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Essays in Energy Economics: The Electricity Industry

by

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ABSTRACT

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Electricity Demand Analysis Using Cointegration and Error-Correction Models with Time Varying Parameters: The Mexican Case. In this essay we show how some flexibility can be allowed in modeling the parameters of the electricity demand function by employing the time varying coefficient (TVC) cointegrating model developed by Park and Hahn (1999). With the income elasticity of electricity demand modeled as a TVC, we perform tests to examine the adequacy of the proposed model against the cointegrating regression with fixed coefficients, as well as against the spuriousness of the regression with TVC. The results reject the specification of the model with fixed coefficients and favor the proposed model. We also show how some flexibility is gained in the specification of the error correction model based on the proposed TVC cointegrating model, by including more lags of the error correction term as predetermined variables. Finally, we present the results of some out-of-sample forecast comparison among competing models.

Electricity Demand and Supply in Mexico. In this essay we present a simplified model of the Mexican electricity transmission network. We use the model to approximate the marginal cost of supplying electricity to consumers in different locations and at different times of the year. We examine how costs and system operations will be affected by proposed investments in generation and transmission capacity given a forecast of growth in regional electricity demands.

Decomposing Electricity Prices with Jumps. In this essay we propose a model that decomposes electricity prices into two independent stochastic processes: one that represents the "normal" pattern of electricity prices and the other that captures temporary shocks, or "jumps", with non-lasting effects in the market. Each contains specific mean reverting parameters to estimate. In order to identify such components we specify a state-space model with regime switching. Using Kim's (1994) filtering algorithm we estimate the parameters of the model, the transition probabilities and the unobservable components for the mean adjusted series of New South Wales' electricity prices. Finally, bootstrap simulations were performed to estimate the expected contribution of each of the components in the overall electricity prices.

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To my wife, Silvia.

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Electricity Demand Analysis Using Cointegration and Error-Correction Models with Time Varying Parameters: The Mexican Case

1.1 Introduction

Cointegration analysis and error correction models (ECM) have become the standard techniques for the study of electricity demand since their formal development by Engle and Granger (1987) and their early application to the forecast of the electricity demand by Engle et al. (1989). Subsequent developments related to this approach have relied on the use of new techniques to identify cointegrating relationships (for example, the Johansen's method (1988, 1991)), as well as on the inclusion of more specific energy-related variables in the model. Some recent examples of these extensions include Beenstock, et al. (1999) which analyzes the demand for electricity in Israel, and Silk and Joutz (1997) who construct an appliance stock index for their study of the US residential electricity demand. In most of these kinds of analyses the demand equation is specified as a linear double-log function, as a way to obtain elasticities directly from its coefficients, and the parameters are estimated using data whose time span is rather long, going beyond forty years in some cases.

Despite the relative popularity of the above techniques, the long time span covered by these studies raises serious concerns about the validity of the fixed coefficients (FC) assumption in the electricity demand equation. This assumption in a double-log functional form of demand simply implies constant elasticities for the entire sample period under study. This feature of the model is indeed questionable in light of the changes that could have taken place in the economy over such a long period of time affecting the demand for electricity. See Hass and Schipper (1998) for more discussions on this issue. Specific examples of the determinants for such changes include the efficiency improvements in electrical equipments, the developmental stage of the economy (whether the economy is in transition to later stages of development and industrialization), and even the government energy policy and the habit persistence of consumers. These determinants are not static, but rather tend to evolve slowly through time and thus they constantly modify the responses of the aggregated electricity demand to variations in income and prices. Therefore, if we use data collected over a relatively long time period to estimate an electricity demand function, we should at least consider the possibility that the parameters in the regression may not be constant.

As a way to capture this evolving nature of the electricity demand, some studies have employed alternative functional forms for the demand equations, such as linear functions, to indirectly calculate the elasticities as functions of the current levels of the variables and the parameters of the demand equation (see, for example, Chang and Hsing (1991)). However, these studies fail to see the possibility of allowing the relevant parameters to vary over time. Another alternative suggested in the literature is to introduce some structural changes into the model, but this approach has obvious shortcomings. Among others, it can neither handle the dynamics of the parameter changes nor provide the perspective of their possible future evolution. To our knowledge, these alternatives have been applied in the energy literature without cointegration analysis, which is necessary to properly identify the long-run relationships among the relevant variables (see, for example, Hass and Schipper (1998)).

In this paper, we estimate the electricity demand function for Mexico by applying a new alternative model that combines cointegration analysis with time varying coefficients in the demand equation. In other words, we look for cointegrating relationships in the electricity market that change over time. Park and Hahn (1999) have developed the idea of the time varying coefficients cointegrating regression, which we employ here to estimate the time varying coefficient (TVC) on the income variable in a double-log functional form of the electricity demand. The underlying assumption in the model is that the TVC is generated by a smooth function that can be approximated by a series of functions which expands appropriately as the sample size grows. Taking into account the intrinsically slow changes in the general factors that affect electricity demand, such as technology, developmental stage of the economy and habit persistency, this basic assumption seems plausible. Park and Hahn (1999) demonstrated that under some regularity conditions the estimators of general TVC cointegrating regression models are consistent, efficient and asymptotically Gaussian. Thus, in addition to the advantage of allowing for flexible coefficients, this approach exploits the available information efficiently to estimate the parameters of the model, and gives a valid basis to forecast the possible path of the TVC into the medium term.

To highlight the essence of the TVC cointegrating regression model we use a basic electricity demand equation with electricity prices and income as explanatory variables. In particular we focus our analyses on the models with time varying income elasticities for three Mexican sectors: residential, commercial and industrial, and work with the data that spans fifteen years from 1985 to 2000. As a proxy for the income variable, we use private consumption for the residential and commercial sectors and industrial production for the industrial sector. As we use monthly data to estimate long-run relationships, we need to properly model the seasonality present in the electricity demand data. For this, we construct a seasonal variable from what we call the temperature response function, which is estimated nonparametrically using intraday temperature data, such as the measures taken every three hours. This seasonal variable provides a temperature measure that reflects the variations in electricity demand due to the factors related to changes in temperature. We work with more general model which is invariant to the distribution of the error term, by employing a modified version of the TVC models based on the method of canonical cointegrating regression (CCR), suggested in Park and Hahn (1999). Nonparametric methods are employed to compute the long-run covariance matrices used in the CCR transformations.

We also perform specification tests to examine the validity of the proposed model against that with fixed coefficient and against the spuriousness of the regression with time varying coefficients. These tests are modified Walt statistics which test the presence of unit roots in the error terms and they were proposed by Park and Hahn (1999). The results from the tests reject the specification of the model with fixed coefficient and favor the proposed TVC cointegrating regression model.

It is also shown that this new specification can be used to extend the flexibility of error correction models by allowing to include more lags of the error correction term as predetermined variables. This is because the presence of the TVC in the error correction terms eliminates the collineality problems between its lags and the lagged differences of the other included variables. Using more lags of the error terms permit to capture more complex adjustment paths in the short run dynamic of the model.

To evaluate the forecasting performance of the proposed model we develop an out-of-sample forecast comparison among the TVC cointegrating regression model, its error correction model and the alternative fixed coefficient model. Based on values of the root mean squared error, we found that the TVC cointegrating regression model gives a better forecast that the alternative model with fixed coefficients.

The rest of the paper is organized as follows. Section 2 introduces the theoretical background for the TVC cointegrating regression model, the CCR methodology, and the model for the seasonality of electricity demand along with the temperature response function. In Section 3, empirical results are obtained from the estimations of the temperature response function, the cointegrating TVC regression, the error correction model and the out-of-sample forecast comparison for each sector. Finally, some concluding remarks are provided in Section 4.

1.2 The Model

1.2.1 The time varying cointegrating regression model

The prototype electricity demand model used in the literature takes the following form

$$d_t = \pi + \gamma y_t + \delta p_t + \phi z_t + u_t$$

where d_t denotes the demand for electricity, y_t the income or production, p_t the real price of electricity, z_t the variable that captures the seasonal component of the demand,[1] u_t the stationary error and π, γ, δ and ϕ the parameters to be estimated. All the economic variables are expressed in natural logarithms.

Let $x_t = (y_t, p_t, z_t)'$, and $\bar{\alpha} = (\gamma, \delta, \phi)'$. Then we may rewrite the above model as

$$d_t = \pi + \bar{\alpha}' x_t + u_t \tag{1.1}$$

In this linear double-log functional form of the demand, the parameters in the vector a represents the elasticities, and they are assumed to be constant over the entire sample period under study. However there is a possibility that the long-run relationships

[1] A detailed description on how to construct this seasonal variable z_t is given in Section 2.3.

among the variables change through time, especially when we are analyzing the model over a relatively long time period, such as ten or more years. In order to take into account the time varying nature of the elasticities, we may allow the parameters to evolve over time and accordingly specify the model as follows

$$d_t = \pi + \alpha_t' x_t + u_t \tag{1.2}$$

where the coefficients α_t are now allowed to change over time.

Furthermore, given that the responses of the electricity demand to the changes in the exogeneous variables could be affected by slowly evolving factors such as the degree of economic development or the habit persistence of the agents, it is assumed that α_t changes in a smooth way. Specifically we let

$$\alpha_t = \alpha\left(\frac{t}{n}\right), \tag{1.3}$$

where n is the sample size, $t \in \{0, 1, 2, ..., n\}$ and α is a smooth function defined on the interval [0,1]. Note that the subscript indicating the dependence of α_t on n has been suppressed for notational simplicity. As an estimand of the function α, we define the following functional

$$\Pi(\alpha) = (\alpha(r_1), ..., \alpha(r_d))', \tag{1.4}$$

where r_i is a number in the unit interval [0,1], and $\Pi : C[0,1] \to R^d$.

If the function α in (1.3) is sufficiently smooth, then it is well known that α can be approximated pointwisely by a linear combination of a sufficiently large number of polynomial and/or trigonometric functions on [0,1]. For our study, we consider the Fourier Flexible Form (FFF) functions, which includes a constant, a linear function, r, and k pairs of the trigonometric series functions, $(\varphi_i)_{i=1}^k$, where each pair φ_i is defined as $\varphi_i = (\cos \lambda_i r, \sin \lambda_i r)'$ with $\lambda_i = 2\pi i$. That is, we assume that the smooth function α can be approximated by the function α_k defined as follows

$$\alpha_k = \beta_{k,1} + \beta_{k,2}\, r + \sum_{i=1}^{k} (\beta_{k,2i+1}, \beta_{k,2i+2}) \cdot \varphi_i, \tag{1.5}$$

with $\beta_{k,j} \in R^3$ for $j = 1, 2, \ldots, 2(k+1)$ and k sufficiently large. In fact, Park and Hahn (1999) showed that the function α given in (1.3) can be arbitrarily well approximated by (α_k) with increasing the number k of the included trigonometric pairs.[2] Alternatively, if we define $f_k(r) = (1, r, \varphi_1'(r), ..., \varphi_k'(r))'$ with $r \in [0,1]$ and $\beta_k = (\beta_{k,1}', \beta_{k,2}', ..., \beta_{k,2k+2}')'$, the function α_k defined in (1.5) can be rewritten as

$$\alpha_k = (f_k' \otimes I_3)\beta_k, \tag{1.6}$$

and the estimand $\Pi(\alpha_k)$ as

$$\Pi(\alpha_k) = (\alpha_k(r_1)', ..., \alpha_k(r_d)')' = T_k\beta_k, \tag{1.7}$$

where T_k is the matrix given by $T_k = F_k \otimes I_3$ with $F_k = (f_k(r_1), ..., f_k(r_d))'$ for $k \geq 1$. Note that we have suppressed the indicator r indicator for notational brevity, but it should be understood that $\Pi(\alpha_k)$ is a function of r.

Estimation of α_k and $\Pi(\alpha_k)$ involves the estimation of the parameters in β_k, as can be seen from (1.6) and (1.7). A natural way to estimate these parameters is to apply the ordinary least squares (OLS) to the following regression

$$d_t = \pi + \beta_k' x_{kt} + u_{kt}, \tag{1.8}$$

where

$$\begin{aligned} x_{kt} &= f_k\left(\frac{t}{n}\right) \otimes x_t \\ u_{kt} &= u_t + (\alpha - \alpha_k)\left(\frac{t}{n}\right)' x_t \end{aligned}$$

[2]This result hold if it is assumed that α is at least twice differentiable, with bounded derivatives on [0,1]. See Park and Hahn (1999, Lemma 2).

using the notations defined earlier. Note that the new error u_{kt} includes an additional term representing the error from approximating the original smooth function α in (1.3) by the series function α_k given in (1.5). From the OLS estimators $\hat{\beta}_{nk} = (\hat{\beta}'_{nk,1}, \hat{\beta}'_{nk,2}, \ldots, \hat{\beta}'_{nk,2k+2})'$ of β_k from regression (1.8), the sample estimates of α_k and $\Pi(\alpha_k)$ can be easily obtained by substituting β_k with its sample estimate $\hat{\beta}_{nk}$ in (1.6) and (1.7). They are given by $\hat{\alpha}_{nk} = (f'_k \otimes I_3)\hat{\beta}_{nk}$ and $\Pi(\hat{\alpha}_{nk}) = T_k\hat{\beta}_{nk}$, where the subscript n is used to make it explicitly that the parameter estimates depend on the sample.

Park and Hahn (1999) showed that $\Pi(\hat{\alpha}_{nk})$ is a consistent estimator of $\Pi(\alpha)$ if the number k of the trigonometric pairs included in the series (1.5) increases along with the sample size n at an appropriate rate. The required expansion rate for k is determined by the smoothness of the function α and the moment conditions of the underlying time series. The required rate becomes lower as the function becomes smoother and the number of the existing moments of the underlying time series gets smaller.[3] Of course, the conditions on the smoothness of the function α can not be verified as α is not observable, and therefore the validity of the resulting estimators would be based on our perception of the way the time varying coefficients evolve through time. They also showed that the convergence rate of the series estimators is $n^{-1}k$, which is slower, by a factor of k, than the convergence rate of the usual OLS estimators for the FC models. They also found that the OLS estimators of model (1.8) are asymptotically inefficient, and in general non-Gaussian,[4] which invalidates the standard inferential procedures based on them, when the errors u_{kt} are allowed to have flexible distributions.

To obtain efficient estimators and a valid inferential basis for the parameters in

[3] The explicit assumption is that $k = cn^r$ with $2/(2q-1) < r < (p-2)/3p$, where c is a constant, n is the sample size, p is the number of moments of the underlying variables and q the number of derivatives of α. See Park and Hahn (1999, Assumption 4).

[4] See Park and Hahn (1999, Theorem 7).

our TVC cointegrating regression model (1.8) while allowing for general error specifications, we employ, as in Park and Hahn (1999), an extension of the canonical cointegrating regression (CCR) method developed by Park (1992). The CCR method is based on the transformations of the variables that are correlated in the long-run with the error term, which effectively remove the long-run endogeneity of the regressors and the serial correlation effects in the errors. In the following section, we apply the CCR methodology for the estimation of our TVC cointegrating regression model (1.2) or (1.8).

1.2.2 CCR Estimation

For the estimation the TVC cointegrating regression model (1.8) by the CCR method, we first construct the required transformations for the variables d_t, y_{kt} and p_{kt} using their stationary components. Let $\tilde{x}_t = (y_t, p_t)'$, $v_t = \Delta\tilde{x}_t$ and $w_t = (u_t, v_t')'$, where (u_t) are the stationary errors in the original TVC model (1.2). For the process w_t, we also need to define the long-run covariance matrix $\Omega = \sum_{j=-\infty}^{\infty} \mathbf{E} w_t w_{t-k}'$, the contemporaneous covariance matrix $\Sigma = \mathbf{E} w_0 w_0'$, and the one-sided long-run covariance matrix $\Delta = \sum_{j=0}^{\infty} \mathbf{E} w_t w_{t-k}'$. We partition Ω, Σ and Δ conformably with the partition of w_t into cell submatrices Ω_{ij}, Σ_{ij} and Δ_{ij}, for $i, j = 1, 2$. Note that Σ_{11} and Ω_{11} represent, respectively, the short and long-run variances of the error u_t.

The CCR estimation of the TVC cointegrating model (1.8) is based on the following regression

$$d_t^* = \pi + \beta_k' x_{kt}^* + u_{kt}^* \tag{1.9}$$

whose elements are defined by

$$\begin{aligned} d_t^* &= d_t - \left(f_k\left(\frac{t}{n}\right) \otimes \Delta_2 \Sigma^{-1} w_t\right)' \beta_k - (0, \Omega_{12}\Omega_{22}^{-1}) w_t \\ x_{kt}^* &= \left(f_k\left(\frac{t}{n}\right) \otimes \tilde{x}_t^*,\ z_t\right) \\ u_{kt}^* &= u_t^* + (\alpha - \alpha_k)\left(\frac{t}{n}\right) x_{kt} \end{aligned}$$

using the transformed nonstationary explanatory variables $\tilde{x}_t^*$ and the modified error u_t^* given below

$$\tilde{x}_t^* = \tilde{x}_t - \Delta_2 \Sigma^{-1} w_t, \quad u_t^* = u_t - \Omega_{12}\Omega_{22}^{-1} \Delta \tilde{x}_{st}$$

where $\Delta_2 = (\Delta_{12}', \Delta_{22}')$. We note that the long-run variance of the CCR error (u_t^*) is given by

$$\varpi_*^2 = \Omega_{11} - \Omega_{12}\Omega_{22}^{-1}\Omega_{21} \tag{1.10}$$

which is the conditional long-run variance of the error (u_t) given the innovations (v_t) of the regressors $(y_t, p_t)'$, and is strictly less than the long-run variance Ω_{11} of u_t, unless the regressors are strictly exogeneous. Hence the CCR estimation, i.e., the OLS estimation of the CCR transformed model (1.9), yields efficient and optimal estimators. In practice, non-parametric methods can be employed to compute consistent estimates of Ω and Δ using the fitted residuals from the OLS estimation of model (1.8).[5] Denote by $\hat{\pi}^*$ and $\hat{\beta}_{nk}^*$ the CCR estimators, which are the OLS estimators of model (1.9). Then we may use them to obtain the efficient estimators

[5] Denote such residuals $(\hat{u}_{kt})$ and define $\hat{w}_{k,t} = (\hat{u}_{k,t}, v_t')'$. Then the components of the autocovariance function can be computed by

$$\hat{\Omega}_{nk} = \frac{1}{n} \sum_{|j| \leq h_n} K\left(\frac{j}{n}\right) \sum_t \hat{w}_{k,t} \hat{w}_{k,t-j}' \tag{1.11}$$

$$\hat{\Delta}_{nk} = \frac{1}{n} \sum_{0 \leq j \leq h_n} K\left(\frac{j}{n}\right) \sum_t \hat{w}_{k,t} \hat{w}_{k,t-j}' \tag{1.12}$$

where K is the kernel function and h_n the window width. Commonly used kernels, for example Barlett, Parzen or the rectangular kernel, will assure the consistence of the estimators.

$\hat{\alpha}^*_{nk} = (f'_k \otimes I_3)\hat{\beta}^*_{nk}$ and $\Pi(\hat{\alpha}^*_{nk}) = T_k\hat{\beta}^*_{nk}$ for α_k and $\Pi(\alpha)$ from the relationships given in (1.6) and (1.7). Park and Hahn (1999) demonstrated that the CCR estimator $\Pi(\hat{\alpha}^*_{nk})$ is a consistent estimator of $\Pi(\alpha)$ and that its limit distribution is normal.[6]

The consistency and efficiency of the CCR estimators of the TVC cointegrating model (1.9) are attained presuming that the original time varying coefficient model (1.2) or (1.8) is correctly specified. Hence it remains to justify the adequacy of the model (1.2), and we will do so by performing two specification tests based on Walt statistics modified to allow for serial correlation in the errors as proposed by Park and Hahn (1999). The first statistic τ^* tests whether or not the TVC model (1.2) is cointegrated against the alternative that the model is spurious, following the variable addition approach suggested in Park (1990). Specifically, the test is defined as

$$\tau^* = \frac{RSS_{TVC} - RSS^s_{TVC}}{\varpi^2_*} \tag{1.13}$$

where ϖ^2_* is the long-run variance estimate of (u^*_t) given in (1.10), and RSS_{TVC} and RSS^s_{TVC} are the sums of squared residuals, respectively, from the CCR transformed TVC model (1.9) and from the same regression augmented with s additional superfluous regressors. Under the null hypothesis that the true model is a TVC cointegrating model, the limit distribution of the test τ^* is a chi-square with s degrees of freedom. The basic idea underlying the test τ^* is to exploit the tendency of the unit root processes to be correlated with superfluous variables with deterministic or stochastic trend. If indeed the model (1.2) is spurious, it is well known that including such superfluous variables will significantly improve the fit of the regression, and therefore reduce the sum of squared residuals, even when they are known to be irrelevant. Otherwise, if the model (1.2) is an authentic cointegrating regression, the inclusion of such variables will hardly affect the estimation results. The choice of the superfluous regressors plays an important role for the actual performance of the test. In this

[6]See Park and Hahn (1999, Theorem 10).

paper, we use time polynomials $t, t^2, t^3, \ldots, t^s$ as superfluous regressors, following the suggestion given in Park (1990).

The second statistic τ_1^* tests the specification of a TVC cointegrating regression model (1.2) against the cointegrating model with fixed coefficients (1.1) and it is given by

$$\tau_1^* = \frac{RSS_{FC} - RSS_{FC}^s}{\varpi_*^2}, \tag{1.14}$$

where as before RSS_{FC} and RSS_{FC}^s are the sums of squared residuals, respectively, from the fixed coefficient cointegrating regression model (1.1)[7] and from the same regression augmented with s additional superfluous regressors. However the error long-run variance ϖ_*^2 corresponds to that of the TVC cointegrating model (1.9). The properties and limit distribution of the statistic are the same as τ^*. Park and Hahn (1999) showed that this statistic diverges under the TVC cointegrating regression model and remarked that the use of the long-run variance from the FC model reduces the divergence rate of the statistic.

Before proceeding to estimate the demand model for the Mexican case, we discuss how we may specify and estimate the variable z_t in our TVC model (1.2) that captures the seasonal component of the electricity demand.

1.2.3 Modeling seasonality

We observe strong seasonality in the electricity demand, especially in high frequency data such as monthly, which needs to be properly modelled for the consistent estimation of the demand equation. Engle et al. (1989) have indeed shown that the parameters in a cointegrating regression will generally be inconsistent if the seasonality is stochastic. The standard approach to overcome such inconsistency problem has

[7] To deal with models with general error specifications the stadistics τ_1^* are based on CCR transformed models.

been to filter the data either by changing its periodicity (for example, from monthly to annual data) or by taking differences of the variables at the seasonal frequencies. The obvious consequences from using such solutions are reduction in sample size or elimination of some long-run variations in the variables, which we want to avoid due to data limitations and the low convergence rate of the series estimators for the parameters in our TVC cointegrating regression model (1.2). An alternative approach is to directly model the seasonality by choosing a variable that captures the seasonal component of the electricity demand. Traditional candidates for such variable are temperature related-measures such as the number of heating and cooling days per period (for example, in a month) and the average temperature. Certainly, this approach will neither reduce the sample size nor eliminate the elements of long-run variations in the data. However, this approach may introduce the risk of incorrectly estimating the effect of temperature on the rate of electrical equipment usage, if based on a broad temperature measure such as those mentioned above. For example, the use of an air conditioner is determined by the high temperatures during the day time, not by the overall daily average temperature. In this paper we take the latter approach, but with a new temperature measure.

We assume that the seasonality of the electricity demand is mainly due to the weather conditions, and construct a variable that captures such seasonality using intraday temperature data. Specifically, we model the seasonality of the electricity demand using a temperature response function that relates seasonal variations of the demand with the current temperature levels. As a guide to construct such a function, we consider three general patterns that characterize the influence of the temperature on electricity demand. First, we observe that extreme temperatures, either high or low, increase the demand for electricity. This means we would see a U shape graph, if we plot demand versus current temperature. Second, which is related to the previous observation, we also observe that the response of the electricity demand to change in temperature is larger when temperature is high compared to when it is low. That is, the response of the demand is different depending on the current temperature level. This phenomenon would be reflected in an *asymmetric* U shape graph when demand is plotted against temperature. Third, when comparing the responses by sectors, we observe that the residential demand shows the largest responsiveness, while the industrial sector demand exhibits the smallest responsiveness to the same change in temperature. These general characteristics are what we attempt to capture with a temperature response function, which will be used later to construct the seasonal component z_t of the demand. We assume that the temperature response function, say g, takes the following FFF functional form

$$g(\tau_p) = c_0 + c_1\tau_p + c_2\tau_p^2 + c_3\cos(2\pi\tau_p) + c_4\sin(2\pi\tau_p) + \cdots \tag{1.15}$$

where $\tau_p \in [0,1]$ is the normalized temperature at time p (ideally with hourly data) and $c_i,\ i = 0,1,2,3,\ldots$, are the parameters to be estimated.

Although in principle the parameters of the above temperature response function g could be estimated by regressing a measure of the seasonal component of the electricity demand against the terms on the right hand side of (1.15), the data limitations we face generally shape the way in which those coefficients are estimated in practice. It is important to notice that the temperature response function (1.15) is defined in terms of current temperature in order to extract the information about extreme temperatures and duration. In general any intraday data such as temperature readings taken every hour or every three hours can be used to estimate the function g. Although temperature data are available at such high frequencies, it is often difficult to find data for the electricity demand at a frequency higher than one month. Consequently we need to come up with a new measure computed from the available temperature data at the frequency that matches with the available electricity demand data. In this case, we may use the following *expected* response function defined over the period of time determined by the frequency of the demand data

$$\begin{aligned}\int_{p\in t} g(\tau_p)f_t(\tau_p)d\tau_p &= c_0 + c_1\int_{p\in t}\tau_p f_t(\tau_p)d\tau_p + c_2\int_{p\in t}\tau_p^2 f_t(\tau_p)d\tau_p \\ &+ c_3\int_{p\in t}\cos(2\pi\tau_p)f_t(\tau_p)d\tau_p \\ &+ c_4\int_{p\in t}\sin(2\pi\tau_p)f_t(\tau_p)d\tau_p + \cdots \end{aligned} \tag{1.16}$$

where t is the period in which the demand data is indexed (for example, a month) and f_t is the density function of the temperature data over the period t. Notice that the density functions f_t of the temperature data are indexed by t, indicating that we allow the temperature densities to differ across different time periods to capture the changing weather conditions from one period to another in the same year or in different years.

Computing the terms in the equation (1.16) is relatively straightforward. Using intraday temperature data (around 720 observations per month if the data is hourly or 240 if the data are collected every three hours) we can estimate the densities f_t by a non-parametric technique, such as kernel estimation, at each t. Once we obtain the estimates $\tilde{f}_t$ for the densities, we can easily compute the Riemann sum approximation of the integrals in the right hand side of the expected response function (1.16). Finally, the estimates for the parameters in (1.16) are obtained by regressing a measure of the seasonal component of the electricity demand (for which we may use the detrended demand series) against a constant term and the temperature variables represented by some of the integrals on the right hand side of the expected temperature response function (1.16). That is, we estimate the following regression

$$\begin{aligned} d_t' &= c_0 + c_1 \int_{p\in t} \tau_p f_t(\tau_p) d\tau_p + c_2 \int_{p\in t} \tau_p^2 f_t(\tau_p) d\tau_p \\ &+ \sum_{i=1}^{q} \left(c_{2i+1} \int_{p\in t} \cos(i2\pi\tau_p) f_t(\tau_p) d\tau_p \right) \\ &+ \sum_{i=1}^{q} \left(c_{2(i+1)} \int_{p\in t} \sin(i2\pi\tau_p) f_t(\tau_p) d\tau_p \right) + \varepsilon_t \end{aligned} \tag{1.17}$$

where d_t' is the seasonal component of the electricity demand, q the number of trigonometric pairs, ε_t the error term, and the other variables and parameters are defined as in (1.16). The OLS estimation of the above regression will give consistent and efficient estimators $(\tilde{c}_0, \tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_{2q+2})'$ of the parameters $(c_0, c_1, c_2, \ldots, c_{2q+2})'$, provided that all of the included variables in the above regression are stationary. With these estimators we can construct an estimate $\tilde{g}$ for the temperature response function g defined in (1.15) as

$$\begin{aligned} \tilde{g}(\tau_p) &= \tilde{c}_0 + \tilde{c}_1\tau_p + \tilde{c}_2\tau_p^2 + \tilde{c}_3\cos(i2\pi\tau_p) + \tilde{c}_4\sin(i2\pi\tau_p) + \cdots \\ &+ \tilde{c}_{2q+1}\cos(i2\pi\tau_p) + \tilde{c}_{2q+2}\sin(i2\pi\tau_p) \end{aligned} \tag{1.18}$$

and in turn use this to define the seasonal variable z_t of our TVC model (1.2) as follows

$$z_t = \int_{p\in t} \tilde{g}(\tau_p)\tilde{f}_t(\tau_p) d\tau_p. \tag{1.19}$$

One advantage of our seasonality modelling described above is that it encompasses other approaches seen in the literature. For example, the approaches that use the first moment of the temperature distribution as their weather-related variable can be easily formulated in our framework simply by imposing the parameter restrictions, $c_i = 0$ for $i \geq 2$, in the temperature response function (1.15).

1.3 Empirical Implementation of the Model: The Mexican Case

1.3.1 Description of the data

We use the TVC cointegrating regression model (1.2) to estimate the demand for electricity in Mexico for the residential, commercial and industrial sectors. Taking into account the fact that the estimators of the parameters in the TVC models converge at a slower rate compared to those in the usual FC models, we work with a relatively large sample consisted of the monthly data from 1985:01 to 2000:05, with 185 monthly observations in total. The electricity data are obtained from the *Comision Federal de Electricidad* (CFE), and include monthly sales and prices.[8] To identify the demand[9] by sector we follow the CFE's classification that categorizes the customers by their energy consumption. For instance, private customers who demand low voltage are classified into the commercial sector and those who demand medium to high voltage are classified into the industrial sector. In the case of the residential sector, CFE has a specific classification for these types of customers. It is important to mention that the reported CFE's data in general do not correspond to the energy consumption of the reported month because of the lag between the month when the consumption was realized and the month when the transaction was actually registered. This is mainly a result of the routine schedule of payments followed by the government. Accordingly we adjust the demand data before the estimation of the model.

In our study, we use a weighted average of electricity prices, since there are differences in the prices across regions of the country and among the levels of energy consumption per customer. Also, to analyze the impact of the price of substitute

[8]The sales of the CFE represents around 80% of the total in the country. The remaining 20% of the sales is from Luz y Fuerza, also a stated owned company, whose data were not completely available to us.

[9]Because the demand and supply of electricity are always in balance, we use without distinction the terms sales and demand throughout the paper.

goods, such as natural gas and diesel, we use relative prices in our regressions.[10] As a proxy for the disposable income, we use private consumption[11] for the residential and commercial sectors, and an indicator for the industrial production that includes mining, manufacturing and construction for the industrial sector.[12] Regarding the frequencies of the data, the indicators for the industrial production are reported on a monthly basis, while the private consumption data are reported on a quarterly basis. To work with monthly data for our estimation, we therefore transform the quarterly consumption data into monthly, using as a pattern the behavior of the monthly industrial production index. Finally, given that Mexico is a relatively large country, we divide the country into five regions and collect the temperature data from their representative cities[13] to obtain the input variables for the temperature response function. Although the frequencies at which the temperature data are collected vary across regions and over time, we were able to obtain the temperature data taken every three hours for all regions and the months covered in our sample period.

1.3.2 Estimation of the temperature response function

For the estimation of the temperature response function defined in (1.15), we need a measure for the seasonal component of the electricity demand, and estimates for the terms in the expected temperature response function (1.16). To estimate the terms in (1.16), we first estimate the temperature densities by kernel estimation, and use them to approximate the integrals in (1.16) for each region. Then, using the regional electricity consumption as weight, we obtain their weighted averages over

[10] All prices are obtained from the components of the Producer Price Index generated by Banco de Mexico.

[11] Here we implicitly assume that consumers first decide the amount of their income that is saved and consumed, and later they decide how much to consume of each good and service.

[12] All the real variables are obtained from INEGI (Instituto Nacional de Estadistica, Geografia e Informática).

[13] Source of the temperature data, Comision Federal del Agua, Mexico.

Table 1.1: Temperature Response Functions

	Residential Sector		Commercial Sector		Industrial Sector	
	Coefficient	t values	Coefficient	t values	Coefficient	t values
c_0	-0.096	-1.129	-0.241	-3.405	-0.042	-0.980
c_1	-1.251	-3.272	-0.188	-0.590	-0.410	-2.150
c_2	2.418	6.356	1.088	3.428	0.822	4.326
R^2	0.829		0.801		0.706	

regions, and use them as the terms on the right hand side of the expected temperature response function (1.16) for the whole country. A normal kernel with optimal[14] fixed bandwidth is used for the estimation of the density functions. On the other hand, as the measure for the seasonal component of the demand, we use the detrended series of the sectorial electricity sales, with the trend estimated as the centered 12 month moving average of the original series. Given that all of the involved variables are stationary, by nature (temperature) or by construction (seasonal component of demand), standard econometric techniques are applied to estimate the parameters of the regression (1.17). In light of the three general observed patterns on the ways temperature influences the electricity demand, we find from on our Mexican data that the best specification for the temperature response function (1.15) is the one that does not include any the trigonometric pair, for all sectors. The OLS estimators for the parameters in the temperature response function for all sectors are presented in Table 1.1 and the shapes of the functions are shown in Figure 1.1.

The shapes of the temperature response functions are as expected. They show the asymmetric "U" shape, with the scale of the estimated parameters reflecting the fluctuations of the seasonal component of the demand around its mean. We illustrate in the following examples how one may interpret the results in Table 1.1. If we look at the residential sector at 25^0C, the estimated value of the response function is 0.0281

[14]Optimal in the sense that it minimizes the Approximation of the Mean Integrated Squared Error (AMISE) for normal kernels.

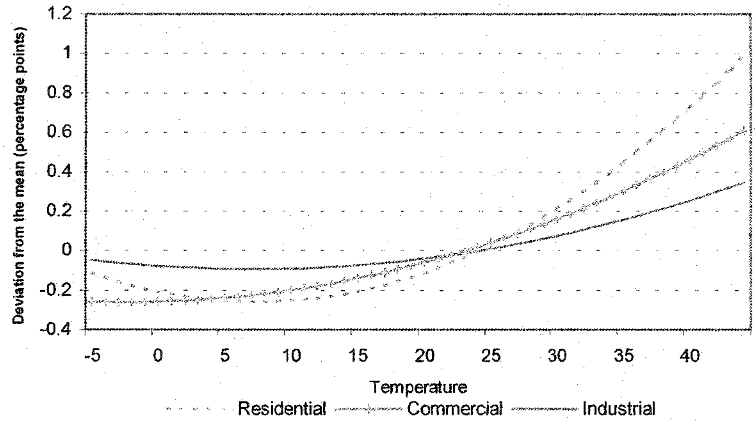

Figure 1.1: Temperature response function by sector.

and at 26⁰C, 0.0617. Hence, if there is an increase in the average temperature from 25⁰C to 26⁰C, the expected result is that the electricity demand will grow by around 3.27 percent.[15] On the other hand, if the temperature drops from 5⁰C to 4⁰C, the expected increase in the demand will be only 0.74 percent. For the industrial sector, the corresponding percentages for the same temperature references will be 1.17 and 0.18 percents, respectively, for an increase and drop in the current temperature by one Celsius degree. These examples show the differences in the responses within the sector, which depend on the current temperature level, as well as the differences across the sectors, with the residential demand being the most responsive to the temperature variations. It is also worth noting from Table 1.1 that the second moment as well as the first moment of the temperature data are important in explaining the seasonal patterns of the demand data. Indeed the second moment is the only variable whose coefficient is statistically significant in the temperature response function for the commercial sector.

[15] Since the response functions give deviations from the average demand, the percentage change is obtained straightforwardly from the following arithmetic operation, $(1+g(s_2))/(1+g(s_1))-1$.

1.3.3 Estimation of the TVC model

In order to properly specify the model for the estimation, we first analyze the non-stationary characteristics of the data. The presence of unit roots in the variables involved is tested using Augmented Dickey Fuller (ADF) test with the short-run dynamics determined by the Schwartz Information Criterion (BIC). According to the results reported in Table 1.2, there is evidence in favor of the presence of unit roots in the private consumption, the industrial production and all the electricity demand series. The results for the price series are, however, mixed and thus inconclusive, which is not surprising given the fact that the electricity prices in Mexico are controlled and heavily regulated by the CFE. Based on these results, we treat the income (y_t) and demand (d_t) series as known to be nonstationary variables, while we allow the price series (p_t) to be either stationary or nonstationary. Then we accordingly specify our TVC model as

$$d_t = \pi + \gamma_t y_t + \delta p_t + \phi z_t + u_t \tag{1.20}$$

Notice that we allow the coefficient γ_t on the known to be nonstationary regressor y_t to vary over time to capture its evolving long-run relationship with the dependent variable d_t, which is also known to be nonstationary. On the other hand, the coefficient δ on the potentially nonstationary regressor p_t is modelled as a fixed parameter. We note here that the CCR methodology, which we will use for the efficient estimation of our TVC model (1.20), is robust to the misspecification about the nonstationarity characteristics of the data, as shown in Kim and Park (1998). Thus, we may just regard the variable p_t, whose nonstationary characteristics is uncertain, as nonstationary and just follow the CCR procedure introduced in Section 2.2.

We specify the time varying coefficient γ_t as a smooth function as in (1.5), and approximate it by a series of functions that include a constant, a linear time trend and

Table 1.2: Unit Root Test (Augmented Dickey-Fuller Test)

Variable	Demeaned Series	Lags	Detrended Series	Lags
d_t				
Residential	-1.183	12	-0.903	12
Commercial	0.250	13	-1.997	13
Industrial	0.550	12	-1.180	12
y_t				
Private Consumption	0.212	16	-1.914	16
Industrial Production	-0.221	2	-3.167	2
p_t				
Residential	-2.876	12	-3.172	12
Commercial	-4.105	1	-3.711	1
Industrial	-2.170	2	-3.515	1
5% critical values	-2.860		-3.41	

Table 1.3: CCR Estimation of TVC Regression Model

	Coefficients by Sector					
Variable	Residential		Commercial		Industrial	
Constant (π)	6.280	(4.04)	6.841	(4.70)	10.33	(7.92)
Price (δ)					-0.048	(-3.6)
z_t (ϕ)	0.995	(28.4)	0.995	(29.5)	0.870	(15.5)
Parameter estimates of the TVC: γ_t						
k	1		2		2	
$\beta_{k,1}$	0.367	(4.81)	0.289	(4.04)	0.226	(3.34)
$\beta_{k,2}$	0.039	(20.5)	0.026	(15.2)	0.041	(20.7)
$\beta_{k,3}$	-0.002	(-8.0)	-0.001	(-5.0)	0.0018	(9.21)
$\beta_{k,4}$	-0.0006	(-1.5)	0.0008	(2.17)	0.0016	(5.43)
$\beta_{k,5}$			0.0014	(5.25)	-0.0017	(-6.9)
$\beta_{k,6}$			0.0003	(1.23)	-0.0006	(-2.3)
long-run variance of the CCR errors						
Ω^*_{11}	0.00278		0.00145		0.00079	
SC	-5.71		-5.90		-6.84	
$\bar{R}^2$	0.975		0.957		0.99	
DW	1.47		2.69		1.56	

Note: The numbers in parentheses are the CCR adjusted t-values.

Table 1.4: CCR Estimation of FC Regression Model

Variable		Coefficients by Sector					
		Residential		Commercial		Industrial	
Constant	(π)	-25.82	(-9.64)	-15.73	(-16.84)	-9.99	(-7.80)
Price	(δ)	-0.44	(-3.47)	-0.07	(-1.09)	-0.25	(-5.82)
Income	(γ)	1.95	(14.93)	1.40	(30.80)	1.29	(19.57)
z_t	(ϕ)	0.70	(5.09)	0.83	(11.63)	0.43	(1.59)
long-run variance of the CCR errors							
Ω^*_{11}		0.0406		0.0068		0.0203	
SC		-4.212		-5.041		-5.028	
$\bar{R}^2$		0.875		0.875		0.928	
DW		1.097		1.867		0.923	

Note: The numbers in parentheses are the CCR adjusted t-values.

k trigonometric pairs, as in (1.5). To determine the number k of the trigonometric pairs to be used in the series estimation of the time varying coefficient γ_t, we use BIC to pick a parsimonious model since it is known to favor simpler models by giving heavier penalties to the models with larger number of parameters. The CCR transformations are based on the differences of the detrended y_t and p_t, and the nonparametric estimators of the long-run Ω and the one-sided long-run Δ covariance matrices defined in (1.11) and (1.12).[16] Table 1.3 reports the final results once the statistically insignificant variables were removed from the models.

Before we analyze the results of our model (1.20), we first examine the validity of our specification. To this end, we use the specification tests τ_1^* and τ^* introduced in Section 2.2, which are constructed here by using four time polynomial terms (t, t^2, t^3, t^4) as the additional superfluous regressors. Table 1.4 reports the results from the fixed coefficient models meanwhile the computed test statistics for the three sectors are presented in Table 1.5. The results of τ_1^* clearly show that the fixed coefficient cointegrating regression model is rejected in favor of the time varying coefficient

[16] For the nonparametric estimation, we used the Parzen window with the lag truncation number selected by using the data-dependent selection rule suggested by Andrews (1991).

Table 1.5: Specification Test

Model by sector	τ_1^*	τ^*
Residential	663.97	6.74
Commercial	438.73	2.47
Industrial	1042.36	11.66
1% critical value	13.28	13.28

(TVC) cointegrating regression model (1.20). Further more, the statistic τ^* suggest that the TVC model is well specified in all sectors at one percent significance level. The evidence is especially strong for the commercial and residential sectors. Notice that in the case of the fixed coefficient model, which specification was rejected, the elasticity of the electricity demand with respect to the income or production is higher than one, and the price elasticity is significant in the residential and industrial sector.

Now that our TVC model (1.20) is tested to be an authentic cointegrated model, we may notice that we allow the coefficient γ_t on the known to be nonstationary regressor y_t to vary over time to capture its evolving long-run relationship with the dependent variable d_t, which is also known to be nonstationary. On the other hand, the coefficient δ on the potentially nonstationary regressor p_t is modelled as a fixed parameter. We note here that the CCR methodology, which we will use for the efficient estimation of our TVC model (1.20), is robust to the misspecification about the nonstationarity characteristics of the data, as shown in Kim and Park (1998). Thus, we may just regard the variable p_t, whose nonstationary characteristics is uncertain, as nonstationary and just follow the CCR procedure introduced in Section 2.2. Now meaningfully interpret the coefficient estimates reported in Table 1.3 as the parameters of the long-run relationships among the variables.

We first note that contrary to the results of the fixed coefficient model, the parameter estimates for the prices are not statistically significant in the demand functions for the residential and commercial sectors. This is still the case even when we include as explanatory variables the indices for the relative electricity prices with respect to the prices of its close substitutes, such as natural gas for domestic use. One possible explanation for this finding is the price distortions from the government subsidies to the electricity prices. Indeed there have been large amount of governmental subsidies in most of the developing countries. In Mexico, for instance, a government report estimates the implicit subsidies to the electricity prices during the year 2000 is in the amount of 4.5 billions of dollars, which amounts to an overall 31 percent subsidy to Mexican electricity prices.[17] The subsidy to the residential customers was approximately 61 percent, while the subsidy to the commercial and industrial customers was only 7 percent with respect to the real cost of electricity. These figures justify very well the lack of explanatory power of the prices in the residential demand for electricity. When there is large amount of subsidy in electricity prices, prices would naturally become weak determinants of the demand for electricity. In such cases, the factors related to electricity availability would become more relevant.

In the commercial sector, much of the burden from the price increases can be treated as cost and eventually passed on to final customers, thereby generating a significant amount of relief for the commercial customers. This along with the lack of flexibility to use alternative energy sources in the commercial sector may explain why the prices are not the significant determinants for the commercial demand for electricity. Also in the industrial sector, we find that the electricity demand does not respond to the electricity prices. However, it turns out that the industrial demand responds to the relative price with respect to the price of diesel, although it did not respond to other relative prices related to the price of natural gas. These findings suggest that generators run by diesel are the main back source of electricity used by the industrial plants for the whole sample period from 1985 to 2000. It is also

[17] SHCP, Source: La Jornada, newspaper, Mexico, March 14, 2001.

consistent with the fact that the use of the generators run by natural gas was promoted only in the last few years. According to our results in Table 1.3, the price elasticity of the industrial electricity demand is around -0.05, which is not nearly as big as those reported for other countries in earlier studies with models of fixed coefficients [18] and that obtained from the rejected fixed coefficient model estimation reported in Table (1.4). In general it is observed that once the TVC is introduced, the estimates for all coefficients in the electricity demand equation become lower than those obtained from the usual FC models used in other studies (see, Westley (1992)).

The estimated values of the time varying coefficient γ_t on the income variable y_t are presented by sector at some representative months in Table 1.6, and Figure 1.2 plots these coefficients for the whole sample period. One consistent result comes out of these estimations is that for all sectors the TVC follows a predominantly increasing path during the entire fifteen years of the study. Since the values of γ_t are less than one but increasing, we can say that in all sectors the demand for electricity is becoming less inelastic with respect to the income variable y_t (private consumption for the residential and commercial sectors, and industrial production for the industrial sector). This suggests either that the stock of electrical equipments and appliances was becoming less efficient in the consumption of energy,[19] or that the new ones are more intensive in the use of electricity. These perspectives are related to the growth sources of the economy and the characteristics of the stock of the electrical equipments. In any case, the changes that have occurred in the values of the time varying income elasticities seem irreversible.

We find remarkable differences among sectors in the behaviors of the estimated time varying coefficients γ_t (income elasticities), and also in the paths they have taken over the sample period. See Table 1.6. In the residential sector, the total

[18] They are between -0.5 and -1. See, for instance, Westley(1992), pp 86.

[19] For example, consider the case when the electrical equipment and appliances are becoming old.

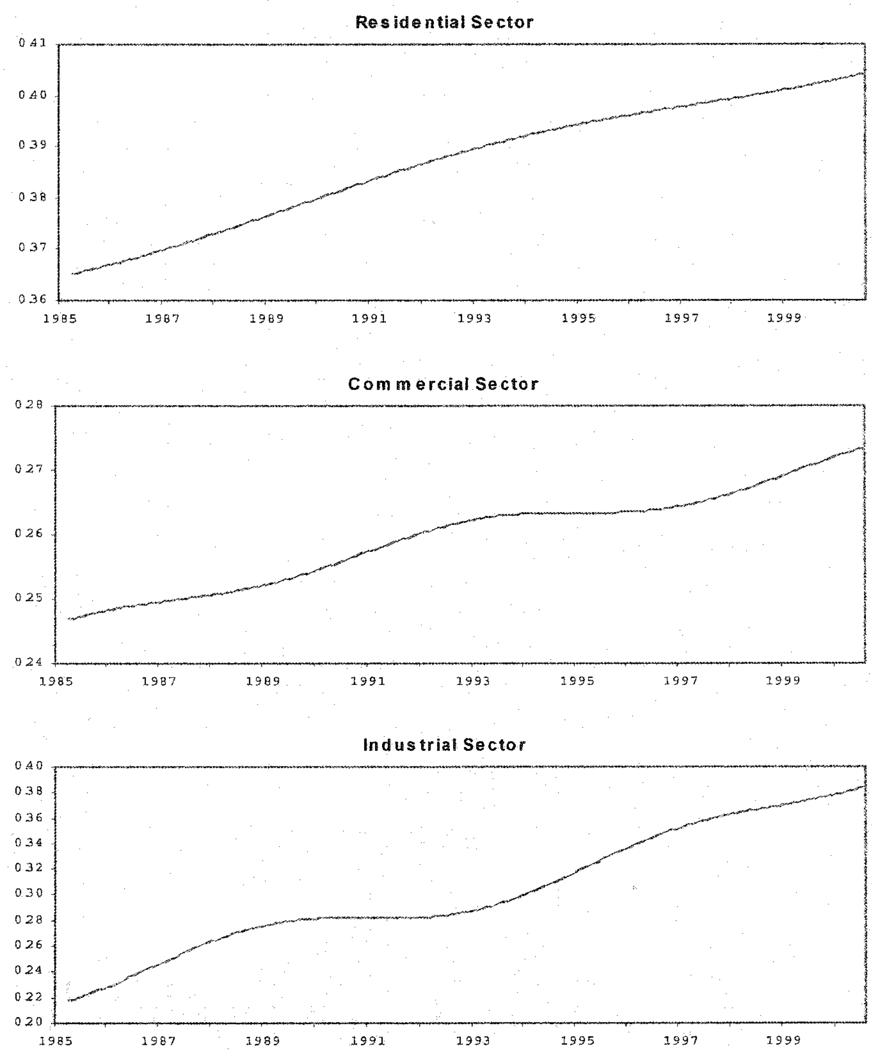

Figure 1.2: Time Varying Coefficient by sector

Table 1.6: Values of the TVC (γ_t)

	Sector								
	Residential			Commercial			Industrial		
Coefficient	Value	a*	b*	Value	a*	b*	Value	a*	b*
$\gamma_{1985:02}$	0.37			0.29			0.23		
$\gamma_{1990:01}$	0.38	4.2	4.2	0.30	2.8	2.8	0.24	6.6	6.6
$\gamma_{1995:01}$	0.39	3.7	8.0	0.31	2.8	5.7	0.25	3.7	10.6
$\gamma_{2000:01}$	0.40	2.2	10.4	0.31	2.9	8.7	0.27	6.3	17.5
$\gamma_{2000:05}$	0.40	0.2	10.6	0.32	0.3	9.0	0.27	0.3	17.9

a* Increment with respect to the previous value of the table (%)
b* Accumulated increment (%)

increments in the values of the income elasticities over the entire sample period is 10%. The path of the elasticity also shows a clear tendency of slowing down. The increments are reduced from 4% in the first five years of the sample to only 2.2% in the last five years, from January 1995 to January 2000. On the other hand, the income elasticity of the commercial electricity demand increased on average 2.7% every five years, and by 8% for the entire fifteen years of the study. We observe much more noticeable variations in the estimates for the TVC (production elasticity) in the industrial sector. The total increments in values of the TVC here is approximately 18% over the entire sample period, which is far greater than those in the residential and commercial sectors. In May 2000, the last period of our sample, the value of the production elasticity reaches the level 0.267, which is still much smaller than the figures reported in other studies of Latin America and the US. They report essentially unitary production elasticity, see Westley (1992, p 87) for example.

In the industrial sector, we find similar patterns of the estimated values of the production elasticity for two sub-periods: the first from 1985 to 1992, and the other from 1993 to 2000. In each sub-sample, the values of the production elasticity increases rapidly for the first 3-4 years, but the increments become smaller for the subsequent years and eventually are stabilized. In both sub-samples, the values of the production elasticity increased by around 6.5%. It is interesting to note that the beginning of the rapid increase in the production elasticity coincides with the periods of recession in the economy (1985 and 1993) as well as with two events that significantly impacted the industrial structure: the inclusion of Mexico to the General Agreement on Tariff and Trade (GATT) organization in 1985 and the negotiation of the North America Free Trade Agreement (NAFTA) in 1993. The recessions may have been reflected in low production levels that did not allow an efficient use of the electrical equipment. If that was the case then the electricity demand response is different depending on the state of the economy: the increment in electricity demand due to an increment in production would be higher if the economy is in recession than if the economy is in expansion. However the increasing path of the production elasticity would be better explained in terms of the specific characteristics of the industry. In this regards the inclusion of Mexico to international trade agreements may have triggered industrial expansion that in turn triggered an intensive use of electricity.

Besides its ability to allow for flexible coefficients, the TVC model also provides a tool for forecasting the future path of the coefficients. The function that is used to model the time varying income elasticity takes the form given in (1.5), which involves only known variables. Hence, once estimated the parameters of the TVC, reported in Table 1.3, such coefficients can be readily used to forecast the path of the production elasticity for the forthcoming months. Property exploited when forecasting electricity demand either by the TVC cointegrating regression model or by the ECMs based on such specification.

1.3.4 ECM and forecasting performance of the model

The ECM is formulated based on the TVC cointegrating regression model of the electricity demand specified in (1.20). From the results on the CCR estimation of the

TVC model (1.20), we first obtain the following error correction terms

$$ec_t = d_t - \hat{\pi}^* - \hat{\gamma}_t^* y_t - \hat{\delta}^* p_t - \hat{\phi}^* z_t,$$

which is nothing but the fitted residuals, and where the values of $\hat{\pi}^*, \hat{\gamma}_t^*, \hat{\delta}^*$ and $\hat{\phi}^*$ are reported in Table 1.3. To focus our analysis on the dynamics of the electricity demand growth driven by those of the economic factors only, we define the following mean and seasonality adjusted demand series

$$\tilde{d}_t = d_t - \hat{\pi}^* - \hat{\phi}^* z_t$$

which extracts the component of the electricity demand explained by income / production and prices (when they appear to be statistically significant).

Then we formulate an ECM for $\tilde{d}_t$ as follows

$$\Delta \tilde{d}_t = \sum_{k=1}^{q} b_{1k} ec_{t-k} + \sum_{k=1}^{p_1} b_{2k} \Delta \tilde{d}_{t-k} + \sum_{k=1}^{p_2} b_{3k} \Delta y_{t-k} + \sum_{k=1}^{p_3} b_{4k} \Delta p_{t-k} + \varepsilon_t \qquad (1.21)$$

We note that more than one lags of the error correction terms ec_t may be included on the right hand side of the above ECM. This is because the presence of the TVC in the error correction term eliminates the collinearity problem between its lags and the lagged differences of the other included variables, which is always an issue in the estimation of the ECMs based on fixed coefficient models. The coefficients b_{1k} of the lagged error correction terms characterize the adjustment path over q periods of time towards the equilibrium value of the demand after an innovation shock from factors not related to the explanatory variables included in the demand equation (1.20). Similar interpretations may also be obtained for the shocks from the variables in the model (1.20).

From the estimation of the ECM we are interested in the coefficients of the lagged error correction terms as they are the new feature of the model. As the data are

Table 1.7: Error Correction Coeficients

	Sector					
	Residential		Commercial		Industrial	
Coefficient	Value	t value	Value	t value	Value	t value
b_{11}	-0.918	-6.487	-0.759	-5.526	-0.791	-5.520

monthly we set p_1, p_2 and p_3 at 12 and focus our attention on the statistical significance of the coefficients b_{1k}. Estimating the model for several values of q we found that including more than one lag of the error correction term in model (1.21) makes all the coefficients b_{1k} statistically not different from cero; however if only one lag of such error term is included the coefficient b_{11} become statistically different from cero and with the expected negative sign which indicates a stable adjustment process towards the long-run equilibrium. Such a result suggests that the adjustment of the electricity demand is concentrated in the immediate period that follows the external shock. The value of the error correction coefficients for each sector are reported in Table 1.7.

Finally to compare the performance of the TVC cointegrating regression model (1.20) with the previous ECM (1.21) and the rejected fixed coefficient model (1.4) we develop an out-of-sample forecast comparison per sector. Our sample data is therefore divided into two subsets: the in-sample set that runs from 1985:01 to 1999:05 and the out-sample set that includes the remaining twelve months. The procedure to forecast the electricity demand for the last year in the sample was the following. All models, the fixed coefficient model (FCM), the TVC cointegrating model (TVCCM) and the ECM were reestimated with the in-sample data. Then a twelve months forecast were estimated using the observed data of the exogeneous variables, y_t, p_t and z_t, and the forecasted values of the time varying coefficients $\hat{\gamma}_t$. The results of such estimation was then compared with the observed electricity demand. In Table 1.8 we present the results of the estimation.

Table 1.8: Forecasting Performance of the Models

	Residential				Commercial				Industrial			
		Forecast				Forecast				Forecast		
t	dt	FCM	TVCCM	ECM	dt	FCM	TVCCM	ECM	dt	FCM	TVCCM	ECM
1999:06	14.807	14.876	14.720	14.713	13.404	13.455	13.428	13.379	15.671	15.717	15.636	15.641
1999:07	14.837	14.785	14.681	14.744	13.502	13.389	13.398	13.468	15.649	15.720	15.629	15.616
1999:08	14.787	14.831	14.749	14.779	13.405	13.427	13.443	13.436	15.650	15.716	15.652	15.676
1999:09	14.679	14.758	14.667	14.633	13.421	13.370	13.390	13.424	15.621	15.701	15.629	15.616
1999:10	14.542	14.807	14.569	14.528	13.279	13.404	13.331	13.265	15.582	15.653	15.592	15.596
1999:11	14.589	14.689	14.494	14.507	13.296	13.350	13.270	13.284	15.591	15.645	15.572	15.575
1999:12	14.563	14.631	14.461	14.498	13.227	13.293	13.227	13.198	15.575	15.646	15.564	15.523
2000:01	14.513	14.512	14.471	14.477	13.314	13.219	13.237	13.289	15.656	15.656	15.578	15.572
2000:02	14.550	14.585	14.535	14.522	13.303	13.281	13.292	13.266	15.625	15.679	15.603	15.584
2000:03	14.650	14.825	14.659	14.639	13.416	13.466	13.396	13.417	15.699	15.816	15.657	15.641
2000:04	14.763	14.786	14.708	14.676	13.446	13.434	13.424	13.389	15.709	15.753	15.667	15.650
2000:05	14.845	15.038	14.805	14.769	13.551	13.576	13.500	13.510	15.733	15.852	15.709	15.703
RMSE		0.119	0.071	0.062		0.067	0.047	0.03		0.073	0.033	0.043

FCM: Fixed Coefficient Model

TVCCM: Time Varying Coeficient Cointegrating Model

ECM: Error Correction Model

RMSE: Root Mean Squared Error

As it was expected based on the specification model tests, the root mean square error (RMSE) of the out-of-sample forecast shows that the TVC cointegrating regression model outperformed the out-of-sample forecast of the fixed coefficient model in all sectors. In particular the reduction of the RMSE is between 30 and 55% between these two models. On the other hand in the residential and commercial sectors the ECM predicts better the path of the electricity demand than the TVC cointegrating model does. However, meanwhile in the residential sector the better performance of the ECM is observed mainly in the short run, i.e. the first three months of the forecasting horizon, in the commercial sector the forecasted demand follows closely the observed levels along all the twelve months of forecast. The better short run response to external shocks observed in the residential sector can be understood taking into account the bimonthly payment schedule followed by the CFE for the sector and the inflexibility of the residential electricity prices. The schedule of payments not only induce some lags in the response of the household but also contribute to dilute quickly its effects on the overall electricity consumption in this two months period. Additionally, the fact that prices do not reflect the conditions of the electricity supply and demand induce a high persistent in households electricity consumption. On the other hand, the long lasting adjustment process of the commercial sector indicates the existence of more economics incentives to actively adjust its electricity demand according to the variability of the private consumption. A different picture is obtained from the forecasting comparison in the industrial sector. The RMSE obtained from the TVC cointegrating regression model outperformed that obtained from the ECM, as it is showed in Table 1.8. Such result suggests that in the industry sector the adjustment in electricity consumption is more related with long term changes than to temporal shocks in the industry. Part of the reason of this pattern is the inflexibility of the equipment to use other kind of energy but also to the lack of available alternative energy sources; for example the natural gas, which is not easily available in Mexico because the limited infrastructure for its distribution. As long as the market becomes less regulated and electricity substitutes become more available, we expect the formation of more economic incentives to continuously adjust electricity consumption and therefore the presence of some lasting effect of the external shocks on the electricity consumption patter of the sector.

1.4 Conclusion

In this chapter we have proposed and applied a time varying coefficient (TVC) cointegrating regression model to estimate the demand for electricity in Mexico with the income/production and electricity prices as explanatory variables. To deal with the unknown distribution of the error term that follows from the approximation of the TVC, we estimate canonical cointegrating regressions with the income/production elasticity modelled as a varying coefficient. Performing Wald type specification model tests we found that the fixed coefficient model was not accepted for any sector, which means that a fixed cointegrating relationship does not exist among the variables. On the contrary, the specification test of the validity of the proposed TVC cointegrating regression model was accepted for all sectors, favoring the notion of a changing relationship between electricity demand and its main determinants. Also we found the following evidences: first, the inclusion of the TVC in the electricity demand model significantly reduced the levels of the estimated coefficients, which represent the elasticities, compared to those estimated from the usual fixed coefficient models. In particular it was found that the income/production elasticity of demand is inelastic for all sectors. This is quite surprising since many earlier studies in the literature reported that the income/production elasticity of electricity demand is near unity. Second, in the last fifteen years such elasticities have taken predominantly increasing paths in all sectors, and do not show evidence of returning to their previous levels. Third, once we assume a TVC in the regression, price becomes irrelevant as an explanatory variable for the long-run behavior of the demand for electricity, except for the case of industrial demand which weakly responded to the relative price of electricity with respect to the price of diesel. This lack of explanatory power of prices in the electricity consumption of the residential and commercial sector may be explained by the rigidities of the prices, they are determined by the government and they are heavily subsidized.

The idea of the temperature response function was also developed to construct a variable that captures the seasonal pattern of the monthly data. In fact the proposed Fourier Flexible Form (FFF) function encompasses other approaches suggested in the literature, for example the inclusion of the average temperature as an explanatory variable in the demand equation. The asymmetric "U" shape form of the function and the differences across sectors were both obtained in our estimations. Using this form, we found that the response of the residential sector is most sensitive to the changes in temperature, while the industrial sector shows the lowest response to similar changes. Another important finding was that the second moment of the temperature data is also a relevant determinant, if not the most important determinant, of the seasonal component of the demand for electricity.

Also we showed the possibility to include more error term lags in the specification of the ECM as a direct result of having TVC in the cointegrating regression model. With this last specification the problems of collinearity presented with fixed coefficients are eliminated. This new feature in the ECM allows to test the possibility of adjustment towards the long-run equilibrium that span for more than one period. For the estimation of the ECM of the electricity demand in Mexico we found that the error correction adjustment process is concentrated in the first period. Also we performed an out-of-sample forecast comparison between the TVC cointegrating regression model, its corresponding ECM and the fixed coefficient model. As it was expected the TVC cointegrating regression model outperform the fixed coefficient model in forecasting electricity demand in all sectors: sometimes reducing the root mean square error more than 50%. In turn, the ECM outperform the TVC cointegrating regression model in the residential and commercial sectors. However some inflexibilities to adjust the electricity demand were found in the industrial sector, which were indicated by the better performance of the TVC cointegrating regression model.

All of these results regarding the evolution and significance of the elasticities and the forecasting performance of the models become relevant when considering the enactment of energy policies based on electricity demand forecasts, in which case the model can be used to forecast the path of the time varying coefficients in the medium run. Finally, among the issues for further investigation are the apparent irreversible increasing trend of the income elasticity, the low level of the price elasticity in the industrial demand and the lack of explanatory power of prices for the residential and commercial demand for electricity.

Chapter 2

Electricity Demand and Supply in Mexico

2.1 Introduction

Wherever consumers obtain electricity supply from an integrated network, altering supply to any one consumer generally affects the cost of supplying remaining consumers connected to the network. In particular, an anticipated expansion of demand in one location could affect the type and level of capital investment in many parts of the network. This consideration is particularly important in a country such as Mexico that is likely to experience not only a rapid expansion in total demand for electricity over the next decade but also a geographical pattern of demand growth that differs somewhat from the historical experience.

In this paper, we first present a model for forecasting electricity demand in Mexico. The model has two components. Forecasts of the aggregate demand for electricity are derived by fitting a time series model to the aggregate production data. Using data disaggregated to the regional level we also estimate a model of regional demand shares. The two models are then combined to yield a forecast of demand at the regional level.

In section 3 of the chapter, we present a simplified model of the Mexican electricity transmission network. We use the model to approximate the marginal cost of supplying electricity to consumers in different locations and at different times of the year. In the final section of the chapter, we examine how costs and system operation will be affected by proposed investments in generation and transmission capacity and the forecast growth in regional electricity demands.

The analysis presented in the chapter has implications for a number of critical policy issues. In particular, our model reveals that the marginal costs of supplying customers differ from electricity prices. Subsets of consumers are either being taxed or subsidized, albeit often in a hidden or implicit way. Since such taxes or subsidies affect the efficiency of resource use, they ought to be important to policy discussions regarding the electricity industry.

The marginal cost of supplying electricity in different locations or under different load conditions also has implications for how regulatory reform is likely to affect different types of customers and therefore the political feasibility of reform. The largest obstacle to such reforms is that they are likely to induce substantial cost reductions, primarily through the elimination of excess employment in the industry. Current employees in the industry therefore constitute a powerful vested interest opposed to reform. Altering the system so that prices more closely reflect marginal costs is also likely, however, to make some consumers worse off and they, too, are likely to oppose reform.

Our demand forecasts also raise some critical policy issues. They imply that large investments in the Mexican electricity industry will be needed over the next decade. If the electricity industry remained fully publicly owned, the government of Mexico would need to raise significant revenue to fund these investments. Mexico has many alternative valuable uses for scarce tax revenues, however, and most of these alternatives are far less amenable to private sector involvement than is electricity supply. It therefore is not surprising that the government has turned to the private sector to supply much of the needed generating capacity. The route the government has taken, however, is to rely on build, lease and transfer (BLT) projects. Under these schemes, the private sector builds the new plant, leases it under a long term contract with the government-owned utility, and ultimately transfers the plant to government ownership at a specified future date. This approach leaves the government firm in charge of operating the plant. It also leaves the government firm bearing all the risks associated with inaccurate forecasts of future electricity demand.

Another approach would be to reform and restructure the industry in a way that allows a competitive wholesale electricity market to develop. Private investors then would not only finance investments in the industry, but also would transfer risks from consumers to the capital markets where they can be borne more efficiently. The reforms would need to split the existing publicly owned firms into many separate firms to ensure that the industry remains competitive enough to protect the interests of Mexican consumers. The transmission, distribution and generation functions of the existing firms would also need to be separated. New entrants to the industry would not have any confidence that they could obtain non-discriminatory access to the transmission and distribution networks if the operator of that system continues to own generating plant.

Another advantage of developing a competitive wholesale market is that prices would more closely reflect the true marginal costs of supply. In particular, a competitive wholesale electricity market would eliminate cross-subsidies hidden in deviations between prices and marginal costs of service.

2.2 Forecasting regional electricity demands

Electricity demand is measured by the metered final consumption of end users. To supply power to consumers, however, generating plants also have to supply sufficient energy to compensate for the losses incurred in the process.[1] Hence, any forecast of power needs must take account of losses that in some cases are hard to identify. In particular, losses in Mexico arise not only from resistance losses on the transmission and distribution wires, but also from theft. The approach we take is to forecast total power generation. This implicitly assumes that there is a constant relationship between losses and total demand.[2]

2.2.1 Modeling aggregate electricity demand

The methodology used to make aggregate demand forecasts is based on the model described in Chapter 1. The model is fit to total power generation data from Comisión Federal de Electricidad (CFE) over the period January 1987 to November 2001. Essentially, the logarithm of total power generation (Q) is related to GDP (y), the relative price of electricity (p), and a variable (z), based on temperature records, that accounts for seasonal variations. Details of the model and the estimated equations can be found in Appendix A.

2.2.2 Using the model to forecast aggregate demand

In order to use the estimated model to forecast electricity demand, we need to forecast the determinants, y, p and z. We use the average pattern holding over the sample period for the temperature variable z. To forecast y, we use the GDP growth forecast for 2002 and 2003 made by specialists and collected and reported by the Central Bank

[1]In the year 1999, for example, Mexican electricity consumption by sectors represented 144,922GWh, or about 80% of the total 180,977GWh produced in the country. Net imports of electricity into Mexico in 1999 were only 524GWh. Consumption within the generating plants was about 8,887GWh, or 5% of total production. The remaining 27,621GWh (approximately 15% of domestic production) represents transmission and distribution losses in the system and losses due to theft.

[2]Given the lack of storability of electricity, the consumption of electricity (losses plus demand from agents) is always equal to its generation.

of Mexico.[3] Beyond 2003, we assume that the annual GDP growth rate converges gradually to an equilibrium level that gives an average growth of 5.2% for the rest of the decade. This is the average growth rate assumed by the CFE in its projections of electricity sales and has the virtue of making our forecasts more comparable to those of the CFE.[4]

In order to forecast p, we note that the Mexican government has a stated policy of applying a monthly adjustment to electricity prices that is aimed at compensating for the effect of inflation. In practice, the adjustments have not kept the relative price of electricity constant. Indeed, as we show in Appendix A, the relative price trends to drift over time. The rate of price adjustment has also varied for different types of customers.[5] Evidently, politics has played a role in setting electricity prices. Since we do not have a model of the political process, we simply assume that real electricity prices will fluctuate around the mean observed in the previous six years. We preserve the monthly seasonal component of p by estimating a regression (also presented in Appendix A) that allows the mean value of p to differ systematically from one month to the next.

Substituting the forecast values of y, p and z into the estimated model, we arrive at the forecast of annual electricity demand in Mexico from 2002 to 2010 as reported in Table 2.1. Our model actually delivers monthly total power generation forecasts. These have been aggregated to yield the corresponding annual values. For some of the subsequent analysis, however, we will be interested in the monthly variations.

For comparison, we have included the results before and after the recent price

[3] Private Expectation Survey, Bank of Mexico, May 20, 2002. The consensus forecast is reported at http://www.banxico.org.mx/eInfoFinanciera/FSinfoFinanciera.html

[4] Secretaría de Energía. "Prospectiva del sector eléctrico 2001-2010". Page 96.

[5] Since January 2001, the montly adjustment for the residential sector has been 1.00526. This corresponds to an annual increment of 6.5%. For the service sector, the average monthly adjustment was 1.00682, yielding an annual increment of 8.5%. The adjustment factor for the electricity price charged to industry is indexed to the price of power generation fuels. This information was obtained from the CFE, http://www.cfe.gob.mx/www2/Tarifas

Table 2.1: Power needs forecast 2002 - 2010

	GDP	Total PowerGeneration			
		With price increase		Without price increase	
Year	Growth (%)	GWh	Growth (%)	GWh	Growth (%)
1991		118,348			
1992	3.54	121,604	2.75		
1993	1.94	125,864	3.50		
1994	4.46	137,684	9.39		
1995	-6.22	142,503	3.50		
1996	5.14	151,890	6.59		
1997	6.78	161,385	6.25		
1998	4.91	170,983	5.95		
1999	3.84	180,917	5.81		
2000	6.92	191,340	5.76		
2001	-0.38	191,340	-0.14		
2002	1.50	199,857	4.60	203,830	6.68
2003	4.30	207,724	3.94	215,895	5.92
2004	5.45	220,942	6.36	229,921	6.50
2005	5.91	234,428	6.10	244,585	6.38
2006	6.20	247,401	5.53	258,742	5.79
2007	5.96	260,008	5.10	272,487	5.31
2008	5.85	273,247	5.09	286,950	5.31
2009	5.90	288,510	5.59	303,660	5.82
2010	5.90	306,221	6.14	323,103	6.40
Average Growth Rates					
1991-2001	3.09		4.94		4.94
2001-2010	5.20		5.38		6.01
1991-2010	4.09		5.15		5.45

Note: The electricity price increaseresults from the reduction of subsidies to households. We calculate this will result in a 6.97% increase in p.

adjustment that reduced federal subsidies in the residential sector. This one time increase in residential electricity prices is estimated to be around 30%.[6] To translate the residential price increase into an effect on p, we note that this sector represented 23.23% of total electricity sales over the last five years. Hence, the overall increase in electricity prices from the subsidy reduction will be about 6.97%. Our estimated model implies that a price increase of that magnitude will reduce the average annual growth rate of electricity generation in the period 2001-2010 from 6.01% to 5.38%, with the effects concentrated in the first two years.[7]

2.2.3 Forecasting regional demand shares

Mexico has large contrasts in climate, topography, resource availability, economic development and population density among its different regions. These contrasts have direct implications for the optimal siting of power generating plant and the distribution of electricity demand around the country. Regions with insufficient natural energy resources, underdeveloped infrastructure, or a large demand for power, are likely to import electricity generated elsewhere. Conversely, regions with substantial hydroelectric generating capacity, or substantial reserves of fossil fuels, are likely to have surplus power available for export. Differences in climates also mean that peak demands for electricity do not necessarily occur at the same time, allowing regions to save on generating capacity by exchanging power with neighboring regions.

To capture the regional differences in the Mexican electricity demand we began with data on electricity sales in the 14 administrative regions of the CFE. Although

[6] According to a report in the newspaper *Reforma* on February 9, 2002, Banxico estimated the reduced subsidy would increase residential electricity prices by 30%.

[7] This estimated reduction in power needs is probably an upper bound. Although household electricity demand is likely to be more elastic than demand in the services sector (where lighting is the dominant use), it would be less elastic than demand in industry. Using the overall elasticity may thus overstate the responsiveness of demand to price. In addition, a price increase for households is likely to raise electricity losses through theft.

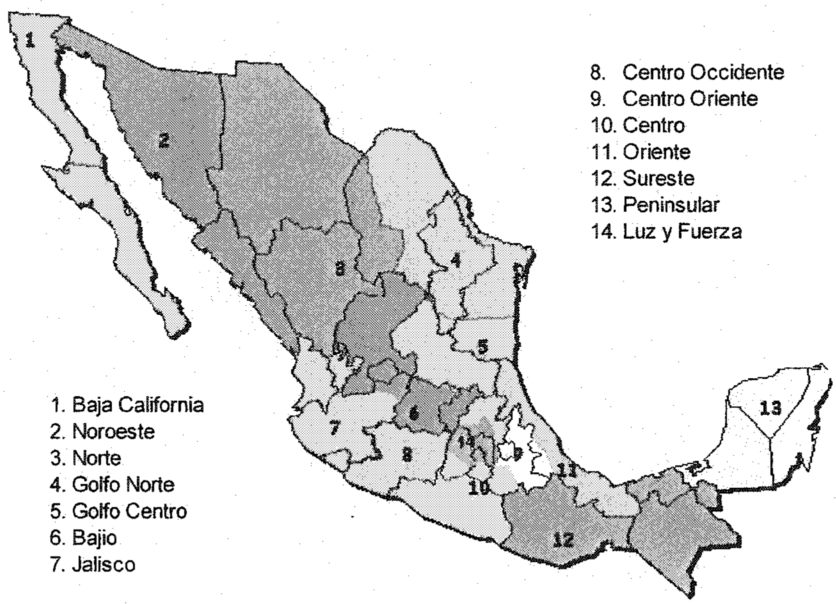

Figure 2.1: Administrative regions of the CFE

sales do not necessarily reflect demand,[8] they are likely to be a better indicator than local production. In most of the cases, regional power consumption will differ from regional power generation because of trading among regions through the transmission system. In order to link electricity supply and demand we also need to account for losses. In this section of the chapter, we compute and forecast regional sales shares as a first approximation to the regional power consumption. The next section focuses on estimation of the losses. The administrative regions of the CFE are illustrated in Figure 2.1.

To forecast regional sales, we hypothesized that sales *shares* would change only slowly through time as the relative industrialization and population growth rates shift from one region to the next. In particular, we estimated a set of equations that allowed the shares S_{it} of demand in region i in period t to vary from one month to the

[8] Electricity demand and sales can differ because of billing lags and the theft of electricity. If the latter factors do not differ systematically across regions, however, the pattern of sales ought to approximate the geographic distribution of demand.

next and to grow at a declining or accelerating rate. Details of the modeling strategy are provided in Appendix A.

The regions with the highest (region 8) and second highest (region 10) positive growth in demand share both include suburban parts of Mexico City. The positive relative growth in both of these regions is, however, slowing down. By contrast, the third fastest growing region (region 4, the north gulf including Monterrey) has an accelerating growth rate. Baja California has an even stronger accelerating growth rate, although its current growth rate is below that of the north gulf. Other regions with a reasonably strong, and statistically significant, growing share of demand include Norte (region 3) and Golfo Centro (region 5), both of which border region 4. Unlike region 4, the growth rate of their demand shares is tending to decline, although the deceleration is not significant in region 3. The Yucatan peninsula (region 13), like region 3 has a positive but weakly decelerating growth in demand share.

The central Mexico City region served by Luz y Fuerza exhibits the strongest declining share of demand and there is little evidence that the trend is changing over time. Since this is already the most developed area in Mexico, it is not surprising that the market has relatively fewer opportunities to grow. The share of demand in region 11 (Sureste, the gulf coast east of Mexico City) is falling almost as fast as for Mexico City, but there is stronger evidence that the rate of decline is slowing. Region 7 (Jalisco) is the only other region with a strong and statistically significant declining share of demand, but it also reveals stronger evidence that the rate of decline is slowing.

The estimated monthly changes in shares (presented in Table 5.6 in Appendix A) allow the regions to be placed into groups with similar patterns of demand variation across months. Regions 1 (Baja California) and 2 (Noroeste) have a tendency to show smaller demand shares February–April and larger shares June–November. Regions

5 (Golfo Central) and 13 (Peninsula) also have significantly smaller demand shares February–April, but do not share the tendency of the two northwestern regions to have significantly higher demand shares in the second half of the year. Region 11 (Oriente), which lies between regions 5 and 13 on the Gulf coast, has demand shares that do not differ significantly from month to month. The remaining northern regions, 3 (Norte) and 4 (Golfo Norte) are like regions 1 and 2 in that they have significantly larger demand shares May–November, but they do not have significantly lower shares in first half of the year.

The remaining central (6, 9 and 14) and southern Pacific coastal (7, 8, 10, 12) regions tend to have smaller, not larger, demand shares in the second half of the year. In regions 7 (Jalisco), 10 (Centro Sur), 12 (Sureste) and 14 (Centro, Luz y Fuerza) the months with significantly lower demand shares last April–November. In regions 8 (Centro Occidente) and 9 (Centro Oriente) the period with significantly lower demand is only July–October. The northernmost of these regions, 6 (Bajio), only has a significantly lower demand share from August–November. Regions 6, 8 and 9 are also the only ones to have significantly larger demand shares in the early part of the year. In region 6 it lasts January–June, while in regions 8 and 9 the period of above average demand share is shorter, lasting February–April.

The estimated regional share model can be used to forecast demand shares by month and year. We can obtain an idea of how the different growth paths influence demand shares by examining forecast annual demand shares for 2005 and 2010. These are presented in Table 2.2. They suggest that by 2005 the demand in Golfo Norte will be approximately equal to, if not slightly above, the demand in the Mexico City area served by Luz y Fuerza. The share of the Luz y Fuerza region is expected to decline further by 2010. The regions surrounding Mexico City (Bajio, Centro Occidente, Centro Oriente and Centro Sur) will, however, all see growing shares of demand.

Table 2.2: Actual 1999 and forecast electricity demand shares by administrative region (%)

	Region	1999	2005	2010
1	Baja California	5.83%	6.65%	7.39%
2	Noreste	7.09%	7.22%	7.13%
3	Norte	7.94%	8.14%	8.17%
4	Golfo Norte	15.28%	17.02%	18.72%
5	Golfo Centro	4.66%	4.56%	4.49%
6	Bajio	8.79%	8.89%	8.95%
7	Jalisco	5.86%	5.69%	5.72%
8	Centro Occidente	5.57%	5.93%	6.08%
9	Centro Oriente	4.42%	4.56%	4.65%
10	Centro Sur	3.70%	3.58%	3.59%
11	Oriente	6.25%	5.47%	5.05%
12	Sureste	2.96%	2.95%	3.00%
13	Peninsular	2.87%	2.98%	3.08%
14	Luz y Fuerza	18.78%	16.36%	13.97%
	Total	100.00	100.00	100.00

Table 2.3: Power demand and demand growth (from 1999) by region

		1999	2005		2010		Annual
	Region	GWh	GWh	% Inc	GWh	% Inc	growth
1	Baja California	8,165	13,312	63.0	20,031	145.3	8.50
2	Noroeste	10,331	14,460	40.0	19,335	87.2	5.86
3	Norte	11,458	16,298	42.2	22,153	93.3	6.18
4	Golfo Norte	21,908	34,105	55.7	50,743	131.6	7.94
5	Golfo Centro	6,589	9,142	38.8	12,170	84.7	5.74
6	Bajio	12,849	17,809	38.6	24,247	88.7	5.94
7	Jalisco	8,454	11,402	34.9	15,506	83.4	5.67
8	Centro Occidente	7,785	11,874	52.5	16,466	111.5	7.05
9	Centro Oriente	6,429	9,140	42.2	12,601	96.0	6.31
10	Centro Sur	5,398	7,165	32.7	9,737	80.4	5.51
11	Oriente	9,128	10,968	20.2	13,684	49.9	3.75
12	Sureste	4,206	5,918	40.7	8,127	93.2	6.17
13	Peninsular	4,144	5,967	44.0	8,337	101.2	6.56
14	Luz y Fuerza	27,445	32,763	19.4	37,868	38.0	2.97
	Total	144,285	200,324	38.8	271,005	87.8	5.90

Baja California, like Golfo Norte, is also likely to see a substantial increase in its share of demand by 2010.

We obtain a forecast of regional electricity demand by combining the overall demand forecast derived in the previous section of the chapter with the forecasts of regional shares. Table 2.3 gives the resulting regional demands (in GWh annually) and total and average annual growth rates for demand in each region.

The substantial differences in forecast regional electricity demand growth rates may have important policy implications. A high overall rate of growth of demand for electricity will require substantial investment in the industry. This problem could be exacerbated, however, if the geographical distribution of future demand differs greatly from the current distribution. The above average growth of demand in the northern regions, for example, is likely to require a substantial increase in generating plant in the north or a substantial upgrading of the transmission links either from further south in Mexico or from the US.

2.3 A model of the electricity supply system

In this section, we discuss a model of the Mexican electrical network that allows us to approximate the spatial and temporal variations in the marginal cost of supplying electricity in 1999. Discussion of some of the more technical issues, including an outline of the equations included in the model, can be found in Appendix B.

The model calculates the least cost pattern of electricity production and transmission required to meet a discrete number of demand loads on the system. The demands are chosen to be "representative" of different times of the year. The geographic dispersion of demand also is approximated in a discrete way by assuming that the demand for a particular region is concentrated at a single "node." The model delivers an estimate of the "usual" short run marginal cost of supplying electricity in different regions and at different times of the year.

The aggregated demand data and the broad assumptions about other technical characteristics of the system make the marginal costs obtained from the model approximations to the true marginal cost. They are useful for indicating how prices might change were they to more closely reflect marginal costs. The model also is useful for examining longer run issues, such as the effects of investment and demand growth on average system costs. Our model would not be useful, however, for dispatching generators to ensure least cost operation of the system or for predicting how costs or system operations are likely to be affected by an emergency.

2.3.1 Approximating spatial and temporal variation

Geographical structure. In principle, the cost of supplying electricity will differ at every single connection point to the transmission network. For our current purposes, it is impractical to calculate all these nodal prices. We instead consider a discrete approximation to the physical layout of the network and the location of major centers of supply and demand.

In general, there is no unique method to determine the boundaries of the geographic regions. The appropriate level of aggregation can depend on the objective of the analysis. For example, a highly aggregated model may be sufficient when the objective is to identify electricity trade among countries, states or utility districts. Small or isolated regions can be subsumed into larger regions without having much of an impact on the questions of interest.

The number of regions included in the model, and the size of each, also depends on the available data. We based the geographical division of the country on the 32 "transmission regions" defined by the CFE. The regional data examined above was based on the CFE accounting records. In order to calculate costs or examine opti-

Table 2.4: Generating capacity, production and estimated demand by transmission region, 1999

Transmission Region	Generators at year end 1999 Total	Type[a]	Total MW	Output GWh	Demand GWh
1. Sonora Norte	4	T	807	3,876	4,691
2. Sonora Sur	6	3T, 3H	746	3,343	3,261
3. Mochis	8	2T, 6H	1,167	3,050	2,288
4. Mazatlán	1	T	616	3,467	992
5. Juárez	1	T	316	1,561	4,197
6. Chihuahua	7	5T, 2H	1,118	6,289	3,698
7. Laguna	5	T	643	3,619	6,168
8. Rió Escondido	5	3T, 2H	2,710	18,359	2,238
9. Monterrey	10	T	1,215	5,841	19,214
10. Huasteca	1	T	800	4,732	3,922
11. Reynosa	2	T	521	2,680	3,090
12. Guadalajara	9	1T, 8H	1,352	2,147	9,620
13. Manzanillo	2	T	1,900	11,194	1,355
14. Ags-SLP	4	1T, 3H	720	3,963	7,384
15. Bajío	13	3T, 9H, 1R	1,447	8,895	17,197
16. Lázaro Cárdenas	3	1T, 2H	3,395	16,043	414
17. Central	20	7T, 13H	3,526	19,023	43,089
18. Oriental	17	3T, 12H, 1N, 1R	4,719	29,835	14,796
19. Acapulco	4	1T, 3H	681	1,498	2,212
20. Temascal	3	2H, 1R	358	1,736	1,521
21. Minatitlan	1	H	26	119	2,989
22. Grijalva	7	H	3,928	17,342	2,918
23. Lerma	2	T	164	902	924
24. Mérida	4	T	277	1,261	2,415
25. Chetumal	1	T	14	12	275
26. Cancún	7	T	529	1,471	1,199
27. Mexicali	5	2T, 3R	684	4,680	3,061
28. Tijuana	2	T	830	2,785	5,118
29. Ensenada	2	T	69	9	906
30. Cd. Constitución	6	5T, 1R	120	402	190
31. La Paz	2	T	156	709	825
32. Cabo San Lucas	1	T	30	59	153
Total	164	83T, 73H, 1N, 7R	35,585	180,901	172,319

a. T = oil, coal or gas thermal, H = hydroelectric, N = nuclear,
R = plant using "renewable" wind and geothermal energy sources.

Figure 2.2: Mexican electricity transmission network, 1999.

mal investments, we need to relate the demand data to the physical supply system, primarily the generating plants and transmission lines. The engineering data supplied by CFE is organized by transmission region. This subdivision highlights the high voltage transmission network that connects the most important industrial and population centers of the country. The geographical distribution of such regions and the 1999 transmission network (with its capacities in MW) are illustrated in Figure 2.2. Table 2.4 gives basic data on generating capacity located in the 32 transmission regions.

The number of transmission regions exceeds the number of accounting regions, and the boundaries of the two sets of regions sometimes overlap. We constructed the demand shares per transmission region by disaggregating the shares for the 14 administrative regions into the 32 transmission regions based on population data of the main Mexican cities.[9] The right-hand column of Table 2.4 shows our allocation of the 1999 demand data. The remainder of the analysis will be based on the transmission regions with demand imputed in this manner.

By the end of 1999, the Mexican electric supply system had 164 active fixed generating plants[10] with a total effective capacity of 35,584 MW. While 44% of the plants were hydroelectric and 46% thermal, the capacity shares were more unequal, with these two types of plant supplying 27% and 63% of the total capacity respectively. Capacity data for each plant were collected from annual public reports of the CFE.[11] We approximated the current annual "availability" of each plant by its maximum annual production in the last three years of operation.

Temporal structure. An important feature of most electricity systems is that the demand load on the system varies over time. In particular, extreme weather conditions can significantly affect the demand for electricity.[12] Our analysis of the regional variation of demand showed that, in the north of Mexico, electricity consumption is considerably higher during the second half of the year. In the southern half of the nation, demand shares tend to be lower during this period.

The demand for electricity for cooking also displays a distinct daily pattern that also tends to coincide with the daily fluctuation in demand for electricity from electrified commuter rail systems. Industrial demand for electricity tends to be higher during daylight hours, although 24 hour operation of some large plants can also raise the demand for electricity during off-peak periods. The demand for electricity for

[9] To allocate the forecast future demand shares to the transmission regions, we used the population growth projections of the *Consejo Nacional de Población* (CONAPO), http://www.conapo.gob.mx, the main governmental institution in Mexico involved in demographic analysis.

[10] Officially, 170 plants were said to be available in December 1999, but not all of them operated at some time during that year.

[11] The relevant CFE reports are titled "Informe de Operacion."

[12] The seasonal pattern of electricity demand also is affected by the fact that many businesses have non-working days at the same time.

lighting (for which there are no good substitutes) is, of course, highest during the night, but drops substantially in the early morning hours. Electrical water heaters can be operated at night when the demand for electricity is otherwise relatively low, but in this application natural gas is a strong competitor for electricity.

In addition to the daily and seasonal fluctuations in demand, there are also substantial weekly patterns. Most obviously, demand is lower on the weekends than during the week.

The seasonal, weekly and daily fluctuations in demand matter because the costs of supplying electricity can change substantially as a function of both the total system load and its geographic distribution. The generating plant have different costs of production, while there are also costs associated with generating electricity in one location and transmitting it large distances to be consumed elsewhere. Furthermore, the difficulty[13] of storing electrical energy makes it difficult to arbitrage price differences over time. We therefore need to approximate the pattern of demand fluctuations over time in order to obtain a realistic idea of how costs vary over time. As with the geographical diversity discussed above, however, a discrete approximation to the time variability allows us to simplify the model.

Again, the optimal level of detail will depend on the purpose for which the model is being constructed. As with the geographical information discussed above, however, the detail we can include in the model is limited by the data that are available to us.

The Secretary of Energy[14] published average *daily* load curves for the year 1999. These curves are available separately for the North and South areas of the country,[15] for two seasons, Summer (May to August) and Fall (November to February), and

[13] In some situations, pumped storage can be used to store a limited amount of energy. More generally, the availability of hydroelectricity increases the intertemporal substitutability of electricity supply.

[14] "Prospectiva del sector eléctrico 2000-2009", Secretary of Energy.

[15] The North region includes the North and Northeast areas. The South region includes the Occidental, Central, Oriental and Peninsular areas.

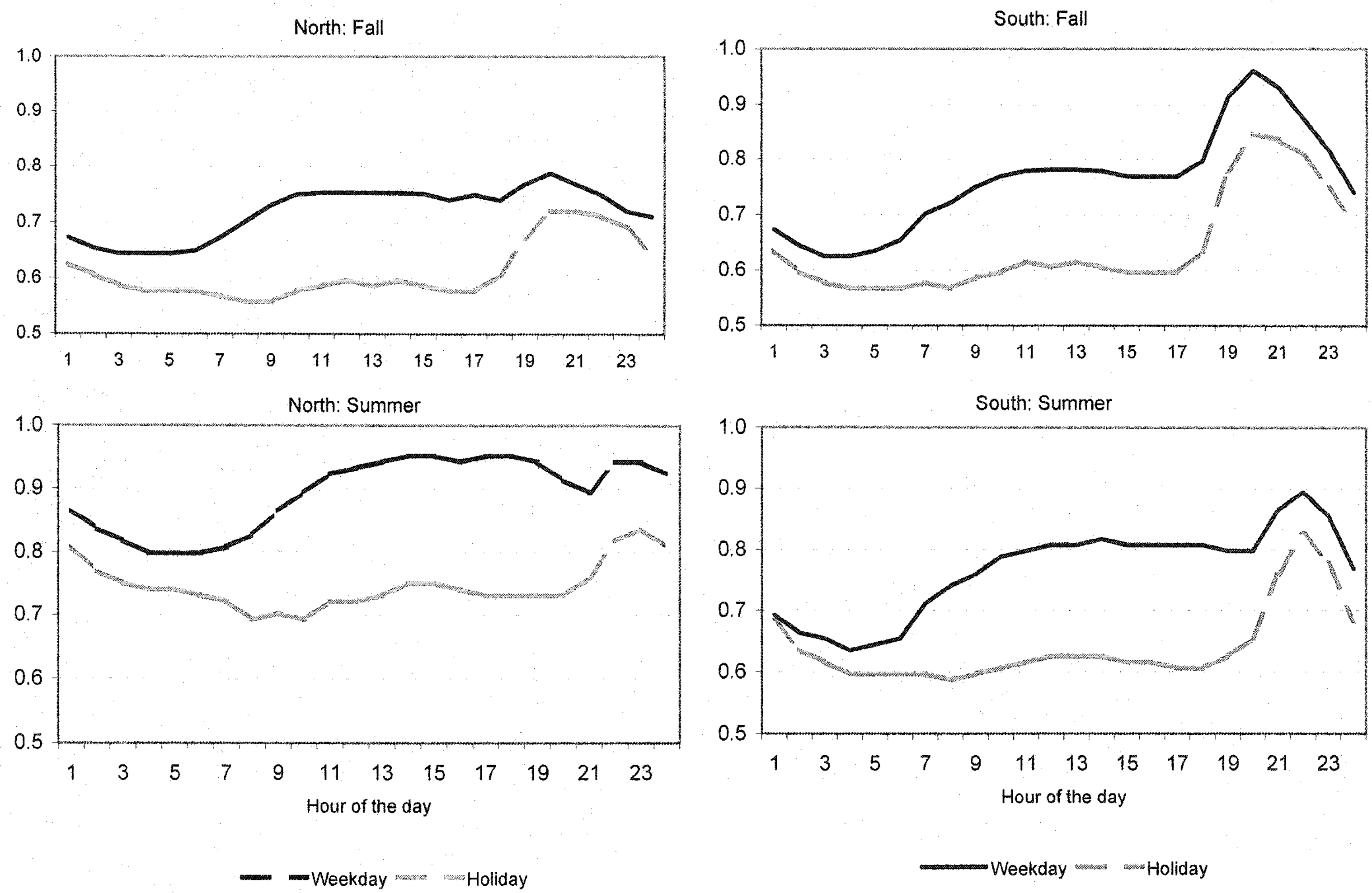

Figure 2.3: Representative daily load curves, normalized to the maximum annual demand, 1999.

for weekdays and holidays. The curves, graphed in Figure 2.3, represent the average demand per hour during a typical day expressed as percentage of the maximum annual demand.[16] For the remaining months (March, April, September and October) we constructed a daily load curve that was a weighted average of the two published curves, having as weights the electricity demands in the Summer and Fall seasons. We assume that all the transmission regions within an area (North or South) have the same daily pattern of electricity demand and thus the same daily load curve shape.

We derived the total demands (weekdays plus weekends and holidays) in each of the 32 transmission regions in each season by aggregating the *monthly* demands. The daily load curves were used to allocate demand in each season to weekdays versus weekends or holidays. Finally, demands in a weekends-holidays "season" were obtained by aggregating the weekend or holiday components across seasons. In summary, the data allows us to calculate, in each of the 32 transmission regions, the electricity demands for four seasons:

1. Fall, covering working days for the 4 months from November to February;
2. Summer, for working days for the 4 months from May to August;
3. Shoulder, for working days for the 4 months of March, April, September and October; and
4. Weekends-Holidays, that includes non-working days during the whole year.

To capture the intraday demand dynamics, we could, in principle, use the average daily load curves in each season to construct hourly electricity demand.[17] However, to keep the model manageable, we approximate the hourly demand fluctuations using step functions. The details of this approximation procedure are provided in

[16] None of the load curves in Figure 2.3 attain the maximum demand since they represent "average" loads in each season.

[17] Even this involves a simplifying assumption that all days in a season have the same demand pattern that can be scaled up or down according to the monthly demand.

Appendix A.

For constructing the hourly demand in 2005, we assumed that the daily load curves are the same as those in 1999. This approach was used because of the limited nature of our investigation. In principle, one could estimate the change in the load duration curves over time based on changes in the prices of electricity (including changes in peak relative to off-peak prices), economic growth (as measured by GDP) and weather conditions. In effect, the demand estimation carried out above would be repeated for different load patterns on the system. The estimated variation in demands by time of day (as determined by system load) could then be used to make forecasts in place of the aggregate forecasts with an unchanging pattern of demand that we have used.

2.3.2 Generation and transmission technologies

To calculate the costs of supply, we need information about the generation and transmission technologies. With regard to the generating plants, we need to know not only generating costs but also capacities and the average level of availability. For the transmission links, we need to know the overall capacity and, to calculate the loss factors, the number of circuits per link.

Generating plant costs. Regardless of the type of generating technology, we assume that the cost function of a plant can be represented by two components. The first component is an annual fixed cost. It includes the fixed components of the operation and maintenance costs of the plant, such as the labor force required to keep the plant operational even if it is not generating electricity. We assume that the fixed costs, given in dollars per MW, are a linear function of the total capacity of the plant set at the beginning of the year. The variable cost is the second component of the generating cost of each plant. It includes the cost of fuel and some other operation and maintenance costs, mainly on the cost of labor, that vary with the amount of electricity that the plant is generating. We assume that this cost is a linear function of the MWh generated by the plant. The variable cost per MWh is constant during a given period, but could vary from one period to the next as a result of seasonal fluctuations in fuel prices in particular.

We based the operation and maintenance costs for thermal plants on cost estimates provided by the CFE (COPAR, 1999) for "typical plants" in Mexico classified by size of the plant and type of technology.[18]

The fuel cost of thermal plants was calculated using the average technical efficiency of each plant (fuel/MWh). In turn, we obtained the average efficiency of a plant by dividing its overall fuel consumption for the year 1999 by its power output in the same year. The monthly cost in pesos was then obtained by multiplying the required fuel input by the monthly fuel prices. The seasonal prices, for example the price for the peak period May-August, were computed as the average price in the months falling into that period. The relevant information was obtained from the CFE.[19]

The hydroelectric plants do not have a fuel cost as such but are required to pay "resource levies" on the cubic meters of water they use. We shall take these "resource levy" payments as part of the variable cost.

The CFE publications do not provide "typical" operation and maintenance costs for hydroelectric plants. This may be because such plants are more heterogeneous than the thermal plants. They vary in size and efficiency much more than do the thermal plants, and the MWh of electricity generated only approximates water use. The CFE publications do, however, provide costs for ten existing large hydroelectric plants and we use these to extrapolate the costs for other plant sizes. Specifically,

[18] "Costos y Parametros de Referencia", COPAR, CFE 1999. In practice, costs are also likely to depend on the age of the plant, but this information was not available to us.

[19] The source for annual power generation and fuel consumption was "Informe de Operacion 1999" and "Unidades Generadoras en Operacion 1999", CFE. The fuel prices were obtained from "Evolucion de Precios Entregados y Fletes de Combustibles 1999-2000", CFE.

we extrapolated the fixed component of the operating and maintenance costs of large hydro plants by regressing the log of costs for the ten hydro plants on the log of their capacities.[20] The relationship reported on page 5.5 of COPAR(1999)[21] was used to compute the variable cost, that is the operation and maintenance costs and resource levies. This equation was estimated using regression analysis with a larger sample than the ten plants whose costs were reported. Finally, we assumed small hydroelectric plants (less than 50 MW) had constant costs (an average fixed cost of 152,802 pesos per MW per year and a variable cost of 10.58 pesos per MWh).

The generating costs do not include any capital cost (that is, interest payments or depreciation). Implicitly, we are anticipating that investment projects would be evaluated on a cash flow basis. Any time a firm could expect market prices to exceed the "short run" costs as calculated here, there would be a positive cash flow that could be offset against the negative up-front costs of a new investment.

In particular, in periods or regions where the demand is pushing against capacity, prices would be expected to rise to ration the demand to the available capacity. This would provide "rents" in excess of the costs excluding interest payments and depreciation. In a competitive market, such rents would attract entrants once the *net* present value of the cash flows flowing from an investment would be positive when discounted at the appropriate risk adjusted rate.[22] The additional capacity would in turn drive prices closer to the short run costs, making entry less attractive to subsequent firms until demand expands further or some old plant is retired.[23] The

[20]The estimated equation for annual fixed costs in pesos/MW was $C_F = 782,784K^{-0.4151}$ where K is the capacity of the plant in MW.

[21]The equation was $C_v = 0.3122Q^{-0.1271}$ where C_V is average costs in pesos/MWh and Q is the output of the plant in MWh.

[22]The model does not, however, explicitly incorporate any decisions regarding investments in new generation and transmission capacity. In this sense, it is a short run model where the optimal generation schedule is based on marginal cost of operating existing plants and a given transmission network. We shall, however, examine the model in 1999 and again in 2005, when additional investments have been made in both generating and transmission capacity and when demand is higher.

[23]Since new capacity is added in discrete "lumps," the gap between *equilibrium* prices in a com-

latter decision in turn will also depend on a net present value calculation comparing the likely revenue in excess of variable operating costs with the fixed maintenance and other costs of keeping the plant operational for another year.

While this argument has been couched in terms of a competitive market, a similar set of calculations ought to drive the investment decisions of a publicly owned firm, such as CFE. The main change would be that the word "rents", interpreted as the "anticipated difference between price and short run costs," would be replaced by the "appropriately calculated shadow price of additional capacity."

Transmission. The model allows trade in electricity through the high voltage transmission network (see Figure 2.2 above). Since the possibility of not using a link at all during the year is not a relevant option, we ignore any managerial, maintenance or capital costs associated with transmission and distribution. We nevertheless need to compute the transmission losses associated with electricity flows, which in turn requires information about the capacity and other technical characteristics of the links. Specifically, the losses on a transmission link depend on the length, the voltage and the number of circuits per link. This information was collected from the Secretary of Energy.[24] We approximated the non-linear transmission losses by piecewise linear functions. Details are provided in Appendix B.

Other losses. The transmission losses are only part of the source of losses in the system. In 1999, for example, the Mexican electricity system generated 180,917 GWh of electricity, but only 145,127 GWh were recorded as sales. Almost 25% of the electricity generated was either lost in the transmission or distribution network for technical

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petitive wholesale electricity market and short run marginal costs could be expected to fluctuate over time. Nevertheless, our model is likely to under-estimate the average equilibrium prices in a competitive wholesale market.

[24] "Prospectiva del sector eléctricol 2000-2009", Secretary of Energy.

reasons or was consumed without monetary compensation. As we shall see later, only about 3 of this 25% can be accounted for by losses in the high voltage transmission network. Consumption within the generating plants was about 8,887GWh, or 5% of total production. We cannot directly measure some sources of losses, including in particular theft of electricity by consumers and losses on the lower voltage transmission and distribution networks. We therefore calibrate the model by including an additional factor that substitutes for these unmeasured losses.

The Luz y Fuerza company reported that in 1999 losses approximated 30% of its total sales.[25] Since Luz y Fuerza sales accounted for about 19% of total sales that year, losses in the Mexico City region served by Luz y Fuerza account for almost another 6 of the 25% of losses. Luz y Fuerza reports that its losses are mainly in distribution and unbilled consumption. The latter, in turn, includes waived debts as well as theft of electricity. We apportioned the remaining losses (about 11% of production) on the basis of regional population. A justification is that the resistance losses in the transformer stations and distribution network, and the losses through undetected leaks and theft, are all likely to increase along with regional population and the number of customers.

2.3.3 The Linear-Optimization Model

We now combine the various components of the model to derive estimates of the least-cost pattern of generation and transmission required to meet the representative demands in each period and region. Minimizing the cost of generation is the basic objective, but setting this as an objective on its own would make no sense. The cost could be minimized by generating zero electricity. The constraints that have to be met ensure that the solution to the problem is non-trivial. The solution process also yields

[25] "Unidades Generadoras en Operacion 1999", CFE, March 2000, pp 99.

values for the "co-state" variables, or the "multipliers" which measure the effects on minimized costs of imposing the various constraints. In particular, the multipliers on the demand constraints can be interpreted as the marginal costs of supplying demand at each node in each time period.

The main constraints that prevent zero generation of electricity from solving the cost minimization problem are that the amounts of electricity supplied need to satisfy the demands of consumers at every node and for every hour in each of the periods. The minimized cost thus represents the cost of meeting the specified demands.[26]

Since electricity can be transmitted over the high voltage network, power plants in each region do not necessary have to meet the demand for electricity in that region. Exchanging electricity through the high voltage network, however, incurs transmission losses as discussed above. Many regions are linked by more than one set of transmission lines. As part of the solution, the model simulates the inter-regional power flows along the high voltage transmission network. The model also calculates how to allocate the required down time for maintenance of generating plant in order to minimize the overall annual costs of production.

Another set of constraints results from the need to maintain plant on a regular basis. Each plant must be off-line a certain amount of time during each year. Random technical problems may also take plant out of operation for hours or several days. Hydroelectric plant may also need to be taken off-line for days or even months to conserve limited supplies of water.

We focus on the planned maintenance schedule as a key determinant of the availability of both generating capacity and electrical energy. We represent this restriction as a limit on the total MWh that the plant can generate in the whole year, while allowing the model to schedule the down time optimally across periods.

[26] This section discusses the cost function and constraints in general terms. Appendix B provides a more precise algebraic formulation of the cost function and the various constraints.

As the equations in Appendix B reveal, we treat large "base" plants in a different way to the remaining plants. The large base plants tend to be operated around the clock when they are used at all. They also typically require a substantial block of time for planned maintenance. Effectively, they can only be off line for complete days and not for just hours.

In addition to generating electricity to satisfy "normal" demand loads, the system needs sufficient reserves of capacity to meet unexpected increases in demand or unexpected equipment failures. In most electricity supply systems, consumers are willing to accept some voltage or frequency fluctuation in return for a lower price of electricity. Consumers with a strong need for stable supply can purchase their own on-site generation plant and many find this worthwhile in countries with weaker systems that are more prone to instability. Nevertheless, one of the advantages of an integrated network is that it can supply reserve capacity to cope with emergencies at a relatively low cost.

One can view reserve capacity, or consumers who agree to have their supply interrupted in return for a payment, as "options contracts." Under specified circumstances, the producer or consumer will be called upon to supply a specified amount of output or demand reduction, in return for a specified payment.[27] The "ancillary services" provided under such contracts can assist with controlling voltage, frequency and power flow or with restarting the system in the event of a failure (when blackouts occur). Contracts to provide ancillary services can be priced just as financial and commodity options are priced. Firms supplying the services could earn revenue even if they are not actually called upon to produce energy. In fact, Australia is gradually introducing a set of such options markets and already has an operational market for

[27] The specified circumstances are analogous to the "strike price" for a financial option, the volume of output or demand reduction is analogous to the number of options contracts purchased, and the specified payment is analogous to the cost of the options contracts.

frequency control services.

In a centralized system managed by a publicly owned monopoly, the amount of reserve capacity should in principle balance the capital cost of excess capacity against the benefits to consumers of a more stable power supply. It is unclear to us how one could in practice obtain the required information about the benefits of reserve capacity in the absence of an ancillary services market. We can, however, calculate the consequences of maintaining a specified level of excess reserves.

To capture the need to maintain reserve capacity to meet unexpected peak demand, we calculate the generating capacity and associated transmission amounts for a set of "virtual" periods of extreme demand. The notion is that such periods last for a brief period and thus do not require a substantial amount of additional energy to be produced. They do, however, require plant capacities to be higher than would be the case if demand was always at its "normal" level.

2.4 Base case results

According to data reported by the CFE,[28] generation costs accounted for 38% of the total cost of supplying electricity in 1999. Depreciation and capital costs accounted for 15.2% and 1.6% respectively.[29] The remaining 45% of expenditures covered administration and the costs of operating the distribution and transmission networks. The expenditure amounts in pesos were: generation costs, 35,448 million pesos; depreciation 14,020 million pesos, financial costs 1,457 million pesos and total cost, 92,397 million pesos.

The linear programming model objective function represents the generation costs alone for the period November 1998 to October 1999, which corresponds to the timing

[28] "Resultados de Explotacion, 1999."

[29] The depreciation and capital costs pertain to the transmission and distribution as well as the generation sectors of the business.

of the four seasons considered in the model. The minimized costs of production from the model for this period were 30,376 million pesos. Our estimation is for the period November 1998-October 1999 rather than calendar 1999. Furthermore, some fixed costs that are absent from the model may have been included in the accounting data. Finally, the lack of data required us to make various approximations to the demand load curves, generating costs and many other factors, so it is not surprising that our minimized costs differ somewhat from the accounting figures.

2.4.1 Production, transmission and consumption

Table 2.5 summarizes the generation, transmission and consumption results for the Base Case. The central region (17) has the highest electricity consumption in the country, with a 26% share of total gross demand. However, this region generated only around 10% of the total power supply. The concentration of population and industry in the central region resulted not only in high consumption but also in levels of losses (or power supplied at zero cost) on the order of 23% of the region's total annual electricity needs.[30] The model results imply that the central region imported 60% of its electricity. Two regions neighboring the central region, Lazaro Cardenas (16) and Oriental (18) are major exporters of power. The Oriental region is also a significant center of electricity consumption. Two other regions connected to the Central one are Bajio (15) and Acapulco (19). Both of these are, however, importers of power. Bajio (the third largest importing region) is a high consumption region with a high level of electricity losses (13.7%). Acapulco on the other hand is primarily an importing region because of its low level of generation.

The hydroelectric plants located on the Grijalva river (region 22) are also a major source of energy for the central region of the country. These plants total more than

[30] As we noted above, the losses in this region were obtained from a report by Luz y Fuerza.

Table 2.5: Base Case, Annual Regional Results (GWh)

Region	Gross Generation[a]	Net Transmission[b]	Gross Demand[c]	Other Losses[d]
1	3,599	752	4,140	4.0%
2	3,159	-139	2,842	2.8%
3	3,080	-913	2,016	3.9%
4	3,789	-2,695	855	1.7%
5	5,110	-1,092	3,813	6.0%
6	2,644	863	3,335	5.3%
7	2,647	3,192	5,685	7.4%
8	17,192	-13,885	1,970	3.0%
9	6,192	13,116	19,019	13.9%
10	5,036	-1,134	3,536	5.2%
11	2,813	134	2,757	4.2%
12	2,146	7,418	9,545	13.9%
13	11,037	-9,229	1,177	1.6%
14	4,700	2,599	6,978	9.7%
15	8,059	9,354	16,983	13.8%
16	16,031	-14,884	354	0.4%
17	18,398	25,603	42,948	23.4%
18	28,697	-12,394	14,909	15.2%
19	1,702	294	1,985	5.0%
20	1,736	-378	1,341	2.8%
21	119	2,560	2,674	4.3%
22	17,342	-14,390	2,660	6.0%
23	964	-82	811	2.0%
24	1,386	898	2,178	4.6%
25	0	238	238	0.6%
26	1,262	-124	1,059	2.6%
27	4,315	-1,420	2,695	3.5%
28	4,197	726	4,641	6.2%
29	147	637	780	1.2%
30	475	-287	166	2.6%
31	641	189	782	10.3%
32	46	88	133	2.1%

a. As estimated by the model.

b. Positive values indicate the net electricity delivered to the region, while negative values indicate the net supply transmitted out of the region.

c. Calibrated sales and theft of electricity, plus distribution and internal generation losses.

d. Distribution and internal generation losses and losses due to theft of electricity.

3,900 MW of capacity and more than 80% of the electricity they produce is exported north not only to the center but also to neighboring region of Minatitlan (21) and the Yucatan peninsula.

Bajio (15), Guadalajara (12) and Ags-SLP (14) constitute a significant area of consumption to the north of the Central region. These areas together form an industrial corridor that links the center of the country with the north. Manzanillo (13) is a major source of energy for these regions as well for the center. It has two thermal plants with a joint capacity of 1,900 MW. Another important regional electricity supplier is Lazaro Cardenas (16), which supplies the corridor (12-14-15) and the center (17), with a thermal plant of 2,100MW capacity and a 1,000MW hydroelectric plant.

The northern city of Monterrey (9) is the second largest consuming and importing region in the country. The large coal-fired plants in Río Escondido (8), with a total capacity of 2,600 MW, are a major source of energy for Monterrey. Other regions neighboring Monterrey are Laguna (7) to the west, Huasteca (10) to the south-east and Reynosa (11) to the north-east. Of these, Laguna is also a moderate importing region while Huasteca is a moderate exporter. Further growth of demand in the north-east of the country is clearly going to require additional generating capacity in the region, or a strengthening of the transmission links from the south of the country or from Texas.

2.4.2 Scheduled maintenance

Any least cost scheduling of generation plants to meet power demands and provide reserve capacities has to allow plants to be taken out of service for maintenance. The optimal solution may involve some rolling maintenance, depending on factors such as the seasonal pattern of the regional demand and the seasonal behavior of fuel prices for different plant types. In our model, plant availabilities are choice variables, and the set of availability percentages per plant and per period are an important model output.

Table 2.6 summarizes the calculated availabilities by region and season. The seasonal variation in availabilities reflects the pattern of aggregate electricity demand, which attains its lowest values during the Fall and is the highest during the Summer months. There are, however, some interesting regional variations. In particular, plants in some regions are made fairly uniformly available throughout the year, enabling them to compensate for the reduced availability of other plant taken off line for maintenance when demands tend to be lower. This backup task appears to be important in Mazatlán (4), which compensates for the low availability of plant in the northwest during the Fall, and Huasteca (10) and Oriental (18), which support the low availability of plant in the northeast during the Fall. Oriental (18) and Manzanillo (13) are interesting in so far as both have lowest availabilities in the Shoulder season, enabling them to provide greater capacity and output during both the Summer and Fall seasons. By contrast plant in Guadalajara (12) and Ags-SLP (14) have their highest availabilities during the Shoulder season of the year.

2.4.3 Calculated costs

A major motivation for constructing the model is that it allows us to examine total, average and marginal costs of electricity supply in Mexico. We wish to compare the marginal costs in particular with current electricity prices. In the next section of the chapter, we study how the forecast increase in demand for 2005, and the completion of the planned new additions to generating and transmission capacity over the next few years, both affect costs.

As noted in the introduction to this section, the total generation costs calculated by the model are 30,376 million pesos for 178,664 GWh generated during the period

Table 2.6: Base Case, Allocation of availability by region and season

Region	Year[a]	Summer	Shoulder	Fall	WE-Hol
1	0.51	0.53	0.53	0.46	0.51
2	0.49	0.59	0.51	0.42	0.42
3	0.32	0.41	0.33	0.21	0.26
4	0.70	0.70	0.70	0.70	0.70
5	0.71	0.84	0.73	0.61	0.62
6	0.51	0.53	0.51	0.51	0.48
7	0.51	0.63	0.55	0.45	0.30
8	0.72	0.75	0.73	0.69	0.73
9	0.62	0.72	0.65	0.33	0.61
10	0.80	0.94	0.45	1.00	0.54
11	0.66	0.83	0.67	0.62	0.41
12	0.63	0.03	0.71	0.02	0.03
13	0.74	0.89	0.35	0.89	0.56
14	0.75	0.81	0.80	0.70	0.69
15	0.65	0.69	0.70	0.68	0.52
16	0.54	0.57	0.60	0.53	0.47
17	0.61	0.67	0.68	0.56	0.50
18	0.70	0.69	0.71	0.73	0.66
19	0.31	0.35	0.36	0.32	0.15
20	0.61	0.75	0.75	0.42	0.36
21	0.52	0.52	0.52	0.52	0.52
22	0.51	0.51	0.55	0.49	0.47
23	0.67	0.67	0.67	0.67	0.67
24	0.59	0.65	0.69	0.53	0.45
25	0.00	0.00	0.00	0.00	0.00
26	0.28	0.36	0.28	0.24	0.22
27	0.58	0.63	0.59	0.52	0.58
28	0.41	0.54	0.40	0.33	0.31
29	0.28	0.16	0.36	0.02	0.01
30	0.45	0.53	0.43	0.40	0.40
31	0.48	0.54	0.51	0.42	0.43
32	0.02	0.02	0.01	0.00	0.00
Average[a]	0.62	0.67	0.63	0.62	0.55

a. Weighted average, with generation per region or season as weights.

under analysis (November 1998 to October 1999). By contrast, the CFE reported that total generation costs for 1999 were 35,448 million pesos. It is therefore possible that the calculated marginal costs are too low. The calculated marginal costs would not be affected, however, if the accounting data includes fixed costs that have been omitted from our objective function.[31]

Tables 2.7, 2.8, 2.9 and 2.10 present the calculated marginal costs of power supply for each transmission region and in each time period. For the peak periods in Summer and Fall, the marginal costs have been separated into the components associated with the demand constraints (5.10) and those associated with the reserve constraints (5.15). Although the latter could in principle bind in any period,[32] we find that they bind only in either the summer or fall periods of peak demands, and even then not for all regions in both seasons.

The weighted average system-wide marginal cost (with weights determined by consumption shares) is 32.08 cents Mexican per kWh. By contrast, the calculated total cost of generation corresponds to an average of only 17.00 cents Mexican per kWh, implying that the marginal cost is around 88% higher than the average cost.

Evidently, generation of electricity in Mexico is not a "natural monopoly" activity in the sense that average costs exceed marginal costs. This is usually the case in all countries, since plant with higher operating costs is used only to supply electricity in peak periods. The marginal costs in peak periods also reflect the cost of maintaining additional generating capacity to cope with emergencies.

The finding that the weighted marginal cost exceeds the average cost has another important implication. If wholesale prices reflected the marginal cost of generation,

[31] Some items that accountants count as costs, including depreciation and interest costs, are appropriately excluded from an economic measure of costs. These items have, however, already been excluded from the reported cost of 35,448 million pesos.

[32] In particular, it is possible that scheduled maintenance, differences in seasonal demands or transmission constraints might cause the reserve constraints to bind in periods other than those of peak demand.

the revenue raised would exceed the costs of generating the electricity. In fact, the excess revenue would more than cover the reported annual "capital costs" for the CFE.[33] If the depreciation and interest charges in the CFE accounts represent a competitive return to capital, then setting wholesale electricity prices equal to the marginal costs of generation ought to attract considerable entry into the industry, were that to be permitted by law. This is another sense in which the generation of electricity in Mexico is not a natural monopoly. The essence of the natural monopoly idea is that a large incumbent firm has a cost advantage relative to smaller potential entrants making entry unattractive. Our calculations suggest that, if wholesale electricity prices reflected marginal costs, new generators would be delighted to set up business in Mexico. Entrants would need to be guaranteed the same access to the transmission network, and receive the same wholesale price for electricity supplied at the same time and location, as the incumbent producers. In reality, this would require the transmission business of the CFE to be separated from the generation business. Effective competition in the wholesale market also would require that the existing generating stations be parceled out into many competing companies and not kept as a monopoly entity.

The spatial and temporal variation of marginal costs is also of interest. Tables 2.7 and 2.8 give the costs arising from both the demand and the reserve constraints for time periods in which the reserve marginal cost is non-zero for at least one region. The "full" marginal costs include both constraints since an increase in "normal" demand within a period is assumed to increase extreme demand in the same proportion. To begin with, however, the discussion will focus on the demand constraints only. These determine the energy requirements for the system and the "usual" pattern of electricity transmissions. The reserve constraints indicate how the

[33] As noted earlier, in the 1999 CFE accounts, capital costs, primarily depreciation and interest payments, were almost equal to 43% of total generation costs.

Table 2.7: Marginal costs by transmission region: Summer (May–August)

(cents per kWh, Mexican Pesos)

	Demand periods						
	1		2		3	4	5
Region	Dem	Res	Dem	Res			
1	27.3	152.0	27.3	9.5	27.3	26.5	26.5
2	26.1	149.6	26.1	9.1	26.1	26.1	26.1
3	24.3	139.4	24.3	0.0	24.3	24.3	24.3
4	25.4	145.8	25.4	0.0	25.4	25.1	25.1
5	23.5	238.1	23.5	0.0	23.5	23.5	23.5
6	26.3	251.5	26.3	0.0	26.3	25.9	25.9
7	27.4	262.2	27.4	0.0	27.4	27.0	27.0
8	25.0	241.9	25.0	0.0	25.0	24.6	24.6
9	26.7	258.4	26.7	0.0	26.7	26.3	26.3
10	25.5	235.6	25.5	0.0	25.5	25.5	25.5
11	26.5	261.1	26.5	0.0	26.2	26.2	26.2
12	27.1	149.5	27.0	0.0	27.0	26.9	26.9
13	25.2	139.0	25.2	0.0	25.2	25.0	25.0
14	28.3	240.9	27.9	0.0	27.9	27.9	27.9
15	28.1	245.8	27.9	0.0	27.9	27.9	27.9
16	24.5	58.8	24.5	0.0	24.5	24.5	24.5
17	27.3	238.4	26.9	0.0	26.9	26.9	26.9
18	24.7	214.0	24.7	0.0	24.7	24.7	24.7
19	27.1	0.0	27.1	0.0	27.1	27.1	27.1
20	22.4	83.9	22.4	0.0	22.4	22.4	22.4
21	21.0	71.4	21.0	0.0	21.0	21.0	21.0
22	19.7	62.0	19.7	0.0	19.7	19.7	19.7
23	86.9	190.9	33.6	0.0	33.6	33.1	33.1
24	90.3	198.3	35.0	0.0	34.9	34.5	34.5
25	96.0	210.9	37.2	0.0	37.1	36.7	36.7
26	84.4	185.3	33.9	0.0	33.9	33.9	33.9
27	125.6	188.4	123.0	0.0	123.0	123.0	121.8
28	130.3	192.8	130.3	0.0	130.3	130.3	130.3
29	133.2	196.4	133.2	0.0	133.2	133.2	133.2
30	103.4	173.5	95.4	0.0	95.1	95.1	95.1
31	111.5	187.1	102.9	0.0	102.6	102.6	102.6
32	108.8	182.6	105.1	0.0	105.1	105.1	105.1

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1–26	243.4	27.1	26.5	26.4	26.4
27–29	320.7	128.1	128.1	128.1	127.7
30–32	294.2	102.0	101.7	101.7	101.7
1–32	248.6	33.7	33.2	33.0	32.9

Table 2.8: Marginal costs by transmission region: Fall (Nov–Feb)

(cents per kWh, Mexican Pesos)

	Demand periods					
	11		12	13	14	15
Region	Dem	Res				
1	25.1	0.0	24.1	24.1	24.1	24.1
2	24.7	0.0	23.7	23.7	23.7	23.7
3	24.1	0.0	24.0	23.6	23.6	23.1
4	25.2	0.0	25.1	24.7	24.7	24.0
5	23.4	0.0	23.4	23.4	23.4	23.4
6	24.6	0.0	24.6	24.6	24.0	24.0
7	26.1	0.0	26.1	26.1	25.9	25.9
8	23.4	0.0	23.4	23.4	23.2	23.2
9	25.0	0.0	25.0	25.0	24.8	24.8
10	24.2	0.0	24.2	24.2	24.0	24.0
11	25.3	0.0	25.3	25.2	25.0	25.0
12	27.1	0.0	27.1	26.6	26.5	25.8
13	25.2	0.0	25.2	24.7	24.7	24.0
14	28.0	196.4	27.7	27.2	27.2	27.2
15	28.5	208.3	28.3	27.7	27.5	27.0
16	24.5	0.0	24.5	24.5	24.5	24.2
17	27.7	214.7	27.4	26.9	26.6	26.2
18	24.7	0.0	24.6	24.1	23.9	23.5
19	27.1	73.9	27.1	27.1	27.1	27.1
20	22.4	0.0	22.4	22.3	22.3	22.1
21	21.0	0.0	21.0	21.0	21.0	21.0
22	19.7	0.0	19.7	19.7	19.7	19.7
23	30.9	0.0	30.4	29.7	29.7	28.8
24	32.1	0.0	31.6	31.0	31.0	31.0
25	34.1	0.0	33.6	33.0	33.0	31.6
26	31.1	0.0	31.1	31.1	31.1	31.1
27	118.1	0.0	117.8	117.8	117.8	117.8
28	126.4	0.0	126.1	126.1	125.8	125.8
29	128.7	0.0	128.7	128.4	128.2	128.2
30	91.9	0.0	91.9	88.3	87.9	87.9
31	98.3	0.0	98.3	90.6	90.6	90.6
32	100.7	0.0	100.7	92.9	92.9	92.9

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

	11	12	13	14	15
1–26	120.7	26.2	25.8	25.6	25.3
27–29	123.8	123.6	123.5	123.4	123.4
30–32	97.6	97.6	90.6	90.5	90.5
1–32	120.8	31.5	30.9	30.6	30.3

Table 2.9: Marginal costs by transmission region:

Shoulder (March, April, Sept, Oct)
(cents per kWh, Mexican Pesos)

	Demand periods				
Region	6	7	8	9	10
1	26.5	26.5	26.5	26.5	25.4
2	26.1	26.1	26.1	26.1	25.0
3	24.3	24.3	24.3	24.3	24.3
4	25.2	25.2	25.2	25.2	25.2
5	23.8	23.8	23.8	23.8	23.8
6	26.1	26.1	26.1	25.9	25.9
7	27.2	27.2	27.2	27.2	27.2
8	24.7	24.7	24.7	24.7	24.7
9	26.4	26.4	26.4	26.4	26.4
10	25.5	25.5	25.5	25.5	25.5
11	26.2	26.2	26.2	26.2	26.2
12	27.1	27.1	27.1	27.1	27.1
13	26.5	26.5	26.5	26.5	26.5
14	28.2	28.0	28.0	28.0	28.0
15	28.4	28.1	28.1	28.1	28.1
16	24.5	24.5	24.5	24.5	24.5
17	27.5	27.3	27.1	27.1	27.1
18	24.7	24.7	24.7	24.7	24.7
19	27.1	27.1	27.1	27.1	27.1
20	22.4	22.4	22.4	22.4	22.4
21	21.0	21.0	21.0	21.0	21.0
22	19.7	19.7	19.7	19.7	19.7
23	51.3	33.5	33.0	32.1	31.7
24	53.3	34.8	34.3	33.4	33.0
25	56.7	37.0	36.5	35.5	35.1
26	50.8	33.8	33.8	33.8	33.8
27	119.6	119.6	119.5	119.5	119.0
28	127.9	127.9	127.9	127.9	127.3
29	130.3	130.3	130.3	130.3	129.7
30	93.0	93.0	93.0	90.5	87.9
31	100.4	99.8	99.8	92.9	92.9
32	102.3	102.3	102.3	95.2	95.2

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1–26	27.3	26.6	26.6	26.5	26.4
27–29	125.3	125.3	125.3	125.3	124.8
30–32	99.4	99.0	99.0	92.8	92.4
1–32	33.2	32.5	32.3	32.2	32.0

Table 2.10: Marginal costs by transmission region: Weekends–Holidays

(cents per kWh, Mexican Pesos)

	Demand periods				
Region	16	17	18	19	20
1	25.3	25.0	24.9	24.9	24.9
2	24.9	24.6	24.6	24.6	24.6
3	24.3	24.0	24.0	24.0	24.0
4	25.2	25.2	25.1	25.1	25.1
5	23.2	23.2	23.2	23.2	23.2
6	25.1	25.1	24.2	24.2	24.2
7	26.7	26.7	26.7	26.7	26.7
8	23.9	23.9	23.6	23.4	23.4
9	25.5	25.5	25.2	25.0	25.0
10	24.7	24.7	24.7	24.7	24.7
11	25.8	25.8	25.8	25.8	25.8
12	27.1	27.0	27.0	27.0	27.0
13	25.4	25.4	25.4	25.4	25.4
14	27.7	27.7	27.7	27.7	27.7
15	27.6	27.6	27.6	27.6	27.6
16	24.5	24.5	24.5	24.5	24.5
17	26.6	26.6	26.6	26.6	26.6
18	24.0	24.0	24.0	24.0	24.0
19	27.1	27.1	27.1	27.1	27.1
20	22.3	22.3	22.3	22.3	22.3
21	21.0	21.0	21.0	21.0	21.0
22	19.7	19.7	19.7	19.7	19.7
23	32.0	31.5	31.5	30.5	30.5
24	33.3	32.8	32.8	32.8	32.8
25	35.4	34.9	34.9	33.5	33.5
26	33.0	33.0	33.0	33.0	33.0
27	119.9	119.9	118.5	118.5	118.5
28	128.3	128.3	126.8	126.8	126.8
29	130.7	130.7	129.2	129.2	129.2
30	93.3	89.7	87.9	87.9	87.9
31	100.2	92.1	92.1	92.1	92.1
32	102.7	94.4	94.4	94.4	94.4

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1–26	26.0	26.0	25.9	25.8	25.8
27–29	125.7	125.7	124.3	124.3	124.3
30–32	99.4	92.0	91.7	91.7	91.7
1–32	32.1	31.8	31.6	31.5	31.5

system behaves under extreme conditions and will be discussed later.

In the North (regions 1 to 11 and all of Baja California), the demand for electricity exhibits a strong seasonality with Summer as the peak season. This behavior of the demand is reflected in marginal costs that are higher in the summer than they are in the fall.

Within a given season, the peak hours represented by periods 1, 2, 6, 11 or 16 tend to have the highest cost. Marginal costs are raised not only by the need to use more expensive generating plant, but also by the higher transmission losses.

In some regions, relatively abundant hydroelectric resources allow the price spikes to be smoothed out or even eliminated. Since stored water can be run through the turbines at any time, the shadow value of using the water to generate electricity should be equal in all periods in which it is used. Otherwise, costs could be reduced by saving water in periods when its value is lower and using it instead when the cost of generating electricity using other technology is higher. Hydroelectric capacity is, in a sense, a substitute for storing electricity. Without it, marginal costs would fluctuate much more as the demand load on the system varies and plants with different operating costs become the marginal source of supply.

If hydroelectricity is available, but the amount of stored water is limited, prices may still fluctuate seasonally. The water is optimally used first to supply electricity at the peak periods. If water remains after doing that, it is used next in the near-peak periods and so on. In the off-peak periods when water is not used, the price of electricity would be lower than in the periods when water is used.

Transmission losses, and transmission constraints, also influence the regional pattern of marginal costs. It is simplest to consider first the case where none of the transmission links is congested. The marginal cost at the sending end of an active link then has to exceed the marginal cost at the receiving end by the marginal transmission loss. If the marginal costs in the two regions differ by less than the transmission loss, transmitting power between them is not worthwhile and the link will be inactive.

Laguna (7) and its neighboring regions (6, 4, 9 and 14) illustrate the effect of transmission losses. In all periods, the marginal cost is higher in Laguna than in the three regions Chihuahua (6), Mazatlán (4) and Monterrey (9) to the north, west and east. Evidently, power flows from these latter regions to Laguna. On the one hand, in all periods the marginal costs are higher in the Ags-SLP region (14) to the south than they are in Laguna. Power must therefore flow from the north to the central region along the Laguna to Ags-SLP link. The differences in marginal costs along these links reflect the marginal transmission losses.

With an annul demand of 5,685 GWh, Laguna is a medium sized consumption center, but its scarce local generating capacity means that about 60% of its electricity needs are supplied from other regions. Laguna is also a trans-shipment point, however, for power flowing from the north to the large demand load in the center of the country. Even though Laguna is a net importer of electricity, the link to the south has power flowing out of the Laguna region. Evidently, the excess demand for power in the central region of the country is even greater than the excess demand in Leguna.

The Monterrey region (9) has the second highest demand for electricity in the country and meets about 68% of its electricity needs with imports from other regions. The marginal costs in Monterrey therefore are higher than in the surrounding regions (8 and 10) that export power to Monterrey. On the other hand, we have already seen that the marginal costs in Monterrey are below those in Laguna so that, even though Monterrey is a net importer of electricity, power nevertheless flows from Monterrey toward Laguna in all of the model periods.

The pattern of marginal costs in Monterrey (9) versus Reynosa (11) is consistent with the direction of power flow reversing over the course of the year. In the summer and shoulder periods, the marginal costs in Monterrey are higher than those in Reynosa, implying that power flows west toward Monterrey. In the fall, and on weekends and holidays, however, the marginal costs are lower in Monterrey implying that power flows east toward Reynosa. This may be the result of the different pattern of scheduled maintenance in the two regions.

There is also a reversal in the direction of power flow between the Huasteca (10) and Oriental (18) regions. For most of the year, the marginal cost is higher in region 10 than in region 18, implying that power flows north. In the two highest demand periods in the fall, however, the marginal cost is higher in region 18 than in region 10 implying that power flows south. As the estimated monthly deviations in demand shares presented in Table 5.6 show, the seasonal fluctuation in demand is less in the south than in the north and also shows a slight peak in the fall as opposed to the summer. These different seasonal patterns can explain the reversals in the direction of flow between the seasons. It is also interesting to note that even though power tends to flow south from Huasteca to Oriental in the fall, for the three lowest demand periods in the fall, the flow is either from south to north or the link is inactive. As the representative daily load curves in Figure 2.3 show, the fall season in the south is characterized by a much greater peak to off-peak daily fluctuation than occurs in either season in the north or in the summer in the south. Thus, demand in the south during the three lowest demand periods in the fall is still low enough that additional power is not required from the north.

The lowest marginal costs occur in the Grijalva region (22). As we noted above, there is more than 3,900 MW of hydroelectric capacity located on the Grijalva river. The total hydroelectric generating capacity in the Grijalva region is sufficient to ensure that marginal generating costs there are constant throughout the year. As one moves away from the Grijalva region to the north, marginal costs reflect more seasonal variation as transmission costs fluctuate with the load and high cost local plant is used to supply peak demands.

Limited transmission capacity also plays a role in allowing costs to fluctuate across seasons and times of the day as one moves away from the Grijalva region. The Yucatan peninsula (regions 23–26) dramatically illustrates how costs are affected when transmission links become congested. The power flowing on the weak link[34] between Grijalva and neighboring Lerma (region 23) is not sufficient to equilibrate marginal costs net of transmission costs. The higher costs are then passed on to regions further down the system. In particular, further weak links between regions Lerma and Mérida (region 24) and Mérida and Chetumal (region 25) produce additional large increments in marginal costs. On the other hand, Cancún (region 26) has marginal costs below those in Mérida and almost as low as the marginal costs in Lerma. The Cancún region has the largest concentration of generating plant in the Yucatan and evidently exports power to the Mérida region despite the high costs of satisfying the local demand. A strengthening of the Cancún to Mérida link would actually raise prices in Cancún even further as more power was exported to the west.

The large marginal cost differences between two regions linked by a binding transmission constraint represents the "shadow value" of increasing the capacity of the link. If there were competitive wholesale power markets at both ends of the link, market prices would reflect the marginal costs in each region. A new entrant building a new link (or strengthening an existing one) could earn the price differential in each period. If the discounted present value of these anticipated revenues were sufficient to cover the capital cost of the link upgrade, the project would be profitable and efficient to undertake. Independent entrepreneurs have already invested in such network

[34] The capacity is 110 MW at 230 kV.

upgrades in the wholesale electricity markets in Australia.

The value of additional links in Mexico is even more apparent in the Baja California peninsula. Currently, there are two systems in Baja that are not connected to the rest of the Mexican grid, although the system in the north of Baja is connected to the United States via California. The marginal costs of generation are in Baja California are higher than they are anywhere else in the country. The region currently depends on diesel generating plants that are expensive to operate. If market prices reflected marginal costs, there would be a large incentive to strengthen connections between Baja California and the remaining networks in both Mexico and the United States.[35]

A change in one network link is likely to have consequences elsewhere in the system. For example, strengthening the Cancún to Mérida link also would reduce the differential in marginal costs between Lerma and Mérida and therefore the implicit value of augmenting the capacity of the Lerma to Mérida link. It is not inefficient, however, for a potential investor in one link to ignore these effects on other links. As in any market, a change in supply or demand conditions can affect the prices paid or received by other consumers or producers. The price changes signal that the opportunity cost of using scarce resources has changed and that supply and demand decisions need to be adjusted accordingly. There is, therefore, no need to centrally coordinate network investment decisions on these grounds.

It might be thought that the need to maintain the physical stability of the network is a different matter. In general, the stability of voltage levels, frequencies and power flows depends on the whole network and not just individual links. Even in this case, however, if there were competitive markets in ancillary services (as discussed

[35]The model does not consider international electricity trade with the USA. There are plans to place new generating plant in Baja California using imported LNG as fuel. These plans, if brought to fruition, would strengthen the transmission grid in Baja and turn the region into a power exporter to the US. One of the perceived advantages of siting the plant in Baja and exporting the power north is that it would enable US utilities to circumvent political constraints on siting new plants in California.

above) actions that stabilize, or destabilize, the network would be priced and private individuals and firms would receive appropriate signals to take these factors into account when making their decisions about supply and demand.

Concerns about imperfect competition, however, may justify oversight of network operation and expansion. Network operation is a "natural monopoly" activity in the sense that only one agency can be responsible for scheduling generators to supply demand while maintaining system operating parameters within specified bounds.[36] A network operator that also owned generating plant or transmission links would have an incentive to manipulate the dispatch of generators to increase returns to its own assets. Similarly, an owner of one network link who owned other links, or generating plants, may have an incentive to limit transmission capacity in order to drive up the rents on other assets. Regulatory oversight may be needed to prevent the abuse of monopoly if the industry is not structured to ensure adequate competition.

Tables 2.7 and 2.8 also report non-zero marginal costs associated with the reserve constraints (5.15). These costs represent the lowest fixed operation and maintenance costs that the system must incur in order to provide the last kW of capacity reserve required to cope with emergencies. While the reserve constraints for each region could bind in any period, in practice they do not bind in periods other than 1, 2 or 11,[37] which are peak periods of demand for some regions of the country. Summer demand in the south, and demand for the system as a whole, peaks in period 1, while period 2 corresponds to the summer peak in the north. Period 11 coincides with the fall peak in the south, which for some regions exceeds the summer peak in period 1. The generating capacities, $\bar{g}_n$, associated with the reserve constraints do not vary period by period. They are established for the year as a whole and potentially constrain

[36] Extensive and frequent use of sub-contracting, however, would allow the construction and maintenance of network facilities to be organized as a competitive industry.

[37] The marginal costs associated with all reserve constraints in periods other than 1, 2 or 11 are zero and have not been reported in the tables.

generation output in each period. Ensuring that capacity is sufficient to cope with extreme demand fluctuations in the peak periods, however, is likely to guarantee also that capacity will be more than sufficient to cope with the same proportional variation in demand in off-peak periods.

In all regions except Acapulco (19), the reserve constraints bind in the peak period for the system as a whole. If there were no binding transmission constraints, we would expect to find the reserve constraints binding only in the peak period for the system as a whole. Even if demand peaked in other periods in particular regions, there would have to be surplus capacity elsewhere in system at those times since the system as a whole needs sufficient capacity to meet the highest overall demand peak. Although there are transmission losses associated with using surplus plant located in other regions to meet local demand surges, such extreme demand surges are brief. The transmission losses generally would be small relative to the cost of keeping additional generating capacity available to supply output for only short periods of time. Regional demand variations that are negatively correlated will not affect the overall system demand as much as positively correlated demand shocks. Analogously to financial markets, the *undiversifiable* component of demand variation is the relevant "risk" that gives rise to a demand for the "insurance" supplied by surplus generating capacity.

The argument that there should be only one period when the reserve constraints bind implicitly assumes, however, that there is an unrestricted ability to arbitrage costs differences between regions. Transmission losses raise the costs of arbitrage, but transmission capacity constraints can prevent arbitrage altogether. In particular, the variation in marginal costs associated with the reserve constraints in Mexico is much more extreme than the variation in marginal costs associated with the demand constraints. Evidently, many of the transmission links in the Mexican system are weak and become congested under conditions of extreme demand.

The Acapulco region (19) provides an obvious example of the effect of transmission constraints. The fact that the reserve constraint does not bind in this region in period 1, despite its connection with the rest of the system, implies that the 240MW link between Acapulco and the Central region (17) must be congested. Table 2.6 provides a further indication of this. The availability of the plant in Acapulco remains at just 35% in the summer season despite the high implicit return to providing capacity to the Central region in times of extreme demand during those months. The reserve constraint in Acapulco thus depends on local demand variation more than system-wide variation in demand, and hence binds at the local peak in the fall rather than the system peak in the summer. The associated marginal cost (in cents per kWh) is determined by the local cost of providing additional capacity and the number of hours over which that cost will be spread.

Transmission constraints also play a role in producing the remaining binding reserve constraints in periods 2 and 11. These cases are somewhat different, however, in that the reserve constraints also bind during the system peak in period 1.

The Ags-SLP (14), Bajío (15) and Central (17) regions have binding reserve constraints in the fall as well as the summer. Bajío and Central both have very high total demand, with a local peak in period 11 during the fall. The reserve constraint can be binding in both periods 1 and 11 since the transmission levels are different. In particular, the fact that the reserve constraints are not binding in regions 7, 12, 16 or 18 in period 11 implies that the transmission links from these regions to regions 14, 15 and 17 must be congested under an extreme demand load during period 11. By contrast, under an extreme demand load during the system peak period, power flows north from region 14 to region 7, for example, so the link from 7 to 14 cannot be congested in the southern direction. Local reserve capacity in regions 14, 15 and 17 that is sufficient to meet the local extreme demand in period 11, with maximum import of power from elsewhere in the network, therefore is not sufficient to meet local extreme demand in period 1 when less power is available from other regions.

A similar explanation applies to the Sonora Norte (1) and Sonora Sur (2) regions, which have binding reserve constraints in the second as well as the first summer period. These regions (as do all regions in the north) have local peak demands during period 2 rather than period 1.[38] Regions 1 and 2 are connected to the rest of the network via a relatively weak 220MW link to region 3 (Mochis). Since the reserve constraint in region 3 is not binding in period 2, the transmission link must be congested under an extreme period 2 load. Under an extreme demand load in period 1, however, the demand for power in southern regions is substantially greater than it is in period 2, leaving less available to satisfy demand in the north. The transmission link between regions 3 and 2 remains uncongested, but more local capacity is required to satisfy the slightly reduced extreme demand load.

Region 16 (Lázaro Cárdenas) has much stronger links (950MW, 460MW and 400MW) to the rest of the network than do the Acapulco or Sonora regions. Nevertheless, it can also be affected by transmission constraints. The marginal reserve cost in period 1 is only 58.8 cents Mexican per kWh in region 16 but 149.5, 238.4 and 245.8 in the three neighboring regions 12, 15 and 17. These differences in marginal cost greatly exceed the transmission losses and indicate congested transmission lines. Lázaro Cárdenas has its local peak in the fall and will need greatest capacity during a temporary demand surge in period 11. The link to region 12 is not congested during period 11, however, and can transmit power to region 16 from the north. As a result, the reserve capacity needed in region 16 in the summer is sufficient to also cover a demand surge during period 11.

[38] Recall, however, that the differences in demand between periods 1 and 2 in the north are slight. This may explain why there are not more northern regions with binding reserve constraints in period 2 in addition to period 1.

Lázaro Cárdenas actually has the smallest reserve marginal cost of any region. As Table 2.4 reveals, this region has only three generating stations with a 1999 capacity of 3,395MW. The marginal cost of expanding the available capacity of these plants evidently is relatively small.

The Grijalva region (22) has marginal reserve costs that are almost as low as those in Lázaro Cárdenas. Table 2.4 shows that the Grijalva region has only hydroelectric plants, with capacity that can be made available at a higher level at relatively low cost. The large jump in marginal reserve cost in period 1 between regions 20 and 18 implies that the transmission link between these regions is congested under extreme demand conditions in period 1. The congested link between regions 18 and 20 prevents the Grijalva hydroelectric plants from providing further relatively low cost capacity to meet demand surges in regions further to the north and west of region 18.

From the values presented in Tables 2.7 and 2.8 it is clear that the high marginal reserve costs in periods 1 and 11 help drive the weighted average marginal cost above the average cost of generation. As we noted above when introducing the reserve constraints, in an ideally structured wholesale market for electricity at least some of these payments would take the form of payments for ancillary services. Under extreme demand loads, additional generating capacity is placed on standby in case it is needed to maintain voltage and frequency levels, or to re-start the system in the event of a blackout. Owners of plant that is cheap to keep on stand-by and fast to convert to supplying output could earn a return for providing the reserve capacity even if they are not actually called upon to supply power.

2.4.4 Prices and marginal costs

The model calculations show that the marginal costs of generating electricity vary by the location of the consumer and the time at which consumption occurs. In reality,

Table 2.11: Average price versus marginal generation cost by region and season

Administrative region	Summer price	Summer cost	Shoulder price	Shoulder cost	Fall price	Fall cost
Baja California	0.6000	1.3445	0.5899	1.2198	0.5312	1.1992
Noroeste	0.5272	0.3372	0.4767	0.2568	0.4787	0.2395
Norte	0.4527	0.3693	0.4645	0.2588	0.5065	0.2484
Golfo Norte	0.4836	0.3770	0.4926	0.2619	0.5166	0.2483
Golfo Centro	0.4712	0.3586	0.4829	0.2554	0.4946	0.2418
Bajío	0.4842	0.3977	0.4865	0.2809	0.5207	0.3755
Jalisco	0.5602	0.3397	0.5675	0.2705	0.5871	0.2638
Centro Occidente	0.4248	0.2740	0.4294	0.2454	0.4453	0.2452
Centro Oriente	0.4887	0.3507	0.5007	0.2470	0.5130	0.2414
Centro Sur	0.5025	0.2712	0.5256	0.2712	0.5490	0.3071
Oriente	0.4617	0.3428	0.4762	0.2449	0.4873	0.2397
Sureste	0.5821	0.2364	0.6034	0.2037	0.6338	0.2036
Peninsular	0.5949	0.4653	0.6236	0.3560	0.6488	0.3101
LyF	0.5831	0.3848	0.6038	0.2714	0.6356	0.3734

the latter dependence primarily reflects different costs of supply as the total load on the system varies.[39] Prices of electricity in Mexico, however, typically do not vary much by location or time of demand and thus do not closely mimic the marginal generation costs. In particular, while there is limited seasonal variation in prices, there is little variation by time of day.

Electricity suppliers incur costs apart from generation, including the costs of maintaining the distribution network and providing customer service, that do not vary as systematically by time or location. Nevertheless, prices are unlikely to accurately signal the marginal costs of supply to consumers unless they vary by location and time of supply.

Table 2.11 presents the average electricity price paid in each administrative re-

[39]Marginal costs also vary by time, however, because of factors such as the need to assign contiguous periods for scheduled maintenance, allowing for holiday periods or seasonal availability of water supplies for hydroelectric plant.

gion in the three main seasons. For comparison, it also provides the weighted average marginal generating costs calculated from the model. The latter are derived by weighting the marginal costs in Tables 2.7, 2.8, 2.9 and 2.10 by the corresponding demands in each transmission region and each season. Since the revenue needs to cover more than generating costs, it is not surprising that prices on average exceed the marginal generating costs. It is somewhat more interesting, however, to note that the average prices vary much less by season and region than do the marginal costs. Furthermore, in many cases, the pattern of marginal cost variation across regions and seasons is not reflected in the price variations. This is particularly apparent for those regions where the reserve marginal costs are positive in periods other than the summer peak. It would appear that consumers, and potential generators of electricity, are not being given very appropriate signals about the costs or benefits of changing electricity demands or supplies at different locations on the network or at different times of the year.

The electricity tariffs in Mexico fall into two main categories. One category, known as "specific rates," classifies customers by the purpose for which they use electricity. The tariffs for residential, commercial, agricultural and public services demand largely fall into this category. The second group of tariffs differentiate between customers based on the amount of energy that they consume and other characteristics of their supply including in particular the voltage level at which they draw power. The latter is important because many losses occur in the distribution network or result from transforming power to lower voltage levels. Hence, it is generally much less costly to supply power to large customers drawing directly from the high voltage transmission network.

Residential tariffs. The price of electricity for households is a step function with three price levels that depend on demand. The prices for each step change according to region and season and thus could, in principle, partially reflect cost differences.[40] All residential customers face the same rate scale in non-summer months. During the summer, however, households are charged different rates according to the average temperature of the region. A common problem with step function tariffs is that different households pay a different price for electricity that costs the same amount to supply to each of them. This leads to inefficiencies since the household paying a higher price would be willing to pay more for the marginal power consumed by the household paying the lower price but is prevented from doing so.

Agricultural tariffs. Agricultural users face two different tariffs depending on the voltage level at which they take supply. In either case, the tariff schedule is a step function with four levels. As with residential tariffs, prices vary somewhat by region and season.

Commercial tariffs. Commercial users also face a step function tariff, with the marginal price determined by the maximum demand and the total consumption within the billing period. In this case, the prices on the steps of the tariff do not vary by region or season, but are changed from one billing cycle to the next via indexation to components of the wholesale price index.

Industrial tariffs. There are 16 different schedules for the industrial sector and two additional rates for firms willing to allow their service to be interrupted at short notice.[41] All but one of the industrial tariffs includes some price differences by region

[40] Such a price structure could not reflect all cost differences since marginal costs vary within a day or across days of the week in addition to seasons.

[41] In the latter case, companies enrolled in the program are asked, at least 15 minutes in advance, to reduce their demand for electricity. They are then credited an amount that depends on the

and by hour of use. The latter differentiation is based on base, intermediate and either semi-peak or peak demand. Charges are further differentiated depending on the voltage level at which service is provided, total energy consumed within the billing period, the overall maximum demand within the billing period or the sum of the maximum daily demands within the period or whether the firm agrees to pay a fixed charge. In this sector, the price for electricity is indexed to the variation of fuel prices and to the producer price of three industrial components of the wholesale price index.

2.4.5 Altered plant availability

The base case has demonstrated that hydroelectricity plays a significant role in the Mexican electricity supply system. An important problem that Mexico faces, however, is that rainfall is not always reliable and the availability of hydroelectric plants can be severely curtailed as a result of drought.

To see how the system is affected by reduced hydroelectric plant availability, we re-computed the costs of meeting the 1999 demand levels but using the availability of plants from 1998. As a result of dry weather, hydroelectric plant had much lower availability levels in 1998 than in 1999. To compensate, many of the thermal plants were run at higher availability levels.

Table 2.12 gives the differences in annual availabilities in the two years by regions. The differences between the two years are not only the result of different availabilities of hydroelectric plant. Using the actual availabilities from 1998, however, allows us to examine what can happen under an alternative "realistic" scenario.

Comparing Table 2.12 with Table 2.4, we see that the main regions with reduced availability in 1998 relative to 1999 are those with substantial hydroelectric generating

reduction in demand. There are two categories of such service, one for demands equal or higher than 10,000 kW in peak hours and another for demands equal or higher than 20,000 kW.

Table 2.12: Difference in availability by region with reduced hydro

Region	1999	1998	% diff
1	0.51	0.53	4.7%
2	0.49	0.52	5.8%
3	0.32	0.35	10.8%
4	0.70	0.70	0.0%
5	0.71	0.79	11.4%
6	0.51	0.52	2.6%
7	0.51	0.68	34.8%
8	0.72	0.73	0.0%
9	0.62	0.64	4.0%
10	0.80	0.78	-2.3%
11	0.66	0.65	-1.2%
12	0.63	0.27	-57.8%
13	0.74	0.78	6.3%
14	0.75	0.77	2.7%
15	0.65	0.70	9.2%
16	0.54	0.56	3.2%
17	0.61	0.67	10.0%
18	0.70	0.70	0.7%
19	0.31	0.25	-20.3%
20	0.61	0.56	-9.3%
21	0.52	0.34	-35.7%
22	0.51	0.31	-39.6%
23	0.67	0.67	0.0%
24	0.59	0.58	-1.5%
25	0.00	0.01	∞
26	0.28	0.33	16.2%
27	0.58	0.65	12.1%
28	0.41	0.39	-4.7%
29	0.28	0.05	-80.8%
30	0.45	0.46	4.0%
31	0.48	0.48	0.0%
32	0.02	0.01	-36.8%
Average[a]	0.62	0.63	2.5%

a. Weighted average, with generation per region as weight.

plant. In particular, the availabilities in regions 21 (Minatitlan) and 22 (Grijalva), which have only hydroelectric plant, were 35.7% and 39.6% lower in 1998 than in 1999. Guadalajara (region 12), which had 57.8% lower availability in 1998, has 8 hydroelectric generating plant and only 1 thermal plant. Other regions with significantly lower availability in 1998 were Acapulco (region 19, with 3 hydroelectric and 1 thermal plant) and Temascal (region 20, with 2 hydroelectric and 1 renewables plant).

Low water supplies were, however, not the only problem in 1998. Three regions in Baja California with only thermal plant (Ensenada, 29, Tijuana, 28, and Cabo San Lucas, 32) each had substantially reduced availability, although the very small Ensenada, and particularly the Cabo San Lucas, plants also had fairly low availabilities in 1999.

The most significant increases in availability in 1998 relative to 1999 typically were in regions with substantial thermal generating plant. Examples include regions 7 (Laguna, with 5 thermal plants), 26 (Cancún, with 7 thermal plants), 27 (Mexicali, with 2 thermal and 3 renewable plants) and 5 (Juárez, with 1 thermal plant). On the other hand, three regions with significant numbers of hydroelectric plant also had higher availabilities in 1998 than 1999. These were Central (region 17, with 13 hydroelectric and 7 thermal plants), Bajío (region 15, with 9 hydroelectric, 3 thermal and 1 renewables plant) and Mochis (region 3, with 6 hydroelectric and 2 thermal plants).

It might be thought that if thermal plant can be made more available in drought years they could be made more available in all years. Using thermal plant to generate more electricity is, however, likely to lead to increased maintenance problems in the future. Higher availability in one year therefore is likely to lead to reduced availability in future years as plants are taken out for maintenance. Running plants harder in one year is also likely to raise the annual maintenance costs in future years. This factor has been ignored in our cost estimates presented below.

We will not discuss all the details of the altered availability scenario.[42] We shall instead focus on the major differences in costs and system operation relative to the base case.

In the scenario with 1998 availabilities, the system generates only 177,971 GWh compared with 178,664 GWh generated in the base case. Both scenarios have the same final demand levels. Hence, the difference between generation levels implies that transmission losses are lower under the altered availability scenario.

The minimized total generating cost of meeting the 1999 demands with the 1998 plant availabilities is 31,595 million pesos compared with 30,376 million pesos in the base case, even though more electricity is generated under the base case. Changing the plant availabilities raises the minimized total costs, and average costs per kWh of power provided to consumers, by about 4%. The differences in marginal costs between the two scenarios are even larger. The weighted average marginal cost (with final demands as weights) in the reduced availability case is 38.58 cents per kWh compared with 32.08 cents per kWh in the base case, which is an increase of 20.3%. The dramatic increase in marginal costs resulting from the reduced availability of hydroelectricity reflects the higher costs of marginal thermal generating plant. It is another indication that electricity generation is not a "natural monopoly" in the sense of exhibiting declining costs as output expands.

Although the weighted average marginal cost is higher under the alternative availability scenario, the *dispersion* in marginal costs across regions is less in all periods, except only for the marginal reserve costs in period 2. This result may seem surprising. Since stored water can be used to generate hydroelectricity at any time, it generally allows the dispersion in costs across time periods to be reduced. Thus, a lower avail-

[42] Complete results are available from the authors upon request.

ability of hydroelectric capacity might be expected to produce more variable marginal costs. In the Mexican system, however, lower availability of hydroelectricity requires a greater use of localized thermal generation to satisfy demand. With less hydroelectricity being produced and transmitted over long distances, the network becomes less congested. When links are being used at less than capacity, a marginal change in local demand can be met by a marginal change in transmission levels. The price differentials between regions then become the marginal transmission losses. These are generally much smaller than the marginal cost of increasing output from different local thermal plants.

The different marginal costs of *reserves* under the two scenarios also reflect the lower extent of network congestion when hydroelectricity is less available. In particular, when it is possible to meet demand fluctuations by adjusting transmission levels, cost differences can be arbitraged away to a greater extent and the network behaves more like a unified system. Except for regions 1 and 2, the reserve marginal costs are positive only in period 1 when the system-wide demand peaks. In particular, transmission links to the central regions 14, 15, 17 and 19 can carry more power in the fall than they do in the summer, allowing the local generating capacity required for the system peak to cope with the local peak in the fall. From Table 2.12, generators in regions 14, 15 and 17 were used much more extensively under the 1998 regime.

In regions 1 and 2, marginal reserve costs are positive during both the local peak (in period 2) and the system-wide peak (in period 1). Since the transmission constraint from region 3 to region 2 is constrained in period 2, higher demand in period 2 can be met only by increased use of local plant.

The marginal costs in the Baja California regions (27–32) are the other major difference between the base and the altered availability scenarios. The Baja California costs are lower under the alternative scenario, while costs in most other regions are higher. The major explanation, as Table 2.12 and Table 2.4 show, is that the regions within Baja California that had increased availability in 1998 tended to have higher available plant capacities in 1999 than the regions with reduced availability.

2.5 The anticipated situation in 2005

In this section, we combine the model of the electricity supply system with the demand forecasts to investigate how planned additions to generating and transmission capacity will enable the system to deal with the anticipated growth between 1999 and 2005. We focus on 2005 since the investment schedule until then has been approved and most of the projects are already under construction. For years beyond 2005, the investment projects are more uncertain.

Table 2.13 presents the expected construction of generating capacity from 2000 to the end of 2004 in each of the 32 transmission regions.[43] Table 2.13 also gives our estimates of the forecast evolution of electricity sales[44] and generation output by transmission region.

The state-owned CFE recently has encouraged greater private investment in electricity generation. This has taken the form of self-generation by large industrial plants with sales back to the CFE when output exceeds the firm's own needs (co-generation), and also private construction under various types of contracts with the CFE. The latter category includes BLT, IPP and "turnkey" plants built by the private sector, but with all of the output produced or purchased by the CFE. Co-generators are allowed to sell only up to 25% of the capacity of their plants to the CFE, and only under very

[43] The data on planned additions to generating capacity and their costs are from the CFE, "Prospectiva del Sector Electrico 2001-10," the Ministry of Finance and Public Debt (SHCP), "Presupuesto de Egresos de la Federacion 2002," available at http://www.shcp.gob.mx/docs/pe2002/pef/temas/pidiregas/cfe.pdf, and the Energy Regulatory Commission (CRE), http://www.cre.gob.mx/estadisticas/stat98/electr.html.

[44] Sales and demand for electricity are different because of the losses.

Table 2.13: Additions to the installed generating capacity by the end of 2004[a]

Region	No.	Type[b]	Capacity (MW) Added	Total	Generation GWh	Demand GWh
1	2	CC	525	1,332	7,075	5,888
2				746	3,159	3,641
3				1,167	3,080	2,760
4				616	3,789	1,161
5	1	CC	268	584	7,334	5,628
6	2	1CC, 1Ga	583	1,701	4,019	4,859
7				643	2,288	8,518
8				2,710	17,192	2,969
9	4	3CC, 1Ga	1,545	3,211	16,512	29,840
10	2	CC	1,591	2,391	16,186	4,970
11	2	CC	1,032	1,544	10,568	4,086
12				1,352	2,146	12,432
13				1,900	9,850	1,516
14	2	O	480	1,200	7,854	9,758
15	5	4CC, 1Ge	1,390	2,837	12,582	26,657
16				3,395	16,031	612
17	1	CC	257	3,614	16,875	49,656
18	2	CC	1,576	6,268	39,281	21,186
19				681	1,496	3,437
20				358	1,736	1,783
21	1	D	25	51	3,623	3,633
22	1	H	936	4,864	21,610	3,530
23	1	CC	261	425	1,829	1,164
24	1	CC	531	808	3,392	3,124
25				14	0	281
26	1	CC	100	629	3	1,582
27	1	Ge	100	784	4,073	3,993
28	2	CC	1,065	2,181	9,122	7,423
29				55	0	1,244
30	3	2D, 1Ge	52	181	951	262
31				156	857	1,235
32				30	25	209
Total	34		12,308	48,398	244,514	228,827

a. Includes some 1999 capacity that was not available until 2000. Expected retirements (of 560MW) are not included since the location of these is unknown.

b. CC = combined cycle, D = Diesel, Ga = gas turbine, Ge = geothermal, H = hydroelectric, O = oil restrictive conditions.

Under the BLT, IPP and turnkey schemes, firms bid through public tender to provide new plants. The BLT plants are operated by the CFE, but leased for a period before being turned over to the CFE. By contrast, the private builder of an IPP plant also operates the plant under a long term contract to supply power to the CFE. In a turnkey project, the private firm constructs the plant for the CFE, which then owns and operates the plant.

Table 2.13 covers all private and public sector projects. In fact, of the expected 69,084 million pesos (in year 2001 currency) of proposed investments in generating plant between 2000 and 2004, 66,891 million pesos will be undertaken by private firms. Seven of these are co-generation projects expected to provide about 1,889 MW of capacity by the end of 2004. Of the 12,308 MW of additional capacity by the end of 2004, 7,303 MW will be built by private firms, with 6,198 MW of this in combined cycle plants. Public investment is expected in just two plants – a 114 MW hydroelectric plant and a 125 MW combined cycle plant.

In addition to new generating plant, the CFE have plans for substantial enhancements to the transmission network. These involve building new links between some regions and enhancing some of the existing links. Figure 2.4 illustrates the changes that are expected to be in place for the period November 2004 to October 2005.

As with the generation investments, much of the investment in the transmission system is being undertaken by the private sector. Of the 75,272 million pesos (in 2001 currency) required to undertake the transmission investments illustrated in Figure 2.4, 46,684 will be financed by the private sector and 28,588 by the public sector. The private schemes are BLT and turnkey projects, or else transmission investments associated with co-generation projects.

The estimated total generation costs in 2005 (in year 2000 currency) are 40,116

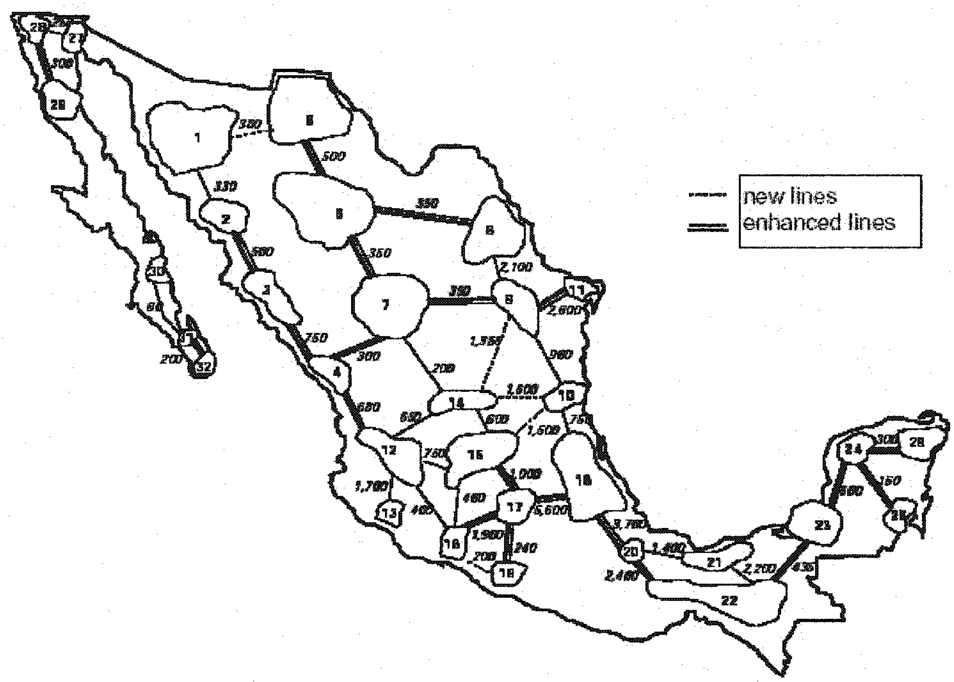

Figure 2.4: Planned changes to the transmission network by 2005

million pesos. The forecast power generated for the period November 2004 to October 2005 is 244,539 GWh. Recall that the corresponding numbers for 1999 were a cost of 30,376 million pesos and a total output of 178,664 GWh. The average generation cost in 2005 is 16.40 cents per kWh compared with 17.00 in 1999. The average generating costs are thus predicted to decline slightly despite a forecast growth in production of almost 6.5% per year. Whether or not the investments are justified depends on the magnitude of the investments relative to the value of the additional electricity generation for consumers. We do not have sufficient information to make this judgment. The rather low price elasticity of demand estimated in the first section of the chapter implies, however, that the loss in consumer surplus associated with a reduction in electricity consumption is likely to be quite large.

If all the planned investments are completed, our model also forecasts that the demand-weighted marginal costs will decline from 32.08 cents per kWh in 1999 to

25.46 cents per kWh in 2005. This is an even larger percentage decline than for the average costs. The geographical and temporal variation of marginal costs is also forecast to change. Tables 2.14, 2.15, 2.16 and 2.17, corresponding to Tables 2.7, 2.8, 2.9 and 2.10 in the base case, present the forecast marginal costs in 2005. In particular, reserve costs are expected to be non-zero only in the summer peak period in 2005, while the marginal costs associated with the demand constraints are also expected to vary less than in 1999. Both of these results suggest that the transmission network is likely to be less constrained in 2005 than it was in 1999.

2.5.1 Reduced transmission investment

The level of planned investment in generating and transmission capacity from 2000–2004 is 144,356 million pesos (in 2001 currency). Of this amount, over 30,000 million pesos is slated to come from the public sector. There are also large planned expenditures for investments in the distribution system and the maintenance of existing capital. The public sector is expected to finance over 50,000 million of the more than 62,000 million pesos expected to be invested in the distribution system, while maintenance expenditure of almost 30,000 million pesos will also need to be financed by the public sector.

The proposed transmission investments rely much more heavily upon direct public expenditures than do the generation investments. If the Mexican government encounters fiscal problems in the next two years, some of the transmission investments may be postponed. We therefore considered a scenario where all the generation investments are made as planned, but some of the investments in the transmission system do not eventuate.

Excluding all transmission investments expected to be completed beyond the end of 2002 made it impossible to meet the forecast demands for 2005 with the planned

Table 2.14: Marginal costs by transmission region: Summer (May–August)

(cents per kWh, Mexican Pesos)

	Demand periods					
	1		2	3	4	5
Region	Dem	Res				
1	25.9	192.1	25.9	25.7	24.4	24.4
2	25.6	189.9	25.6	25.6	24.7	24.7
3	25.1	180.0	25.1	25.1	25.1	25.1
4	26.0	186.2	26.0	26.0	25.8	25.8
5	26.1	195.6	25.7	25.2	24.0	23.9
6	26.5	199.3	26.2	25.7	24.5	24.4
7	28.3	218.3	27.9	27.5	26.5	26.5
8	25.0	195.0	24.7	24.2	23.5	23.3
9	26.8	206.3	26.4	25.8	25.1	24.9
10	25.2	186.3	24.8	24.8	24.8	24.8
11	25.7	198.0	25.3	24.8	24.1	23.9
12	26.8	188.6	26.7	26.5	26.5	26.5
13	24.7	174.1	24.7	24.7	24.7	24.7
14	27.1	203.8	26.7	26.3	26.0	26.0
15	27.5	202.3	27.1	26.9	26.7	26.7
16	24.9	170.0	24.9	24.9	24.9	24.9
17	26.3	183.5	25.5	25.5	25.5	25.5
18	24.4	170.1	24.4	24.4	24.4	24.4
19	25.9	180.3	25.9	25.9	25.9	25.9
20	22.3	148.4	22.3	22.3	22.3	22.3
21	20.8	132.6	20.8	20.8	20.8	20.8
22	20.4	124.9	20.4	20.4	20.4	20.4
23	21.2	176.4	21.2	21.2	20.8	20.7
24	21.7	183.2	21.5	21.5	21.2	20.9
25	22.0	185.8	21.8	21.8	21.5	21.2
26	21.9	185.3	21.8	21.8	21.4	21.2
27	24.2	329.0	24.2	24.2	24.2	22.0
28	23.8	312.7	23.8	23.8	23.8	22.4
29	24.8	325.8	24.8	24.8	24.2	22.7
30	101.2	180.5	97.6	97.6	97.6	86.3
31	106.9	189.9	103.4	103.4	102.6	90.8
32	105.1	186.8	105.1	105.1	104.3	92.3

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1–26	215.5	25.6	25.4	25.0	25.0
27–29	343.3	24.1	24.1	24.0	22.3
30–32	293.7	102.7	102.7	102.0	90.3
1–32	225.3	26.2	26.0	25.6	25.4

Table 2.15: Marginal costs by transmission region: Fall (Nov–Feb)

(cents per kWh, Mexican Pesos)

	Demand periods				
	11	12	13	14	15
Region					
1	24.1	24.1	23.5	23.5	23.5
2	24.5	24.4	23.8	23.8	23.8
3	25.0	24.8	24.2	24.2	24.2
4	25.9	25.7	25.1	25.0	24.8
5	23.6	23.6	23.6	23.6	23.6
6	24.1	24.1	23.9	23.9	23.9
7	26.4	26.2	26.2	26.0	25.7
8	23.3	23.2	23.2	23.2	23.2
9	24.9	24.8	24.8	24.8	24.8
10	24.1	24.0	24.0	23.9	23.9
11	23.9	23.8	23.8	23.8	23.8
12	26.8	26.4	25.8	25.7	25.5
13	24.7	24.4	24.0	24.0	23.9
14	26.3	25.9	25.8	25.6	25.2
15	27.5	27.1	26.4	26.1	25.9
16	24.9	24.4	23.7	23.5	23.5
17	26.8	26.4	25.6	25.2	24.7
18	24.7	24.4	23.8	23.8	23.6
19	26.4	25.9	25.9	25.5	25.0
20	22.3	22.3	22.3	22.3	22.2
21	20.8	20.8	20.8	20.8	20.8
22	20.4	20.4	20.4	20.4	20.4
23	21.2	21.2	20.7	20.7	20.5
24	21.6	21.5	21.0	20.9	20.6
25	21.9	21.8	21.3	21.2	20.9
26	21.9	21.8	21.2	21.2	20.9
27	22.8	22.0	22.0	22.0	22.0
28	22.4	22.4	22.4	22.4	22.4
29	22.7	22.7	22.7	22.7	22.7
30	94.2	86.2	86.2	86.2	86.2
31	99.1	90.7	90.6	90.6	90.6
32	100.7	92.2	92.1	92.1	92.1

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1–26	25.5	25.2	24.8	24.6	24.4
27–29	22.5	22.3	22.3	22.3	22.3
30–32	98.5	90.2	90.1	90.1	90.1
1–32	25.9	25.5	25.1	24.9	24.7

Table 2.16: Marginal costs by transmission region:

Shoulder (March, April, Sept, Oct)
(cents per kWh, Mexican Pesos)

	Demand periods				
Region	6	7	8	9	10
1	24.4	24.4	24.4	24.4	24.4
2	24.7	24.7	24.7	24.7	24.7
3	25.1	25.1	25.1	25.1	25.1
4	26.0	26.0	26.0	26.0	26.0
5	24.3	24.3	24.3	24.0	23.9
6	24.7	24.7	24.7	24.5	24.4
7	27.1	27.1	27.1	26.7	26.7
8	24.0	24.0	24.0	23.6	23.4
9	25.6	25.6	25.6	25.2	25.0
10	24.8	24.8	24.8	24.8	24.8
11	24.6	24.6	24.6	24.2	24.0
12	27.0	26.8	26.8	26.8	26.8
13	26.4	26.4	26.4	26.4	26.4
14	26.6	26.5	26.4	26.1	26.1
15	27.5	27.2	27.1	26.9	26.9
16	24.9	24.9	24.9	24.9	24.9
17	26.6	26.3	25.6	25.6	25.6
18	24.5	24.5	24.5	24.5	24.5
19	25.9	25.9	25.9	25.9	25.9
20	22.3	22.3	22.3	22.3	22.3
21	20.8	20.8	20.8	20.8	20.8
22	20.4	20.4	20.4	20.4	20.4
23	21.2	21.2	20.8	20.8	20.7
24	21.6	21.6	21.2	21.2	20.9
25	21.9	21.9	21.5	21.5	21.2
26	21.9	21.9	21.4	21.4	21.2
27	24.3	24.3	23.6	22.0	22.0
28	23.9	23.9	23.2	22.4	22.4
29	24.2	24.2	23.5	22.7	22.7
30	95.5	95.5	86.4	86.4	86.4
31	100.6	100.5	90.9	90.9	90.9
32	102.3	102.2	92.4	92.4	92.4

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1-26	25.6	25.5	25.3	25.2	25.1
27-29	24.0	24.0	23.3	22.3	22.3
30-32	100.0	99.9	90.3	90.3	90.3
1-32	26.1	26.0	25.7	25.5	25.4

Table 2.17: Marginal costs by transmission region: Weekends–Holidays

(cents per kWh, Mexican Pesos)

	Demand periods				
Region	16	17	18	19	20
1	23.9	23.9	23.8	23.8	23.8
2	24.4	24.4	24.1	24.1	24.1
3	24.8	24.8	24.5	24.5	24.5
4	25.7	25.7	25.3	25.3	25.3
5	23.5	23.5	23.4	23.4	23.4
6	23.9	23.9	23.9	23.9	23.9
7	26.2	26.2	26.2	26.2	26.2
8	23.2	23.2	23.2	23.2	23.2
9	24.8	24.8	24.8	24.8	24.8
10	24.0	24.0	24.0	24.0	24.0
11	23.8	23.8	23.8	23.8	23.8
12	26.5	26.4	26.1	26.1	26.1
13	25.4	25.4	25.4	25.4	25.4
14	25.8	25.8	25.8	25.8	25.8
15	26.5	26.5	26.4	26.4	26.4
16	24.4	24.4	24.4	24.4	24.4
17	25.5	25.1	25.1	25.1	25.1
18	23.8	23.8	23.8	23.8	23.8
19	25.9	25.9	25.9	25.9	25.7
20	22.3	22.3	22.3	22.3	22.3
21	20.8	20.8	20.8	20.8	20.8
22	20.4	20.4	20.4	20.4	20.4
23	20.8	20.7	20.7	20.7	20.5
24	21.2	21.0	20.9	20.8	20.6
25	21.5	21.3	21.2	21.1	20.9
26	21.4	21.2	21.2	21.0	20.9
27	22.8	22.0	22.0	22.0	22.0
28	22.4	22.4	22.4	22.4	22.4
29	22.7	22.7	22.7	22.7	22.7
30	86.2	86.2	86.2	86.2	86.2
31	90.7	90.7	90.7	90.7	90.7
32	92.2	92.2	92.2	92.2	92.2

Weighted averages across groups of regions (with the shares of group electricity needs as weights):

1-26	24.8	24.7	24.7	24.7	24.7
27-29	22.5	22.3	22.3	22.3	22.3
30-32	90.2	90.2	90.2	90.2	90.2
1-32	25.2	25.1	25.0	25.0	25.0

additions to generating capacity. If planned transmission investments beyond 2002 do not eventuate, therefore, additional investment in generating capacity would be needed to meet the forecast demand growth.

We then examined the transmission investments expected to be completed by the end of 2003. Five major transmission projects should be completed in that year. There are three new links between nodes 1 and 5 (380MW), nodes 9 and 14 (568MW) and nodes 10 and 14 (1,500MW). There are also two significant upgrades between nodes 18 and 20 (an additional 1,600MW of capacity) and nodes 20 and 22 (an additional 1,000MW of capacity).

The projects to upgrade the links between regions 22–18 increase the amount of power that can be transmitted from the hydroelectric plants in the Grijalva river region (22) to the central part of the nation. We found that these projects are critical. If they are not completed by the end of 2004, the forecast demands from November 2004 to October 2005 cannot be met without building more generating capacity.

On the other hand, if the upgrade projects are completed on time while the three new links slated for completion in 2003 are not, the resulting system (with all new generating plant completed on schedule) is capable of satisfying the forecast demand in 2005. The resulting average cost of generation is 16.57 cents per kWh instead of 16.40 cents per kWh if all planned transmission investments are completed. On the other hand, the weighted marginal cost (at 25.34 cents per kWh) is actually lower if the new links are not built. The marginal costs are more variable across regions and seasons when the system is less well-connected. In the two regions with the largest demands (the central and Monterrey areas), however, the marginal costs are lower in the system with weaker links. These results show that marginal and average costs do not necessarily move in the same direction as a result of new investments. In particular, if prices reflected marginal costs, stronger transmission links could make some consumers worse off by facilitating increased arbitrage and equilibration of marginal costs across the network.

Another interesting consequence of not building the 1,500MW link from region 10 to region 14, while nevertheless adding all the new generating capacity planned for region 10, is that the reserve constraint does not bind in region 10 in any season. This result illustrates how transmission and generating investments interact. Without the accompanying transmission investment, some of the investment in new generating capacity can be wasted.

2.6 Conclusion

Although our analysis reveals the necessity of substantial investments to meet the growing demand for electricity in Mexico over the years 2002-2010, the forecasted investment proposed by the government for the year 2005 will be sufficient, according to the results of our supply model, to take advantage of the low production costs of the new private owned power plants. It is questionable, however, if the method that has been chosen to encourage private investment is the most suitable. In particular, BLT, IPP and turnkey projects leave most of the risks to the public sector. One of the major functions of the privately owned companies and equity holders in the power sector is to share risks optimally and facilitate the funding of these large, long-term and risky investments. The return required to compensate investors for the risks they are bearing represents also the appropriate return for investment evaluation purposes. The lack of such information makes it much more difficult for publicly owned companies to analyze whether an investment is attractive or not.

Another potential disadvantage of BLT and turnkey projects is that the operation of the facility remains the responsibility of the publicly owned company. One of the major reasons for the inefficiencies resulting from public ownership is that the state-owned company is not receiving a strong incentive to minimize its operating costs. Even the owners of IPP projects are not very motivated to control costs if these define the contractual capacity and energy rates, which is normally the case.

On the other hand, the estimated costs for the year 2005, assuming that all the planned investment is completed on time, anticipate that the electricity system will be in good conditions to start restructuring the industry, as there will be no risk of a price escalation due to the lack of generating capacity, at least during the first years of the reform.

The second major conclusion from our analysis is that in Mexico there are substantial differences between the electricity prices and the marginal costs of supply. In particular, the regional and the intertemporal price variations are not closely related to the corresponding variations in marginal costs. As a result, consumers are not receiving accurate signals about the costs related to their demands and are not getting a clear guidance about the benefits of changing their location, or the timing of their electricity demands, so as to reduce the costs for the system as a whole.

Allowing the private sector to enter the wholesale market for electricity, and setting prices through an auction mechanism, may also help to define the tariffs on a cost base. Before introducing such reforms, however, the existing state-owned suppliers would need to be split according to their functions (with transmission and distribution separated from generation) and the remaining generating assets allocated to various competing companies. It may even be counter-productive to introduce a wholesale market for electricity that is not competitive. The price signals sent to consumers and potential producers would provide a distorted reflection of the costs, encouraging inefficient consumption and production decisions.

The third major conclusion from our analysis is that the hydroelectric plants in Mexico are quite valuable as a mechanism to smooth temporal and geographical variations in marginal generation costs. In effect, the storage of water compensates to some extent the inability to store electricity. However, the benefits of hydro plants are limited by the existing lack of transmission capacity. The major hydro plants are located in the Grijalva river region in the south of the country and the transmission links to other regions can often become congested. Upgrading the transmission links is thus a major priority. The public sector is expected to remain the main investor in transmission facilities in the immediate future. However, there is a risk that the required funds may be sacrificed for fiscal reasons that have nothing to do with the needs of the electricity industry

Chapter 3

Decomposing Electricity Prices with Jumps

3.1 Introduction

When considering deregulation of the electricity industry, it is first necessary to determine a mechanism to price electricity in a competitive framework given the non storability of electricity and the permanent need for maintaining the balance between demand and supply. Now after more than ten years of international experience in competitive electricity markets, there exists a set of alternative mechanisms based on the interaction between the demand and supply that warrants the uninterruptible operation of the power market. However, the specific characteristics of the industry and the decentralized decisions about when, where and how much power to produce have resulted in greater price volatility, which is also accompanied by huge spikes in prices. For example it is not uncommon to see power price levels that peak at 100 times the normal rate. These characteristics of electricity spot prices have encouraged the development of financial derivatives that help market participants to hedge price risks in the new and volatile environment. Pricing those financial instruments has become one of the main topics in the research agenda that traditional financial literature has yet to satisfactory model. In particular the high dependence of such derivatives on the assumption regarding the stochastic processes that follow the underlying assets has opened a discussion about models that best fit the particulars of electricity spot prices. This study tries to contribute to the still developing discussion of modeling electricity prices in a deregulated market.

The standard approach to modeling electricity prices has been take from the theory of finance. Some of the first attempts to model electricity prices were assuming standard diffusion processes such as Geometric Brownian motion or Ornstein-Uhlenbeck types of processes. However, although they aim to capture some characteristics of electricity prices, such as its strong mean reversion, they did not capture the presence of spikes in prices. One natural method of modeling such spikes was to use the diffusion-jump model developed by Press (1967). Press considered that the daily (log) returns in security markets can be divided in two components: the continuous diffusion part, which can be described by a Wiener process, and a discontinuous jump that represents shocks in the market and that can be modeled as a compound Poisson process. Under this specification, the resulting distribution of the (log) prices becomes a Poisson mixture of normal distributions whose parameters have to be estimated simultaneously. This approach was later used to model all types of financial instruments and became one of the standard models for series that present continuous jumps in their paths. In modeling electricity prices such jump-diffusion part is in general added to mean reversion models to account the relative short life of the jumps.

Although appealing, such jump-diffusion approaches have some limitations in practice. The main problems come from an identification problem as the resulting distribution of the (log) prices is a mixture of normal distributions and the estimation methods imply the use of the same data to estimate the parameters of both processes simultaneously (i.e. see Huisman, et. al. (2001)). The outcome of estimating such models is well known. Bates (1995) has documented that the jump-diffusion specification in general tends to capture small and high frequency jumps, which is exactly the opposite of what is relevant in the study of electricity prices.

Alternatively, there is a more natural approach to model such spikes in electricity prices assuming a diffusion process augmented with regime-switching. Sudden jumps in electricity prices are always related with the state of the generation and transmission system. If the electrical system is in a shortage of electricity state (because some lines become congested or because the sudden break down of a generation plant), market prices adjust drastically to balance the supply and demand of electricity. This is the response in prices regardless of the policy with respect of the maximum level of prices that can be achieved in the market.

In the last few years there has been an increase in the use of regime-switching models in the literature. Examples of this trend include Deng (2000), who developed a general model in which the regime-switching is used to capture the seasonal components of electricity prices; Chourdakis (2000), who generalized the idea of discrete regime-switching models to a continuous framework; and Huisman and Mahieu (2001) who observed the need for modeling jumps as regime-jumps as a way to separately estimate the parameters of the "normal" component of electricity prices.

However modeling electricity prices as a switching Markov process implies that the effect of a shock in price tends to die out rather quickly, even when new jumps are allowed for the following periods. A close inspection of the electricity price raises some doubt about using only a switching Markov process, as the effects of price shocks in this market do not die out quickly. If that is the case the scenario in which the effects of shocks in prices remain at least for a while would be an empirically testable feature of electricity as a stochastic process. For that event we propose a model in which electricity price is compounded by two parts: what we call the "normal" behavior of prices, represented by a Ornstein-Uhlenbeck type process, and the "jump" component, which follows a mean reverting process with regime-jumps. With this specification the degree of mean reversion of the "jump" component becomes an explicit and separate parameter to be estimated in the model. To focus our attention on the jumps and spikes of electricity markets, we abstract from the seasonality and other components of prices and estimate the model for the Australian market. To estimate the probabilities of the regimes, the unobservable variables and the parameters of the diffusion processes, the model is treated as state-space model with regime switching and the estimation is made using the algorithm developed by Kim (1994), who extended the Hamilton Markov-switching model to the state-space representation of dynamic linear models.

The remainder of the chapter is organized as follows. In the next section we describe briefly how prices are determined in a deregulated electricity sector. In section three we present the model and in section four we describe the estimation method. Finally in section five we present the results for the demeaned Australian electricity prices.

3.2 How Power Prices are Determined

As in any other market, competitive electricity prices are determined by the interaction of demand and supply. Ideally the price clearing mechanism for this market will involve a two-side biding process, one for each side of the market. However, the atomization of the demand side has been one of the main obstacles of its complete implementation. Alternatively many countries have adopted a one side bid mechanism or have limited the participation to customers with high electricity demand, including the distribution companies that buy electricity in the wholesale market and then distribute the power to small consumers. In fact, the implementation of a supply side bid mechanism, sometimes with participation of large customers in the demand

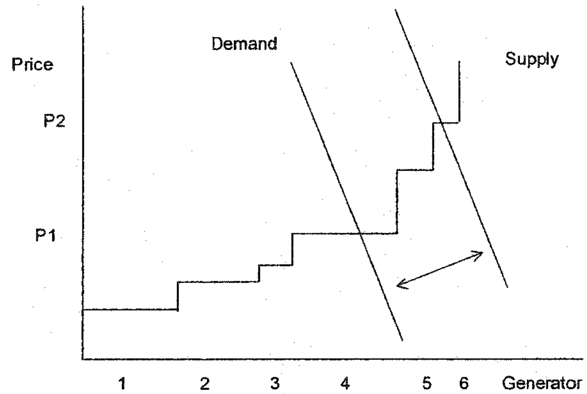

Figure 3.1: Balance between demand and supply in power markets. Shock in demand.

side, is considered the first step towards the liberalization of the sector.

In practice the one side bid mechanism may be described as follows. For each trading period (in general for each hour of the day) all the private power generators submit prices and the amount of power that they are willing to trade (in general in a day ahead market). Once the bids are submitted, the pool's regulators order the bids from the lowest to the highest prices and create an aggregate supply curve for the sector, which is matched with aggregate electricity demand to determine the spot prices and the dispatching order of generators. In this setting the marginal generator is the one which determines the clearing price in the market. One example of such a price clearing mechanism is illustrated in Figure 3.1.

Among the determinants of the supply curve are the number of generation plants, their technology and the transmission lines that connect generators with consumption centers. If there is a large number of generators with similar technology and unrestricted transmission capacity, we would expect to observe gradual changes in prices as long as demand changes gradually. In the real world, however, there is a big variation in technologies across power plants, some of them better suited to supply power under specific conditions. For instance in order to recover its fixed costs, big plants with low variable costs are scheduled to operate most of the time. Meanwhile, plants with high marginal cost but low cost of capital are economically better suited to operate only during periods of peak demand. There are some peaking plants that work a relatively small number of hours during the year but charge a high price for their power as a way to cover fixed costs. If the maximum electricity demand is close to the total generation capacity of the system, such peaking plants are most probable to be scheduled to operate. In such case, electricity prices tend to rise drastically in face of any increase in demand.

Sudden and drastic changes in prices that quickly revert can be the result of a temporary surge in demand (for example, due to temporal changes in temperatures) or the result of temporary drops in supply (for example, due to temporal generators or transmission failures). These temporary movements are called the "jump" state in this chapter . Demand shocks may be identified with temporal movements of the demand curve to the right and the corresponding schedule of higher cost generators in the system. Figure 3.1 illustrates this movement: given the shock in demand, generator 6 at price P2 is dispatched. On the other hand, in the case of a shock on the supply side there would be a temporal movement of the supply curve to the left. Figure 3.2 illustrates this situation: if generator 4 temporarily goes off line, generators 5 and 6 will be activated at the higher price P2. It is even possible that because of such shocks, demand will not intersect the supply curve. In such a case electricity prices must be determined exogenously from the market mechanism, either by the regulators or by the price of exogenous power sources (i. e. price charged by power plants external to the pool). Although there are several mechanism to price electricity when demand is higher than the total capacity, generally prices are set at such a high level to induce the entrance of new generator plants.

A different kind of pattern in power prices is observed when electricity demand

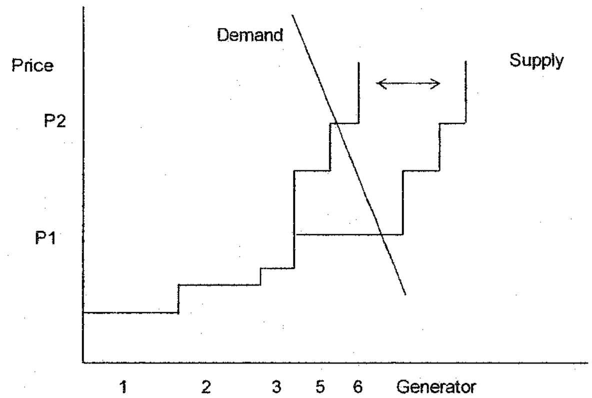

Figure 3.2: Shock in supply.

or supply is not exposed to extremely temporal shocks that require most or all the generation capacity. This condition is called in the study the "normal" state and it is characterized by the lack of extreme jumps in prices.

Similar to other competitive markets, electricity prices play the role of signals of the general conditions in the sector. Therefore it is important to distinguish between changes in prices that represent temporary shocks with non-lasting effects and changes in prices that correspond more closely to the intrinsic dynamics of the market. The goal of the next section is to explicitly differentiate these two components.

3.3 Model

Taking into account that the extreme jumps which revert quickly correspond to different dynamics than the normal pattern in electricity prices, we consider a model that breaks apart such components. Specifically we express the electricity price P_t, as the sum of two independent stochastic processes, one that represents the normal behavior of prices (X_t) and other that represents the effect of temporary shocks (Y_t):

$$P_t = X_t + Y_t \tag{3.1}$$

We also assume that X_t and Y_t are governed by the following stochastic differential equations:

$$dX_t = k(a - X_t)dt + \sigma dB_t \tag{3.2}$$

$$dY_t = -\alpha Y_t dt + z_t dq_t \tag{3.3}$$

with dB_t representing an increment to a standard Brownian motion B_t and dq_t representing a Poisson process. Both the Poisson and the diffusion process are assumed to be independent of each other.

Notice that X_t follows an Ornstein-Uhlenbeck process, with instantaneous variance σ^2, long-run mean a, and a speed of adjustment $k > 0$. This specification of the normal pattern of prices attempts to capture the mean reverting property which is a characteristics of electricity prices. One straightforward extension of such specification is to allow a to change through time; either because it would be a function of exogenous variables (such as the average price of the inputs to generate electricity) or because the seasonality pattern of the electricity demand. In such case the model would be specified with a varying parameter a_t instead of fixed a. For the purposes of the present study, that focus on modeling the "jump" component of prices, we assume that the long-run mean is constant.

On the other hand, Y_t is also specified to evolve as a mean-reverting process, with zero long-run mean and reverting rate $\alpha > 0$. However its stochastic part is defined as a Poisson error component (dq_t) with an arrival frequency parameter λ and jump size z_t. Finally, z_t is assumed to be drawn from a normal distribution, with mean μ_z and variance δ^2, independent of the diffusion and Poisson processes.

In order to estimate the model we approximate the Poisson error component of Y_t with a Markov-switching model. Consider the following specification of (3.3) that involves the latent variable S_t

$$dY_t = -\alpha Y_t dt + z_{t,S_t} \tag{3.4}$$

where

$z_{t,0} = 0$,with probability $1 - \lambda\Delta t + o(\Delta t)^2$,

$z_{t,1} = z_t$,with probability $\lambda\Delta t + o(\Delta t)^2$,

$z_{t,n} = n \cdot z_t$, $n \geqslant 2$ with probability $o(\Delta t)$,

$S_t = 0, 1, 2, ...n$ is a latent variable and

$z_t\tilde{}N(\mu_z, \delta^2)$ is the size of the jump.

Notice that the expressions of the probabilities that govern z_{t,S_t} are obtained from the Taylor series expansion of the Poisson density; i.e. the probability of no jump in a "small" interval of time is approximately $1 - \lambda\Delta t$, and of one jump, $\lambda\Delta t$.

To translate this specification to a Markovian switching model we construct a manageable transition probability matrix to define the evolution of the state variable. In order to specify a Markov-switching model with two states, the "normal" state with $S_t = 0$ and the "jump" state with $S_t = 1$, we first assume that the probability of more than one jump in one unit of time is negligible[1]. We also assume a first order Markov-switching process for S_t, that is, the discrete variable S_t will depend only upon S_{t-1}. In order to capture the spikes in prices due to short-lived shocks we assume that once the state variable indicates a jump at period t it will return to the "normal" state at period $t+1$ with probability m_{10} and it will jump again with probability $m_{11} = 1 - m_{10}$. Therefore the relevant transition probabilities for the model are $\Pr[S_t = 0|S_{t-1} = 0] = m_{00}$ (that approximate the probabilities of the Poisson distribution $1-\lambda\Delta t$) and $\Pr[S_t = 1|S_{t-1} = 1] = m_{11}$, with the complementary

[1]In fact if data is available with high enough frequency, as is the case of electricity prices (for instance, hourly data), we can assume that in a short period of time only one jump may occur.

probabilities $\Pr[S_t = 1|S_{t-1} = 0] = m_{01} = 1 - m_{00}$ and $\Pr[S_t = 0|S_{t-1} = 1] = m_{10} = 1 - m_{11}$.

Notice that in (3.4) the mean reverting component of Y_t is not affected by the latent variable, S_t, hence there is a continuous adjustment even when the temporal shock has disappeared. This characteristic of the model gives some flexibility to capture possible lags in the effect of supply and demand shocks over the behavior of immediate future prices.

3.4 Estimation Method

The proposed model contains inferences about the undistinguished variables X_t and Y_t, as well as inference about the evolution of the state variable S_t. To solve the model we can take advantage of its state-space representation and use Kim's (1994) filtering algorithm, which merge switching states with dynamic models involving unobservable variables.

Assuming an Euler approximation to the stochastic differential equations (3.2) and (3.4), we can write the state-space representation of the system as follows:

Measurement Equation:

$$P_t = H\beta_t, \tag{3.5}$$

Transition Equations:

$$X_t = ka\Delta t + (1 - k\Delta t)X_{t-\Delta t} + \sigma\Delta t\varepsilon_t \tag{3.6}$$

$$Y_t = (1 - \alpha\Delta t)Y_{t-\Delta t} + e_{S_t} \tag{3.7}$$

with $\varepsilon_t \tilde{} N(0,1)$, $e_{S_t} = \mu_z S_t + \delta S_t e_t$, $e_t \tilde{} N(0,1)$ and $S_t = 1, 0$.

Or in matrix notation, and normalizing $\Delta t = 1$:

$$\beta_t = \bar{\mu}_{S_t} + F\beta_{t-1} + Q_{S_t} v_t \tag{3.8}$$

with

$$\beta_t = \begin{bmatrix} X_t \\ Y_t \end{bmatrix}, H = [1\ 1], \bar{\mu}_{S_t} = \begin{bmatrix} ka \\ \mu_z S_t \end{bmatrix}, F = \begin{bmatrix} (1-k) & 0 \\ 0 & (1-\alpha) \end{bmatrix},$$

$$Q_{S_t} = \begin{bmatrix} \sigma & 0 \\ 0 & \delta S_t \end{bmatrix} \text{ and } v_t = \begin{bmatrix} \varepsilon_t \\ e_{S_t} \end{bmatrix}.$$

The subscripts in $\bar{\mu}_{S_t}$ and Q_{S_t} indicate that these expressions depend on the unobservable switching variable S_t, whose transition probabilities are given by

$$M = \begin{pmatrix} m_{00} & 1-m_{11} \\ 1-m_{00} & m_{11} \end{pmatrix} \tag{3.9}$$

where as before $Pr[S_t = 0|S_{t-1} = 0] = m_{00}$, and $Pr[S_t = 1|S_{t-1} = 1] = m_{11}$.

Kim's algorithm is a mixture of Kalman and Hamilton filters, and includes a "collapsing" step to avoid the explosion of possible paths of the state vector due to the transition probability matrix. A complete discussion of the algorithm can be found in Kim (1994) and Kim and Nelson (1999). In this section we summarize the principal equations of the algorithm fitted to our model.

The goal of the filter is to form a forecast of β_t based on the vector of observations available up to $t-1$ (ψ_{t-1}), but also conditional on the random variables S_t and S_{t-1}. In terms of notation we have

$$\beta_{t|t-1}^{(i,j)} = E[\beta_t|\psi_{t-1}, S_t = j, S_{t-1} = i],$$

and the associated mean squared error matrix is

$$P_{t|t-1}^{(i,j)} = E[(\beta_t - \beta_{t|t-1})(\beta_t - \beta_{t|t-1})'|\psi_{t-1}, S_t = j, S_{t-1} = i].$$

Conditional on $S_t = j$ and $S_{t-1} = i$, the Kalman filter algorithm follows the next computational steps:

$$\beta^{(i,j)}_{t|t-1} = \bar{\mu}_j + F\beta^{i}_{t-1|t-1},$$

$$P^{(i,j)}_{t|t-1} = FP^{i}_{t-1|t-1}F' + Q_jQ_j',$$

$$\eta^{(i,j)}_{t|t-1} = p_t - H\beta^{(i,j)}_{t|t-1},$$

$$f^{(i,j)}_{t|t-1} = HP^{(i,j)}_{t|t-1}H',$$

$$\beta^{(i,j)}_{t|t} = \beta^{(i,j)}_{t|t-1} + P^{(i,j)}_{t|t-1}H'[f^{(i,j)}_{t|t-1}]^{-1}\eta^{(i,j)}_{t|t-1},$$

$$P^{(i,j)}_{t|t} = (I - P^{(i,j)}_{t|t-1}H'[f^{(i,j)}_{t|t-1}]^{-1}H_j)P^{(i,j)}_{t|t-1},$$

where $\eta^{(i,j)}_{t|t-1}$ is the conditional forecast error of p_t given ψ_{t-1}, $S_t = j$ and $S_{t-1} = i$; and $f^{(i,j)}_{t|t-1}$ is the conditional variance of forecast error $\eta^{(i,j)}_{t|t-1}$,with $i, j = 0, 1$.

Notice that each iteration of the Kalman filter produces two more cases to consider per estimation of $\beta^{(i,j)}_{t|t}$ [2].

The Hamilton filter component focuses on calculating $Pr[S_t, S_{t-1}|\psi_t]$ and $Pr[S_t|\psi_t]$ as follows:

$$Pr[S_t = j, S_{t-1} = i|\psi_{t-1}] = Pr[S_t = j|S_t = i] \cdot Pr[S_{t-1} = i|\psi_{t-1}] = m_{ij} \cdot \pi_i$$

$$Pr[S_t = j, S_{t-1} = i|\psi_t] = \frac{f(p_t|S_t=j, S_{t-1}=i, \psi_{t-1}) \cdot Pr[S_t=j, S_{t-1}=i|\psi_{t-1}]}{f(r_t|\psi_{t-1})}$$

$$Pr[S_t = j|\psi_t] = \sum_{i=1}^{2} Pr[S_t = j, S_{t-1} = i|\psi_t]$$

with

$$p_t|S_t = j, S_{t-1} = i, \psi_{t-1} \tilde{} N(\eta^{(i,j)}_{t|t-1}, f^{(i,j)}_{t|t-1}),$$

[2] The size of the transition probability matrix (M).

$$f(p_t, S_t = j, S_{t-1} = i|\psi_{t-1}) = f(p_t|S_t = j, S_{t-1} = i, \psi_{t-1}) \cdot Pr[S_t = j, S_{t-1} = i|\psi_{t-1}],$$

$$f(p_t|\psi_{t-1}) = \sum_{j=1}^{2}\sum_{i=1}^{2} f(p_t, S_t = j, S_{t-1} = i|\psi_{t-1}).$$

where π_i is the steady state probability of $S_{t-1} = i$ and m_{ij} is taken from the transition probability matrix (3.9).

To avoid the explosion of the number of cases to consider, Kim (1994) proposed the following approximation that collapses the number of terms $\beta_{t|t}^{(i,j)}$ and their corresponding mean squared errors $P_{t|t}^{(i,j)}$ to only two cases (those corresponding to the number of states of S_t):

$$\beta_{t|t}^{i} = \frac{\sum_{j=1}^{2} Pr[S_t=j, S_{t-1}=i|\psi_t] \cdot \beta_{t|t}^{(i,j)}}{Pr[S_t=j|\psi_t]},$$

$$P_{t|t}^{i} = \frac{\sum_{j=1}^{2} Pr[S_t=j, S_{t-1}=i|\psi_t] \cdot \{P_{t|t}^{(i,j)} + (\beta_{t|t}^{i} - \beta_{t|t}^{(i,j)})(\beta_{t|t}^{i} - \beta_{t|t}^{(i,j)})'\}}{Pr[S_t=j|\psi_t]}.$$

With this approximation, $\beta_{t|t}^{i}$ is no longer the linear projection of β_t on ψ_t as in the pure Kalman filter, but now the algorithm is manageable and Kim has showed that the loss in efficiency produced by the approximation is only marginal. In our case, this algorithm is used to identify two stochastic components of electricity prices and therefore it permits us to estimate the parameters of the "normal" electricity process without considering the noise of temporal shocks. What follows is an application of the above model to a competitive wholesale electricity market.

3.5 Application: Electricity Spot Prices in New South Wales, Australia.

In this section we show the results of applying the above model to New South Wales' electricity spot prices[3]. This market began operations as regional market in 1996.

[3]Data source: http://www.nemco.com.au

Later, it was integrated into the national grid creating the Australian National Electricity Market (NEM). The NEM operates a supply bidding mechanism that sets electricity prices every half hour. The period studied in this analysis begins with the integration of the national market on January 1999 and ends on May 2002 with a total of 59,835 observations.

Secondary markets have traditionally used average daily prices to price futures and other derivatives in electricity markets[4]. Following this practice we based our estimations on average daily prices, which results in a total sample of 1,247 daily observations. With this transformation we also avoid the strong intraday cyclical behavior of the electricity market.

A complete characterization of the stochastic process of electricity prices involves specifying its seasonal component as well as its relationship with other exogenous variables that may determine its trend, such as the average cost of the inputs. In the model we assume that all of these elements are captured with the time varying mean (a_t) of the normal component. However, to focus on the decomposition into "normal" and "jump" components, we estimate a_t with nonparametric techniques instead of explicitly assuming a specific functional form [5]. Once we have estimated such time varying "mean" to which the "normal" component is reverted, we proceed to estimate the diffusion parameters (3.6) and (3.7) over the prices' deviations from that mean. Figure 3.3 shows the original and the transformed data the estimations of our model are based on.

With the transformed price series we estimate the parameters of the transition

[4] For example see Lucia and Schwartz (2001) for a description of the Nordic Power Exchange.

[5] Specifically we follow the next three steps to transform the data. (1) We decompose the original price series into a pseudo "normal" and a pseudo "jump" component using Kim's algorithm (they are called pseudo components because they still capture some movements in a_t). (2) Taking as our data the pseudo "normal" component, we non-parametrically estimate its mean using a normal kernel with the optimal window width $h = 0.25\sigma_t n^{-1/5}$ and $t = 1, 2 \ldots n$.(3) Finally we substract the estimated mean from the original prices.

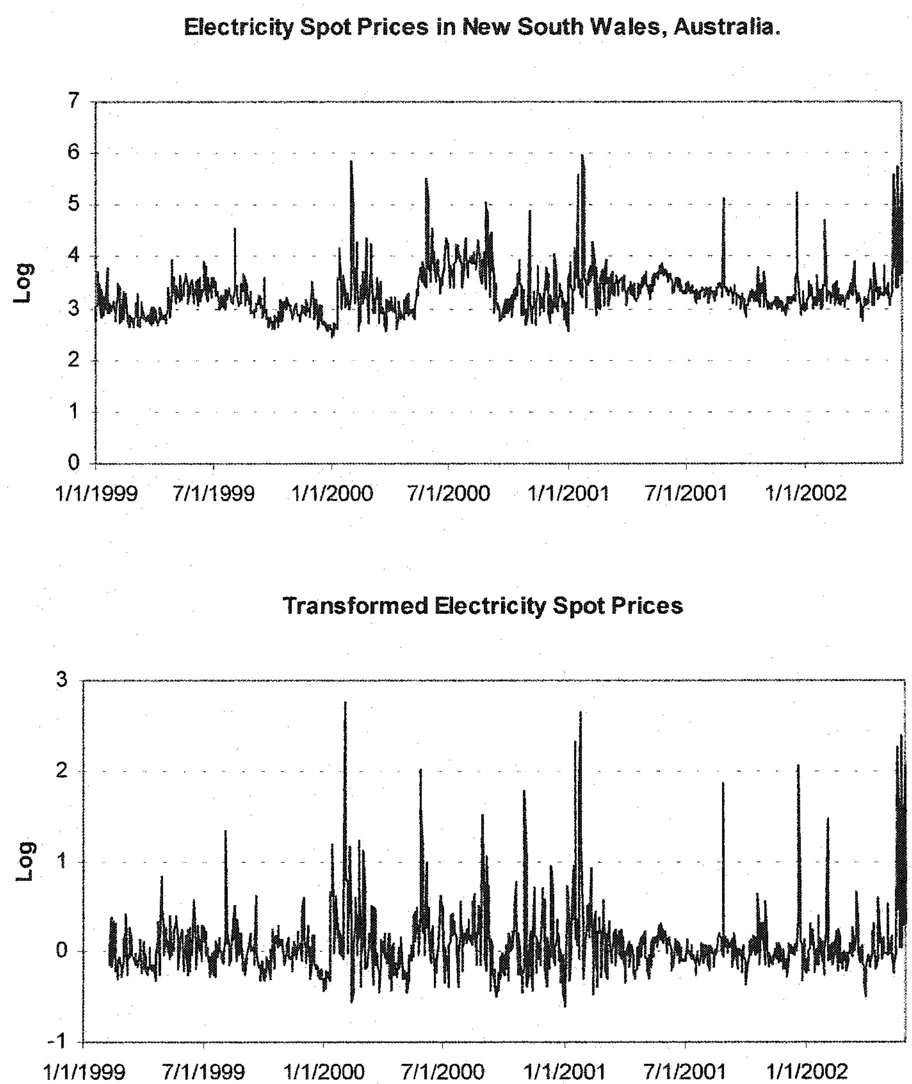

Figure 3.3: Electricity Spot Prices and its transformation (demeaned series).

Table 3.1: Estimation results of the model

Parameter	Estimates	Std. err.	t values
Transition Probability Matrix			
m_{00}	0.9567	0.2157	14.349
m_{11}	0.7160	0.2821	3.279
"Normal" component			
k	0.2392	0.0221	10.844
a	-0.0039	0.0195	-0.202
σ	0.1457	0.0050	28.926
"Jump" component			
α	0.7509	0.0869	8.645
μ_z	0.4811	0.0883	5.451
δ_z	0.6101	0.0436	14.008
ML	0.168604		

equations (3.6) and (3.7) and the probabilities of the transition probability matrix (3.9). Maximum Likelihood estimates of the parameters are shown in Table 3.1.

By examining the results, it seems clear that the conditional probability of the occurrence of a jump given, provided that there was already a jump in the previous period, is not negligible ($m_{11} = 0.75$). This means that "jumps" are significantly correlated in the NSW market, implying that for modeling purposes such parameters must at least be checked to be different from zero. From the parameters of the Markov transition matrix we can also compute the unconditional probability that the process will be in a "jump" state as follows:

$$\hat{\pi}_1 = \Pr[S_0 = 1|\psi_0] = \frac{1 - \hat{m}_{00}}{2 - \hat{m}_{00} - \hat{m}_{11}} = 0.1323.$$

On the other hand, it is not surprising that the long-run mean of the "normal" component is not significantly different from zero since we worked with mean adjusted series. The results show that in spite of a high reverting parameter for the "jump" component ($\alpha = 0.75$), prices, after a jump, do not fall back completely on the day after , but follow a gradually decreasing adjustment process. Such a result raises doubts about the assumption of short-lived effects on the jumps in other studies (i.e.

Huisman and Mahieu (2001)), and suggests the need of considering such gradual adjustment in electricity prices. One explanation of this result may be that after a supply failure or a sudden demand change, the market participants are unsure of the likelihood that such behavior is repeated in the subsequent periods (observation consistent with the high value of m_{11}). As a consequence, the participants adjust the prices gradually.

As part of the estimation process, the filtering algorithm also split electricity prices into two components, $\{X_t\}$ and $\{Y_t\}$, and estimates the unconditional probability that the process will be in a jump state at any period. The decomposition and the probabilities are plotted in Figure 3.4.

A direct application of the decomposition of electricity prices is the estimation of the contribution of the "jump" component contribution to the average electricity price in a certain period of time. Since financial instruments are traded according to their price per kilowatt-hour and the amount of electricity delivered in a certain period time, the knowledge about the contribution of the "jump" switching process provides a cost estimate of having a market mechanism that allows certain frequency, size and persistence of the jumps.

As an illustrative example we consider the contribution of each component on the average monthly price of the sample over the last four months and the average weekly price over the last two months. The results from this decomposition are given in Table 3.2.

3.6 Bootstrap simulation

We use the bootstrap method to simulate electricity prices and estimate their expected value in the future. In particular we are interested in knowing the price component

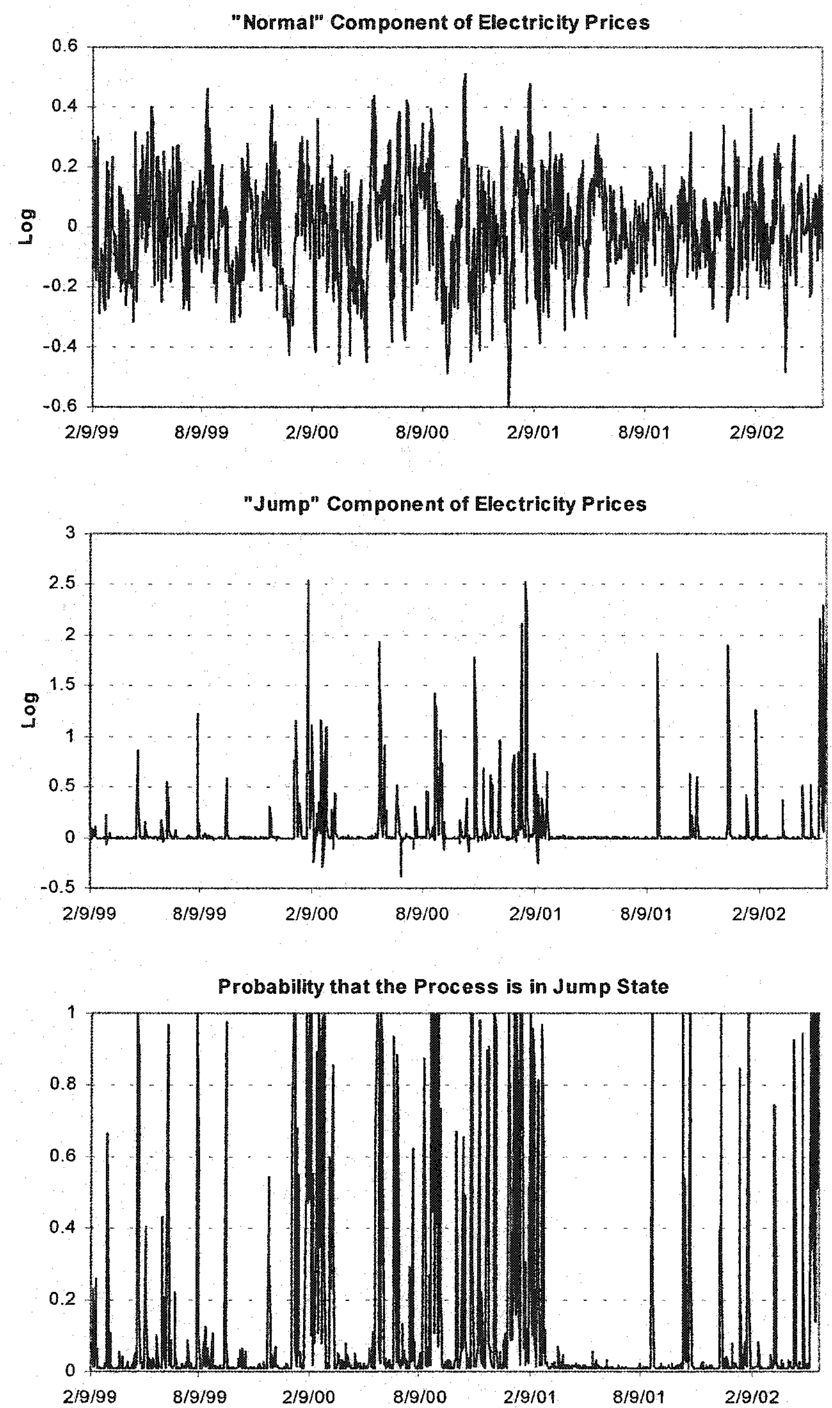

Figure 3.4: Decomposition of electricity prices and unconditional probabilities

Table 3.2: Estimated Decomposition of the Average Electricity Price for the Year 2002 (Australian Dollars)

Period	Observed Prices	Normal Component	Jump Component
January	25.50	24.91	0.59
February	29.53	26.61	2.92
March	25.89	25.25	0.64
April	26.59	25.74	0.84
May	74.94	28.02	46.91
April/06-April/12	25.68	25.63	0.05
April/13-April/19	25.73	25.69	0.04
April/20-April/26	30.87	27.37	3.49
April/27-May/03	26.97	26.94	0.03
May/04-May/10	30.91	27.60	3.32
May/11-May/17	25.72	25.73	-0.001
May/18-May/24	114.75	29.19	85.56
May/25-May/31	149.27	30.39	118.89

that is attributable to the "jump" state in comparison with the contribution of the "normal" state in the industry. This price decomposition may be used to evaluate the benefits of reducing the size or frequency of such "jumps". Also, based on the previous model, the bootstrap technique provides an alternative method to estimate the price of futures and other derivatives in the electricity market.

The bootstrap method is mainly used for estimating test statistics or the distribution of an estimator through simulation techniques that resample the real data set. Here we use the method to simulate the electricity price pattern from decomposing the contribution of the "normal" and "jump" components[6]. From the simulations we may calculate the expected value of the average price for future weeks or months, the periods of time in which electricity flows are generally traded.

The simulation is based on the Euler approximation (3.6) and (3.7). Notice that the parametric model of the "normal" component of electricity prices (3.6) reduces

[6]The discussion does not attempt to provide a detailed description of the bootstrap method. For a comprehensive description of the method see, for example, Horowitz (1999).

its data generation process to a transformation of the independent random variable ε_t. Then a bootstrap sample of $\{X^*\}$ can be directly generated by random sampling the residuals from the fitted model. That is, we estimate

$$X_t^* = \hat{k}\hat{a} + (1 - \hat{k})X_{t-1}^* + \hat{\sigma}\varepsilon_t^*,$$

where $\hat{k}$, $\hat{a}$ and $\hat{\sigma}$ are the Maximum Likelihood (ML) estimates of the parameters of (3.6) and $\{\varepsilon_t^*\}$ is a random sample of the normalized estimated residual $\{\hat{\varepsilon}_t\}$.

In a similar way we can generate bootstrap sample of $\{Y^*\}$ taking into account that the parametric model (3.7) does not produce independent errors because of the first order Markov-switching process that governs S_t. Such bootstrap sample can be generated using the following relationship

$$Y_t^* = (1 - \hat{\alpha})Y_{t-1}^* + e_{S_t}^*,$$

where $\hat{\alpha}$ is the ML estimate of α and $\{e_{S_t}^*\}$ is a conditional sample of the estimated residual $\{\hat{e}_{St}\}$.

To deal with the dependence of the fitted errors we performed a conditional bootstrap sample of the residuals as follows:

First, we identify a jump in any particular period using estimated unconditional probabilities of observing a jump obtained from Kim's smoothing algorithm (see Figure 3.4). If this probability is greater than that deduced from the estimated parameters we consider that there was a jump in that particular period. In terms of notation there is a jump if the following condition applies:

$$\hat{P}(S_t = 1|\Psi_t) > \hat{\pi}_1 = \frac{1 - \hat{m}_{00}}{2 - \hat{m}_{00} - \hat{m}_{11}}.$$

where $\hat{P}$ is obtained from the smoothing algorithm and $\hat{m}_{00}$ and $\hat{m}_{11}$ are the ML estimates of m_{00} and m_{11} respectively.

Once we identified the periods in which a jump in prices has occurred, we classified the estimated residuals in two subsamples: one that collects all the residuals that follow a jump, sub-sample called J_j, and another that collects all the residuals that do not follow a jump, sub-sample called J_n. Then we generate bootstrap samples of $\{e^*_{S_t}\}$ by randomly sampling these two sets conditional on the state at $t-1$ ($S_{t-1}=0$ in the "normal" state or $S_{t-1}=1$ in the "jump" state) as follows

$$e^*_{S_t} = \begin{cases} e^*_t \in J_n \text{ if } S_{t-1} = 0, \\ e^*_t \in J_j \text{ if } S_{t-1} = 1. \end{cases}$$

For comparative and illustrative purposes we estimate by bootstrap simulation the expected average price of electricity by October 1st, 2001, for energy to be delivered during the same periods as in Table 3.2. As before, we assumed that the mean of the normal component is given exogenously and computed the decomposition of electricity prices based on deviation from that mean. To estimate the expected monthly and weekly average price, we simulate 10,000 paths of electricity prices for the period between October, 2001 and May, 2002. The expected average price by component and the probability interval for the maximum average price is reported in Table 3.3. From the same simulations we compute the probability density of the average electricity prices for a specific month and week, the result of which is shown in Figure 3.5.

According to the simulation results, the percentage of the expected price attributable to the "jump" component is around 14% for both monthly and weekly average prices. This average contribution appears to be low if compared with "jumps" that rise up to 10 times the average price in a single day. Also, if we compare the expected average price with the observed average in Table 3.2, we notice that May 2002 was an exceptionally high price period, with the highest prices primarily concentrated in the last two weeks of the month. Looking at the estimated confidence

Table 3.3: Estimated Decomposition of the Expected Average Prices for the Year 2002 by October 2001 (Australian Dollars)

Period	Expected Average Price	Normal Component	Jump Component	Participation Jump Component	Maximum Average Price at 95% confidence	
	(A)	(B)	(C)	(C/ A)	(D)	(D/A)
January	28.658	25.114	3.544	0.141	39.080	1.364
February	29.672	25.986	3.686	0.142	40.880	1.378
March	29.342	25.653	3.689	0.144	39.820	1.357
April	29.823	26.029	3.794	0.146	41.140	1.379
May	32.114	28.056	4.058	0.145	43.740	1.362
Average	29.922	26.168	3.754	0.143	40.932	1.368
April/06-April/12	29.380	25.643	3.736	0.147	49.728	1.693
April/13-April/19	29.666	25.986	3.680	0.142	49.832	1.680
April/20-April/26	30.221	26.368	3.852	0.146	50.976	1.687
April/27-May/03	30.765	26.815	3.951	0.147	51.964	1.689
May/04-May/10	31.170	27.332	3.838	0.140	51.288	1.645
May/11-May/17	32.190	27.952	4.238	0.152	54.980	1.708
May/18-May/24	32.512	28.463	4.049	0.142	54.720	1.683
May/25-May/31	33.087	28.946	4.141	0.143	55.604	1.681
Average	31.124	27.188	3.936	0.144	52.387	1.683

Note: The mean is assumed to be given.

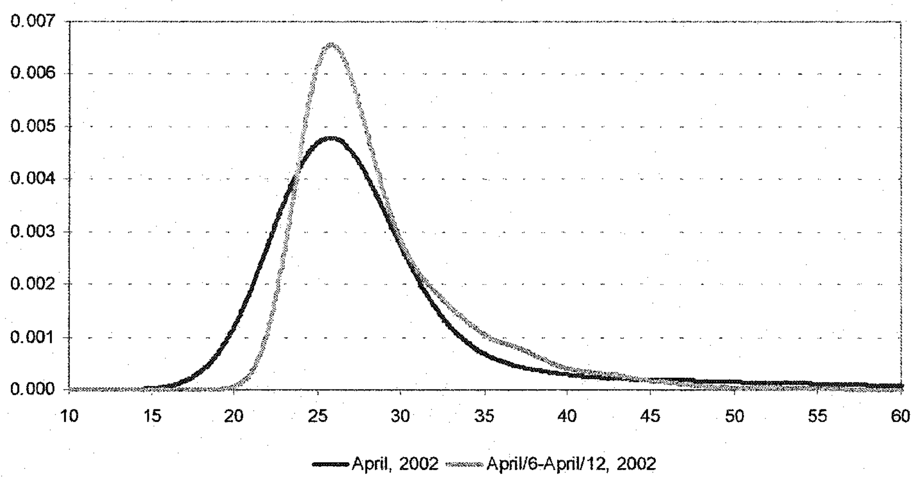

Figure 3.5: Comparison of the Estimated Probability Density of the Monthly and Weekly Average Electricity Prices by October 2001.

interval of the average prices, we find that as an average there is a 95% of probability that average prices do not increase more than 37% of the expected monthly value and not more than 68% of the expected weekly average. These expected average prices appear to be maintained regardless of the starting date of the simulation, provided that there is enough time to dissipate the initial shock in prices.

3.7 Conclusion

This study highlights the necessity of decomposing the electricity prices movement into two components: one driven by normal market conditions and the other that captures the effect of supply failures and/or constraints, or sudden increases in the demand. The proposed model treats the stochastic process of each component as independent from the other, each one with its own mean reverting parameter. It is also maintained that considering the jumps and spikes in prices as a jump switching process in which the effects do not disappear quickly, bears a certain advantages, since, technologically speaking, it is natural to consider two states, the failure and the normal state, in electricity markets. Technically this approach overcomes identification problems by capturing the big jumps with low frequency instead of the small jumps with high frequency, as is usually the case in jump-diffusion type processes.

We applied the model to New South Wales' electricity spot prices and found all the parameters of the model to be statistically significant. One of the most important results is that the estimated mean reverting parameter of the jump component does not completely eliminate the effect of a jump in the next period. There is evidence that jumps are not independent but correlated in this market. This results contrast with the assumptions of other studies, suggesting the need of explicitly testing the mean reverting speed of the jumps and their independence. With respect to the decomposition of the observed average electricity prices, we found that in May 2002 the jump component rose up to 70% above the average of the normal component, and up to 300% in the last week of the same month.

The bootstrap simulation technique was also implemented to estimate the expected average price over a future month or week. It was found that as an average the expected contribution of the "jump" component in the expected average price is around 14% in the NSW electricity market. On the other hand it was estimated that there is 95% of probability that average prices do not increase by more than 37% of the expected monthly value and not more than 68% of the expected weekly average.

Finally, although the model deals with the identification of the "normal" and "jump" components in prices, seasonality is another factor that is not treated explicitly in this study. The assumption from which we construct our decomposition is that prices do not follow a time varying mean to which they revert, but that there is a fixed long-run mean in the "normal" component. This assumption is obviously not true for markets with strong seasonality or in situations in which exogenous variables play an important role in the price determination, such as the price of natural gas.

However the model can be extended to explicitly include such components, allowing functional specification of the time varying mean of the "normal" component.

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Appendix

5.1 Appendix A: Modeling electricity demand

As we noted in the text, the aggregate demand forecast is derived by relating the logarithm of total power generation to GDP, the relative price of electricity, and a variable, based on temperature records, that accounts for seasonal variations.

Income. The GDP can be viewed as a proxy either for "household income" or for "industrial input demand." The data was converted from a quarterly to a monthly frequency using the relationship between industrial production and GDP. Specifically, the GDP for each quarter was allocated to each month in the quarter using the relative values of industrial production for each of those months in the quarter. The variable included in the analysis, denoted y_t, is the natural logarithm of the estimated monthly GDP. Information other than the electricity data obtained from the CFE was obtained from the *Instituto Nacional de Geografía e Informática.* [1]

Electricity prices. The relative price of electricity was calculated by dividing an implicit price for electricity by the producer price index. The implicit price for electricity was in turn obtained by dividing CFE monthly revenues by the quantity of

[1] Instituto Nacional de Geografía e Informática (INEGI), http://www.inegi.gob.mx

Table 5.1: Estimated monthly component of relative electricity prices

Parameter	Coefficient	t value
α_0	0.1897	(133.7234)
α_3	-0.0074	(-2.7073)
α_4	-0.0120	(-4.4114)
α_5	-0.0110	(-3.9850)
α_6	-0.0123	(-4.5365)
α_7	-0.0096	(-3.5232)
α_8	-0.0085	(-3.1285)
α_9	-0.0061	(-2.2384)
α_{10}	-0.0080	(-2.9543)
α_{11}	-0.0061	(-2.2607)
R^2	0.30	
Observations	70	

electricity that CFE sold in each month. We use lagged prices in the regression to allow for the lags between consumption and billing (when most of the consumers realize how much they consumed). The variable included in the analysis, denoted p_t, is actually the natural logarithm of the relative price lagged three periods.[2] When forecasting the relative price of electricity, we need to preserve the monthly seasonal component. To do so, we estimated the following regression:

$$p_t = \alpha_o + \sum_{i=1}^{11} \alpha_i D_i + \omega_t, \tag{5.1}$$

where α_0 represents the mean value of p in December, D_i is an indicator variable for months i other than December and hence α_i represents the difference in the average value of p in month i relative to its value on December. The sample covers the period from February 1996 to November 2001. The estimates from this regression are reported in Table 5.1.

Seasonality. The aggregate demand for electricity is known to depend on seasonal factors in addition to GDP and the relative price of electricity. Since weather is the

[2] Although most bills are issued every two months, there is an additional one month grace period for paying the bill.

main determinant of seasonality in electricity demand, temperature variables should capture seasonality in a more parsimonious way than a set of monthly indicator variables.[3]

Following Chapter 1, to capture such seasonality the total power generation Q_t was decomposed into an annual moving average[4] and a "short run" deviation, denoted q_t, from that moving average. The short run component was then related to the weighted average per region[5] of the mean (z_{1t}) and variance (z_{2t}) of the temperature, using the following regression (observations $N = 179$, $\bar{R}^2 = 0.8657$, t-values of the coefficients are in parentheses):

$$\begin{array}{rcl} q_t & = & -0.1833 + 0.1333 \cdot z_{1t} + 0.3522 \cdot z_{2t} + \varepsilon_t \\ & & (-5.57) \quad (0.899) \qquad\quad (2.395) \end{array} \tag{5.2}$$

The variable z_t was then defined as the predicted value of q_t based on (5.2).

Long run relationships. Variables that are systematically related to each other in the long run display a consistent pattern in their trends. Deviations from these long run relationships constitute stationary shocks that gradually disappear over time.

For most time series of economic variables, trends primarily result from permanent shocks that accumulate over time and lead to "unit roots" in the series. While the series itself displays a trend, *changes* in the series from one period to the next are driven by shocks drawn from a stationary distribution. Table 5.2 presents results of tests for the presence of unit roots in the natural logarithms of total power generation (denoted Q_t), GDP and the relative price of electricity. If a unit root is absent, the series itself is stationary, and the test statistic presented in Table 5.2 should be below

[3] Factors such as holidays, or even variations in the number of days in each month may, however, also contribute to seasonal effects that are not readily captured by temperature changes.

[4] For a given month t, the moving average was calculated as $(1/13)\sum_{l=-6}^{6} Q_{t+l}$.

[5] We consider six region as in Chapter 1 and the weights are the share of electricity consumption per region with respect to the total.

the 5% critical values listed in the bottom row of the table. The tests for the presence of stochastic trends can be affected if the series have trends that are deterministic functions of time or if the variables are strongly serially correlated. The tests were performed using two different criteria (Akike and Schwartz) to select the number of lags included to eliminate serial correlation. Two separate sets of tests allowing for the presence or absence of a deterministic time trend also were conducted. In eleven of the twelve results, the evidence indicates the presence of a unit root in the series.

Although each of the variables Q, y and p is non-stationary, if the demand for electricity is a stable function of these variables the relationship between them will be stationary (the variables will be "co-integrated"). One of the innovative features of the model of electricity demand presented in Chapter 1 is that allows the long run relationship between the dependent variable, in this case Q, and its determinants, in this case y and p, to change gradually over time in a deterministic fashion. This modification may be especially important in a country such as Mexico that has recently undergone substantial economic change. In particular, the recent rapid growth of the Mexican economy, and the change in industry structure resulting from the NAFTA, both are likely to have changed the relationship between electricity demand and its key determinants. Following Chapter 1, the time varying elasticities of total power generation with respect to GDP and the relative price, γ_t and δ_t in the equation:

$$Q_t = \pi + \gamma_t y_t + \delta_t p_t + \phi z_t + u_t, \tag{5.3}$$

are approximated by a Fourier Flexible Form (FFF) function, using the Schwartz criterion to select the number of terms in the functions. The estimates were derived using the method of canonical co-integrating regression (CCR) suggested by Park and Hahn (1999). The results are reported in Table 5.3.[6]

[6]Although z_t is stationary, it is included in the co-integrating regression to help control for seasonality in Q, y and p. In the estimation of the adjustment process presented below, we allow z_t

Table 5.2: Augmented Dickey-Fuller (ADF) tests for stationarity

Variable Lag selection criterion[a]	Demeaned series	lags	Detrended series	lags
Total power generation, Q_t				
AIC	0.4167	12	-2.641	12
SC	0.4167	12	-4.798	7
GDP, y_t				
AIC	0.6244	16	-1.110	16
SC	0.6244	16	-1.110	16
Relative prices, p_t				
AIC	-2.013	14	-1.4549	14
SC	-1.330	4	-1.9035	5
5% critical values	-2.86		-3.41	

a. Akike (AIC) and Schwartz (SC) criterion

Table 5.3: Estimated cointegrating relationship for total power generation

Variable	Coefficients	(t values[a])
Constant (π)	7.0766	(4.7866)
z_t (ϕ)	1.0632	(20.4203)
Parameters of the TVC: γ_t		
k	0[b]	
$\beta_{\gamma,k,1}$	0.4261	(5.9735)
$\beta_{\gamma,k,2}$	-0.0161	(-2.2235)
Parameters of the TVC: δ_t		
k	2	
$\beta_{\delta,k,2}$	-0.5025[c]	(-6.5293)
$\beta_{\delta,k,3}$	0.0047[d]	(2.3271)
SC = -6.7665	R^2 =0.9839	DW =2.01
observations $N = 176$		
Long run variance of the CCR errors		
Ω^*_{11}	0.0010	
Unit root test for estationary of the errors u_t of the regression[e]		
τ^*	10.6039	Critical value 1%: 13.28

a. Computed using CCR standard errors.

b. Indicates that there are no trigonometric terms.

c. Coefficient of the linear trend.

d. Coefficient of the trigonometric term $\cos(4\pi r)$.

e. $\tau^* \sim \chi^2(4)$ for H_0 : errors are stationary. Park and Hahn (1999) statistic.

We found that the long run elasticity of Q_t with respect to the GDP, γ_t, can be approximated by a series function that includes a constant coefficient ($\beta_{\gamma,k,1}$) and a linear trend (with slope $\beta_{\gamma,k,2}$). The parameter estimates imply that γ_t has been decreasing over time from 0.426 at the beginning of the sample to about 0.4099 at the end of the sample. This is consistent with industrialization and economic growth leading to more widespread use of grid electricity.

In the case of the relative price of electricity, the results in Table 5.3 imply that the elasticity, δ_t, of power generation with respect to p can be approximated by a linear trend ($\beta_{\delta,k,2}$) and a trigonometric function ($\cos(4\pi i), i = 1 \ldots n$). The estimated coefficients on the relative price variables imply that, while electricity demand was insensitive to price at the beginning of the sample by the end of the period the elasticity of demand with respect to price was about -0.5006. Such a change might again be consistent with a growth in the relative importance of industry in the economy, which probably has more options to alter demand in response to price variations.

The final panel of Table 5.3 presents the results of a test of whether the errors from the regression, u_t, contain a unit root. Since the value of the test statistic is below the 1% critical value, it would appear that, once the model allows for time varying coefficients, power generation, GDP and the relative price of electricity are cointegrated.

Short run adjustments. Equation 5.3 represents the long run relationship between total power generation , GDP and relative price of electricity. The dynamic adjustment of the model is driven in part by deviations of power demand from the long run relationship. The short run dynamic adjustment process can be represented by a so-called "error-correction model" (ECM). This equation relates the change in

and its lags to enter separately from u_t, so including z_t in equation 5.3 does not restrict the dynamic adjustment of Q to z.

electricity demand (which is a stationary variable) to the lagged error term u_{t-1} and other stationary variables. For a stable adjustment process, we would expect the coefficient of u_{t-1} to be negative. Then, if electricity demand is above its long run equilibrium relationship with GDP and the relative price, demand will tend to fall and conversely. In addition, the adjustment could occur gradually. For example, an increase in the electricity price initially may influence the length of time that equipment is used. If the higher price persists, however, firms may buy new equipment that requires lower electricity input. Including the lagged change in electricity demand as another explanatory variable can accommodate such a lagged adjustment process. The estimated ECM can be written as:

$$\begin{aligned}\Delta Q_t = &\sum_{l=1}^{p_1} b_{1,l}\Delta Q_{t-l} + \sum_{l=1}^{p_2} b_{2,l}u_{t-l} + \\ &\sum_{l=0}^{p_3} b_{3,l}\Delta y_{t-l} + \sum_{l=0}^{p_4} b_{4,l}\Delta p_{t-l} + \sum_{l=0}^{p_5} b_{5,l}z_{t-l} + \varepsilon_t\end{aligned} \tag{5.4}$$

There is little theoretical reason for expecting one dynamic pattern of adjustment rather than another. To determine the lags of each variable included in the model, we first estimate a general model with $p_1, p_2, p_3, p_4, p_5 = 12$. Lags were then progressively eliminated beginning with those having coefficients $b_{j,l}$ that were least statistically significantly different from zero. The lags retained in the model, and reported in Table 5.4, all have coefficients that are not statistically different from zero at the 5% level. Table 5.4 also reports a Box-Pierce statistic that tests for the presence of serial correlation in the error term ε. The p-value of more than 0.29 suggests that sufficient lags have been included in the model to eliminate the serial correlation.

The parameter estimates in Table 5.4, and the negative coefficient on the error term u_{t-1} in particular, imply that a gap between power generation and its long run determinants sets up an adjustment process that eventually restores the long run relationship. If power generation is above the long run equilibrium level ($u > 0$),

Table 5.4: Estimated dynamic adjustment equation for $\Delta\hat{Q}_t$

Parameter	Variable					
	ΔQ_{t-l} $(j=1)$		u_{t-l} $(j=2)$			
	Coeff.	(t val.)	Coeff.	(t val.)		
$b_{j,1}$	-0.1695	(-3.86)	-0.4631	(-7.78)		
$b_{j,4}$	0.1231	(2.94)				
$b_{j,5}$	0.1480	(3.78)				
$b_{j,12}$	0.5263	(12.74)				
	Δy_{t-l} $(j=3)$		Δp_{t-l} $(j=4)$		z_{t-l} $(j=5)$	
	Coeff.	(t val.)	Coeff.	(t val.)	Coeff.	(t val.)
$b_{j,0}$	0.3469	(8.02)	-0.1662	(-2.39)	0.5835	(7.30)
$b_{j,3}$	0.1717	(5.00)				
$b_{j,4}$			-0.1295	(-2.41)		
$b_{j,5}$			0.1514	(2.76)		
$b_{j,8}$	0.1430	(2.79)				
$b_{j,11}$					0.3130	(3.91)
$b_{j,12}$	-0.2340	(-5.35)	0.1065	(2.07)	-0.2910	(-3.40)
$\bar{R}^2$	0.9115					
Box-Pierce χ^2_{40}	44.3359	p-value 0.2938				

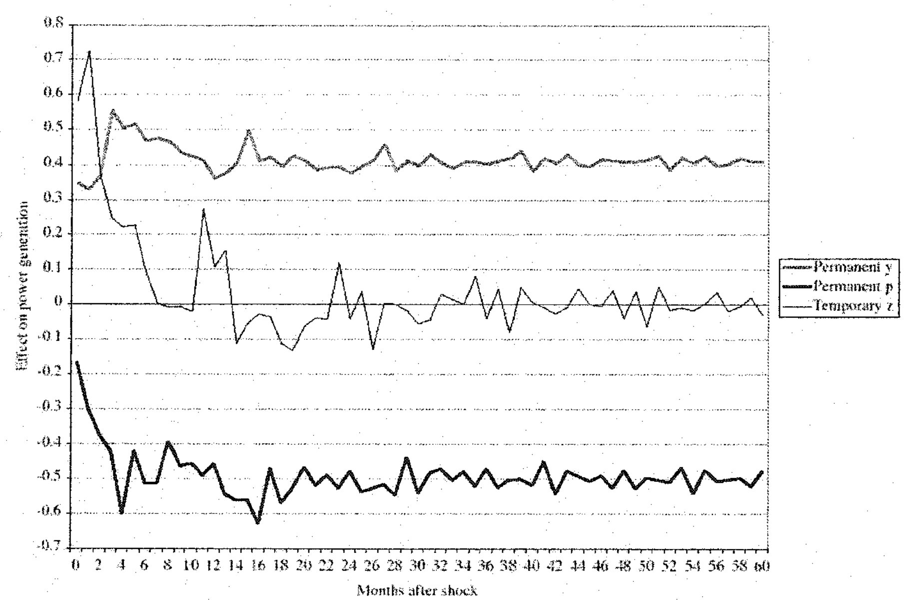

Figure 5.1: Implied dynamic adjustment of power generation to shocks

generation in subsequent periods will decline ($\Delta Q < 0$). Further adjustments will occur in subsequent periods as prior movements in ΔQ continue to produce continuing movements as a result of the significant $b_{1,l}$ coefficients. Eventually, however, the adjustments will decay to zero.

The dynamic adjustment process implied by the estimated ECM is illustrated in Figure 5.1. This graphs the response of Q to a one percent *permanent* shock to GDP, y, and relative prices of electricity, p, and a 1% temporary shock to z. The adjustments graphed in 5.1 have been calculated setting the long run elasticities of power demand with respect to y and p to their values at the end of the sample period. In reality, we would expect these elasticities will continue to change over time, making the adjustment process a function of the time when the shocks occur.

As Figure 5.1 illustrates, $\Delta Q \rightarrow \gamma_T = 0.4099$ for a permanent 1% shock to y, $\Delta Q \rightarrow \delta_T = -0.50057$ for a permanent 1% shock to p, and $\Delta Q \rightarrow 0$ for a temporary shock to the stationary variable z. In all cases, there is a seasonality to the response with "patterns" in the adjustment process being "mirrored" with 12-month lags. The annual seasonality is also evident in the large estimated coefficients at lag 12 in Table 5.4. Any change in income, prices or weather that induces a home or business to alter their stock of electrical equipment or appliances is likely to have continuing effects on power demand in similar seasons in subsequent years.

The response of total power generation to a permanent increase in GDP is, for the first two months, somewhat below the ultimate long run response. Generation then "overshoots" the long run response for the remainder of the first year. Thereafter, the pattern is more or less repeated on an annual frequency with ever smaller fluctuations around the ultimate long run effect.

An increase in the relative price of electricity produces a different type of adjustment process. Whereas a permanent increase in y causes Q to jump almost immediately to values in the proximity of the long run effect, the response to price changes is more gradual. Such a delay in the responsiveness of demand to price changes may be explained in part by the infrequent billing schedule, and perhaps by the fact that a significant amount of electricity appears to be taken illegally. It is also possible that the seasonal component in prices makes it difficult for consumers to clearly identify price changes. In addition to displaying a more gradual adjustment of Q toward its long run value, the price response path displays much less "overshooting" than does the response to y. Again, however, the adjustment pattern set for months 4 through 16 has a tendency to be repeated, albeit with oscillations of declining magnitude, in months 16 through 28, 28 through 40 and so on.

A temporary shock to the temperature variable z also ultimately produces an adjustment path that tends to repeat in an annual cycle. In this case, however, the initial period of response lasts about 10 months instead of 4. The response of Q to z, like its response to a GDP shock, is rapid. On the other hand, like the response to p, the response to z does not involve sustained "overshooting".

Regional demand shares. The regional shares of aggregate demand are, by definition, bounded between 0 and 1. In addition, as the share of demand in any one region increases toward 1 (or decreases toward zero) we would expect further increases (respectively, decreases) to be much less likely. A natural way of representing such behavior in a way that is also likely to yield normally distributed error terms (which range from $-\infty$ to $+\infty$) is to use a logistic functional form:

$$\ln\left(\frac{S_{it}}{1-S_{it}}\right) = X'_{it}\varphi_i + e_{it} \tag{5.5}$$

Since we do not have data on regional GDP or industrial production we used monthly indicator variables, time and time^2 as components of X. The monthly indicators capture differences in the seasonal patterns of demand across regions. The linear trend terms indicate regions where electricity demand is growing faster (the coefficient of time is positive), or slower (the coefficient is negative), than in the nation as a whole. The coefficient on time^2 indicates whether the trend is accelerating (the quadratic and linear coefficients have the same sign) or decelerating (the coefficients have opposite signs). When making forecasts, we proportionally adjust the estimated shares in each region to ensure that they always sum to 1.0 in all periods.[7]

Table 5.5 gives the estimated quadratic equations for the regional demand shares. Table 5.6 presents the estimated monthly effects on the demand shares for January through November *relative to* shares in the month of December.

Daily demand variation. Since the load on the system is the most important feature of the demand fluctuations, we first convert the load curves in Figure 2.3 to load duration curves. A daily load duration curve is analogous to a probability distribution function and plots the number of hours in the day that electricity demand exceeds a given load. For the minimum load of the day, the load duration curve will have a value of 24 hours. For the maximum load of the day, the load duration curve will be 0 hours. Essentially, the load duration curve orders times of the day not according to where they come by the clock but by what the demand load on the electricity system was at that time. A step function approximation to the load duration curve then divides the day into periods of roughly constant levels of demand.

In the model, we need to divide each day into time periods that cover the same hours of the day in both the north and the south region. The bottom two panels in Figure 2.3 show that, during the summer season, the peak demand is in the afternoon hours in the north, but in the evening hours in the south. Therefore it is not possible to define a time period that yields a coincident peak in both regions. Since the load

[7] Although the error terms in the share equations will be correlated, there is no value in estimating the equations as a seemingly unrelated set since they have identical regressors.

curves are different shapes it is difficult to group hours into a small number of blocks of roughly constant demand. Instead of approximating the individual load duration curves, we partitioned the curves in such a way that the durations of the steps coincide in both regions.

Table 5.5: Estimated time variations in shares[a]

Region	Constant	Time	$Time^2$	Adjusted R^2
1 Baja	-3.0915	$4.5x10^{-4}$	$1.4x10^{-5}$	0.8791
California	(0.0233)	($6.1x10^{-4}$)	($5.1x10^{-6}$)	
2 Noroeste	-2.5813	$-2.9x10^{-4}$	$-2.8x10^{-6}$	0.9211
	(0.0178)	($4.6x10^{-4}$)	($3.9x10^{-6}$)	
3 Norte	-26098	$1.1x10^{-3}$	$-3.5x10^{-6}$	0.8229
	(0.0134)	($3.5x10^{-4}$)	($2.9x10^{-6}$)	
4 Golfo	-1.9964	$1.7x10^{-3}$	$2.7x10^{-6}$	0.9493
Norte	(0.0094)	($2.4x10^{-4}$)	($2.0x10^{-6}$)	
5 Golfo	-2.9886	$1.2x10^{-3}$	$-1.4x10^{-5}$	0.3729
Centro	(0.0012)	($3.8x10^{-4}$)	($3.2x10^{-6}$)	
6 Bajio	-2.3829	$7.2x10^{-4}$	$-4.9x10^{-6}$	0.6792
	(0.0236)	($6.1x10^{-4}$)	($5.1x10^{-6}$)	
7 Jalisco	-2.6334	$-1.8x10^{-3}$	$7.3x10^{-6}$	0.6491
	(0.0153)	($4.0x10^{-4}$)	($3.3x10^{-6}$)	
8 Centro	-3.2295	$6.3x10^{-3}$	$-2.5x10^{-5}$	0.8312
Occidente	(0.0267)	($7.0x10^{-4}$)	($5.8x10^{-6}$)	
9 Centro	-3.1237	$7.4x10^{-5}$	$7.5x10^{-6}$	0.6684
Oriente	(0.0204)	($5.3x10^{-4}$)	($4.4x10^{-6}$)	
10 Centro	-3.3450	$3.5x10^{-3}$	$-1.8x10^{-5}$	0.6740
Sur	(0.0230)	($6.0x10^{-4}$)	($5.0x10^{-6}$)	
11 Oriente	-2.5389	$-2.1x10^{-3}$	$1.0x10^{-5}$	0.1412
	(0.0334)	($8.7x10^{-4}$)	($7.3x10^{-6}$)	
12 Sureste	-3.3673	$-7.0x10^{-4}$	$-1.6x10^{-7}$	0.3661
	(0.0265)	($6.9x10^{-4}$)	($5.8x10^{-6}$)	
13 Peninsula	-3.5776	$1.0x10^{-3}$	$-4.6x10^{-6}$	0.3233
	(0.0199)	($5.2x10^{-4}$)	($4.3x10^{-6}$)	
14 Centro	-1.0879	$-2.8x10^{-3}$	$6.1x10^{-7}$	0.9009
Luz y Fuerza	(0.0166)	($4.3x10^{-4}$)	($3.6x10^{-6}$)	

a. Estimated standard errors are given in parentheses.

Table 5.6: Monthly deviations in demand shares relative to December [a]

	Region	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
1	Baja	0.004	-0.029	-0.043	-0.04	0.012	0.057	0.197	0.295	0.322	0.233	0.089
	California	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
2	Noroeste	-0.079	-0.121	-0.083	-0.045	0.012	0.065	0.206	0.235	0.277	0.224	0.18
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
3	Norte	0.008	0.01	0.026	0.092	0.123	0.148	0.164	0.168	0.147	0.103	0.044
		(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
4	Golfo	0.025	-0.006	0.022	-0.016	0.04	0.087	0.141	0.162	0.152	0.136	0.071
	Norte	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
5	Golfo	0.011	-0.027	-0.04	-0.044	-0.014	-0.01	0.007	-0.013	-0.019	0.01	-0.005
	Centro	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
6	Bajio	0.05	0.072	0.063	0.13	0.138	0.125	-0.003	-0.062	-0.088	-0.089	-0.049
		(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
7	Jalisco	-0.008	0.002	-0.022	-0.04	-0.042	-0.062	-0.076	-0.099	-0.112	-0.084	-0.05
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
8	Centro	0.052	0.045	0.087	0.081	0.013	-0.025	-0.09	-0.123	-0.139	-0.081	-0.069
	Occidente	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
9	Centro	0.044	0.047	0.079	0.051	-0.025	-0.06	-0.094	-0.098	-0.103	-0.062	-0.003
	Oriente	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
10	Centro	-0.021	0.001	-0.005	-0.026	-0.067	-0.11	-0.145	-0.136	-0.166	-0.139	-0.067
	Sur	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
11	Oriente	0.032	-0.01	0.012	-0.024	-0.013	-0.029	-0.045	-0.045	-0.059	-0.041	-0.021
		(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)	(0.036)	(0.036)
12	Sureste	-0.017	-0.018	-0.054	-0.009	-0.066	-0.054	-0.122	-0.119	-0.098	-0.123	-0.085
		(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
13	Peninsula	-0.041	-0.053	-0.063	-0.022	0.033	-0.001	0.019	0.004	0.018	-0.002	0.013
		(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
14	Centro	-0.039	0.012	-0.024	-0.054	-0.107	-0.138	-0.183	-0.197	-0.18	-0.137	-0.069
	Luz y Fuer	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)

a. Estimated standard errors are given in parentheses.

Figure 2.3 shows that the north has a higher peak demand in the summer, while the south has a higher peak demand in the remaining periods. Thus, we arranged the hours according to the load duration curve for the north in the summer period while we used the load duration curves for the south for the remaining periods. Table 5.7 shows, however, that we defined period 1 in the summer season and period 6 in the shoulder season to correspond with the daily peak periods for the south. Total demand in the south (which includes the central region) is so much larger than in the north, and the differences between peak and second highest demand in the north are so small, that the overall system peak demand corresponds with the southern one.

Figure 5.2 illustrates the step function approximations to the load duration curve for the north in the summer season and the load duration curves in the south for the remaining seasons. We used five steps in the approximations for each of four seasons, yielding a total of twenty time periods in our model. Figure 5.2 also graphs the load curves for the south during the summer season, and for the north during the remaining seasons, with clock time rearranged in the same manner as was done to obtain the load duration curves. The different shapes of the northern and southern load curves are reflected in the fact that the rearranged southern curve in the summer, and the rearranged northern curves in the other seasons, do not appear as load duration curves ordered from highest to lowest demand. Finally, Figure 5.2 also shows how we approximated the rearranged loan curves using the same time periods as for the load duration curve approximations in each period. The durations and sizes of each the steps in the approximations were determined to maximize the fit between the approximations and the real load curves subject to the constraint that the areas under the step function approximations equaled the areas under the real load curves. As Figure 5.2 shows, five steps allowed us to fit the shapes of the curves reasonably well. The worst fit is for the south in the summer season.

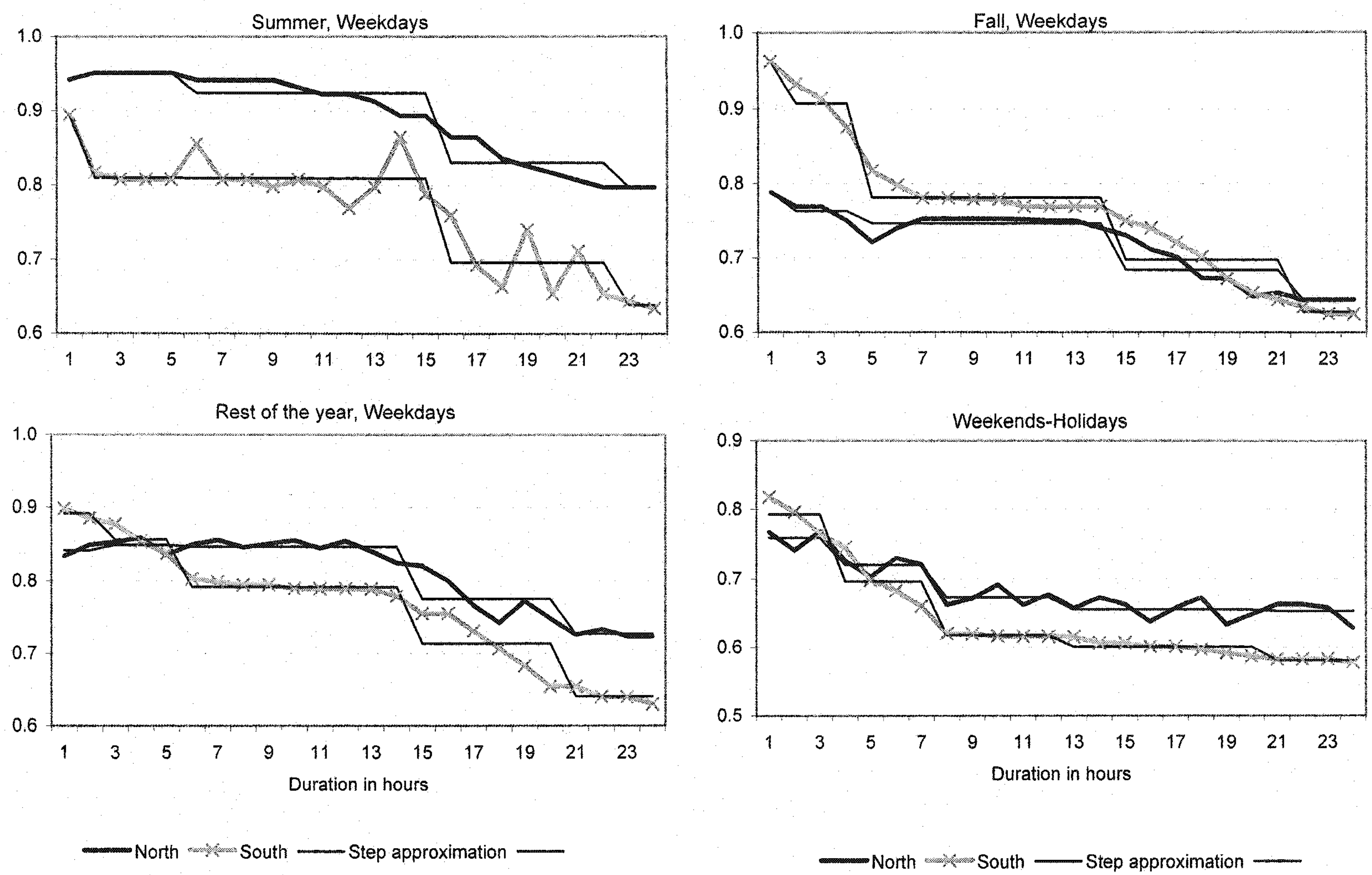

Figure 5.2: Step function approximations to the 1999 load curves.

The step function approximations were converted back to demands in each transmission region using the following procedure. Use SL to denote the season length (in days). An aggregated seasonal step load duration function in hours per season is obtained by multiplying the daily period length of each step (PL) by the number of days in the season ($PL \times SL$). The share of total power demand that is consumed at a specific period of time t in season s in the Northern ($k = N$) or Southern ($k = S$) regions the country can be computed from this seasonal step function as follows:

$$d^k_{s,t} = \frac{RLS_{k,s,t} \cdot SL_{s,t} \cdot PL_{s,t}}{\sum_{t \in s} RLS_{k,s,t} \cdot SL_{s,t} \cdot PL_{s,t}},$$

where $RLS_{k,s,t}$ is the relative demand load in region k, period t, and season s. Table 5.7 provides numerical values for these variables in our approximation.

To compute the level of power demand for each transmission region i in a particular time period and season, we used the formula:

$$d_{i,s,t} = \delta_{i,s} \cdot d^k_{s,t} \cdot \bar{d}_s$$

where $\delta^k_{i,s}$ is the share of total demand in region k and season s originating in transmission area i and $\bar{d}_s$ is the aggregate demand in GWh in season s. Including a set of multiplicative scaling factors $Z_s > 0$ in this formula allows us to calibrate demand to compensate for the (unknown) power losses per season:

$$d_{i,s,t} = \delta_{i,s} \cdot d^k_{s,t} \cdot \bar{d}_s \cdot Z_s.$$

Table 5.7: System Load Curve (%)

Period No. (*t*)	*Period Length* (*hrs., PL*)	*Season* (*s*)	*Season Length* (*days, SL*)	*Relative Load Steps* North (RLS_N)	South (RLS_S)
1	1	Summer	82	0.94	0.89
2	4	(May-Aug)		0.95	0.81
3	10			0.93	0.81
4	7			0.83	0.70
5	2			0.80	0.64
6	1	Shoulder	87	0.84	0.89
7	3	(March, April		0.85	0.86
8	10	Sep., Oct.)		0.85	0.79
9	7			0.78	0.71
10	3			0.73	0.64
11	2	Fall	83	0.79	0.96
12	3	(Nov.-Feb.)		0.79	0.91
13	9			0.75	0.78
14	6			0.68	0.70
15	4			0.64	0.63
16	3	Weekends-	113	0.76	0.79
17	4	Holidays		0.72	0.70
18	5			0.67	0.62
19	8			0.66	0.60
20	4			0.65	0.58

5.2 Appendix B: Modeling electricity supply

Since details of system operation at hourly or finer time scales are not relevant to our main objectives, most of the stochastic components are eliminated from the problem.[8] We instead examine a deterministic linear programming model based on expected values of demand and supply variables. We also modify the model, however, to incorporate "normal" levels of excess capacity that are maintained to cope with unusual emergencies.

Generating costs. The generating plant costs were based on data provided by the CFE as discussed in the text. The total cost of generation for N plants in the system during the year is approximated by

$$\mathrm{C} = \sum_{n=1}^{N} b_n \bar{g}_n + \sum_{n=1}^{N} \sum_{t=1}^{T} h_t c_{nt} g_{nt}, \tag{5.6}$$

where $n = 1, \ldots N$ indexes the plants, $t = 1, \ldots T$ denotes the period (where now one period represents a set of hours of the day throughout a season), and h_t is the number of hours in period t (number of hours per day times number of days per season). The annual fixed cost per MW of total capacity of plant n is b_n. The total capacity of plant n, $\bar{g}_n$, is set for the whole year and constrains the variable output levels, g_{nt}, of each plant n in each period t:

$$0 \leq g_{nt} \leq \bar{g}_n, \quad \forall t, n \tag{5.7}$$

$$0 \leq \bar{g}_n \leq G_n, \quad \forall t, n \tag{5.8}$$

where G_n is the *designed* capacity of the plant. The variable cost of plant n in period t is c_{nt}.

[8] For stochastic programming models of power markets look at Wallace, Stein W. and Fleten Stein-Erik. (2002) "Stochastic programming models in energy," Working Paper 01-02, Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology. http://ideas.uqam.ca/ideas/data/Papers/wpawuwpge0201001.html

Transmission losses. Transmission losses on a link are a function of the power flowing between two nodes and the resistance of the line. Specifically, transmission losses rise with the square of the current being transmitted on a link:

$$L_{ij} = 3R_{ij}\tau_{ij}^2 \tag{5.9}$$

where the subscripts (i, j) indicate the nodes that are connected by the line, L_{ij} equals the losses (in MW/km), R_{ij} is the resistance of the line (ohm/km) and τ_{ij} is the current (in kamps, where 1 kamp = 1,000 amps). The relationship between current and power for a three-phase alternating current circuit is given by the formula:

$$P = \sqrt{3} \cdot E \cdot I \cdot pf$$

where P is the power (in watts), E is the voltage (in volts), I is the current (in amps), and pf is the "power factor" of circuit. The latter term determines the relationship between direct and alternating current and, for our calculations, was assumed to be 0.6 (its typical gross value). In general, the engineers try to maintain the system so that there are minimal fluctuations in the voltage E, so this, too, can be subsumed in a constant.

Finally, the resistance depends on the physical characteristics of the transmission lines.[9] Table 5.8 shows the typical resistance we used to compute the losses specified in (5.9). These figures are based on data collected by Scherer (1977, 213) and EIRRG (1998).[10]

To include transmission losses in the linear programming model, we approximate equation 5.9 with linear functions as is illustrated in Figure 5.3 in the case of a two step approximation.

[9] Lower resistance can be obtained by using additional circuits or heavier gage wire, but this raises the capital costs of the towers needed to support the wires and the land needed for the right of way. Implicitly, another optimization problem underlies the design of the transmission network

[10] The resistance of the 115kv lines was taken from Scherer (1977) pp. 213. For the 400kV lines, the resistance was linearly extrapolated from lines with nominal voltages of 345kV and 500kV, EIRRG (1998) http://www.nrcce.wvu.edu/special/electricity/elecpaper5.htm.

Table 5.8: Typical resistance of transmission lines

Nominal Voltage	115 kv	230 kv	400 kv
R (ohm/km)	0.068	0.050	0.033

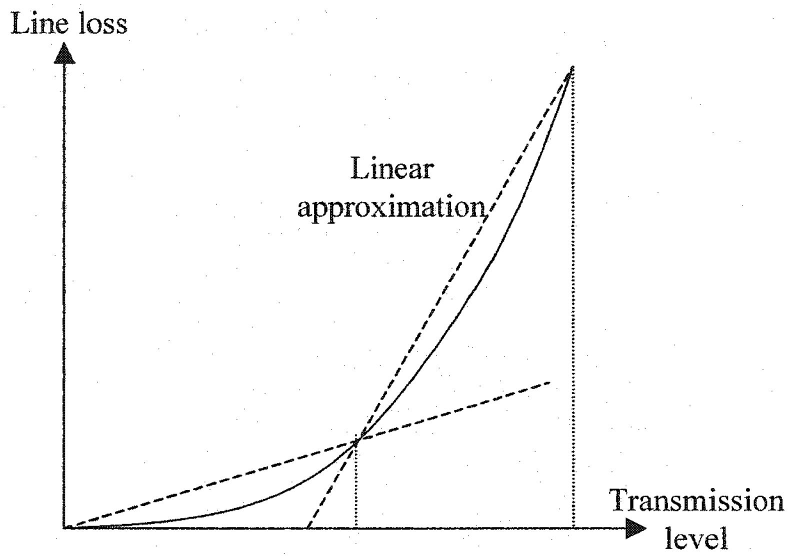

Figure 5.3: Approximation of quadratic transmission losses

For a two step approximation, the piecewise linear function that minimizes the difference between equation 5.9 and its approximation has a break point at half the total transmission capacity of the line. The slope of the first linear function represents the average losses (in percentage terms) for transmission up to half of the line capacity, while the slope of the second function captures the average losses for the remaining transmitted current. A similar interpretation can be given for the slopes of the linear pieces when more than two steps are involved in the approximation.[11] Table 5.9 presents some characteristics of the transmission lines as reported by the Secretary of Energy together with the estimated loss coefficients we calculated. The numbering

[11] For links with more than one transmission line, the number of steps in the transmission loss function can be increased.

of the transmission regions in this table corresponds to the numbers assigned in Figure 2.2 and Table 2.4 above.

Table 5.9: Characteristics of the transmission lines

Link	Voltage kV	Total Cap. MW	Loss coefficients Step 1	Step 2	Step 3	Step 4
1-2	230	330	0.016	0.0479		
2-3	230	220	0.0245	0.0735		
4-3	230	350	0.0462	0.1387		
4-7	230	240	0.0261	0.0784		
4-12	400	260	0.0173	0.0520		
6-5	230	230	0.0250	0.0751		
6-8	400	140	0.0117	0.0351		
7-6	230	235	0.0426	0.1279		
7-9	400	260	0.0103	0.0308		
	230		0.0241	0.0723		
7-14	230	200	0.0352	0.1057		
8-9	400	2100	0.0234	0.0703		
	230		0.0447	0.1341		
	400		0.0158	0.0474		
9-10	400	900	0.0224	0.0672		
9-11	400	250	0.0073	0.0220		
	230		0.0221	0.0664		
10-18	400	750	0.0233	0.0700		
12-14	400	650	0.0158	0.0474		
	400		0.0162	0.0485		
12-15	400	750	0.0134	0.0402		
	230		0.039	0.0926		
	400		0.0083	0.0249		
13-14	400	1700	0.0157	0.0470		
	400		0.0173	0.0520		
	230		0.0250	0.0749		
15-14	230	600	0.0202	0.0606		
	230		0.0350	0.1049		
15-17	400	750	0.0216	0.0647		
	230		0.0398	0.1194		
	230		0.0310	0.0929		
16-15	400	450	0.0204	0.0611		
16-12	400	400	0.0235	0.0706		
16-17	400	950	0.0193	0.0580		
18-17	400	3100	0.0105	0.0316		
	400		0.0263	0.0790		
	400		0.0239	0.0718		
	400		0.0206	0.0618		

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Table 5.9 Continued

Link	Voltage kV	Total Cap. MW	Loss coefficients Step 1	Step 2	Step 3	Step 4
	230		0.0463	0.1390		
	230		0.0507	0.1521		
18-20	400	2100	0.0146	0.0437	0.0728	0.1020
	400		0.0135	0.04040	0.0673	0.0943
	230		0.0200	0.0599	0.0998	0.1397
19-17	230	240	0.0199	0.0597		
20-21	400	1400	0.0174	0.0522	0.0871	0.1219
20-22	400	1000	0.0136	0.0407	0.0678	0.0950
21-22	400	2200	0.0149	0.0448	0.0746	0.1045
22-23	230	110	0.0188	0.0564		
23-24	230	150	0.0134	0.0403		
	115		0.0090	0.0270		
	115		0.0162	0.0487		
	115		0.0083	0.0249		
24-26	230	100	0.0104	0.0312		
	115		0.0105	0.0314		
	115		0.0105	0.0449		
24-25	115	45	0.0135	0.0405		
27-28	230	250	0.0233	0.0700		
28-29	230	180	0.0187	0.0560		
30-31	115	60	0.0168	0.0504		
31-32	115	40	0.0160	0.0480		
24-26	230	100	0.0104	0.0312		
	115		0.0105	0.0314		
	115		0.0105	0.0449		
24-25	115	45	0.0135	0.0405		
27-28	230	250	0.0233	0.0700		
28-29	230	180	0.0187	0.0560		
30-31	115	60	0.0168	0.0504		
31-32	115	40	0.0160	0.0480		

The general regional demand constraint can be written:

$$\sum_{n\in N(i)} \eta_n g_{nt} + \sum_{j\in S(i)} \sum_{l}^{\ell(i,j)} \tau_{ji,t}^{l} = \sum_{j\in S(i)} \sum_{l}^{\ell(i,j)} (1+\rho_{ij}^{l})\tau_{ij,t}^{l} + d_{it}, \qquad \forall i,t \tag{5.10}$$

where $i = 1, \ldots\ldots, D$ denotes the region, $N(i)$ denotes the set of generation plants located in region i, η_n is the fraction of electricity generated by plant i that is sent out to the electrical system (so $(1-\eta_n)g_{nt}$ is consumed within the plant), $S(i)$ denotes the set of regions connected to region i, $\ell(i,j)$ denotes number of steps in transmission loss function for the link between i and j, $\tau^l_{ji,t}$ is the power transmission flow from region j to region i in period t and on step l of the loss function, ρ^l_{ij} is the loss factor on step l of the transmission loss function of link (i,j), and d_{it} is the hourly electricity demand at region i in period t.

The demand restrictions allow transmission to incur in either direction. Since all variables in the model are required to be non-negative, we double the number of transmission variables. The links (i,j) and (j,i) represent the same physical wires but the different indices indicate opposite directions of the flow. The physical wires limit the amount of electricity that can be transmitted between two regions. Thus, if $\bar{\tau}_{ij}$ denotes the transmission capacity between regions i and j in MW:

$$\sum_{l}^{\ell(i,j)} \tau^l_{ji,t} + \sum_{l}^{\ell(i,j)} \tau^l_{ij,t} \leq \bar{\tau}_{ij}, \quad \forall t, \quad (i,j) \in L \tag{5.11}$$

where L is the set of transmission links in the system. Since all the variables are non-negative, (5.11) implies $0 \leq \tau^l_{ij,t} \leq \bar{\tau}^l_{ij}, \quad \forall t, \forall i,j \in S(i), \forall l$. Furthermore, since transmissions involve losses, the program will not choose to have power flowing in both directions at once, that is, only one of $\sum_l^{\ell(i,j)} \tau^l_{ij,t}$ or $\sum_l^{\ell(j,i)} \tau^l_{ji,t}$ will be strictly positive.

Availability constraints. The plant availability restrictions can be represented algebraically as follows:

$$\sum_{t=1}^{T} h_t g_{nt} \leq 8760 \alpha_n G_n, \quad \forall n, \tag{5.12}$$

where 8,760 is the number of hours in a year and α_n is the faction of hours that plan n is available for generation in the whole year.

For the subset of large "base" plants, we imposed additional restrictions:

$$g^b_{nt} \leq g^b_{ns}, \forall s, \text{ with } s = 1, ...S, \tag{5.13}$$

$$\sum_{s=1}^{S} h_s g^b_{ns} \leq 8760\alpha^b_n G^b_n, \tag{5.14}$$

where the superscript b indicates a "base" plant, S is the number of seasons in a year and h_s is the number of hours in season s. With this restriction, the allocation of the optimal maintenance schedule for base plants is over seasons and not over periods. Whereas a non-base plant could be off line for just two or three hours every day, planned maintenance of a base plant must affect availability in all periods within a season. Thus, maintenance of base plant must affect availability for complete days at a time.

Reserve constraints. These constraints require that plant capacities $\bar{g}_n$ be large enough to meet brief periods of extreme demands. Since the periods are brief, they do not require substantial additional energy production. We denote the transmission levels in such extreme demand periods by $\hat{\tau}_{ij,t}$ and modify the demand constraints (5.10) to become:

$$\sum_{n\in N(i)} \bar{g}_n + \sum_{j\in S(i)} \sum_{l}^{\ell(i,j)} \hat{\tau}^l_{ji,t} \geq \sum_{j\in S(i)} \sum_{l}^{\ell(i,j)} (1+\rho^l_{ij})\hat{\tau}^l_{ij,t} + (1+\Psi)d_{it}, \quad \forall i, t \tag{5.15}$$

where Ψ is the percentage increment in demand that would be covered in an emergency. The reported average load for all of Mexico in 1999 was 20,827 MW while the maximum load observed in that year was 29,580 MW.[12] Using our assumed load curves, such a difference between the annual average load and the maximum demand in a year corresponds to a 13% gap between the average demand for the peak season and the peak demand for the year. Hence, we set Ψ =13%.[13] While (5.15) is

[12]Source: "Prospectiva del sector electrico 2001-2010", Secretary of Energy, pp 66.

[13]For the year 2005, we use the same percentage increase to represent unexpected demand. According to the CFE, the projected average and maximum load for the year 2005 will be 41,159 and

required to hold for every period, in practice the constraint would not be binding in most periods. The plant capacities $\bar{g}_n$ are fixed for all periods. Reserve capacity sufficient to cover extraordinary demand levels at the peak would also more than cover extraordinary demand during the off-peak periods.

In addition to satisfying (5.15), the "virtual" extreme demand transmission levels $\hat{\tau}_{ji,t}$ must satisfy constraints analogous to (5.11):

$$\sum_{l}^{\ell(i,j)} \hat{\tau}^{l}_{ji,t} + \sum_{l}^{\ell(i,j)} \hat{\tau}^{l}_{ij,t} \leq \bar{\tau}_{ij}, \quad \forall t, \quad (i,j) \in L \tag{5.16}$$

where L is the set of transmission links in the system.

29,293 MW respectively. The ratio of these two figures is similar to that for the year 1999. Source: "Prospectiva del sector electrico 2001-2010", Secretary of Energy, pp 106.