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Survey of Models on Demand, Customer Base-Line and Demand Response and Their Relationships in the Power Market

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ABSTRACT

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The increasing use of demand-side management as a tool to reliably meet electricity demand at peak time has stimulated interest among researchers, consumers and producer organizations, managers, regulators and policymakers, This research reviews the growing literature on models used to study demand, consumer baseline (CBL) and demand response in the electricity market. After characterizing the general demand models, it reviews consumer baseline based on which further study the demand response models. Given the experience gained from the review and exiting conditions it combines an appropriate model for each case for possible application to the electricity market and discusses the implications of the results. In the literature these aspects are studied independently. The main contribution of this survey is attributed to the simultaneous treatment of the three issues as sequentially interdependent. The review is expected to provide a full understanding of the demand, CBL and demand response in the power market and their relationships. It enhances demand response in the electricity market. The objective is through a combination of demand and supply side managements to reduce demand through different demand response programs during peak times and thereby save costly power generation and energy resources and at the same time reduce vulnerability.

JEL Classification: C50, D10, D40, H30, L11, L51, L94, N70, O13, Q21, Q43

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1. INTRODUCTION

In recent two decades many governments around the world have decided to reconstruct their electricity markets. As part of the liberalization or restructuring, generation and distribution segments of the electricity market are privatized often. The restructuring plans have the objectives to divest and privatize the generation and distribution segments, implementation of open access transmission, wholesale competition, and introduction of retail competition. The ultimate aim is to promote efficiency and conservation in provision of the service. In some cases, such policy has been partially suspended. As an example, the suspension decision in Korea in 2004 followed an intensive debate about the appropriateness of the timing regarding the electricity market reform (see Lee and Ahn, 2006). The reform proponents were of the view that electricity can be treated as normal goods and exchangeable in the competitive market, and problems caused by the transition to the market system should be manageable. The reform opponents, on the other hand, argued that an effective competition of the power industry is not yet feasible. The infeasibility is attributed to the idiosyncratic nature of electricity such as; low-price elasticity of demand, electricity is not storable at low cost, and the isolated electricity network. The decision of suspension was thus made on the ground that the benefits of reform are theoretical and uncertain, while the costs to society and potential risks are substantial and harmful.

The literature on restructuring segments of the service sector, associated theories, and approaches to analysis and empirical findings is voluminous. Phlips (1988), for example, a survey introduces the reader to developments in the theory of price discrimination. The survey is structured around Pigou's distinction between perfect, second-degree and third-degree price discriminations. In another survey, Peerbocus (2007) assesses reforms in the electricity supply industry. Review of empirical studies suggests that progress has been made in form of increased competition in the market and efficiency gains. A better connection between the wholesale and retail markets will allow consumers to optimally reap those gains. Mao and Hare (1989) review the changes in pricing institutions in China since 1949. The emphasis is on the shift from equilibrium to a distorted price system. The authors argue that distorted prices are harmful to economic growth even in a planned economy. The central point of China's economic reform has been the extension of decision-making power to enterprises and the introduction of a market mechanism so as to improve microeconomic efficiency. In the authors view, such a goal cannot easily be achieved due to the false information provided by the distorted price system. However, the recent decades of double-digit annual growth in China provides sufficient evidence that the goal has easily been achieved.

The literature on energy (electricity) consumption-economic growth causality nexus is reviewed by Ozturk (2010). The empirical studies here focus on either the role of energy (electricity) in stimulating growth or examining the direction of their causality. The former is a stylized fact but there is no consensus in the latter case. Acaravci and Ozturk (2010) investigate the electricity consumption-growth nexus in transition countries. Their focus is on the long-term relationship and causality between electricity consumption and economic growth using panel data. The results show that electricity consumption related policies have no effect or relation on the level of real output in the long run. The application of a similar approach (see Ozturk and Acaravci, 2011) to MENA countries data shows no evidence of causal relationship between electricity consumption and economic growth in most of the countries. The evidence indicates that policies of energy conservation can have little or no impact on economic growth. Payne (2010) discusses the various hypotheses associated with the causal relationship between electricity consumption and economic growth. A survey of the econometric methodologies used and empirical results show evidence of support for neutrality, conservation, growth and feedback hypothesis.

There are few studies in addition to those arguing for theh introduction of flexible pricing and institutional changes to improve microeconomic efficiency. Cavaliere and Scabrosetti (2008) review the theoretical literature on privatization and efficiency by tracing its evolution from agency theory including the field of political economy. The former addresses privatization issues by comparing state-owned enterprises with private but regulated firms, while the latter separates privatization from restructuring decisions. They either explore bargaining between managers and politicians or analyze the impact of privatization. Empirical results show that privatization may increase productive efficiency when restructuring takes place but its effects on allocative efficiency still remain uncertain. In a related survey Linares and Labandeira (2010) consider energy efficiency and conservation as major factors in the reduction of the environmental impact regarding the energy sector. Energy efficiency also contributes to reducing external dependence and vulnerabilities. They discuss the factors that influence energy efficiency and conservation decisions, and the appropriate policies for their promotion. Although not all public policies seem justified, they argue that specific policies for promoting energy conservation may be required, based on economic instruments or on the provision of information to consumers. Demand response experience in Europe is examined by Torriti et al. (2010) focusing on policies, programs and implementation. The importance of information and education of customers on potential benefits and costs of different demand response models are emphasized in Albadi and El-Sasdany (2007 and 2008). In another paper closely related to energy conservation and efficiency, Worthington and Hoffman (2008) discuss the increased reliance on demand-side management policies as an urban water consumption management tool. This has fostered an increasing volume of research aimed at providing best-practice estimates concerning price and income elasticities, quantifying the impact of non-price water restrictions and gauging the impact of non-discretionary environmental factors affecting residential water demand. It provides a survey of empirical water demand analyses and their findings.

The literature on performance in the public sector is also growing. Heshmati (2003) surveys contributions to, and developments of, the relationship between outsourcing, efficiency and productivity growth in manufacturing and services. It provides discussion on data and the core methods of measuring efficiency and productivity. Measurement of inputs and outputs in manufacturing and services are discussed. To promote research, a number of factors important to the above relationship in the service sector including electric utilities are summarised. Simpson (2009) also discusses issues arising in the measurement of productivity in public services. Compared to measuring productivity in the private sector, difficulties arise because the output of public services is often not priced and because some public services are consumed collectively. A key problem in this context in his view is measuring the range of outputs and quality improvements delivered by public sector organizations. Simpson discusses the measurement of public sector productivity in practice and reviews studies that examine factors underlying productivity differences and growth in public and private sector organizations. Public sector reforms present opportunities for empirical research to identify possible causal effects on productivity.

After having provided a brief review of the literature on public sector reform, their efficiency aims and outcomes, this research reviews the literature on models employed to study demand for electricity. After characterizing the electricity demand, this study reviews the consumer base-line (CBL) in the power market which is used in estimation of demand response (DR) models aimed at reducing consumption at peak time. It is conducted in a number of steps including: survey of general demand and demand response models, review of the type of models on CBL in the power market. The review is expected to provide a full understanding of the demand, CBL and demand response in the power market and their relationships. Knowledge enhances demand response in the electricity market. Given the actual conditions, an appropriate model for possible application is selected, to develop load forecasting analysis for evaluating a CBL and actual application of the model and presentation of the result to the electricity market along with suggesting implications of the result.

In the literature these aspects are studied independently though they are sequentially interdependent and as such, they suffer from this strong limitation which might create some bias among the results and thus, not help decision makers. Therefore, the main contribution of this survey is attributed to the simultaneous treatment of the three issues as sequentially interdependent. Access to information, models and methods determining the load profile, forecasting value and calculated error value are important issue in this context. The load management is often conducted through load management equipment for demand control and incentive provision by determinants of CBL regarding customer load for load reduction. Statistical and regression methods are used to estimate load patterns by adopting weather and time adjustments. The demand side focuses on taking advantage of the price (and income) sensitivity of demand, while provisions of incentives are used as supply side to reduce peak time consumption as a demand response measure. In this relation CBL allows for forecasting and estimation of the effects. The objective is through a combination of demand and supply side managements to reduce demand through different demand response programs during peak time and thereby save costly power generation and energy resources while also reducing vulnerability consistent with the efficiency and conservation arguments discussed above.

The remaining part of this report is organized as follows. Chapter 2 is an in-depth review of the general electricity demand models as well as their key determinants and estimated impacts from industrialized and newly industrialized economies. Chapter 3 introduces consumer base-line and their calculations for a demand response program to reduce demand during peak time. Chapter 4 covers demand response models to promote energy conservation again sourced from industrialized nations. The final chapter concludes this study and suggests implications of the results.

2. ELECTRICITY DEMAND MODEL

2.1 Introduction to electricity demand models

This chapter provides a brief overview of various operating electricity markets. It reviews the standard regression demand models for electricity and provides a summary of such models and their key determinants and findings in the form of different elasticities. The purpose is to enable ex ante evaluation with regards to the impacts of designed demand response programs and also screening customer enrollment into such programs. The focus is on generalized regression models for demand reduction through different demand response programs. These regression models employ load sensitivity and representative load patterns as well as other consumer, producer and market characteristics as explanatory and control variables in the demand analysis.

Economic and technology development and the patterns of advancement is the general source of growing energy demand. The growing demand of electricity is a result of population growth, economic growth, the rapid spread of power using modern technologies and climate change. Mideksa and Kallbekken (2010) review the research concerning the impact of climate change on electricity demand and supply. Higher temperature is expected to raise electricity demand for cooling, decrease demand for heating and reduce electricity production from thermal power plants. Evidence regarding the positive effects for the restructuring of electricity markets has renewed interest in electricity demand and in particular in its key determinant. It reflects a desire to improve energy use efficiency of the markets on the one side and reducing the negative impacts of price changes on consumers' welfare in the form of reduced consumption and increased expenditures on the other side. Similar to other areas, modeling demand has evolved from simple demand, price and income relationships and is extended to account for other consumer, market, structural and weather characteristics and their interactive effects resulting in improved prediction performance and analysis. Worthington and Hoffman (2008) refer to literature for the analysis of market and non-market systems with different tariff structures in which they share a common focus for providing best-practice estimates of price and income elasticities for designing better charging regimes to quantify non-price service restrictions to judge their effectiveness in controlling water demand and gauging the impact of environmental factors.

This chapter is organized into a number of sections. Following this introductory section, section two discusses the different electricity markets. In the third section we provide a review of sector-specific demand models based on industry and residential market segments and present summaries of their distinguishing characteristics and main findings. The focus is on the residential market segment and the typical econometric models employed in modeling peak demand, hourly demand, and demand reduction models. The fourth section discusses econometric issues concerning determinants of demand, and model specification, estimation and testing procedures. An account will be made for data, selection, non-linearity, time variance parameters, weather, intraday and seasonal variations, as well as policy results and their implications, and model performance and forecasting. Finally, based on the experience gained, the fifth section presents an appropriate model of electricity demand.

2.2 Electricity market and systems models

There are different market organizations regarding the electricity industry. Barroso et al. (2005) provide an overview of various existing operating electricity markets. They classify the organization and functioning of these markets independent of their industry structures, service management and regulatory aspects. Two main types of market organizations are distinguished, namely power pool or centralized markets and bilateral contract or decentralized market models. It is mentioned that most electricity markets can be classified as one of these two types or a combination of their variants. In relation with liberalization of the electricity market regimes, Foley et al. (2010) review the changing role of electricity systems modeling in a strategic manner, focusing on the liberalization process, i.e. moving away from a monopoly to liberalized market regimes in the US and Europe and complexity brought about by policy targets for renewable energy and emissions. Lima et al. (2011) analysis for the amount of CO2 reduction attributed to higher electricity prices finds that given the price inelastic behavior of residential customers in both the US and Europe, public policies must be combined with other measures to foster conservation and transition to a more sustainable energy system. Atanasiu and Bertoldi (2008) in assessing the saving potential of residential electricity consumption in new member states and candidate countries find that better equipment efficiency will limit the growing demand and reduce CO2 emissions.

In the power pool case, all generating companies offer price-quantity to form the aggregate market supply of electricity. The determined price can be based on predetermined variable cost (cost based) or generator freely offered (price based) pools. The demand side can be a one sided pool where the market operator forecasts demand based on which dispatch it selected with regards to the available generating units against it, or a two sided pool where consumers also bid. The pool can operate on a day-ahead market or close to an intraday real time market. Under the condition of power pool, the network is treated as a “copper plate” resulting in a single energy price in the whole control area. By this system, the cheapest generator gets priority, and depending on congestion, some out-of-merit generators are dispatched to satisfy demand. This system is called “constrained-on/off” generation. Alternatively, the price is composed mainly of generation cost but accounts for the physical aspects of the transmission system are made by allowing the location specific marginal pricing of power.

In the alternative (bilateral contract) model of market organization, the market mechanism established is based on physical bilateral contracts among the two parts. Here sellers (generators) and buyers (distribution companies) freely enter into bilateral contracts for power supply where transaction over the counter is allowed. In parallel to bilateral contracts, a voluntary power exchange could be set up offering day-ahead and intra-day trade with the possibility of great benefits to the participants. This type of organization is something between the two extreme types discussed. This model has previously been implemented in several European countries. As an example, Leuthold et al. (2008) applied nodal pricing as an economic approach towards the efficient use of electricity networks utilization in regards to the German grid. The model is applied to analyze the impact of extended German wind power production on the power grid. The results demonstrate that by taking into account physical and technical constraints, they contribute to the assessment and optimization of system configuration and operation.

It should be noted that the power pool and bilateral contract models described above are equivalent in a world without transaction costs, else they are different, but can also coexist in the same market. The central dispatch model has the advantages that it allows for the integrated treatment of generation units, transmission networks, locational marginal pricing, and efficient management of potential transmission constraints. The Barroso et al. (2005) survey results show that a wide variety of power sector models and arrangements can be found with evidence of both success and failures. Performance of the models can change depending on conditions and locations. A mix of political and regulatory issues are the main factors causing delays in the planning and development of the power market which faces challenges to ensure sufficient generation capacity and investment capital in order to face their growing power demand. The same factors under conductive conditions can be the source of optimal development and efficient performance.

2.3 The typical demand models

There are few electricity demand studies at different levels of aggregation. These studies require different types of data, specified somewhat differently and are using different estimation methods. The models include micro household, aggregate sector and aggregate national levels. Price and income play a key role in the determination of electricity demand. Depending on the aggregation level for different consumers, market and climate characteristics such as weather and seasonal factors, firm and industry characteristics, population and household composition, as well as non-price consumption controlling variables like restrictions, education and campaigns are incorporated in the model specification. While cross sectional models aim at capturing consumer heterogeneity, time series models focus on dynamics, trends and forecasts of future sectorial and national levels demand.

The types of econometric demand models employed are highly determined by availability and type of data and the objective of the study. The models are generally divided into aggregate national or sectorial models based on time series data and analysis, and disaggregate sectorial models based on cross sectional micro data where customers are observed in one single year or a sequence of years (panel data). Increased availability of micro data and development of cross sections and panel data models and estimation procedures have been in favor of the later models. These models generate interesting and detailed results about heterogeneity and temporal variations in consumer’s responsiveness by allowing for evaluation of targeted market segment public policy. In this section we briefly introduce typical econometrics models particularly employed in modeling peak electricity demand, hourly demand, and demand reduction.

It is worth mentioning that, the overall market aggregated and modeled as a time series is useful in the analysis of trend, but it fails to account for heterogeneity in the demand by different market segments and their development, which is of great interest in electricity demand modeling. The power market is divided into a number of market segments such as: industry, residential, agriculture and public sector. These segments demands differ in level, development and characteristics and as such are subject to different price policy measures with different impacts. The first two segments are discussed below.

2.3.1 Residential electricity demand models

In a survey on the demand for electricity Taylor (1975) criticized the econometric literature on the demand for electricity on the basis that most of the focus is on residential demand. Taylor suggested that a single price variable, and average or marginal price, is insufficient. The demand functions for electricity should include marginal price and a second price either average price for blocks or total payment for blocks. Nordin (1975) proposed a modification suggesting it is better to use the excess of total payment over average price for blocks other than the final block. Shin (1985) investigated the effect of the (marginal) price information problem on the consumers' price perception when information is costly. The result indicates that consumers respond to average price perceived from the electricity bill. Epsey et al. (1997) based on a meta-analysis, concluded that studies using Nordin's price difference variable yielded higher estimates of price elasticity than those based on only marginal price. Meta-analysis is used to determine if there are factors that systematically affect the price elasticity estimates obtained in previous studies as the dependent variable.

Residential or household is a key market segment and main target for demand analysis. Recent efforts to reconstruct electricity markets have renewed interest and methods used in assessment of consumers' price responsiveness. Reiss and White (2005) indicate that econometric methods used to assess the effects of electricity price changes presents several challenges including the nonlinear structure of tariff schedules, aggregation of consumption over time and appliances, and the interdependence of energy use with household's decisions over appliance ownership and dwelling characteristics. The first two introduce a simultaneous problem between marginal price and consumption, while the third one imposes high household level data requirements and it creates heterogeneity in consumption responses related to the characteristics of the households durable goods. Ignoring these issues might provide an incomplete assessment of demand responses and give potentially misleading predictions of optimal tariff designs.

Following Reiss and White (2005), most nonlinear price schedules take the form of multi-part tariffs implying that consumers face a nonlinear or kinked budget constraint where demand behavior will depend on the entire price schedules. In order to make the estimation tractable, the demand analysis linearizes the nonlinear budget constraint. The general demand function represented as $x(p,y)$ indicates the consumer's desired quantity (x) facing a constant price (p) and income (y). Assuming the consumer faces an increasing price schedule, the optimal consumption level (x^*) satisfies, $x^*=x(p^*,y^*)$, where p^* and y^* are the consumer's equilibrium marginal willingness to pay and income level that would induce the optimal consumption x^*.

Two important issues are to be noted in this context. First, since p^* and x^* are endogenously determined, OLS estimation using p^* will yield biased and inconsistent estimates of the demand parameters. The use of an exogenous proxy for the marginal price or instrumental variables (IV) method can be used to alleviate the endogeneity problem, but in turn they introduce biases of their own. In practice the natural set of instruments is the components of the price schedule itself. A second concern arises in relation with aggregation of consumption decisions over time within a year or across services, which in the presence of nonlinear prices makes the IV procedure infeasible and as a result, marginal prices are not observed or estimated incorrectly.

In an attempt, Reiss and White (2005) handle the abovementioned problems in an integrated way by assuming the consumers demand takes the econometric form x(p,y,z,ε;β) where z and ε represent observed and unobserved consumer's and other characteristics, p represents a multi-tier price schedule and β is a set of unknown parameters of interest to be estimated. The model is a nonlinear censored regression model estimated by the maximum likelihood method. However, it becomes computationally intractable when the mixed discrete/continuous model is aggregated over time. Consequently, a moment-based approach is used to estimate the model.

In accounting for consumer characteristics in modeling demand, the durability of the household appliances enable one to distinguish between short-run and long-run demand elasticity's without using a lag dependent variable. Here, the short-run refers to demand behavior given the existing stock of appliances, while the long-run accounts for both changes in utilization behavior and in the stock of household appliances. Accounting for this distinction, the total demand as a sum of electricity used by K distinct appliance categories is modeled as:

(1) $$x_k = \alpha_k p + \gamma_k y + z'_k \delta_k + \varepsilon_k$$

where p is price of electricity, y household income, z vector of observable household characteristics and ε vector of unobservable household characteristics. The demand model aggregated over appliance categories is written then as:

(2) $$x = \alpha p + \gamma y + z'\delta + \varepsilon$$

where $\alpha = \sum_k d_k \alpha_k$, $\gamma = \sum_k d_k \gamma_k$, $\delta = \sum_k d_k \delta_k$, and in each case $d_k = 1$ if the household owns appliance type k, and $d_k = 0$ otherwise. The conventional demand function x(p,y) is a restricted version and the abovementioned extended demand model. The model can be estimated using nonlinear least squares procedure, but due to a problem in estimating the variance, the authors employ generalized methods of moment (GMM) procedure. The model is estimated using data from the Residential Energy Consumption Survey for California's investor-owned and municipal/public electric utilities in 1993 and 1997. The data contains information on 1,307 households. Parameter estimates and marginal effects, price (-0.39) and income (0.00) elasticities, are presented for household categories with baseline use, electric space heating, no electric space heating, central or room air conditioning, no air conditioning or neither space heating or air conditioning ownerships. The model's validity using both within and out of the sample tests are conducted. In the authors view, although the model under predicts the average consumption, it does well at fitting the sample data and delivers reasonable predictions for household responses to electricity price changes in California.

The residential electricity demand function in Seoul is estimated by Yoo et al. (2007). They employ a bivariate model to rectify the sample selection bias effect of unit non-response from not providing electricity price (expenditure) information. For the estimation, they use a small sample of 380 households observed for the month of May 2005. A bivariate sample selection model consisting of response and demand equations is estimated where the model specification in addition to household's income and electricity price contains characteristics such as family size, house size, and plasma display panel TV, air conditioner, and refrigerator ownerships. Specification test results suggest evidence of sample selection. The result indicates positive association between electricity consumption and household's response. Estimation results show that, as expected, the price elasticity is negative (-0.2463), the income elasticity is positive (0.0593), and family elasticity (0.1434) shows evidence of economies of scale.

While Yoo et al. (2007) accounted for sample selection, it also controlled for the effects of various important characteristics. In a more recent study Saad (2009) estimate an electricity demand function for Korean residential sector, in which he examines the effects of determinants of household's energy consumption such as improved energy efficiency, structural factors and household lifestyles on electricity consumption. The energy efficiency improvement is related to the use of appliances and equipment with desirable technology characteristics. Structural factors include size of households, household members' age distribution, number of wage earners in a household and climate conditions. The life styles refers to the urbanization impact on the choice of energy source and the resulting substitution of biofuels first by oil and coal and then by electricity and gas, known as "stepping up the fuel ladder". This issue is further investigated by Alberini et al. (2011) who studied residential consumption of gas and electricity in the 50 largest metropolitan areas in the US with a focus on the role of prices and income. Contrary to earlier literature they find large and significant price elasticities which do not vary across households. The results suggest the existence of greater potential for policies which affect energy price.

Unlike some previous studies such as Yoo et al. (2007) which used micro household data, here time series data for the period 1973 to 2007 is used by Saad (2009). The author uses a structural time series model to estimate long-term price and income elasticities and annual growth of the underlying energy demand trend at the end of the study period. The residential demand for electricity is specified as:

(3) $$\alpha(L)e_t = \mu_t + \beta(L)y_t + \delta(L)p_t + \varepsilon_t,$$

(4) $$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \text{ where } \beta_t = \beta_{t-1} + \zeta_t$$

The components e_t, y_t, p_t are logarithm of per capita household electricity consumption in kWh, per capita real GDP and the weighted average of real prices of electricity paid by households. μ_t is the stochastic trend component used as proxy for the growth trend, β and δ are short run elasticity's and $\alpha(L), \beta(L), \delta(L)$ are lag operators. The long term income and price elasticities are derived from the ratios $\beta(L)/\alpha(L)$ and $\delta(L)/\alpha(L)$.

The model is estimated by the maximum likelihood method. The estimation results are presented in the form of estimated long-term price (-0.27), income (1.33) elasticity's and annual growth rate (-0.93). The low price elasticity and high income elasticity suggest that in order to encourage further energy efficiency, the market price policies of demand management in the form of increased tariffs and taxes alone may not discourage electricity consumption sufficiently. Saad suggests that, the public pricing policies should be complemented with non-market policies such as mandatory minimum energy efficiency standards and public enlightenment to curb increasing electricity consumption and to encourage efficiency and conservation in the residential sector of the market. The impact of energy efficiency programs on growth of electricity sales in the United States is studied by Berry (2008) using statistical methods. The results show an association between the utility efficiency program expenditures, the range of efficiency programs offered and the reduction in the growth of power sales. States with the most aggressive programs reduced the growth rate by 60% compared with states with no efficiency programs implemented.

Another alternative of energy demand model estimation is by using an artificial neural network (see Geem and Roper; 2009). It is a regression technique representing higher nonlinearity between independent and dependent variables. The model consists of three layers attributed to inputs, hidden and output(s). Demand is explained by the level of GDP, population size, and import and export amounts for the period 1980-2007. The model performed better than a linear regression model or an exponential model in terms of the size of root means squares error. Further testing based on four scenarios showed unanticipated results where energy demands peaked during 2018-2023 and then decrease gradually.

The aggregate residential demand for electricity in the US is estimated by Dergiades and Tsoulfidis (2008). The demand is estimated as function of per capita income, price of electricity, price of heating oil, the weather conditions and the stock of occupied housing. The empirical findings give support to stable short- and long-run relationships. Kucukali (2010) in commenting on Geem and Roper (2009) model specification suggest that the energy demand of South Korea could be estimated simpler by only using GDP as the explanatory variable. This will make the over-fitted neural network model more simple and practical. Kucukali shows that, despite the neural network models power in capturing highly nonlinear relationships, a Fuzy logic model as another alternative would minimize the model deviation from the true and provide more accurate results.

Among other demand models are Nakajima (2010) who examines residential demand for electricity in Japan using panel data methodology to determine whether the variables of interest are stationary. Results show that price is elastic but income inelastic. A similar conclusion is made by Ziramba (2008) in examining the residential demand for electricity in South Africa. Ziramba uses the bounds testing approach to cointegrate with an autoregressive distributed lag framework to test for a long-run level relationship in the demand for residential electricity. The price and income elasticities of electricity demand in Pakistan are analyzed at aggregate and sector-wise levels using cointegration and vector error correction approaches. The price and income elasticities differ across sectors and in the short and long-run perspectives. Variation in the short- and long-run time-of-use price and income elasticities in residential electricity demand across Swiss cities is shown in Pilippini (2011) to differ. The estimated demand models for peak and off-peak consumption using static and dynamic partial adjustment approaches estimated for panel data show that peak and off-peak electricity are substitutes. Time differentiated prices should provide an economic incentive to consumers to modify their consumption patterns through conservation and shifting demand. A postponement model for demand management is proposed by Iyer et al. (2003) as a strategy to handle potential demand surges. Price elasticity for electricity demand in South Australia is estimated by Fan and Hyndman (2011) to determine the relationship between price and demand quantities at each half-hour of the day in different regions and systems.

2.3.2 Industrial and commercial electricity demand models

There is few industry and commercial sector based electricity demand models estimated in practice. This issue was raised by Taylor (1975) in a survey criticizing the econometric literature on the demand for electricity. The reason might be attributed to little potential reductions in industrial consumption or lack of data availability. The low potential is due to ex post investment decision fixed energy input in production, exogenously and capacity determined production level, and fixed operation hours and weekdays. However, the abovementioned cross sectional or panel data models and associated estimation methods used for residential market segment are directly applicable to industry market segment's demand analysis by replacing income with firms' revenues (production) and replacing household characteristics with firms', and other relevant market and public energy policy characteristics.

To mention a few applications here, Hosoe and Akiyama (2009) estimated the regional power demand functions for nine regions in Japan to quantify the short- and long-run price elasticity of electricity demand. An inter-regional comparison shows that price elasticity in rural regions is larger than in urban regions. In another study Dilaver and Hunt (2011) estimated industrial electricity demand for Turkey using a structural time series methodology. The focus of analysis is on the relationship between industrial electricity consumption, industrial value added and electricity prices to forecast future demand. Energy demand with declining rate schedules for the US commercial sector is estimated by Denton et al. (2003) where marginal prices, temperature variables and several building characteristics are incorporated as explanatory variables to simultaneously determine demand and prices.

Considering the agricultural segment of the market, the demand models specified for residential customers, with small modifications concerning consumer (farm) characteristics, are directly applicable to farm level data, while the industry demand models apply easily to agribusiness firms. No applications of demand analyses for these consumer categories were identified to be reviewed.

2.4 Econometric issues

Depending on the type and nature of the data, the electricity demand models are estimated with suitable parametric, semi-parametric, and non-parametric econometric techniques. When cross-sectional data on users is available, the parametric estimation techniques involves one or a combination of techniques including ordinary least squares (OLS), feasible generalized least squares (FGLS), two- and three stages least squares (2SLS and 3SLS), probit, as well as logit and instrumental variable (IV) methods. When time series data is available, the following traditional vector autoregressive models and cointegration techniques are used. When pooled cross-sections of time-series data is used, the demand models are estimated by the methods mentioned in the cases of cross-sectional data and in addition, the maximum likelihood method can be used. Consistency, unbiasedness and efficiency are determinants in the choice of estimation method.

There are a number of econometric issues that arise under different circumstances and are dealt with in variety of ways in different demand studies. Endogeneity, sample selection, non-linearity, functional form, specification, estimation and type of data used seem to be the main issues that individually or combined, are frequently discussed and dealt with in the exiting electricity demand literature. Here, we briefly summarize a few such problems and present the researchers suggested solutions to alleviate their negative effects on the estimated elasticities of interest. These together provide a somewhat complete picture of formulation for a general model and its proper specification and estimation.

A variety of functional forms can be used to specify a demand model. For instance, a simple linear model of electricity demand can easily be estimated where change in quantity demanded is related to changes in price and income assuming the response is constant for every price and income level. In logarithmic (linear) form known as Cobb-Douglas the estimated price and income coefficients are directly interpretable and represent the partial elasticity of electricity demand with respect to price and income, ceteris paribus. In order to incorporate non-linearity in the models they are generalized to include squares and interactions. Translog functional form (Christensen et al., 1973) is a model which is more commonly used and the simpler form described above is nested in it and statistically testable. The model is linear in constant parameters but the total elasticity can be computed at each point of data and thereby vary in different dimensions like characteristics of the users and over time. A log-linear form but yet non-linear by employing the Stone-Geary utility function (Gaudin et al., 2001) allows for a minimum amount of electricity or subsistence level demand, irrespective of price and income.

As an example, Yoo et al. (2007) in estimation of residential electricity demand point to the issues of sample selection bias. The sample selection is attributed to missing data and price non-response. The first issue is dealt with by using instruments, while the latter is managed by estimation of the model using a combined bivariate selection and response equation models. Estimation of the univariate and bivariate models by the maximum likelihood method and testing model specifications shows evidence of sample selection, which may cause inconsistent parameter estimates and distortion in mean values of elasticities leading to mistakes in policy analysis and program evaluations.

In another study, Saad (2009) refers to the fact that it is widely accepted that the demand for electricity is determined by a household's income and electricity price. Saad suggests that there are other factors that are also important in determining the demand. These include efficiency improvement, structural factors, and lifestyle. He argues that it is instructive to consider all these factors to avoid producing biased estimates of the key price and income elasticity's due to excluded relevant variables direct and interactive effects. Application of a structural time series model in this study conditional on the abovementioned characteristics allowed for the maximum likelihood estimation of annual growth in demand and separation of short- and long-run elasticities reflecting current stock and future changes in stock of household's appliances and equipment.

A third study is by White (2005) who emphasizes modeling demand with nonlinear prices and accounting for endogeneity problems. Endogeneity arises in relation with the use of income and price as determinants of demand which are by themselves endogenously determined. The first issue is dealt with by using instruments, while the latter is managed by the specification of a model accounting for heterogeneity in responses. The model can be used to evaluate alternative tariff designs and focuses on heterogeneity in household's demand elasticities and their relations with appliance holdings and other household characteristics. The model is estimated by generalized methods of moment. In modeling and estimation, account is made for type of data, aggregation, non-linearity, time variance of parameters, model performance, and forecasting performance. Denton et al. (2003) also estimated demand and price rate schedule as a simultaneous system using endogenous marginal prices rather than exogenous average prices.

2.5 Appropriate model of electricity demand

The electricity market organization and structure are often characterized as centralized power pool. However, the public nature of the organization affects the role of generating companies in their offer of price-quantity in forming the aggregate supply of electricity. The price is cost based and yet heterogeneous reflects the government's sectorial policy and priorities. The planning and development of the power market, capacity, investment and selection of generators as base, as well as medium and peak loads is often determined centrally by the energy policy and based on energy security concerns. This limits bilateral contracts between supplier and consumers for power supply and practice of locational marginal cost pricing. These factors affect the form of an appropriate model for electricity demand at different levels of aggregation.

Given the presence of strong sectorial policy, it is reasonable to formulate either sector specific (household, industry, agriculture) demand models or specify a national model, which accounts for the specific characteristics of the sectors and heterogeneous public energy policies concerning the supply and pricing of electricity. The choice of model (cross section, time series or panel) will depend on availability of data and the interest in heterogeneity vs. dynamics or combined effects in response analysis. It is desirable that suitable survey questionnaire are designed and waves of stratified data of optimal size is collected on a regular basis. Creation of standardized time series sector and national data levels complemented with relevant determinants and characteristics will improve the quality of data and analysis.

In the event of using cross sectional household or firm level data, following Reiss and White (2005) and Yoo et al. (2007) a model to be specified to assess consumers price and income responsiveness which also accounts for sector specific characteristics such as the nonlinear structure of tariff schedules, aggregation of consumption over time, appliances ownership, dwelling and industry characteristics and general energy market situation, as well as unobserved consumer characteristics. The total demand for electricity used by household/firm/industry unit *i* in sector *j* is then modeled as:

(5) $$x_{ij} = \alpha_j + \alpha_j p_{ij} + \gamma_j y_{it} + z'_{ij} \delta_j + \varepsilon_{ij}$$

where x is electricity demand, p is price of electricity, y consumer income, z vector of observable household/firm/industry characteristics and ε vector of unobservable household/firm/industry characteristics. Account might be made for possible sample selection bias in estimation of the bivariate response and demand equations and aggregation over a specific time period. The model allows for both intercept and slope (responsive) heterogeneity by sector, which is statistically testable. The household characteristics are demographic and appliance related, while for firm/industry the characteristics might be industry sector, type of energy and day/night time shift related. It is worth mentioning that, residential consumers are more flexible in changing demand and in their responsiveness to price changes than firms or industries. If data is available for a number of periods, the model in (5) can be written as panel data with three dimensional data. The error term will be composed of unobserved time-invariant household/firm, industry, time and random error terms and possibly their interactive spatial effects:

(6) $$\varepsilon_{ijt} = \mu_i + \zeta_j + \lambda_t + v_{ijt} .$$

When time series data is available, following Saad (2009), one should preferably specify an electricity demand model for residential and industry sectors. The model can desirably be specified such that it allows for examination of effects of improved energy efficiency, structural factors and lifestyles on energy consumption. These are attributed to the use of equipment, household demography and urbanization, and choice of energy source. The structural time series model can be used to estimate long-term price and income elasticities and the annual growth of underlying energy demand trends. The aggregate residential/industry demand for electricity is specified as:

(7) $$\alpha(L)e_t = \mu_t + \beta(L)y_t + \delta(L)p_t + \xi z_t + \varepsilon_t ,$$

(8) $$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t , \text{ where } \beta_t = \beta_{t-1} + \zeta_t$$

where e_t, y_t, p_t are logarithm of per capita household/industry electricity consumption in kWh, per capita real income/GDP and the weighted average of real prices of electricity. The model is estimated, conditional on characteristics z. μ_t is the stochastic trend component and $\alpha(L), \beta(L)$ and $\delta(L)$ are lag operators. As mentioned previously, the long run income and price elasticities can be derived.

3. CUSTOMER BASE-LINE

3.1 Introduction to CBL

Demand for electricity in most countries, in particular in developing and newly industrialized economies, is continuously increasing with their economic development. The electricity industry is facing the challenge of increasing costs for reliably meeting the growth in demand. Meanwhile, it attempt to comply with recent decades of nationally legislative renewable standards and internationally committed greenhouse gas reduction targets. The challenge is that in general an electric utility's tariff is constant which often does not have heterogeneous or flexible rates that differ by consumer category, increase with consumption volume or vary by within a day of use. Such a less developed and inflexible tariff system does not fully exploit the markets potential benefits from various customer conservation and load shifting measures. The issue of electricity pricing for conservation and load shifting is discussed in Orans et al. (2010). This chapter is a review of the progress in consumer base-line (CBL) calculations for a socially optimal demand response program and policy.

In recent years, independent system operators and electric utilities are increasingly attempting to engage the end users in cooperation to implement demand response (DR) programs with the aim to operate the power system efficiently. CBL is an important tool used to measure performance of a DR program. It uses historical data on the users' behaviors and provides a valid forecast of users' consumption. In short it is defined as the pattern of electricity demand under normal circumstances and helps in the establishment of potential saving reductions and quantification of incentives to achieve the desired reductions. CBL as a time series determines the minimum values of consumption needed to be satisfied. Given the characteristics of the market, CBL provides information on electricity demand, conservation and load shifting level by calculating the difference between CBL, and the actual load representing the customer's DR performance. It is a mechanism that enables the system operator the ability to explain users' consumption.

One limitation of traditional demand models is their focus on average rather than peak demand which arise on an hourly, daily, weekly or seasonal basis. Estimation of price elasticity must be viewed within the various peak demand perspectives. In addition, the use of price and average marginal cost in reducing peak demand is limited as demand might be relatively price inelastic rendering price as an ineffective tool in peak demand management. CBL allows use for more appropriate mechanisms regarding the regulation of electricity consumption by using multi-tariff, non-price controls and strategies encompassing public education campaigns, power rationing, electricity use restrictions and various subsidy programs to adopt more power efficient technologies. Their effects in form of deadweight loss, redistribution of welfare, administrative burden and unpopularity are among the arguments against non-price controls. For these arguments in the context of water consumption see Warthington and Hoffman (2008).

In this chapter we investigate the main issues needed, such as data, method and market characteristics, to construct a CBL which is important to the formulation and efficient operation of demand response programs. After this introductory section, in the second section the international experience with CBL is reviewed. The third section covers different CBL load forecasting and calculation methods concerning type of data, verification, and methods employed. Based on the review of the literature and gained experience in the fourth section, we present a modified model to calculate the CBL for a demand response program in the electricity market. This section also discusses the determinants, other information requirements and conditions for the successful implementation and evaluation of the modified model.

3.2 International experience on CBL load forecasting

There are several studies on load management and load forecasting which are using statistical techniques. These are considered as essential elements of efficient planning and operation of power systems. A review of the literature shows that univariate and bivariate forecasting models, time varying period splines, one-hour-ahead and one-day-ahead load forecasting methods adding correction to the selected similar day data, neural networks in load forecasting, regression-based methods using prior days averaging and weather matching techniques, and cluster-temperature sensitivity regression are among the statistical techniques used in load studies. Each of these methods is described below.

The best conditional models seem to be nonlinear, complex, time-varying and generalized where the model analysis evolves from a simple to general model specification. Engle et al. (1992) estimate a model for forecasting the maximal hourly load one day in advance using information on today's peak, average load, and weather. The nonlinear model incorporates among others deterministic influence (holidays), stochastic influences (average loads), and exogenous influences (weather). The simplest model is a univariate forecasting model written as:

$$PEAK_t = \alpha_0 + \alpha_1 PEAK_{t-1} + \alpha_2 H + \alpha_3 H_{t-1} + \alpha_4 SAT + \alpha_5 SUN + \alpha_6 MON + \varepsilon_t \tag{9}$$

where *H* is holiday and other variables self-explained. In order to improve model performance, information on the past daily average load (*AVG*) was added. The relation is estimated as the following bivariate interdependent forecasting model:

$$\begin{aligned} PEAK_t = {} & \alpha_0 + \alpha_1 PEAK_{t-1} + \alpha_2 H + \alpha_3 H_{t-1} + \alpha_4 SAT + \alpha_5 SUN + \alpha_6 MON \\ & + \alpha_6 AVG_t + \varepsilon 1_t \end{aligned} \tag{10}$$

$$\begin{aligned} AVG_t = {} & \beta_0 + \beta_1 AVG_{t-1} + \beta_2 H + \beta_3 H_{t-1} + \beta_4 SAT + \beta_5 SUN + \beta_6 MON \\ & + \beta_6 PEAK_t + \varepsilon 2_t \end{aligned} \tag{11}$$

The abovementioned univariate peak models (9 and 10) are further extended with weather, which is very important for predicting peak load. Since weather itself is not easily predictable, in some cases one can use past weather as an instrument instead of predicted weather. Here, the weather is proxied by constructed cooling and heating degree variables. The generalized model conditioned on weather is written as:

$$PEAK_t = \alpha_0 + \alpha_1 PEAK_{t-1} + \alpha_2 H + \alpha_3 H_{t-1} + \alpha_4 SAT + \alpha_5 SUN + \alpha_6 MON \\ + \alpha_6 AVG_t + \alpha_7 CDD65 + \alpha_8 HDD75 + \varepsilon_t \tag{12}$$

where *CDD65* and *HDD75* are the cooling and heating days measured as the average of the daily high and low temperature minus the base (50 and 65 degrees). The diagnosis tests show that the general model (12) is the preferred model of specification, but it performs no better than the reduced form model (9). The peak forecast error can be decomposed into two sources attributed to average load and other load factors.

Harvey and Koopman (1993) developed a method for a modeling situation with a changing periodic pattern. The method is applied in a model with time varying periodic splines to forecast hourly electricity demand. The periodic movements are intra-day or intra-weekly. In addition the model contains other components such as modeled temperature response also using splines. The result shows that the time-varying periodic spline component provides a good way of modeling the changing electricity load pattern within a week. The overall forecasts by accounting for nonlinear response to temperature captured by fixed spline are found to be relatively accurate. If load is decomposed into permanent and transitory components, the deterministic intra-day or intra-weekly periodic permanent movements are important in the case of firms, while weather is added to the transitory component of the load. In a recent study, Lee and Chiu (2011) applied a non-linear panel smooth transition regression model taking into account the potential endogeneity biases in order to investigate the demand for electricity for 24 OECD countries. Empirical results show evidence of a strong non-linear link among electricity consumption, real income, electricity price and temperature. The impact of temperature on electricity demand is becoming more important in recent years.

Senjyu et al. (2002) argue that since the relation between load power and factors influencing it nonlinearly, the conventional linear models are unable to capture the nonlinearity. Most studies use 24-hours-ahead peak load forecasting of demand by using information of the day being similar to the weather condition of the forecast day. Despite such improvement, however, rapid changes in temperature within a day lead to increased forecasting error. The neural network which uses all similar day's data is a very complex way of capturing the pattern. In order to reduce the complexity of a neural network structure, the authors propose a one-hour-ahead load forecasting method adding correction to the selected similar day data. The proposed approach is applied to the actual data of Okinawa Electric Power Company in Japan from 1995 to 1997. In order to verify the predictive ability of the method the authors perform simulations for four cases and forecast the load power in 1997. In addition, they calculate the mean absolute percentage error to assess prediction ability of the proposed method.

Despite popularity of the neural networks in nonlinear load forecasting, some authors remain skeptical about the advantages of the method. Hippert et al. (2001) investigate the reasons for such skepticism by examining a collection of papers that applied the method to short term load forecasting. The aim is to critically evaluate the way the neural network methods were proposed, designed and tested empirically. Hippert et al. mentioned in their conclusion, that some studies suggested systems in which a number of neural networks work together to compute the forecast, while others used Fuzzy logic, an artificial intelligence technique, combined with neural networks. The examination highlighted two facts that may be among the reasons for skepticism. One is the problem of over-fitting and over-parameterization of the models and another is that the test results performed were good but not convincing as most models can be misspecified.

Won et al. (2009) classified load management programs in Korea into two classes: one is related to load management equipment and the other is related with incentive for load reduction by consumer's willingness. The equipment includes demand controller, remote control air conditioner, and thermal storage systems. As expected, the determination of the CBL of customer base load plays an important element for the incentive based load reduction program. The authors used regression and statistical methods to get the CBL determination model.

In estimating individual customer baseline loads, following the statistical method the average load profile of a number of days prior to the load reduction event is used. This method was recommended by Goldberg and Agnew (2003). The method performs well in cases with highly intra time period variable loads. Scalar or additive methods are used to adjust the method to correct for daily conditions such as weather. Herter (2007) investigates how critical-peak pricing affects households with different usage and income levels. In another related study, Herter et al. (2007) identifies baseline loads for a residential pricing program accounting for weather conditions by matching days with similar weather conditions.

The regression-based method is often used in prior days averaging and weather matching techniques based on analysis of covariance in studying hourly loads. It is used to calculate consumers' response to a dynamic rate or a load program. Won et al. (2009) indicate that most utilities use the statistical averaging method with weather adjustment. The prior days are selected as: 5 prior day averaging, 5 highest daily kWh usage days from a pool of 10 days, average of the 3 highest energy use days of the past 10 days, and average of 5 weekdays out of 10 days, all with weather adjustments. The used adjustment method is based on load data 1-2 hours before a load reduction event request.

In a recent study based on regression models for demand reduction Yamaguchi et al. (2009) used cluster analysis of load profiles. Customer clustering methods include: modified follow-the-leader, hierarchical clustering, k-means and fuzzy k-means algorithm based partitioning clustering and Kohonen self-organizing map. This study uses the k-means clustering method. The proposed model employs load sensitivity to air temperature and representative load pattern indices which are derived from cluster analysis of customer base-line load as explanatory variables. The model is used to examine load profile data of Pacific Gas and Electric Company's commercial and industrial customers participating in the 2008 critical peak pricing program. Results show that a combination of load sensitivity and cluster analysis improves the performance of the regression models but the goodness of fit for the model remains low.

3.3 Different CBL load forecasting and calculation methods

There are a few studies regarding consumer base-line which are reviewed in this section. The review is in respect with CBL calculation and requirements in the form of type of data, method of calculation and conditional market characteristics, as well as verification and methods employed. The type of data and verification are important elements of CBL calculations. The data is of two types: historical and real time data sets. Historical data refers to past data collected and archived, while real time data refers to information obtained in real time. Historical data with high frequency are often subject to missing units. It should be noted that, incomplete gaps in the historical data might be imputed using statistical methods. Various methods including lead, lag, averages accounting for heterogeneity across individual users, and their size over time can be used to impute missing data.

Concerning verification, Edgar et al. (2008) suggest three options to verify specific CBL series. These include average real error, average error and average squared root error. The first option shows the absolute error between the real consumption (RC) data and CBL values, the second shows if the method forecasted values over- or underestimate the real consumption information, while the third case which is based on the second moment helps to state the accuracy of the method to forecast a series of consumptions. The three methods are written as the following:

(13) $$ARE = \frac{\sum_{i=0}^{n} \left| \frac{CBL_i - RC_i}{RC_i} \right|}{n}, \quad AE = \frac{\sum_{i=0}^{n} \frac{CBL_i - RC_i}{RC_i}}{n}, \quad ASRE = \frac{\sum_{i=0}^{n} \frac{(CBL_i - RC_i)^2}{RC_i^2}}{n}$$

Edgar et al. (2008) classify the CBL methods into 7 different methods. These include simple average, selective average, scalar adjustment, relative, additive adjustment, percentage, and time series. In a systematic sensitivity analysis, the time series method is further divided into four different methods involving linear regression, holt winters, modified linear regression and decomposition.

The simple average CBL method forecasts with the average of ten days. The selective average is made from the top 5 chosen values. In the case of scalar adjustment, the selective average is adjusted with the difference between the real data of consumption and the value created from the CBL (4 hours ahead). Relative refers to a case where the operator uses data that has relevance in the load concerning temperature, humidity, and temperature-humidity index. The additive adjustment works with the simple average, and then is adjusted with the difference between the real data and the CBL (2 hours ahead). In the case of percentage, the operator accepts the forecast as a percentage of the previous period. Finally, time series CBL method uses statistics and econometrics methods to identify and characterize particular information.

Edgar et al. (2008) employed the method described above to produce a CBL model to be used by the first demand response program to guarantee the reliability in the supply of electricity in Colombia. The program includes a voluntary load reduction (VLR) program designed to operate when the expected demand surpasses the maximum installed capacity at the peak periods. The VLR aims to translate high peak consumptions to lower the period's consumption in exchange of an incentive. The authors propose the appropriate statistical method to be used for time series data. They find the decomposition method to complete every need for the CBL in a four stage process. The four stages include: data capture and transformation (105 days), moving average (7 periods) index estimates, slope estimate based on seasonal index, and forecast for a week's consumption. Confidence interval for the forecast is calculated by using the predicted consumption and its estimated dispersion.

There are few studies conducted on load management in Korea. As mentioned previously, Won et al. (2009) tested several methods of domestic industrial loads in Korea. Assuming a number of conditions (such as weekdays, time of the day, reduction size, CBL scenarios, adjustment, error analysis) CBL error analysis was conducted for 10 industrial customers where 8 days in November 2008 are considered for 3 CBL determination methods. The best CBL method is selected following an error analysis. The results suggest that the 10 prior weekdays averaging method using an adjustment for CBL determination is appropriate for Korean industrial customers.

In another related study, Wi et al. (2009) employed an exponential smoothing model with weather adjustment multiplicatively to calculate CBL. The procedure involves data selection, basic load estimation and weather elements adjustment stages. The aim is to estimate the daily electric load patterns of participating customers in a demand response program. The authors argue that the existing methods are not able to handle recent changes of electricity demand. For this reason, their selected method assigns different weights to each data point in near order to a day regarding the DR program event. Thus, it weighs past observations with exponentially decreasing weights to forecast future values. The weather adjustments are effective in reducing the difference between the calculated CBL and the actual demand. The weather adjustment is often based on additive or multiplicative forms.

Recently in a patent application, Ko et al. (2010a) present a day-ahead reduction system based on CBL load for inducing a user to efficiently manage energy consumption by applying an incentive to achieve the desired load reduction and load decentralization. The system operates with a number of components including a provider and user terminals connected through a network. It induces reduction in the load of the user and a translator collects the load profile data stored in a meter data warehouse. A meter data management system monitors and analyzes the load profile data in real time. A demand response operating system manage the demand by using the load profile data and performs overall management, analysis and verification of a day-ahead load reduction event. A consumer energy management system provides information on the load to the user through the user terminal in real time to allow the user to control the load. Finally, an account system calculates an incentive for the day-ahead load reduction event and notifies the provider and the user the incentive through their terminals.

In another patent application, Ko et al. (2010b) present a load forecasting analysis system for calculation of the CBL load. It is the CBL component of the day-ahead reduction system described above. The load forecasting system also includes a number of components such as: a CBL forecaster for receiving load profiles and providing a CBL forecasting method, a period selector for selecting conditions used to calculate the CBL using the load profile, a CBL processor for calculating a forecasting value, and finally a CBL determiner for calculating an error value by comparing the load profile with the forecasting value.

3.4 A modified model to calculate the CBL

Based on the review of the literature on consumer baseline in this section a modified composite model is suggested to calculate the CBL with desirable properties. The load management programs in general are divided into two classes: one is those related to load management equipment and the other is those related with the incentive for load reduction. The determination of the CBL for the consumer base load plays an important role in the design of incentives provided and desired reductions achieved.

We identified several studies on load management and load forecasting using statistical techniques. The key issues here are the data, method of calculation, characteristics of the market and accuracy of verifications. The best conditional models were found to be non-linear, complex, time-varying and specified in general form. A bivariate forecasting model consisting of peak and average load models accounting for the influence of holidays, weekdays, and adjusting for cooling and heating days measured as the average of temperature adjusted for base temperature are found adequate. In forecasting, for 24 hours-ahead peak load forecasting of demand, it is common to use information of the day being similar to the weather conditions of the forecast day. In some studies a combination of cluster analysis and load sensitivity to outside temperature and humidity including their interaction and seasonal variations and other exogenous factors improved the performance of the models. The peak forecast error based on mean absolute percentage error can be decomposed. This allows for identification of the sources of error and quantification of its share of the total error.

The reviewed studies on calculation of CBL load can serve as a base for the development of an appropriate CBL calculation model and a method that best reflects the actual situation and also be useful for DR analysis in the market. Won et al. (2009) study sheds light on load management for industry customers and through comprehensive sensitivity analysis, they found that the 10 prior weekdays averaging method using adjustment for CBL determination to be appropriate for industry customers. Wi el al. (2009) on the other hand focused on flexibility of the model and weather adjustment to calculate CBL. In calculating the daily electric load patterns of consumer’s participation in a DR program, the authors suggest assigning different weights to past observations exponentially decreasing in order to forecast future values more accurately and to reduce forecast error by adjustment for weather.

The abovementioned improvements could ideally be integrated into the Ko et al. (2011a and 2011b) system where they introduce a day-head demand reduction system based on CBL load for inducing a user to efficiently manage energy consumption by applying an incentive to achieve load reduction. They also present a load forecasting analysis system for calculation of CBL load and determine the error value by comparing the load profile with the forecasting value. The application of such a general model to real data and decomposition and analysis of the error will show how good the forecast model is and in what way it can be further improved through the process of learning by doing.

The specification of the CBL model is determined by data availability. The proposed CBL model below can be specified and estimated using the econometric model and method. Let's suppose we set up the fixed effects panel data model for hourly CBL estimation as the following:

$$
\begin{aligned}
c_{it} &= \alpha_0 + \alpha_i + \sum_{i=2}^{24}\gamma_{1i}c_{it-1} + \sum_{i=2}^{24}\gamma_{2i}D_i + \beta y_{it} + \delta_1 p_{it} + \sum_{i=2}^{24}\delta_{2i}p_{it}D_i + \sum_{i=2}^{M}\delta_{3m}p_{it}D_m \\
&+ \sum_{i\in wd}\delta_{4i}p_{it}D_i + \sum_{i\in wdH}\delta_{5i}p_{it}D_i + \sum_{i\in SH}\delta_{6i}p_{it}D_t + \delta_7 p_{it}Size_{it} \qquad (14) \\
&+ \lambda_1 CDD_{it} + \lambda_2 HDD_{it} + \lambda_3 Humd + \lambda_4 \Pr od_{it} + \eta_i D_{wd} + \eta_2 D_{day} + \varepsilon_{it}
\end{aligned}
$$

where, c_{it} is log of power consumption; c_{it-1} is lagged log power consumption; y_{it} is log income or revenue, p_{it} is log real price in according to contract type; D_i is a dummy variable for lagged hours of the day; D_m is a dummy variable for weather region; *wdH* is index of weekdays that coincides with holidays; *SH* is index for special holidays of New year's day and Thanks giving day; *CDD*, *HDD*, *Humd* are cooling degree days, heating degree days, and humidity, respectively; *Prod* is production index; D_{wd} are weekday dummies from Monday to Saturday; D_{wdH} is daytime hour dummies; $D_{i\in SW}$ is a dummy for the potential period of DR during Summer and Winter; $D_{i\in DR}$ is a dummy for the days when the selected company participated in DR; α_i is fixed company effects; ε_{it} are random error terms assumed to have zero mean and constant variance, and the subscripts *i*, *t* and *m* refer to company, time period and regions.

The model specification accounts for price sensitivity and a number of fixed firm-specific effects, time-specific effects and captures possible fixed weekdays, holidays, and hour variations. The model is highly general and allows for variability in price elasticity along, hours, weekdays, holidays, seasons, regions, contract type and potential period of DR dimensions. In addition, one can estimate the short and long run price elasticities. The flexibility comes at the cost of the increased number of parameters. However, the number of parameters can be limited by using non-linear modeling and imposing parameter restrictions.

Due to the inclusion of many exogenous continuations, categorical variables, and dummies, a long time series for each company is required to estimate the model for each company. Test of CBL calculation is restricted to the days on which date selected companies participate in the DR program. Estimation is based on data covering the period prior to the forecast days. For a better understanding of the forecast result, data fitting several days prior to the forecast days are investigated graphically. In each case, the CBL is also calculated, predicted and the error difference computed.

4. DEMAND RESPONSE IN ELECTRICITY MARKET

4.1 Introduction to demand response models

This chapter presents a summary of demand response (DR) in deregulated electricity markets. The definition and the classification of DR are presented and their potential benefits and associated cost components are compared. The experiences with different demand response programs are also discussed.

In situations with expansion of demand for electricity, it might be cheaper to reduce demand than to increase supply. This is evidenced in particular in cases where price is regulated below the cost of incremental supply which does not give incentives to consumers to conserve and therefore an expansion of supply under such circumstances is not profitable. In such cases, it is worth the utility to pay price corrections in exchange for consumer demand reductions to balance supply and demand. The collapse of oil prices in 1998-1999 led to increased capacity expansion and the following energy price surge led to excess capacity which further increased its cost coverage regarding electricity prices. Electricity price is considered critical to explaining and forecasting electricity demand.

In relation with the above discussion Ruff (2002) mentions that improving the ability of electricity demand to respond to wholesale spot prices reduces the total costs of meeting demand reliably. In addition, it can reduce the level and volatility of spot prices during critical peak periods. Ruff criticizes the growing interest in short-run demand response for containing little discussion of the basic economic principles. The observed benefits can lead to unrealistic expectations and inappropriate policies adding to supply rather than a reduction to demand and as such they are often incorrect in concept and inefficient in practice. With reference to the abovementioned possible effects, Ruff reviews the basic principles of DR and discusses the implications for electricity markets. In particular, he focuses on decreasing demand in response to price spikes during critical peak periods.

Public policymakers have recognized the benefits of demand response as part of a comprehensive solution to address rising electricity demand, increasing primary energy prices and concerns over global warming. Empirical results show evidence of substantial gains in wholesale market efficiency from demand response in the form of reduced need for additional resources. For instance, Faruqui and George (2005) show that residential and small to medium commercial and industrial customers in California reduced peak-period energy use in response to time-varying prices. This has led to encouragement and increased efforts to design more effective models providing incentives to customer to use electricity more efficiently. Sheffrin et al. (2008) describes the role of independent service operators and regional transmission operators in fostering demand response.

This chapter is organized under several sections. The second section covers energy conservation initiatives and its effectiveness. In the third section we introduce the theory of DR. The fourth section elaborates with the state of DR technology and the policy and barriers to market efficiency. The fifth section provides some results and experiences in industrialized countries. Based on the experience gained we suggest an appropriate DR model for the electricity market in the sixth section.

4.2 Energy conservation initiative

Historically, power providers have focused on supply, assuming that consumers are unable or unwilling to change their consumption behavior. Under such condition the hourly, daily and seasonal fluctuation required additional generating capacity by peaking plants. In recent years, energy prices development and environmental issued have led to changes in attitude and consumers are expected to respond to higher prices by reducing demand, purchasing more efficient appliances and by shifting their demand from peak time to off-peak. Here, following Spees and Lave (2007) the energy conservation initiative and its effectiveness as efficiency standard, demand side management (DSM) and the role of energy service companies in this context are discussed. The benefits and challenges of DSM in the context of UK electricity system are discussed by Strbac (2008). There is significant scope for DSM to contribute to increasing the efficiency of the system investment. The negative effects of DSM and the potential benefits are discussed in the context of generation, transmission and distribution networks, as well as the value of DSM in balancing generation and demand in future UK electricity systems with significant variable renewable generation.

Different methodologies are used in setting the price under regulation, which in Greer's (2011) view rarely leads to Pareto efficient outcomes where no one is made better off if someone else is worse off. The use of marginal cost pricing (also called real-time or time-of-use pricing) in providing service to various end-users is both allocatively and productively efficient. Greer discusses the revenue requirement to recover the utility's expenses and required returns for the period when the regulated rate is in effect. She further discusses how the revenue requirement would be allocated among different customer classes and which methodology to be employed to enhance optimal consumption, investment and conservation. The revenue requirement or total cost of service is calculated as the sum of capital, operation and maintenance, administrative, and taxes.

In discussion of the theory for efficient prices, Greer presents several pricing alternatives including first best solution, average cost, two-part tariffs, multipart tariffs, time-of-use rates, and real-time pricing. The first two alternatives where price is higher than the optimal price lead to deadweight loss. The two part tariff allows fixed cost to be recovered via fixed charges and variable costs by marginal-cost pricing. In the multi-part tariffs case consumers are differentiated based on the quantity of power usage. The charges include usage charge, customer charge and demand charge, which are based on the class of customers. A further extension of the multi-parts tariff is that of time-of-use rates. It includes a critical peak price in addition to a peak and off-peak price to provide incentives to shift consumption or alternatively to reduce demand. The real-time pricing tariffs vary hourly and are revenue neutral. As such, the utilities revenue recovery is not guaranteed.

In choosing alternative tariffs, Greer (2011) indicates that one needs to price electricity efficiently accounting for emissions and return to investment in alternative energy sources. Price should signal to end users that can respond to the determined tariffs. Ideally, the charges should have an increasing-block tariff and reflect marginal costs and increase with usage. The use of time-of-use and real-time pricing requires investment in infrastructure, like smart meters, on the part of producers and users and proper empirical estimation of marginal costs for providing electricity for optimal rate setting. Tanaka (2006) points to cases with real-time pricing with ramping costs and suggests a new approach to managing a steep change in electricity demand which explicitly takes into account the ramping costs. Allcott (2011) evaluated the first real-time pricing program in the US. The results show that consumers are price elastic and respond by conserving energy during peak hours without increasing consumption during off-peak hours. There was a minor increase in consumer surplus, but the potential additional benefit from investment in retail smart grid applications is larger.

4.3 Demand response in electricity industry

An overview of the demand response in electricity markets is provided by Albadi and El-Saadany (2007 and 2008). Here, the DR is defined as the changes in electric usage by end-users from their normal consumption patterns in response to changes in price of electricity over time. Alternatively, it can also be defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is at risk of being jeopardized. In sum, DR programs include all intentional modifications towards consumption patterns of electricity of end-use customers initiated by suppliers or national energy policy. The modifications are induced mainly through price changes that are intended to alter the timing level of demand or the total consumption.

DR programs are classified in Albadi and El-Saadany (2007 and 2008) into: incentive based and price based programs. The former is divided into: classical and market based sub-programs. The classical programs include direct load control and interruptible/curtailable programs, while market based programs include demand bidding, emergency, capacity and ancillary services. Price based programs include: time of use, critical peak, extreme day critical peak, extreme day, and real time pricing. Customer response to a program is achieved in three ways: (i) customers can reduce their usage during critical peak periods and without changes to consumption during other periods, (ii) customers may respond to high prices by shifting some of their peak demand operation to off-peak periods, and (iii) consumers can use onsite generation with no change in their electricity usage pattern.

There are potential benefits and associated costs that are attributed to each of the abovementioned DR programs. The benefits fall under four main categories: participants, market-wide, reliability, and market performance. DR costs, on the other hand, are born by the participant and program owners, which each incur initial and running costs. Each of these cost categories are further divided into a number of sub-categories. A full schematic picture of the costs and benefits of different DR models are shown in Albadi and El-Sasdany (2007 and 2008). Education of customers about the potential benefits of the initiated programs, and information about the costs and continuous marketing play a major role to the successfulness of different DR strategies in achieving their targets.

Since the ultimate objective of DR program is to reduce peak demand, the actual and percentage actual peak demand reduction is used as an indicator of how successful a DR program is. In addition to peak load reduction, the performance of the dynamic pricing program is measured in the form of demand price elasticity representing sensitivity of customer demand to the price of electricity. In this context, it measures substitution between peak and off-peak period's electricity consumption. The effectiveness of the program will, however, depend on customer's acceptance, enrolment and responsiveness. The authors mention that in simulation studies, three types of DR quantification studies are distinguished, which show evidence regarding the substantial benefits of these programs.

4.4 DR technology, policy and barriers to market efficiency

In relation to DR programs, consumers benefits from DR and load shifting by using less expensive energy, producers avoid costly peak generation and capacity expansion, and as such, the systems benefits from economic load response is larger than end user benefits. The net difference is related to congestion relief, improved reliability and lower generation capacity requirement at peak time. Spees and Lave (2007) mention that day-ahead prices have been used to allow the end user to obtain advanced information about time and to plan and respond without having to invest in automated enabling (smart meter) technology that acts on behalf of the end user in response to an electric price broadcast. As an illustration, the authors review the DR programs in the US which show that the operators offer a combination of economic load response, emergency response, and ancillary programs. The main motivations for the offers are found to be customer retention, peak management, load growth and regulatory compliance.

In relation to deployment of DR programs, Zibelman and Krapels (2008) refer to the use of DR as a dispatchable resource in the real-time organized energy markets which should be encouraged. This valuable "fifth fuel" resource in the energy continuum is fully exploitable using smart-grid technology which is increasingly available in the market. The authors promote the abandonment of CBL measurement as it does not enable the use of DR as a real-time dynamic resource. Large industrial/commercial entities and aggregators of smaller customer loads are encouraged to participate in the real time markets. Furthermore, policies and rules governing the bidding and measurement of DR should reflect the technological advancements of recent times.

Barriers to electricity market efficiency are discussed by Spees and Lave (2007). These barriers are related to site and to adopting energy efficiency technology to realize efficiency investments giving reasons to enact correcting policy. In a different way they can also be divided into: hidden costs to efficiency and non-cost barriers to efficiency. The former are related to the costumer's ability and time to calculate the return to energy efficiency investments, which tend to lower energy efficiency. In the latter case, lack of consumer knowledge about energy efficiency and related costs in the form of purchases with credit cards at high cost can be seen as a market failure. The role of service operating companies and their responsibilities as well as national standards and support programs are emphasized to obtain the highest rate of market efficiency.

In another study Kim and Shcherbakova (2011) discuss the common failures of DR programs. The main challenges that DR programs face are divided into three categories: consumer, producer and structural barriers to market efficiency. Consumer barriers are consumer knowledge, availability of technology, information feeds, response fatigue, technology cost and financing, potential savings and satisfying behavior in switching patterns. The producer barriers are among others investment recovery, promotional responsibility and managerial incentives. Finally, the structural barriers involve program structure (rate, technology), regulatory process and policy support. The authors state that, empirical evidence reveals that in many cases the barriers are related to lack of consumer knowledge, availability, and high cost of technology or an incompatible reform process. Ek and Söderholm (2008) analyze factors affecting household's switching behavior between electricity suppliers in Sweden using probit regression techniques. There is a focus on switching to a new supplier and renegotiating electricity contracts with the prevailing supplier. Results show a positive association between the size of potential gain and switching suppliers. Customer's ability to search and process information are important to the household's choice to switch to a new service provider.

4.5 DR experience in industrialized countries

There is growing evidence of DR experience in industrialized countries. Such empirical evidence is needed in order to establish baseline conditions, to develop standardized methods to assess DR availability and performance, and to build confidence among policymakers, utilities, system operators, and stakeholders where DR resources offer a cost effective alternative to supply side resources. Cappers et al. (2010) summarize the existing conditions of DR resources in US retail and wholesale electric power markets. The focus is on enrolment and performance of incentive-based DR programs. DR is offered mainly in the form of time-based retail rates, using interval meters for customers. Empirical evidence in the US shows that DR is a growing industry with the potential of a 10% peak load reduction between 2006 and 2010. However, the authors point out that, there is an indication that the effect is overestimated. Lack of standardized reporting practices and metrics hinder the programs reliability assessments. The creation of flexible DR resources to reduce exposure to high market prices, organized wholesale markets and direct policy support have expanded the DR industry leading to improved product and service innovation.

Orans et al. (2010) discuss the limitations of the electricity industry in having tariff rates that increase with consumption volume or vary by time of use. This pricing design and flexibility implies that the potential benefits from consumer conservation and load shifting is not adapted or fully exploited. The authors introduce a new general pricing scheme which combines the incentive payment and an existing tariff of any design. The new scheme result in a three parts bill: (i) the consumer CBL priced under the existing design, (ii) consumer's kWh deviations from the CBL priced, and (iii) the cost avoided by a change in the consumer's on-peak consumption share. The multi-part bill in addition to allowing for a detailed decomposition of the cost, also contributes to identification and quantification of the potential benefits arriving from conservation and load shifting. It helps the different players in the electricity market in optimizing their investment, generation, supply, consumption, and design of public policies and regulations.

Despite incomplete market restructuring, there is evidence of participation, performance and existing DR programs in the Korean electricity market. Lee and Ahn (2006) stated that the restructuring of the electricity industry was suspended on the ground that the benefits of the reform are uncertain, while the real costs and risks were judged to be substantial. A number of studies reviewed below indicate more flexibility than what has been stated in the joint study team report. For instance, Hur (2010) describes the status and perspectives of demand resource markets in Korea's electricity industry which opened in 2008 to reduce the customer's consumption at critical times and to secure the load that can be shut down. The market is operated by either forward week-ahead or spot day-ahead markets. Hur focuses mainly on the spot market as the DR program has matured in the smart grid environment and the development of the real-time demand resource trading system is close to being completed. The evaluation accounts for actual load reductions, degree of fulfillment, market prices and factors preventing exploitation of potential market power.

In 2001, the responsibility of the demand-side management program was transferred from KEPCO to the government to manage peak load occurrence efficiently. The challenges of current programs were understood to be related to lack of information in program development, lack of expertise and flexibility in program operation, lack of reliability in program evaluation, and lack of effectiveness in direct load control. For these reasons, the government issued a roadmap for DR development to facilitate demand side resources as means to adopt market based approaches. Kim et al. (2009) present the visions and targets in the roadmap for DR in the electricity market and explain the potential strategies and effective plans to achieve the targets. With this in mind, another study Lee et al. (2010) criticizes the current DR program in Korea for having many disadvantages. They propose a more effective bid-based DR program to protect the participant's returns and to make sure that the information and control structure is suitable for the environment.

We already reported a number of studies of electricity demand where the following traditional income and price elasticities are estimated. Saad (2009) in estimation of the demand for the residential sector in Korea examined the effects of improved efficiency, structural factors and household lifestyle on electricity consumption. A residential electricity demand model for Seoul is also estimated by Yoo et al. (2007) where they control for house and household sizes and plasma TV ownership. However, these studies are not related to DR and the price effect is estimated as a constant responsiveness. In a follow up study Yoo et al. (2011) argue for development of reliability-based DR programs in Korea because of the difficulty in implementing the economic-based DR program. The authors mention that there is a tendency to transit the conventional DR program system (summer vacation and demand bidding) to novel DR reliability based programs. The novel DR system proposed is composed of forward, day-ahead, and real-time DR markets.

The abovementioned reliability DR response programs are preferential in smart grid environments. Chao (2010) suggests that price-responsive demand is essential for the success of a smart grid. In Chao's view, the existing DR programs with an administrative customer baseline and excessive incentive for consumers to under-consume even when low cost supplies are available run the risk of causing inefficient price formation in wholesale markets leading to moral hazard and adverse selection. As a consequence the market price may not reflect the true marginal cost. The author indicates that this problem can be solved if each retail customer could establish a contract-based-baseline through demand subscription before joining a DR system. Assuming fixed-price, real-time price, and demand reduction, five cases are numerically studied showing that price-responsive demand is essential to realize the benefits of smart grid systems. Modeling and prioritizing DR programs in a power market is an important responsibility of the power market regulator. The multi attribute decision making method is suggested by Aalami et al. (2010) for handling such optimization problems. An extensive responsive load economic model is developed and uses order preference similar to the ideal solution method and an analytical hierarchy process to select the most effective DR program. Numerical results on the load curve of the Iranian power grid are also provided. Azzami et al. (2011) proposed a multi-objective optimal power flow model to study the impact of a model for a DR program on price spikes reduction. It is aimed as a solution for local marginal price management in power markets. The study result shows evidence of effectiveness regarding these programs in an electricity market.

Won et al. (2009) use three kinds of CBL determination statistical methods applied to data from Korean industrial customers. Determination of CBL for customer load is an important element for an incentive based load reduction program. Wi et al. (2009) calculated CBL by using the exponential smoothing model with weather adjustment. The daily electric load pattern of customers who participate in a DR program is estimated with the improved accuracy of CBL. The error of CBL simulation is conducted under 5 cases. Regression models for demand reduction of DR programs and screening for recruiting customer enrolment into the program is employed by Yamaguchi et al. (2009). They used cluster analysis of load profiles. The models employ load sensitivity to outside air temperature and load pattern as explanatory variables to improve the models performance.

As a result of increasing costs of reliably meeting demand growth and complying with legislative reductions, the electricity pricing and its variability by time and consumption volume for conservation and load shifting is investigated by Orans et al. (2010). The empirical part is based on US data. Despite evidence of benefits for such programs, Spees and Lave (2007) refer to barriers towards adapting energy efficiency technology and Kim and Shcherbakova (2011) point to the common failures of demand response emphasizing the role of the central structural and behavioral obstacles towards the success of DR programs and outline some solutions to improve their functionality and success.

Ko et al. (2010a) present a comprehensive day-ahead reduction system based on CBL load for inducing a user to efficiently manage energy consumption by applying an incentive to achieve load reduction and load decentralization. The system proposed operates with a number of components including provider and user terminals, a translator collecting load profile data, a meter data management system, a demand response operating system to manage the demand, a consumer energy management system and an account system operating to calculate an incentive for the day-ahead load reduction. In another study Ko et al. (2010b) present a load forecasting analysis system for calculation of CBL load.

Developing countries are also increasingly becoming aware of the benefits of DR programs. Major electricity customer pricing options in Saudi Arabia is investigated by Azzouni et al. (2008). The electricity sector is in transition where future policies are required to be compatible with the sector's changing structure. The aim of such policies is to design appropriate pricing principles and specific tariffs for large customers. The authors recommend short-run marginal costs as the appropriate basis for most tariffs involving large customers. Furthermore, the marginal costs should be time-differentiated seasonally and diurnally and be forecast out for the period the actual tariffs or contract arrangements are likely to be in effect. Thus, design of the pricing principle and tariffs require detailed information and advanced forecasting methodology.

Other applications to developing countries include Louw et al. (2008) who attempted to identify factors affecting the decision making process for electricity consumption of newly electrified low income African households. Income, wood fuel, iron ownership and credit obtained were found to determine the consumption level. Access and affordability of electricity in developing countries (Bangladesh, Brazil and South Africa) is discussed by Winkler et al. (2011). They recommend policies, instruments and regulatory measures to tackle the changes of affordability. Murata et al. (2008) estimate current and future used of electricity in the Chinese urban household sector. The aim is to estimate potential energy saving through improving the efficiency of end-use through the type of equipment. Improving the efficiency of end-use appliances is estimated to reach 28% by 2020.

4.6 A proposed DR model for the electricity market

The aforementioned experiences gained suggest an appropriate DR model with better properties for the electricity market. DR programs are inventive based and price based programs. The proposed model here is not to be considered as a radical innovation, but a mixture of the existing one complemented with improvements brought from different countries experiences in their design and implementations. In these cases, DR is recognized as part of public policy to address rising electricity demand, increasing energy price and concerns over global warming. In certain situations like peak period, DR is employed to reduce demand which is preferred to the traditional supply management and expansion of capacity. If designed and managed well, the total cost of meeting demand reliably or balancing supply and demand in this case is lower and in addition volatility of spot prices during critical peak periods is reduced which smoothens demand over time.

In addition to explanation and forecasting demand, electricity price is considered a critical explanatory variable in DR models. There is evidence that residential and industrial customers reduced peak-period energy use in response to time-varying prices. However, the degree of price responsiveness varies by price rate, climate zone and household/firm characteristics. This has led to increased efforts to design effective models to provide incentives to use electricity more effectively. It is important to have a realistic expectation of DR programs and to avoid inappropriate policies not to add to inefficiency. The potential benefits and associated costs of DR programs have been identified. Education of customers about the benefits and information about the costs and marketing play a role in the successfulness of DR strategies in achieving their targets and affecting the rate of acceptance, enrollment and responsiveness. Attention should be paid to consumer, producer and structural barriers in particular barriers to adapting energy efficient technology.

There is evidence that energy price development and environmental issues has led to changes in attitude and consumers response to higher prices by purchasing more efficient appliances and by shifting their demand. The use of marginal cost pricing also called real-time or time-of-use pricing in providing service to various end-users is allocatively and productively efficient. Revenue requirements should be designed heterogeneously across end-users to not only cover the total costs of capital including returns, operation and maintenance, administration and taxes but also to enhance optimal consumption, investment and conservation. Price should also account for emission and signal to end-users. Multi-tariffs, time-of-use, real-time pricing differentiating consumers by quantity of use, critical peak, peak and off-peak periods are preferred in order to provide incentives to reduce and shift consumption. Real-time pricing programs seem to be the most direct and efficient DR programs. Investment in infrastructure requirements incurs a disadvantage.

The size and scope of existing DR in the electricity market was also discussed by focusing on the results and experiences from participation and performance of existing DR programs. The market is operated by either forward or spot markets. The government also intervenes in demand-side management to manage peak-load occurrence efficiently. The challenges of current DR programs are related to lack of information, expertise and flexibility, reliability and effectiveness in design, as well as operation and evaluation of the programs. More bid-based DR programs are recommended to protect the participant’s returns and to plan power system operations within the variations of demand. DR programs are preferential in smart grid environments, but price responsive demand is essential to realize the benefits of the smart grid system.

Determination of CBL for customer load is an important element for an incentive based load reduction program. A flexible form model for demand reduction with a weather sensitivity adjustment and load patterns as explanatory variables is recommended. In sum, the costs of reliably meeting demand growth is increasing, inducing compliance with stated national goals. Flexible electricity pricing and its variability by time and consumption volume for end-users conservation and load shifting need to be combined with measures to eliminate barriers and to avoid common failures of DR to improve their functionality and success. Ko et al. (2011a and 2011b) day-ahead reduction system and load forecasting analysis system can serve as a good base for a nation-wide DR program. The basic structure can be extended to account for additional improvements to the DR model through the elimination of the possible weaknesses listed above.

5. SUMMARY AND CONCLUSION

The primary aim of this research is to review the literature on various models and measures employed to study changes in demand for electricity. After characterizing a general electricity demand, the consumer base-line in the power market is reviewed which is utilized in estimation of demand response models aimed at reducing electricity consumption at critical peak times. Given the actual conditions and findings in the literature appropriate demand, CBL and DR models are suggested.

Review of general electricity demand models resulted in the suggestion of an appropriate model for a typical market. The electricity market organization and structure is often characterized as a centralized power pool. The public nature of the organization affects the role of generating companies in forming the aggregate supply of electricity. The price is cost based and yet determined heterogeneous reflecting the governments sectorial policy and priorities. Most decisions on planning, development, capacity expansion, investment and selection of loads is determined centrally by energy policy and security concerns. This limits application of bilateral contracts between supplier and consumers, for power supply and practice of marginal cost pricing. These factors will strongly affect the shaping of the demand model at different levels of aggregation.

In the presence of sectorial public policy, it is reasonable to formulate either sector specific (household, industry, agriculture) demand models or specify a national model, which accounts for the specific sectorial characteristics of the market and heterogeneous public energy policy priorities. The choice of the econometrics model (cross section, time series or pooled) will depend on availability of data, the nature of heterogeneity, and dynamics or their combined response analysis. It is desirable that suitable survey questionnaires are designed and repeated waves of stratified data of optimal size are collected on a regular basis. The creation of standardized data complemented with relevant determinants and characteristics will improve the quality of data and analysis.

In the event of using cross sectional household, firm or farm level data, a model must be specified to assess consumer price and income responsiveness which also accounts for sector specific characteristics such as the nonlinear structure of tariff schedules, aggregation of consumption over a period of time, appliances ownership, dwelling, farm and industry characteristics, general energy market situation, as well as unobserved consumer effects. If necessary, account should be made for possible sample selection bias in estimation of the bivariate response and demand equations. The model should allow for both intercept and slope heterogeneity by sector. The household characteristics are demographic and appliance related, while firms or sub-sector characteristics might be type of energy and day/night time production shift related. Residential consumers seem to be more flexible in changing demand and in their responsiveness to price changes than industries are.

When time series data is available, one should preferably specify an electricity demand model for residential and industry sectors. The model must be desirably specified such that it allows for examination of effects of technological change in the form of improved energy efficiency, structural factors and lifestyle changes on energy consumption. These are attributed to the use of equipment, household demography, as well as location and energy sources. The structural time series model can be estimated conditionally and unconditionally based on these characteristics. The model should be specified nonlinearly from simple to general form to avoid having an over-fitted model and to ease interpretation of the results.

Based on the review of the literature a modified composite model is suggested to calculate the CBL with desirable properties. The load management programs in general are divided into those related to load management equipment and those related with incentive for load reduction. We identified several studies on load management and load forecasting using statistical techniques. The best conditional models were found to be non-linear, complex and time-varying. A bivariate forecasting model consisting of peak and average load models accounting for influence of holidays, weekdays and adjustment for cooling and heating days further adjusted for base temperature are found to be adequate. In forecasting 24 hours-ahead peak load, as it is common, information of the day being similar to weather condition of the forecast day should be used. Loads are sensitive to outside temperature and humidity including their interaction. Decomposition of the peak forecast error allows for identification of the sources of error and quantification of their shares of the total error. In calculating the daily electric load patterns of consumers participating in a DR program it is suggested to assign higher weights to the near past observations in forecasting the future values more accurately and to reduce forecast error by adjustment for weather.

DR programs are inventive and price based programs. Here the proposed model is to be considered as a mixture of the existing ones but complemented with incremental improvements brought from foreign countries experience. DR is recognized as part of public policy to address rising electricity demand, increasing energy price and concerns over global warming. If DR is designed and managed well, the total cost of balancing supply and demand reliably decreases and in addition, price volatility is reduced and demand increasingly smoothens over time. Despite the observed benefits, it is important to have a realistic expectation of DR programs not to add to inefficiency and increased supply. Education of customers about the benefits and information concerning costs and marketing seem to play a role in the successfulness of DR programs. Attention should also be paid to consumers, producers and structural barriers towards adapting energy efficiency technologies.

Energy price development and environmental issues has led to changes in attitude and consumers response to higher prices by purchasing more efficient appliances and by shifting demand. Through the use of real-time or time-of-use marginal cost pricing revenue, requirements should be designed heterogeneously to cover the total costs and also to enhance optimal consumption, investment and conservation. In addition, the price should also account for the emission and signal towards end-users. Multi-tariffs, time-of-use and real-time pricing differentiating consumers by quantity of use, peak and off-peak periods are preferred to provide incentives to both reduce and shift consumption. Real-time pricing programs are the most efficient DR programs, but investment in infrastructure requirements is a disadvantage. The experience from participation and performance of DR programs showed that challenges are related to lack of information, expertise and flexibility, effectiveness in design, as well as operation and evaluation of the programs. In sum, flexible electricity pricing needs to be combined with measures to eliminate barriers and to avoid common failures of DR to improve their functionality and overall success.

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Table 1. Summary Table of the empirical analysis of electricity demand

Author(s)	Area	Data type	Sample and period	Pricing structure	Dependent variable (s)	Independent variable(s)	Estimation method(s)	Price elasticity	Income elasticity	Other findings
Aalami, Moghaddam and Yousefi (2010)	Demand response simulation	Time Series data	Iranian Power grid on 28/08/2007	Price of electricity in Iran			Technique for Order Preference is similar to Ideal Solution (TOPSIS) method. The final programs is extracted using Analytical Hierarchy Process (AHP) technique			Evaluating portfolio sorting methodology
AcaravciandOzturk (2010)	Causal relationships	Country level Panel data	15 Transition countries 1990-2006		Real GDP per capita	Electric power consumption	Panel cointegration and panel causality analysis			The electricity consumption related policies have no effect or relation on/with the level of real output in the long run for these transition countries.
Albadi and El-Saadany (2007)	Review of demand response									
Albadi and El-Saadany (2008)	Review of demand response									
Alberini, Gans and Velez-Lopez (2011)	Consumption	Household survey	U.S. 1997-2007	Price of electricity and gas	Consumption of electricity and gas	Price of electricity and gas, income, temperature house and household characteristics	Static and Dynamic models using GLS	own price elasticity of electricity demand in the −0.667 to −0.868 range; the own price elasticity of gas demand is −0.566 to −0.693.	-	Find no evidence of significantly different elasticities across households with electric and gas heat. There might be greater potential for policies which affect energy price.
Allcott (2011)	Real time electricity	Program Household	U.S. May-Dec. in	Real time electricity price for	Utility;	Wealth, vector of electricity prices and High price	Derive demand function through Gorman-form indirect	The overall reduced-form price elasticity		Enrolled households are statistically significantly price elastic and consumers responded

	pricing	Survey	2002; RTP experiment May-Dec. in 2003; Price light experiment June-Oct. in 2006	retails	Demand	alerts in future days; Pre-program average hourly consumption, household size, log(income); indicator for alert; hourly fixed effect.	utility.	of demand is about -0.1		by conserving energy during peak hours, but remarkably did not increase average consumption during off-peak times. The program increases consumer surplus. There is a potential additional benefit from investment in retail Smart Grid application.
Atanasiu and Bertoldi (2008)	Residential electricity consumptio n	Summary data provided by professiona ls	EU-15; NMS(New Member States);CC(C andidate Countries)							In NMS and CC the household electricity consumption is mainly due to appliances and lighting use. The relative saving potential in percentage is much greater than in the EU-15.
Azami, Aflaki and Haghifam (2011)	Demand response	Time series data	Mid-Atlantic region of New York network	Electricity energy price	LMPs at each node in emergency state		Emergency demand response program model; New formulation for LMP calculating with EDRP in normal and emergency states	Self-elasticity of the demand in ith hour is -0.02		Demand-side management (DSM) programs have been effective to address LMPs (local marginal pricing) in the market and system operators experience throughout their day-to-day activities. These programs can help independent system operator to reduce price volatility during peak demand hours.
Azzouni, Parmesano and Al-Rashed (2008)	Electricity Customer pricing options									Short-run marginal costs are the appropriate basis for most tariffs involving large customers, and should mimic the market prices that will emerge as wholesale- and eventually retail-competition is introduced.
Barroso, Cavalcanti, Giesbertz and Purchala(2005)	Electricity market models	Questionnai re data	23 countries				It presents the general structure of the questionnaire and an overview of the main findings.			Provides an overview of various international operating electricity markets. Describes and classifies the organization and function of electricity markets independent of industry structures, management of

										congestion, ancillary services management and regulatory aspects.
Berry (2008)	Energy efficiency program	Time series data	U.S. 2001-2006		Change in electricity sales from 2001 to 2006 in state i.	Energy efficiency effort, change in economic activity, electricity prices or changes in price, changes in weather, total electricity sales made to industrial customers	Model 1 the basic model of the impact of efficiency program effort on the growth in electricity sales (OLS) Model 2 disaggregates energy efficiency program effort into ACEEE scores for utility spending on energy efficiency and for all other programs. Model 3 is similar to Model 1, but it includes the percentage change in average electricity prices instead of the 2006 average price.			The higher the utility efficiency program expenditure per capita and the greater the range of other efficiency programs offered, the greater the reduction in the growth of power sales. Application of the portfolio of energy efficiency programs used in the states with most aggressive programs would have reduced the growth in a state's electricity sales by about 60% relative to the case where no efficiency programs were implemented.
Cappers, Goldman and Kathan (2010)	Demand response		U.S. data reported by utilities, ISOs and CSPs				Index analysis, survey data analysis			Summarizes the existing contribution of DR resources in U.S. electric power market. The development of open and organized wholesale markets coupled with direct policy support by the Federal Energy Regulatory Commission has facilitated new entry by curtailment service providers, which has expanded the demand response and led to product and service innovation.
Cavaliere and Scabrosetti (2008)	Privatizatio n and efficiency						Survey the theoretical literature			The benefits of privatization may derive either from the constraints on agents or from the impossibility of commitment by a government. Contributions dealing with political economy

										issues separate privatization from restructuring decisions. The relation between privatization and efficiency do not lead to any definitive conclusion.
Chao (2010)	Price-responsive demand managemen t						Case study			Price-responsive demand is essential for the success of a smart grid. However, existing demand-response programs run the risk of causing inefficient price formation. This problem can be solved if each retail customer could establish a contract-based baseline through demand subscription before joining a demand-response program.
Christensen, Jorgenson and Lau (1973)	Functional forms									
Denton, Mountain and Spencer (2003)	Energy demand	Commercia l Building Energy Consumpti on Survey	Canada 1986 and 1992	Marginal price of gas and electricity	Demand of electricity Demand of electricity and gas	Marginal prices, temperature variables and large number of building characteristics	Two Demand models (OLS and 2SLS)	OLS: -1.25; 2SLS:-0.70 OLS:-0.87; 2SLS:-0.38		The effects on price elasticities of using (endogenous) marginal rather than (exogenous) average prices are estimated to be quite large.
Dergiades and Tsoulfidis (2008)	Residential electricity demand	Time series data	U.S. 1965-2006	Average real retail prices of electricity in cents per KWh for residential sector	Residential demand for electricity	Per capita income, the price of electricity, the price of oil for heating purposes, the weather conditions and the stock of occupied housing	ARDL bounds-testing procedure	-1.0652	0.2728	It gives support to a stable long-run relationship implying also short-run and long-run elasticities whose size and sign are comparable to other similar studies.
Dilaver and Hunt (2011)	Industrial electricity	Times series data	Turkey	Real industrial electricity	Industrial electricity	Industrial value added, real industrial	Structural time series technique	-0.16		Output and real electricity prices and a UEDT are important to drive the electricity demand thus

	demand		1960-2008	price	demand	electricity price, underlying Energy Demand Trend for the Turkish industrial sector				should be incorporated when modeling. The estimated UEDT should be considered in future energy policy decision. There is an increase UEDT and it is predicted that Turkish industrial electricity demand will be somewhere between 97-148 TWh by 2020.
Edgar, et al. (2008)	CBL calculation and Demand response	Historical Data	Colombia				Statistical valid methods appropriate for time series			It presents a method to produce a Baseline electricity consumption model to be used by the first Demand Response Program in Colombia.
Ek and Söderholm (2008)	Household supplier switching behavior	Household survey data	Sweden, 2005		Binary variable (Switch supplier) Binary variable (choice to renegotiation)	Income level, electric heating, low competition cause the high prices, related-knowledge, cost of changing, perception of others' degree of activity. Age, children in household, electric heating, area of residence, related-knowledge, cost of changing.	Probit Regression techniques			Household that anticipates significant economic benefits from choosing a more active behavior are also more likely to switch to new electricity supplier. Cost and related knowledge are important determinants. Benefits of status quo appear to represent one of those simplifying rules. Social interaction and media discourses also show influences on household's decision.
Engle, Mustafa and Rice (1992)	Peak electricity demand	Daily data	Michigan 1983		Peaks	Current weather, past average load, past peak load, holiday and weekend	Univariate forecasting models and Bivariate models			The models specify the relations between peaks, loads, holidays and weather in a sequential analysis from simple to general models. Specify the best overall model and conditional model. It also suggests that a structural change between the sample period and the forecast period such as an increase in error

										variance.
Espey, Espey and Shaw (1997)	Residential demand for water	24 journal articles published	1967-1993		Price elasticity	Functional form, cross-sectional versus time series, water price specification, rate structure, location, season and estimation technique	Meta-analysis (OLS with Box-Cox transformation)	-0.02 to -0.33		Inclusion of income, rainfall, and evapotranspiration are all found to influence the estimate of the price elasticity. Population density, household size, and temperature do not significantly influence the estimate of price elasticity. Pricing structure and season are also found to significantly influence the estimate of the price elasticity.
Fan and Hyndman (2011)	Demand for electricity	Time series	South Australia, 01/07/1997 – 30/06/2008	Average electricity price	Demand minus Major mining loads	Temperature, calendar, economic and demographic effects	Log non-linear demand model Log-linear demand model	-0.0363 to - 0.4280 -0.4165		Industrial commercial and residential demands have mainly been affected by the cycle of their own activities and state wide electricity demand are largely driven by the economy, demography and weather. The price elasticity varies thus pricing schemes could be applied.
Faruqui and George (2005)	Demand response	2500 individuals' date	07/2003-12/2004							California's statewide pricing pilot experiment showed that residential and small to medium commercial and industrial customers reduced peak-period energy use in response to time-varying prices. Responsiveness varied with rate type, climate zone, season, air conditioning ownership, and other customer characteristics.
Filippini (2011)	Residential electricity demand	Panel data	22 Swiss cities 2000-2006	Price of electricity	Electricity consumption per customer (peak period/off-peak period)	Price of electricity (peak period/off-peak period); Household size; Taxable income per household;	Static (LSDV and RE) and dynamic (LSDV and corrected LSDV) partial adjustment approaches	Static Peak(LSDV/RE): -0.805/ -0.890 Off-peak - 0.901/-0.948	Static Peak(LSD V/RE): 0.622/ 0.497 Off-peak	Peak of off-peak electricity are substitutes. Time differentiated prices should provide an economic incentive to customers so that they can modify consumption patterns by reducing peak demand and shifting electricity consumption

						heating degree days; cooling degree days		Dynamics Short run peak -0.778 /-0.835 Off-peak -0. 652/ -0.758 Long run peak -1,608/ -2.266 Off-peak - 1.273/ -1.652	0.078/0.05 8 Dynamic peak 0.114 /0.035 Off-peak -0. 065/ - 0.106	from peak to off-peak periods.
Foley, Gallachoir, Hur, Baldick and McKeogh (2010)	Review of electricity system models									Provides an overview of electricity systems modeling techniques and discusses a number of key proprietary electricity systems models used in the USA and EU and provides information resources on the choice of model to investigate different aspects of the electricity system.
Gaudin, Griffin and Sickles (2001)	Demand for water	Panel data	Taxa municipalitie s 1981-1985	Average price of water	Demand of water	Average price, income, Spanish population, days with rainfall, 60-year average	OLS, GLS	-0.35 to -0.47	0.11 to 0.19	The Stone-Geary specification also provides an estimate of portion of water use that may not be responsive to price, and is useful in analyzing price structures and designing conservation policies.
Geem and Roper (2009)	Energy demand	Time series data	1980-2007		Demand of energy	GDP, population, import, export amounts	Artificial neural network model			This model is better than many other models in terms of estimating and forecasting. Instead of growing permanently, the energy demands peaked at certain points, and then decreased gradually. This trend is quite different from the results by regression model.

Goldberg and Agnew (2003)	Demand response calculations									Introduction of demand response measurement.
Greer (2011)	Efficient electricity pricing									It examines the various methodologies by which rates are set under regulation and the reasons that these rarely lead to a Pareto efficient outcome. Only by pricing at marginal cost, which is both allocatively and productively efficient, does such an outcome result.
Harvey and Koopman (1993)	Electricity demand forecasting	Time series	Puget Sound, 1985-1991		Electricity demand	A random walk, deterministic cycle of period 1 year, time-varying weekly spline, temperature spine	Structure time series model			A time-varying periodic spine component provide a good way of modeling the changing electricity load pattern within the week. The effect of the non-linear response to temperature may be captured by a fixed spine, and the overall forecasts are relatively accurate.
Herter (2007)	Residential critical peak pricing	California Statewide Pricing Pilot data	California 2003-2004				Calculate of average load change during summer event, annual percent bill change, post experiment satisfaction rating, which are categorized by historical usage and income levels			The results challenge the strategy of targeting only high-use customers for CPP tariffs. The results are compatible with a strategy of full-scale implementation of CPP rates in the residential sector. Suggest that any residential CPP implementation might consider targeting high-use customer group for increased energy efficiency efforts.
Herter, McAuliffe and Rosenfeld (2007)	Residential demand response	Critical peak pricing (CPP) experiment data	California, 2003 (for 15 months)							Offers convincing evidence that the residential sector can provide substantial contributions to retail demand response, which is considered a potential tool for mitigating market power, stabilizing wholesale market prices, managing system reliability, and maintaining

										system resource adequacy.
Heshmati (2003)	Review of performance analysis in public services									The main focus is on the empirical analysis of the relationship between productivity growth, efficiency and outsourcing in manufacturing and services at the micro level.
Hippert, Pedreira and Souza (2001)	Load forecasting	Published paper between 1991 and 1999								Most of the proposed models, especially the ones designed to forecast profiles, seemed to have been over-parameterized. The results of the tests performed on these NNs were not always very convincing.
Hosoe and Akiyama (2009)	Regional electricity demand	Federation of electric power companies of Japan (panel data)	1976-2006	producer price index of petroleum products	Power demand	GRP, cooling degree days, heating degree days, producer price index of petroleum products, deregulation in retail sector, lagged-dependent variable.	OLS Panel estimation method	Short run 0.09 to 0.30 Long run 0.12 to 0.56		Price elasticity in rural regions is larger than that in urban regions. Popular assumptions of small elasticity could be suitable for examining Japan's aggregate power demand but not power demand functions that focus on respective regions. Assumptions about smaller elasticity values such as 0.01 and 0 could not be supported statistically.
Hur (2010)	Demand resource market	Pilot test data	2009							Managing the demand resources is expected to enhance the system reliability and capability to prevent the full potential of market power exploitation. Korea Power Exchange will complete the development of the real-time demand resource trading system, taking into account an integrated dispatch system.
Iyer, Deshpande and Wu (2003)	Demand managemen				The optimal postpone	Expected to postpone period costs which	Postponement model			The value of postponement may be significant depending on cost and demand parameters; a

	t				period costs	depends on fraction of demand to be satisfied in the regular period, demand to be satisfied in the postponement period and capacity in the postponement period.				postponement strategy may lead to reduced investment in initial capacity; and it may be optimal to do no demand postponement over a range of demands even after observing a higher demand signal.
Jamil and Ahmad (2011)	Sector-wise demand analysis	Time series data	Pakistan 1970-2005	Price of electricity	Electricity demand	Temperature index, price of diesel oil and capital stock at aggregate and sectoral levels	Cointegration and vector error correction modeling approaches	-0.19 to 0.07	-0.39 to 0.19	Mechanization of the economy significantly affect electricity demand at macro level. Elastic electricity demand with respect to electricity price in most of the sectors implies that electricity price as a policy tool can be used for efficient use and conservation.
Kim, Hahn and Yang (2009)	Demand response		Korea							Korean government's concerns to eliminate the obstacles to the innovation of current demand-side management programs and to build market based on DSM operation systems were expressed.
Kim and Shcherbakova (2011)	Demand response									Examines the central structural and behavioral obstacles to success of DR programs and outlines some potential solutions which could greatly improve the functionality and success of such programs in the future.
Ko, Jung, Kim and Yu (2010)	CBL load forecasting	Time series	Korea, 2007				Future value forecasting method; Average load profile for n days; Moving average method			A load forecasting analysis system for calculating a customer baseline load includes a CBL forecaster for receiving a load profile and providing a CBL forecasting method, a period selector for selecting

										conditions used to calculate using the load profile, a CBL processor for calculating a forecasting value according to the load profile and the conditions, and a CBL determiner for calculating an error value by comparing the load profile with the forecasting value.
Ko, Jung, Kim and Yu (2010)	CBL load	Load profile data	Korea 2007							Provide a day-ahead load reduction system based on a customer baseline load for inducing a user to efficiently manage energy consumption by applying an incentive to achieve load reduction and load decentralization.
Kucukali (2010)	Energy demand	Time series	Korea 1980-2007		Energy demand	GDP				The energy demand of South Korea could be estimated by GDP. This could make the model more simple and practical. Moreover, using soft computing methods such as artificial neural network and fuzzy logic would minimize the model deviation and provide more accurate results than regression equation.
Lee and Ahn (2006)	Electricity industry restructurin g		Korea							In Korea, the market-driven restructuring of electricity industry has created intense controversies on both theoretical and experiential ground. The current administration accepted the final conclusion that the alleged benefits of reform are theoretical and uncertain, while the real costs and risks are substantial.
Lee and Chiu	Electricity	Panel data	24 OECD	Electricity	Electricity	Real income, electricity price,	Panel smooth transition regression	-0.122 to -0.223	-1.600 to	A strongly non-linear link among electricity consumption,

(2011)	demand		countries, 1978-2004	price	consumption	temperature	with instrumental variable approach		0.264	real income, electricity price and temperature. Electricity demand is income inelastic, price inelastic and temperature inelastic. The impact of temperature on electricity demand is becoming more important in recent years.
Lee, Lee, Yoo, Noh, Na, Park, Moon and Yoon (2010)	Demand response		Korea							Proposes a more effective DR program than the conventional one to protect the participant returns. The new program can indicate an effective direction of load management to allow the planning of the power system operation within the variations of demand. And its information and control structure suitable for the electrical environment.
Leuthold, Weigt and von Hirschhausen (2008)	Efficient electricity pricing	Interconnec ted Network of UCTE	Germany		Losses	Power flow; and the line resistance between two nodes	Nodal pricing DC load flow model			Shows that economic modeling, taking into account physical and technical constraints, makes important contributions to the assessment and optimization of system configuration and operation.
Lima-Azevedo, Granger and Lave (2011)	Residential and regional electricity consumptio n	Panel data	U.S. and EU 1990-2004	Retail electricity price	Consumption	Retail electricity price, Consumption expenditure, annual average heating degree day, year	Fixed-effects panel model	Jointly -0.18 to -0.21 U.S. -0.21 to -0.25 EU -0.20 to -0.21	Jointly 0.19 to 0.21 U.S. -0.019 to -0.157 EU 0.25 to 0.38	Given the price-inelastic behavior in both the U.S. and EU regions, public policies aimed at fostering a transition to a more sustainable energy system in order to address the climate change challenge will require more than increase in electricity retail price.
Linares and Labandeira (2010)	Energy efficiency									It suggests that specific policies for promoting energy conservation may be required, preferably based on economic instruments or on the provision

										of information to consumers
Louw, Conradie, Howells and Dekenah (2008)	Electricity demand	Household data	African countries	Price of electricity	Average number of watt hours used in every 5-min	Price of electricity, price of alternative fuels, size of household, cost of appliances, number of the year household has been electrified for, number of working electric lights installed, access to credit, income	OLS Ramsey RESET test	Statistically insignificant	0.243-0.532	It finds that income, wood fuel usage, iron ownership and credit obtained are main determinants of consumption. Price and cross-price were difficult to assess due to lack of data within the sample.
Mao and Hare (1989)	Price mechanism									The authors argue that the goal of economic reform cannot be achieved due to the false information provided by the distorted price. So price adjustment becomes an issue of primary importance, and the authors discuss the difficulties for price adjustment posed by various interest groups.
Mideksa and Kallbekken (2010)	Climate change and electricity market									Reviews the climate impacts on electricity demand, supply and transmission by type of climatic change. Four significant gaps in the current research are regional studies of demand side impacts for Africa, Asia, the Caribbean and Latin America, the effects of extreme weather events on electricity generation, transmission and demand, changes to the adoption rate of air conditionings.

Murata, Kondou, Hailin and Weisheng (2008)	Household electricity demand	Questionnaire survey	China 2003-2004		Unit consumption of electricity by end-use , Annual electricity-consumption by end-use per household in 2003, electricity-consumption per household and by end-use in 2020 and feasibility of electricity conservation					Electricity used for various purposes in China's urban-households is evaluated, considering climate conditions specific to the target regions and the possession of end-use appliances. How much electricity could be saved in the future by improving the efficiency of end-use lighting equipment room air-conditioners, refrigerators, and TV sets is estimated. About 28% reduction could be achieved in the year of 2020 by means of improving the efficiency of these end-use appliances.
Nakajima (2010)	Residential electricity demand	Panel data	Japan 1975-2005	Overall unit price of electricity for general consumers	Residential demand for electricity	Real disposable income per household, real overall unit price of the residential electricity	Panel analysis techniques of panel unit root test, a panel cointegration test, and group mean dynamic ordinary least squared	Lead and lag K=2 -1.127/-1.204	Lead and lag K=3 0.602/0.651	It divides Japan into a number of regions so that the estimation of coefficients becomes more powerful due to the increased degree of freedom from the utilization of the panel data. Japan is chosen for this analysis on the basis of the deregulation of the residential electric power supply that is scheduled for the new future.
Nordin (1976)	Demand analysis									In estimating demand functions for electricity, it is inappropriate to use a variable either average price for blocks other than the final one or total payment for block other the final one. It is appropriate to use a variable equivalent to a lump-sum payment the customer must make before buying as many units as he wants, at the

										marginal price.
Orans, Woo, Horii, Chait and DeBenedictis (2010)	Electricity pricing and load shifting									Though the electricity industry is facing several challenges, the electric utility's existing tariffs often don't have rates that increase with consumption volume or vary by time of use, thus not fully exploiting the potential benefits from customer conservation and load shifting.
Ozturk (2010)	Survey on energy-growth causality									Literature produce conflicting results and there is no consensus neither on the existence nor on the direction of causality between energy consumption and economic growth. Authors may use the autoregressive distributed lags bounds test, two-regime threshold co-integration models, panel data approach and multivariate models including new variables. New approaches and perspectives are suggested.
Ozturk and Acaravci (2011)	Electricity-GDP causality	Panel data	11 Middle East and North African countries, 1971-2006				Autoregressive Distributed Lag bounds testing approach of cointegration and vector error-correction			The overall results indicate that there is no relationship between the electricity consumption and the economic growth in most of the MENA countries. Further evidence indicates that policies for energy conservation can have a little or no impact on economic growth in most of the MENA countries.
Payne (2010)	Survey electricity-growth causality									The survey focuses on country coverage, variables selected and model specification, econometric approaches, various methodological issues, and empirical results. The results for the specific countries surveyed show that 31.15% supported the

										neutrality hypothesis, 27.87% the conservation hypothesis, 22.95% the growth hypothesis and 18.03% the feedback hypothesis.
Peerbocus (2007)	Survey of reforms of the electricity supply industry									This empirical review suggests that progress has been made in bringing competition into the inherently complex and challenging electricity market, generating substantial efficiency gains. But the large disconnect between the wholesale and retail market indicates that much effort is needed to allow consumers to optimally reap those gains.
Phlips (1988)	Survey of price discriminati on						Pigou's distinction between perfect, second-degree and third degree price discrimination.			The purpose of this survey is twofold. First it introduces the reader to recent development in the theory of price discrimination. Second, the exposition aims at being self-contained and accessible to the non-specialist reader.
Reiss and White (2005)	Household electricity demand	Household data	California, 2000-2001	Price of electricity	Electricity demand	Price of electricity, household income, weather, appliance, dwelling structure characteristics, applicant attributes.	GMM and OLS. The model concurrently addresses several interrelated difficulties posed by non-linear pricing, heterogeneity in consumer price sensitivity, and consumption aggregation over appliances and time.	GMM/OLS -0.39/0.16	GMM/OL S 0/0	It implies a strikingly skewed distribution of household electricity price elasticities in the population, with a small fraction of households accounting for most aggregate demand response. After the estimation of the aggregate and distributional consequences of recent tariff structure changes in California, the consumption effects of which have been the subject of considerable debate.
Ruff (2002)	Demand response									The focus is on decreasing demand in response to price spikes during critical periods-called "peak" periods here, even

										if the cause is a drop in supply more than an increase in demand- because that is the most pressing issue for the SMD that FERC is defining for Independent Transmission Providers.
Saad (2009)	Residential electricity demand	Time series	Korea, 1973-2007	Electricity Price	Demand for electricity	Per capita real GDP, weighted average of real prices of electricity, stochastic trend component used as a proxy for the underlying energy demand trend.	Structural time series model	-0.27	1.33	It suggests that, in order to encourage energy efficiency in the residential sector, the government should complement the market based pricing policies with non-market policies such as minimum energy efficiency stands and public enlightment.
Senjyu, Takara, Uezato and Funabashi (2002)	Load forecasting	Time series data	Okinawa 1995-1997				Proposed neural network prediction method			To overcome the problems in traditional methods of load forecasting, proposes a one-hour-ahead load forecasting method using the correlation of similar day data. In the proposed prediction method, the forecasted load power is obtained by adding a correction to the selected similar day data.
Sheffrin, Yoshimura, LaPlante and Neenan (2006)	Electricity demand	Cross section	U.S. 2007							Demand-response resources are integrated into ISO and RTO operations and provide. It shows how demand response resources play an important role. Collectively, by reducing costs, improving reliability, and ensuring that wholesale market prices reflect the value of electricity to consumers, they demonstrate the diversity that demand response resources add to the electric power system.

Shin (1985)	Residential electricity demand	Pooled annual data	Ohio, 1960-1980	Perceived real price of electricity, Average real price of natural gas	Demand for electricity per customer	Mean real per capita personal income, the perceived real price of electricity, the average real price of natural gas, the heating and cooling degree days	Houthakker-Taylor logarithmic Koyck model (LSDV and IV)	LSDV/IV -0.143/ -0.120	LSDV/IV 0.172/ 0.185	The empirical results support the hypothesis that consumers respond to average price perceived from the electricity bill.
Simpson (2009)	Review of productivity in public services									Empirical studies of productivity for public sector organizations have demonstrated that efficiency measures and rankings can be sensitive to the techniques used to drive them. Productivity measurement for private sector organizations also presents a number of difficulties. The results of studies are robust to different assumptions and to the use of different productivity measurement techniques.
Spees and Lave (2007)	Demand response and market efficiency									Customer response is a neglected way of solving electricity industry problems. Historically, providers have focused on supply, assuming that consumers are unwilling or unable to modify their consumption. Contrary to these expectations, customers respond to higher prices that they expect to continue by purchasing more efficient appliances and taking other efficiency measures.
Strbac (2008)	Demand side managemen t		UK							It discusses the major benefits and challenges of electricity demand side management in UK. The relatively low utilization of generation and networks means that there is

										significant scope for DSM to contribute to increasing the efficiency of the system investment. The importance of diversity of electricity load and negative effects of DSM on load diversity are illustrated.
Tanaka (2006)	Real-time pricing									It generalizes the concept of ramping costs, and derives an extended form of RTP that achieves the optimal rate of change in quantity demanded by explicitly taking the ramping costs into account. As a result, the steepness of the load curve will be remarkably controlled, which will reduce both the ramping costs and the possibility of a large-scale blackout.
Taylor (1975)	Survey of demand for electricity									Most of the focus is on residential demand, but few about commercial and industrial demand. Special attention is given to the singular features of electricity demand
Torriti, Hassan and Leach (2010)	Demand response experience		European electricity market							The common reasons as to why coordinated DR policies have been slow to emerge. This is because of the limited knowledge on DR energy saving capacities, high cost estimates for DR technologies and infrastructures and policies focused on creating the conditions for liberalizing the EU energy markets.
Wi, Kim, Joo, Park and Oh (2009)	CBL calculations	Daily data	Korea, 2002/2003/2008/2009				Exponential smoothing model with weather adjustment multiplicative.			The numerical test results show that the proposed method can improve the accuracy of consumer baseline load.

Winkler, Simoes, La Rovere, Alam, Rahman and Mwakasonda (2011)	Access and affordability to electricity		Bangladesh, Brazil, South Africa							Access to a grid connection does not guarantee use of electricity for all end uses, in particular by poor households. Consumption levels in newly connected households remain lower than expected for some time. Affordability requires specific policy interventions.
Won, Yoon, Choi and Yi (2009)	CBL load determinatio n	Daily data	Korea, 2008				Regression, statistical method			It is suggested that statistical method is better than regression at very random loads. Proposes case study analysis of the statistical method in real Korean customers.
Worthington and Hoffman (2008)	Survey of residential water demand	Studies published since 1980						Long run 0.5 to 1 Short run 0 to 0.5	Small and positive	Two dimensions of price specification have been recognized. First, most water tariffs have complex structures that combine fixed and variable charges. Second, an additional complication arises where modeling techniques are required to compensate for the potential income effect of variable block tariffs.
Yamagychi, Han, Ghatikar, Kiliccote, Piette and Asano (2009)	Demand reduction	Load profile data	Customers who participated the Critical Peak Pricing program U.S. 2008				Temperature sensitivity Regression models Cluster regression model Cluster-Temperature sensitivity regression model			Auto-DR facilitates higher and reliable demand reduction than non-auto-DR participants. Load sensitivity to OAT is suitable as explanatory variable of models for demand reduction. Cluster analysis and its algorithms is one of the effective tools to estimate demand reduction. Combination of load sensitivity and cluster analysis improve the performance of the models.
Yoo, Kwon, Lee, Rhee, Yoon and Park (2011)	Demand response program		Korea							In Korean market situation, there is need for developing reliability-based DR program primarily because of difficulty in

										implementing the economic based DR program. Traditional DR programs must be restructured and as well as the function of DR resources using as a reserve.
Yoo, Lee and Kwak (2007)	Residential electricity demand	Household data	Seoul	Electricity price	Residential electricity demand	Size of family, size of house, dummies for having television and air conditioner, household income, electricity price.	Bivariate model correction for sample selection bias	-0.2463	0.0593	It suggests that residential electricity demand in Seoul is price and income inelastic. Such useful information is expected to help policy-makers regulate the residential electricity supply and predict the effect of the price on the residential electricity demand in the future.
Zibelman and Krapels (2008)	Demand response									The use of DR as a dispatchable resource in the real-time energy markets should be encouraged, not discouraged. It is fortunate that the smart-grid technology now exists to fully exploit this valuable resource.
Ziramba (2008)	Residential electricity demand	Time series data	South Africa, 1978-2005	Price of electricity	Demand of electricity	Real gross domestic product per capita, the price of electricity, time trend	Bounds testing to cointegration within an autoregressive distributed lag (ARDL) framework, OLS	ARLD/OLS -0.04/-0.01	ARLD/OL S 0.31/0.87	In the long run, income is the main determinant of electricity demand, while electricity price is insignificant.