A REVIEW OF LOAD FORECASTING METHODOLOGIES

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ABSTRACT

In response to increasing criticisms of their load forecasts and forecasting methods, Iowa's electric utilities sponsored an independent review of past and present load forecasting methodologies. The review was conducted by an Iowa research team and followed two approaches. One was to evaluate various energy and peak demand models used by United States' electrical utilities, with emphasis on models developed during the period 1973 through 1979. The second approach involved construction of econometric energy demand models for an Iowa utility.

Historical energy and peak demand models were classified by methodology (statistical, econometric-end use analysis) and demand class (residential, commercial, and industrial). Statistical and econometric models were examined for forecast and backcast accuracy and parameter stability over time. Econometric-end use simulation models were observed for parameter sensitivity and, when possible, accuracy.

The energy demand models were constructed for the residential and commercial classes with the purpose of incorporating variables considered relevant by economic theory and available literature. These variables, and their various combinations, were tested for statistical significance and logical applicability to Iowa.

The results of this study will provide a foundation on which to begin construction of a comprehensive set of load forecasting models for use by Iowa utilities and legislators.

Key words: peak demand, energy demand, trend extrapolation, econometric models, end-use models

I. INTRODUCTION

Ten years ago the demand for electricity in the United States was increasing at an annual rate in excess of 7 percent (1). Many utilities and power authorities observed this and, accordingly, scheduled construction of generating facilities in a manner to meet this rapidly growing demand. By 1982, the annual growth of demand had fallen to 3 percent and it became painfully obvious that many of the power plants coming on line would not be needed in the near term. Several explanations for this drop in demand have been offered. The most convincing is the slowdown of economic activity during the late 1970's and early 1980's. Another possibility raised by some is a structural change in the U.S. economy during this time, as evidenced by falling energy (including electricity) use per dollar of GNP.

At any rate, the resulting excess generating reserves have become a major area of conflict between investor owned utilities, their customers, and state legislators. The conflict centers around the issue of who will pay the cost of carrying these excess reserves. In Iowa, the state legislature decided that these costs should be shared by both the stockholders of the utility and the ratepayer. The exact fraction of the over- capacity to be paid by each group is very controversial and has not yet been determined.

The Iowa State Commerce Commission has considerable input in deciding who pays for how much of the excess reserve. Most important, the commission must decide if the utilities involved acted in a prudent manner in determining the necessity of the plant itself. This focuses a great deal of attention on the forecasts of future load growth projected at that time. Several consumer groups and state legislators have argued that the methodologies used by Iowa utilities to forecast load growth were extremely primitive. The utilities, however, feel they used the best methods commonly available at the time. In response to this a small research team consisting of representatives from the Economics and Engineering Departments of both major state universities was hired by the Iowa Utilities. The objectives of this study was to review forecasting methodologies used by major utilities across the U.S. during the last decade, especially during the period 1973 to 1979, when many of the currently surplus power plants were sited. The research team was also asked to identify the important factors, or variables, critical in forecasting electricity demand in Iowa. The remainder of the paper focuses on the preliminary results of this study.

II. FORECASTING THE DEMAND FOR ELECTRICITY

Two distinctions must be made before one can proceed with analyzing and developing load forecasting models. One is the dependent variable to be forecasted. Electricity demand can take two forms, energy demand, as measured in kilowatt-hours (or megawatt-hours) and peak demand, measured in kilowatts (megawatts). The distinction is important and can affect the choice of forecast methodology. Electric energy demand has, in the past, been a part of the corporate and financial planning divisions of utilities. Rate change requests and capital investment decisions depend a great deal on forecasts of future electricity sales. Peak demand forecasting, on the other hand, has often been done by engineers or planners in the system planning divisions. Although forecasting peak demand has not received the attention in the literature that energy demand has, it is of no less importance. Most midwestern utilities experience sharp summer and winter peaks - making peak demand forecasts a critical element in the planning of future capacity additions.

Energy and peak demands can be linked by the system's load factor, a measure of utilized capacity (3). In fact, many utilities dedicate most of their forecasting resources to their energy demand models and use the load factor to convert energy forecasts to peak demand forecasts. The problem with this arises when a utility is experiencing growth or decline of weather sensitive load over time. The load factor becomes as hard to forecast as the peak itself.

The other distinction that must be made before analyzing a forecasting model is the scope of the forecast. Is it a short term forecast (2 or 3 years or less) or a long term one (3 years or greater)? Many types of models have enjoyed success in the short run and have been useful for near term management. However, the problems of today are results of erroneous long term forecasts, and since it commonly takes nearly a decade to plan, site, build, and test a power plant, the long term forecasts are of utmost importance. Nearly all electrical regulatory agencies require a 10 year demand forecast from their constituents.

Methodologies Used for Forecasting Demand

The methodologies used to forecast energy and peak electricity demand are rapidly evolving and increasing in sophistication. In general they fall into 3 categories: trend extrapolation, single and multiple equation econometric models, and end-use models. These techniques have been used for forecasting residential, commerical, industrial, and combined sector demands. All utilities use one or more of these methodologies and many use all three. Additionally, these methods are not mutually exclusive and many use hybrids of two or more model types.

A planner will rarely use the output of one method. More often than not, the planner will use several different forecast methodologies to develop ranges within which demand will probably fall and use his or her expertise to pinpoint a likely outcome. Scenario approaches are also used. This involves developing a range of future demands by assuming alternative exogenous shocks to the economy and/or the utility industry. Assumptions that have often been made include low and high economic growth scenarios and future utility (rate) deregulation.

The actual modelling methodologies and their associated strengths and weaknesses should now be discussed. Consideration will be given to examples of users of each type and their success or failure in forecasting with them.

1. Trend Extrapolation

Trend models were a dominant forecasting methodology used by utilities until the mid 1970's. They are still used today for many types of short term forecasts and as a check for reasonableness of forecasts using other methods. Trend models cover a broad range of complexity. At one extreme is the simple linear, log-linear, or log-log time trend. The other extreme could be characterized by the Box-Jenkins ARIMA (autoregressive, integrated moving average) models.

Both the advantage and disadvantage of trend extropolation models is in the nature of the models themselves - they are usually a purely statistical relationship between demand and time, containing little analytical information. Therefore, data requirements are few, usually only consistency of the dependent variable over a given period of time. Additionally, the sophisication of trend models has increased a great deal in the last 15 years, allowing both seasonal and trend components of electricity demand, especially peak demand, to be accurately modeled. However, the limiting aspect of the model, its lack of analytical power, remains. Trend models are very sensitive to the underlying assumptions built into them, as represented in their specification.

Simple time trends, both linear and nonlinear, need little explanation. One simply fits an equation to the observations over time by an estimation technique, usually least squares, and extrapolates future values of the dependent variable. This brings to mind an image of a planner with a straight edge and semi-log graph paper.

An interesting application of a more advanced trend method was in the determination of the necessity for an Iowa power plant. In 1976, a Chicago based consulting firm prepared a 36 year monthly forecast of combined peak demand for several Iowa utilities, using 22 years of data. The data covered the months between 1955 and 1976 and forecasted monthly peaks through 2013. The forecast, along with supporting documents, were filed with the Iowa State Commerce Commission as evidence of the necessity of a 650 megawatt generating station. The power plant came on-line in 1983 and is currently unneeded, making it a symbol in the conflict between the consumer, legislation, and investor owned utilities.

The specification used in this forecasting model was as follows:

$$P_t = \delta + \phi P_{t-1} + P_{t-12} - \phi P_{t-13} - \theta U_{t-1} + \tau U_{t-12} + \theta\tau U_{t-13}$$

where P is the natural log of the estimated monthly peak, P is the observed peak, and the U's are autoregressive residuals. This equation represents a univariate ARIMA model which estimates the difference between the current peak and the peak 12 months previous. The parameter δ is a trending parameter. The model was estimated with a maximum likelihood technique.

The performance of the model to date has not been very good. Table 1 summarizes the percent errors in forecasting the sharp January and July peaks in Iowa.

Table 1. Percent error of univariate ARIMA model for given months (Forecast-Actual/Actual)

Year	January	July
1977	-1.0	-1.2
1978	-4.5	8.8
1979	-1.0	17.0
1980	7.3	7.6
1981	17.3	13.4
1982	20.3	40.1
1983	41.2	24.2

The forecast accuracy appears to be deteriorating over time. Since there is so little analytical power in the model, there are few ways to pinpoint the source of errors. By re-estimating the model with the additional 7 years of data between 1977 and 1983, it was evident that the coefficients of the equation's parameter change a great deal (4). This parameter instability over time illustrates the model's long term forecasting limitations.

The Iowa utilities were not the only ones using their model type to forecast montly peaks. Bonneville Power, for example, used a very similar methodology in their forecast documentation in 1982 (5). They were careful to state its limitations, however. A northern midwest utility justified the use of this techniqueby including supporting arguments from a noted statistician in their forecast documentation (6). The statistician, however, commented that the long term forecasts were sensitive to initial assumptions about the path of load growth.

Multivariate ARIMA models (MARIMA) contain more information than their univariate counterparts. They link the movement of the dependent variable, energy or peak demand, to the movement of other variables, such as fuel prices, personal income, weather flucuations, etc. Separate univariate ARIMA models are used to forecast future value of the independent variables. These future values are then linked by a cross correlation function to forecast the dependent variable.

Very few examples of MARIMA models used by actual utilities are in the literature. Jenkins (7) used a time series of electricity energy demand and mean monthly temperature to forecast energy demand in the United Kingdom. He found, like in the univariate case, the model was sensitive to its initial identification and specification.

Trend extrapolation models, then, are probably best suited for forecasting electricity demand in the near term. Their general lack of explanatory power may make them hard to defend in forecasts for long term capital additions. Econometric, composite econometric and trend, end-use, and econometric end-use models are more common methodologies for longer term forecasting.

2. Econometric models

An econometric model is a single or multiple equation representation of the relationship between the dependent variable, here electricity demand, to the levels of various, mostly economic, independent variables.

For load forecasting, the quantity of electricity demanded, q_t, can be represented by:

$q_t = f(A_t, R_t)$

where A_t is the stock of appliances and R_t is the utilization rate of the appliances; and

$A_t = g(P_t, Y_t, X_t)$

$R_t = h(P_t, Y_t, Z_t)$

where P_t is a vector of fuel prices including electricity, Y_t is an income measure, and X_t and Z_t are vectors of other relevant variables possibly relating to weather and demographics. Substituting for A_t and R_t:

$q_i = k(P_t, Y_t, X_t, Z_t)$

which resembles the form of most utilities econometric models.

a. Energy demand models

Most work on econometric modeling for utilities has concentrated on the energy, rather than peak, demand aspect. The Iowa research team examined econometric energy models used in the recent past for all demand sectors from various utilities across the United States. The models examined have many similar structural and forecasting characteristics. All models used the average price of electricity (8), the price of substitute fuels (when applicable), and an income measure as independent variables. Additionally, most lacked the degrees of freedom necessary for confident long term forecasting. Few data sets went further back in time than 1965 and then only included one observation per variable per year. A model developed in 1976, then, would only have had 11 or 12 past observations and was expected to forecast accurately 10 years into the future. Finally, most models were estimated using ordinary least squares, and some suffered from autocorrelation problems, reducing the reliability of the forecasts and their summary statistics. Few documents included with the companies' forecasts discuss the estimation process and the problems with correlated residuals.

In general, all of the energy models had high R-square, low standard errors, and statistically significant parameters. However, the forecast accuracy resulting from these apparently good-fitting models is not as good. The forecast error associated with the models ranged in absolute values from 4 to 17 percent, and increasing over time. This is because of two sources of error. One is measurement error from inaccurate forecasts of independent variables. The growth of the income variable in many of the models was (not surprisingly) significantly overestimated during the period 1980 through 1982. The second source is related to temporal stability of the coefficients in the estimated forecast equation. Dummy variable tests revealed that the coefficient estimates of many of the parameters changed during the period between 1973 through 1982. Although this does not mean that the coefficients will necessarily change (or not change) in the future, it does limit the confidence one can place in these models' long term forecasting abilities.

Despite the poor record in the recent past, econometric models still have the analytical ability to identify major components of demand and their affects on total demand. With this in mind, the Iowa research team used the econometric framework to develop a residential energy demand model for an anonymous Iowa utility. The purpose of this was to investigate the applicability of independent variables used in energy models from other parts of the country. It also served to examine the effect of other important variables such as marginal (as well as average) electric price (7), and weather measures - variables generally not included in utilities' econometric energy models during the 1970's.

The model used monthly observations over the years 1965 through 1982, giving it considerable more observations than other models discussed. Variables found to have statistical significance in Iowa included the marginal and average prices of electricity and natural gas, income, heating and cooling degree days, the wholesale price index, and demand lagged 12 months. Ordinary least squares provided unbiased estimates; autocorrelation was not found to be a problem and R-squared was near .90.

Expost forecasting with the Iowa model yielded a mean forecast error of 7.75 percent during the period between 1977 and 1982, although no errors exceeded 10 percent. Unfortunately, like the other energy demand models discussed, there is a tendency for the estimated coefficients to change over time.

b. Peak demand models

Peak demand is modeled similarly to energy demand and uses most of the same variables. Weather variables tend to be of more importance in the peak demand econometric models, though. Many companies use separate models to forecast winter and summer peaks. In the midwest, the winter model may include such variables as electricity prices, gas or fuel oil prices, income, and measure of wind speed, temperature, and/or day length. The summer model may include only the price of electricity, income, and measures of temperature and humidity.

Many companies separate peak demand into two components, (weather sensitive load and non-weather sensitive load), and forecast them separately. Non weather sensitive (or base) load usually follows a more stable trend and can be forecasted with a relatively higher degree of accuracy than weathersensitive load. This seasonal component is often forecasted with some sort of ARIMA procedure.

Few peak demand econometric models were available for examination. If more were available, it is very likely they would be found to have many of the same long term forecasting qualities as the energy models.

An exception to this, however, was a model used by an eastern consulting company to forecast peak demand for several utilities in Iowa. It used electricity price, personal income, and a temperature/humidity index to forecast summer peaks over the period 1978 through 1995. Annual data from 1965 through 1977 was used to estimate its equation. Despite the lack of degrees of freedom the model has enjoyed modest success in forecasting summer peak during the last 5 years, with a 6 percent mean absolute deviation and stable parameters.

The Iowa State Commerce Commission uses an econometric model to forecast hourly load (including peaks) for Iowa utilities (9). They use a 24 equation model, one for each hour of the day, and use (real) average price, income, land values (as a measure of wealth), HDD, CDD, and summer wind as independent variables. Additionally, they use dummy variables to account for load changes during weekends and holidays. The model has been quite successful in forecasting loads in the short term (2 years and less) but has not yet been used for long term forecasting.

3. End use models

End-use models explicitly recognize that the demand for electricity is derived from demand for services offered by electricity using appliances. For this reason they have intuitive appeal.

The end-use model itself is a fairly simple accounting indentity which sums electricity use over many appliance groups. This can be expressed as:

$$A_j = \sum_{t=1}^{I} A_{ij} \cdot UEC_{ij}$$

where A_j is the quantity of electricity demanded in the jth sector (residential, commerical, etc) and A_{ij} is the number, or saturation, of appliance i in demand class j. UEC represents the unitary consumption of each appliance i for demand sector j. Summary over all demand classes yields total electricity, peak or energy, demand, Q.

$$Q = \sum_{j=1}^{J} Q_j$$

The number of existing appliances can usually be found through surveys. Future values of saturation are forecasted exogenously using economic and demographic variables such as income, future appliance cost, and population. Future appliance saturation is theorized to grow along an S-shaped curve. Past surveys help identify where one is at on the curve and future saturations are extropolated from there. The electricity consumption of an appliance is also calculated exogenously and can be measured as its annual energy use of by its contribution to peak demand. End use models, then, can be used to forecast either type of electricity demand.

Users of end-use models tend to be larger utilities with sufficient resources to conduct the surveys and monitor appliance usage. Only a few utilities contacted by the Iowa research team used these models in the past. Many are currently developing end-use models to strengthen the defensibility of their forecasting procedures. Legislators are becoming increasingly critical of utilities' requests to construct new power plants and often want an assessment of alternatives such as conservation, off-peak pricing, and other load management programs. Through manipulation of the UEC component, the end-use model can explicitly address the effects of these issues.

End-use models have been criticized for consistently underforecasting actual electricity use. A model used by a southeastern utility organization showed this to be true in their residential sector during the period 1964 through 1974 (6). Since then it has overestimated actual demand significantly. A residential peak model used in 1976 by a northeastern firm also overestimated demand since that time. The latter firm apparently estimated appliance saturation fairly accurately, but overestimated future usage per appliance.

4. Integrated end-use models

Integrated econometric end-use and simulation end-use models are logical extensions of the end-use methodology. The relationships which determine saturation and usage are made endogenous with econometric and/or simulation models. Much current research is devoted to these models.

Current econometric end-use models are often similar to the residential and commercial sector energy models developed by the Department of Energy's Oak Ridge National Lab. (11,12). The residential model forecasts energy use by 4 fuel types (electricity, natural gas, fuel oil, and "other"), 8 end-uses (lighting refrigeration, air conditioning, heating, etc.) and three building types (single and multi family and mobile homes). The DOE commercial energy model uses the four fuels, 5 end uses, and 8 commercial business classifications. Basically, the models minimize the life cycle costs of providing the services of the appliances. The relative prices of electricity, natural gas and fuel oil combine with other economic and demographic variables to determine saturations. Usage is determined endogenously by economic and engineering relationships. Total electricity demand is the sum of usages over each fuel, building, and appliance types.

Very few econometric end-use models were implemented at the utility level before 1979. Since then, the California Energy Commission has developed a similar methodology for use by themselves and the larger California utilities. They are especially interested in analysis of conservation programs with these models. Bonneville Power implemented the DOE methodology in 1981 and has allocated large amounts of resources to developing a reliable regional model. Utilities in Florida, New York, Georgia, and other areas are currently adopting the econometric end-use methodologies.

From an ex-post standpoint, the econometric end-use models forecast accuracy has been validated. Due to their fairly recent adoption, however, their long term forecasting accuracy has not been determined. Sensitivity tests of the effects of exogenous shocks of the independent variables on total electricity demand were conducted by Bonneville Power and the Iowa research team. Both found that price and income elasticities derived from the DOE models were consistent with those derived from econometric models.

Simulation end-use models are currently being refined for use by utilities. A major difference between econometric and simulation end-use models are the methodologies employed for choosing appliances. Rather than minimizing the life cycle cost of the services, the simulation model can employ additional criteria in the selection of appliances. Many appliance decisions are interdependent. For example, the selection of a natural gas furnace often means that the water heater will also be gas powered. Simulation can provide for a more accurate picture of consumer choices.

The definitive simulation end-use model is the REEPS model developed in 1981 at the Electrical Power Research Institute (10). They are currently refining this model for more wide-spread use by small, as well as large, utilities.

III. CONCLUSIONS

Emphasis in this study has been given to electricity demand forecasting models used during the period 1973 to about 1979. This is the period that many of the decisions to build the current exccss generating reserves were made. For the most part, trend extrapolation and econometric models were used to forecast both future energy and peak electricity demand. End-use models were not as prevalent during this period but are currently gaining in importance. They appear to have the best potential for assessing load conservation programs.

Most models used during the period 1973 through 1979 significantly overestimated future electricity demand. This is because of erroneous prediction of exogenous variables (especially income and other economic variables) and temporal instability of coefficients in the forecasting equations. The degree to which type of error occurred varies geographically. It should be noted, however, that the time period in question was a very volatile one for the energy industry, and the economy as a whole. The oil embargo of 1973 preceded the first real increases in energy prices seen in the United States in many years. It is of little surprise, then, that the models exhibited some structural instability. The causal relationships seen today between energy prices and energy demand had not yet established themselves.

Forecasting methods employed in determining the need for future generating capacity will no doubt be put under a great deal of scrutiny by all parties involved. Although recent innovations in modeling will not guarantee accurate long term forecasts, they will be more explicit in addressing the determinants of electrically demand and the future path of these determinants.

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2. A problem in this approach has been a consistent definition of what constitutes needed v. excess reserves.

3. The load factor is derived from the equation:

$$\text{Load factor} = \frac{\text{Energy demand (in kwh)}}{\text{Peak demand (in kw)* 8760 hrs/yr}}$$

If the energy demand and load factor are known or can be reliably forecasted, one can rearrange the equation to solve for the (coincidental) peak demand.

4. The estimates of the model, and their 1983 re-estimates are as follows:

Parameter	1977	1983
δ	.0515	.0523
ϕ	-.208	.074
θ	.721	.632
τ	.143	.620

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8. The average price of electricity is defined by the total sector's revenue divided by its sales. Actually, electricity is usually priced on a declining block basis where each successive "block" of electricity is less expensive than the previous one. Mar_'nal price is the price at the lowest block the consumer has reached. It is always less than the average cost with a declining block rate schedule. Theoretically, then, there are some problems with using an average price proxy. See Taylor, The Bell Journal of Economics, No. 74-110, 1975.

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