*|
12	-0.25898	|*****
13	-0.10098	*****|
14	0.03489	**|
15	0.19680	|*
16	-0.05395	|****
17	-0.08751	*|
18	-0.07212	**|
19	-0.08174	**|
20	0.10463	|**
21	-0.11452	**|
22	-0.12418	**|
23	0.06555	|*
24	-0.09106	**|

APPENDIX D(3)

CHILE : 1971-1982 partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	0.05268	|*
2	0.00237	|
3	0.08801	|**
4	-0.30681	******|
5	-0.13417	***|
6	-0.10913	**|
7	0.04765	|*
8	0.08587	|**
9	-0.20165	****|
10	0.00318	|
11	0.08382	|**
12	-0.00491	|
13	0.17817	|****
14	0.15099	|***
15	-0.01709	|
16	-0.09413	**|
17	0.02861	|*
18	-0.03882	*|
19	-0.10481	**|
20	-0.02352	|
21	-0.12515	***|
22	-0.03783	*|
23	0.01696	|
24	-0.02644	*|

APPENDIX D(4)

CHILE : 1971-1982 autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.00000	|********************
1	0.52684	|*
2	0.00514	|
3	0.08816	|**
4	-0.29435	******|
5	-0.15951	***|
6	-0.10484	**|
7	-0.02390	|
8	0.13383	|***
9	-0.10476	**|
10	0.07629	|**
11	0.12263	|**
12	-0.08695	**|
13	0.20137	|****
14	0.16408	|***
15	-0.05052	*|
16	-0.03954	*|
17	-0.07993	**|
18	-0.15031	***|
19	-0.16165	***|
20	-0.04195	*|
21	-0.00236	|
22	0.01562	|
23	0.07055	|*
24	0.07862	|**

Source : CEPAL, using SAS's ARIMA computer program.
Note : "." marks two standard errors.
CORR. = CORRELATION

APPENDIX E(1)

CHILE : 1971-1982 autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.

```
LAG   CORR.    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 0    1.00000 |          |********************|
 1   -0.31949 |    ******|                    |
 2   -0.20236 |      ****|                    |
 3    0.11375 |          |**                  |
 4   -0.02066 |          |                    |
 5   -0.01940 |          |                    |
 6    0.04660 |          |*                   |
 7   -0.00102 |          |                    |
 8   -0.05673 |         *|                    |
 9    0.05274 |          |*                   |
10    0.14533 |          |***                 |
11    0.13989 |          |***                 |
12   -0.48834 |**********|                    |
13    0.11767 |          |**                  |
14    0.12981 |          |***                 |
15   -0.08415 |        **|                    |
16   -0.01739 |          |                    |
17    0.08843 |          |**                  |
18    0.02290 |          |                    |
19   -0.10657 |        **|                    |
20    0.12187 |          |**                  |
21   -0.04919 |         *|                    |
22   -0.14833 |       ***|                    |
23    0.03950 |       ***|                    |
24    0.20538 |         *|                    |
```

APPENDIX E(2)

CHILE : 1971-1982 partial autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.

```
LAG   CORR.    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1   -0.31949 |    ******|                    |
 2   -0.33905 |   *******|                    |
 3   -0.10211 |        **|                    |
 4   -0.09934 |        **|                    |
 5   -0.05523 |         *|                    |
 6    0.00633 |          |                    |
 7    0.01911 |          |                    |
 8   -0.03712 |         *|                    |
 9    0.02343 |          |                    |
10    0.19612 |          |****                |
11    0.40971 |          |********            |
12   -0.25724 |     *****|                    |
13   -0.15217 |       ***|                    |
14   -0.13977 |       ***|                    |
15   -0.07622 |        **|                    |
16   -0.14348 |       ***|                    |
17   -0.00552 |          |                    |
18    0.14568 |          |***                 |
19   -0.02259 |          |                    |
20    0.03173 |          |*                   |
21    0.03244 |          |*                   |
22    0.01300 |          |                    |
23    0.13394 |          |***                 |
24    0.07794 |          |**                  |
```

APPENDIX E(3)

CHILE : 1971-1982 partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of 81° motor gasoline.

```
LAG   CORR.    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1    0.00579 |          |                    |
 2   -0.00495 |          |                    |
 3    0.03599 |          |*                   |
 4    0.02442 |          |                    |
 5    0.15229 |          |***                 |
 6    0.16087 |          |***                 |
 7    0.04305 |          |*                   |
 8    0.02606 |          |*                   |
 9    0.18078 |          |****                |
10    0.11047 |          |**                  |
11    0.04451 |          |*                   |
12   -0.06820 |         *|                    |
13   -0.08500 |        **|                    |
14   -0.02900 |         *|                    |
15   -0.08600 |        **|                    |
16   -0.12320 |        **|                    |
17    0.09409 |          |**                  |
18    0.08753 |          |**                  |
19   -0.03383 |         *|                    |
20    0.02498 |          |                    |
21   -0.01188 |          |                    |
22   -0.03109 |         *|                    |
23    0.07372 |          |*                   |
24    0.09610 |          |**                  |
```

APPENDIX E(4)

CHILE : 1971-1982 autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.

```
LAG   CORR.    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 0    1.00000 |          |********************|
 1    0.00579 |          |                    |
 2   -0.00491 |          |                    |
 3    0.03593 |          |*                   |
 4    0.02484 |          |                    |
 5    0.15191 |          |***                 |
 6    0.15886 |          |***                 |
 7    0.03690 |          |*                   |
 8    0.03032 |          |*                   |
 9    0.18655 |          |****                |
10    0.12173 |          |**                  |
11    0.07273 |          |*                   |
12   -0.03053 |         *|                    |
13   -0.04879 |         *|                    |
14    0.04952 |          |*                   |
15    0.01842 |          |                    |
16   -0.03627 |         *|                    |
17    0.12406 |          |**                  |
18    0.08032 |          |**                  |
19   -0.02505 |         *|                    |
20    0.04014 |          |*                   |
21   -0.05429 |         *|                    |
22   -0.05498 |         *|                    |
23    0.10368 |          |**                  |
24    0.08560 |          |**                  |
```

Source : CEPAL, using SAS's ARIMA computer program.
Note : "." marks two standard errors.
CORR. = CORRELATION

APPENDIX F(1)

CHILE : 1971-1982 *autocorrelation coefficients for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.*

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.00000	|********************
1	-0.28307	******|
2	-0.16933	****|
3	0.06449	|*
4	-0.05215	*|
5	0.19393	|****
6	-0.17961	****|
7	0.07233	|*
8	0.03135	|*
9	-0.08157	**|
10	0.11990	|**
11	0.08153	|**
12	-0.34394	*******|
13	0.08853	|**
14	-0.03665	*|
15	0.04033	|*
16	-0.02365	|
17	-0.11635	**|
18	0.21855	|****
19	-0.21294	****|
20	0.03337	|*
21	0.08585	|**
22	-0.09506	**|
23	0.08527	|**
24	-0.11505	**|

APPENDIX F(2)

CHILE : 1971-1982 *partial autocorrelation coefficients for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.*

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.29307	******|
2	-0.27119	*****|
3	-0.08590	**|
4	-0.12166	**|
5	0.16605	|***
6	-0.10036	**|
7	0.08161	|**
8	0.01058	|
9	-0.01899	|
10	0.06317	|*
11	0.20646	|****
12	-0.32634	*******|
13	-0.05391	*|
14	-0.24120	*****|
15	-0.05457	*|
16	-0.17872	****|
17	-0.00510	|
18	0.02137	|
19	-0.06841	*|
20	-0.03773	*|
21	0.06829	|*
22	-0.00986	|
23	0.15626	|***
24	-0.16024	***|

APPENDIX F(3)

CHILE : 1971-1982 partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.03631	*|
2	-0.06617	*|
3	-0.09037	**|
4	-0.05091	*|
5	0.18401	|****
6	-0.15746	***|
7	0.12779	|***
8	0.03171	|*
9	0.01561	|
10	-0.04426	*|
11	0.09830	|**
12	0.05165	|*
13	0.03779	|*
14	-0.01969	|
15	-0.04141	*|
16	-0.03964	*|
17	-0.09584	**|
18	0.05639	|*
19	-0.13293	***|
20	0.04950	|*
21	0.08959	|**
22	-0.04758	*|
23	0.04423	|*
24	0.03634	|*

APPENDIX F(4)

CHILE : 1971-1982 autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	1.00000	|********************
1	-0.03631	*|
2	-0.06477	*|
3	-0.08495	**|
4	-0.03862	*|
5	0.19697	|****
6	-0.15258	***|
7	0.10979	|**
8	0.01738	|
9	0.00826	|
10	-0.01567	|
11	0.01491	|
12	0.11735	|**
13	0.00344	|
14	-0.02596	*|
15	-0.07016	*|
16	-0.00879	|
17	-0.06376	*|
18	0.05781	|*
19	-0.08859	**|
20	0.04222	|*
21	0.10160	|**
22	-0.07813	**|
23	0.07256	|*
24	-0.05118	*|

Source : CEPAL, using SAS's ARIMA computer program.
Note : "." marks two standard errors.
CORR. = CORRELATION

APPENDIX G(1)

CHILE : 1971-1982 autocorrelation coefficients for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
0	1.00000		********************
1	-0.19997	****	
2	-0.13183	***	
3	0.14377		***
4	-0.06155	*	
5	-0.06397	*	
6	-0.07873	**	
7	0.04846		*
8	0.03863		*
9	-0.13765	***	
10	0.16324		***
11	0.16963		***
12	-0.37005	*******	
13	0.05704		*
14	0.10837		**
15	-0.10281	**	
16	-0.02654	*	
17	0.05766		*
18	0.05381		*
19	-0.10754	**	
20	0.04907		*
21	0.06542		*
22	-0.07010	*	
23	-0.07885	**	
24	0.18986		****

APPENDIX G(2)

CHILE : 1971-1982 partial autocorrelation coefficient for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
1	-0.19997	****	
2	-0.17898	****	
3	0.08275		**
4	-0.03712	*	
5	-0.05556	*	
6	-0.14119	***	
7	-0.00550		
8	0.03273		*
9	-0.10927	**	
10	0.10882		**
11	0.19745		****
12	-0.27688	******	
13	-0.07179	*	
14	0.02051		
15	-0.00622		
16	-0.02863	*	
17	0.02609		*
18	-0.00265		
19	-0.08442	**	
20	0.05102		*
21	-0.04174	*	
22	0.01553		
23	0.01877		
24	0.07248		*

APPENDIX G(3)

CHILE : 1971-1982 partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
1	0.00338		
2	-0.38035	*	
3	0.07158		*
4	-0.07513	**	
5	-0.07718	**	
6	-0.14376	***	
7	-0.01347		
8	0.03048		*
9	-0.06094	*	
10	0.13877		***
11	0.11162		**
12	0.00672		
13	-0.02771	*	
14	0.07517		**
15	-0.00003		
16	0.00311		
17	0.03101		*
18	0.00522		
19	-0.07731	**	
20	0.07151		*
21	-0.09952	**	
22	0.01334		
23	0.01254		
24	-0.04272	*	

APPENDIX G(4)

CHILE : 1971-1982 autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.

LAG	CORR.	-1 9 8 7 6 5 4 3 2 1	0 1 2 3 4 5 6 7 8 9 1
0	1.00000		********************
1	0.00338		
2	-0.03902	*	
3	0.07121		*
4	-0.07250	*	
5	-0.08301	**	
6	-0.13160	***	
7	-0.01736		
8	0.03482		*
9	-0.06605	*	
10	0.15546		***
11	0.13930		***
12	-0.00116		
13	-0.00701		
14	0.06923		*
15	-0.02288		
16	-0.05581	*	
17	0.00035		
18	0.00568		
19	-0.08904	**	
20	0.06441		*
21	-0.04898	*	
22	0.02430		
23	0.02045		
24	-0.03465	*	

Source : CEPAL, using SAS's ARIMA computer program.
Note : "." marks two standard errors.

Notes

1/ Excluded from consideration here are two other cases of mixed models: first, the simple one in which a time trend is included in a causal regression equation to capture a steadily evolving 'shift' effect; and, second, the case in which lagged values of the dependent and, perhaps, independent variable(s) are introduced into a static causal regression equation to make it dynamic. This might be done to retain the usefulness of the equation for intermediate or longer-term forecasting, via the non-lagged expressions of the equation, while increasing its near-term forecasting power via the newly inserted time-lagged expressions.

2/ Data limitations prohibited the inclusion of 93° motorgasoline but not of 81° motorgasoline. The former fuel dominates the Chilean motorgasoline market. The latter fuel is gradually disappearing from it. Since the purpose of this study is not to forecast but, rather, to present case studies in time series forecasting, the inclusion of 81° motorgasoline was accepted, despite this pattern of small and declining volumes of its sales. In fact, the unusual track of this variable during 1970-1982 makes it an interesting one for this forecast exercise.

3/ International Monetary Fund, "Estadísticas Financieras Internacionales, Anuario" (in Spanish), 1987, pp. S286-287, line 996. The data are for "PIB, a precios de 1980". The average annual rate of growth in Chile's total real output during 1976-1982, diesel oil's sample period, was 4.3%.

4/ In 1986 and 1987, the U.S. economy held in inventory about three months of annual oil sales, roughly five weeks each in crude oil and unfinished oils, the rest in refined oil products. Inventory held in the Strategic Petroleum Reserve was excluded in calculating these oil inventory figures. See: "Survey of Current Business", April, 1988, Vol. 68, Nº4, p. S-28.

5/ The derivation of this figure is: 1/3 [$.40/gal] + 1/3 [$.40 gal] + 1/3 [($.40/gal) + ($.30/gal)] = US$.50/gal, the estimated weighted average out-of-pocket investment in crude oil and refined product inventory, excluding interest. The US$ .40/gallon figure is the result of dividing the assumed cost of US$17/bbl. of crude oil by the figure of 42 gallons per barrel of crude oil. The US$.30/gallon figure is an estimate of the out-of-pocket costs of refining a gallon of refined oil product. Thus, conceptually, both the US$.40 and US$ .30 figures are short-run marginal costs per gallon. This means that the estimated carrying cost of US$ .50 per gallon of oil inventory grossly underestimates the total unit long-run cost of holding oil inventory. Hence, it biases strongly downward the payout of the investment in improved forecast accuracy as developed very roughly in the text in terms of short-run marginal costs. Finally, the discussion in the text ignores the macroeconomic benefits of improved inventory management through better energy forecasting, and it also ignores some other savings in resource inputs achieved through lower average inventory levels. These considerations strongly suggest that actual rates of return, both economically and financially, on investments in impoved forecasting are even higher than those developed in a very approximate way in the text.

6/ The relevance of each criteria depends on the time series method. For example, a t-test on fitted coefficients is valid for Box-Jenkins ARIMA models but not for the slope coefficients of exponential and harmonic smoothing models.

7/ Basically, this means that: (1) all parameter values of the ARIMA model should fall within the limits of plus unity and minus unity; (2) the sum of the parameter values of all the AR terms and of all the MA terms, each group treated separately, should be less than unity; (3) the value of the parameters in the AR and in the MA components of the model should fall off steadily over time; and (4) in an ARIMA model with a second order AR term or with a second order MA term, the difference between the value of the coefficient of the second order term less that of the first order term (for the AR and MA components separately) should be less than unity [5, 6].

8/ The tests for heteroskedasticity are those of Cochrane [10], two versions of the Goldfeld-Quandt test [11,12], the tests of Hartley [13] and Bartlet [11], a simple F-test [1], and Spearman's rank order correlation test [8]. In one of the Goldfeld-Quandt tests, the residuals are split into two equal groups, while in the other test the middle one-quarter of the residuals are initially removed, and the remaining residuals are split into two equal sets which are then used to test for the presence of heteroskedasticity.

GLOSSARY

Accuracy

The accuracy of a forecast refers to the closeness of predicted to actual values of a forecast variable. There is no perfect measure of forecast accuracy. In this text, preference is given to the mean absolute percentage error (MAPE); the root mean square percentage error (RMSPE); and the mean percentage error (MPE). The error concepts used in the text are defined below. Let Y_i and $\hat{Y}_i$ be actual and fitted observations, $\bar{Y}$ be the mean of the series, "n" the number of observations in the series, and let S represent $\sum_{i=1}^{n}$, then:

1) $$\text{MAPE} = \frac{S \dfrac{\left| Y_i - \hat{Y}_i \right| \cdot 100}{Y_i}}{n}$$

2) $$\text{RMSPE} = \sqrt{\frac{S\left[\dfrac{Y_i - \hat{Y}_i}{Y_i} \cdot 100\right]^2}{n}}$$

3) $$\text{MSE} = \frac{S\,(Y_i - \hat{Y}_i)^2}{n}$$

4) Maximum error, the absolutely highest of a series of error terms.

5) RMSE, the root mean square error:

$$\sqrt{\frac{S\ (Y_i - \hat{Y}_i)^2}{n}}$$

6) SSE, the sum of squared errors:

$$S\ (Y_i - \hat{Y}_i)^2$$

7) SDE, the standard deviation of error:

$$\sqrt{\frac{S\ (Y_i - \hat{Y}_i)^2}{n-1}}$$

8) ME, the mean error:

$$\frac{S\ (Y_i - \hat{Y}_i)}{n-1}$$

9) MPE, the mean percentage error:

$$\frac{S\ \dfrac{(Y_i - \hat{Y}_i)}{Y_i} \cdot 100}{n}$$

10) MAD, the mean absolute error:

$$\frac{S \left| Y_i - \hat{Y}_i \right|}{n}$$

Adaptive filtering model	An autoregressive (AR) model or a moving average model (MA) in which the parameters are determined by a non-linear least squares approach using the method of steepest descent. A learning constant is used to regulate the rate of change of old parameter values to new ones. Stationary data inputs are required for this model.
Adaptive response rate single exponential smoothing	A time series forecast method in the smoothing category that reacts relatively quickly to changes in the pattern of a time series when they occur; and when they do not occur, it is structured to emphasize even more the smoothing of randomness.

ARMA (ARIMA) model	An autoregressive (AR)/moving average (MA) model. AR processes assume that future values of a variable are a function of linear combination of past values of it; and MA processes assume that future values are linear combinations of past forecast errors. ARIMA refers to an ARMA integrated model, that is, an ARMA model applied to data that have been differenced to achieve stationarity. ARMA/ARIMA models require stationary data inputs. The ARMA or ARIMA method is often referred to as the Box-Jenkins method. However, the generalized adaptive filtering model and variants of it, are also ARIMA-type models.
ARMA adaptive filtering model	An adaptive filtering model applied simultaneously to autoregressive (AR) and moving average (AM) terms.
Autocorrelated residuals	The degree of association between the values of the residuals of an equation for some given lag between them.
Autocorrelation	The degree of association between values of the same variable at different time periods.

Autocorrelation coefficient (Autos)	The degree of association (R) or mutual dependence between the values of the same time series at different time periods, or lags.
Autoregression	A regression of a variable on previous values of itself for some specified lag.
Average absolute percentage change	The average absolute percentage change in a variable (Y) for a given lag (t,t-1) for n observations is given as:

$$\frac{\sum_{i=2}^{n} \left| \frac{Y_i - Y_{i-1}}{Y_i} \right|}{n-1}$$

Average change	The average change in a variable (Y) for a given lag (t,t-1) for n observations is given as:

$$\frac{\sum_{i=2}^{n} \frac{Y_i - Y_{i-1}}{Y_i}}{n-1}$$

Black box	A term used to designate the unknown, but precise way in which an input, or a cause, is transformed into an output, or an effect. It is "black" because the way that the transformation is effected is not known, and it is a "box" because, again, it is not transparently obvious, or clear, to the observer, how the transformation is really effected.
Box-Jenkins method	See ARMA.
Box-Jenkins three-parameter smoothing method	A time series technique that is based on the principle of smoothing errors and which can be applied to either stationary or non-stationary data.
Box-Pierce Q-statistic	A statistic used to test whether several partial or autocorrelation coefficients (or other statistics, such as the autocorrelation of residual errors) are significantly different from zero.
Brown's one-parameter adaptive method	A time series forecast method that uses smoothed values of current errors and previous values of the time series to predict.

Brown's one-parameter linear exponential smoothing method	An instance of a linear exponential smoothing method for forecasting. It uses a single and a doubled smoothed series and a trend adjustment to forecast.
Census method	A time series forecasting method that is essentially an extension of the classical decomposition method in terms of both statistical procedures and outputs.
Chow's adaptive control method	A time series method that is basically similar to the adaptive-response-rate single exponential smoothing technique with the difference that it can be used for non-stationary data.
Classical decomposition	A time series forecasting technique that isolates and then forecasts separately the trend, cycle, and seasonal components of a time series. The method presents its forecast as the sum of these three component forecasts, randomness, the fourth component, not being forecastable.
Cochran-Orcutt correction	A method for correcting coefficients for the bias resulting from autocorrelation of residuals.

Coefficient of determination (R^2)	The square of R, or the ratio of explained to total variation; and, as such, a measure of how well a regression fits the data.
Confidence limits	A set of bounds, or limits, within which it can be asserted that a certain percentage of the actual values probably will fall, according to statistical theory and a relevant probability distribution.
Correlation coefficient (R)	A measure of the degree of relationship between two variables.
Correlation matrix	A matrix that shows the coefficient of correlation between each pair of variables contained in it.
Cycle component	As used in time series analysis, this term refers to fluctuations in data due to economic forces associated with the business cycle.
Delphi method	A qualitative forecast method that uses the opinion of experts as the key input.
Deseasonalized data	A time series that has been produced by removing the seasonal pattern from the original data.

Difference	The value of a variable at one time period (Y_t) less its value at an earlier period (Y_{t-1}), or: (Y_t)-(Y_{t-1}). Differences may be of first, second, or higher orders.
Durbin-Watson statistic	This statistic is used to test the hypothesis that there is no autocorrelation of the first order i.e., of one time lag, in a series of residuals.
Exponential smoothing	A class of time series forecasting methods that generate a forecast by weighting, or smoothing, the past values of a time series. The more popular methods of exponential smoothing are simple exponential smoothing and those of Brown, Holt, and Winters.
Fitting	In a statistical sense, this word means passing a line, curve, surface, or higher expression through a set of data points to characterize them generally. Typically, a mathematical technique, such as simple or multiple regression or the maximum likelihood method, is used to specify the parameters of the function used in this way. When only one or two independent variables are involved, the line,curve, or surface can be passed through the data points intuitively, without utilizing a formal mathematical technique.

Least squares estimation	A method of calculating parameter values for an equation based on the criterion of minimizing the sum of the squares of the deviations between the actual values and the fitted values of the model.
Linear exponential smoothing	A time series forecast method that uses an equation which has exponentially decreasing weights assigned to past observations.
Linear moving averages	A time series forecast technique in which an average of fixed length is initially constructed; and then that average is recalculated repeatedly by adding each new observation and deleting the oldest one. This new average, each time, is used to forecast the value of the variable for the next period. This series of averages of fixed length is called a moving average.
Janus coefficient	A measure of the prospective forecast power of an equation. This coefficient is defined as the ratio of the average squared error made in predictions outside the sample range to predictions made inside it.

Heteroskedasticity	A condition of inequality of variance in the observation of a time series, which means that the error is not constant over the series'range. When this condition exists, it violates one of the basic assumptions that must hold for the use of time series and regression methods.
Holt's two-parameter linear exponential smoothing method	A time series forecast method that is similar to the method of single exponential smoothing but corrects for trend.
Homoskedasticity	A condition of constant error variance over the range of a variable. It is the opposite of heteroskedasticity.
Intervention analysis	An extension of the multivariate autoregressive/moving average (MARMA) model to assess the impact on the dependent variable of a change in the value of an independent variable.
Iteration	Estimation by a series of repeating approximations.
Lag	The length of time between time periods.

Model	A representation of reality. As used in this study, it is an equation or set of equations characterizing a set of observations on a variable.
Multicollinearity	A condition that exists when two or more independent variables are highly related to each other.
Multivariate	More than one variable.
MARMA models	A multivariate autoregressive/moving average model. This class of forecast models combine the time series and structural approach to forecasting.
Naive forecast	A highly simple forecast method that can be employed very rapidly and at low cost.
NF 1	Naive forecast model 1. This model predicts tomorrow's value of a variable as equal to today's actual value of that variable.
NF 2	Naive forecast model 2. This model takes today's actual seasonally adjusted value of a variable as equal to the seasonally adjusted value predicted for tomorrow.

Kalman filter	A general engineering-based approach to forecasting that mathematically incorporates all forecasting methods as special cases of it.
Kurtosis	The degree of peakedness in a distribution.
Marquandt's algorithm	The Marquandt method of constrained optimization is one method available to solve parameter values of ARIMA models. This method combines the Gauss-Newton and the steepest descent iterative approaches.
Maximum likelihood	A method for obtaining estimates of parameter values which consists in the maximization of the likelihood function. Basically, this method chooses parameter values that maximize the joint probability of the observed sample values.
Mean	The sum of the values (Y_i) of a series divided by the number of values (n) in the series.
Mixed models	Models that combine the time series and structural approaches to model building.

Parsimonious model	This concept refers to the objective of minimizing the number of parameters used to fit a model to a set of data. A simple model is one in which the parameters of a model are of low power (i.e., low exponent value). A forecast equation should be both parsimonious and simple.
Partial autocorrelation coefficient (Partials)	The extent of relationship (R) between current values of a time series and previous values of it, for a given time lag, holding constant the effects of all other time lags.
Pattern	The structural relationships underlying and generating the data. This concept specifically excludes randomness in the data.
Randomness	The inherently unpredictable fluctuations, or noise, contained in a set of observations on a variable.
Ratio-to-moving average method	The time series method of classical decomposition.
Regression (simple and multiple)	A quantitative technique that facilitates comparison of a dependent variable and either one independent variable (simple) or more than one independent variables (multiple).

Noise	Unpredictable, random fluctuations in a time series.
Non-stationary time series	A time series that does not oscillate about a steady mean and, as such, a time series that contains a trend.
Observation	A value of a variable at a given time.
Optimum forecast (OF)	The forecast that is used in this study as a proxy for the best forecast that can be realistically expected. It is taken here, for approximation purposes, as that forecast which has a MAPE equal to the MAPE of the random component of the CENSUS decomposition technique as generated by the Sibyl-Runner time series programme.
Outlier	An unusually high or low observation.
Overfitting	As used in this study, applying an overly complex ARIMA model to the data.
Parameter	As used in this study, a coefficient of an equation.

Seasonal ARMA models	An ARMA model that incorporates seasonality. In sequential ARMA adaptive filtering models, the number of parameters is set equal to the length of seasonality or, if this approach fails, the number of coefficients is then selected on the basis of a study of autocorrelation coefficients. In the Box-Jenkins approach, the parameters of the ARMA model are specified on the basis of an analysis of the pattern of autocorrelation and partial autocorrelation coefficients of the seasonally differenced data.
Seasonality component	Fluctuations in a time series related to a fixed seasonal factor, such as the seasons, the months of the year, the days of the week, or the like.
Second fit test	A measure of forecast power in which the actual values of the variable are regressed on the forecast values and a constant. If the constant and slope of this linear regression test insignificantly different from zero and one, respectively, at, say, a 95% confidence level, then the equation is taken as an attractive predictor.

Residual	The difference between an observed value and its fitted value; or the unexplained portion of the variables' value at a point in time. It is the error, calculated as the difference between the actual and forecast values of a variable.
SAS	The software programme used to process the ARIMA models generated in the study.
Scenario development	A qualitative forecast method that departs from a few key assumptions and generates a simulation of what those assumptions might imply for the future of one or more variables. Imagination is a key ingredient in this method.
S-curve	A curve depicting the life trajectory of a product or process as, for example, the S-curve for the sales of transistor radios. The curve can be fitted using any number of life-cycle functions. That function is then used to forecast the values of the variable under study.

Smoothing	Averaging by some rule as a means of tempering or eliminating fluctuations in the data.
Spearman's R	Spearman's coefficient R reports the degree of rank order correlation between two variables.
Stationary time series	A time series that oscillates around a constant mean and, as such, a series without a trend.
Stochastic	Random, as in a random process. Also used in the sense of 'probabilistic'.
Structural	Used in models to mean an associative relationship between variables; also, used in a highly qualified way as synonymous with 'causal'.
Time series	A time-ordered set of observations on a variable.
Time series methods	A set of forecast methods that predicts the future as a function of past values of the variable being forecasted and perhaps a time trend variable. No other variables than these are included in the specification of time series models.

Sequential ARMA adaptive filtering	An ARMA adaptive filtering model in which initially a moving average model (MA) is fit to the residuals of an autoregressive model; and, then, MA models are fit sequentially to residuals until a random pattern of residuals emerges. A filter is used in this method to regulate the speed with which old parameter values are converted to new ones in the sequential modelling operation.
Sibyl-Runner time series programme	The programme used to process the smoothing, decomposition, time series multiple regression, and the sequential generalized adaptive filtering (GAF) seasonal models used in this study.
Sign change	A change in the sign of change from one set of time series observations to another.
Simple model	See "Parsimonious Model".
Skewness	The degree of symmetry in a distribution.
Slope	The average change in the dependent variable divided by the average change in the independent variable.

Turning point	A change in the direction of a time series from up to down or from down to up, and, therefore, a change in the sign of change from one set of observations in the time series to another, adjacent one.
Univariate	One variable.
Variance	A measure of the distribution of all population values about the mean. It is defined as the sum of squared deviations from the mean divided by the number of observations. For a sample, it is defined as the sum of the squared differences between each observation and the mean of a time series divided by the number of observations in the series less one, an adjustment for degrees of freedom.
Weight (parameter)	The importance given to an item; for example, the value of a coefficient of an equation is an expression of the weight, or the importance, of that variable.
Winter's linear and seasonal exponential smoothing method	A time series forecasting method based on the use of three smoothing equations, one each for smoothing the parameter associated with the stationary, linear, and seasonal components.

EXHIBITS AND APPENDICES

APPENDIX C (2)	Chile: 1976-1982, partial autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.
APPENDIX C (3)	Chile: 1976-1982, partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.
APPENDIX C (4)	Chile: 1976-1982, autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of diesel oil.
APPENDIX D (1)	Chile: 1971-1982, autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.
APPENDIX D (2)	Chile: 1971-1982, partial autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.
APPENDIX D (3)	Chile: 1971-1982, partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.
APPENDIX D (4)	Chile: 1971-1982, autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of household kerosene.
APPENDIX E (1)	Chile: 1971-1982, autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.
APPENDIX E (2)	Chile: 1971-1982, partial autocorrelation coefficients for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.
APPENDIX E (3)	Chile: 1971-1982, partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.
APPENDIX E (4)	Chile: 1971-1982, autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of the apparent consumption of 81° motorgasoline.

APPENDIX F (1)	Chile: 1971-1982, autocorrelation coefficients for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.
APPENDIX F (2)	Chile: 1971-1982, partial autocorrelation coefficients for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.
APPENDIX F (3)	Chile: 1971-1982, partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.
APPENDIX F (4)	Chile: 1971-1972, autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of gross electricity generation in Chile's interconnected electric power system.
APPENDIX G (1)	Chile: 1971-1982, autocorrelation coefficients for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.
APPENDIX G (2)	Chile: 1971-1982, partial autocorrelation coefficients for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.
APPENDIX G (3)	Chile: 1971-1982, partial autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.
APPENDIX G (4)	Chile: 1971-1982, autocorrelation coefficients of the residuals for the first twenty-four lags of the monthly values of peak electricity demand in Chile's interconnected electric power system.

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