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AN ECONOMETRIC MODEL OF MONTHLY PEAK LOAD: CASE STUDY FOR AN ELECTRIC UTILITY SYSTEM

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CASE STUDY FOR AN ELECTRIC UTILITY SYSTEM

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CHAPTER I

INTRODUCTION

The drastic changes in energy markets since the 1973-1974 energy crisis and the expectation of continuing change in the forthcoming years have made capacity planning by electric utilities increasingly difficult. Along with growing uncertainty in the capacity planning, the costs of electric generation is also rapidly increasing because of rising fuel, capital and construction costs. According to a study of capital and fuel costs for utilities conducted after the energy crisis, the interest rate for new utility bonds more than doubled and the average electric utility cost of fuel quadrupled during the ten-year period of 1965 and 1975.[1]

As the uncertainty of forecasting expands, also escalates the consequential cost of planning based on inaccurate forecasts. Utility planners therefore have begun to accelerate efforts to develop new and

[1]Electric Utility Rate Design Study, Rate Design and Load Control: Issues and Directions (Palo Alto, California: Electric Power Research Institute, Nov. 1977), pp. 10-11.

more effective methodologies for load forecasting.[2] The need for accurate intermediate and long-range forecasts in capacity planning is becoming more important than ever as the lead times required for capacity additions increase. New environmental concerns, greater complexity in new generation technologies and longer regulatory proceedings have almost doubled nuclear power plant lead times in the last decade.[3] Coal-fired power plant lead times also have increased from six years in 1974 to eight years in 1977.[4]

Estimates of both peak load (Kilowatts) and energy (kilowatt-hours) requirements in the future constitute the foundation for planning in electric utilities. Even though the majority of existing econometric studies of the demand for electricity are concentrated on the estimation of kilowatt-hour demand, the energy demand forecasting is only partially useful for the utility planning purposes.[5] Because capacity is built to meet system peak demand, utilities must be concerned in the maximum level

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[2]The imminent necessity of new and more complicated forecasting methods led the Electric Power Research Institute (EPRI) to create the Energy Modeling Forum in 1977. The forum was intended to help utilities deal with the new complexity and uncertainty of forecasting and operated through a working group with participants from utilities, government agencies, universities, and consulting firms. Energy Modeling Forum, Electric Load Forecasting: Probing the Issues with Models (Palo Alto, California: Electric Power Research Institute, April 1979).

[3]At least ten years are expected now for nuclear power plant lead time which was five and one-half years in 1967. Ibid., p. 2.

[4]Ibid., p. 41.

[5]In his 1975 survey of the econometric models of electricity demand, Taylor found that all of the econometric studies are concerned about the energy demand with only one exception of Cargill and Meyer's. L. D. Taylor, "The Demand for Electricity: A Survey," The Bell Journal of Economics, Vol. 6, No. 1 (Spring 1975), p. 92; and T. F. Cargill and R. A. Meyer, "Estimating the Demand for Electricity by Time of Day," Applied Economics, Vol. 3, No. 4, pp. 233-246.

of demand as well as the total energy to be consumed. However, there has been very little empirical attention to provide detailed investigations of the factors determining level of peak demand while theoretical aspects of the peak load problem in electricity generation have been analyzed by many economists.[6] Consequently, the desire of electric utility planners to develop a well-defined model of peak load has been increasing over the recent years.

The primary goal of this dissertation is to identify and appraise the effects of economic, demographic and weather variables on the level of peak electricity demand. An affordable and flexible model is developed by an econometric modeling technique for the sensitivity analyses and the load forecasting. In the study, the entire process of peak load formation is divided into three time horizons: 1) short run, 2) long-run adjustment period and 3) long-run equilibrium stage.

Chapter II provides a thorough review of the literature concerning the peak load forecasting. Each forecasting model is classified by the methodology used and evaluated for the appropriateness of its application and its selection of explanatory variables. Shortcomings of the models are also discussed.

Chapter III presents an analytical framework to be used in this study for analyzing the determining factors of the peak demand for

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[6]For example, see H. S. Houthakker, "Electricity Tariffs in Theory and Practice," The Economic Journal, Vol. 61, No. 241 (March 1951), pp. 1-25; P. O. Steiner, "Peak Loads and Efficient Pricing." Quarterly Journal of Economics, Vol. 71, No. 4 (Nov. 1957), pp. 585-610; Ralph Turvey, "Peak-Load Pricing," Journal of Political Economy, Vol. 76, No. 1 (Jan./Feb. 1968), pp. 101-113; J. T. Wenders, "Peak Load Pricing in the Electric Utility Industry," The Bell Journal of Economics, Vol. 7, No. 1 (Spring 1976), pp. 232-241; and O. E. Williamson, "Peak-Load Pricing and Optimal Capacity under Indivisibility Constraints," The American Economic Review, Vol. 56, No. 4 (Sept. 1966), pp. 810-827.

eletricity. An econometric model is developed by adopting a neoclassical concept of stock adjustment for electricity-consuming appliances.

In chapter IV, the econometric model equations developed in the previous chapter are empirically estimated for an electric utility system. Some practical issues for the model estimation are discussed. The theoretical model specifications are then adjusted and refined through the empirical study. The statistical validity of the explanatory variables is tested and the accuracy of the model forecasts is assessed. Based on monthly data over the 1969-1982 period, short-run, long-run adjustment and long-run equilibrium elasticities of the peak load are examined for the variables included in the model. Some policy implications for capacity planning, peak load pricing and direct load management measures are also discussed in this chapter.

Chapter V synthesizes the conclusions drawn from the previous chapters and proposes some suggestions for improvement in peak load forecasting.

CHAPTER II

PRESENT STATE OF THE ART FOR PEAK LOAD FORECASTING

Comprehensive surveys of the electric load forecasting models conducted in 1975 and 1976 uncovered almost no literature of peak load forecasting.[1] This lack of concern in peak load forecasting prior to 1973 was mainly due to the low costs of electric generation and the stable growth trends experienced by most of electric utilities. In many instances, energy sales were steadily increasing and load factors remained stable over the years.[2] There has been a sizable increase in resources devoted to the peak load forecasting since the 1973-1974 energy crisis. However, nearly all peak load modeling research is still performed by utilities. While academic models tend to be better structured and documented, the interest of academicians has been primarily confined to investigating the impacts of peak load pricing rather than forecasting the loads.

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[1] L. D. Taylor, "The Demand for Electricity: A Survey," The Bell Journal of Economics, Vol. 6, No. 1 (Spring 1975), pp. 74-110; and Charles River Associates, Long-Range Forecasting Properties of State-of-the-Art Models of Demand for Electric Energy (Palo Alto, California: Electric Power Research Institute, December 1976).

[2] Load factor is a ratio of average hourly demand to peak hour demand in a given period.

Despite a short history of research, a wide variety of methodologies have been tried for peak load modeling. Although further classification within a group is necessary, the various approaches used for peak load forecasting are basically grouped into indirect methods and direct methods.

A. Indirect Methods

According to the survey of load forecasting methodologies conducted by Federal Power Commission in 1969, about half of the thirty utilities responded prepare an energy forecast as the primary forecast and produce a peak load forecast by using the energy forecast and load factor relationship.[3] Advantages argued for the indirect forecasting methods are: 1) that energy use data are usually less erratic over time than peak demand data and are therefore a better indicator of underlying growth trends; 2) that load factors are no more volatile than peak loads in the short run and in many cases tend to be stable over the long run; and 3) that detailed data are available for energy, but not for peak demand, by classes of services and geographical sub-divisions and can be easily related to appropriate explanatory variables, such as weather, income and population.[4] Based on modeling sophistication, the indirect forecasting methods are further classified by the system load factor approach and the class of service coincident load factor approach.

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[3] L. D. Taylor, "A Review of Load-Forecasting Methodologies in the Electric Utility Industry," Proceedings on Forecasting Methodology for Time-of-Day and Seasonal Electric Utility Needs (Palo Alto, California: Electric Power Research Institute, March 1976), p. 85.

[4] Ibid., p. 86.

1. System Load Factor Approach

The simplest peak load forecasting technique employed by utilities is a trend extrapolation of system load factor. The trend-forecasted load factor is then applied aginst the energy demand forecast to generate the peak load forecast. Since much of peak load and energy sales fluctuations from trend-determined values is due to abnormal weather situations, direct use of historical load factors for the trend analysis will impede establishing a true trend. Therefore, historical values of the peak load and the energy use need to be weather-normalized by the weather sensitivity determined for each year. The weather-normalized historical load factors are then computed and trends are established.

This approach emphasizes the stability of the weather-corrected load factors and suggests a simple extrapolation technique for the trend setting. However, the post-energy-crisis experience in the last decade shows that load factors are frequently erratic and difficult to project. While it may be true that energy demand can be projected with greater accuracy than peak demand, forecasting the load factor, which is necessary to convert energy to peak demand forecast, may involve more work than a direct forecast of peak demand. After attempting to forecast the peak demand both directly and indirectly, a recent empirical study of peak electricity demand with the monthly load data of twelve different utilities concludes that it is more difficult to predict the load factor than either peak demand or average demand.[5] The second disadvantage of

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[5] R. R. Betancourt, "An Econometric Analysis of Peak Electricity Demand in the Short Run," Energy Economics, Vol. 3, No. 1 (January 1981), p. 25.

this approach is that a lack of hebavioral structure prohibits any impact analysis of policy changes on peak load growth.

2. Class of Service Coincident Load Factor Approach

One way to refine the system load factor forecast discussed above is to separately forecast load factors by class of service. System peak load forecast is then produced by multiplying the projected class of service coincident load factors by forecasts of energy usage by class of service.[6] An advantage of this approach is that it provides more structure than the system load factor approach and is amenable to piecewise improvement.

Changes in the system load factor are attributable to either or both of the two factors: 1) changes in the proportions of energy sales to classes of service which have different load factors; and 2) changes in the load factors of individual service classes. The class of service load factor approach was used by Northeast Utilities Service Company (NUSC) for their long-range load forecasting.[7] The NUSC model measures the effect of changes in the proportions of energy sales to service classes on the system load factor but does not attempt to estimate the changes in the class load factors. Nebraska Public Power District (NPPD) is another utility which adopted the class load factor approach for their peak load forecasting. Like NUSC, NPPD also used constant class load factors for

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[6]The coincident load factors by class of service are, in this case, the class of service load factors at the time of system peak demand.

[7]Northeast Utilities Service Company, The Northeast Utilities System Ten- and Twenty-Year Forecasts of Loads and Resources (Hartford, Connecticut: Northeast Utilities Service Company, January 1976).

their forecast of annual peaks for a twenty-year period.[8] In the NPPD model, the class load factors are not based on NPPD-specific data because such data are not available. Rather, they used the load research data compiled by other utilities which have similar service characteristics. Since the effects of changes in class load factors are ignored, both of the utility models are only partial models.

The major data requirements for estimating the model are class of service coincident load profiles. While many utilities have the time of day load data required for estimating coincident load responsibilities for large industrial customers, little data on coincident loads for residential and commercial customers exists until recently. Besides the estimation problem, use of the model for forecasting may be equally or even more difficult than most of the direct forecasting methods. This is because the model requires forecasts of changes in the coincident load factors and changes in energy sales by class of service at the same time.

B. Direct Methods

A counterpart of the load factor approach is direct modeling of peak loads. In the direct models, peak load is forecasted independently of underlying energy demand. Reasons cited for using the direct modeling method are: 1) it is reasonable to model directly what a utility system considers the most important forecast for capacity planning; 2) load factors are frequently erratic and difficult to project; and 3) peak demand data can be more directly related to certain vital variables such

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[8] ICF, Inc., Nebraska Public Power District System Demand and Energy Requirements: 1981 Projections (Columbus, Nebraska: Nebraska Public Power District, May 1982).

as weather and appliance stocks than energy usage data.[9] Depending on the explanatory variables used for modeling and the design of model structure, direct models are classified into time-series approaches, end-use approaches, econometric approaches and hybrid approaches.

1. Time-Series Approaches

Time-series techniques are designed to project future values of a variable such as peak load of electricity on the basis of a historical trend of that variable. The main advantage for this method is that data requirement for modeling is minimal. However, the model parameters are not intuitively meaningful because they do not provide any insight into causality. Given the expected changes in future trends of causal factors, time-series models are generally appropriate for short-run forecasting situations. The models are relatively unstable and accuracy of the model forecasts decreases over time. Despite its problem for long-run forecasting, time-series analysis has been widely used for both short-run and long-run forecasting of peak electricity demand. Model types range from simple extrapolation techniques to more sophisticated models such as autoregressive-moving average (ARMA) models. Three different types of time-series analysis will be discussed in this section: 1) trend analysis, 2) stochastic analysis and 3) ARMA (or Box-Jenkins) modeling. The models reviewed below are selected because they are considered to be milestones in the application of state of the art for peak load forecasting.

a) Trend analysis. Simple trend extrapolation technique was a popular method of load forecasting shared by many utilities in early days.

[9] L. D. Taylor, "A Review of Load-Forecasting Methodologies in the Electric Utility Industry," p. 86.

The procedure here is to fit a trend curve to historical values of peak load and generate a forecast by extrapolating this trend curve forward to the desired horizon. The effect of weather on the peak is ignored assuming that similar weather conditions will prevail every year at the time of peak demands. However, the environments which produce the peak demand can change significantly. For example, increasing rates of saturation for air-conditioning appliances makes the electric load more weather-sensitive. Under this circumstance, the load forecast based on the simple trend analysis will be less reliable with more distant history of load to be analyzed.

Recognizing the need of seasonal adjustment or weather-normalization of the load data to be used for a trend analysis, Gupta proposes a load forecasting procedure based on separation of seasonally adjusted and seasonal components of peak demand.[10] With weekly peak demand data of a particular utility and associated weather data for a 12-year period, the demand data are deseasonalized using a moving average technique. A second-order polynomial trend is then fitted for the seasonally adjusted demand data using a generalized least square estimation method, by which the observations are weighted exponentially with a declining scheme starting from the most recent observation. On the other hand, the seasonal component is divided into a summer component and a winter component. The separation of seasonal components is necessiated by the difference between cooling load and heating load. Therefore, two different weather-load models are needed. Two weather-load models are specified for each year by regression coefficients, K_s and K_w, which are estimated by correlating

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[10] P. C. Gupta, "Statistical and Stochastic Techniques for Peak Power Demand Forecasting in Electric Utility Systems," PEREC Report No. 51, Engineering Experiment Station, Purdue University, August 1969.

the summer and the winter components of the weather-sensitive demand with coincident dry bulb temperature measured as a deviation from its mean, respectively. Therefore, the values of K_s and K_w estimated in the regression analysis are expected to vary year to year. In order to reflect their evolution in load forecasts, future values of K_s and K_w are projected by a trend extrapolation based on Gompertz or polynomial curve fitting.[11] The total peak demand forecast is then obtained by combining the forecasts of seasonally adjusted and seasonal components.

Along with the procedure described above, Gupta discusses an approach in which the load is decomposed directly into weather-senstive and non-weather-sensitive components.[12] First, weekday peak demand and weather data are used to determine weather-load models year by year or season by season.[13] Once the weather-load models are determined, it is possible to separate the observed values of weekly peak demand into weather-sensitive and non-weather-sensitive components. A trend curve is fitted to the non-weather-sensitive component of demand and then extrapolated to the future. The changing coefficients of the weather-load models are fitted by a growth curve and the expected values of the coefficients at the desired time of the forecast are obtained by extrapolating the growth curve. Historical means and variances of the weather

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[11] Gompertz curve is preferable to simple time polynomials in the cases where the development of air-conditioning load is well established, because the market for air-conditioning equipment is near saturation.

[12] Gupta, "Statistical and Stochastic Techniques."

[13] Gupta uses the dry bulb temperatures of 50°F and 70°F as the threshold temperatures for heating load and cooling load, respectively. Therefore, his weather-load model would be

$$D = D_0 + K_w(T - 50)\delta_1 + K_s(T - 70)\delta_2 + u$$

where δ's are binary dummy variables and u is a residual term.

variables at the times of weekly peak loads are then used to forecast the weather-sensitive component of future peak demand. Finally, the weather-sensitive demand forecast is combined with the non-weather-sensitive demand forecast to yield an estimate of future peak.

b) Stochastic analysis. The third forecasting approach considered by Gupta is a stochastic model which assumes that peak demand is the sum of trend, seasonal and irregular components.[14] A base model for peak demand in month t will be then

$$D_t = T_t + S_t + I_t \tag{1}$$

where T, S and I denote the trend, seasonal and irregular components of D, respectively. The stochastic model is formulated by specifying models for each of these components. The trend component is

$$T_t = T_{t-1} + q_t \tag{2}$$

$$q_t = q_{t-1} + u_t \tag{3}$$

where q_t is the change in trend from time t-1 to time t and u_t is a random error term with zero mean and unknown variance σ_u^2. Combining (2) and (3),

$$T_t = T_{t-1} + q_{t-1} + u_t = 2T_{t-1} - T_{t-2} + u_t. \tag{4}$$

Letting U denote the one-period lag operator, (4) can be written as

$$T_t - 2UT_t + U^2T_t = u_t \tag{5}$$

or $$(1 - U)^2T_t = u_t. \tag{6}$$

The model postulated for the seasonal component is

$$S_t = S_{t-12} + r_t \tag{7}$$

$$r_t = r_{t-12} + (1-\rho)v_t + v_{t-1}. \tag{8}$$

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[14]K. N. Stanton and P. C. Gupta, "Forecasting Annual or Seasonal Peak Demand in Electric Utility System," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-89, No. 5 (May/June 1970), pp. 954-959.

S_t is therefore assumed to be changing with a linear trend of random slope, ρ, which can vary between zero and one. This model connects the successive monthly peak demands in a regressive manner with ρ and v_{t-1}. v_t is a stationary zero-mean white-noise process with unknown variance σ_v^2.

Combining (7) and (8),

$$(1 - U^{12})^2 S_t = (1 - \rho + \rho U)v_t. \qquad (9)$$

The irregular component I_t is assumed to be sampled from a purely random process w_t with zero mean and unknown variance σ_w^2:

$$I_t = w_t. \qquad (10)$$

From equations (6), (9) and (10), equation (1) can be written as

$$D_t = \frac{U_t}{(1 - U)^2} + \frac{(1 - \rho - \rho U)}{(1 - U^{12})^2} v_t + w_t. \qquad (11)$$

Four unknown parameters, σ_u^2, σ_v^2, σ_w^2 and ρ, must be estimated for the postulated model (11) to be complete. This involves matching the statistics of the historical demand data with corresponding statistics for the output of the postulated model. However, no meaningful statistics can be produced from the historical data or the model output because of their nonstationarity. Since the seasonal component in equation (8) involves a linear trend, S_t is nonstationary and T_t has a similar problem. Hence an indirect approach is undertaken by using a reversible transformation which converts the nonstationary process D_t into a stationary time series D_t^*:

$$D_t^* = (1 - U)^2(1 - U^{12})^2 D_t. \qquad (12)$$

From equation (11),

$$D_t^* = (1 - U^{12})^2 u_t + (1 - \rho + \rho U)(1 - U)^2 v_t$$
$$+ (1 - U)^2(1 - U^{12})^2 w_t \qquad (13)$$

which is the stochastic model producing the stationary random process D_t^*. The four unknown parameters of the stochastic model are now determined by matching the power-density spectra of the model output and the transformed historical demand data.

Once the model parameters are estimated, forecasts are produced in either of two ways. The first method is to obtain the moving-average representation of the process D_t^* and to forecast D_t by using equation (12). The second way is to apply a Monte Carlo gaming approach, assuming the error terms u, v and w are all Gaussian with variances σ_u^2, σ_v^2 and 1, respectively and using the estimated value for ρ. A large number of realizations of the process are generated. The mean of the realizations for the desired t is used as the forecast.

Regarding practical application, a purely stochastic model, such as the model discussed above, appears to have limited significance for the demand forecasting. Serious computational difficulties are associated with conversion of the stochastic model to a suitable form for forecasting purpose. However, once an appropriate model is obtained, forecasts are produced quite rapidly. Since the model is nonstationary, it does not have to be updated as frequently as the trend curves and the weather-load models discussed earlier. Therefore, the combination of simple stochastic models with more conventional techniques such as weather-load models may have a great potential.

c) ARMA (or Box-Jenkins) modeling. Econometric models are often misspecified due to over-simplification, data limitations or the practice of prefiltering data. This is especially true for utility load forecasting where univariate adjustments of load data for the impacts of weather, seasonality, and rates are often attempted. Data limitation is a common problem for small utilities where reliable service area data exists on only a subset of the theoretically important causal variables. Claiming that econometric models are not the final answer to good forecasts, Uri poineered the application of ARMA (or Box-Jenkins) modeling techniques to electric load forecasting as an alternative to econometric models.[15]

In his effort to build a Box-Jenkins model for intermediate term forecasting of system loads, time-series data of monthly average daily peak system loads obtained from a large electric utility in the western United States for the years 1961 through 1973 were analyzed.[16] Since he noticed that the size of seasonal effect increases with an increase in the level of the series, logarithms of the original observations were taken in order to fit a model with an additive seasonal effect. Letting the observed monthly average daily peak load at time t be denoted by x_t and the log-transformed value by z_t,

$$z_t = \ln x_t$$

The first stage of the Box-Jenkins procedure is to difference the series z_t until a stationary series w_t is obtained. Because the series has a trend and seasonal patterns completing one cycle every twelve observations, the sample autocorrelation fuctions of the series $\nabla^d \nabla_{12}^D z_t$ need to be examined, where ∇_s^D indicates that the difference operator,

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[15] N. D. Uri, "A New Approach to Load Forecasting in the Electrical Energy Industry," Working Paper No. 31, U. S. Department of Labor, Bureau of Labor Statistics, November 1974.

[16] N. D. Uri, "Intermediate Term Forecasting of System Loads Using Box-Jenkins Time Series Analysis," Proceedings on Forecasting Methodology for Time-of-Day and Seasonal Electric Utility Needs (Palo Alto, California: Electric Power Research Institute, March 1976), pp. 60-76.

$$\nabla_s z_t = (1 - B^s)z_t = z_t - z_{t-s},$$

is applied D times and B is the lag operator. The operator $\nabla\nabla_{12}$ will remove a linear trend and a stable seasonal pattern. The time-series data used in the study showed that the autocorrelation coefficients at lags 1 and 12 are significant and that a lag of greater than 12 can be regarded to exert no influence. Given these results, the following simple model was tentatively entertained to represent the seasonal dependence in the series:

$$(1 - B^{12})z_t = (1 - \theta_{12}B^{12})e_t$$

where e_t are independently distributed random disturbances. After removing the between-years seasonal correlation, the between-months serial correlation in the e_t must also be removed. The between-months correlations could be explained by a moving-average model of order q = 1. That is,

$$(1 - B)e_t = (1 - \theta_1 B)a_t$$

where a_t is white noise. Then, a modified model for the observations z_t will be

$$(1 - B)(1 - B^{12})z_t = (1 - \theta_1 B)(1 - \theta_{12}B^{12})a_t$$

where the parameters, θ_1 and θ_{12}, are empirically estimated.[17]

Using the model specified above with the estimated parameters, $\hat{\theta}_1$ and $\hat{\theta}_{12}$, forecasts of the monthly average daily peak loads for the years 1971 through 1973 were generated. Since the data used to estimate the model ran from January 1961 to December 1970, residual analysis of the forecasts is an empirical test of the forecasting ability of the model. During the period of relatively smooth growth, the Box-Jenkins model

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[17]In fact, the between-months correlations can be more effectively removed by using the first differential terms of z_t and e_t. Then, the model can be further refined to explain the seasonality of autoregressive terms: $(1 - \phi_{12}B^{12})\Delta z_t = (1 - \theta_{12}B^{12})\Delta e_t$ where the parameters, ϕ_{12} and θ_{12}, are to be estimated.

predicts remarkably well. However, the model is not expected to perform so well over the turbulent years like 1974-1977 because no causal variables are included in the model to explain different structural effects.

The Box-Jenkins method discussed above uses a three-stage model building procedure--identification, estimation and diagnostic checking. Since the model identification is based on examination of the various patterns formed by autocorrelation and partial autocorrelation functions of AR, MA and ARMA models, the Box-Jenkins method has limited use for on-line forecasting and does not necessarily select the model which produces the best results. As an advanced technique to the conventional Box-Jenkins technique, Nelson and Vemuri presented a method with which the model selection process is very simple and on-line forecasting of hourly electric loads is automatically possible.[18] The method processes the historical hourly loads with a sequential least-squares estimator to identify a finite-order autoregressive model which in turn is used to obtain a parsimonious ARMA model. A procedure is also provided for incorporating temperature as a variable to improve forecasts of weather-sensitive loads. Compared with the Box-Jenkins method, the advanced method involves much less human intervention and improved model identification.

The ARMA model of (p, q) can be written as

$$\omega(B)z_t = \theta(B)a_t \qquad (1)$$

where $\omega(B) = \sum_{i=0}^{p} \omega_i B^i$, $\omega_0 = 1$ and

$\theta(B) = \sum_{i=0}^{q} \theta_j B^j$, $\theta_0 = 1$.

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[18] D. J. Nelson and S. Vemuri, Automatic Load Forecasting (Palo Alto, California: Electric Power Research Institute, March 1981).

Alternatively, the above model can be represented by the infinite-order AR model of

$$\pi(B)z_t = a_t \tag{2}$$

where $\pi(B) = \theta^{-1}(B)\omega(B) = \sum_{i=0}^{\infty} \pi_i B^i$, $\pi_0 = 1$.

For practical application, assuming a finite order for the AR model,

$$\pi_h(B) = \sum_{i=0}^{h} \pi_i B^i \tag{3}$$

where h is the order of the AR process. In a matrix form,

$$z_t = \underline{\pi}^T \underline{z}_t + a_t \tag{4}$$

where $\underline{\pi}^T = [-\pi_1, -\pi_2, \ldots, -\pi_h]$

$\underline{z}_t = [z_{t-1}, z_{t-2}, \ldots, z_{t-h}]$

and T is the transpose.

For a given order h, the estimate of π, $\hat{\pi}$ which minimizes the variance of the residuals of the AR model, is obtained by using the following sequential least-squares estimator:

$$\underline{\hat{\pi}}_N = \underline{\hat{\pi}}_{N-1} + \underline{R}_N \underline{z}_N (z_N - \underline{z}_N^T \underline{\pi}_{N-1}) \tag{5}$$

where $\underline{R}_N = \underline{R}_{N-1} - \underline{R}_{N-1}\underline{z}_N(1 + \underline{z}_N^T \underline{R}_{N-1}\underline{z}_N)^{-1}\underline{z}_N^T\underline{R}_{N-1}$

and $\underline{R}_N = [\sum_{t=1}^{N} \underline{z}_t \underline{z}_t^T]^{-1}$

for N measurements of z_t.

Without any information on $\underline{R}_0$ and $\hat{\pi}_0$, the iterative procedure is started by assuming large values for $\underline{R}_0$ and $\hat{\pi}_0 = \underline{0}$. The components π_i of the vector $\hat{\pi}_N$ are the estimates for h of the parameters of the true infinite ordered AR process. Value of h is also determined iteratively such that the variance of the error between a_t and $\hat{a}_t$ is minimized. In practice, the residual variance has approximately the same value for many values of h. The lowest value of h is chosen from those values of h for which the residual variance is about the same.

For a parsimonious model, the next step is to identify the parameters of the ARMA model of equation (1) from the h ordered AR process determined in the previous step. From equation (2),

$$a_t = \hat{\pi}_h(B)z_t + \sum_{i=0}^{h} \hat{\pi}_i z_{t-i}. \qquad (6)$$

Treating $\hat{a}_t$ as the measurable input, equation (1) can be modified as

$$z_t = \underline{\xi}^T \underline{\Gamma}_t \qquad (7)$$

where $\underline{\Gamma}_t = [z_{t-1}, z_{t-2}, \ldots, z_{t-p}, \hat{a}_t, \hat{a}_{t-1}, \ldots, \hat{a}_{t-q}]$

and $\underline{\xi}^T = [-\omega_1, -\omega_2, \ldots, -\omega_p, \theta_1, \theta_2, \ldots, \theta_q]$

Equation (7) is similar to equation (4). The parameter vector $\underline{\xi}$ can be estimated by the least-squares sequential estimator:

$$\hat{\underline{\xi}}_N = \hat{\underline{\xi}}_{N-1} + \underline{P}_N \underline{\Gamma}_N (z_N - \underline{\Gamma}_N^T \hat{\underline{\xi}}_{N-1}) \qquad (8)$$

where $\underline{P}_N = [\underline{I} - \underline{P}_{N-1} \underline{\Gamma}_N (1 + \underline{\Gamma}_N^T \underline{P}_{N-1} \underline{\Gamma}_N)^{-1} \underline{\Gamma}_N^T] \underline{P}_{N-1}$

and $\underline{P}_N = [\sum_{t=1}^{N} \underline{\Gamma}_t \underline{\Gamma}_t^T]^{-1}$.

The estimate $\hat{\underline{\xi}}$ gives the desired parameters for the ARMA model of equation (1). The order (p, q) of the ARMA model is determined by a search procedure to give the orders which best fit the higher-order AR model identified in the previous step.

There are three alternatives proposed to incorporate weather variables into the time-series model discussed above. The first method is to expand the least-squares estimation so as to include dependence, not only on past values of load but also on current and previous values of weather variables. Then, the modified AR model will be

$$(1 + \sum_{i=1}^{m} \alpha_i B^i) z_t = (1 + \sum_{j=1}^{n} \beta_j B^j) w_t + v_t \qquad (9)$$

where z_t = hourly load

w_t = hourly weather variable

v_t = residual noise

B = lag operator

α_i = the coefficient for the ith delayed load

β_j = the coefficient for the jth delayed weather variable.

The second method is to incorporate the weather variables into the moving average portion of the algorithm. The model will be the same as (9) but the way to develop the β_j is different. The third method is to use the ARMA model as developed in the previous steps. The residuals of the ARMA model are then analyzed in place of z_t in equation (9). This analysis would provide a correction to be added to the original forecast in a stepwise fashion.

Nelson and Vemuri tested the on-line forecasting method using three hourly data from the Lincoln Electric System, Lincoln, Nebraska. In the exhaustive analyses performed on this data base, they demonstrated that their method produced significantly better results than the Box-Jenkins method. Although they improved the data processing capability of the commonly used Box-Jenkins method by minimizing the human intervention in developing the stochastic models and introduced a possible means of incorporating weather variables into a pure time-series model, their method is still short of a mechanism to take account of structural changes. The method was designed only for forecasting short-term (hourly) load.

2. End-Use (or Engineering) Approaches

End-use modeling approaches are characterized by their primary reliance on physical analyses of the energy-consuming equipment. Models are developed as functions of the capacity and efficiency of equipment, rates of saturation (ownerships) for the equipment, rates of utilization at the time of peak demand, weather, etc. Engineering principles are typically used to develop a simplified mathematical representation which relates energy utilization to the thermal properties of environments and the electro-mechanical characteristics of the energy-using equipment. End-use models are attracted by their ability to explicitly evaluate various conservation policies and load management programs and to provide detailed analyses of new technology impacts on electric energy demand. For load forecasting purpose, this approach would produce accurate forecasts provided that a user can make accurate forecasts of end-use inventories. Estimation of the engineering models, however, requires creation of a vast data base of end-use inventories and load curves. Therefore, the large data requirements and intense modeling efforts imply a trade-off between level of disaggregation and quality of component forecasts. While the lack of adequate data continues to inhibit a wide-spread application of the end-use models, the role of end-use models has expanded greatly since the oil embargo. For example, they are intensively used in evaluating the impacts of conservation programs established by Congress and state legislatures.[19]

Application of the end-use modeling approaches to peak load forecasting was pioneered by the California Energy Commission (CEC) in 1976.[20] In its efforts to build a peak-load forecasting model for the electric

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[19]See S. C. Carhart, S. S. Mulherkar and S. Yasuko, The Brookhaven Buildings Energy Conservation Optimization Model, prepared for the Division of Buildings and Community Systems, U.S. Department of Energy, January 1978; J. R. Jackson, An Econometric - Engineering Analysis of Federal Energy Conservation Programs in the Commercial Sector (Oak Ridge, Tennessee: Oak Ridge National Laboratory, January 1979); and U.S. Department of Energy, Nonresidential Buildings Energy Consumption Survey: Buildings Characterristics, DOE/EIA-0278, June 1981.

[20]California Energy Commission, "Technical Documentation of Procedures for Estimating Peak Demand," Mimeograph, October 4, 1976.

utilities in California, CEC used the daily peak load history of Pacific Gas and Electric Co. (PG&E) for July and August of the years 1961-1975 to estimate the following equation:

$$D = NWD + \beta TAS + \varepsilon$$

where D = daily peak demand in megawatts, excluding weekends and holidays;

NWD = non-weather-sensitive demand to be estimated;

TAS = a composite temperature-appliance saturation index calculated as $\sum_{i=1}^{n} [(TEMP_i > 75°) \times AC_i]$

with $TEMP_i$ = daily average dry-bulb temperature at weather station i;

AC_i = number of electric central air conditioners in region i; and

n = number of sub-regions in the system; for the case of PG&E, n = 3;

β = parameter to be estimated; and

ε = random error term.

The above model specification involves two strong prior assumptions: 1) the common β coefficient for all of the sub-regions presumes that the dependence of weather-sensitive peak demands on daily summer temperatures is the same for each of the sub-regions; and 2) temperatures above 75°F only interacts with air conditioner saturation in the equation. After estimating the equation for each of the years 1961-1975, the non-weather-sensitive demand component, NWD, as estimated from each year's PEAK regression, was then regressed on annual KWh sales in a bivariate equation,

$$\widehat{NWD} = \gamma + \delta ES$$

where ES = annual KWh sales and

γ, δ = parameters to be estimated.

In order to use the above equations for peak-load forecasting, energy(kWh) sales must be forecasted independently. With the forecasted value of NWD and appliance saturations in hand, stability of the β coefficient is now questionable. Efficiency and utilization rates of air conditioners represented by the magnitude of the β coefficient actually change over time as a function of the socioeconomic variables, such as price of electricity, income, household size, business conditions in commercial and industrial sectors, etc. Generally speaking, the CEC model has an obvious weakness caused by over-simplification. The presence of positive first-order serial corrélation in the first equation reveals the misspecification problem. However, the model served as a stepping stone to the imporved methods that appeared later.

A more formal and integrated end-use model was developed for the New England Power Pool by Battelle Columbus Laboratories in 1977.[21] Although the model is an integrated load curve forecasting model, peak load is determined by finding the peak on the curve. The model has hourly load curve for each detailed end uses. Hourly load on the curve for a given end use is derived by multiplying per-unit use value for the end use times the number of appliances of the type times the probability of the equipment being in use at a particular hour. Seasonality is accounted for by making the use probabilities a function of temperature for weather-

[21] New England Power Pool Load Forecasting Task Force and Battelle Columbus Laboratories, Model for Long-Range Forecasting of Electric Energy Demand (West Springfield, MA: NEPLAN, June 1977).

sensitive appliances. The principal data requirements for the model estimation are end-use inventory data and unit load curves. These formidable data requirements pose a real impediment for practical application of the modeling approach. The inventory data set alone requires an extremely expensive survey and maintenance cost. Furthermore, the unit load curve data are virtually unavailable for some appliances. Therefore, the model estimation is started with initial guesses of the model parameters and then refined by simulation with actual system load data. To produce a load forecast, the model requires the forecasts of appliance stocks and unit load curves. Without any major policy or energy market changes, the unit load curves are assumed to remain constant. For the appliance inventory forecasts, Battelle uses a saturation curve fitting method. A major advantage with the model is that its end use detail provides a considerable potential for impact analysis of various load management measures. However, the inevitable compromises with data availability results in substantial inaccuracies. Complete absence of economic factors is another shortcoming of the model. The use of constant unit load curves and saturation curve fitting for the appliance inventory forecasts make the model insensitive to changes in energy market conditions.

The main advantage of an end-use model is recognized to be the capability to incorporate the impact of a given conservation program into the load forecast. However, the energy reducing effects of conservation programs or improved appliance efficiency are actually overstated by end-use models. By ignoring the interaction between economic and engineering effects, end-use models fail to account for increased electricity use by consumers who have installed conservation measures.[22] When a consumer replaces an old air conditioner with one which is twice as efficient, the effective price of electricity for air conditioning drops to half of what it used to be. If the consumer's price elasticity of demand for electricity is not zero, he will react to the lower effective price by increasing the number of hours in usage of the air conditioner. Therefore, engineering models tend to overestimate the energy reduction achieved by the efficiency improvement by ignoring the feedback from the engineering side to the economic side. Another problem encountered when an end-use model is used to assess the impact of conservation measures is a double counting problem. Since end-use models implicitly assume ceteris paribus conditions for other relevant factors such as weather, income, and price, one can make a mistake of double counting if those other relevant factors do not actually remain constant. Load reduction attributed to an audit program can be overstated by an engineering model because the model does not take into account the conservation effect induced by rising price of electricity.

A real disadvantage of an end-use model is the high cost of data gathering. Given resource limitations and the benefit of increased accuracy, the appropriateness of the end-use modeling approach needs to be evaluated case by case on the basis of cost-benefit considerations.

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[22] This problem was pointed out by Bentley, Cosgrove and Stallcup at the third EPRI Load-Forecasting Symposium held in March 1981. Recently, the problem has been reissued with practical examples by Khazzoom. See W. G. Bently, C. E. Cosgrove and P. W. Stallcup, "Integrating Econometric and End-Use Models: A Realistic Approach to Conservation Programs," Approaches to Load Forecasting: Proceedings of the Third EPRI Load-Forecasting Symposium (Palo Alto, California: Electric Power Research Institute, July 1982), pp. 44-76; and J. D. Khazzoom, "Integrating Residential Conservation Measures into Utility Demand Forecasts," Public Utilities Fortnightly, March 31, 1983, pp. 23-30.

Another disadvantage of an engineering model is that no probability statement can be attached to the results of impact analysis or the forecasts of end-use models.

3. Econometric Approaches

Econometric methods rely on the statistical analysis of historical time-series and/or cross section data to develop a model of peak load as a function of behavioral and structural variables such as economic activities, population and weather. Economic theory is usally used to develop a mathematical structure of the model and the model parameters are estimated by some type of regression analysis. Econometric approach is the most popular method of peak-load forecasting in the electric utility industry.[23] Since the econometric approach requires modest efforts for data development and model estimation to be implemented, it is a well-accepted approach. Compared with the time-series methods and the end-use methods, econometric methods are much better suited for long-run forecasting because long-run analyses should include econometric-type structural relationships. Evaluation of the modeling results with statistical criteria is another advantage. However, estimated model coefficients are frequently biased due to omitted variables, misspecification of functional form, errors in variables and/or inadequate dynamic representation. Multicollinearity is also a common problem which discourages the use of econometric models.

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[23]According to a recent survey of electric utility load forecasters, more than 60 percent of the participating utilities list the econometric method as the most important method to be used for peak load forecasting. See A. G. Lawrence, A Survey of Electric Utility Load Forecasting Methods, Preliminary Issues (Los Altos, California: Applied Forecasting & Analysis Inc., January 1983).

There has been a rapid evolution of the econometric techniques of peak load forecasting during the last decade. Depending on how the model is set up to treat the relationship of demand for electricity and the requisite appliances in the short-run and the long-run, various econometric models developed so far are classified into four types: 1) static equilibrium model, 2) flow-adjustment model, 3) stock-adjustment model and 4) two-stage model. Aside from the problem of short-run vs. long-run analyses of peak load formation, short-run variability of price elasticity and weather sensitivity is evaluated in an econometric model recently developed.

a) Static equilibrium model. Application of the econometric techniques to hourly load forecasting was pioneered by Cargill and Meyer in 1971.[24] In an attempt to provide detailed empirical investigations of the factors determining the peak load demand, they developed the following hourly load demand model:

$$y_i = \beta_{1i} + \beta_{2i}\frac{PE}{PG} + \beta_{3i}Y + \beta_{4i}Y^2 + \beta_{5i}M + \beta_{6i}t + u_i$$

where y = total system load per capita at time i in Kw

PE = average revenue per KWh

PG = average price per therm for gas

Y = real per capita personal income

M = employment of production workers in manufacturing

t = monthly trend variable

u = random error term.

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[24]Cargill and Meyer, "Estimating the Demand for Electricity by Time of Day," pp. 233-246.

Cargill and Meyer estimated the equation for each of the 24 hours in a day using seasonally-adjusted monthly means of each hourly loads for a four-year period from January 1965 through December 1968. There are 48 observations and the equations were estimated for two regions markedly different in terms of climate and industrial activity. The first region is a midwest industrial city and the second is a west coast city. According to the modeling results, their equations explain about 90 percent of the total variation in monthly hourly demand in both regions. The price of electricity relative to price of gas has a negative effect as expected but is statistically significant for the first region only. The income variable shows little significance for both regions.

Cargill and Meyer's model was primarily motivated by quantification of the impact of electricity price on the load curve. However, their goal is mitigated by the fact that electiricy price did not vary by hour of day. Another problem with their model is the assumption of independence between the hourly loads; which is not likely in a real situation. Moreover, they failed to see the dynamic features of electricity demand formation. By not distinguishing between short-run and long-run effects of the economic variables, the model implicitly assumes instantaneous adjustment in the electicity-using capital stock to change in the economic variables. Consequently, their model becomes a static equilibrium model, like many earlier model. Since the static equilibrium models are not designed to track short-run time-series variation in electricity demand nor designed to incorporate the size or characteristics of the electricity-consuming capital stock, they can not provide accurate measurements of price and income elasticities.

b) Flow-adjustment model. Electricity is required as an energy input to utilize capital stock of some durability and does not yield any utility in and of itself. The demand for electricity is therefore a derived demand--derived from the demand for the services produced by electric equipment which yields utility. Since durable goods are involved in the process of electric demand, there is a need to distinguish between a short-run demand for electricity and a long-run demand.

Rather than assuming instantaneous adjustment of the capital stock, dynamic models take account of possible short-run disequilibrium in the demand for electricity. As electric demand responds to changing economic conditions, the stock of appliances does not adjust as rapidly because of its durability. Due to the time lags involved for the capital stock adjustment, the level of electric demand can only partially adjust in the short-run. Flow-adjustment models assume that actual change in demand is proportional to the difference between desired and previous levels of demand. Therefore, in the short-run,

$$D_t - D_{t-1} = \lambda(D_t^* - D_{t-1}) \qquad (1)$$

where D_t is actual demand in period t, D_t^* is desired demand and λ is an adjustment factor which takes a value between 0 and 1. Given sufficient time to adjust, λ becomes 1 and the equilibrium quantity, D_t^*, will be demanded. The concept of flow-adjustment modeling originated with Houthakker and Taylor.[25] In the flow-adjustment model originally formulated by Houthakker and Taylor, the demand for electricity is expressed as a function of the electricity consumption lagged one period and the

[25] H. S. Houthakker and L. D. Taylor, Consumer Demand in the United States, 2nd ed. (Cambridge, Mass.: Harvard University Press, 1970).

exogeneous variables measured as sum of their current and one-period lagged values. For example, both current and lagged prices of electricity are included as exogeneous variables but the coefficients of those two variables are constrained to be equal. Later, the Koyck version of the flow-adjustment model was investigated by Taylor, Blattenberger and Verleger in an empirical study of residential demand for electricity.[26] The Koyck lag distributed model is derived by specifying the flow adjustment process directly in discrete time as shown in euqation (1) while the original Houthakker-Taylor model is based on the specification in continuous time with a translation to discrete time.[27] The Koyck model takes the demand for electricity as a function of the electricity comsumption lagged one period and current values of the exogenous variables.

Acknowledging the time required to adjust capital stocks and usage, Spann and Beauvais developed a dynamic model of monthly peak demand for Virginia Electric Power Company (VEPCO) by utilizing a Koyck type of distributed lag structure.[28] The monthly peak demand model estimated with the time series data of VEPCO for the period

$$\ln KW = \alpha + \beta_1 \ln E + \beta_2 \ln D + \beta_3 \ln I + \beta_4 T + \beta_5 \ln INDEX + \beta_6 \ln O + \lambda_1 \ln KW_1 + \lambda_2 \ln KW_{12} + \varepsilon$$

where $\ln KW$ = log of peak kilowatt demand

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[26] L. D. Taylor, G. R. Blattenberger and P. K. Verleger, Jr. of Data Resources, Inc., The Residential Demand for Energy (Palo Alto, California: Electric Power Research Institute, January 1977), Chapter 5.

[27] See Houthakker and Taylor, Consumer Demand in the United States, pp. 13-17, 26-27.

[28] R. M. Spann and E. C. Beauvais, "Econometric Estimation of Peak Electricity Demands," Forecasting and Modeling Time-of-Day and Seasonal Electricity Demands (Palo Alto, California: Electric Power Research Institute, December 1977), Section 2, pp. 3-22.

$\ln E$ = sum of the logs of the marginal energy prices for residential, industrial and commercial revenue classes

$\ln D$ = sum of the logs of the marginal demand prices for commercial and industrial revenue classes

$\ln I$ = log of total taxable income

T = temperature

$\ln INDEX$ = log of the activity index for electricity-intensive industries

$\ln O$ = log of the price of residual fuel oil

$\ln KW_1$ = log of peak demand in the previoud month

$\ln KW_{12}$ = log of peak demand lagged twelve months

ε = a random residual term.

Since the model equation is double-logarithmic and involves a distributed lag structure, coefficients of the economic variables are the short-run elasticities of demand. Coefficients of the lagged dependent variables, λ_1 and λ_2 represent a partial adjustment of the demand flow and the sum of these two coefficients is interpreted as the percentage of any adjustment to a change in the economic variables which does not take place in the short-run. Long-run elasticities are computed by dividing the short-run elasticities by $1 - \lambda_1 - \lambda_2$.

Besides the separate estimation of short-run and long-run elasticities, Spann and Beauvais present the following important empirical findings obtained through the study:

i) Price elasticities of peak demand are smaller than existing estimates of price elasticities of KWh sales. This means that utility load factors may deteriorate with rising real prices of electricity and the optimal capacity mix should move toward more peaking units. However, implementation of peak load pricing or any effective load management measure could reduce the pressure of capacity additions. Absolute magnitudes of the price elasticities far smaller than 1.0 also imply that peak load pricing may increase the total revenues of electric utilities.

ii) Income elasticity of peak demand is larger than income elasticity of KWh sales. Therefore, increasing real incomes would lead to more purchases and utilization of appliances which tend to be operating at the time of peak demand. Air conditioner is a good example.

iii) Peak demands are sensitive to alternative fuel prices. This result indicates a strong substitution possibility between electricity and other fuels.

One difficulty with the simple flow-adjustment model described above is its implicit assumption of static expectations. The model implicitly assumes that consumers expect current levels of prices and income to maintain and persist indefinitely. It is, however, implausible to assume that the current KW demand depends solely on the current values of the economic variables. Since the economic variables are subject to change from period to period, it might not be rational to base important decisions entirely on the current values. One possible way to introduce a concept of dynamic expectation into the model is to apply an adoptive expectation scheme, which assumes that expectations are updated each period by a fraction of the discrepancy between the current observed value of the variable and the previous expected value.[29] With adoptive expectations, the current values of the economic variables in the model are replaced by

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[29] J. Johnston, Econometric Methods, 2nd ed. (New York: McGraw-Hill Book Co., 1972), p. 301.

the expected values. Each of the expected values is obtained from a geometrically declining lag distribution similar to the Koyck scheme.

c) Stock-adjustment model. While capital stock adjustment is indirectly reflected in the flow-adjustment models, capital stock is an explicit argument in the stock-adjustment models. Following Fisher and Kaysen, stock of electricity-using appliances is measured by the number of watts that the stock can potentially draw.[30] In the capital stock model, consumption of electricity is expressed as a product of utilization rate times the stock of appliances. Rather than forcing a single equation to deal with the potential disequilibria in electricity and capital demand as in the case of the flow-adjustment model, the stock-adjustment model utilizes explicit and separate equations for each decision. Therefore, the model is composed of a set of appliance stock and utilization equations. For example, a simple form of the model could be

$$D = U(x, \pi, z)S \qquad (1)$$

$$U = \alpha_0 + \alpha_1 x + \alpha_2 \pi + \alpha_3 z \qquad (2)$$

$$S = \sum_{i=1}^{n} w_i s_i$$

$$s_i = \beta_0 + \beta_1 x + \beta_2 \pi + \beta_3 (r + \delta) P_i + \beta_4 z \qquad (4)$$

where D = demand for electricity

U = composite rate of utilization for all end uses as an aggregate

S = stock of electric appliances measured in terms of potential use of watts

x = income

π = price of electricity

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[30] F. M. Fisher and C. Kaysen, A Study in Econometrics: The Demand for Electricity in the United States (Amsterdam: North Holland Publishing Co., 1962).

z = any other factors that might be relevant

s_i = stock of the i^{th} type of appliance

w_i = weight for the i^{th} appliance, defined as $w_i = \frac{u_i^*}{\Sigma u_i^*}$ where

u_i^* denotes the normal rate of utilization for the i^{th} appliance

r = market rate of interest

δ = rate of depreciation of the i^{th} appliance stock

$\bar{P}_i$ = price per watt of additions to the i^{th} appliance sotck.

In the stock-adjustment model, the distinction between short-run and long-run is made by fixity of the capital stock. The stock of electric appliances is assumed to be fixed in the short-run. Therefore, the short-run demand for electricity can be regarded as a choice of utilization rate for the existing stock. Since the capital stock is variable and the utilization rate is at equilibrium in the long-run, the long-run demand for electricity is equivalent to the demand for an equilibrium stock of electricity-consuming capital goods.

The stock-adjustment model described above was originally conceived by Taylor and later used for residential electricity demand forecasting.[31] In their modeling efforts, the utilization equations were aggregated over all appliances by weighting the individual appliances with normal KWh usage. The stock equations were estimated separately for ten of the eleven most popular electric appliances for residential use.[32]

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[31] Taylor, "The Demand for Electricity: A Survey," pp. 80-83; and Taylor et al., The Residential Demand for Energy, Chapters 3 and 6.

[32] The eleven appliances are refrigerators, room air conditioners, electric water heaters, electric stoves, automatic clothes washers, conventional clothes washers, electric clothes dryers, dishwashers, electric space heating and central air conditioners. Among those eleven appliances, no equation was estimated for dishwashers.

The major concern with stock-adjustment models is the data availability for detailed appliance stocks. The appliance data requirements become formidable in the case of peak demand modeling which covers all sectors of the utility system. There are all kinds of appliances to be analized for the entire system. Although Taylor and others were lucky enough to obtain a good data base of appliance stocks constructed by Data Resources, Inc., they are still concerned about the potential heteroscedasticity in the error terms of the appliance stock equations.[33] This problem is generally attributed to weaknesses in the estimation data base. While a great deal of time and efforts were put into construction of the appliance data base, there still remains much room for improvement. Since the data refer to saturation rates rather than to capacity, they do not reflect multiple ownership of appliances and changes in rated efficiency. Another deficiency in the data base is the absence of information on the amount of living space and the thermal characteristics of existing housing structures. Availability of that information should considerably improve the model's ability to explain the amount of space cooling and heating energy use.

While the stock-adjustment model is conceptually superior to the flow-adjustment model, its serious empirical weakness is the formidable data requirements. Data limitations often lead to a number of bold assumptions that could produce biased forecasts. Use of the stock-adjustment approach for peak load modeling is much more difficult than the case of residential energy sales modeling. Because a system's peak demand is the maximum level of demand which is achieved coincidently by

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[33]Taylor et al., p. 5 of Chapter 10.

all sectors of a utility system, the peak demand forecast should be derived by selecting the highest value of the hourly load forecasts. Therefore, hourly load profiles for each of the appliances are required for the modeling, in addition to the stock data. Due to these virtually impossible data requirements, no stock-adjustment model of peak demand has been developed so far.

d) Two-stage (or time-varying parameter) model. A typical hourly load demand is decomposed into base and weather-sensitive components. The base component is demanded to meet daily life style and business requirements while the weather-sensitive component corresponds to space cooling and heating requirements. Short-run fluctuations of the load demand at a specific hour of a day of the week are mainly induced by changes in weather conditions. In the long-run, however, impacts of the weather variables normalized over time and long-run attributes, such as changes in income, population, appliance stock and industrial mix, become predominant factors to determine the level of load demand. To produce long-term forecasts of hourly electricity consumption, Quantitative Economic Research, Inc. (QUERI) used a two-stage modeling method.[34] The two-stage (or time-varying parameter) model of electricity demand was estimated with hourly load, weather, economic and demographic data for 32 regions of the U.S. for the period 1962-1974. In the first stage, a short-run model was estimated by relating the hourly demand in each region to weather and time-of-day variables. The set of short-run parameters

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[34] Quantitative Economic Research, Inc., Regional Load-Curve Models: QUERI's Model Specification, Estimation, and Validation (Palo Alto, California: Electric Power Research Institute, August 1981), Volume 2.

estimated in the first stage were then related to the long-run variables in the second stage.

A simplified version of the QUERI's model estimated in the first stage is

$$y_t = \beta_0 + \beta_1 \text{HOUR14} + \beta_2 \text{COMFORT INDEX}_t + u_t$$

where y_t is the load demand at hour t, HOUR14 is a dummy variable which takes on the value of unity from one to two o'clock in the afternoon and zero otherwise, COMFORT INDEX_t is a temperature-humidity index measured at hour t and u_t is a random disturbance term. Since all of the β's are expected to have positive signs, the daily peak in the summer would normally occur at 2 p.m. for this simplified system. But abnormal weather or a large value of u can change the time of peak. The actual model estimated by QUERI is much more complicated and represents the average hourly load curve in a given region for a given quarter of the year. The short-run model has a total of 55 explanatory variables: constant term, 23 hourly binaries, a binary for early Monday morning hours, 6 day binaries, 8 sine and cosine terms for Saturdays and Sundays, a time trend and 15 weather variables including a 24-hour moving average temperature and a moving average of 5 past-midnight temperatures to account for cumulative temperature effects.

In the second stage, a pooled time-series cross-section analysis was performed to explain the differences in the shapes of the load curves across regions and also over time, by relating the β coefficients estimated in the first stage to the economic and demographic variables. A simplified version of the QUERI's second stage model for region k and year v and season s is

$$\beta_{1kvs} = \gamma_{10} + \gamma_{11} \text{ APPLIANCE STOCK}$$

$$\beta_{2kvs} = \gamma_{20} + \gamma_{21} \text{ CENTRAL AIR.}$$

Again, the actual equations estimated are much more complicated. In total, 50 socioeconomic variables are included: constant term, 32 regional binaries, 3 demographic variables, employment per thousand population in eight energy-intensive industries to capture the industry mix, per capita income, number of electrically heated homes, stocks of central and room air conditioners, a weighted average stock of eight commonly used weather-insensitive appliances, and the average residential and industrial prices of electricity.

Although the two-stage modeling method was designed for a big geographical region which has both time-series and cross-section data, the time-varying parameter model can be also successfully implemented at a utility service area level. With the time-series data only, the two-stage modeling is achieved by estimating the short-run model coefficients with the hourly load and weather data for each year and then regressing the short-run model coefficients estimated in the first stage with the annual economic and demographic data to estimate the long-run model coefficients. Although the examples provided for two- stage modeling are confined to the hourly-load curve forecasting, the methodology discussed above is also applicable to the case of peak load modeling.

So far, most of the hourly demand models developed by the utilities have been only for short-term forecasting and can not explain the shifts of the hourly load curves over time. To meet both the short-term and the long-term needs of hourly load or daily peak load forecasting, QUERI's two-stage model is quite promising. Building a long-range hourly load model requires that a tremendous amount of data be analyzed. For example, the number of observations on each of the load and the weather variables will equal 8,760 values per year of the history used. This sums to be 113,880 when the sampling period covers thirteen years as in the case of QUERI's study. Rather than model this huge data in one expensive and unwieldy step, the two-stage method synthesizes the original data into fewer data points through a time-series parameterization phase before getting into an econometric estimation phase.

Although the estimated results with the QUERI model are generally encouraging, some of the model coefficients involve sign problems. Particularly, the effect of per capita income on the constant term of the first-stage equation was significantly negative for summer and the industrial electricity price coefficient was significantly positive during the evenings of spring and summer quarters. However, since the income variable has significant positive effects in many of the hourly binaries and some weather variables as well, the combined effect of income was definitely positive. This is why QUERI estimated the income elasticities not from partial regression coefficients but from total simulation effects. The simulation exercises also indicate that the combined price elasticity is indeed negative as one would expect. One possible reason for the sign problems might be the multicollinearity among the variables in the second-stage equation. The multicollinearity was caused by mixing appliance stock variables with income, price and demographic variables which are in turn determining factors of the sizes of appliance stocks.

A similar type of two-stage model was independently developed by Data Resources, Inc. (DRI) and estimated over a common data base.[35] The DRI model differs in the choice of functional form used to decompose hourly loads into weather-sensitive and base components and in the specification used to model economic and sociodemographic effects. While the DRI model is free of the sign problems, the load characteristics of the commercial and industrial sectors need to be modeled in greater detail.

e) Variable elasticity model. The functional form most widely used for electricity demand modeling is double logarithmic. In a double-log demand model, elasticity of the demand with respect to each of the variables in the model is directly represented by the model coefficient for the corresponding variable. Since the model coefficients are fixed, the double-log demand model is also called a "Constant-elasticity model." However, this constant-elasticity assumption conflicts with the actual phenomena observed in the recent years. The sensitivity of electricity demand to price changes has increased with the substantial rise in energy costs after the energy crisis. In fact, this experience can be explained by the Slutsky equation in which the price elasticity of the ordinary demand curve equals the price elasticity of the compensated demand curve minus the corresponding income elasticity multiplied by the portion of total expenditures spent on the commodity in question.[36] Since electricity demand is commonly believed to be price inelastic, the share of the

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[35] Data Resources, Inc., Regional Load Curve Models: Specification and Estimation of the DRI model (Palo Alto, California: Electric Power Research Institute, January 1981), Volume 1.

[36] J. M. Henderson and R. E. Quandt, Microeconomic Theory: A Mathematical Approach, 2nd ed. (New York: McGraw-Hill, Inc., 1971), pp. 31-32.

commodity in the consumer's budget will increase as the price of electricity goes up. Therefore, the price elasticity of the uncompensated demand for electricity is getting larger with the increase in electricity price, with other things being equal. Another phenomenon frequently observed but conflicting with the constant-elasticity assumption is that the price elasticity becomes lower in the peak demand period than in the average demand period. This is because the need for electricity is greater at the time of peak when weather conditions are more extreme. In terms of the Slutsky equation, the income elasticity of electricity demand decreases as the weather becomes more extreme and the electricity becomes more of a necessity. Therefore, the uncompensated price elasticity of electricity demand should be lower with more extreme weather conditions.

The above two properties of the price elasticity of electricity demand are well embodied in the short-run model of monthly peak demand developed by Betancourt.[37] Using the monthly data of 12 different utilities over 1972-76 period, some useful alternative functional forms to the traditional double-log model are estimated and analyzed. These alternative functional forms are characterized by an increasing elasticity of the demand to price changes as price increase and a decreasing elasticity as the weather becomes more extreme. The new functional forms employed in Betancourt's study result from a simple generalization of the double-log demand functions with constant coefficients to allow the price elasticity of the demand to vary with constant coefficients to allow the price elasticity of the demand to vary with the previous levels of the

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[37] R. R. Betancourt, "An Econometric Analysis of Peak Electricity Demand in the Short Run," Energy Economics, Vol. 3, No. 1, January 1981, pp. 14-29.

electricity price and weather variables. In his study, the short-run period is defined as the time period in which the composition of the stocks of electric appliances is stable. Changes in the 'average' utilization rate of the units of electric equipment in the study area are, therefore, mainly due to changes in the utilization rates of the equipment.[38] With the above definition, specification of the short-run demand for electricity is equivalent to the specification of a functional form for the average utilization rate. In a simple form, his model descrived as

$$D_t = U_t(Y, P, X)S = (\alpha_0 Y^{\alpha_1} P^{\alpha_2(P_{-1},\ Z_t)} X^{\alpha_3})S \qquad (1)$$

where D_t = electricity demand at the time of peak

Y = income

P = price of electricity

P_{-1} = one-period lagged price of electricity

X = other exogenous variables such as weather conditions

Z_t = hourly average of heating and cooling degrees for the day of monthly peak and the day before the peak

S = the maximum number of KW that can be consumed by the units of equipment in the study area

α's = coefficients to be estimated.

Several alternative specifications were selected for the function $\alpha_2(P_{-1}, Z_t)$ in this study. They are

$$\alpha_2(P_{-1}, Z_t) = \alpha_2 \qquad (2)$$

$$\alpha_2(P_{-1}, Z_t) = \alpha_2(P_{-1}) = \beta P_{-1} \qquad (3)$$

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[38]The average utilization rate is a weighted average of the utilization rates of the different units of equipment in the study area where the current stocks of the units of the equipment are used as the weights.

$$\alpha_2(P_{-1}, Z_t) = \alpha_2(Z_t) = \alpha_2 + \gamma Z_t^H + \delta Z_t^C \tag{4}$$

$$\alpha_2(P_{-1}, Z_t) = \beta P_{-1} + \gamma Z_t^H + \delta Z_t^C \tag{5}$$

where Z_t^H and Z_t^C are average heating degree hours and cooling degree hours for the day of monthly peak and the day before the peak.

If the effects of the lagged price and the weather variables on the absolute value of the price elasticity are both significant, equation (5) can be incorporated with equation (1). In this model, one would expect the coefficients, γ and δ, to be positive while the coefficient β is expected to be negative. Without restrictions on the values of γ, δ and β coefficients, it is therefore possible to obtain positive price elasticities which are inconsistent with the utility maximization theory. In a double logarithmic form, equation (1) will be

$$\ln D_p = \ln\alpha_0 + \alpha_1 \ln Y + \alpha_2(P_{-1}, Z_t) \ln P + \alpha_3 \ln X + \ln S. \tag{6}$$

For empirical purposes, it would be advantageous to convert equation (6) into the first-difference equation. With a time-series data, existence of linear time trends in the independent variables is likely to cause multicollinearity problems and the first-differencing of the equation will take care of the problems. Combining equation (6) with equation (5) and converting the resulting equation into yearly first difference,

$$d_p = \bar{\alpha}_0 + \alpha_1 y + \beta P^* + \gamma W^H + \delta W^C + \alpha_3 x + s \tag{7}$$

where the lower case letters, d_p, y, x and s, denote the yearly rates of growth in the respective variables and

$$P^* = P_{-1}(p) + (\ln P_{-1})(P_{-1} - P_{-2}) \tag{8}$$

$$W^H = Z_t^H(p) + \ln P_{-1}(Z_t^H - Z_{t-1}^H) \tag{9}$$

$$W^C = Z_t^C(p) + \ln P_{-1}(Z_t^C - Z_{t-1}^C). \tag{10}$$

In the absence of a time trend, the intercept term in equation (7), $\bar{\alpha}_0$, should be zero.

Betancourt estimated equation (7) and three other equations formulated with the alternative specifications for $\alpha_2(P_{-1}, Z_t)$ shown in equations (2), (3) and (4). A point worth noting is that the rate of growth of new residential customers was used as a proxy for the rate of growth of the stock of electricity-using equipment (s). It should be also noted that the weather variables involved in x were suppressed because in the early stages of the empirical research they led to substantial multicollinearity problems with the weather variables in W^H and W^C. A similar problem arose when a constant term was introduced in equations (3) and (5). Therefore, the models he actually estimated are not nested models. The most interesting aspect of the empirical results is the variation in the price elasticity estimates under extreme conditions. Evaluating the price elasticity at the mean value of price in the sample, all of the four models show the estimates of the price elasticities under normal conditions to be fairly inelastic. However, an increase in peak price to two standard deviations above the sample mean raises the price elasticity substantially. Since the price elasticities under normal conditions are so low, a sharp price differential for the peak period may be required to successfully manage peak demand. The impacts of extreme weather conditions were also tested in the models. The priori expectations of the less price elasticities with the more cooling and heating degree hours were confirmed by the positive value of the estimated γ and δ coefficients. In order to measure the changes in price elasticities, the extreme heating situations are defined by the temperatues ranging 9°F to 48°F depending on the locations of the different utility service areas under the study. The extreme cooling situations are set for the temperatures of 81°F to 90°F. Through the analysis, the extreme cooling is found to be far more powerful in making the electric load demand inelastic than the extreme heating. An implication of this finding for peak load management is that substantially different peak prices for the summer and the winter peaks may be necessary. In sum, the variable elasticity models developed by Betancourt provide valuable tools to evaluate the impacts of various tim-of-day pricing schemes on electricity consumption. The study results suggest that even if the demand for electricity is not very sensitive to the price of electricity under normal circumstances, it can be very sensitive when the price increases substantially. However, it should be also recognized that the price impact on the electricity demand is partially cancelled by extreme weather condtions.

A defect of Betancourt's peak demand model lies in the treatment of the weather variables. In the model, the weather variables are viewed as the indirect factors which influence the load demand formation only through changing the level of price elasticity. However, it may be unreasonable to treat the weather variables as only supplementary to the price variable because weather-sensitivity analysis is also an important purpose of peak demand modeling. If the weather elasticity of the load demand is larger than the price elasticity in absolute terms as observed in many empirical studies, the model certainly has a problem to accomodate the impacts of weather correctly. Moreover, the weather variables used in the model are too crude. This is a main reason why the model estimation did not produce impressive statistical results for explanatory power.

Considering a neutral zone of temperatures which does not require any space air conditioning, use of 65°F as the base temperature for both heating and cooling in load demand modeling may not be appropriate. Another problem with the temperature variables in the model is the assumption of a strict linear relation between the temperatures and the weather-sensitive loads. Different slopes for various temperature ranges could be tried to reflect a non-linearity. By using the simple average heating degree hours and cooling degree hours calculated for the peak day and the day before the peak, the model actually restrained the coefficients of the current day's temperature variable and the previous day's temperature variable to be equal. However, impact of the current day's weather is normally expected to be bigger than the previous day's which is included in the model to merely take account of an accumulation effect.

4. Hybrid Approaches

Evolution of the peak load modeling techniques has followed three primary paths--time-series approaches, end-use approaches and econometric approaches. As discussed in the previous sections, each of the methods has its own strengths and limitations. Time-series models require a minimal amount of the data to be analyzed but do not provide any insight into causality. The models are relatively unstable and accuracy of the model forecasts decreases over time. Although end-use models have the capability to explicitly evaluate various conservation policies and load management programs and to provide detailed analyses of new technology impacts on electricity demand, enormous data requirements and intense modeling efforts pose a trade-off problem between the level of disaggregation and the quality of component forecasts. Because of the huge data requirements, most electric utilities have been reluctant to undertake the development of end-use models. Another major problem with end-use models is the difficulty in capturing price and income effects on the intensity of appliance usage and the stock of appliances. The econometric method is a widely-accepted approach and requires only modest efforts for data development and model estimation. Inclusion of economic, demographic and weather variables in the model increases precision of the model forecasts. Evaluation of the modeling results with statistical criteria is another advantage. However, the models are aggregate in nature and can not provide the detailed analyses concerning conservation policies and load management programs. Since the model development is based on past behavioral relationships, the models are also limited in their ability to respond to abrupt structural changes and new technologies of energy use.

None of the three modeling approaches is the ultimate solution to the load forecasting and demand analysis problems. One way to improve the existing modeling techniques is to develop an integrated model by combining them for the advantages inherent in each of the techniques. Recent efforts to integrate the three primary modeling methods are classified into three groups: 1) time-series/econometric model, 2) econometric/time-series model and 3) end-use/econometric model.

a) Time-series/econometric model. Pure time-series approaches have been extensively criticized because one can not provide an explanation when the resulting forecasts are poor. Since the time-series models are void of economic theory, they can not be used to test hypotheses about economic phenomena. However, simple time-series models can often outperform large econometric models, especially for short-range forecasting purposes. To mitigate the intensity of the criticisms of a pure time-series approach and to produce an improved method of peak load forecasting, Uri considered a hybrid model which combines a Box-Jenkins analysis with an econometric approach whereby variation in the time-series model coefficients is explained by various independent variables over time.[39]

Following the Uri's ARMA model discussed earlier in ARMA modeling section of this study,

$$(1 - B)(1 - B^{12})z_t = (1 - \theta_1 B)(1 - \theta_{12} B)a_t \qquad (1)$$

where z_t = log-transformed value of observed monthly peak system load

B = backward shift operator

a_t = white noise

θ_1, θ_{12} = parameters to be empirically estimated.

Assume that the parameters θ_1 and θ_{12} are estimated by a Box-Jenkins procedure with a historical data set of 48 monthly peak system load observations. Also, assume that the forecasting equation is reestimated at intervals of three months and forecasts made at time t are based on parameters estimated with the preceding 48 observations. The procedure just described will produce a sequence of estimates for θ_1 and θ_{12} which will vary through time. A time-series approach could be utilized to analize the evolution of this sequence. However, Uri proposes an econometric approach instead. In his model, θ_1 and θ_{12} are functions of price of electricity, income, temperature, etc., and a regression analysis is

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[39] N. D. Uri, "A Mixed Time-Series/Econometric Approach to Forecasting Peak System Load," Annals of Applied Econometrics, January 1979, pp. 155-174.

performed accordingly. Therefore, letting $\underline{\theta}_1$ and $\underline{\theta}_{12}$ represent vectors of θ_1 and θ_{12} reestimated every three months and X denote a set of economic and weather-related variables,

$$\underline{\theta}_1 = X\alpha + u \tag{2}$$

$$\underline{\theta}_{12} = X\beta + v \tag{3}$$

where α and β are appropriate vectors of coefficients and u and v are random error terms.

Based on the assumption that the model equation (1) is reestimated at quarterly intervals, the error terms u and v in the equations (2) and (3) will be necessarily autocorrelated and will also likely be heteroscedastic. The existence of autocorrelation is due to the fact that, with a data set of 48 observations, the data sets utilized for estimating $\hat{\theta}$'s at the time t and the time t-3 have 45 observations in common, the data sets for $\hat{\theta}$'s at the time t and the time t-6 have 42 observations in common, and so on. Consequently, the first 15 subdiagonals of the covariance matrices of u and v will be in the proportions of 0.9375, 0.8750, 0.75, ..., respectively, to the main diagonal. Therefore, a generalized least-squares method is to be used in estimating α and β. Namely, α and β should be estimated by

$$\hat{\alpha} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}\underline{\theta}_1 \tag{4}$$

$$\beta = (X'\varphi^{-1}X)^{-1}X'\varphi^{-1}\underline{\theta}_{12} \tag{5}$$

where

$$\Omega = \begin{pmatrix} \hat{\sigma}_1^2 & 0.9375\hat{\sigma}_1^2 & 0.8750\hat{\sigma}_1^2 & \cdots & 0 & 0 \\ 0.9375\hat{\sigma}_1^2 & \hat{\sigma}_2^2 & 0.9375\hat{\sigma}_2^2 & \cdots & 0 & 0 \\ 0.8750\hat{\sigma}_1^2 & \vdots & \vdots & & \vdots & \vdots \\ \vdots & & & & \vdots & \vdots \\ 0 & \cdots & \cdots & \cdots & \hat{\sigma}_{T-1}^2 & 0.9375\hat{\sigma}_{T-1}^2 \\ 0 & \cdots & \cdots & \cdots & 0.9375\hat{\sigma}_{T-1}^2 & \hat{\sigma}_T^2 \end{pmatrix}$$

and $\hat{\sigma}_i^2$ is the estimated variance of the i^{th} element in $\underline{\theta}_1$. The covariance matrix φ is defined similarly.

Uri used Pacific Gas and Electric Company (PG&E) data for January 1961 through December 1969 to estimate his model. After the model was estimated by both Box-Jenkins methods and econometric techniques, a monthly load forecast was produced for the period January 1970 through December 1973. First, the quarterly forecasts of θ_1 and θ_{12} were made for this period. Then, forecasts of the monthly peak system load were made with the forecasting equation being updated at quarterly intervals. The results indicate that the hybrid model performs better in 42 of 48 months than the pure time-series model. The hybrid model outperforms the pure time-series model by adjusting the model parameters to capture economic and demographic effects.

The hybrid model discussed above clearly provided an improvement over a conventional Box-Jenkins forecasting model. However, the approach involves some pitfalls and conceptual problems. In the first stage of model estimation, the time-series model is estimated for subperiods. Since the model is explicitly nonstationary, autocovariances are not available over the whole sample period. Then, the model identification becomes a lot more difficult than in conventional time-series analysis. In the second stage of model estimation, the dependent variable is the series of parameter estimates from the time-series model. Since the absolute values of the dependent variable should be constrained to be smaller than 1.0, there may be problems with the linear regression specification. For example, if the electricity price increases drastically, the estimated moving-average coefficient will exceed unity and the model will not be invertable. If the model is not invertable, the forecast error will increase over time. Another problem is in the interpretation of the econometric model parameters. The independent variables in the regression model are not used to determine the level of peak demand. Rather, they are used to determine the serial correlation properties of the peak.

Uri's approach can be viewed as sturcturally estimating the parameters of a time-series model by supplanting a moving average filter with a structural equation model. Since the regression model tries to explain the seasonal component by structural factors, the model estimation might be more useful after deseasonalization and detrending. In hybrid approach similar to Uri's, Hendricks, Koenker and Poirier suggest a method for the deseasonalization.[40] In the first stage of their hourly load modeling efforts, daily load shape is approximated by connecting adjacent periods with a polynomial function--cubic spline. In brief, a cubic spline is a continuous piecewise cubic polynomial with continuous first and second derivatives and allows jumps in its third derivative at predetermined knots. The cubic spline approach removes serial correlation from the residuals of the time-series model. Finally, innovations of the time series are structurally estimated by relating the knots of the spline function to explanatory variables in an econometric model. The cubic spline analysis is surely an improvement on the time-series techniques used in load forecasting. However, there are two disadvantages with the analysis. First, the model is inherently short-run and no attempt has been

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[40] W. Hendricks, R. Koenker, and D. J. Poirier, "Residential Demand for Electricity," Annals of Applied Econometrics, January 1979, pp. 33-57.

made to explain year to year changes in the model parameters. Second, the model parameters are not robust and not necessarily intuitive. The authors presented the empirical results for 1972 and 1973. The model coefficients are dissimilar in many places and imply very different forecasts.

b) Econometric/time-series model. Another hybrid approach considered by Uri is that one takes an econometric approach in estimating the parameters of a model, uses the estimated coefficients to compute the residuals between the actual and ex post forecasts, reduces these residuals to white noise by a Box-Jenkins method and produces final forecasts using a combined model.[41] Using a flow-adjustment model of demand, the econometric model equation becomes

$$\ln D_t = \alpha + \beta_1 \delta \ln P_{t-1} + \beta_2 \delta \ln y_t + \beta_3 \delta \ln TMAX_t + \beta_4 \delta \ln TAVG_t + (1 - \delta) \ln D_{t-1} + \delta \varepsilon_t$$

where D_t = peak demand in period t

P_{t-1} = average price of electricity lagged one period

y_t = average weekly earnings for period t

$TMAX_t$ = maximum temperature in period t

$TAVG_t$ = average temperature for period t

ε = an error term

α, δ, β_1, β_2, β_3 and β_4 = parameters to be estimated.

With the same PG&E data he used before, the logarithmic flow adjustment model was estimated by an ordinary least-squares estimation method. Once the demand model was estimated, the residuals representing differences

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[41] Uri, "A Mixed Time-Series/Econometric Approach to Forecasting Peak System Load," pp. 155-174.

between the actual and fitted values of the peak system load can be computed. Then, a Box-Jenkins time-series analysis was performed on the residuals to identify and estimate a second-order moving-average model,

$$(1 - \phi_{12}B^{12})z_t = (1 - \theta_1 B - \theta_2 B^2)a_t$$

where $\hat{\varepsilon}_t$ represents the estimated residuals and a_t represents independent random deviates with zero mean and variance σ_a^2.

Once the time-series model was identified and estimated, the final step in using the Box-Jenkins technique was to forecast with it. The forecasts of the residuals were then combined with the forecasts of the econometric model to produce the final forecasts. A pure econometrician might argue that any regularity discovered in the residuals is the result of an improperly specified econometric model. Given the goal of improved forecasts and at the same time being constrained by the availability of short-run data, however, this approach can provide a good compromise. Comparing the ex post forecasts for the period of January 1970-December 1973, Uri found that the combined model outperforms a pure econometric model in 37 of 48 periods. When compared with the time-series/econometric model, the econometric/time-series model requires substantially less efforts to estimate, forecast and combine the various components.

The model discussed above is a special case of distributed lag models. Since the use of Box-Jenkins analysis for the residuals does not have any basis in economic theory or any particular restrictions to be used, there appears to be no necessity to be confined only to the Box-Jenkins approach. A conventional distributed lag model may be even better. Serially correlated errors in a regression model with a lagged dependent variable lead to inconsistent estimates of the model parameters. The two-stage estimation of the combined model even sacrifices asymtotic efficiency. Therefore, joint estimation of the parameters is to be done whenever it becomes possible. However, the forecasting performance of the combined model appears to be not demaged by the two-stage estimation procedure because inconsistencies among the estimated parameters may have actually cancelled each other.

c) End-use/econometric model. Econometric models allow important economic and demographic factors to be incorporated into the forecasting process. But, they are lacking in the ability to respond to structural and technological changes occuring over time. End-use models are capable to explicitly analyze impacts of conservation and other changes in consumption patterns and have been increasingly used by the electric utilities lately. They are, however, costly to develop and maintain and mostly incapable of incorporating economic and demographic effects. With increasing necessity to evaluate a broad range of policy impacts in recent years, utility planners have been putting much of their efforts to develop more complex and structurally detailed forecasting models by integrating the econometric and the end-use methods.[42] Here again, most of the efforts are concentrated in energy sales forecasting--especially in sectoral sales models.[43] The integrated

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[42]After studying electric load forecasting issues and models, the first Utility Modeling Forum (UMF) working group, composed of 43 utility members, concluded that development of appropriate techniques for integrating end-use and econometric models is a forecasting challenge of the '80s. See Booz. Allen & Hamilton Inc., Electric Load Forecasting: Challenge for the '80s (Palo Alto, California: Electric Power Research Institute, September 1980), p. 5-11.

[43]See, for example, The University of Arizona Engineering Experiment Station, Proceedings: End-Use Models and Conservation Analysis (Palo Alto, California: Electric Power Research Institute, July 1982).

models exhibit structural details which is the strength of traditional end-use approach while maintaining firm behavioral foundations in the economic theory of consumer choice. The models treat the major appliances explicitly, projecting their respective market penetrations, operating efficiencies and utilization patterns. Besides the usefulness for the impact analysis of various load management and conservation measures, the model is also expected to produce a more accurate forecast because the aggregated type of econometric approach and the disaggregated type of end-use approach complement each other in a single model. Like a conventional end-use model, a major drawback to implement the model is huge requirements for data collection and parameter estimation. And the expanded complexity of the model makes evaluation of simulation results difficult.

Compared with the energy sales models, there have been quite a few efforts to apply the integrated approach to peak load modeling. The lack of efforts is not due to less importance of peak load analysis in utility planning, but attributable to technical difficulties and data limitations to implement the modeling approach. Since level of peak demand is determined by the energy use of all customer classes at the peak hour, a separate model for contribution of each customer class to peak is ideal but practically rejected at a utility level because of resource and data limitations. Since peak demand modeling covers all revenue sectors, the end-use and economic data requirements for an integrated model of peak load are tremendous when compared with a sectoral energy sales model.

Georgia Power Company made an early effort of integrating end-use analysis to improve the forecasts of their econometric model of annual system peak demand.[44] Georgia Power Company's model is a multi-stage process in which actual peaks were first weather-normalized by using dry-bulb temperature, a dummy variable reflecting the time of day that the annual peak occured and a trend term represented by the Julian date of the year. The normalized historical loads and state macroeconomic data were then analyzed using econometric analysis techniques to develop a long-range forecasting model. However, some change from historical relationships, such as air conditioners approaching saturation, appliance efficiency improvements, conservation as an ethic, the use of more solar energy and electric vehicles, can be expected during the forecast period. Therefore, adjustments to the econometrically-based forecasts were made by utilizing end-use information, in order to capture those expected structural changes into the model. Finally, the annual growth rates projected by the long-range model were combined with the short-range model forecasts which were separately derived from the model developed by a multivariate time-series analysis similar to the econometric/time-series approach discussed in the previous section. Although flexibility needed for scenario evaluation and the ability to defend the results before both management and regulators are increased by taking into account the fashionable issues, the Georgia model itself is still viewed as an econometric model, not an integrated model. Even, some of the adjustment

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[44] Charles Broder, "Method for Forecasting Peak Demand," Approaches to Load Forecasting: Proceedings of the Third EPRI Load-Forecasting Symposium (Palo Alto, California: Electric Power Research Institute, July 1982), pp. 168-194.

factors covered in the final stage could enter the model directly. For example, air-conditioning saturation and weather variables can be combined and used as independent variables of the econometric model. In that case, the weather-normalization done in the first stage of the modeling is not necessary. Generally speaking, the Georgia model is crude and its forecasts are exceedingly based on judgements and arbitrary assumptions.[45]

Because of the intrinsic limitations of the macroeconometric approach to explain the impacts of conservation and load management standards, the California Energy Commission (CEC) has recently developed a peak demand model using a microeconometric end-use approach.[46] The CEC approach: 1) uses both engineering and econometric techniques, 2) is a partially indirect modeling method which initially forecasts energy sales for seven distinct sectors and takes the sectoral energy sales forecasts as inputs to three submodels of peak load at the customer level, 3) analyzes and forecasts electricity as part of the total energy picture, and 4) uses a very large and diverse data base. To obtain the forecast of system peak demand, two components are added later for the transmission and distribution losses and for the effect of voltage regulation.[47]

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[45] Their econometric model has nothing but income variables as explanatory variables and the future appliance efficiency improvement assumed in the adjustment stage is too arbitrary. With a subjective judgement, it is simply assumed that a 15 percent improvement over pre-1974 efficiency standards will come about in a linear fashion, increasing by 1 percent per year until it levels off in 1988. There are several other cases of arbitrary assumptions made to supplement the lack of data.

[46] M. R. Jaske, "Analysis of Peak Load Demand Using An End Use Load Forecasting Model," Proceedings: End-Use Models and Conservation Analysis, Section 11, pp. 1-59.

[47] The California Public Utilities Commission (CPUC) and several municipal utilities have a staged program to more closely regulate final line voltages and substation stepdown. These activities are expected to save energy and peak load.

The CEC energy sales model has seven categories of customer types which need special model structure, types of input data, explanatory variables, etc. The seven sales categories are: 1) residential energy sales, 2) commercial building energy sales, 3) street lighting energy sales, 4) transportation, communications, utilities and national defense energy sales, 4) industrial energy sales, 6) agricultural energy sales and 7) domestic water pumping energy sales. Residential energy sales model consists of three principal components: 1) saturations of end uses of various competing fuel sources, 2) numbers of households living in a single family, multi-family and mobile homes and 3) unit energy consumption (UEC) of individual end uses. Total residential energy sales in a given year is then the product of total number of households multiplied by the fraction of households using a particular electric appliance multiplied by the year average UEC for that appliance, summed over all of the residential end uses. Because the choice of appliance types and their energy consumption varies among different housing types, the model separately considers energy use in single family, multi-family and mobile home dwellings. The UEC estimates are based on studies of actual appliance efficiency standards, fuel prices, household income and household size. The commercial buildings forecasting model is similar to the residential model. The model is composed of three basic components: 1) square feet of floor space, 2) fraction of floor space using each end use and fuel type and 3) energy consumption per square foot of floor space. The commercial building energy sales model is disaggregated into 11 building types, eight end uses and three fuel types. The commercial model is a refined version of the Oak Ridge commercial building model developed by J. Jackson and W. Johnson earlier.[48] The street lighting energy sales model is a simple function of residential customers and street lighting demand lagged one year. The lagged street lighting energy sales is included to explain the stock adjustment mechanism inherent in demand for durable goods. For transportation, communications, utilities and national defense energy sales, each two-digit SIC code industry is modeled using a constant energy efficiency ratio which is determined by dividing the 1978 quarterly fuel and energy summary consumption data by values of each explanatory variable, such as employment, personal income or hourseholds. Forecasts are then simply the product of the ratio times projected values of explanatory variables. The CEC industrial energy sales model uses an industry-specific macroeconometric approach, which separately estimates consumption for 20 different manufacturing industries, 5 mining and extraction industries and 3 construction industries. The model incorporates the energy consumption increase associated with complying with federal and state air pollution requirements, the impact of nonresidential building standards and the industrial energy-savings audits conducted by the utilities. Agricultural energy sales model has two submodels: a crop production model and a dairy and livestock production model. Crop production accounts for 80 percent of total agricultural energy consumption with irrigation-water pumping using most of the energy. The crop production energy sales forecasts are obtained by multiplying the forecasts of future acreage by estimates of energy requirement per acre. The energy demand for dairy and livestock

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[48] J. Jackson and W. Johnson, Commercial Energy Use: A Disaggregation by Fuel, Building Type and End Use (Oak Ridge, Tennessee: Oak Ridge National Laboratory, February 1978).

production is assumed to be directly related to the level of beef and dairy production. In domestic water pumping energy sales model, estimates of future domestic water demands in the 11 hydrologic areas are multiplied by the amount of energy needed to distribute surface and ground water to project energy use for domestic water requirements.

When used for peak load forecasting, the annual energy sales forecasts for all sectors are disaggregated into monthly quantities using an analysis of actual billing records. Each monthly consumption is then partitioned into daily energy use. The base energy uses in the residential and the industrial sectors are assumed to be equally distributed for each day in a given month. The amount of space conditioning energy depends on the weather occured on that day. Commercial customers have various consumption patterns depending on the type of business. Finally, hourly loads on a given day are determined by using a load profile which is distinct for each residential end use, each commercial end use by building type and each industrial two-digit SIC code.

The peak load forecasting methodology comprises five parts. The first two parts forecast hourly load in the residential and the commercial buildings sectors where an end-use model was used to forecast sales. The third part produces hourly load forecasts for the transportation, communications, utilities and national defense sector, street lighting, industrial, agricultural and domestic water pumping sectors in which the forecasts are made for each individual industry. The fourth component adjusts the hourly load forecasts to the system level by adding transmission and distribution losses and subtracting voltage regulation savings. The fifth component extracts annual peak load from the hourly load forecasts for all days, calibrates to the actual observed peak for 1978 and adjusts the original load forecasts by the calibration factor to produce a final forecast for each year.

Empirical tests of the CEC model were conducted using the data developed for two southern California Utilities--San Diego Gas and Electric Company and Southern California Edison Company. The conservation analysis performed for peak loads demonstrates the capability of the model to quantify the savings resulting from conservation measures. The load forecasting model produces detailed end use output for each of the major submodels --residential, commercial buildings, industrial, etc. Therefore, the model provides a basis for detailed analysis of the effect of conservation measures on individual end uses. Intersectoral shifts in load composition can also be analyzed conveniently.

While the macroeconometric models require relatively little data, the microeconometric end-use models, such as the CEC model, require prodigious amounts of data. Joint CEC/utility surveys of over 50,000 customers were conducted to collect the body of knowledge about how energy is used in the state, such as residential appliance ownership and use, household characteristics, commercial buildings characteristics and fuel choices in businesses. In addition, the CEC relied on the data from numerous sources not connected with the utilities: a detailed survey of energy use in 500 commercial buildings conducted by an independent contractor, end-use metering of a few selected commercial buildings, floorspace construction data on 280 building types purchased from the F. W. Dodge Company, detailed hourly weather data from National Oceanic and Atmospheric Administration (NOAA), end-use load profiles from the reports of Association of Edison Illuminating Companies (AEIC), operating characteristics of end uses reported by equipment manufacturers, etc. However, the data base used by the CEC still has much room to be improved. For example, lack of buildings energy use simulation data and end-use metering data forced the CEC to use the hourly load profiles based on the AEIC load research samples which does not necessarily fit for the study area.

Two important factors influencing the shape of future hourly load curve and therefore the level of peak demand are market penetration of electric appliances and sectoral difference in load growth. While the sectoral load growth differential has received a full attention in the CEC peak demand model, virtually nothing has been done to take account of changes in appliance stocks. Use of the fixed hourly load profiles for hourly energy allocation is another problem, because changes in life style can significantly alter the shape of the hourly load curve for a given end use in the long-run. Although the CEC model has been used to produce forecasts through the year 2000, the absence of appliance penetration functions and fixity of hourly load profiles make the model static and valid only for short-run forecasting. Modeling the penetration of new technologies, such as electric heat pump and solar systems, is also an important factor to be considered as more new technologies become marketable.

CHAPTER III

DEVELOPMENT OF AN ECONOMETRIC MODEL OF MONTHLY PEAK LOAD

The survey of various peak load modeling approahces, discussed in Chapter II, indicated that the most refined and desirable way to model the peak load demand is the integrated end-use/econometric approach. Although the modeling method is still at a pioneering stage, advantages of the integrated approach are quite encouraging. By incorporating behavioral foundations of econometric models and engineering information concerning energy use and the opportunity for capital-energy substitution from end-use models, the integrated model can provide explicit representation of conservation and load control measures. Since the aggregated analysis of econometric modeling is combined with the disaggregated method of end-use modeling, the integrated model is expected to provide a more accurate forecast by reducing the error resulting from aggregation across end use, building type, equipment age, etc. The model also has a capability to evaluate market penetration of new technologies. However, huge data requirements and model estimation efforts discourage implementation of the hybrid modeling approach. Another disadvantage of the model, due to its complexity, is the difficulty to conduct elasticity analyses.

The end-use/econometric model can be viewed as a special case of the stock-adjustment model. Three main elements of the end-use/ econometric model are rate of utilization, efficiency choice (or energy use requirement) and equipment choice for each end use, while the main arguments of the stock-adjustment model are composite rate of utilization for all end uses and appliance stocks. Since the efficiency choice and equipment choice equations are essentially two separate expressions of the stock adjustment process, the integrated modeling approach is a highly disaggregated version of the stock-adjustment modeling method.

Besides being accurate and defensible, a practical forecasting model should be flexible and affordable. In terms of the affordability, the end-use/econometric modeling approach has an obvious problem when used in a utility environment. As a matter of course, the utilities can gradually improve and expand their data bases and eventually ready themselves for the integrated modeling. The aggregate stock-adjustment model has a good potential to evolve to a microeconometric end-use model by increasing the level of disaggregation through the end-use and load research data that become available. Since the model is flexible, the levels of disaggregation for both the utilization rate and the appliance stock variables can be controlled by the data availability. Another advantage of the aggregate stock-adjustment model is that sensitivity analyses of the economic variables, such as prices and income, are relatively straightforward because the model handles the system peak load as an aggregate, not through sectoral energy sales models.

The stock-adjustment modeling approach was systematically formulated by Taylor and later adopted for residential electricity demand modeling.[1] While the stock-adjustment model of residential energy demand developed by Taylor et al. distinguishes the long-run demand from the short-run by the fixity of capital stocks, the capital stock-adjustment process itself is not reflected in either the short-run or the long-run elasticity analyses. In their theoretical model, the short-run demand for electricity is viewed as the choice of a utilization rate for the existing stock of electric appliances, while the long-run demand for electricity is equivalent to the demand for an equilibrium stock of electricity-consuming capital goods. There is a missing link between the short-run and the long-run demand formation, which is the capital stock-adjustment stage. In the empirical section of the study, however, Taylor and others seem to recognize that the short-run model developed for theoretical exposition does not cover the short-run effects of price and income on appliance stocks.[2] The model equations they actually estimated are utilization rate equations and appliance saturation rate equations in various functional forms. While the utilization rate equations are estimated for a composite rate aggregated for all appliances, the appliance saturation rate equations with a Koyck's distributed lag are regressed for each of ten major household appliances. For empirical presentation of the price and income elasticities of residential electricity sales, the elasticities calculated from the short-run equation holding the stock of appliance fixed (or the utilization rate equation only) are no longer called short-run elasticities. The value defined as

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[1]Taylor, "The Demand for Electricity: A Survey," pp. 80-83; and Taylor et al., The Residential Demand for Energy, Chapter 3.

[2]Taylor et al., The Residential Demand for Energy, Chapter 6.

a short-run elasticity in the theoretical development of the model is now retermed to be short-run partial adjustment elasticity. Total short-run elasticity is then measured by summing the partial adjustment elasticity calculated from the utilization rate equation and the weighted average of short-run elasticities of appliance stocks estimated from the appliance saturation rate equations. The weights used to aggregate the elasticities of appliance stocks are the normal utilization rates of each appliances. Long-run elasticity for the electricity sales is calculated by adding the short-run partial adjustment elasticity obtained from the utilization rate equation and the weighted average of long-run elasticities of appliance stocks obtained from the appliance saturation rate equations.

The fact that the appliance data used for the empirical study are in terms of saturation rates, while the theoretical models have been formulated in terms of capacity, causes some pratical problems. Since the saturation rate is defined as the proportion of households having the appliance in question, the rates would be equivalent to a stock series only when capacities of the appliances are constant across households and time. However, appliance capacity usually varies among households and through time. An additional problem associated with the use of saturation rates is that many households own more than one refrigerator, room air conditioner, etc. Therefore, the saturation rates provide only lower-bound estimates of the number of appliances in a region. Because true values of the normal utilization rates are not observable, the aggregated short-run and long-run elasticities of appliance stocks are destined to involve an approximation and affect the accuracy of the estimated total elasticities of electric demand. As a matter of fact, the normal utilization rates used for weighting the elasticities calculated from the ten appliance saturation rate equations are the normal consumption estimates for the year 1971 provided in a Stanford Research Institute study.[3] The data used for the empirical estimation is, however, an annual series for the years 1960 through 1972. Since the aggregate appliance saturation series used to calculate the historical composite utilization rates from the energy sales data is also obtained by weighting the saturation rates of eleven selected individual appliances with the 1971 normal usage rates, the estimates of the short-run partial adjustment elasticities involve the same approximation problem.[4] Accuracy of the model forecasts of the energy sales is also in doubt, because the energy sales forecasts are produced with the projected utilization rates and appliance saturation rates, not with the projected potential load of appliances.

Most of the problems with Taylor's stock-adjustment model are due to the lack of the appliance usage and capacity data required to successfully implement the model. In this chapter, an econometric model of peak load demand will be developed by following a neoclassical concept of capital stock adjustment. The model is macroeconometric and therefore does not involve the problem of extensive data requirements and can be easily implemented in a utility environment. Since the peak demand measured in megawatts is the dependent variable in the model, elasticity

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[3] Ibid., Appendix 1.

[4] Among the eleven major appliances, dishwashers were excluded in the estimation of appliance saturation rate equations.

analyses and forecast generation are straightforward. The capital stock-adjustment process is explicitly included in the model and plays a direct role in the demand analysis. In the peak load model to be developed, the entire process of electricity demand formation is divided into three time horizons: 1) short run characterized by variable utilization rate but fixed capital stock, 2) long-run adjustment period featured by variable utilization rate and capital stock adjustment and 3) long-run equilibrium stage.

In a general functional form, peak load demand is given by

$$D_t = U_t K_t \tag{1}$$

where D_t = demand for electricity at the time of peak load

K_t = stock of electricity-using capital goods measured in terms of potential use of watts

U_t = composite rate of utilization for all electric appliances at the time of peak load.

To obtain the value of K_t, it is necessary to aggregate across appliances. Since the probability of operation at the time of system peak load is different among the appliances, a simple summation of the potential watt usage of the appliances would be inaccurate. An obvious way to aggregate the appliances would be to weight each appliance by a long-run probability of operation at the time of peak load. Then,

$$K_t = \sum_{i=1}^{n} P_i(t) k_i \tag{2}$$

where k_i denotes the stock of the i^{th} appliance measured in potential watt usage and $P_i(t)$ is the long-run probability of operation at the time of peak for the i^{th} appliance.

A. Short Run

The short run is defined as the period in which a fixed stock of electricity-consuming capital goods exists and, due to time limitation, there is no possibility for the stock to change. Therefore, the peak demand for electricity in this period can be viewed as the choice of utilization rate for the existing stock of electricity-using capital goods.

Empirically assuming that

$$U_t = u(PE_t, W_t) = \alpha_0 PE_t^{\alpha_1} W_t^{\alpha_2} \tag{3}$$

where PE = price of electricity

W = any other factors that might be relevant (e.g., weather variables),

$$D_t = U_t K_t = (\alpha_0 PE_t^{\alpha_1} W_t^{\alpha_2})K_t.$$

Since K_t is invariable in the short run,

$$D_t = APE_t^{\alpha_1} W_t^{\alpha_2} \tag{4}$$

where $A = \alpha_0 K_t$.

Allowing price elasticity of the demand to vary with the previous levels of the electricity price,

$$\alpha_1 = \alpha_1(PE_{t-1}) = \Phi PE_{t-1}.\text{[5]} \tag{5}$$

Combining the equations (4) and (5),

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[5]As discussed in Chapter II, the section on the variable elasticity model, this hypothesis is explained by the Slutsky equation. The price elasticity of the ordinary demand curve equals the price elasticity of the compensated demand curve minus the corresponding income elasticity multiplied by the portion of total expenditure spent on the commodity in question. Since the demand for electricity is commonly believed to be price inelastic in the short run, the share of the electric bill in the consumer's budget will increase with a higher price of electricity. Consequently, the price elasticity of the uncompensated demand for electricity gets larger with the increase in the price of electricity itself.

$$D_t = APE_t^{\Phi PE_{t-1}} W_t^{\alpha_2} \tag{6}$$

The equation (6) can be easily estimated in a double-logarithmic form and the model estimated would take the form,

$$\ln D_t = \ln A + \Phi PE_{t-1} \ln PE_t + \alpha_2 \ln W_t + \epsilon_t . \tag{7}$$

With the model equation (7), the immediate-run demand for electricity at the time of system peak has a constant weather elasticity, α_2, but variable price elasticity, ΦPE_{t-1}.

B. Long-Run Adjustment

The long-run adjustment period is defined as the time duration which is long enough to vary both the rate of utilization and the stock of electric appliances within certain limits. The time duration is, however, not long enough to achieve an equilibrium stock. In the long-run adjustment period, consumers attempt to bring their actual stock of the capital goods into line with a certain desired level which is determined by the level of income, prices and other factors. However, the actual level of the capital stock will be still different from the desired level because of psychological, institutional or technological barriers to the speed at which a descrepancy between actual and desired levels can be eliminated.

Assuming a simple adjustment process given by

$$\frac{K_t}{K_{t-1}} = \left(\frac{K_t^*}{K_{t-1}}\right)^{\lambda} \tag{8}$$

where K_t^* = desired level of the capital stock

λ = adjustment factor which takes a value between 0 and 1,

$$K_t = (K_t^*)^{\lambda}(K_{t-1})^{1-\lambda}. \tag{9}$$

Let K_t^* be determined by

$$K_t^* = k(PE_t, PG_t, PK_t, Y_t, O_t) = \beta_0 PE_t^{\beta_1} PG_t^{\beta_2} PK_t^{\beta_3} Y_t^{\beta_4} O_t^{\beta_5} \qquad (10)$$

where PG = price of competing fuel source such as nutural gas

PK = price of electricity-consuming capital goods

Y = per capita income

O = other relevant factors such as population, depreciation rate of the appliance stock and market interest rate.

Then,

$$K_t = \beta_0^{\lambda} PE_t^{\lambda\beta_1} PG_t^{\lambda\beta_2} PK_t^{\lambda\beta_3} Y_t^{\lambda\beta_4} O_t^{\lambda\beta_5} K_{t-1}^{1-\lambda} \qquad (11)$$

Combining the equations, (1), (3) and (11),

$$\begin{aligned} D_t &= U_t K_t \\ &= \alpha_0 PE_t^{\alpha_1} W_t^{\alpha_2} \beta_0^{\lambda} PE_t^{\lambda\beta_1} PG_t^{\lambda\beta_2} PK_t^{\lambda\beta_3} Y_t^{\lambda\beta_4} O_t^{\lambda\beta_5} K_{t-1}^{1-\lambda} \\ &= \alpha_0\beta_0 PE_t^{\alpha_1+\lambda\beta_1} W_t^{\alpha_2} PG_t^{\lambda\beta_2} PK_t^{\lambda\beta_3} Y_t^{\lambda\beta_4} O_t^{\lambda\beta_5} K_{t-1}^{1-\lambda} \qquad (12) \end{aligned}$$

Since $K_{t-1} = \dfrac{D_{t-1}}{U_{t-1}}$,

$$K_{t-1}^{1-\lambda} = D_{t-1}^{1-\lambda} U_{t-1}^{-(1-\lambda)} = D_{t-1}^{1-\lambda} \alpha_0 PE_{t-1}^{-\alpha_1+\lambda\alpha_1} W_{t-1}^{-\alpha_2+\lambda\alpha_2}. \qquad (13)$$

Substituting $K_{t-1}^{1-\lambda}$ in the equation (12) with the equation (13),

$$D_t = \alpha^2 \beta^{\lambda} PE_t^{\alpha_1+\lambda\beta_1} PE_{t-1}^{-\alpha_1+\lambda\alpha_1} W_t^{\alpha_2} W_{t-1}^{-\alpha_2+\lambda\alpha_2} PG_t^{\lambda\beta_2} PK_t^{\lambda\beta_3} Y_t^{\lambda\beta_4} O_t^{\lambda\beta_5} D_{t-1}^{1-\lambda}. \qquad (14)$$

The long-run adjustment model equation in a double-logarithmic form will be then,

$$\begin{aligned} \ln D_t = {} & \gamma_0 + \gamma_1 \ln PE_t + \gamma_2 \ln PE_{t-1} + \gamma_3 \ln W_t + \gamma_4 \ln W_{t-1} + \gamma_5 \ln PG_t \\ & + \gamma_6 \ln PK_t + \gamma_7 \ln Y_t + \gamma_8 \ln O_t + \gamma_9 \ln D_{t-1} + \epsilon_t \qquad (15) \end{aligned}$$

where $\gamma_0 = 2 \ln\alpha_0 + \lambda \ln\beta_0$

$\gamma_1 = \alpha_1 + \lambda\beta_1$

$\gamma_2 = -\alpha_1 + \lambda\alpha_1$

$$\gamma_3 = \alpha_2$$

$$\gamma_4 = -\alpha_2 + \lambda\alpha_2$$

$$\gamma_5 = \lambda\beta_2$$

$$\gamma_6 = \lambda\beta_3$$

$$\gamma_7 = \lambda\beta_4$$

$$\gamma_8 = \lambda\beta_5$$

$$\gamma_9 = 1 - \lambda.$$

Therefore, the long-run adjustment model becomes a combination of the state-adjustment model of Houthakker and Taylor and the geometrically distributed lag model of Koyck.[6]

The reduced model equation (15) involves an identification problem to be used for empirical estimation of the original model parameters. The parameters, α's, β's and λ, are nonlinear functions of the unrestricted coefficients, γ's. After the equation (15) is estimated, solution for the restricted parameters of the long-run adjustment model will be,

$$\alpha_1 = -\frac{\gamma_2}{\gamma_9}$$

$$\alpha_2 = \gamma_3 \text{ or } -\frac{\gamma_4}{\gamma_9}$$

$$\beta_1 = \frac{\gamma_1\gamma_9 + \gamma_2}{\gamma_9(1 - \gamma_9)}$$

[6]The state-adjustment model of Houthakker and Taylor differs from their flow-adjustment model in that the coefficients of the one-period lagged exogenous variables are not constrained to be equal to their counterparts for the current variables. See Houthakker and Taylor, Consumer Demand in the United States, pp. 9-24.

$$\beta_2 = \frac{\gamma_5}{1 - \gamma_9}$$

$$\beta_3 = \frac{\gamma_6}{1 - \gamma_9}$$

$$\beta_4 = \frac{\gamma_7}{1 - \gamma_9}$$

$$\beta_5 = \frac{\gamma_8}{1 - \gamma_9}$$

$$\lambda = 1 - \gamma_9.$$

As shown above, α_2 is overidentified. The identification problem can be solved by estimating the restricted parameters by the nonlinear least-squres estimation method or the maximum likelihood estimation method.[7] But with the nonlinear regression analysis, computations are very complicated and the maximum of the likelihood function can be a local one rather than a global one. The variables causing the overidentification problem are the current and one-period lagged weather variables. Therefore, another way to solve the problem is to remove the weather-sensitive portion from the demand or weather-normalize the demand before regressing the model equation. Thus, rearranging the equation (15),

$$\ln\left(\frac{D_t}{W_t^{\alpha_2}}\right) = \gamma_0 + \gamma_1 \ln PE_t + \gamma_2 \ln PE_{t-1} + \gamma_5 \ln PG_t + \gamma_6 \ln PK_t + \gamma_7 \ln Y_t + \gamma_8 \ln O_t + \gamma_9 \ln\left(\frac{D_{t-1}}{W_{t-1}^{\alpha_2}}\right) + \varepsilon_t \qquad (16)$$

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[7] J. Kmenta, Elements of Econometrics (New York: Macmillan Publishing Co. Inc., 1971), pp. 446-447.

where γ's are as defined for the equation (15). As far as the value of α_2 is predetermined, the equation (16) is exactly identified. In this case, we can use the ordinary least-squares (OLS) estimation method to estimate the unrestricted coefficients of the equation (16) and use the solution for γ's to obtain the estimates of α_1, β's and λ. The resulting estimators inherit the desirable asymtotic, but not small-sample properties from the unconstrained estimates of γ's. This is because the model parameters are nonlinear functions of the unconstrained coefficients and unbiasedness does not carry over via nonlinear functions.[8] With the equation (16), the unconstrained estimators themselves are not unbiased due to the presence of D_{t-1} among the explanatory variables, so that none of the constrained estimators are unbiased. However, if the disturbance terms, ϵ_t, are randomly distributed, the presence of D_{t-1} will produce the OLS estimators which are still consistent though biased in finite samples. Since the negative bias in the OLS estimators is an inverse function of sample size, the problem of biased estimators becomes negligible with a sufficiently large number of observations.[9]

To make the model equation (16) estimable with the OLS method, the value of α_2 should be known in advance. Although the true value is unknown, the best linear unbiased estimate (BLUE) of α_2 obtained by regressing the immediate-run model equation (7) can be used as a

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[8]Consistency of the estimators carries over through a continuous function but the same does not, in general, apply to unbiasedness. Ibid., p. 166.

[9]For a simple model, $D_t = \beta D_{t-1} + v_t$, which has a lagged dependent variable but serially uncorrelated v's, $E(\hat{\beta}) - \beta = -2\beta/n$ where n = sample size. See Johnston, Econometric Methods, pp. 305-306.

predetermined value. Using the predetermined value of $\alpha_2(\hat{\alpha}_2)$, the actual levels of peak demand will be seasonally adjusted by removing the weather impacts on the load. After the reduced model equation (16) is estimated for the non-weather-sensitive portion of the demand, all of the original model parameters, α's, β's and λ, can be identified. Since the model is double-logarithmic, long-run adjustment elasticities of the demand are directly represented by the estimated coefficients, γ's, for the corresponding explanatory variables. Finally, the long-run forecast of peak load will be produced by combining the base (or non-weather-sensitive) load forecast generated with the equation (16) and the weather-sensitive load forecast obtained by using $\hat{\alpha}_2$ and the normal values of the weather variables.[10]

C. Long Run Equilibrium

The long-run equilibrium will be established when the actual level of the capital stock reaches the desired level. Since $K_t = K_t^*$, $\lambda = 1.0$. From the equation (12), the long-run equilibrium model will be then,

$$\begin{aligned} D_t &= U_t K_t = U_t K_t^* \\ &= \alpha_0 \beta_0 PE_t^{\alpha_1 + \beta_1} W_t^{\alpha_2} PG_t^{\beta_2} PK_t^{\beta_3} Y_t^{\beta_4} O_t^{\beta_5} \end{aligned} \tag{17}$$

Rewriting the model in a double-logarithmic form,

$$\ln D_t = \delta_0 + \delta_1 \ln PE_t + \delta_2 W_t + \delta_3 PG_t + \delta_4 PK_t + \delta_5 Y_t + \delta_6 O_t + \varepsilon_t \tag{18}$$

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[10] As occasionally exampled in Chapter II, separate modeling of the base load and the weather load or weather-normalization of the load history before the model estimation is a common practice in the utility load forecasting. For an intensive study of weather-normalization techniques, see Cambridge Systematics, Inc. and Quantitative Economic Research, Inc., Weather Normalization of Electricity Sales (Palo Alto, California: Electric Power Research Institute, June 1983).

where $\delta_0 = \ln\alpha_0 + \ln\beta_0$

$\delta_1 = \alpha_1 + \beta_1$

$\delta_2 = \alpha_2$

$\delta_3 = \beta_2$

$\delta_4 = \beta_3$

$\delta_5 = \beta_4$

$\delta_6 = \beta_5$.

When matched with the long-run adjustment model equation (16), long-run equilibrium model equation will be

$$\ln\left(\frac{D_t}{W_t^{\alpha_2}}\right) = \delta_0 + \delta_1 \ln PE_t + \delta_3 PG_t + \delta_4 PK_t + \delta_5 Y_t + \delta_6 O_t + \epsilon_t \quad (19)$$

where δ's are as defined for the equation (18). Because the value of λ was less than 1.0 in the long-run adjustment period, elasticity of demand becomes larger in the long-run equilibrium stage for all of the explanatory variables except for the weather variable where the long-run coefficient is the same as the short-run's.

CHAPTER IV

EMPIRICAL APPLICATION

The peak load demand models developed in Chapter III will be estimated for an electric utility system. The electric utility selected for the empirical study is Lincoln Electric System (LES) operating in a major metropolitan area (Lincoln SMSA or Lancaster county) of Nebraska. LES is a summer peaking utility and experienced an annual peak load of 428 megawatts (MW) in August 1983, excluding transmission losses. The empirical results of the model estimation will be used for identifying and appraising the effects of economic, demographic and weather variables on the level of monthly peak demand. The model forecasts of the peak loads for 1983-2000 will be produced and evaluated. Finally, some policy implications of the empirical results will be explored for power supply planning, peak-load pricing and direct load control measures.

A. Practical Issues for Model Estimation

In order to practically apply the theoretical model equations presented in the previous chapter, they need to be substantiated for real world situations. Before going into a model estimation stage, several practical issues concerning the explanatory variables of the model will be discussed. Then, the model specifications are to be adjusted for empirical estimation.

1. Marginal Price vs. Average Price

In his 1975 survey article, Taylor criticized the conventional use of ex post average price in the electricity demand modeling and maintained that the use of ex post price leads to the problem of simultaneity and identification.[1] A correct procedure is, according to him, to include both a marginal and an average prices taken from actual tariff schedules, not calculated ex post, as predictors in the demand function. The marginal price refers to the last block of the rate that energy was consumed in, while the average price is the average price per KWh of the electricity consumed up to, but not including, the final block. Empirical use of the electricity price represented by the marginal price plus the measure of intramarginal expenditure has been successfully tested for residential energy demand modeling by Taylor and others.[2]

However, construction of the composite price variable for peak load modeling is not so easy because system peak load is the sum of coincident demands of all revenue classes at the time of system peak and utilities usually have different rate structures for various classes of customers. In the case of LES, residential and small commercial customers are charged with a seasonally differentiated rate which is higher for the

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[1]Taylor, "The Demand for Electricity: A Survey," p. 79.

[2]Taylor et al., The Residential Demand for Energy; and L. D. Taylor, G. R. Blattenberger and R. K. Rennhack of Data Resources, Inc., Residential Demand for Energy (Palo Alto, California: Electric Power Research Institute, April 1982), Vol. I.

summer energy use.[3] The summer seasonal energy charge is flat regardless of usage amount and includes a summer conservation credit provision to low users in order to minimize the impact of the seasonal rate structure on non-air conditioning customers. In the winter months, residential customers are classified into electric space heating customers and non-electric space heating customers. While non-electric space heating customers pay a flat energy charge, electric space heating customers are charged with a one-step declining-block rate to address the winter heating energy sales. Electric heating customers of small commercial and industrial classes can apply for a special end-use heating service rate in the winter months. The energy charge for that heating service is the same as the residential heating customers' which is lower than the regular commercial rate. Large commercial and industrial bills are determined by a three-part tariff which consists of energy, demand (or capacity) and customer charges. The demand charge for large customers are based on the individual customer's monthly load factor.

As illustrated above, the rate structure of a particular utility system is complex and involves much more than the declining-block rate Taylor assumed. In order to include the effects of differing marginal energy prices with the declining-block rate and the two-part (energy and demand charges) nature of electricity tariffs in the industrial and commercial sectors, Spann and Beauvais used two price variables, an aggregate energy price and an aggregate demand price, in their econometric model of peak load for Virginia Electric Power Company (VEPCO).[4] The energy price

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[3]Lincoln Electric System, Rate Schedules, Service Regulations for 1982 and 1983 (Lincoln, Nebraska: Lincoln Electric System, 1982).

[4]Spann and Beauvais, "Econometric Estimation," p. 6.

is the sum of the logs of the marginal energy prices in the industrial and commercial sectors plus the sum of the logs of two marginal energy prices in the residential sector. Utilization of these simple aggregate price variables implicitly assumes that the elasticities of peak demand with respect to energy prices and with respect to demand prices are the same for all classes of customers. There is no priori reason to believe that this is the case. An alternative approach would be to weight the marginal price charged each customer class with the percentage of total system sales to that customer class. This weighting scheme could appropriately include the effects of different growth rates of the prices for different classes and the effects of changes in customer mix on the peak demand and the price elasticity at the time of peak. Besides the problem of weighting, the VEPCO model is still lacking an intramarginal price variable or a price variable measuring changes in the customer charge.

A considerable amount of effort is required to obtain information on the marginal and intramarginal prices from the tariff structures for various customer classes. Taylor's call for use of the marginal price in the last consumption block and the average price to that point is based on the conventional utility maximizing model for an individual customer. He did not discuss the difficulty associated with aggregation across individuals in different final blocks. Especially for peak demand modeling, relevance of such framework for the data aggregated over individual customers in different customer classes with different tariff schedules seems to be questionable. Meanwhile, the information on average price is readily available from the utilities' sales and revenue data. Betancourt provides an interesting analysis of the problems with the ex post average price variable by utilizing the results of Levi's study on the effects of measurement errors on Ordinary Least-Squares (OLS) estimates.[5] The use of ex post average price can be interpreted as introducing an errors-in-the-variables problem into a demand equation. Application of OLS to the demand equation leads to inconsistent estimates unless the error is constant from observation to observation. Extending the derivation given by Levi in his equation (8),

$$\text{plim}\ \hat{\beta}_j = \beta_j + \frac{(-\beta_1\sigma_e^2 + \sigma_{eu})\Sigma_{1j}}{|\Sigma| + \sigma_e^2\ \Sigma_{11}}$$

where $\hat{\beta}_j$ = estimated coefficient for variable j

β_j = true parameter for variable j

β_1 = true coefficient of monthly average price

σ_e^2 = variance of the error in the price variable

σ_{eu} = covariance of the error in the equation and the error in the price variable

Σ = variance-covariance matrix of independent variables when using the true price variable

and subscript 1 indicates the price variable measured with error.[6] Because Σ_{11}, $|\Sigma|$, σ_e^2 and $-\beta_1$ are positive, the estimated coefficient of the price variable will be asymtotically biased toward zero with $\sigma_{eu} = 0$. Since the electricity consumption at the peak hour in a month is only a small protion of the total electricity use during the month, it may be reasonable to assume $\sigma_{eu} = 0$. Therefore, the price elasticity of peak

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[5]Betancourt, "An Econometric Analysis of Peak Electricity Demand in the Short Run," p. 19 and p. 283; and M. Levi, "Measurement Errors and Bounded OLS Estimates," Journal of Econometrics, Vol. 6, 1977, pp. 166-167.

[6]Betancourt, "An Econometric Analysis," p. 28.

demand measured with the ex post average price is not biased in the probability limit.

The specification errors resulting from using the ex post average price were measured and tested by Smith for 27 investor-owned utilities over the period 1957-1972.[7] The test he conducted for the errors in the average price models is the regression specification error test (RESET) developed by Ramsey. RESET examines the null hypothesis of full ideal conditions against the alternative hypothesis of a non-null mean vector for the error by applying the usual F test.[8] Completing the tests for the residential demand in each of 27 electric utilities, he concluded that the average revenue price measure, if deflated and adjusted for simultaneity, provides estimates of the residential demand which would not be rejected on statistical grounds. The problem of simultaneity and identification with the ex post average price variable is due to a declining relation between nominal average revenue and quantity consumed. If a real average price which is the average revenue deflated by consumer price index is used in a double-log model, an exact linear relation between the average revenue and the deflator will serve to identify the demand function.[9]

The electricity price variable in the empirical model will be an weighted moving average of real average prices for the previous twelve months. The average price variable, converted into real terms for use in

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[7] V. K. Smith, "Estimating the Price Elasticity of US Electricity Demand," Energy Economics, Vol. 2, No. 2, April 1980, pp. 81-85.

[8] J. B. Ramsey, "Classical Model Selection through Specification Error Tests," in P. Zarembka (ed.), Frontiers in Econometrics (New York: Academic Press, Inc., 1974), pp. 30-40.

[9] Smith, "Estimating the Price Elasticity," p. 83.

a rational consumption model, has a distributed lag structure to explain a dynamic adjustment of consumer's behavior. The lagged real average price variable has another important advantage--the price variable is free of the simultaneity and identification problem while only a little effort is required to calculate it. The distributed lag structure of the variable will be explained in the next section.

2. Lagged Effects of Price and Income Variables

All of the nominal price and income variables in the theoretical models will be transformed into real terms. The consumer price index for all items (CPI-all items) will be used to deflate the prices of electricity and natural gas while the total personal consumption expenditure (PCE) deflator will be used for per capita real personal income.[10] Local price data for electric appliances are rarely available. As a proxy for the real price of electricity-consuming capital stock, CPI-household appliances divided by CPI-all items is adopted.

A problem with the simple stock-adjustment model presented in the previous chapter is its implicit assumption of static expectations. It is implausible to assume that the optimum level of demand for the appliance stock is solely dependent upon the current values of prices and income. Because of the time lag between the actual use of energy and the billing, current average prices of electricity and natural gas are not even observable until the end of billing cycle. Consequently, the electricity price variables in the short-run model equation (equation (7)

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[10]Since natural gas is a predominant fuel source for heating and fuel oil takes a minimal share of the heating energy market in Lincoln SMSA, natural gas is viewed as the only competing fuel source against electricity.

in the previous chapter) need to be lagged by one period. Besides the utility-specific billing problem, it might not be rational to base the investment decisions about the durable goods entirely on the current prices of fuel sources and appliances. The concept of dynamic expectations can be added into the model by applying an adoptive-expectation scheme. With the assumption of dynamic expectations, the current price variables in the simple model are replaced by the expected values of those variables. A simple form of adoptive expectation is expressed by

$$P_t^* - P_{t-1}^* = \delta(P_t - P_{t-1}^*) \qquad (1)$$

where P = price of electricity, natural gas or appliance stock

P^* = expected level of P

δ = adjustment factor which takes a value between 0 and 1.[11]

According to the equation described above, expectations are updated each period by a fraction of the discrepancy between the current observed value of the variable and the previous expected value. Rewriting the equation (1),

$$\begin{aligned} P_t^* &= \delta P_t + (1-\delta)P_{t-1}^* \\ &= \delta P_t + (1-\delta)[\delta P_{t-1} + (1-\delta)P_{t-2}^*] \\ &= \delta[P_t + (1-\delta)P_{t-1}] + (1-\delta)^2 P_{t-2}^* \\ &= \delta[P_t + (1-\delta)P_{t-1} + (1-\delta)^2 P_{t-2} + \ldots + (1-\delta)^i P_{t-i}] \\ &\quad + (1-\delta)^n P_{t-n}^* \qquad (2) \end{aligned}$$

where n = i + 1.

Since $(1-\delta)^n P_{t-n}^*$ will be have an insignificant magnitude with a sufficiently large value of n, the equation (2) becomes

$$P_t^* = \delta \sum_{i=0}^{n} (1-\delta)^i P_{t-1}. \qquad (3)$$

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[11] Johnston, Econometric Methods, p. 301.

Therefore, the empirical model to be estimated will have the price variables caculated with a geometrically declining lag distribution.

Due to the billing procedures of electric and gas utilities, consumers do not know the current average prices paid until the end of the period. Since the current prices are not observable, the equation (3) is modified to be

$$PE_t^* = \delta \sum_{i=1}^{n} (1 - \delta)^{i-1} PE_{t-i} \text{ for electricity price and} \tag{4}$$

$$PG_t^* = \delta \sum_{i=1}^{n} (1 - \delta)^{i-1} PG_{t-i} \text{ for natural gas price,} \tag{5}$$

while

$$PK_t^* = \delta \sum_{i=0}^{n-1} (1 - \delta)^{i} PK_{t-i} \text{ for appliance stock price.} \tag{6}$$

Preliminary model estimations were conducted to find the appropriate value for n. Depending on the different values of n, values of δ were set for the sum of all the weighting factors in each case to be equal to 1.0. After checking with 3-month, 6-month, 12-month and 24-month period, the 12-month moving average price variables were found to provide the best fit. Value of the adjustment factor, δ, is 0.8 for the adjustment period of twelve months.

Cost of appliance stock is actually more than the purchase price alone. Depreciation of the equipment is to be considered as a variable cost. Interest payment, if any, is a fixed cost to be added to the purchase price. It is practically impossible to obtain the data of depreciation rates for all electric appliances in the utility service area. The history for market interest rates is, however, readily available from the financial publications. Omitting the depreciation rates but combining the market interest rates with the price of electric quipment, the equation (6) will be

$$[(1 + r_t)PK_t]^* = \delta \sum_{i=0}^{11} (1 - \delta)^i [(1 + r_{t-i})PK_{t-i}] \qquad (7)$$

where r = market rate of interest.[12]

The real income variable in the empirical model will also be a weighted moving average for twelve-month period. However, the calculation method of the weighted moving average is different. Following Friedman's approach to empirically estimate the permanent income, the distributed lag income to be used in the model is shown by the formula,

$$Y_t^* = \beta \sum_{i=0}^{11} (1 - \beta + \alpha)^i Y_{t-i}$$

where Y_t^* = per capita permanent real income which is a weighted moving average income for twelve-month period

α = trend parameter (0.0194 for this case)

β = adjustment parameter (0.194 for this case).

The values for α and β were determined such that the sum of all weighting factors for twelve months is equal to 1.0.

3. Selection of Weather Variables and Threshold Temperatures for Various Weather Impacts

Change in weather conditions has a vital role in the electric demand formation. This is especially true in summer and winter months

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[12] The interest rate to be used for this case is the interest rate charged by commercial banks for personal installment loan. Unfortunately, the data for terms of consumer installment credit are available only from 1980. As a proxy for the interest charge for installment loans, monthly series of annual prime rates will be used.

when the weather-sensitive cooling and heating loads constitute a substantial portion of the consumer's total energy requirement. A preliminary but intensive study of the impact of weather on peak load demand was performed with some monthly weather-load models. The daily peak demand and hourly weather observations for 1978-1982 were utilized in the study. The weather variables tested in the preliminary study are air temperature, dew point temperature, relative humidity, wind speed and sky cover. The composite weather variables, such as temperature-humidity index (THI) and wind chill (WC), were also tested. The formulas used for calculating THI and WC are[13]

$$THI = 0.55T + 0.2T_{dp} + 17.5$$

$$WC = (10\sqrt{WV} + 10.45 - WV)(33.0 - T_c)$$

where THI = temperature-humidity index

T = air temperature °F

T_{dp} = dew point temperature °F

WC = wind chill measured in terms of kilogram calorie loss per hour and square meter[14]

WV = wind velocity in meters per second

T_c = air temperature °C.

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[13] The wind chill equation cannot be used for wind speed higher than 20 meters per second (45 MPH). For source of the equation, see Siple Passel, "Measurement of Dry Atmospheric Cooling in Subfreezing Temperatures," Proceedings of the American Philosophical Society, Vol. 89 (1945), pp. 177-199.

[14] Wind chill factor which is normally used in a weather report is a wind-chill equivalent temperature which is estimated by subtracting the wind chill from air temperature. Since wind chill is calculated in Kilogram calories, the wind chill factor unavoidably involves a human guess when the wind chill is converted to temperature units.

In addition to the weather variables, the monthly weather-load models also include a yearly trend variable to grasp a secular growth trend and the type-of-day dummy variables to distinguish the different consumption patterns on weekdays, Saturdays, Sundays and some special holidays like Christmas day and the Thanksgiving weekend. To find the best specification for each of the monthly model equations, various possible combinations of the weather variables were applied to two plausible functional forms of equation--simple linear and double logarithmic forms. Because space air-conditioning and heating equipment is not operated within certain temperature range, application of the threshold concept to the temperature variables will make the model coefficients more appropriate and precise to measure the true weather sensitivity of air-conditioning and space-heating loads. Appropriate but different threshold temperatures were found for each of the weather variables by a grid search process based on the statistical significance tests repeated after the regression runs with different threshold points.

The weather study presents the following important findings:

1) Wind chill at the time of peak demand is the most significant weather variable in determining the level of peak demand in the winter months. But, the wind chill variable is effective only when the air temperature is below 40°F.
2) Cold weather build-up effect of temperature and wind speed is proved to be significant by including the 24-hour moving average of wind chill before the time of peak. But this is possible only when the 24-hour moving average temperature is below 32°F. The 48-hour moving average was tested to allow a longer time period for the weather

build-up but found to be insignificant.

3) Temperature-humidity index at the time of peak is the most powerful factor to explain the summer daily peak loads. However, the value of THI should be at least 75.0 before producing any effect on the load.

4) Warm weather accumulation effect appears to be very significant by the large magnitude of the coefficient and t-statistic of the cooling-degree-day variable calculated with the 24-hour moving average termperature before the time of peak.

5) Humidity does not have a significant build-up effect on the cooling load while wind speed shows a lagged impact on the heating load in the extremely cold weather situation. Lagged values of THI were tested for significance but failed.

6) No winter weather build-up effect was detected in the transition months, April and October. However, the summer weather storage effect, which is measured by the cooling degree days based on the 24-hour moving average temperature from the time of peak, is still significant in those two swing months.

7) Due to a partial operation of the existing air-conditioning equipment in April and May, it would be necessary to separately estimate the coefficients of the summer weather variables into two groups, the early summer months and the mid through late summer months. Many consumers, expecially residential users, are reluctant to turn on the air-conditioners in April and May unless warm weather prevails for a sufficiently long period. Therefore, summer-weather elasticity of the loads in April and May tends to be samller than the mid and late summer months, such as June through early October.

4. Model Specifications Adjusted and Refined for Empirical Study

It is ideal to use a cross-section data for the short-run model estimation and a time-series data for the long-run adjustment and the long-run equilibrium model estimation. However, limited availability of the data does not permit this. Since LES is a municipal utility and the samllest local unit used in most of the economic and demographic data reports is a city or county, it is hard to conduct a cross-section analysis. Data for the period of January 1969 through December 1982 will be used to estimate the coefficients of the both the short-run and the long-run adjustment model equations. The long-run equilibrium elasticities of the demand will be derived from the long-run adjustment model coefficients.

a) Short run. Use of the time-series data for the short-run model estimation has a direct conflict with the fixity of capital stock assumed in the short run. The stock of electric appliances is freely changeable during the 14-year period covered in the time-series data while the fluctuation of monthly peak load in the short run is supposed to be only due to the changes in the rate of utilization. Therefore, the load growth induced by the change in capital stock should be separated from the total load growth before the short-run model coefficients are estimated. Assumming that the electricity-consuming capital stock has grown exponentially during the years,

$$K_t = K_0 e^{\alpha_3 T}$$

where K_0 = capital stock in the base year (1968 in this case)

T = trend term which is equal to the year minus 1968

α_3 = coefficient for the yearly trend term, T.

Combining the equation (1) with the equations (1) and (3) of Chapter III,

$$D_t = U_t K_t = (\alpha_0 PE_t^{\alpha_1} W_t^{\alpha_2}) K_t = CPE_t^{\alpha_1} W_t^{\alpha_2} e^{\alpha_3 T} \tag{2}$$

where $C = \alpha_0 K_0$.

Since $\alpha_1 = \Phi PE_{t-1}$ from the equation (5) in Chapter III,

$$D_t = CPE_t^{\Phi PE_{t-1}} W_t^{\alpha_2} e^{\alpha_3 T}. \tag{3}$$

Taking a double-logarithmic form, the equation (3) will be,

$$\ln D_t = \ln C + \Phi PE_{t-1} \ln PE_t + \alpha_2 \ln W_t + \alpha_3 T. \tag{4}$$

Because the portion of the load growth produced by the change in capital stock is discounted by $\alpha_3 T$, the short-run coefficients, Φ and α_2, can be estimated with the time-series data, still maintaining the assumption of fixed capital stock. As explained in the previous sections, the electricity price variables need to be lagged by one period to reflect the time lag between the actual use of energy and the billing. The weather impact on the load is not as simple to explain as shown in the equation (4). Utilizing the results of the preliminary weather-load model estimation discussed in the previous section, the short-run model equation expanded for the empirical study will be,

$$\begin{aligned} \ln D_t = {} & \ln C + \Phi PE_{t-2} \ln PE_{t-1} + \theta_1 DW_1 DTEMP_{40} \ln WC_t \\ & + \theta_2 DW_2 DATEMP_{32} \ln WC24_t + \theta_3 D_4 \ln (THI - 75)_t \\ & + \theta_4 D_5 \ln (THI - 75)_t + \theta_5 DS \ln (THI - 75)_t \\ & + \theta_6 D_4 \ln CDD24_t + \theta_7 D_5 \ln CDD24_t \\ & + \theta_8 DS \ln CDD24_t + \alpha_3 T + \varepsilon_t \end{aligned} \tag{5}$$

where D_t = monthly peak load (MW)

C = constant term

PE_t = real average price of electricity per MWh ($)

DW_1 = dummy variable for the swing and the winter months which is equal to 1 for January-April and October-December and equal to 0 otherwise

DW_2 = dummy variable for the winter months which is equal to 1 for January-March and November-December and equal to 0 otherwise

$DTEMP_{40}$ = dummy variable for the temperature at the time of monthly peak load below 40°F

$DATEMP_{32}$ = dummy variable for the average temperature during the 24-hour period before the time of monthly peak load below 32°F

WC_t = wind chill at the time of monthly peak load

$WC24_t$ = average wind chill calculated for the 24-hour period before the time of monthly peak load

D_4 = dummy variable for April

D_5 = dummy variable for May

DS = dummy variable for the summer months which is equal to 1 for June-October and equal to 0 otherwise

THI_t = temperature-humidity index at the time of monthly peak load; if $THI \leq 75$, $THI - 75 = 1$

$CDD24_t$ = cooling degree days calculated with the average temperature for the 24-hour period before the time of monthly peak load

T = yearly growth trend variable equal to the year minus 1968

Φ, α_3 and θ's = coefficients to be estimated

ϵ = residual term

b) Long-run adjustment. As presented in the equation (16) of Chapter III, the actual level of peak demand needs to be seasonally adjusted by removing the weather-sensitive component. This adjustment is necessary to avoid the overidentification problem of the model parameters. Since the true values of the weather variable coefficients are unknown, the best linear unbiased estimates of θ's ($\hat{\theta}$'s) obtained by regressing the short-run model equation (5) will be used to calculate the weather-sensitive component of the load. Therefore, the seasonally-adjusted demand will be represented by,

$$\begin{aligned} \ln D_t' = \ln\left(\frac{D_t}{W_t^{\alpha_2}}\right) = \ln D_t - [&\hat{\theta}_1 DW_1 DTEMP_{40} \ln WC_t + \hat{\theta}_2 DW_2 DATEMP_{32} \ln WC24_t \\ &+ \hat{\theta}_3 D_4 \ln (THI - 75)_t + \hat{\theta}_4 D_5 \ln (THI - 75)_t \\ &+ \hat{\theta}_5 DS \ln (THI - 75) + \hat{\theta}_6 D_4 \ln CDD24_t \\ &+ \hat{\theta}_7 D_5 \ln CDD24_t + \hat{\theta}_8 DS \ln CDD24_t] \end{aligned} \quad (6)$$

As explained in the second section of this chapter, the price and income variables in the long-run adjustment model will be the 12-month weighted moving average of the previous values. Along with the economic variables, population of the utility service territory is introduced into the model equation. The demographic variable has an equivalent role as the number of consumers in an ordinary aggregate demand function. Using the weighted moving average values for the price and income variables and assigning the population variable for O_t in the equation (16) of Chapter III, the long-run adjustment model equation to be estimated for empirical analysis will be,

$$\begin{aligned} \ln D_t' = \gamma_0 &+ \gamma_1 \ln PE_t^* + \gamma_2 \ln PE_{t-1}^* + \gamma_5 \ln PG_t^* + \gamma_6 \ln [(1 + r_t)PK_t]^* \\ &+ \gamma_7 \ln Y_t^* + \gamma_8 \ln POP_t + \gamma_9 \ln D_{t-1}' + \varepsilon_t \end{aligned} \quad (7)$$

where D_t' = weather-independent portion of monthly peak demand (MW)

$$PE_t^* = 0.8 \sum_{i=1}^{12} (1 - 0.8)^{i-1} PE_{t-i}$$

PE_t = real average price of electricity per MWh ($)

$$PG_t^* = 0.8 \sum_{i=0}^{12} (1 - 0.8)^{i-1} PG_{t-i}$$

PG_t = real average price of natural gas per Mcf ($)

$$[(1 + r_t)PK_t]^* = 0.8 \sum_{i=0}^{11} (1 - 0.8)^i [(1 + r_{t-i})PK_{t-i}]$$

r_t = annual prime rate reported for the month

PK_t = real price of electricity-consumming capital stock approximated by CPI-household appliances divided by CPI-all items

$$Y_t^* = 0.194 \sum_{i=0}^{11} (1 - 0.194 + 0.0194)^i Y_{t-i}$$

Y_t = per capita real income ($)

POP_t = population of Lincoln SMSA

γ's = coefficients to be estimated

ϵ_t = residual term.

c) Long-run equilibrium. Adopting the adoptive-expectation scheme for the economic variables as already done for the long-run adjustment modeling, the equation (19) of Chapter III is converted to,

$$\ln D_t' = \delta_0 + \delta_1 \ln PE_t^* + \delta_3 \ln PG_t^* + \delta_4 \ln [(1 + r_t)PK_t]^* + \delta_5 \ln Y_t^* + \delta_6 \ln POP_t + \epsilon_t \qquad (8)$$

where D_t', PE_t^*, PG_t^*, $[(1 + r_t)PK_t]^*$, Y_t^* and POP_t are the same variables already defined earlier. The equations (15) and (18) of chapter III show that the long-run coefficients, δ's, are linearly related to the long-run adjustment model coefficients, γ's. Once γ's are estimated in the long-run adjustment analysis, the long-run equilibrium price, income and population elasticities will be measured by the following relations:

$$\delta_1 = \frac{\gamma_1 + \gamma_2}{\lambda}$$

$$\delta_3 = \frac{\gamma_5}{\lambda}$$

$$\delta_4 = \frac{\gamma_6}{\lambda}$$

$$\delta_5 = \frac{\gamma_7}{\lambda}$$

$$\delta_6 = \frac{\gamma_8}{\lambda}$$

where $\lambda = 1 - \gamma_9$. Since λ takes a value between 0 and 1, the long-run equilibrium elasticities are expected to be larger than the long-run adjustment model's.

B. Data Base

The econometric model of monthly peak load developed in this study accompanies an extensive data base. In addition to a 14-year (1969-1982) history of monthly peak demand by the LES customers, the data base includes economic, demographic and weather information suitable for the LES service area.

1. Source of Information

Sources of the data used for the empirical study of the model are provided below:

Variables	Sources
Peak Electricity Demand	Lincoln Electric System, Demand and Energy Statistics, monthly history for January 1969-December 1983.

Variables	Sources
Consumer Price Index and Personal Consumption Expenditure Deflator	U.S. Dept. of Commerce, Bureau of Economic Analysis, Business Conditions Digest, Vol. 20, No. 5 (May 1980), p. 99; U.S. Dept. of Commerce, Bureau of Economic Analysis, Survey of Current Business, Vol. 59, No. 11 (November 1979), p. 38; and Council of Economic Advisers, Economic Indicators, monthly issues for August 1979-January 1984, p. 2 and p. 23.
Price of Electricity	Lincoln Electric System, Financial and Operating Statement, monthly reports for January 1968-December 1983, p. 7.
Price of Natural Gas	Consumption and revenue data for January 1968-December 1983 reported by Cengas, a local subsidiary of Minnegasco in Lincoln, Nebraska.
Price of Capital Stock	U.S. Dept. of Labor, Bureau of Labor Statistics, The Consumer Price Index, monthly issues for February 1968-July 1974; and U.S. Dept. of Labor, Bureau of Labor Statistics, CPI Deatiled Report, monthly issues for August 1974-January 1983.
Interest Rate	Board of Governors of the Federal Reserve System, Federal Reserve Bulletin, monthly issues for January 1969-December 1982.
Personal Income	U.S. Dept. of Commerce, Bureau of Economic Analysis, Survey of Current Business, p. 51 of Vol. 60, No. 4 (April 1980), p. 55 of Vol. 61, No. 4 (April 1981), p. 62 of Vol. 62, No. 4 (April 1982) and p. 42 of Vol. 63, No. 4 (April 1983); U.S. Dept. of Commerce, Bureau of Economic Analysis, 1980 OBERS BEA Regional Projections, Vol. 3, July 1981, p. 138; and the data compiled by Bureau of Business Research, University of Nebraska-Lincoln.

Variables	Sources
Population	U.S. Dept. of Commerce, Bureau of the Census, 1970 Census of Population and 1980 Census of Population, Vol. I (Number of Inhabitants), Part 29 (Nebraska), p. 25 and p. 17 respectively; Jerome A. Deichert, Nebraska Population Projections 1990 - 2020 (Lincoln, Nebraska: Bureau of Business Research, University of Nebraska-Lincoln, November 1982), p. 123; and the data compiled by Bureau of Business Research, University of Nebraska-Lincoln.
Local Weather Data	U.S. Dept. of Commerce, National Oceanic and Atmospheric Administration, Local Climatological Data: Lincoln, Nebraska, monthly reports for January 1968-December 1983; and U.S. Dept. of Commerce, National Weather Service, Surface Weather Observations at Lincoln, Nebraska, unpublished hourly records for January 1968-August 1972.

2. Processings and Formation of Data Sets

Although monthly data for most of the variables were obtained from the sources described above, only annual values are available for the population and personal income at a county level. Monthly population of Lancaster county for January 1969 through April 1980 was therefore estimated by linearly interpolating the annual figures. The annual population figures were treated as the population for July of the corresponding year, with the exception of 1970 and 1980 in which population censuses were conducted and the census figures represent the population as of April. The population estimates for the months after April 1980 were produced by extrapolating the 1980 census figure with the average monthly compound growth rate implied by the county population projection made by Bureau of Business Research of University of Nebraska-Lincoln for 1985.[15]

Monthly total personal income for 1970-1980 was estimated by adjusting the annual total personal income figures with the monthly adjustment factors calculated from the Lincoln SMSA annual wage earnings by industry and the monthly employment by industry for January 1970-December 1980.[16] Due to the lack of industrial wage and employment data, monthly income adjustment for 1968-1969 and 1981-1982 was conducted with the Lincoln SMSA manufacturing employment and average hourly wage rate for the month.[17] Since the 1982 annual total personal income figure for Lancaster county is not available yet, the 1982 per capita personal income for Lancaster county was estimated by multiplying the 1982 U.S. per capita personal income with the 1981 ratio of the Lancaster per capita income to the U.S. per capita income, 0.984.[18] The

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[15] J. A. Deichert, Nebraska Population Projections 1990-2020 (Lincoln, Nebraska: Bureau of Business Research, University of Nebraska-Lincoln, November 1982), p. 123.

[16] The industrial wage earnings by Lancaster county are reported in U.S. Dept. of Commerce, Bureau of Economic Analysis, Local Area Personal Income 1970-1975, Vol. 5, August 1977, p. 252 and Local Area Personal Income 1975-1980, Vol. 5, June 1982, p. 138. The monthly industrial employment figures are published in Nebraska Dept. of Labor, Division of Employment, Employment Review, monthly issues for January 1970-December 1980.

[17] The monthly manufacturing employment and hourly wage data were collected from Nebraska Dept. of Labor, Division of Employment, Employment Review, monthly issues for January 1968-December 1969; and Nebraska Dept. of Labor, Division of Employment, Nebraska Work Trends, monthly issues for January 1981-December 1982.

[18] The 1982 per capita personal income for the U.S. is reported in U.S. Dept. of Commerce, Bureau of Economic Analysis, Survey of Current Business, Vol. 63, No. 8 (August 1983), p. 50.

total personal income figure for 1982 was then obtained by multiplying the per capita income estimate with the population estimate for the year.

In order to be used in a rational consumption model, all of the economic variables measured in nominal terms were transformed into real terms. The consumer price index for all items was used to deflate the price variables while the total personal consumption expenditure deflator was used for real personal income. After being deflated into real terms, the economic variables still require a further processing to obtain the proper values for the model estimation. Using the formulas presented in the previous section, the 12-month weighted moving average values were calculated for the electricity and natural gas prices, the purchase cost of capital stock and the per capita real personal income. Since the National Weather Service does not report the values of temperature-humidity index and wind chill, the two composite weather variables were calculated from air temperature, dew point temperature and wind speed by using the formulas shown in the earlier section. The 24-hour moving average values of the weather variables were also prepared by using the hourly weather data compiled for Lincoln, Nebraska.

C. Results of Model Estimation and Interpretations

The coefficients of the empirical model equations were estimated with the time-series data of 168 monthly observations for 1969-1982. A general computer program for econometric analysis called "SHAZAM" was utilized in the model estimation and statistical test process.[19] The

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[19] K. J. White, "A General Computer Program for Econometric Methods - SHAZAM," Econometrica, Vol. 46, No. 1 (January 1978), pp. 239-240; and K. J. White, SHAZAM - An Econometrics Computer Program, Version 4.5. (Vancouver, B.C., Canada: University of British Columbia, January 1983).

estimates of the model coefficients are provided in a equational form, along with the t-statistics in parantheses. Summary statistics for the estimated equation are shown below the equation. The summary statistics include degrees of freedom (df), multiple correlation coefficient adjusted for degrees of freedom ($\bar{R}^2$), standard error of regression ($S_{\hat{y}}$) and Durbin-Watson statistic (DW).

1. Short Run

The model equation was first estimated by Ordinary Least-Squares (OLS) estimation method. However, the estimated equation revealed an autocorrelation problem. The Durbin-Watson statistic calculated for the residuals was 1.01 while the lower limit for the significance level of 5 percent is 1.57. One practical solution for the first-order autocorrelation problem is the use of Cochrane-Orcutt interative process.[20] The short-run model equation was then reestimated by taking a Cochrane-Orcutt procedure with the value of convergence, 0.001. The estimation results are as shown below:

$$
\begin{aligned}
\ln D_t = {} & \underset{(61.871)}{4.7766} - \underset{(-0.024)}{0.00005}\, PE_{t-2} \ln PE_{t-1} + \underset{(3.700)}{0.01296}\, DW_1 DTEMP_{40} \ln WC_t \\
& + \underset{(2.105)}{0.00546}\, DW_2 DATEMP_{32} \ln WC24_t + \underset{(0.738)}{0.03190}\, D_4 \ln (\tilde{T}HI - 75)_t \\
& + \underset{(0.901)}{0.02886}\, D_5 \ln (THI - 75)_t + \underset{(7.038)}{0.10179}\, DS \ln (THI - 75)_t \\
& + \underset{(3.707)}{0.07006}\, D_4 \ln CDD24_t + \underset{(10.563)}{0.14264}\, D_5 \ln CDD24_t \\
& + \underset{(13.568)}{0.15826}\, DS \ln CDD24_t + \underset{(10.335)}{0.04028}\, T
\end{aligned}
$$

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[20]Johnston, Econometric Methods, p. 262.

$$df = 157$$

$$\bar{R}^2 = 0.9377$$

$$S_{\hat{y}} = 0.07686$$

$$DW = 2.234$$

$$\hat{\rho}_1 = \underset{(8.641)}{0.55471}$$

where $\hat{\rho}_1$ is the estimate of the first-order autocorrelation coefficient and the t-ratio for the coefficient is provided in paranthesis. All of the summary statistics were calculated for the original equation, not the first-difference equation. According to the Durbin-Watson statistic calculated after the second regression, the serial correlation in the error term was mostly first-ordered and the problem is not significant any longer. The explanatory power of the equation indicated by $\bar{R}^2$ is sufficiently large and the standard error of regression is reasonably small. Although the signs of the coefficient estimates are as expected, electricity price, THI in April and THI in May turn out to be insignificant to explain the level of peak load. The absolute magnitudes of the t-ratios and the coefficients for those variables are very small. Otherwise, the model specification produces fairly acceptable estimation results.

An analysis of the regression results reveals the following facts:

1) Fluctuations of the monthly peak demand in the short run are mainly caused by changes in the weather conditions.
2) Price of electricity has a negligable impact on the peak load. Values of the t-statistic and the coefficient of the price variable are close to zero.

3) Regression results for the weather variables are consistent with the findings reported after the preliminary study of weather-load relationship.
4) Separate estimation of the coefficients for the summer weather variables in April and May is justified. The estimated coefficients for the transition months are significantly smaller than the coefficients for the mid and late summer months, because only a part of the existing air conditioners in the utility system are being operated in April and May. The separate coefficient estimation also proves that THI at the time of peak demand has a neglegible influence on the levels of April and May peak loads. Although the temperature variable, CDD24, still exerts a significant impact, the mild and sporadic nature of April and May weather makes the impact of humidity ineffective.
5) The yearly trend variable, T, seems to be playing a proper role to discount the secular growth of the peak load accrued by the increase in appliance stock over the period of the time-series data. According to the estimated coefficient of T, the weather-normalized load has been growing at an average annual growth rate of 4.03 percent.

2. Long-Run Adjustment

Weather-sensitive portion of the monthly peak load was removed from the actual load history by using the actual weather values and the coefficients of the weather variables estimated in the previous step. Once the data series of D_t' and D_{t-1}' were established, the long-run adjustment model equation was estimated by the OLS estimation method. The regression results are provided below:

$$\ln D'_t = \underset{(-4.625)}{-14.6470} - \underset{(-0.585)}{0.08252} \ln PE^*_t + \underset{(1.065)}{0.15305} \ln PE^*_{t-1} + \underset{(1.858)}{0.05227} \ln PG^*_t$$

$$+ \underset{(2.198)}{0.69863} \ln [(1 + r_t)PK_t]^* + \underset{(3.513)}{0.66210} \ln Y^*_t + \underset{(3.754)}{2.4139} \ln POP$$

$$+ \underset{(3.809)}{0.28635} \ln D'_{t-1}$$

$$df = 160$$

$$\bar{R}^2 = 0.8724$$

$$S_{\hat{y}} = 0.06694$$

$$h = -0.076$$

where h is Durbin h statistic. Since the model equation has a lagged dependent variable on the right-hand side, the conventional durbin-Watson test is biased towards the value for a random disturbance.[21] As the autocorrelation coefficient, ρ, tends to unity, the asymptotic bias tends to the value of 1.0 minus the coefficient of D'_{t-1}. A large sample test for serial correlation when lagged dependent variables are present can be done by computing Durbin h statistic.[22] The statistic h is then tested as a standard normal deviate. Because $h = -0.076 > -1.645$, one would accept the hypothesis of no autocorrelation at the 5 percent level.

From $U_t = \alpha_0 PE_t^{\alpha_1} W_t^{\alpha_2}$

$K^*_t = \beta_0 PE_t^{\beta_1} PG_t^{\beta_2} PK_t^{\beta_3} Y_t^{\beta_4} O_t^{\beta_5}$ and

$K_t = (K^*_t)^{\lambda} (K_{t-1})^{1-\lambda}$,

---

[21] Johnston, Econometric Methods, p. 307.

[22] Ibid., pp. 312-313. The formula for Durbin h statistic is $h = r\sqrt{\frac{n}{1 - n\hat{v}(b)}}$ where $r = 1 - \frac{1}{2}d$, d = conventional Durbin-Watson statistic, n = number of observations, and $\hat{v}(b)$ = estimate of the sampling variance for the coefficient of the lagged dependent variable.

$\alpha_0>0$, $\alpha_1<0$, $\alpha_2>0$, $\beta_0>0$, $\beta_1<0$, $\beta_2>0$, $\beta_3<0$, $\beta_4>0$, $\beta_5>0$ (if O_t = POP) and $0<\lambda<1$. Then, signs of the long-run adjustment model coefficients should be

$$
\begin{array}{ll}
\gamma_1 = \alpha_1 + \lambda\beta_1 < 0 \text{ for} & PE_t^* \\
\gamma_2 = -\alpha_1 + \lambda\alpha_1 > 0 & PE_{t-1}^* \\
\gamma_5 = \lambda\beta_2 > 0 & PG_t^* \\
\gamma_6 = \lambda\beta_3 < 0 & [(1 + r_t)PK_t]^* \\
\gamma_7 = \lambda\beta_4 > 0 & Y_t^* \\
\gamma_8 = \lambda\beta_5 > 0 & POP \\
\gamma_9 = 1 - \lambda > 0 & D'_{t-1}.
\end{array}
$$

With one exception of the capital stock price variable, all the coefficient estimates have correct signs. One important factor responsible for the positive sign of the appliance price variable is the technical innovation achieved by the electric appliance manufacturing industry. Since the 1973-1974 energy crisis, a great deal of energy efficiency improvement has been achieved by the appliance manufacturers. Furthermore, real purchase costs of the appliances also declined. According to the time-series data compiled for this study, the real purchase cost index was 1.023 in January 1969, but gradually decreased to 0.711 by December 1982. Conservation through capital investment, such as solar energy, more frequent maintenance of the appliances and increased thermal integrity of buildings, has strengthened the positive relationship between the capital stock price variable and the energy use requirement of the capital stock.

In order to measure the net effect of the appliance price variable, an annual trend variable was added into the model. The trend variable is purported to explain the decrease in the load capacity of capital stock attained by the efficiency improvement and conservation activities taken after the energy crisis. The base year of the trend variable was selected by a search process--taking each of the years after 1973 as the base year and proceeding as follows:

1) The trend variable was calculated by using the formula,

$$\ln (TR_{by})_{cy} = \ln (cy - by)$$

where by = base year, cy = current year and $(TR_{by})_{cy} = 1.0$ if $cy \leq by$.

2) The trend variable was added into the model and the model coefficients were reestimated.

3) The steps 1) and 2) were repeated until the absolute magnitude of the t-ratio for the trend variable became sufficiently large. After the search process, it was found that the conservation activities and the appliance efficiency improvement provoked by the energy crisis had started to draw a significant amount of the system-wide load reduction from 1976.

The OLS estimation results for the new model equation are as follows:

$$\ln D'_t = \underset{(-4.235)}{-12.6910} - \underset{(-0.820)}{0.10851} \ln PE^*_t + \underset{(1.306)}{0.17613} \ln PE^*_{t-1} + \underset{(3.429)}{0.09555} \ln PG^*_t$$

$$\underset{(-0.254)}{-0.08616} \ln [(1 + r_t)PK_t]^* + \underset{(4.834)}{0.88236} \ln Y^*_t + \underset{(2.850)}{1.7614} \ln POP$$

$$+ \underset{(2.545)}{0.18691} \ln D'_{t-1} - \underset{(-4.801)}{0.07261} \ln TR_{1975}$$

$$df = 159$$

$$\bar{R}^2 = 0.8879$$

$$S_{\hat{y}} = 0.06276$$

$$h = 0.655$$

where TR_{1975} = yearly trend term for the conservation and efficiency improvement which is equal to the year minus 1975. With the trend variable added into the model, all of the coefficients are estimated with the correct signs. The annual trend for declining capital stock due to the conservation measures and efficiency improvement is fairly evident and overall explanatory power of the model equation is slightly improved. The capital stock price variable now has a negative coefficient but significance of the price variable in the model is negligable. Insignificance of the capital stock price variable is due to durability of the capital stock. Higher appliance price is normally expected to discourage new additions to the capital stock. However, the increased price does not necessarily mean a reduced capital stock because of the durability of existing capital stock. In some cases, the higher appliance price could maintain the higher load levels from the existing capital stock by deterring the replacement of obsolete units with more energy efficient units.

Besides the problem of low t-ratios, the estimated coefficients of the current and lagged electricity price variables lead to a wrong sign for a restricted parameter, β_1. From the equation (15) of chapter III,

$$\gamma_1 = \alpha_1 + \lambda\beta_1, \quad \gamma_2 = -\alpha_1 + \lambda\alpha_1 \quad \text{and} \quad \lambda = 1 - \gamma_9.$$

Therefore,

$$\alpha_1 = -\frac{\gamma_2}{\gamma_9} \quad \text{and} \quad \beta_1 = \frac{\gamma_1\gamma_9 + \gamma_2}{\gamma_9(1 - \gamma_9)}.$$

Because α_1 is the electricity price elasticity of the short-run demand and β_1 is the electricity price elasticity of the desired capital stock, both of the estimated coefficients, $\hat{\alpha}_1$ and $\hat{\beta}_1$ should have negative values. Since $\hat{\gamma}_1 = -0.10851$, $\hat{\gamma}_2 = 0.17613$ and $\hat{\gamma}_9 = 0.18691$, $\hat{\alpha}_1 = -0.94233$ and $\hat{\beta}_1 = 1.02549$. The sign of $\hat{\alpha}_1$ is correctly negative but the positive value of $\hat{\beta}_1$ is clearly wrong. For the value of $\hat{\beta}_1$ to be less than zero, $\hat{\gamma}_1 \quad -\frac{\hat{\gamma}_2}{\hat{\gamma}_9}$.

The long-run adjustment model was reestimated without the capital stock price variable. The reestimation results are reported below:

$$
\begin{aligned}
\ln D_t' = &\underset{(-8.902)}{-13.3480} - \underset{(-0.802)}{0.10540}\ln PE_t^* + \underset{(1.329)}{0.17834}\ln PE_{t-1}^* + \underset{(3.454)}{0.09588}\ln PG_t^* \\
&+ \underset{(4.857)}{0.87628}\ln Y_t^* + \underset{(6.235)}{1.8976}\ln POP + \underset{(2.548)}{0.18655}\ln D_{t-1}' \\
&- \underset{(-5.353)}{0.07077}\ln TR_{1975}
\end{aligned}
$$

$$
\begin{aligned}
df &= 160 \\
\bar{R}^2 &= 0.8885 \\
S_{\hat{y}} &= 0.06258 \\
h &= 0.671
\end{aligned}
$$

While the overall fitness of the model gets slightly better, virtually no improvement is seen for the estimated coefficients of the electricity price variables. The primary reason for the poor t-statistics and the distorted values of the estimated coefficients is a collinearity between PE_t^* and PE_{t-1}^*. Because the time gap between PE_t^* and PE_{t-1}^* is only a month, PE_{t-1}^* closely tracks PE_t^*. This seems to be an inevitable weakness of a monthly model.

Some useful inference about the electricity price effect can be drawn from the short-run and the long-run adjustment model estimation results for the electricity price and the natural gas price variables.

The price of electricity has dual effects on the level of peak load. One effect is through a change in utilization rate and the other effect is by way of a change in capital stock. As the time duration increases from the short run to the lon-run adjustment period, the electricity price elasticity of the utilization rate at the time of peak demand becomes larger but the level of the price effect remains insignificant. If the electricity price has any notable impact on the peak load lovel, it is through a substitution between electric and natural gas appliances. For example, the average real price of natural gas paid by the residential customers in Lincoln, Nebraska increased 87.1 percent from 93¢ per Mcf in 1969 to $1.74 per Mcf in 1982. Meanwhile, the average real price of electricity paid by the same customers rose only 14.8 percent from $16.24 per MWh in 1969 to $18.64 per MWh in 1982. As a result, the percentage of electric space-heating customers in the residential sector became more than doubled from 2.1 percent to 5.7 percent for the same period. This appliance substitution effect is confirmed by the significance of the natural gas price variable in the model. The current electricity price variable, PE_t^*, does not show much significance for the appliance switch, probably because the real price of electricity in Lincoln had been very stable.

An appropriate way to explain the appliance substitution effect is through the use of the relative price of electricity to the natural gas price. The data is not readily available, but the addition of the relative purchase cost of the electric appliances to the natural gas counterparts would make the model specification more palusible. Combining PE_t^* and PG_t^* to create the relative price variable and giving up PE_{t-1}^*

which originated from the utilization rate equation, the long-run adjustment model was regressed again. The regression results for the revised equation are presented below:

$$\ln D'_t = \underset{(-8.627)}{-12.8610} - \underset{(-1.801)}{0.00649} \ln (PE^*_t/PG^*_t) + \underset{(5.793)}{0.96021} \ln Y^*_t$$

$$+ \underset{(5.675)}{1.6552} \ln POP + \underset{(3.088)}{0.23458} \ln D'_{t-1} - \underset{(-3.826)}{0.04647} \ln TR_{1975}$$

$$df = 162$$

$$\bar{R}^2 = 0.8810$$

$$S_{\hat{y}} = 0.06466$$

$$h = -0.890$$

Compared with the previous model equation, all of the coefficients in the new model equation have correct signs and sufficiently large t-statistics for significance maintaining about the same levels of $\bar{R}^2$ and $S_{\hat{y}}$. Relatively low values of the coefficient and t-ratio for the price variable still may be a concern. But, the small price effect can be easily explained by durability of the appliances. The appliance conversion induced by a change in the relative fuel price is checked and slowed by the durability of capital stock.

The weighted moving average income and the population of the utility service area are two important factors determining the level of peak electric demand. Since the model equation is double-logarithmic, the estimated coefficients directly measure the long-run adjustment elasticities of the peak load in terms of the corresponding economic and demobraphic variables. As indicated earlier, the peak demand is quite inelastic with respect to the electricity and natural gas prices.

Income elasticity of the demand is close to 1.0 and it tells that the peak load will grow at the same rate of the income growth. The peak load demand will increase faster than the population growth. The capital stock-adjustment process is evidenced by the positive coefficient and a sufficiently large t-ratio of the lagged dependent variable. The adjustment factor, λ, is estimated to be 0.76542. The annual trend for the conservation activities and the appliance efficiency improvement is significant and expected to continue for a while.

3. Long-Run Equilibrium

The long-run equilibrium elasticities of the peak demand are estimated by linearly relating to the long-run adjustment model coefficients. Since PE^*_{t-1} and PK^*_t have been removed from the long-run adjustment model, the long-run equilibrium model specification is accordingly revised into,

$$\ln D'_t = \delta_0 + \delta_3 \ln (PE^*_t/PG^*_t) + \delta_5 \ln Y^*_t + \delta_6 \ln POP_t + \epsilon_t .$$

TR_{1975} is excluded because the conservation and efficiency improvement will be phased out in the stock equilibrium stage. The long-run equilibrium elasticities of the load demand, δ's, are then obtained by dividing the long-run adjustment model coefficients with λ:

$$\delta_3 = \frac{0.00649}{0.76542} = 0.00848$$

$$\delta_5 = \frac{0.96021}{0.76542} = 1.2545$$

$$\delta_6 = \frac{1.6552}{0.76542} = 2.1625.$$

While the income elasticity of the peak demand becomes greater than 1.0

in the long-run equilibrium, the price elasticity is still minimal. The population elasticity gets fairly large.

D. Forecasting Evaluation and Policy Implications

The peak load model equations estimated in the previous section are ready to be used for the load forecasting. In this section, the forecasting performance of the demand model is evaluated by simulating the monthly peak loads in 1983 and comparing the estimated values with the actual loads. The model equations are also used to produce the annual peak load forecasts for 1984-2000. The modeling and forecasting results are then utilized to draw some policy implications for power supply planning, peak-load and direct load control.

1. Preparation of Input Data for Forecasting

Since the econometric model of monthly peak load employs economic, demographic and weather variables to explain the growth and monthly variations of the load, the model forecasts are directly affected by the assumptions for the future growth trends of the input variables.

a) Population. Lancaster county population estimates for 1983-2000 are based on the monthly average compound growth rates projected by the Bureau of Business Research (BBR) in its population forecasts for the selected years of 1980-2000.[23] The annual average compound growth rates associated with the population estimates are 1.020 percent for 1983-1985, 0.818 percent for 1985-1990, 0.845 percent for 1990-1995 and 0.810 percent for 1995-2000.

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[23] Deichert, Nebraska Population Projections 1990-2020, p. 123.

b) Per capita real personal income. The annual total real personal income for 1984-2000 were prepared on the basis of the average annual growth rates projected by the Bureau of Economic Analysis (BEA) in its forecasts of the Lincoln SMSA income growth for the case of a moderate change in the industrial share.[24] However, some adjustment to the BEA's forecasts was made because the projected growth rates look too high in light of a thirteen-year (1970-1982) history. While the average annual growth rate for 1970-1982 was 2.88 percent and the average growth rate in the future years is not expected to be higher than the historical rate, the BEA's projected growth rate for 1978-1985 is 3.95 percent per year. The over-projection is due to the fact that the BEA's income projections were produced before the economic recession of 1980-1982 and the 1978 actual figure was used as a base for compounding. Therefore, the historical average annual growth rate, 2.88 percent, was assumed for 1984-1985 and the average annual growth rates for the remaining years in the forecasting period were projected by proportionally reducing the BEA's projections with the ratio of 2.88 to 3.95. The adjusted forecasts of average annual growth rates are 2.56 percent for 1985-1990 and 2.11 percent for 1990-2000. Monthly income estimates for 1983 were prepared by using the near-term forecasts of quarterly growth rates published by Manuafcturers Hanover Trust Company.[25] Annual average income forecasts were then generated for 1984-2000 by applying the average annual growth rates projected in the previous step to the 1983 annual income estimate.

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[24]U.S. Dept. of Commerce, Bureau of Economic Analysis, 1980 OBERS BEA Regional Projections, Vol. 3, July 1981, p. 138.

[25]Manufacturers Hanover Trust Co., Economic Report, monthly issue for June 1983, pp. 2-3.

Monthly income forecasts for 1984-2000 were obtained by adjusting the annual average income forecasts with the fifteen-year (1968-1982) average monthly adjustment factors. Next, monthly per capita real personal income projections were produced by dividing the total income forecasts with the population estimates. Finally, the 12-month weighted moving average values were calculated with the monthly per capita real personal income projections.

c) Prices of electricity and natural gas. Actual data were compiled for the average real prices of electricity and natural gas in the months of 1983. Through a discussion with the Resource and Transmission Planning Department of LES about the prospects for capacity sales, future costs of fuel sources and debt coverage schedules, the real price of electricity is projected to grow at an annual rate of 3.0 percent for 1984-1985 and no growth after 1985. Future growth rates for the real price of natural gas was estimated by analyzing the future rate increase schedule announced by Northern Natural Gas Co., the natural gas wholesaler to Lincoln SMSA, and the results of the recent study on future fuel availability and prices by the Fuel Cell Users Group.[26] The estimated annual rates of increase in the real price of natural gas are 5.0 percent for 1984 and 3.0 percent thereafter. The electricity and natural gas price forecasts were then used to calculate the 12-month weighted moving average prices for each month of the forecasting period.

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[26]The Fuels and Fuels Processing Subcommittee, Report on the Availability and Prices of Alternative Fuels to Supply Fuel Cell Power Plants (Washington, D.C.: The Fuel Cell Unsers Group of the Electric Utility Industry, July 1983), p. 7.

d) Weather values. The actual weather data for 1983 is available from the National Weather Service in Lincoln, Nebraska. The fifteen-year (1968-1982) mean values of the weather variables are used as the normal values for the forecasting period.

2. Forecasting Evaluation

Weather-sensitive components of the monthly peak loads in 1983 were simulated by using the estimated coefficients of the weather variables in the short-run equation and the actual monthly weather values. Weather-independent components of the loads were simulated by applying the prepared input values to the long-run adjustment model equation estimated in the final regression. The model estimates of the 1983 monthly peak loads were then obtained by combining the weather-sensitive components and the weather-independent components separately simulated for each month. The ex post forecasts of the monthly peak loads are compared with the actual values as follows:

Month	Actual Load (MW)	Estimated Load (MW)	Forecasting Error (%)
1	226.0	218.9	-3.14
2	225.0	216.5	-3.78
3	219.0	208.6	-4.75
4	216.0	194.9	-9.77
5	221.0	253.9	14.89
6	357.0	371.3	4.01
7	412.0	415.9	0.95
8	428.0	427.2	0.19
9	402.0	402.1	0.03
10	204.0	194.5	-4.66

Month	Actual Load (MW)	Estimated Load (MW)	Forecasting Error (%)
11	235.0	222.8	-5.19
12	271.0	232.0	-14.39

The mean absolute error percentage of the estimated loads is 5.48. This seems to be within a reasonable range. However, consistent underestimation of the winter-month loads is a problem.. This bias of the model estimates was found to be caused by three unusual things happened in the utility service area during the year of 1983. A recent survey done by LES revealed that

1) an extraordinarily large increase in the number of residential dwelling units with electric space and water heating produced an extra weather-sensitive load of approximately 2,050 KW,
2) over 5,000 portable electric heaters were sold with a total estimated load of over 7,000 KW compared with only 600 units with a combined load of 900 KW sold in 1972, and
3) three large commercial customers had converted to electric space heating for a total estimated load of 200 KW as a result of the promotional efforts made by LES.[27]

Therefore, over 9 MW of extra load in electric heating equipment was sold and installed in the system during 1983. To accomodate this type of unusual load growth, the model needs a heating end-use variable to be incorporated with the winter weather variables. If the data is available, a space-heating saturation variable weighted by load capacity of the appliances would be a good candidate.

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[27] Lincoln Electric System, "Many Factors Caused LES to Establish New Winter Peak," LES Talk, Vol. 12, NO. 1 (January 1984), pp. 4-5.

The monthly peak load forecasts for 1984-2000 were generated in the same way as the 1983 load simulation except that the normal weather values were used. The weather-normalized forecasts of annual peaks for 1984-2000 are presented below:

Year	Annual Peak Demand Forecast (MW)
1984	415.3
1985	427.2
1986	437.8
1987	449.1
1988	460.3
1989	472.7
1990	485.9
1991	498.5
1992	511.2
1993	524.2
1994	537.6
1995	551.4
1996	565.5
1997	580.0
1998	595.5
1999	610.7
2000	626.9

The projected average annual growth rate of the peak demand is 2.86 percent for 1984-1985, 2.61 percent for 1985-1990, 2.56 percent for 1990-1995 and 2.60 percent for 1995-2000. Compared with the historical average annual growth rates, 3.68 percent for 1973-1978 and 3.01

percent for 1978-1983, the projected load growth rates seem to be reasonable.

3. Policy Implications of the Empirical Results

a) Power supply planning. Along with the forecasts of system inlet energy, the projected levels and seasonal variations of peak load guide a utility system extensively for generation capacity planning, power generation and purchase scheduling, financial analysis including rate makings, etc. In the previous section, the annual peak loads for 1984-2000 were estimated by choosing the maximum value for each year from the monthly load forecasts generated through the model developed in this study. Throughout the forecast years, the annual peak is expected to occur in July. The annual peak load forecasts, for example, provide a direct use for the capacity planning. According to a recent report on LES' power supply capacity, sum of the existing and committed power supply resources is about 672 MW in the summer months (May-October) and 626 MW in the winter months (November-April).[28] On the other hand, the expected power supply requirement which is the sum of the projected annual peak, transmission losses (19 MW), reserve requirement and participation sales to the Mid-Continent Area Power Pool (approximately 21 percent of the projected peak) is 669 MW in 1994 and 684 MW in 1995. Therefore, the demand model foretells that the utility system have a power shortage after 1994 without any increase in generation capacity or power purchase committment. Growth rates of the projected peak loads are sensitive to different assumptions concerning the growth rates of the economic and

[28] Lincoln Electric System, Power Supply Division, Load and Capacity Summary, August 1983.

demographic factors included in the model. Such uncertainties in forecasting the future loads should be considered in the capacity planning. Given these uncertainties, flexibility and the degree to which a capacity expansion program can be slowed or accelerated are as important as the problem of minimizing the costs of meeting a future load requirement. Utility system planning is therefore to be done through a stochastic optimization framework.

b) Load management. A critical lesson learned from the 1970s is the importance of efficient utilization of non-renewable energy resources. A key challenge of the electric utilities in the 1980s will be a successfull integration of the traditional supply planning and operations with the emerging measures of actively influencing the level of demand for the mutual benefit of the utilities and their customers. The demand-side management of the electric load can be operated by a price mechanism or a direct load control. The primary objective of the load management is to shift the time of use of electric power and reduce energy consumption during the utility's peak-load period. A reduction in the utility's peak load lowers costs of generating and distributing electricity by either detering construction of a new power plant or allowing the substitution of base-load generating plant (which involves a large fixed investment but uses less costly fuel sources) for peak-load generating plant (which usually burns expensive petroleum-based fuels). According to the argument made above, the demand-side management of the load appears to be clearly beneficial. Inappropriate application of the load management, however, can be harmful to the economies of the utility and its customers. Therefore, a systematic assessment of the costs and benefits of proposed load management measure is necessary before implementing the measure.

Peak-load pricing is an indirect measure to reduce the system's peak demand. Although welfare aspects of the peak-load pricing has been discussed by many theoretical studies, a utility-specific impact of the pricing measure should be predicted by analyzing the empirical estimates of the electricity price elasticities. The monthly model estimates of the price elasticities for all of the three time horizons consistently show that the peak load demand is highly inelastic. The measured price elasticities were close to zero and the price variable is even insignificant in the short run when the price elasticity of the load is reduced by extreme weather conditions. Meanwhile, the utility's recent estimates of the price elasticities of kilowatt-hour sales are much higher than the model estimates of the price elasticities of peak load.[29] The price elasticities of residential and commercial energy sales which take more than 70 percent of total sales are estimated to be 0.53 for the summer residential, 0.21 for the winter residential, 0.57 for the summer commercial and 0.45 for the winter commercial energy sales. Besides higher elasticities, the price variable is fairly significant in the energy sales model. The fact that peak demand price elasticities are significantly less than the price elasticities of energy sales implies that increased peak price with decreased off-peak price will increase kilowatt-hour sales, both absolutely and relatively to system peaks. Thus, the primary effect of peak-load pricing will be a reduced fuel cost for power generation

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[29] Lincoln Electric System, Power Supply Division, 1983 Econometric Forecasting of Energy Sales, Load Requirements and Number of Customers, November 1983, pp. 29-35.

through a shift in the mix of capacity additions toward a base-load plant. In addition, the peak load pricing will increase the total revenue of the utility because a price increase in the inelastic portion of a demand curve and a price decrease in a more elastic portion of the demand curve increase total revenue. The extremely low price elasticities of the peak load demand casts a doubt about the effectiveness of the load control through price mechanism. A fairly big difference between peak and off-peak prices is required to see any noticeable reduction in the peak load. The price differential, however, should be cost-justified, in order to maintain a rate equity between classes of customers and a fair return on investment for the utilities.

Many utilities are currently faced with staggering capital investment requirements for new plants, significant fluctuations in the load growth, declining financial performance and regulatory and consumers concern about rising prices. For such utilities, direct load control can provide an effective means to reduce or postpone construction of new generating facilities. Electric water heater and residential central air conditioner are two prime candidates considered for a load control. From the utility point of view, direct load control affects both costs and revenues. While the load management measure lowers generation and capacity costs by inducing a more favorable load shape, there are also costs incurred from purchase and installation of control devices and program implementation. A cost-benefit analysis will determine the present value of changes in net revenue by implementation of the program. From the participating customer's point of view, the load management program offers opportunities such as a lower quality of service at a lower rate (industrial interruptible service) and about the same quality of service at a lower rate (residential air-conditioning or water heating load control where the customer does not perceive that his load is being controlled). If a load control program is mandatory, it can also result in some customers having lower quality service at the same or a higher price. A cost-benefit analysis takes these possible effects into account by determining the amount of income a customer would have to gain or lose in order to be as well-off under the load management program as without the program. Required income changes must be determined for a substantial number of years and discounted to obtain the present value of customer's benefits or losses.

To evaluate the effectiveness of a load control system and technique, it is necessary to estimate the amount of KW demand reduction. For this purpose, an end-use (or engineering) model is definitely preferable to an econometric model. Given the lack of data for end-use modeling, however, a weather-load model similar to the short-run model developed in this study can provide a good analytical tool for the cases of weather-sensitive load control. If a fixed-time cycling of residential central air conditioners is considered as a load control measure, the weather-load model will be regressed for the central air-conditioning residential customers. The estimated coefficients of the weather variables will be used to simulate the total air-conditioning load without control under the weather conditions at the time of peak demand. Then, the amount of load reduction with a given time-based control can be estimated by multiplying the total air-conditioning load with the corresponding rate of interruption. Finally, an optimum level of the interruption rate will be determined by a cost-benefit analysis and the level of customers' tolerance.

CHAPTER V

CONCLUSIONS

Forecasts of peak load (KW) and energy demand (KWh) are two key elements for electric utility power supply planning. Until recently, most of the modeling studies on electricity demand have concentrated on the estimation of energy demand. Because capacity is built to meet system peak demand, peak-load forecasting is equally important for the utility planning purposes. Since there has been very little empirical analysis that provides detailed investigations of the determining factors of peak demand, the desire of utility planners to develop an effective and well-defined method of peak load modeling has been increasing over the recent years.

Despite a short history, a wide variety of methodologies have been tested for peak load modeling. Depending on the explanatory variables used for modeling and the design of model structure, direct modeling methods are classified into time-series approaches, end-use approaches, econometric approaches and hybrid approaches. Time-series models require a minimal amount of the data to be analyzed but do not provide any insight into causality. Given the expected changes in future trends of causal factors, time-series models are generally appropriate for short-run forecasting situations. End-use models have the capability to explicitly evaluate various conservation policies, load management programs and the impacts of new technology on electricity demand. However, due to a huge data requirement and intense modeling efforts, most electric utilities are reluctant to undertake the development of end-use models. Another disadvantage with the end-use model is the difficulty in capturing price and income effects on the load demand. Econometric modeling is the most popular method and requires only modest efforts for data development and model estimation. Evaluation of the modeling results with well-recognized statistical criteria is another advantage. Meanwhile, the models are aggregate in nature and can not provide the detailed analyses of conservation policies and load management measures. Econometric models are also limited in their ability to respond to abrupt change and new technologies for energy use.

Since none of the three modeling approaches can provide an ideal solution, there have been vigorous efforts to develop an integrated model by combining them for the advantages inherent in each of the methods. The most promising and desirable way to model the peak load demand seems to be an integrated end-use/econometric approach. The integrated models exhibit structural details which is the strength of traditional end-use approach while maintaining firm behavioral foundations in the economic theory of consumer choice. Since the models treat the major appliances individually and project market penetrations, operating efficiencies and utilization patterns of the appliances, they allow explicit representation of conservation programs, load control measures and new technologies. The integrated models are also expected to produce a more accurate forecast because the disaggregated method of end-use modeling is supplementary to the aggregated analysis of econometric modeling reducing the error resulted from aggregation across end use, building type, equipment age, etc. On the other hand, enormous data requirements and model estimation efforts discourage implementation of the hybrid modeling approach. The end-use/econometric modeling approach has an obvious problem of affordability when considered for use in a utility environment.

The end-use/econometric model is viewed as a special case of the stock-adjustment model which belongs to the category of econometric modeling approaches. Since the integrated modeling approach is a disaggregated version of the stock-adjustment modeling method, the stock-adjustment model has the potential to evolve to a microeconometric end-use model by increasing the level of disaggregation as more end-use and load research data become available. In addition to a modest requirement for data and for modeling efforts, an advantage of the stock-adjustment model over the integrated model is that sensitivity analyses of the explanatory variables are relatively straightforward because the econometric model handles the system peak load as an aggregate, not through the sectoral energy sales models, as the integrated modeling approach does.

A stock-adjustment model of peak load demand has been developed in this study. The model is macroeconometric and divides the entire process of electricity demand formation into: 1) the short run characterized by variable utilization rates but fixed appliance stock,

2) the long-run adjustment featured by variable utilization and appliance stock adjustment and 3) the long-run equilibrium stage. Since the model is aggregate in nature and does not require detailed appliance stock data, it is not difficult to implement in a utility environment. In the double-log model developed in the study, the short-run demand for electricity at the time of peak has constant weather elasticity but variable electricity price elasticity. The price elasticity of the uncompensated demand for electricity gets larger with an increase in the price of electricity itself. The long-run adjustment model becomes a combination of the state-adjustment model of Houthakker and Taylor and the geometrically distributed lag model of Koyck. The long-run adjustment model involves an overidentification problem with the lagged weather variable coefficients. The problem can be solved by removing the weather-sensitive portion from the load demand or weather-normalize the demand before estimating the model. Since the model is double-logarithmic, elasticities of the demand are directly represented by the coefficients of the corresponding variables. In the long-run equilibrium, the actual level of the appliance stock reaches a desired level. Because of the perfect adjustment of the appliance stock, elasticity of the load demand tends to be larger in the long-run equilibrium stage for the economic and demographic factors included in the model. Changes in weather conditions affect the level of peak load by changing the weather-sensitive appliance utilization rates. Since weather variables are believed to have no impact on the volume of existing appliance stock, weather elasticities of the demand are held constant throughout the three time horizons.

In order to be used practically, the theoretical model specifications must be adjusted and refined. Assuming rational comsumption behavior, all the nominal variables are converted into real terms. When elaborated for real world situations, the concept of dynamic expectations is added into the long-run models by using the 12-month weighted moving average values for price and income variables. Although the price variables in the demand model are average revenues, the distributed lag structure of the real values prevents the problem of simultaneity and identification. The price variables are lagged by a month to take account of the time lag between the actual use of energy and the billing. A great deal of effort has been made to detail the weather-load relations.

The stock-adjustment model of peak demand has been estimated for the Lincoln Electric System (LES) using a time-series data for January 1969-December 1982. Since the use of time-series data for the short-run model estimation has a direct conflict with the fixity of capital stock assumed in the short run, the load growth induced by the change in appliance stock is separated by utilizing a yearly growth trend variable. After evaluating the empirical estimation results, the following conclusions are drawn:

1) Fluctuations of the monthly peak demand in the short run are mainly caused by weather variations.
2) Due to a partial operation of existing air-conditioners, summer-weather variable coefficients for April and May peak demand are significantly lower than the same coefficients for the mid and late summer months.
3) Air temperature is the most powerful weather variable determining the level of monthly peak load. In addition, wind speed has a significant

impact on the winter-month loads while humidity has a vital effect on the mid and late summer-month loads.

4) The importance of both cold and warm weather build-up effects is demonstrated by the significant effect of the 24-hour moving average temperature variables. Although wind speed shows some accumulation impact on the heating load in extremely cold weather situations, humidity does not seem to have a noticeable build-up effect on the cooling load.

5) No winter weather build-up effect is detected in seasonal transition months, April and October. However, the summer weather storage effect is still significant in these two swing months.

6) The conservation activities including improvements in appliance efficiency induced by the energy crisis has resulted in a considerable amount of load reduction since 1976.

7) Price elasticity of the peak load demand is fairly low and most of the price effect is through a switch between electric and natural gas appliances. Price elasticity of the short-run demand is actually reduced by extreme weather situations at the time of peak load. The electricity price variable in the short run has the values of t-ratio and coefficient close to zero. The relative price of electricity to natural gas in the long-run adjustment model also shows a very low coefficient but a significant t-ststistic.

8) Per capita real personal income and population of the utility service area are two important factors determining the level of peak load in the long run.

9) The appliance stock-adjustment process is confirmed by a positive

coefficient and a sufficiently large t-ratio of the lagged dependent variable in the long-run adjustment model.

10) While the income elasticity of the peak demand becomes larger than 1.0 in the long-run equilibrium, the price elasticity is still negligable.

The forecasting performance of the estimated model equations has been evaluated by simulating the monthly peak loads in 1983. The performance turns out to be reasonably good except for the winter months when the utility system experienced some unusual growth of heating load. The estimated model equations also have been used to predict the annual peak loads for 1984-2000. Comparison of the model forecasts with the existing and committed power supply resources tells that the utility system will have a power supply shortage after 1994 without increase in generation capacity or purchase committments. The model estimation results provide some interesting policy implications for peak-load pricing. For example, since the estimated price elasticities of peak load are considerably less than the price elasticities of energy sales which were separately estimated by the utility, increased peak price with decreased off-peak price will increase energy sales both absolutely and relatively to system peaks. Total revenue of the utility will increase and fuel cost for power generation will be reduced through a shift in the resource mix toward base-load plants. The extremely low price elasticities of the peak demand also imply that a sharp difference between peak and off-peak prices may be required to see any noticeable effect of the load control through price mechanism. From another view point, the short-run model has a good potential to be used to analyze the impact of direct weather-sensitive load control programs, such as time-based cycling of residential central air conditioners.

Although the monthly peak demand modeling study has been completed without any mojor problem, use of a time-series data for the short-run model estimation is still a concern. The per capita income variable is considered to be a good explanatory variable for the short-run demand. However, inclusion of the income variable in the short-run equation will subsequently bring a lagged income variable into the long-run adjustment model as in the case of the electricity price variable. When a time-series data is used, the current and the one-month lagged income variables are likely to have a collinearity problem. Along with the same problem between the current and the lagged price variables, the long-run adjustment model estimation will result in chaos. If a cross-section data is available, an ideal case is using the cross-section data for the short-run model estimation and a pooled cross-section/time-series data for the long-run adjustment model estimation.

As more end-use and load research data become available, the stock-adjustment model of peak demand can gradually evolve to an integrated end-use/econometric model by increasing the level of disaggregation for both the utilization rate and the appliance stock. The first step to the integrated model can be made by incorporating the weather variables with the electric space-heating and air-doncitioning saturation variables. Besides that weather-sensitive load takes a sizable portion of the peak load, the seasonal component of the load is easily separable. Furthermore, the stocks of weather-sensitive appliances and non-weather-sensitive appliances are likely to grow at different rates. For example, income and price elasticities of the air conditioners which are near saturation are expected to be much lower than the elasticities of other electric appliances, such as electric cooking and home entertainment appliances. The weather-sensitive portion of the peak load in the long run will be, therefore, more accurately explained by directly relating the weather-induced change in utilization rate to the variable stock of space-conditioning appliances. The appliance saturation variables are prepared as a composite rate which takes account of both the number of units and load capacity for different types of the appliances.

As an illustration, a composite saturation rate of residential air conditioners is calculated by 1) categorizing the residential air conditioners into central units and window units, 2) disaggregating the type of housing served by the air conditioners into single-family and multiple-family dwelling units, 3) assigning typical values of potential load (KW) for each of the different types of air conditioners in different housing types, 4) calculating the sum of potential loads for all of the existing air conditioners and 5) dividing the total potential load of the existing air conditioners with the maximum possible potential load. The maximum possible potential load is estimated by multiplying the typical value of load capacity for a central air conditioner in a single-family housing with the total number of housing units in the utility service area. For the air conditioners in commercial and industrial establishments, the composite saturation rates can be calculated by using the information of air conditioner capacity and the floor space data of currently air-conditioned area versus total potential area for air-conditioning. The total composite saturation rate for the utility system will be obtained by aggregating the residential, commercial and industrial saturation rates weighted with the volume of summer-seasonal energy sales to each sectors. Once a composite air-conditioning saturation rate is prepared, the summer weather variables in the short-run model will be replaced by the products of the saturation rate and the weather variables. A composite space-heating saturation variable can be prepared in the same way described above and can be combined with the winter weather variables in the long-run adjustment model. The stock-adjustment model can be further refined by utilizing more information about end uses, such as the production processes and fuels used by the industrial consumers. The preparation of an adequate data base for the end-use variables is required to improve the model.

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