Forecasting Needs for the Emerging Cultural/ Social Energy Paradigm

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Purely economic issues have motivated much of the previous interest and efforts in the development of energy forecasting methods for the residential, commercial and industrial sectors. An emerging cultural/social paradigm of energy end-use, however requires examination of the underlying assumptions of these methods. Particularly important to this effort will be an understanding of imperfect information and how economic entities process that information and form preferences or make decisions. Incorporating these processes into the energy demand forecasting models will require the usage of new or hybrids of current techniques.

Introduction

A new conceptual framework or paradigm for the analysis of energy consumption is emerging. This viewpoint no longer relies totally on price or income or the availability of technologies as the motivating factors for changes in energy consumption patterns or levels. The basis for this paradigm is a greater understanding of the linkages between cultural or sociological characteristics and energy consumption. This is a departure from previous approaches to the analysis of energy consumption, which have relied on either the economic assumptions of price or income or the engineering assumptions involving the feasibility and availability of energy producing and end-use technologies. This paradigm is the result of cross-national or cross-cultural comparisons of energy usage. These comparisons have demonstrated that although changes of price and income will affect energy consumption, other factors play a major role in determining energy consumption levels and patterns of end-use. This has been shown to be true particularly for the residential sector, but similar effects are suspected for both the industrial and the commercial or service sectors.

Three general types of forecasting methods have been used in the prediction of energy end-use patterns and levels. These methods have a statistical foundation with at least two of the methods having a basis in economic theory. With the emerging culturally based paradigm of energy analysis, different forecasting strategies will be needed to meet the requirements of this conceptual framework. These strategies will involve the collection of new types and of expanded sets of data, as well as a greater understanding of the underlying processes that are assumed to exist. That is the underlying assumptions for the forecasting process will have to be examined. This creates a challenge for forecasters to produce and use a set of tools not currently in use.

This paper will provide an overview of the economic issues and econometric methods incumbent in the forecasting of energy demand for the residential, commercial, and industrial sectors for such purposes as space conditioning, appliance usage, and process energy. The first section of this paper will consider the underlying economic and policy issues motivating interest in this topic, as well as some of the technical background underlying current interest. The second section of this paper will discuss the econometric methods previously used in this effort. Included in this section will not only be a discussion of the benefits of each of these methods, but also the shortcomings of each method. The fourth section of this paper will consider the potential changes in methods and techniques that may occur in response to underlying economic and policy concerns in this area.

Background

Although purely economic issues have motivated much of the previous interest and efforts in the development of energy demand forecasting methods for the residential, commercial and industrial sectors, other issues are now of primary interest. Public utilities and other energy producing firms have traditionally had as part of their planning process, a forecasting effort of future demand. The purpose of this effort was to ensure the efficient allocation of resources, an economic and engineering problem. The effects of such economic issues as shifts from regulated markets to more competitive market structures with changes in cost of supply could be reasonably evaluated using the context of price and some measure of income. Particularly when large changes in either measure occurred, econometric methods were fairly accurate in predicting changes in energy consumption. However, when other concerns such as interests in preserving environmental quality or improving the standard of living become motivating factors for changes in energy consumption, the assumptions of price and income need to be evaluated in the forecasting context (Lutzenhiser 1992a).

Recent work in the area of energy end-use has indicated that other factors in the absence of major changes in price and income influence levels of energy demand (Schipper, Bartlett, Hawk, and Vine 1989). This work indicates that factors other than energy-using stock influence levels of energy consumption, particularly in the residential sector. International comparisons of energy end-use patterns indicate that when income changes, measured on both household and national bases, energy consumption patterns change (Schipper and Meyers 1992). In the residential sector, changes in energy consumption have been attributed primarily to declining household size and home occupancy. Changes in these characteristics can be attributed to cultural factors such as women increasingly entering the labor force, improved educational levels, and movement through the life-cycle of the family. As a country undergoes structural change and shifts from heavy manufacturing to more service related efforts, energy consumption patterns and levels in both the industrial and commercial or service sectors also change. Shifts in these two sectors will result from increasingly skilled workforces, and higher levels of national income. These types of changes can influence the pattern of energy end-use and need to be explicitly incorporated into the forecasting process.

The human factors that determine energy usage have been primarily explored for the residential sector, however, these same factors are hypothesized to affect other sectors as well (Lutzenhiser 1992a). The primary thesis of this work is that human beings are responsible for not only the construction of energy using stock but also the use of that stock. Further, that these individuals are not “rational” actors, responding to price and income changes, as neoclassical economic theory suggests. In lieu of response to price changes, behavioral changes such as changing patterns of the allocation of time between work and leisure will affect energy consumption patterns. Behavior by corporate decision-makers will determine the development of new energy-efficient products. This behavior and those decisions are affected by complex interactions within the business organization as well as with the market place. Incorporation of these types of behavioral changes into the forecasting process, require the adoption of expanded or revised assumptions. Those assumptions will arise from the study of cognitive behavior, and the assimilation of information.

The selection of a forecasting method depends upon the availability and accuracy of data (Pollack and Joiner 1979). Much of the data that is used in the estimation of energy demand is from aggregated sources. The data most readily available for forecasting purposes is reported on a state, regional or national basis. To disaggregate by sector requires the collection of this data at the point of sale. As a result, measurement of energy consumed at a micro level for particular end-uses, such as space-conditioning or appliance usage, is available for only limited areas through limited surveys, both in terms of numbers of consumers surveyed and periods of time. Very often during the collection of this type of survey data, critical pieces of information for the analysis of behavioral changes are not solicited. A primary example of a missing piece of data is the description of the detailed usage of household time for various activities. Other data such as appliance stock or demographic characteristics is collected on a routine basis by governmental agencies in developed countries. However, these efforts are expensive and are conducted on a sporadic basis. With increasing costs of collection, these efforts at data acquisition are becoming less comprehensive and more infrequent. A prime example, is the current move to decrease the level of detail on households collected by the U.S. Census Bureau due to the expense of the effort (U. S. Census Bureau, 1993).

Forecasting Methods

Background

Forecasting models for energy demand by the residential, commercial, and industrial sectors may be divided into three general categories: econometric, time series, and end use models (Poirer 1978; Uri 1978; Limaye and Whitmore 1984; Charles River Associates, Inc. 1984; Cambridge Systematic, Inc., Christensen Associates, Inc., and Scientific Systems, Inc. 1991). Time series models incorporate the stochastic nature of time-dependent data. Econometric models, on the other hand, attempt to explain the statistical relationship between consumption and economic variables. End-use models are “bottom-up” models based on individual appliance usage, space conditioning, or process energy requirements. Over time, these three types of models have met various criteria for acceptance. Criteria for acceptance of any modeling technique include consistency of results, explainability, data availability, statistical tests, stability over time, sensitivity analysis, and sensibility of the forecast results (Huss 1985a, 1985b). In current application, as demonstrated by survey between 40 and 75 percent of the time for all three sectors, the largest single set of forecasting techniques involves the application of econometric techniques. In the residential sector, end-use models are used almost as often, approximately 50 percent of the time. Used almost exclusively in the industrial sector, process models can be used to forecast demand by scheduling production operations. Time series methods have received some application to electrical demand forecasting, however, this application has been limited.

Econometric Models

Econometric models may take a number of forms (Huss 1985a). The simplest form consists of an aggregate single equation, which often has a linear or log-log formulation of sales versus such independent variables as gross national product, price, degree days, or other variables. A refinement on this method is the disaggregation into sectors, such as residential, commercial, and industrial. Most recently, multi-equation econometric methods have been applied to demand forecasts. These models usually involve several equations per sector. Flexible functional forms are often used to include a wide variety of exogenous variables. Considerable debate has occurred concerning the level of complexity that an econometric model should assume. Complex econometric models seem to outperform simpler models in the short-term (two years). However, simple econometric models appear to perform better for longer horizons (Huss 1985b). These conclusions are debatable, with other work demonstrating opposite results (Armstrong 1984).

The primary advantage of econometric models is their foundation in economic theory. However, this relationship must be specified. Various types of model specifications have been used previously. A model specification grounded in economic theory assumes that individual consumers are trying to maximize their utility, while firms in the industrial and commercial or service sectors are trying to maximize profits or minimize costs. To capture these types of underlying relationships requires the selection of various explanatory variables. As a result, model specification depends heavily on the type of data available. If misspecified, results from a model will not properly represent the underlying causal process. Often the processes being modeled are dynamic in nature. That is that a consumer or firm in the short-run will have some sort of response to price, but this response will not be as great due to a fixed stock. Longer time horizons allow for the change in energy-using stock. Therefore, rather than just using only cross-sectional data, a time element needs to be injected into the modeling process. As a result the number of lags must be selected, which capture potential changes in energy using stock. Also factors other than price and income, which affect energy consumption levels or responses to price, are difficult to represent in the modeling process. If the model becomes too complex, computational problems and expense increase dramatically. Finally, econometric models can be extremely data intensive, which makes them very expensive to develop and to maintain.

End-Use Models

End-use models are in close contention with econometric methods for load forecasting purposes in most industrial forecasting settings. An end-use load curve is the collection of hourly loads drawn for a specific appliance for a specific customer group, for example residential water heating (ICF Inc. 1984). In the residential sector, these models are characterized by forecasts of appliance saturation. In the commercial or industrial sector, these forecasts are generally done by equipment type (Huss 1985a). Estimates of load growth are achieved by forecasting with econometric methods, changes in appliance saturations or class size (Fitzpatrick 1982). End-use models seem to out perform econometric techniques for all time horizons (Huss 1985b). However, although end-use models appear to provide better accuracy, the key issue becomes how much is this additional accuracy worth in terms of data collection and development costs.

Implementation of this type of model requires two types of data: (1) average stratified per customer load curves or average per unit end-use load curves, and (2) weights based on stratum of populations or end-use saturations. A utility load curve is developed by adding component load shapes at the class or subclass level. Although this method appears intuitively simple, there are some analytical issues which must be addressed with the use of this type of model. These issues include the choice of appropriate end-use load curves, the determination of expansion factors for aggregation, and the treatment of minor, or basic, end uses (ICF Inc. 1984). The description of an end-use curve is subject to the availability of data. Without the detailed knowledge of appliance saturation percentages, end-use curves cannot be applied to a population. Also the aggregation of load for minor uses such as televisions, lights, etc., can result in a fairly healthy contribution particularly in the residential sector. This interjects a fair amount of uncertainty into the estimation process.

In preparing an end-use forecast, the forecaster has two choices of method: (1) construction of a load curve for each end-use on the basis of many attributes, or (2) selection of a suitable donor and perhaps modifying its load data where major attributes differ significantly. Incorporating all the variables that impact a load curve can be very costly, therefore the second method is most often used. The major attributes that would be used to modify a load curve are (1) appliance saturation, which is usually estimated from customer survey data; (2) rate level and structure; (3) average income per capita; (4) population density of a service area; (5) number and age of occupants per household; and (6) the number of single versus multi-worker households. In particular, three major household appliance loads affect the load shape. These are space heating, air conditioning, and water heating.

A major advantage of end-use models is that they are inherently more understandable and straightforward. However, the successful use of these models depends on the availability and quality of end-use load data. Very often this data is not collected by a local utility, therefore this method can not be applied. Also end-use models usually do not explicitly consider the effect of price on consumption of electricity (Shaw 1979). Finally, unless explicitly interjected into the modeling process, the impacts on appliance saturation of demographic changes are not reflected in the forecast results.

Time Series Models

Time-series methods have been applied previously to estimation of energy demand. Time-series models utilized include Box-Jenkins, moving average, exponential smoothing, adaptive estimation procedures, window moving average regressions, etc. Empirical time series analysis includes elements of probability theory, statistical theory, numerical analysis, and systems theory. Use of all of these elements results in a parsimonious approach to time-dependent data, which has been widely applied in a number of settings (Brockwell and Davis 1987; Shumway 1988). Time-series methods originated in 1807, when the French mathematician Fourier claimed that any series can be approximated as a sum of sine and cosine terms. These methods received extensive treatment by Yule during the 1920s. A comprehensive theory of ARMA (autoregressive moving average) schemes was developed by Weld during the late 1930s. Filtering techniques were developed by Wiener, Kolomogroff, and Kalman. The late 1950s and early 1960s saw development of modern computers, and the cumbersome computations found in connection with spectral analysis were easily handled.

The goal of time-series analysis is to discover characteristics of the phenomenon underlying the series. The term "time-series" refers to a set of observations ordered sequentially in time. Current methods of analysis assume that time series can be adequately described in terms of previous values of the series itself and/or previous error terms. During the course of analysis, noise is separated from output, resulting in a series which truly represents the outcome of the generating process. This is referred to as a stationary series, which means that the series fluctuates around a constant mean.

As a tool for additional analysis of energy data, time series methods have excellent potential. A general recommendation for time series methods is that they are cheaper to develop and utilize than econometric or end-use models (Makridakis 1976, 1978; Makridakis, et al., 1984). However, it has been previously claimed that time-series methods have no basis in economic theory, therefore cannot be used directly to test hypotheses about economic phenomena (Uri 1979). On the contrary, some of the most recent work on time-series modeling of economic series suggests that a causal link between economic theory and parameter estimates exists (Cambridge Systematic, Inc. 1991; Greening 1992). These linkages, however, are not well understood. Also to develop a forecast utilizing time-series methods requires collection of a fairly substantial series of consistent data over time.

General Comments on Forecasting Methods

All of these methods, as currently practiced, in one form or another do not address the current concerns or issues under discussion. It should be remembered inherent in the forecasting process is the assumption that "what has been will be". And that the past behavior upon which the forecasted behavior is based will continue without alteration throughout the forecasting horizon. Therefore, we get the "straightline" syndrome or type of projection. Further, these types of forecasting methods examine only the "average" behavior. Due to the aggregated nature of the data used in the forecasting effort and the amounts of data required to obtain a successful forecast, disaggregation of a forecast into subgroups within the population will not usually be possible. As a result, we are not able to examine the energy consuming behavior of culturally distinct groups within the population. The explicit inclusion of sociodemographic characteristics in the forecasting process is key to predicting future changes in levels of energy consumption as a result of behavioral changes. Although a number of models have previously included these variables in the specification, these variables have been only used to examine changes in levels of energy consumption, not differences in response to price and income changes across population subgroups. That is, these variables only shifted the intercept of the estimation equation, Finally, the forecasting methods currently in use have applicability to limited intervals of time.

Anticipated Cultural and Social Trends

The types of cultural and social trends which will be affecting energy consumption and which need to be incorporated into current forecasting methods are many and diverse. The inertias of established energy using practices, including current technologies and cultural biases toward those technologies, will need to be represented in the modeling process. These types of biases will certainly slow changes in levels and patterns of energy consumption, if not alter the path of change all together. Cultural biases toward large homes, or air conditioned office buildings and other energy intensive activities will not alter easily. Established building practices will continue to promote the construction of these types of structures.

Population growth, combined with expectations of an improving standard of living and changing family structures, will promote in some cases energy consumption and in other cases reduce energy consumption. Population growth will promote increases in energy consumption. However, increased standards of living and higher levels of education will result in smaller family sizes. This means that the number of family units will increase and that those units will have greater demands for energy due to expectations of a higher standard of living. Higher levels of education, particularly among women, will mean an expanding work force with a different occupational structure than has been seen in the past. This shift in occupational structure will be less energy intensive and will result in altered patterns of energy consumption.

At work also are a number of cultural and social trends that are difficult to measure. Concerns over environmental degradation have been shown to be a powerful force in alteration of consumption patterns (Kempton, 1993). Consumer preferences for products, which have been demonstrated to have a direct linkages to environmental degradation such ozone depleting chlorofluorocarbons (CFCs), have been voluntarily altered as information has been disseminated and the urgency of the problem perceived. This voluntary alteration of behavior is not restricted to consumers. In the case of the voluntary reduction of the usage of CFCs, corporate decision makers also played a role. Production processes have been altered to eliminate usage. In both cases, the prices of substitutes for CFCs were greater. As a result of experiences such as this, the process of information perception has been demonstrated to be a powerful market behavior altering force. However, particularly in the case of consumers, however, this process is not well understood or easily quantifiable in a forecasting context (Kempton, 1982).

The types of behavioral changes that are anticipated to occur will not be apparent within the next two to five years. Instead we are talking about time periods of ten years or more for behavioral and the resulting preference changes to manifest themselves. These types of behavioral changes will be in response not only to increases in current marginal costs of energy production and usage as well as increased marginal costs due to the implementation of more expensive, but cleaner technologies, but also cultural and social trends. As markets for newer technologies develop and marginal costs fall, and cultural and social attitudes towards energy usage change, forecasts of energy consumption based on historical data utilizing current costs will fail to estimate actual levels of energy consumption.

Anticipated Trends in Forecasting

To improve our forecasting capabilities in the area of energy end-use, a number of changes will need to occur in our approach to the problem. Many of these improvements will arise from a better understanding of the underlying processes and incorporating them into the forecasting process. Perhaps the biggest improvements will occur due to the examination of the linkage between price and income and changes in consumption. Recent work in the transportation area indicates that subgroups within the population will have discernible differences in marginal response to changes in price and income (Greening, Jeng, Formby, and Cheng 1994). Differentiable responses to marginal changes in price and income by subgroups in the population means that such policy instruments as carbon taxes, which effectively raise the price of fuel, will not have the anticipated results, which were estimated utilizing a population-wide response. Therefore, these differences can affect the successful implementation of energy conserving policies. Identifying and understanding those differences is of major importance to the forecasting process. To examine differences between subgroups in the population will require the use of statistical techniques for the identification and description of subgroup characteristics. Also, this type of effort will require the concerted acquisition of broad detailed sets of data across populations in terms of detailed energy end-use and demographic characteristics.

Understanding of economic behavior in terms other than price and income will be necessary. How consumers or firms process new information in light of differential access to information or new technologies, and the market penetration process of those technologies, is vital to correctly representing in our forecasting models responses to efforts at improving energy end-use efficiency, and responses to other concerns such as environmental degradation. Much of this effort at understanding the information process, involves understanding the calculus that goes into making these decisions. In other words, understanding the formation of personal preferences or the corporate decision making process and incorporating those into a modeling or forecasting context is necessary.

New forecasting techniques or hybrids of current techniques will need to be developed to meet the challenges imposed by this evolving energy paradigm. These types of models will need to explicitly recognize the social and demographic factors which result in changes in energy end-use patterns and levels. Potential economic modeling tools will take advantage of techniques used by other disciplines.

As a result of the emerging paradigm of energy analysis, energy analysts may no longer just be economists, or engineers. They must be sociologists, anthropologists, and mathematicians. To capture all of the facets of energy analysis embedded in this new paradigm will require the development of interdisciplinary teams, expert in one discipline, but conversant in others.

Acknowledgments

The comments of Dr. Willett Kempton were greatly appreciated during the preparation of this paper. The intellectual contributions, comments, and critiques of Dr. Lee Schipper have been critical for the author's ongoing research and are most humbly and gratefully acknowledged.

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